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# IS DIGITAL TRADE AFFECTING CITY HOUSE PRICES? AN ARTIFICIAL INTELLIGENCE PERSPECTIVE

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**Abstract.** As a new engine of economic growth, digital trade is playing an increasingly pivotal role in shaping urban dynamics, including housing markets. This study investigated how the development of digital trade influenced city-level house prices in China. A digital trade index and an urban AI index were constructed using the entropy-TOPSIS method and text mining techniques, respectively. Empirical results showed that digital trade exerted a significant and robust positive linear effect on urban house prices, with no evidence of a nonlinear relationship. AI significantly strengthened this effect, acting as a positive moderator, while trade openness weakened it. Further heterogeneity analysis revealed that the impact of digital trade was more pronounced in coastal and high-income cities, yet AI integration substantially boosted this effect in non-coastal and low-income cities, suggesting strong potential for digital catch-up in underdeveloped regions. These findings indicated that digital trade, AI adoption, and regional characteristics jointly shape urban housing outcomes. Therefore, beyond advocating for stronger governmental support for digital infrastructure and emerging technologies, this study also highlighted the importance of enhancing AI capability and optimising trade openness strategies to ensure balanced urban development and sustainable real estate growth.

**Keywords:** China, digital trade, house prices, AI, trade openness.

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## 1. Introduction

House prices are one of the key indicators of an economy that have a profound impact both on the well-being of households and the stability and growth of national economies (Ding et al., 2023). The density of population and resources in cities contribute to the dynamics of the housing market, where the rise and fall of house prices can have repercussions towards a variety of areas, including consumer spending, financial markets, and urban development policies (Duranton & Puga, 2020). Consequently, the study of house prices changes has attracted much attention from policymakers and scholars. Given that housing is the largest household expenditure and is the centre of wealth accumulation, understanding house prices movements is crucial for sustainable economic development (Ansell, 2014; Ding et al., 2023a).

In recent years, the rapid development of the digital economy has become a key driver of global and regional economic transformation (Cong et al., 2024). The proliferation of digital technologies, including big data, cloud computing, and artificial intelligence (AI), has profoundly reshaped traditional production, communication, and trade models (Wang et al., 2024a). Central to this transformation is the rise of digital trade, which has effectively broken down geographical barriers, enabling the integration of global markets through digital platforms and e-commerce (Sikder & Rolfe, 2023). As a result, digital trade has not only accelerated the flow of goods and services but also facilitated the smooth transmission of information, reshaping competitive dynamics across industries and influencing the spatial distribution of economic activities (Chang et al., 2020). This far-reaching transformation has started to manifest in various sectors, notably in the real estate market. The increased flow of digital trade and the rapid evolution of urban infrastructure driven by digital technologies are having a tangible impact on city housing markets (Donner et al., 2018). In this context, the role of digital trade in shaping urban development patterns, particularly in relation to housing prices, warrants urgent and in-depth exploration.

The intersection of digital trade and housing markets creates an attractive area of research, as digital trade offers both opportunities and challenges to the structure of urban economies. On the one hand, empirical studies show that early stages of digital economy development can boost urban housing demand by promoting economic growth and attracting talent to cities (Cong et al., 2024; Howard et al., 2023). On the other hand, the rise of teleworking and digital platforms have reshaped commuting patterns and residential choices, reducing demand in central cities and increasing it in suburban or peripheral areas

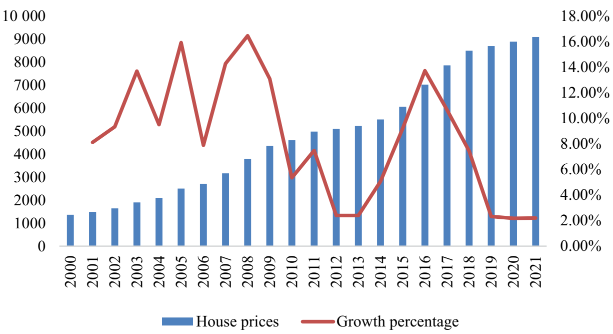


**Figure 1.** Average house prices and growth rates in Chinese cities (source: Compiled from housing transaction websites such as Anjuke, Fangtianxia, and Housing Price Market)

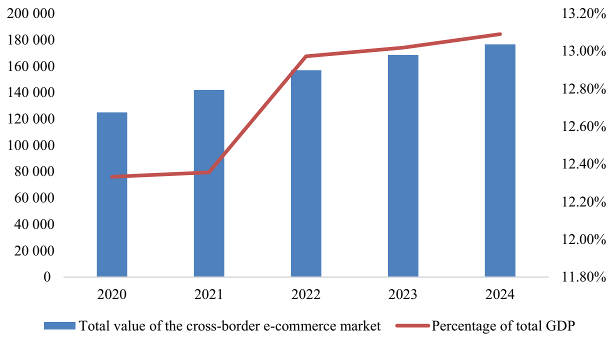


**Figure 2.** Total cross-border e-commerce market size and its proportion of China's actual GDP (source: Wang, 2025)

(Delventhal et al., 2023; Schulz et al., 2023; Tsuboi, 2022). Furthermore, online housing platforms themselves influence urban housing markets by concentrating information and potentially reinforcing spatial inequalities. These findings underscore the complexity and duality of digital trade's impacts on housing market dynamics.

Figure 1 presents the average house prices in Chinese cities from 2000 to 2022 along with their annual growth rates. It shows a general upward trend in house prices, rising from approximately 1,367 RMB per square meter in 2000 to over 8,600 RMB in 2022. The period from 2003 to 2008 witnessed significant spikes in growth—some exceeding 16%—driven by rapid urbanisation and housing demand. However, after 2010, price growth gradually stabilised, and in 2022, the market recorded a rare contraction of –4.87%, indicating the onset of structural adjustments within the real estate sector.

Figure 2 highlights the total market size of cross-border e-commerce from 2020 to 2024 and its share of China's actual GDP. The total value of cross-border e-commerce rose from 12.5 trillion RMB in 2020 to 17.66 trillion RMB in 2024, with its GDP share increasing from 12.33% to 13.09%. Cross-border e-commerce represents a core component of digital trade, underpinned by the integration of digital platforms, real-time logistics systems, and global payment infrastructures (Yang et al., 2023). The rationale for choosing cross-border e-commerce rather than digital trade as a general concept lies in its clarity, data availability, and concrete economic implications (Tanodomdej, 2023). It reflects the real and measurable dimension of digital trade that directly engages urban enterprises, consumers, and labour markets.

Moreover, the incorporation of AI adds a new dimension to this relationship. AI technology enhances the operational efficiency of digital trade platforms, optimises supply chain systems, and provides instantaneous market information, further reinforcing the transformative effects of digital trade (Ismaeil, 2024). It has had both direct and indirect effects on urban house prices by influencing labour markets, income distribution patterns, and regional competitiveness. For example, cities with advanced digital infrastructure and AI prowess may experience a rapid rise in housing demand, while those with less digital acceptance may face stagnation or decline.

Figure 3 illustrates the trends in the proportion of cross-border e-commerce transactions and real estate sales in GDP. Notably, from 2013 to 2020, the two series exhibit broadly consistent movements, suggesting a potential linkage between the development of digital trade and housing prices. This observation motivates the empirical investigation conducted in this study.

Given the growing importance of the digital economy and the centrality of housing markets to cities and national economies, it is both urgent and critical to explore the effects of digital trade on urban house prices. Despite the transformative power of digital trade, much of current research has focused on impacts to trade flows, industry structure, and consumer behaviour, while less attention has been paid to its impact on housing markets. For example, Cong et al. (2024) analysed the role of the digital economy on urban house prices, revealing that the digital economy has an upgrading effect on house prices through industrial upgrading and the urban environment. However, it should be noted that digital economy and digital trade are two different concepts. The digital economy is broader in scope, covering the comprehensive promotion of digital technology to various industries, while digital trade focuses on the cross-border flow of goods and services

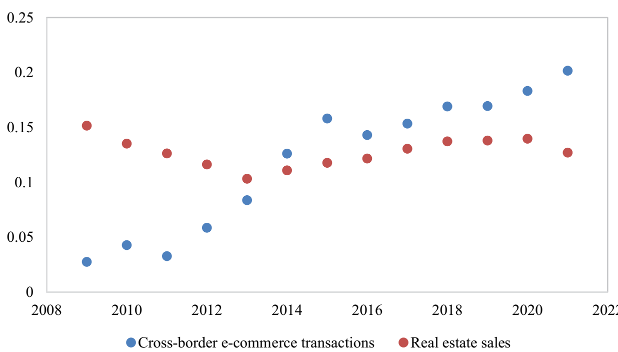


**Figure 3.** Trends in the share of cross-border e-commerce and real estate sales in GDP (source: Wang, 2025)

through digital technology, which is more trade-specific (Ma & Kang, 2025). Therefore, this study selected digital trade as the perspective to further refine the research direction towards the impact of digitalisation on urban house prices, which is unique in terms of conceptual clarity and research content.

Compared with the existing literature, this study was the first to take a new approach by explicitly setting the relationship between digital trade and urban house prices as the core of the study. Previous studies had either focused on the overall impact of the digital economy or the role of traditional trade on urban development; they rarely touched on the unique and dynamic emerging field of digital trade. This study developed a digital trade index to provide a new tool for quantifying its impact on the housing market. At the same time, AI was integrated into the analytical framework to construct an urban AI index to explore its mechanism effect on the relationship between digital trade and urban house prices, a perspective rarely found in existing literature. In addition, based on the heterogeneity of urban development, the sample was grouped by geographical location and economic development level to analyse the differences in the impact of digital trade across multiple dimensions. This analytical approach not only broadened the scope of the study but also provided a more detailed reference for the design of various urban policies.

In summary, the contributions of this study covered the following aspects: First, this study is the first to assess the relationship between digital trade and urban house prices, aiming to explore the impact of digital trade development on urban housing prices. Second, the study created a digital trade index and an urban AI index, providing scientific methodological support for quantifying the level of both. Third, the paper explored the moderating role of AI in the relationship between digital trade and urban house prices, thereby clarifying how specific digital technologies, notably AI, can amplify or mitigate the effects of digital trade. Importantly, this study maintained a clear distinction between digital trade, AI, and digital technology: while digital trade referred specifically to cross-border transactions enabled by digital platforms, AI represented a distinct subset of digital technologies with unique capacities to optimise trade logistics, match supply and demand, and influence urban labour dynamics. By isolating AI as a moderator rather than conflating it with the broader digital economy, this paper provided a more nuanced understanding of the mechanisms through which digital trade impacted the housing market. In addition, based on the characteristics of urban development and geographic location, this paper subdivided the full sample into multiple subsamples for heterogeneity analysis, aiming to distinguish the differences in the impact of digital trade on house prices for different city types. Therefore, this study not only enriches the theoretical framework for researching the interaction between digital trade and urban economies but also focuses on an issue that has received little attention in this field of research, namely, the impact of digital trade on the housing prices. This paper contributes to the existing research and lays the groundwork for future studies in this field. Compared with previous studies, this paper makes three distinct contributions. First, it deepens the understanding of the relationship between digital trade and urban house prices, an area that has received limited attention in existing literature. Second, it is the first to construct a comprehensive digital trade index and empirically quantify the impact of digital trade on urban housing markets using city-level panel data, thereby offering a novel and focused analytical framework. Third, the findings provide a solid empirical foundation for policymakers to optimise urban housing market strategies through the lens of digital trade development, rather than relying on the broader and often ambiguous concept of the digital economy. These contributions highlight the academic value and policy relevance of this study. By concentrating explicitly on the mechanisms through which digital trade influences housing markets, the paper opens a clear and focused path for future research on the urban impacts of digital globalisation.

## 2. Literature review and development of hypotheses

### 2.1. Literature review

The spatial mechanism underlying the impact of digital trade on urban house prices can be effectively interpreted through the lens of the New Economic Geography (NEG), originally proposed by Krugman (1991). NEG emphasises that economic activities tend to agglomerate in specific urban cores due to increasing returns to scale, reduced transportation and transaction costs, and greater market accessibility. This agglomeration leads to the emergence of "core-periphery" structures, wherein core cities concentrate capital, talent, and innovation capacity. In the context of digital trade, this spatial inequality is further intensified. Digital trade relies heavily on digital infrastructure, high-skilled labour, and technological capacity, which are factors that are disproportionately concentrated in first-tier or economically advanced cities (Li et al., 2024). This amplifies urban disparities, as digital trade lowers information and logistics costs, encourages firms to centralise research and development (R&D) and operational functions in core cities, and accelerates the inflow of high-income professionals. The resulting industrial clustering drives up housing demand, while rising incomes further strengthen purchasing power, leading to notable increases in house prices (He et al., 2021; Zhang et al., 2024). As the NEG theory suggests, the concentration of resources and competitiveness in these digital hubs not only leads to higher house prices within core cities, but also widens the price gap with peripheral urban areas. Therefore, NEG offers a valuable theoretical foundation for understanding how digital trade reinforces spatial polarisation and contributes to heterogeneous housing market outcomes across cities.

While a large body of literature has investigated the determinants of urban house prices, including macroeconomic factors, public infrastructure, environmental attributes, and demographic shifts, it often lacks a unified analytical framework. More importantly, little attention has been paid to how emerging structural forces such as digital trade may reshape the underlying logic of house prices formation. This review responds to these underexplored areas by synthesising relevant research across four key domains: (1) traditional influencing factors of house prices with a focus on supply and demand mechanisms; (2) the macro- and micro-level economic effects of digital trade; (3) the interaction between digital transformation and housing markets; and (4) AI-based approaches to real estate modelling and their role in exploring this evolving relationship.

1. Traditional influencing factors of house prices: Emphasising supply and demand

Urban house prices are fundamentally determined by the interplay between demand-side forces—such as income, population growth, and consumption preferences—and supply-side constraints including land availability and zoning regulations. For example, Wen and Goodman (2013) demonstrated a strong linkage between per capita disposable income and house prices in China, while Hilber and Vermeulen (2016) showed that house prices elasticity was significantly higher in supply-constrained regions of England. Other studies have addressed how transportation infrastructure (Duncan, 2011; Levkovich et al., 2016), school quality (Downes & Zabel, 2002), natural amenities (Wen et al., 2015), and demographic changes (Akbari & Aydede, 2012) contribute to price variation. However, these studies typically analyse static conditions or localised impacts, often neglecting the evolving role of digital connectivity and new forms of demand generated by digital trade and remote labour mobility.

2. Economic effects of digital trade: Macro and micro perspectives

Digital trade, defined as cross-border commerce conducted via digital platforms, has wide-reaching implications for regional development. At the macro level, it promotes manufacturing upgrading (Tang & Lan, 2024), boosts competitiveness through foreign direct investment and innovation (Ma & Kang, 2025), and enhances green total factor productivity across cities (Dai et al., 2025). Ji et al. (2023) found that digital trade also contributes to carbon emission reduction via industrial transformation and technological upgrading. At the micro level, digital trade reduces market entry barriers, stimulates entrepreneurial activity, and increases employment, especially in digitally mature cities (Zhao et al., 2025). These economic benefits may indirectly affect housing markets by shifting income distribution, changing population flows, and modifying the spatial distribution of demand for housing.

3. Digital trade and the housing market: An emerging linkage

Although still nascent, recent research has begun to explore the interaction between digital transformation and urban real estate dynamics. Zhang et al. (2024) found that a 0.1 unit increase in a city's digital economy index corresponds to a nearly 10% increase in housing costs, particularly in cities with resource mismatches. Their findings suggest that digital infrastructure and digital policy initiatives, such as the "Broadband China" strategy, may inadvertently raise house prices by concentrating on economic opportunities. Wang et al. (2024b) explored how digital industrial platforms reshaped housing construction through enhanced efficiency and customisation. Meanwhile, cross-border trade flows and the internationalisation of digital services have been found to alter income patterns and employment geographies (Jiang et al., 2022; Zhao & Gao, 2024), adding further complexity to housing market outcomes. Despite these insights, the literature still lacks an integrated framework for understanding how digital trade directly and indirectly influences urban housing systems.

4. AI-based approaches to real estate research: Enhancing modelling and insight

AI has revolutionised real estate valuation and prediction by improving accuracy and capturing non-linear patterns in housing data. Studies by Abidoye et al. (2019), Njo et al. (2025), and Alzain et al. (2022) showed that artificial neural networks (ANNs) outperform traditional econometric models in forecasting house prices across varied geographic contexts. Recent developments in explainable AI (XAI) methods, such as Shapley Additive Explanations (SHAP) and interpretable hedonic models, enable researchers to pinpoint the marginal effects of amenities, transport access, and environmental quality on house prices (Dou et al., 2023; Lee et al., 2025). These models also offer new pathways to explore how digital infrastructure, teleworking, and platform economies impact housing demand, particularly in rapidly digitising urban environments.

Collectively, these strands of literature underscore a growing yet still fragmented understanding of how digital trade reshapes the formation and distribution of urban house prices. While strong theoretical and empirical foundations exist regarding classical supply-demand interactions and the economic benefits of digital trade, few studies have integrated these domains. Therefore, this study contributed to the emerging field by developing an integrated analytical approach that connects digital trade and urban house prices dynamics.

## 2.2. Hypothesis development

The relationship between digital trade and urban house prices can be systematically analysed through the extended lens of spatial economics and the urban growth theory. While previous studies have mainly focused on macro-level trade and growth links, recent literature emphasised the role of digital transformation in reshaping spatial economic hierarchies (Moretti, 2012; Autor, 2019). As digital trade reduces information asymmetries, improves matching efficiency between firms and consumers, and allows cross-border services to flourish, it tends to reinforce agglomeration in urban centres equipped with advanced digital infrastructure and knowledge-intensive industries (Chen & Wang, 2019; Goldfarb & Tucker, 2019).

This digital agglomeration promotes wage increases and labour demand in high-productivity cities, intensifying housing demand and ultimately contributing to localised house price surges (Glaeser et al., 2005; Hilber & Vermeulen, 2016). The economic geography created by digital trade is not just a redistribution of commerce; it reshapes urban competitiveness and land value dynamics. Based on this logic, the following hypothesis was proposed:

H1a: Digital trade affects urban house prices.

H1b: Digital trade does not affect urban house prices.

Digital trade is closely intertwined with general-purpose technologies (GPTs), among which artificial intelligence (AI) has emerged as a particularly transformative force. As a GPT, AI is not confined to a single sector; instead, it penetrates multiple industries simultaneously, reshaping production processes, organizational models, and resource allocation mechanisms (Brynjolfsson & McAfee, 2017). Through enhanced information processing and predictive capabilities, AI improves the efficiency of capital and labor allocation, which in turn contributes to higher productivity and more efficient market functioning.

In the real estate sector, the application of AI is especially salient. On the one hand, AI-driven predictive analytics, automated valuation models, and demand forecasting systems can reduce informational asymmetries, improve pricing accuracy, and help align housing supply with genuine demand (Li & Azman, 2022; Alsahan & AlZaidan, 2024). These mechanisms may mitigate market volatility and contribute to the stabilization of housing prices. On the other hand, AI technologies also empower investors with more sophisticated tools for speculation, reduce transaction costs by accelerating information flows, and enhance investor confidence through greater transparency (Solomou & Sengupta, 2024). These dynamics can intensify demand pressures, amplify price fluctuations, and in some cases fuel housing market bubbles.

Taken together, these arguments suggest that AI has the potential to reshape the linkage between digital trade and housing markets in complex ways. Rather than exerting a purely positive or negative influence, AI may act as a moderator, conditioning the extent to which digital trade affects housing prices. Accordingly, we propose the following competing hypotheses:

H2a: AI moderates the relationship between digital trade and urban house prices.

H2b: AI does not moderate the relationship between digital trade and urban house prices.

Another critical contextual factor is trade openness, often measured by the ratio of total trade to GDP or the degree of cross-border digital services integration. Openness enhances productivity and economic spillovers by improving access to global markets, ideas, and technologies (Dollar & Kraay, 2004; Alesina et al., 2005). Cities that are more open to international digital trade tend to attract higher levels of foreign investment and talent inflow, which can fuel housing demand (Sturzenegger & Tommasi, 1998; Wang et al., 2021). However, these effects are far from uniform. Regional institutional quality, housing policy strictness, and infrastructure capacity all mediate how openness impacts local housing markets (Rodrik, 2007; Duran & Ozkan, 2015). Therefore, trade openness can serve as the mechanism linking digital trade to urban house prices, as hypothesised below:

H3a: Trade openness moderates the relationship between digital trade and urban house prices.

H3b: Trade openness does not moderate the relationship between digital trade and urban house prices.

During the initial adoption phase, cities may experience rapid demand growth as digital trade boosts employment, consumption, and services concentration. Yet as digital adoption reaches saturation, marginal economic gains diminish and policy regulation strengthens (Acemoglu & Restrepo, 2018). This causes threshold effects or turning points in how digital trade affects house prices, possibly even reversing trends in overburdened or supply-constrained cities (Ali & Song, 2022). Therefore, it is hypothesised that:

H4a: The effect of digital trade on urban house prices is non-linear.

H4b: The effect of digital trade on urban house prices is linear.

## 3. Methodology and data

### 3.1. Empirical methodology

Referring to the findings of Ding et al. (2023b) and Cong et al. (2025b), this study employed a two-way fixed-effects model, which aimed to control city and time fixed-effects differences, thus refining the analysis of the relationship between digital trade and city house prices. This model effectively attenuated intra- and inter-unit variability and enhanced the internal validity of the study. Logarithmic transformation was implemented for the dependent variable Hprice and some control variables (GDPc, POP, HUM, FAI, TER), while the other control variables (FDI) were treated by adding one and then taking the logarithm, aiming at shrinking the heteroskedasticity, shown in Equations (1) and (2). To explore the nonlinear effect of digital trade on city house prices, the squared term of trade was incorporated in Equations (3) and (4). If $\alpha_1$ and $\alpha_2$ had opposite signs and possessed significance, it implied a nonlinear association, as predicted by H4a. To verify this, a U-test was also implemented. If the U-test did not hold, H4a would be ruled out in favour of H4b, whereby the squared term of trade would be removed, and Equations (1) and (2) would be reapplied for estimation.

$$\text{Ln}\left(Hprice_{it}\right) = \alpha_0 + \alpha_1(Trade_{it}) + \mu_i + \nu_t + \varepsilon_{it}; \quad (1)$$

$$\text{Ln}\left(Hprice_{it}\right) = \alpha_0 + \alpha_1(Trade_{it}) + \alpha_2 Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (2)$$

$$\text{Ln}\left(Hprice_{it}\right) = \alpha_0 + \alpha_1(Trade_{it}) + \alpha_2\left(Trade\right)_{it}^2 + \mu_i + \nu_t + \varepsilon_{it}; \quad (3)$$

$$\text{Ln}\left(Hprice_{it}\right) = \alpha_0 + \alpha_1(Trade_{it}) + \alpha_2\left(Trade\right)_{it}^2 + \alpha_3 Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (4)$$

In Equation (2), $Z$ refers to the control variables, $\varepsilon_{it}$ is the error term, and $\alpha_1$, $\alpha_2$, and $\alpha_3$ are the coefficients to be estimated.

To investigate whether there was a moderating effect of AI and trade openness in the process of digital trade affecting urban house prices, Equations (5) to (8) were constructed. Equations (5) to (6) represented the moderating effect of AI in the process of digital trade affecting urban house prices, while Equations (7) to (8) represented the moderating effect of trade openness in the process of digital trade affecting urban house prices.

$$\text{Ln}\left(Hprice_{it}\right) = \beta_0 + \beta_1(Trade_{it}) + \beta_2\left(AI_{it}\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (5)$$

$$\text{Ln}\left(Hprice_{it}\right) = \beta_0 + \beta_1(Trade_{it}) + \beta_2\left(AI_{it}\right) + \beta_3\left(\left(AI_{it}\right)\times\left(Trade_{it}\right)\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (6)$$

$$\text{Ln}\left(Hprice_{it}\right) = \beta_0 + \beta_1(Trade_{it}) + \beta_2\left(Open_{it}\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (7)$$

$$\text{Ln}\left(Hprice_{it}\right) = \beta_0 + \beta_1(Trade_{it}) + \beta_2\left(Open_{it}\right) + \beta_3\left(\left(Open_{it}\right)\times\left(Trade_{it}\right)\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (8)$$

This study implemented several robustness tests aimed at verifying the credibility of the baseline regression results. Given the potentially undetected problems in the study design, the association between digital trade and city house prices revealed by the baseline regression may only be a spurious effect. Therefore, we performed a spurious effects test, following the steps of Ding et al. (2023c) by first removing the full sample data and then randomly assigning it to be re-estimated based on the adjusted dataset. If the effect of digital trade on city house prices in the baseline regression did exist, the false effects test should not show this causal chain. Subsequently, the sample period would be shortened from 2021 to 2019 to assess the role of digital trade on city house prices in-depth, while circumventing the potential interference of COVID-19 on house prices. Meanwhile, we employed an endogenous solution. Despite applying a panel fixed-effects regression model to reduce systematic bias, the endogeneity problem may remain and lead to instability in the relationship. To address this issue, we used an instrumental variables approach. The interaction term between the distance to the nearest seaport of each city and the logarithm of the number of Internet broadnd access ports in that city was selected as an instrumental variable, which met both homogeneity and correlation requirements. Distance to the nearest seaport had no direct effect on city house prices, while the number of Internet broadband access ports significantly contributed to the delopment of digital trade in the city. The interaction term had an indirect effect on city house prices by acting on digital trade and was, therefore, an appropriate instrumental variable to deal with the eogeneity problem.

In addition, the accuracy of the benchmark results was enhanced by the variable substitution strategy. Accordingly, we adopted principal component analysis to construct a digital trade index to replace the original digital trade development index obtained by the entropy method and reassess the role of digital trade on urban house prices. Finally, we implemented the robustness test using the system GMM method. To address the endogeneity issue, we incorporated the lagged terms of the explanatory variables as instrumental variables in the panel data model, as described in Equation (9).

$$\text{Ln}\left(Price_{i,t}\right) = \alpha_0 + \alpha_1\text{Ln}(Price_{i,t-1}) + \alpha_2 Trade_{i,t} + \beta Z_{i,t} + \varepsilon_{i,t}. \quad (9)$$

## 3.2. Dependent variable

Urban house prices (denoted as *Hprice*) refers to the market price of residential real estate in an urban area, which is usually reflected by the price of homes sold in the buying and selling market. Urban house prices are an important indicator of the state of a city's real estate market and is often used to analyse trends in house prices, the health of the real estate market, and the affordability of residents to buy homes. It is an important indicator of real estate market conditions in a city. This study referred to the research results of Ding et al. (2023b) and adopted the average sales price of houses in Chinese cities to measure urban house prices, which is a more comprehensive index to measure the level of house prices in Chinese cities. The data regarding prices was drawn from China's real estate information network organised by the country's State Information Centre.

## 3.3. Independent variable

This paper used the Urban Digital Trade Development Environment Index (denoted as *Dtrade*) as the core independent variable. Digital trade refers to cross-border or domestic commerce and trade activities enabled by the Internet and information and communication technology (ICT), covering all stages including online purchasing, marketing, transactions, logistics, and after-sales services. Unlike traditional measurement approaches that relied heavily on ICT exports or high-tech product exports (Suh & Roh, 2023; Liu et al., 2023), which may be biased and lack subnational granularity, this study adopted a multidimensional evaluation framework inspired by Cong et al. (2025c). Specifically, we employed the entropy-TOPSIS method to construct a composite index that reflects the development environment of digital trade at the city level. This method captures a city's comprehensive digital trade readiness and potential.

The revised indicator system integrates five key dimensions: Internet environment, logistics environment, policy support, trade development potential, and digital technol-

**Table 1.** Indicator system for the urban digital trade development index

| Tier 1 indicators | Tier 2 indicators | Tier 3 indicators | Direction of indicators |
|---|---|---|---|
| Urban digital trade development | Internet environment | Revenue from telecommunication services | + |
| | | Mobile phone subscribers at year-end | + |
| | | Number of Internet broadband access users<br>Long-distance optical cable density | + |
| | | Number of Internet domain names | + |
| | | Telecommunications revenue per capita | + |
| | Logistics environment | Number of employees in the transport, storage, and postal sector | + |
| | | Postal business revenue | + |
| | | Land area for logistics and warehousing | + |
| | Policy environment | Cross-border e-commerce pilot cities | + |
| | | Comprehensive experimental zones for cross-border e-commerce | + |
| | Trade development potential | Retail sales of social consumer goods | + |
| | | Number of new trading enterprises | + |
| | | Total amount of imports and exports | + |
| | | Number of employees in wholesale and retail trade | + |
| | | Total e-commerce sales | + |
| | | Total merchandise sales of wholesale and retail trade with limited capacity or above | + |
| | Digital technology innovation environment | Number of employees in scientific research and technical services | + |
| | | Number of employees in information transmission, computer services, and software industry | + |
| | | Software business revenue as a percentage of GDP | + |

ogy innovation. To better reflect the enabling conditions of digital trade, we expanded the set of third-tier indicators from the original 15 to include measures of digital infrastructure, e-commerce activity, and digital industry output. Representative indicators now cover, among others, long-distance optical cable density, number of Internet domain names, telecommunications revenue per capita, total e-commerce sales, and software business revenue as a share of GDP, in addition to broadband users, postal revenue, e-commerce pilot zones, total imports/exports, and ICT-related employment. These indicators were selected not only for their empirical relevance but also for their consistency with the growing body of literature evaluating digital trade development via enabling factors.

Numerous studies have adopted similar multidimensional frameworks that go beyond direct transaction data. For example, Ma et al. (2019) proposed an international digital trade index using infrastructure, payment systems, and regulatory indicators. Wen and Zhu (2024) measured digital trade by infrastructure, industrialisation, innovation, and policy environment dimensions. Tang and Lan (2024) constructed a comprehensive city-level digital trade capability index including broadband access, postal activity, and digital innovation. Wan et al. (2024) and Zhu and Zhou (2024) also used data on logistics, broadband penetration, and urban-level e-commerce capacity. Given the lack of official city-level digital trade volume data, this study aligns with established methodology by treating urban-level digital trade development as a latent construct reflected through key enabling conditions. The full list of indicators and their directionality is provided in Table 1.

## 3.4. Mechanism variables

AI is a branch of computer science that focuses on the R&D of systems and technologies that simulate and replicate human intelligence. Using machine learning, deep learning, natural language processing, computer vision, and more, AI enables computers to perform tasks that traditionally require human intelligence, such as language comprehension, image recognition, decision-making, and problem-solving. To accurately assess the level of AI development in cities, we utilised Python crawler technology to extract data from the "Business Scope" and "Company Name" columns on the Enterprise Search platform. Keywords such as "intelligent", "cloud" technologies", "cloud", "data", "IoT", "machine learning" and others were employed to conduct fuzzy matching queries[1]. The results were summarised by year and region to obtain the panel data of AI enterprises in each city. The logarithmic value

[1] The following keywords related to artificial intelligence were employed for conducting fuzzy matching queries: "intelligent", "artificial intelligence", "AI", "machine learning", "deep learning", "neural networks", "natural language processing", "computer vision", "reinforcement learning", "data science", "predictive analytics", "cognitive computing", "AI algorithms", "AI technologies", "AI models", "intelligent systems", "automation", "AI applications", and "AI-driven".

of the number of AI enterprises in that city during a given year was used as the basis for measuring the level of AI in that region.

Trade openness (denoted as *Open*) refers to the relaxation or even elimination of foreign trade restrictions in a country or region, enabling the free flow of goods, services, capital, and technology in the international market. It is often characterised by tariff reductions, the reduction of non-tariff barriers, the signing of free trade agreements, and the abolition of quotas. To accurately assess the degree of trade openness of a city, based on the study of Le et al. (2016), the proportion of total international trade to the city's GDP was used as a measure.

### 3.5. Control variables

To rigorously evaluate the impact of digital trade on urban house prices, this study introduced six control variables that had been widely acknowledged in the literature to influence property values (Leung, 2003; Turok & McGranahan, 2013; Yang et al., 2020; Yeap & Lean, 2020; Li et al., 2022; Cong et al., 2025a; Chen & Chen, 2023). The inclusion of these variables helped isolate the independent effect of digital trade. The variables and their expected relationships with house prices were as follows:

1. City economic development (*GDPc*): Measured by GDP per capita. Higher economic development typically leads to rising household income and investment demand, thereby positively influencing house prices.
2. Urban population (*POP*): Total resident population of the city. A larger population base generally increases housing demand and exerts upward pressure on house prices. However, excessive population without matching infrastructure may exert downward pressure in the long run due to congestion or declining quality of life.
3. Foreign direct investment (*FDI*): Captured by the annual inflow of FDI. FDI may improve employment and stimulate local economic growth, thus positively affecting house prices. Nonetheless, in certain industrial-heavy contexts, FDI can also increase pollution or crowd out domestic sectors, potentially having mixed effects.
4. Human capital (*HUM*): This variable is measured by the number of college students per 10,000 people in each city. A higher HUM value indicates a greater concentration of educated individuals, reflecting the city's capacity to generate and attract human capital. Human capital plays a crucial role in urban development by improving labour productivity, fostering innovation, and enhancing the overall competitiveness of cities.
5. Fixed asset investment (*FAI*): Total urban fixed asset investment. This investment improves infrastructure and public amenities, typically exerting a positive influence on house prices. However, overinvestment in non-productive sectors may lead to inefficiencies or housing oversupply, potentially leading to downward adjustments.
6. Tertiary industry proportion (*TER*): The share of the tertiary sector in GDP. A higher TER ratio suggests a more service-oriented, innovation-driven economy, which usually correlates with rising incomes and urban attractiveness, thus having a positive effect on house prices.

### 3.6. Data description

Based on data availability, the panel data of this study covered 198 cities in China from 2009 to 2021[2]. All data were from the China Urban Statistical Yearbook. Table 2 presents the descriptive statistics of the full sample. In addition, the multiple covariance test showed that the variance inflation factor (VIF) values of all variables were less than 5, and there was no multicollinearity[3]. Before proceeding with the baseline regressions, we examine the stationarity properties of the panel variables. The results of the LLC and IPS unit root tests are reported in Appendix Table A1.

**Table 2.** Descriptive analysis results of full sample

| Category | Variable name | Measurement | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|---|
| Dependent variable | *Hprice* | RMB | 6855.497 | 5731.103 | 2048 | 59695.5 |
| Independent variable | *Trade* | Index | 0.032107 | 0.5965082 | –0.301 | 7.93 |
| Moderating variables | *AI* | Index | 4.827144 | 1.781202 | 0.693147 | 11.03132 |
| | *Open* | Percentage | 0.1857731 | 0.2929901 | 2.72e-06 | 2.462339 |
| Control variables | *GDPc* | RMB | 54123.11 | 35086.59 | 4491 | 467749 |
| | *POP* | Per 10,000 | 472.0052 | 375.9483 | 48.76 | 3212.43 |
| | *FDI* | RMB 10,000 | 112389.2 | 247606.3 | 0 | 3100000 |
| | *HUM* | Percentage | 201.2828 | 224.0272 | 2 | 1294 |
| | *FAI* | RMB 10,000 | 2.25e+07 | 2.70e+07 | 48768 | 3.30e+08 |
| | *TER* | Percentage | 41.8547 | 10.5156 | 14.36 | 83.87 |

[2] List of cities are available on request.

[3] Multicollinearity test results are available on request.

## 4. Findings and discussion

### 4.1. Baseline results

Columns I to IV in Table 3 show the results of the baseline test. The control variables were included in columns I and III but not in columns II and IV. Columns I and II show that digital trade had a significant impact on urban house prices, verifying H1a. Columns III and IV passed the nonlinear U-test, indicating that digital trade had no nonlinear impact on urban house prices, confirming H4b. This means that the development of digital trade significantly raised urban house prices, and the nonlinear impact did not exist. Its development reduced transaction costs, broadened the market, promoted urban economic growth and enterprise competitiveness, drove the prosperity of productive industries and services, increased employment opportunities, raised residents' income, stimulated housing demand, and raised house prices. At the same time, digital trade accompanied by scientific and technological innovation attracted high-tech enterprises and high-end talents, promoted the upgrading of urban industries, enhanced overall competitiveness and attractiveness, and further raised the demand

**Table 3.** Baseline and robustness estimation results

| | Baseline check | | | | Robustness checks | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Fixed effect models | | | | Placebo | Shorten two years | Endogenous solution | | Variable replacement | SYS-GMM |
| | I | II | III | IV | V | VI | VII(2SLS 1) | VII(2SLS II) | VIII | IX |
| *Trade* | 0.0903*** | 0.0087*** | 0.1012*** | 0.0752*** | –1.0043 | 0.0096*** | | 0.0701*** | 0.0674*** | 0.1021*** |
| | (8.9087) | (3.453) | (5.0261) | (4.4756) | (–0.4002) | (5.7122) | | (6.5423) | (9.3652) | (6.8484) |
| (*Trade*)$^2$ | | | 0.0009 | 0.0020 | | | | | | |
| | | | (0.2277) | (0.6501) | | | | | | |
| *GDPc* | | 0.724*** | | 0.2739*** | 0.0213 | 0.3325*** | 0.0684* | 0.0232** | 0.2703*** | 0.2512*** |
| | | (4.014) | | (7.2405) | (0.6696) | (6.9152) | (1.8112) | (3.5128) | (7.8031) | (3.1693) |
| *POP* | | 0.102*** | | 0.0921*** | 0.0919*** | 0.1354*** | 0.8528*** | 0.0103*** | 0.1053*** | 03011*** |
| | | (5.543) | | (5.6371) | (2.5794) | (8.9713) | (11.7805) | (3.5128) | (6.9025) | (10.9651) |
| *FDI* | | 0.002 | | –0.0049 | –0.0002 | –0.0001 | 0.0041 | 0.0031*** | –0.0039 | –0.0122*** |
| | | (1.585) | | (–1.2527) | (–0.1400) | (–0.0130) | (0.3283) | (4.5124) | (–1.0080) | (–3.1964) |
| *HUM* | | 0.021*** | | 0.0136** | 1.1821 | –0.0048 | 0.2753*** | 0.0163* | –0.0078 | 0.0048 |
| | | (3.399) | | (2.0883) | (1.2251) | (–0.7271) | (6.4261) | (1.5173) | (–1.2155) | (1.3192) |
| FAI | | 0.124*** | | 0.0387*** | 0.1517 | 0.0284*** | 0.0173 | 0.0183** | 0.0356*** | 0.0114 |
| | | (4.156) | | (4.5984) | (0.9681) | (3.3218) | (1.2568) | (6.8213) | (4.2649) | (0.9182) |
| *TER* | | 0.1001*** | | 0.4885*** | 0.0152 | 0.4120*** | 0.0113* | 0.1232*** | 0.4704*** | 0.6910*** |
| | | (6.7751) | | (9.6841) | (1.2412) | (6.8421) | (1.8952) | (3.3224) | (8.5841) | (6.9812) |
| *Hprice* | | | | | | | | | | 0.1101*** |
| | | | | | | | | | | (5.2698) |
| *IV* | | | | | | | 0.0712*** | | | |
| | | | | | | | (4.1639) | | | |
| Constant | 8.3231*** | 6.725*** | 8.3744*** | 7.8205*** | –6.0031 | 2.0361*** | 8.2014*** | 0.8921** | 7.0147*** | |
| | (67.5206) | (23.9055) | (74.7068) | (19.2787) | (–0.2558) | (11.7588) | (18.4552) | (2.1761) | (19.8514) | |
| $R$-squared | 0.709 | 0.710 | 0.709 | 0.729 | 0.736 | 0.720 | | | 0.731 | |
| Sargan test | | | | | | | | | | 0.135 |
| AR(1) | | | | | | | | | | 0.000 |
| AR(2) | | | | | | | | | | 0.842 |
| DWH | | | | | | | 64.93 ($p$ = 0.000) | | | |
| Shea's Partial $R^2$ | | | | | | | 0.739 (*Trade*) | | | |
| | | | | | | | 0.718 (*Trade*$^2$) | | | |
| U Test | | | | | | | | | | |
| Extreme point | | | 7.5027 | | | | | | | |
| | | | Lower | Upper | | | | | | |
| Interval | | | –0.3 | 6.98 | | | | | | |
| Slope | | | 0.38 | 0.025 | | | | | | |

*Notes*: *t*-statistics in parenthesis, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Test: $H_1$: Inverse U-shape vs. $H_0$: Monotone or U-shape.

for real estate. Therefore, the impact of digital trade on house prices was linear, and house prices continued to rise with its development, with no obvious non-linear effect or critical point.

At the level of control variables, the level of economy, population size, and human capital accumulation, the scale of investment in fixed assets, and the rise of tertiary industry had obvious positive effects on urban house prices. First and foremost, economically developed cities tended to provide more capital and resources, which supported infrastructure construction and enhanced residents' income and purchasing power, which in turn stimulated real estate market demand and raises house prices. Li and Song (2016) pointed out that a high degree of economic development optimised housing market conditions, enhanced residents' purchasing power, and raised house prices. Second, the expansion of population size implied an increase in labour supply and market demand, which further stimulated innovation diversity and market dynamics, and intensified housing demand. Ali et al. (2020) argued that population growth was often accompanied by higher housing demand, especially in large cities, where population growth significantly drove housing market development. Furthermore, the growth of fixed asset investment, especially the upgrading of infrastructure and public facilities was found to improve the overall competitiveness and attractiveness of cities, attracting more firms and talent. Chen and Chen (2023) emphasised that fixed asset investment had a significant impact on house prices, boosting property values by facilitating the development of residential and commercial areas. The high quality of human capital was also an important driver of house prices increases. High-quality labour enhanced the city's innovation capacity, attracted high-end enterprises and industries, and expanded the demand for high-quality housing, driving up house prices (Haslam McKenzie & Rowley, 2013). Finally, the growth of the tertiary industry had a profound impact on urban house prices. Along with the development of the tertiary sector, especially in finance, technology, information, education, and healthcare, the city's service industry and quality of life improved, further promoting the prosperity of the housing market.

## 4.2. Robustness results

Columns V through VIII of Table 3 show the results of the robustness tests of the baseline model. Item V reveals that the placebo test effect was insignificant and far from the baseline regression results, verifying that the baseline results were true and did not stem from a placebo effect. In item VI, the results remained significant after shortening the sample period, indicating that the baseline results were robust and effectively circumvented the effect of COVID-19. Meanwhile, the two-stage least squares method was used to address the potential endogeneity issue, with a DWH test statistic as high as 63.29, rejecting the original hypothesis of exogenous explanatory variables at the 1% significance level. The instrumental variables also did not show weak instrumentality problems, with an $R^2$ value of about 0.1. In summary, this assessment confirmed that digital trade had a linear contribution to urban house prices, again validating the robustness of the benchmark model. Item VIII was assessed using the digital trade index constructed by principal component analysis, which demonstrated the linear positive correlation between digital trade and city house prices, further reinforcing the reliability of the benchmark results. Item IX, the systematic GMM estimation results in column IX were consistent with the benchmark regression results.

## 4.3. Mechanism effect analysis

To explore the mechanisms through which digital trade influenced urban house prices, this study introduced two moderating variables: AI and trade openness. Table 4 presents the estimation results of these interaction effects, offering deeper insights into the channels through which digital trade impacts the real estate market. Columns I and II of Table 4 examine the moderating effect of AI. In column I, the standalone coefficient of AI was found to be significantly positive, indicating that cities with higher levels of AI development tended to exhibit higher house prices. Column II further revealed that the interaction term between digital trade and AI (*Trade*AI*) was also positive and statistically significant. This confirmed Hypothesis H2a, suggesting that AI amplified the positive effect of digital trade on urban house prices. This finding was consistent with existing research that highlighted how AI adoption enhanced productivity, reduced information asymmetries, and improved resource allocation (Ahmad et al., 2021; Mishra et al., 2022). Cities that were more AI-intensive have also been found to be better equipped to integrate digital trade mechanisms across sectors, accelerating industrial transformation and attracting high-income professionals (Zhao et al., 2024). In industries such as finance, logistics, and advanced manufacturing, AI-driven automation and analytics have enabled smarter decision-making and operational efficiency, resulting in enhanced firm performance and spatial economic shifts (Alzain et al., 2022; Njo et al., 2025). Moreover, AI fosters the formation of new industrial clusters in digitally capable cities, attracting both firms and skilled labour. This process stimulates localized demand for housing, especially in second-tier and emerging cities that offer cost advantages and policy incentives (Lee et al., 2025). The role of AI here is twofold: it not only strengthens the transmission mechanism of digital trade but also acts as a catalyst for decentralising growth from megacities to smaller urban hubs. These dynamics are increasingly visible in China's inland cities with high digital readiness, such as Chengdu or Hefei, where AI applications have spurred rapid industrial restructuring and corresponding surges in real estate demand.

Columns III and IV of Table 4 focus on trade openness as a moderating variable. Column III shows that trade openness itself had a significant negative relationship with city house prices, while Column IV shows that the inter-

**Table 4.** Mechanism effect results

| | AI | | Trade openness | |
|---|---|---|---|---|
| | I | II | III | IV |
| *Trade* | | 0.2096*** | | 0.1271*** |
| | | (4.3985) | | (7.8423) |
| *GDPc* | 0.1011*** | 0.1051*** | 0.2674*** | 0.2014*** |
| | (8.9654) | (6.4548) | (8.9864) | (8.2984) |
| *POP* | 0.0862*** | 0.0150 | 0.2068*** | 0.0829*** |
| | (5.6507) | (0.9098) | (9.9261) | (5.5837) |
| *FDI* | 0.0142*** | 0.0117*** | –0.0213*** | –0.0149*** |
| | (3.5602) | (3.4858) | (–5.9658) | (–4.9213) |
| *HUM* | –0.0217*** | –0.0236*** | –0.0088 | –0.0091 |
| | (–4.9564) | (–5.8411) | (–1.3301) | (–1.4465) |
| *FAI* | 0.0211** | 0.0017 | 0.0523*** | 0.0632*** |
| | (2.5305) | (0.2086) | (6.9451) | (8.9544) |
| *TER* | 0.2695*** | 0.2137*** | 0.5375*** | 0.4512*** |
| | (9.3502) | (8.9151) | (5.9841) | (6.0074) |
| *AI* | 0.0148*** | 0.0332** | | |
| | (5.1906) | (1.9731) | | |
| *AI*Trade* | | 0.0323*** | | |
| | | (7.6952) | | |
| *Open* | | | –0.1841*** | –0.1348*** |
| | | | (–5.4216) | (–3.9021) |
| *Open*Trade* | | | | –0.1089*** |
| | | | | (–5.5961) |
| Constant | 5.0608*** | 7.8242*** | 7.5149*** | 7.8407*** |
| | (20.6467) | (19.4145) | (18.5560) | (19.4562) |

*Note*: See notes in Table 3.

action term (*Trade*Open*) was also significantly negative. This finding supported Hypothesis H3a, suggesting that greater trade openness mitigated the upward pressure of digital trade on house prices. This phenomenon can be interpreted through the lens of economic decentralisation and labour mobility. As cities become more open to international trade, capital and talent increasingly flow to non-core, lower-cost cities, reducing congestion and overheating in traditional economic centres (Lévy, 2007; Jiang et al., 2022). Digital trade, when combined with open trade environments, enables industries to relocate operations to regions with better incentives or cost structures, thus redistributing economic activities more evenly (Wang et al., 2024b). This process reduces demand-side pressure in first-tier cities and contributes to more balanced regional development. Furthermore, trade openness fosters competition and introduces foreign firms into local markets, which may alter income distribution and investment preferences. Some studies have shown that openness can lead to capital outflows in specific sectors or even displace domestic enterprises, weakening local purchasing power (Ma & Kang, 2025). Consequently, the moderating effect of trade openness reflects a "diffusion effect", wherein the positive externalities of digital trade are spread across a broader spatial spectrum, leading to a flattening rather than a concentration of housing market impacts. The trend is further amplified by the rise of teleworking and remote digital service exports, which reduce the necessity of physical proximity to urban centres and allow professionals to relocate to affordable housing markets with good infrastructure (Schulz et al., 2023; Tsuboi, 2022). As such, openness, while critical for economic growth, may inadvertently suppress housing price inflation in high-tier cities by promoting interregional mobility and economic diffusion.

## 5. Heterogeneity analysis

To further investigate the differential impact of digital trade on urban house prices, this study conducted a heterogeneity analysis along two key dimensions: geographic location (coastal vs. non-coastal cities) and economic status (high-income vs. low-income cities). The motivation for distinguishing between coastal and non-coastal cities stemmed from China's pronounced regional development disparities[4]. Coastal cities are generally characterised by earlier market liberalisation, higher degrees of openness,

[4] A list of specific cities is available upon request.

stronger industrial bases, and better-developed digital infrastructure. They are also more integrated into global trade networks and benefit from favourable policy environments, all of which facilitate the development and transmission of digital trade. In contrast, non-coastal cities often lag behind in digital penetration, resource allocation, and connectivity to international markets. These structural differences may lead to varying capacities to absorb and translate the benefits of digital trade into local economic and housing market outcomes.

Similarly, income-level heterogeneity was introduced to capture how the economic foundation of a city affects the relationship between digital trade and house prices. High-income cities tend to have greater consumption capacity, higher levels of education and digital literacy, and a more robust digital economy ecosystem. These characteristics not only enhance the ability of residents to participate in digital trade but also attract high-quality labour and capital, which in turn increase housing demand and price levels. On the other hand, low-income cities may face constraints in accessing and utilising digital trade opportunities due to weaker infrastructure, limited economic activity, and reduced market responsiveness. The impact of digital trade in such contexts may be more muted or operate through different channels. By analysing these two dimensions of heterogeneity, this study aimed to reveal whether the influence of digital trade was inclusive across diverse city types or disproportionately concentrated in economically and geographically advantaged areas. This provided a more comprehensive understanding of the mechanisms at work and helped inform region-specific housing and digital development policies.

## 5.1. Geographical heterogeneity

As can be observed from Table 5, the impact of digital trade on house prices in coastal cities was significantly greater than that in non-coastal cities. This phenomenon was closely related to the economic openness, trade foundation, and overall development level of coastal cities. In coastal cities, the trade variable showed a significant positive effect in all models, revealing the strong driving force of digital trade on house prices. This effect may be attributed to the more complete trade facilities, higher economic openness, stronger international market connectivity, and high attraction to capital and technology in coastal cities. In addition, the interaction factor (*AI*Trade*) between AI and digital trade also showed a significant impact in coastal cities, indicating that the application of AI technology can further amplify the driving effect of digital trade on house prices. This synergistic effect may be due to the first-mover advantage of coastal cities in the fields of AI and digital economy, which enabled them to more effectively use emerging technologies to raise house

**Table 5.** Heterogeneity analysis results – coastal cities vs non-coastal cities

| | Coastal cities | | | Non-coastal cities | | |
|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI |
| *Trade* | $0.0729^{***}$ | $0.2041^{**}$ | $0.1201^{***}$ | $0.1122^{***}$ | $0.2394^{***}$ | $0.1482^{***}$ |
| | (2.8952) | (2.0065) | (3.7964) | (7.9851) | (3.8932) | (6.3073) |
| *GDPc* | $0.5340^{***}$ | $0.2576^{***}$ | $0.4217^{***}$ | $0.0440^{*}$ | $0.0421^{*}$ | $0.0496^{**}$ |
| | (10.8481) | (4.3971) | (7.8608) | (1.7535) | (1.6563) | (1.9706) |
| *POP* | $0.2608^{***}$ | $0.1407^{***}$ | $0.2269^{***}$ | $0.0933^{**}$ | $0.1256^{***}$ | $0.0857^{*}$ |
| | (6.7026) | (3.2778) | (5.8497) | (2.0813) | (2.8062) | (1.9056) |
| *FDI* | –0.0260 | 0.0131 | $-0.0450^{***}$ | $0.0249^{***}$ | $0.0240^{***}$ | $0.0251^{***}$ |
| | (–1.6333) | (0.8623) | (–2.7903) | (6.5815) | (6.3726) | (6.6032) |
| *HUM* | –0.0206 | $-0.0396^{**}$ | –0.0069 | 0.0110 | 0.0099 | 0.0105 |
| | (–0.9478) | (–2.0095) | (–0.3248) | (1.1979) | (1.0883) | (1.1412) |
| *FAI* | –0.0327 | $-0.0845^{***}$ | 0.0364 | $0.0726^{***}$ | $0.0719^{***}$ | $0.0730^{***}$ |
| | (–1.3434) | (–3.7095) | (1.3146) | (9.5988) | (9.5932) | (9.6441) |
| *TER* | $0.9710^{***}$ | $0.4056^{***}$ | $1.0478^{***}$ | –0.0026 | 0.0020 | 0.0061 |
| | (8.9503) | (3.3420) | (9.7707) | (–0.0746) | (0.0563) | (0.1725) |
| *AI*Trade* | | $0.0255^{***}$ | | | $0.0385^{***}$ | |
| | | (2.8853) | | | (6.2171) | |
| *Open*Trade* | | | $-0.1166^{**}$ | | | $-0.0988^{*}$ |
| | | | (–2.4611) | | | (–1.8143) |
| Constant | $5.3130^{***}$ | $5.7233^{***}$ | $6.1041^{***}$ | $7.8446^{***}$ | $7.8588^{***}$ | $7.8365^{***}$ |
| | (3.0354) | (3.3210) | (3.4408) | (19.0132) | (19.1222) | (19.0047) |
| *R*-squared | 0.759 | 0.768 | 0.767 | 0.728 | 0.733 | 0.728 |

*Note*: See notes in Table 3.

prices. In general, coastal cities had a significant driving effect of digital trade on house prices due to their excellent economic environment, complete industrial structure, and population inflow advantages, while the integration of technological innovation and trade further intensified the growth trend of house prices.

In contrast, digital trade in non-coastal cities had a significant impact on house prices, but its degree was weaker than that of coastal cities. This may be related to the low economic openness, single industrial structure, and backward digital infrastructure of non-coastal cities. However, it is worth noting that the coefficient for the interaction term of AI and digital trade (*AI*Trade*) was higher in non-coastal cities, indicating that digital technology played a greater role in making up for the economic shortcomings of non-coastal cities. This may be because non-coastal cities had encountered bottlenecks in the traditional economy, whereby the combination of AI and digital trade had shown great potential under technological innovation, bringing positive impetus to house prices. In short, although non-coastal cities had weak economic and digital trade foundations, they showed strong latecomer advantages driven by AI and digital technology, laying the foundation for future economic development and house prices growth. The synergistic effect of the combination of digital trade and technology was particularly critical for non-coastal cities and was the main direction of future development.

## 5.2. Heterogeneity in economic development

As shown in Table 6, digital trade had a significant positive impact on house prices in both types of cities, but the magnitude and stability of this impact varied significantly. In high-income cities, the regression coefficient of Trade fluctuated between 0.1140 and 0.2491 across all models. It was consistently positive, indicating that the expansion of digital trade contributed to rising house prices. This may be attributed to the more developed digital infrastructure, better supporting services, and stronger consumption capacity in high-income cities, which enabled the development of digital trade to effectively stimulate urban economic activity and real estate demand. In low-income cities, however, the positive impact of digital trade on house prices was more pronounced. This may be because the digital economy was still in a rapid expansion phase in these cities, with stronger marginal effects, driving the emergence of new business models, population inflows, and investment expectations, thereby rapidly pushing up house prices. This structural driving effect was particularly evident in low-income cities with a higher proportion of traditional industries, leading to a sharp rise in house prices in the short term. Additionally, the interaction term between AI development level and Trade was positive and significant in high-income cities, indicating that advancements in AI technology further enhanced the positive impact of digital trade on house prices. This suggests that in

**Table 6.** Heterogeneity analysis results – high income cities vs low income cities

| | High income cities | | | Low income cities | | |
|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI |
| *Trade* | 0.1140*** | 0.2368*** | 0.2491*** | 0.0489*** | 0.1933*** | 0.1666*** |
| | (8.3015) | (3.6509) | (3.0026) | (4.2239) | (3.2894) | (3.9319) |
| *GDPc* | 0.0509 | 0.0521 | 0.0456 | 0.2810*** | 0.0687** | 0.2692*** |
| | (1.5507) | (1.5796) | (1.3866) | (11.7861) | (2.5716) | (11.1778) |
| *POP* | 0.1395*** | 0.1592*** | 0.1491*** | 0.1280*** | 0.0210 | 0.1221*** |
| | (2.8716) | (3.3194) | (3.0787) | (6.0298) | (0.9768) | (5.7532) |
| *FDI* | 0.0214*** | 0.0218*** | 0.0247** | –0.0098** | 0.0100** | –0.0001 |
| | (3.7463) | (3.8799) | (1.9970) | (–2.1479) | (2.2201) | (–0.0110) |
| *HUM* | 0.0687*** | 0.0702*** | 0.0720*** | 0.0504*** | 0.0195* | 0.0554*** |
| | (7.4242) | (7.7163) | (7.7268) | (4.3086) | (1.7440) | (4.7180) |
| *FAI* | –0.2033*** | –0.2137*** | –0.2214*** | 0.5445*** | 0.3025*** | 0.5431*** |
| | (–3.8114) | (–4.0703) | (–4.1553) | (17.9300) | (9.1806) | (17.9142) |
| *TER* | 0.1140*** | –0.2368*** | –0.6491*** | 0.1489*** | 0.3933*** | 1.3666*** |
| | (8.3015) | (–3.6509) | (–3.0026) | (4.2239) | (3.2894) | (3.9319) |
| *AI*Trade* | | 0.0321*** | | | –0.0492*** | |
| | | (5.5610) | | | (–3.2823) | |
| *Open*Trade* | | | 0.2803*** | | | –0.4709*** |
| | | | (3.5345) | | | (–3.5282) |
| Constant | 8.2799*** | 8.1134*** | 8.4031*** | 2.1465*** | 5.6685*** | 2.5641*** |
| | (15.8085) | (15.7010) | (14.6827) | (8.8427) | (16.9264) | (8.7933) |
| *R*-squared | 0.784 | 0.791 | 0.787 | 0.720 | 0.771 | 0.723 |

*Note*: See notes in Table 3.

high-income cities, AI further promoted the high-quality development of the digital economy by empowering digital platforms, optimising logistics chains, and improving transaction efficiency, thereby intensifying the activity of the real estate market.

Conversely, in low-income cities, this interaction term was negative and significant, indicating that AI development in such cities may not yet have formed an effective support system and may even have a substitution effect on traditional employment in the short term, thereby suppressing residents' expectations or ability to purchase housing. Similarly, the interaction term between trade openness and Trade exhibited the same heterogeneous characteristics as the AI moderating term. In high-income cities, the coefficient of this term was 0.2803 and significantly positive, indicating that the higher the degree of openness, the stronger the impact of digital trade on house prices. This may be attributed to factors such as institutional environments, foreign capital inflows, and improved efficiency in international resource allocation. In low-income cities, the interaction term was negative, indicating that higher openness weakened the positive impact of digital trade on house prices. This may be due to resource outflows or the displacement of local industries by foreign capital, thereby weakening the positive spillover effects of digital trade on the local economy. This suggests that urban policymakers should consider local digital infrastructure, openness levels, and AI technology maturity when formulating digital economic development and real estate regulation strategies to achieve inclusive economic growth.

## 6. Conclusions and policy implications

This paper empirically examined the impact of digital trade on urban house prices in 198 Chinese cities from 2009 to 2021 using a two-way fixed effects model and two-stage least squares method. The main findings can be summarised as follows:

First, digital trade had a significant and robust positive linear effect on urban house prices, with no evidence of a nonlinear relationship. Cities with higher levels of digital trade tended to experience stronger growth in house prices.

Second, AI significantly enhanced this effect. The moderating effect of AI implied that the more developed a city's AI ecosystem, the greater the amplification of digital trade's influence on house prices. Specifically, in cities where AI-related firms were more prevalent, digital trade was more effective in stimulating economic activity and real estate demand.

Third, trade openness played an opposite moderating role. While digital trade expanded urban economic potential, higher trade openness actually dampened its effect on house prices. This suggests that increased exposure to global markets might decentralise economic activity, relieve housing pressure in major cities, or lead to capital outflows.

Fourth, the heterogeneity analysis revealed that digital trade had a greater impact in coastal and high-income cities, however, AI integration significantly boosted its effect in non-coastal and low-income cities. This indicated a strong potential for digital and technological catch-up in underdeveloped regions, provided infrastructure and talent were adequately supported.

To effectively respond to these insights, policy and strategic responses should come not only from the government but also from enterprises, institutions, and the broader society. In light of the urgent need to stabilize housing prices and transform China's economic structure, the following multi-level recommendations are proposed:

First, the government should continue to promote digital trade by building digital infrastructure, providing financial and regulatory support, and fostering a business environment conducive to innovation. This will not only expand the dividends of digital trade but also serve as a strategic response to the prolonged downturn in the real estate market. Additionally, the government should implement measures to stabilize market confidence, such as regulating the real estate market to avoid excessive fluctuations in housing prices and ensure long-term market stability.

Second, the government should support the integration of AI into urban digital ecosystems, particularly in non-coastal and low-income cities. Investment in AI education, incentives for AI firms, and the cultivation of digital talent can create positive spillovers in housing demand by stimulating new employment opportunities and industrial clusters. The spread of AI technologies will drive the development of emerging industries, thereby providing new sources of demand for housing.

Third, to balance the negative moderating effect of trade openness, policies should focus on improving the quality of trade rather than merely increasing openness. This can be achieved by encouraging domestic value creation, supporting small and medium-sized digital exporters, and strengthening local supply chains to reduce over-dependence on foreign capital. This approach would help optimize China's economic structure, making it more self-sustaining and resilient to external shocks that could impact the housing market.

Fourth, enterprises should actively embrace digital transformation. By participating in digital trade platforms and adopting AI-driven technologies, companies can enhance operational efficiency, create new forms of employment, and attract high-quality talent. These structural changes can increase urban vitality and stimulate moderate yet sustainable housing demand, shifting away from an over-reliance on traditional real estate-driven economic models.

Fifth, it is important to reflect on the notion that rising house prices are inherently positive. From a consumer perspective, excessive price increases reduce affordability and may hinder inclusive urban development. Policymakers should prioritize housing price rationality through targeted housing regulations, land supply adjustments, and differentiated credit policies to prevent over-speculation while ensuring housing remains accessible to all.

In conclusion, this paper highlights the strategic role of digital trade in shaping urban housing dynamics and underscores that its benefits must be guided through balanced governance, inclusive digital policies, and cross-sector cooperation. A future-oriented housing market should not only capture digital opportunities but also align with social equity and economic sustainability goals, ensuring long-term stability for urban housing development.

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## Availability of data

Authors provide data on request.

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## Appendix

**Table A1.** Panel unit root test results

| | Variables | Hprices | Trade | GDPc | POP | FDI | HUM | FAI | TER |
|---|---|---|---|---|---|---|---|---|---|
| Level form | LLC | – | −1.012*** | −2.232** | −2.208*** | −1.032 | −1.212*** | −0.402 | −3.033*** |
| | IPS | −4.413*** | −8.524*** | −10.424*** | −2.326*** | −3.552 | −3.228*** | −2.222** | −3.553*** |
| 1st | LLC | – | −17.022*** | −6.453*** | −5.358*** | −8.022*** | −7.302*** | −11.079*** | −8.022*** |
| | IPS | −16.215*** | −18.122*** | −17.322*** | −13.699*** | −16.032*** | −9.073*** | −15.437*** | −16.032*** |

*Notes*: *** and ** indicate statistical significance at the 1% and 5% levels, respectively. "–" indicates that the statistic is not applicable or not reported. The Stata commands xtunitroot llc (for LLC) and xtunitroot ips (for IPS) were employed to estimate the results in this table.