ISSN: 1648-715X / eISSN: 1648-9179

INTERNATIONAL JOURNAL OF STRATEGIC PROPERTY MANAGEMENT

2024
Volume 28
Issue 1
Pages 45–63
https://doi.org/10.3846/ijspm.2024.21096

HOUSE PRICE VOLATILITY IN CHINA: A PERVASIVE PATTERN WITH GEOGRAPHIC DISPARITY

Xiaomeng LIU[1], Ziliang YU[2,*], Yang LI[3,**]

[1] *School of Finance, Tianjin University of Finance and Economics, Tianjin, China*
[2] *School of Finance, Nankai University, Tianjin, China*
[3] *School of Business, Singapore University of Social Sciences, Singapore, Singapore*

Article History:
- received 16 October 2023
- accepted 28 February 2024

Abstract. The booming real estate sector has been regarded as the "gray rhino" risk emerging in China over the past decade. Yet, the house price volatility per se has not been thoroughly examined. Filling the gap in the literature, this paper explores the house price volatility and its determinants for 70 large and medium-sized cities in China, using an extensive monthly data set from 2005 to 2019. We find evidence of significant geographical disparities in both the GARCH effects and the best-fitted volatility specification. Significant GARCH effects are found in 57 cities, among which 40% of cities show a persistent volatility pattern. We also find that both the house price volatility pattern and the associated volatility value are affected significantly by education and healthcare amenities.

Keywords: house price, geographic disparity, volatility, GARCH, model selection, China.

[*] Corresponding author. E-mail: *yuziliang@nankai.edu.cn*
[**] Corresponding author. E-mail: *liyang@suss.edu.sg*

1. Introduction

House is the most important asset class in almost every economy, accounting for approximately two-thirds of an average household's asset portfolio in the U.S. and China (Campbell & Cocco, 2003; Fang et al., 2016). House price volatility does not only carry important implications for consumption, investment choice, and the mortgage payment of a household at the microlevel (Mian & Sufi, 2015; Mian et al., 2015), but also play a vital role in the economy and business cycles at the macrolevel (Leamer, 2007; Piazzesi & Schneider, 2016). In particular, as pointed out by Miller and Peng (2006, p. 6), "...the greater the housing price volatility, the greater is the probability of negative home equity and more severe mortgage foreclosure losses". The 2007–2008 global financial crisis is a recent startling instance showing how house price volatility can evolve into a catastrophe for the whole financial system and the real economy. Despite the importance of house price volatility, related studies are limited and focus primarily on the U.S. housing market (e.g., Dolde & Tirtiroglu, 2002; Miles, 2008; Miller & Peng, 2006; Webb et al., 2016).

Since the Chinese welfare housing system of state-owned enterprises was abolished entirely in 1998 (Peng et al., 2020), the fraction of real estate investment to GDP rose from about 4% in 1997 to 15% in 2014. Nowadays, the real estate sector accounts for approximately 15% of total fixed investment, 20% of loans, and 15% of urban employment in China (Chivakul et al., 2015; Fang et al., 2016; Glaeser et al., 2017). The total commercial housing sales in China were about 13.37 trillion yuan (i.e., approximately 1.98 trillion U.S. dollars) in 2017, equivalent to 16.4% of the GDP (Liu & Xiong, 2018). Rogoff and Yang (2020) have revealed that the real estate sector contributes to as high as 29% of China's total GDP directly or indirectly. Considering the input-output linkages, the importance of the real estate sector in the Chinese economy is indeed much higher (Chan et al., 2016). Apparently, the real estate sector has grown into an important growth engine of the Chinese economy, with a rapid increase in house prices in China's major cities.

Recently, the Chinese government has implemented several restriction policies to curb soaring house prices. This fact has caused worldwide concerns that the potential price correction in the long-lasting booming Chinese real estate market could become another catastrophe resembling the U.S. subprime crisis, especially at the same time China's economic growth began to slow down.[1] Recent

[1] For example, International Monetary Fund (2011) lists "potential steep price correction in Chinese property markets" as one major risk in global recovery from the financial crisis; Bardhan et al. (2014) investigate Chinese housing market stability and its potential global contagion.

studies have investigated several important issues in China's housing markets, mainly focusing on the fundamental conditions and the bubble (Fang et al., 2016; Glaeser et al., 2017; Li et al., 2020; Ren et al., 2012; Rogoff & Yang, 2020; Wu et al., 2012, 2016) and intercity housing market spillovers (Gong et al., 2016b, 2020; Tsai & Chiang, 2019; Xu & Zhang, 2022; Yang et al., 2018, 2021, 2022, 2023). Little attention has been paid to the most direct measure of house market risks – volatility, even if there exist frequent discussions of the risks in the housing market and their potential influence on the financial system and real economy (Brandt & Rawski, 2008; Song & Xiong, 2018; Su et al., 2021; Yang et al., 2017, 2019).

House price volatility is crucial to understanding the real estate risk and forming efficient intervention policies and related risk management (Cotter et al., 2015; Begiazi & Katsiampa, 2019). In China, a few large state-owned banks (i.e., the Big Four–Agricultural Bank of China, Bank of China, China Construction Bank, and Industrial and Commercial Bank of China) dominate the financial system and issue a dominant portion of mortgages for nationwide home buyers (Yang et al., 2017; Song & Xiong, 2018); a handful listed real estate companies develop and sale a large portion of residential housing units across the country (Nong et al., 2023); and households own multiple properties outside the working city is a common phenomenon (Coulson & Tang, 2013; Yang et al., 2018, 2021). Geographic diversification is also a prevailing risk management strategy for investors and issuers of mortgage and mortgage-related securities (Cotter et al., 2015). Therefore, the disparities in geographic distribution and persistent patterns of house price volatility are crucial to quantitatively analyze the real estate risk, like calculating the value-at-risk (VaR) and implementing policy interventions. The existence of GARCH effect in house prices revealed in earlier studies for the developed markets (Dolde & Tirtiroglu, 2002; Hossain & Latif, 2009; Tsai et al., 2010; Wong et al., 2006) suggests that "…the conditional variance can be much larger than the unconditional variance, and hence there is a much greater risk of large losses during periods of high volatility" (Miles, 2011, p. 330). Additionally, the persistence of house price volatility reflects the housing market's stability (Holmes & Grimes, 2008) and influences government responses to exogenous shocks (Miles, 2011; Gil-Alana et al., 2014). Nevertheless, to our knowledge, Chinese house price volatility has not been thoroughly explored. This paper tries to fill the gap.

Specifically, in three aspects, we explore the distribution pattern and related determinants of the house price volatility in China's 70 large and medium-sized cities from 2005 to 2019. First, we examine whether there is an ARCH/GARCH effect for each 70 house return series using the McLeod-Li test (McLeod & Li, 1983). Our results show that 57 out of the 70 cities under examination present time-varying volatility. This rate is much higher than what has been detected in the U.S. metropolitan housing markets (i.e., 17%) (Miller & Peng, 2006). Second, we use a model selection approach to choose the best-fitted volatility model from a dozen candidate models for each of the above 57 series, considering both the asymmetry and persistence of time-varying volatility. Finally, we attempt to find the determinants of house price volatility by answering the questions of what fundamental factors mainly affect the volatility pattern and the volatility value respectively.[2]

Our contributions to related literature are achieved in two aspects. First, this study contributes to the growing body of literature on the Chinese housing market by thoroughly exploring whether there is an ARCH/GARCH effect for the house price return series and what is the best-fitted volatility model specification. The only two studies close to ours, to our knowledge, are Deng et al. (2018) and Germaschewski (2023). The former examined the hypothesis about the fundamentals and house price volatility in Beijing and Shanghai – China's two largest cities, using a bubble testing approach. The latter investigated the supply and demand factors that affect Chinese house price volatility at the national level, using a dynamic stochastic general equilibrium (DSGE) method. Our study differs from theirs in several dimensions. We thoroughly explore the house price volatility in China's 70 large and medium-sized cities, including Beijing and Shanghai, using the model selection approach. The nationwide sample cities also enable us to detect the geographical distribution of the cities with time-varying volatility and further investigate related determinants from dozens of suggested potential factors.

Second, our study contributes to the literature on the determinants of house price volatility by providing novel knowledge from the case of the Chinese real estate market. Earlier studies on house price volatility, as mentioned, primarily focus on the U.S. housing markets and related real estate investment trusts (REITs). Besides exploring the volatility spillovers (Cotter & Stevenson, 2006; Dolde & Tirtiroglu, 1997; Fei et al., 2010; Miao et al., 2011; Zhu et al., 2013; Zimmer, 2015), forecasting the volatility (Crawford & Fratantoni, 2003; Zhou & Kang, 2011), and examining the influence of volatility (Chang et al., 2012; Chen et al., 2010), a large body of literature explores the volatility behaviors and related determinants for the U.S. house prices (Dolde & Tirtiroglu, 2002; Miles, 2011; Miller & Peng, 2006; Webb et al., 2016; Zhou & Haurin, 2010). Similar topics have also been explored in other developed economies like Australia (Lee & Reed, 2014), Canada (Hossain & Latif, 2009), and the UK (Begiazi & Katsiampa, 2019).

However, unlike house transactions are dominated by second-hand house units in developed countries, newly-built housing units account for 64% of whole housing transactions in China (Wu et al., 2014; Yang et al., 2018). The soaring house price in China has also been accompanied by massive urbanization, rural-urban migration, and heavy participation and intervention from local and central governments (Liu & Xiong, 2018; Peng et al., 2020; Yang et al., 2021, 2022). These unique traits of the Chinese house market provide novel knowledge on the determinants of house price volatility. Our results present a much

[2] We will discuss all the GARCH model specifications considered in our analysis in Section 2.

more pervasive and persistent volatility pattern in China, compared to that of the metropolitan areas in the U.S. (Miller & Peng, 2006). More interestingly, we find evidence of both whether the house price volatility is persistent and what the associated value of volatility is significantly determined by fundamental-based factors.

The rest of this paper is organized as follows. The next section illustrates the data and empirical methodology; Section 3 interprets the empirical results; Section 4 further investigates significant determinants for the volatility pattern; Section 5 concludes the paper.

2. Data and methodology

2.1. Data

The data used in this study come from the *Price Indices for Real Estate in 70 Large- and Medium-Sized Cities* (70 City Indices), which are calculated and reported by the National Bureau of Statistics of China (NBSC) using an approach like the repeated sales method (Bai et al., 2014; Yang et al., 2018). Specifically, the local branch of NBSC survey team collects the monthly transaction information of the sample complexes; for each housing complex, it carries out a comparison between the monthly average price and that of the previous month. The city level index (previous month = 100) is calculated as a weighted average (by transaction volume) of price changes of all housing complexes in that month.

The 70 City Indices is the only official housing index for China's housing market. Before July 2005, NBSC released quarterly residential housing indices for 35 cities. These cities include four provincial-level municipalities (i.e., Beijing, Shanghai, Tianjin, and Chongqing), 26 province capital cities, and five vice-provincial-level cities (i.e., Shenzhen, Dalian, Qingdao, Ningbo, and Xiamen), which are the most economic developed with highest administrative levels (see Yang et al., 2018). Since July 2005, NBSC has extended the sample cities into 70 cities and released the indices at monthly frequency. These 70 cities, accounting for approximately 20% of Chinese prefectural-level-and-above cities, are the most economically and politically important cities covering all the area groups and the first-, second-, and mostly third-tier cities in China. Yang et al. (2018, 2022), using the same data source, have illustrated the details about the regional groups, tier groups, and other economic fundamentals for these cities.

As in earlier literature on China's housing market (Gong et al., 2016a; Yang et al., 2018, 2021), we focus on the newly built residential markets that carry the most significant weight in China's real estate market.[3] The original data of the 70 City Index for newly-built residential housing markets are collected from the CEIC database, and the sample period is from July 2005 to June 2019. We construct the monthly housing returns of each city as the logarithm percentage change of house prices, which is used interchangeably with the term (percentage) price changes.[4]

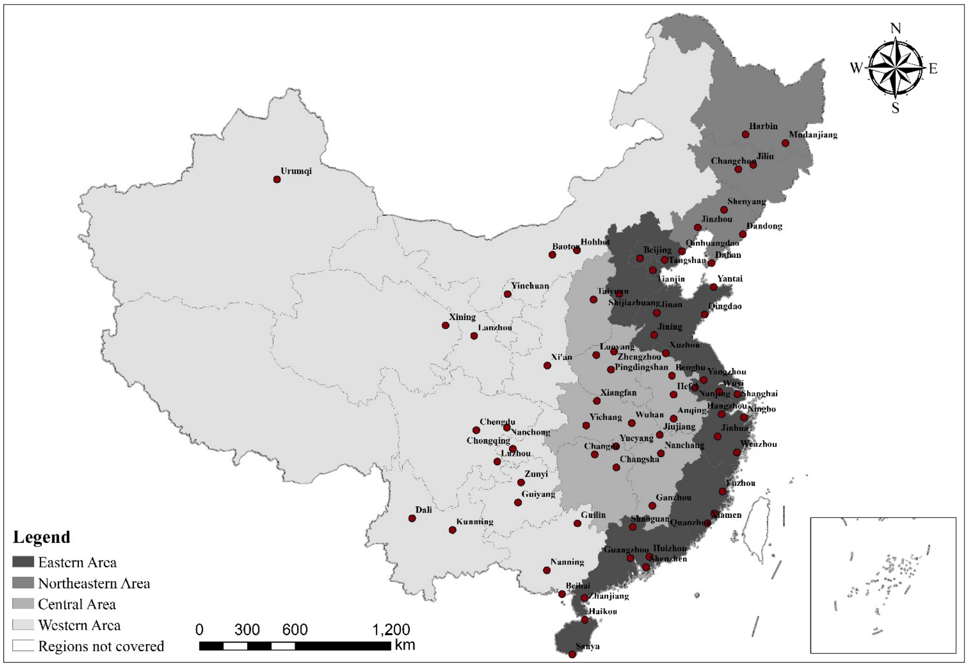

Figure 1. Geographical distribution of sample (70) cities

[3] According to the statistics from the Ministry of Housing and Urban-Rural Development of China, newly constructed units account for 64% of all private housing units sold at the national level (Wu et al., 2014).

[4] As NBSC reports, the 70 City Index has previous month = 100, with which we can calculate the monthly house price change (i.e., logarithm return) for each city simply as 100 × (log(value of current price index) – log(value of previous month price index)).

Table 1. Regional groups, and the summary statistics of each city's monthly housing return

City	Mean	Se	Min	Max	City	Mean	Se	Min	Max
Eastern Area (28 cities)					Central Area (16 cities)				
Beijing	0.5569	1.0255	–1.3085	4.7837	Taiyuan	0.3488	0.5597	–1.6129	2.0783
Tianjin	0.3587	0.8195	–1.1061	4.1142	Hefei	0.5425	1.2597	–1.2073	5.638
Shijiazhuang	0.5011	0.8447	–1.2073	4.3059	Nanchang	0.3968	0.701	–1.4099	2.3717
Shanghai	0.6166	1.1789	–1.4099	5.0693	Zhengzhou	0.5241	1.0811	–0.9041	7.3250
Nanjing	0.5526	1.1546	–1.3085	4.3059	Wuhan	0.5223	0.867	–1.8164	3.8259
Hangzhou	0.3223	1.2375	–4.7092	5.3541	Changsha	0.4430	0.8959	–1.6129	4.4017
Ningbo	0.2315	0.7214	–2.2246	1.9803	Bengbu	0.2224	0.7517	–1.9183	3.3435
Fuzhou	0.4554	1.0331	–1.8164	4.9742	Anqing	0.2089	0.5753	–1.4099	2.1761
Xiamen	0.6596	1.2437	–0.5013	5.3541	Jiujaing	0.3133	0.6127	–1.3085	1.8822
Jinan	0.4251	0.936	–1.3085	5.0693	Ganzhou	0.2435	0.6839	–1.6129	3.0529
Qingdao	0.2891	0.8562	–1.7146	4.5929	Luoyang	0.3685	0.6912	–1.2073	2.4693
Guangzhou	0.6637	0.9698	–1.4099	3.0529	Pingdingshan	0.2786	0.5365	–1.2073	1.3903
Shenzhen	0.7749	1.5616	–1.1061	6.9526	Yichang	0.3298	0.629	–1.0050	2.8587
Haikou	0.2829	0.7698	–1.0050	3.8259	Xiangfan	0.2679	0.6841	–1.2073	2.8587
Tangshan	0.2157	0.5900	–1.3085	2.8587	Yueyang	0.2287	0.6981	–1.5114	2.2739
Qinhuangdao	0.3672	0.7388	–1.6129	2.7615	Changde	0.2731	0.6390	–1.1061	2.6642
Wuxi	0.3710	1.2403	–1.0050	7.8811	Western Area (18 cities)				
Xuzhou	0.4611	0.7127	–1.5114	3.2467	Hohhot	0.3482	0.7994	–1.7146	2.8587
Wenzhou	–0.1048	0.8775	–5.0241	1.5873	Nanning	0.5526	1.1546	–1.3085	4.3059
Jinhua	0.2204	0.7696	–4.7092	1.8822	Chengdu	0.2758	0.6676	–1.2073	2.4693
Quanzhou	0.1138	0.5991	–1.7146	2.0783	Guiyang	0.4506	0.6841	–1.5114	4.1142
Yantai	0.3202	0.6140	–1.6129	2.8587	Kunming	0.3716	0.6749	–1.2073	2.8587
Jining	0.1584	0.6784	–1.4099	2.2739	Chongqing	0.3651	0.6234	–1.8164	1.7840
Huizhou	0.3373	0.8178	–1.7146	3.8259	Xi'an	0.5660	0.8905	–1.4099	6.0154
Zhanjiang	0.3042	0.6590	–1.6129	2.5668	Lanzhou	0.2554	0.4679	–0.8032	1.6857
Yangzhou	0.3696	0.6801	–1.8164	2.7615	Xining	0.3113	0.6199	–1.3085	2.6642
Shaoguan	0.2228	0.6966	–1.7146	2.2739	Yinchuan	0.2513	0.5119	–1.6129	1.6857
Sanya	0.2653	0.7728	–2.4293	3.6332	Urumqi	0.2833	0.5681	–1.4099	1.8822
Northeastern Area (8 cities)					Baotou	0.1753	0.6292	–1.7146	2.4693
Shenyang	0.3546	0.7290	–1.7146	2.0783	Guilin	0.2782	0.7495	–1.9183	2.8587
Dalian	0.3394	0.6632	–1.6129	1.7840	Beihai	0.3634	0.7223	–1.4099	3.1499
Changchun	0.3224	0.5598	–1.3085	1.8822	Luzhou	0.2464	0.6894	–1.9183	2.5668
Harbin	0.3581	0.6479	–1.3085	2.1761	Nanchong	0.2804	0.7169	–1.7146	2.5668
Dandong	0.2118	0.8581	–1.7146	5.1643	Zunyi	0.2951	0.5479	–1.1061	1.8822
Jinzhou	0.1584	0.6784	–1.4099	2.2739	Dali	0.3441	0.6947	–1.2073	2.7615
Jilin	0.2841	0.5906	–1.6129	2.2739					
Mudanjiang	0.2178	0.5562	–1.0050	2.0783					

Notes: This table reports the classification and summary statistics of the 70-city housing returns. Cities are classified into four regional groups: the Eastern, Central, Northeastern, and Western areas. The Eastern area consists of 10 provincial-level regions, including the Hebei province, Beijing municipality, Tianjin municipality, Shandong province, Jiangsu province, Shanghai municipality, Zhejiang province, Fujian province, Guangdong province, and Hainan province. The Central area consists of 6 provinces, i.e., Henan province, Hubei province, Hunan province, Jiangxi province, Anhui province, and Shanxi province. The Northeastern area consists of 3 provinces, including Liaoning province, Jilin province, and Heilongjiang province. The Western area consists of 12 provincial-level regions, i.e., the Inner Mongolia autonomous region, Shaanxi province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, Qinghai province, Tibet, Chongqing municipality, Sichuan province, Guizhou province, Yunnan province, and Guangxi Zhuang Autonomous Region. The "Se" in this table denotes standard error, Min is minimum, and Max denotes Maximum. Additionally, the sample period is from July 2005 to June 2019.

Table 1 summarizes the key statistics of the logarithm monthly housing returns for each of the 70 cities, and Figure 1 depicts the geographical distribution of the 70 cities. In Table 1, we group the cities by their geographical location, including the Eastern area, the Northeastern area, the Central area, and the Western area.[5] The Eastern area, located along the Southeastern coast, is the area with the highest developed level. Although there are some

[5] Please refer to Yang et al. (2018) for the details on such classification.

well-developed cities located in other areas, the overall level of development in these areas is relatively low to that of the Eastern area. The average monthly price change in the Eastern area is 0.3683 and the average change in the Northeastern area, the Central area, and the Western area are 0.2808, 0.3445, and 0.3341 respectively. This fact means that the Eastern area with the highest developed level also has a higher level of house price increase during our sample period. Note that all cities encounter an increase in house prices except Wenzhou, which reflects the overall trend of Chinese house prices in the last 20 years. For Wenzhou, the fall in house prices is due to its relatively soaring price before the sample period. Moreover, the average standard deviation of the Eastern area is also higher than that of other areas, which implies the house price of a well-developed area could be more volatile. To investigate the determinants for house price volatility and examine whether these factors are fundamental-based, we consider amenities of the community, amenities of consumption, demographic and economic factors, education and healthcare amenities, and weather and environmental factors. All the explanatory variables are collected from the CEIC database, and the detailed description and summary statistics are reported in the Appendix Tables A1 and A2.

2.2. Empirical methodology

To explore the house price volatility, we first examine whether there is heteroscedasticity in the house price series. Following Miller and Peng (2006) and Miles (2008), we use the McLeod-Li (1983) test to identify whether there is an ARCH/GARCH effect for every 70 cities' house price return series.

Specifically, let r_t be the monthly logarithm return of a house price for every 70 cities at time t. Throughout this analysis, μ_t is referred to as the mean equation for r_t, σ_t^2 is referred to as the volatility equation for r_t, and σ_t is the positive square root of σ_t^2. Before applying the McLeod and Li (1983) test, for ease in notation, let $a_t = r_t - \mu_t$ be the residuals of the mean equation. Here, a_t is referred to as the shock or innovation of the house price return at time t. The squared series a_t^2 is then used to check for conditional heteroscedasticity, which is also known as the ARCH effect.

The McLeod and Li (1983) test is to apply the usual Ljung-Box statistics $Q(m)$ to the $\{a_t^2\}$ series and the null hypothesis is that the first m lags of ACF of the a_t^2 series are zero. This test is equivalent to the usual F statistic for testing $\alpha_i = 0\,(i = 1,\ldots,m)$ in the linear regression:

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + a_m a_{t-m}^2 + e_t,\; t = m+1,\ldots,T,$$

where e_t denotes the error term; m is a pre-specified positive integer; T is the sample size. Specifically, the null hypothesis is H_0: $\alpha_1 = \ldots = \alpha_m = 0$. Let $SSR_0 = \sum_{t=m+1}^{T}\left(a_t^2 - \bar{\omega}\right)^2$, where $\bar{\omega} = (1/T)\sum_{t=1}^{T} a_t^2$ is the sample mean of a_t^2, and $SSR_1 = \sum_{t=m+1}^{T} \hat{e}_t^2$, where $\hat{e}_t$ is the least-square residual of the prior linear regression. Then we have:

$$F = \frac{\left(SSR_0 - SSR_1\right)/m}{SSR_1/\left(T - 2m - 1\right)}, \tag{1}$$

which is asymptotically distributed as a chi-squared distribution with m degrees of freedom under the null hypothesis. The decision is to reject the null hypothesis if $F > \chi_m^2(\alpha)$, where $\chi_m^2(\alpha)$ is the upper $100(1-\alpha)$th percentile of χ_m^2, or the p-value of F is less than α, type-I error. In this study, we choose the best-fitted ARMA model for each city from all ARMA specifications with a lag of no more than 12.[6] The Ljung-Box statistics give us strong ARCH effects based on the p-value which is close to zero.

Secondly, we employ various candidate specifications to distinguish patterns of volatility for cities with heteroscedasticity. As one of the most used volatility models, the GARCH model and its extensions are widely used in the research of volatility (Crawford & Fratantoni, 2003; Dolde & Tirtiroglu, 1997; Miles, 2008). Engle (1982) first describes the heteroscedasticity of time series by ARCH models, which breaks the assumption of homoscedasticity in ARMA models. As a generalization of the ARCH model, Bollerslev (1986) proposes the GARCH model to obtain a more parsimonious estimation. Following Bollerslev (1986), a series of extensions of the GARCH model is developed by researchers to improve the fitting and predictive power of volatility. In general, these extensions again define $a_t = r_t - \mu_t$ as the innovation at time t given the logarithm return r_t and its mean function μ_t. Then a_t follows a GARCH(m,s) model if:

$$a_t = \sigma_t \epsilon_t, \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2, \tag{2}$$

where $\{\epsilon_t\}$ is a sequence of *i.i.d* random variables with mean 0 and variance 1, $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$, and $\sum_{i=1}^{\max(m,s)}\left(\alpha_i + \beta_i\right) < 1$. The latter constraint on $\alpha_i + \beta_i$ implies that the unconditional variance of a_t is finite, whereas its conditional variance σ_t^2 evolves.

To overcome the weakness of the GARCH model in solving the problem of asymmetry of volatility (leverage effect), Nelson (1991) proposes the exponential GARCH (EGARCH) model, which allows for asymmetric effects between positive and negative asset returns responding to good news and bad news. An EGARCH(m,s) model can be written as:

$$\begin{aligned} a_t &= \sigma_t \epsilon_t, \ln\left(\sigma_t^2\right) = \alpha_0 + \frac{1 + \beta_1 B + \ldots + \beta_{s-1} B^{s-1}}{1 - \alpha_1 B - \ldots - \alpha_m B^m} g\left(\epsilon_{t-1}\right) \\ g\left(\epsilon_{t-1}\right) &= \begin{cases} \left(\theta + \gamma\right)\epsilon_t - \gamma E\left(\left|\epsilon_t\right|\right) & \text{if } \epsilon_t \geq 0 \\ \left(\theta - \gamma\right)\epsilon_t - \gamma E\left(\left|\epsilon_t\right|\right) & \text{if } \epsilon_t < 0 \end{cases} \end{aligned}, \tag{3}$$

where θ and γ are real constants, both ϵ_t and $\left|\epsilon_t\right| - E\left(\left|\epsilon_t\right|\right)$ are zero-mean *i.i.d.* sequences with continuous distributions; B is the back-shift (or lag) operator such that $Bg\left(\epsilon_t\right) = g\left(\epsilon_{t-1}\right)$, $1 + \beta_1 B + \ldots + \beta_{s-1} B^{s-1}$, and $1 - \alpha_1 B - \ldots - \alpha_m B^m$ are polynomials with zeros outside the unit circle and have no com-

[6] In our setting, the pool of candidates includes 169 candidates from ARMA (0,0) to ARMA (12,12).

mon factors. By outside the unit circle, we mean that the absolute values of the zeros are greater than 1.

In addition, Nelson (1990) introduces an integrated GARCH (IGARCH) model to fit a time series with persistent volatility. Unlike previous GARCH models, IGARCH modes are unit-root GARCH models with $\sum_{i=1}^{\max(m,s)}\left(\alpha_i+\beta_i\right)=1$. In our analysis, if the return series of a city picks IGARCH as its best-fitted model, it implies that a high persistence exists in the volatility of this city.

Moreover, Engle et al. (1987) introduce the ARCH-M model to contain the information on volatility in the mean equation, which explains the need for an excess return of holding a risky asset. In other words, the return of a series may depend on its volatility. The formulation of this model can be written as:

$$\begin{aligned} r_t &= \mu + c\sigma_t^2 + a_t,\ a_t = \sigma_t \epsilon_t; \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2, \end{aligned} \tag{4}$$

where μ and c are constants. The above equation indicates that there are serial correlations in the return series r_t. These serial correlations are introduced by those in the volatility process σ_t^2.

In this study, we choose GARCH, EGARCH, and IGARCH as candidate specifications for house price volatility as in Miles (2011) and Liu et al. (2018). We also consider the ARCH-M effect as an option for GARCH models following Miles (2008), which investigates the house price volatility in the U.S. and finds the ARCH-M effect in three-quarters of the states with heteroscedasticity.

Besides assessing the fit for each house price series, choosing an appropriate order is also critical for fitting a GARCH-framework model. The GARCH model and its extensions contain higher-order lagged information in a_{t-i}, which can be rewritten as the polynomial of σ_{t-i}^2 by iteration. And that is why lower-order GARCH models, outperform their higher-order counterparts. Hansen and Lunde (2005) find that GARCH(1,1) outperforms other models with a more complex specification. According to Alexander and Lazar (2006), GARCH(1,1) has stronger predictive power than other higher-order GARCH models. Since the mechanism of the GARCH model and empirical results mentioned above, we focus on the GARCH(1,1), EGARCH(1,1), GARCH-M(1,1), and EGARCH-M(1,1) for cities with heteroscedasticity and satisfying the constraint $\alpha_1+\beta_1<1$. If there is more than one specification, we select the best-fitted model according to the Schwarz Bayesian criterion (SBC). We assign IGARCH to cities when all specifications mentioned above cannot satisfy the restriction of convergence $\alpha_1+\beta_1<1$ or the sum approaching one, which implies a high level of persistence in the volatility.

We further use regression analysis to investigate the determinants for house price volatility and examine whether these factors are fundamental-based. As in Yang et al. (2018, 2021), we use the following simple two-way fixed effects model:

$$Volatility_{it} = \alpha_0 + \beta X_{it} + city + time + \varepsilon_{it}, \tag{5}$$

where $Volatility_{it}$ is the volatility pattern indicator with the values of 0, 1, and 2 for no-GARCH effect, GARCH effect with conventional GARCH(1,1) or EGARCH(1,1) specification, and GARCH effect with IGARCH specification for each of the 70 cities, respectively. Here, X_{it} is the vector of certain factors that may affect house price volatility, including amenities of the community, amenities of consumption, demographic and economic factors, education and healthcare amenities, and weather and environmental factors; the *city* is the city-fixed effects, the *time* denotes the time-fixed effects, and both two fixed effects are captured by city and year dummies. As usual, α_0 is the constant term and ε_{it} is the error term.

Note that when we test for the determinants of the volatility per se, $Volatility_{it}$ is then the extracted volatility series of the 57 cities with GARCH effect. In the following tests for the extracted volatility series as the dependent variable, we will conduct a two-way fixed effect regression with a robust standard error to control for potential heterogeneity and auto-correlation in the disturbances. Note also that for the $Volatility_{it}$ variable with the assigned value of 0, 1, and 2 to indicate the persistence of house price volatility, we use the ordinal regression.

3. Empirical results

3.1. The heteroscedasticity of volatility in house price

Table 2 reports the results of the McLeod-Li test for each of the 70 house price return series, and Figure 2 plots the geographical distribution of the cities with or without the GARCH effect. The results present three interesting patterns for house price volatility in China. First, the phenomenon of Chinese house prices with heteroscedasticity in volatility is so pervasive that approximately 81% (57 out of 70) of cities show heteroscedasticity in their volatility at a 5% significance level.[7] Miller and Peng (2006) find that about 17% (48 out of 277) of the metropolitan statistical areas in the U.S. have heteroscedasticity; while Miles (2008) finds this ratio is about 58% (29 out of 50) of cities for the U.S. state-level housing markets. Compared to these previous findings from the U.S., China's city-level housing markets are more likely to have heteroscedasticity in house prices.

Second, the results show a significant disparity in geographical distribution even if most of these housing return series have heteroscedasticity in volatility. The ratio of cities showing the GARCH effect in house price volatility is 75% for the Eastern area, 81% for the Central area, 89% for the Western area, and 88% for the Northeastern area, respectively. The Eastern area is the most developed area in

[7] In fact, there are 85.71% (60 of 70) cities show heteroscedasticity in their volatility at a 10% significant level. Following Miller and Peng (2006), our discussion is based on the 5% significant level.

China, where a housing market has emerged and matured since the housing system reform was launched in 1998 (Yang et al., 2021). Nevertheless, the Eastern area shows the lowest ratio of cities with the GARCH effect in house price volatility. Such a geographical disparity illustrates that it is less volatile in Chinese housing markets of developed regions, which is consistent with the relatively lower ratios of the GARCH effect in the U.S. MSAs or state-level housing markets (Miller & Peng, 2006; Miles, 2008). Our second finding indicates that the house price volatility may be not fully caused by the higher level of development.

Third, we can find that the highest and lowest hierarchy cities tend to be more likely with the GARCH effect in house price volatility and that the cities without GARCH effect are generally the relatively lower hierarchy cities in the city cluster.[8] Specifically, the middle hierarchy cities or lower hierarchy cities geographically close to the principal or vice-principal cities are less likely to have a GARCH effect on the house price volatility. For example, Tangshan, Shijiazhuang, and Tianjin, which are close to the principal city of Beijing in the *Jing-Jin-Ji* area, show no GARCH effect in house price volatility; this pattern also appears in the non-principal provincial capital cities like Fuzhou, Hefei, Hohhot, and Yinchuan.

The intuition for the above pattern is straightforward. The principal cities of China, which own a higher level of education and healthcare amenities and better job opportunities, have encountered the largest house price appreciation and the largest scale of urbanization and rural-urban migration during the past two decades (Garriga et al., 2021). As demonstrated by Yang et al. (2021), many migrants working in those principal cities of China are unable to meet the requirements to be qualified homeowners, or to afford a house due to the high house prices. As a result, the better choice for those migrants is to purchase a house in the lower hierarchy cities close to the principal cities. Even if a few migrants afford a home in the principal cities, they often need support from their parents by selling houses in their hometown cities (Wu et al., 2020). Therefore, house prices tend to be more volatile in these highest (lowest) hierarchy cities due to the housing demand (supply) from the migrants. As previously discussed, the clustering of house price volatility, also referred to as the GARCH effect, suggests an increased likelihood of significant price losses. Consequently, it is necessary for the government to prioritize the monitoring and regulation of house prices in both major metropolitan areas and lowest hierarchy cities (Miles, 2011).

3.2. The model specification in 70 large and medium-sized cities

Based on the previous McLeod-Li test shown in Table 2, we use the model-selection approach to select the best-fitted volatility model for each of the 57 house price returns along with the estimation of the key parameters in the volatility model (Alpha and Beta) reported in Table 3. Graphically, Figure 3 depicts the geographical distribution of different volatility model specifications.

Three interesting patterns appear in the volatility model specifications and associated geographical distribution. First, the IGARCH volatility model is dominant among all the selected best-fitted specifications.[9] Specifically, there are 23 out of the 57 cities with GARCH effect in the house price volatility chose the IGARCH model as the best-fitted volatility model; while 18 cities chose the GARCH(1,1) specification and the remaining 16 cities chose the EGARCH specification. According to Kim and Linton (2011), the IGARCH process persists in the volatility shocks. In other words, this fact means that the cities with IGARCH volatility specifications will be more long-lasting in price volatility.

Second, the IGARCH volatility model is also dominant among all the selected best-fitted specifications for the cities in the Eastern area. Specifically, the ratio of cities chose the IGARCH model is 62% (13 out of 21 cities) in the Eastern area, while the ratio is only 23% (3 out of 13 cities) for the Central area, 38% (6 out of 16 cities) for the Western area, and 14% (1 out of 7 cities) for the Northeastern area. We further observe that 12 out of those 13 cities that chose the IGARCH model in the Easter area are generally the higher hierarchy cities with higher economic development levels in that region, including Beijing, Shanghai, Nanjing, Hangzhou, Xiamen, Wuxi, Shenzhen, Changsha, Kunming, Xi'an, Lanzhou, Urumqi. This finding also echoes the disparity in city hierarchy groups.

The reason for the persistent volatility emerging in the Eastern area cities is the unique features of China's housing market. In China, the land is legislatively owned by the state and is controlled and supplied by the local governments. As demonstrated previously, the Chinese housing market is dominated by newly-built housing units and the land transfer fees of the new buildings account for approximately half of the fiscal revenue of local governments (Peng et al., 2020). Due to the important role of

[8] In China, the city cluster is the most important economic development strategy (The State Council of China, 2014; National Development and Reform Commission, 2016). In general, there are one principal city and dozens of lower hierarchy cities within a city cluster, and the economic development of the whole area is led by the principal city. In some regions, there are a few vice-principal cities or a few equal principal cities within a city cluster. The three most economically developed areas are *Jing-Jin-Ji*, *Yangtze River Delta*, and *Pearl River Delta*, which are all located in the Eastern area of China. Beijing is the principal city while Tianjin and Shijiazhuang are the two vice-principal cities of the *Jing-Jin-Ji* area; Shanghai is the principal city while Nanjing and Hangzhou are the two vice-principal cities of the *Yangtze River Delta area*; and Guangzhou and Shenzhen are the two principal cities of the *Pearl Reviser Delta* area (see The State Council of China, 2014).

[9] The dominance of IGARCH specification in modeling the housing price volatility echoes the dual roles of housing units in China as both a consumer good for living and an investment good for investing (Liu & Xiong, 2018). Bollerslev et al. (2016) also find that the behavior of daily housing price volatility is quite similar to that of other financial assets.

Table 2. Results of the McLeod-Li test

City	McLeod-Li	City	McLeod-Li
Eastern Area (28 cities)		Central Area (16 cities)	
Beijing	8.7682**	Taiyuan	103.0232***
Tianjin	7.2400	Hefei	2.8944
Shijiazhuang	11.9065	Nanchang	12.8454***
Shanghai	33.5964***	Zhengzhou	37.7236***
Nanjing	42.7081***	Wuhan	6.2160**
Hangzhou	42.7081***	Changsha	83.1556***
Ningbo	42.0185***	Bengbu	37.7292***
Fuzhou	1.4575	Anqing	68.7483***
Xiamen	21.3512***	Jiujiang	17.7275***
Jinan	8.2221**	Ganzhou	1.5232
Qingdao	15.7247***	Luoyang	9.1628***
Guangzhou	14.8507*	Pingdingshan	20.7816***
Shenzhen	59.9574***	Yichang	17.6111
Haikou	6.0058**	Xiangfan	31.0551***
Tangshan	3.3072*	Yueyang	57.7053***
Qinhuangdao	23.3504**	Changde	27.7018***
Wuxi	36.2319***	Western Area (18 cities)	
Xuzhou	36.7602***	Hohhot	0.1956
Wenzhou	3.7549*	Nanning	22.9512***
Jinhua	25.2014***	Chengdu	32.2475***
Quanzhou	27.1745***	Guiyang	32.2475***
Yantai	58.0617***	Kunming	92.6198***
Yangzhou	1.2360	Chongqing	38.9777***
Jining	21.6183***	Xi’an	33.5471***
Huizhou	40.4985***	Lanzhou	28.7433***
Zhanjiang	21.7509**	Xining	61.2354***
Shaoguan	58.6848***	Yinchuan	3.0907
Sanya	4.5706**	Urumqi	105.8988***
Northeastern Area (8 cities)		Baotou	88.5600***
Shenyang	36.5062***	Guilin	20.7608***
Dalian	52.026***	Beihai	41.3639***
Changchun	19.8030***	Luzhou	20.4618**
Harbin	0.2108	Nanchong	54.1236***
Dandong	64.3474***	Zunyi	18.0346***
Jinzhou	59.4372***	Dali	55.8562***
Jilin	106.4971***		
Mudanjiang	44.5897***		

Notes: *, **, and *** denote rejecting the null hypothesis of no GARCH effect in the volatility series at 10%, 5%, and 1% significant levels, respectively.

the real estate sector played in developing economy, the central and local governments have frequently intervened the housing markets, especially the largest ones such as the 12 cities mentioned above. We indeed do not model the government interventions (or other important external shocks) into the candidate volatility model specifications, because our main research purpose of this study is to identify whether there is a GARCH effect in the house price volatility and what is the best-fitted volatility model specification.[10] As theoretically pointed out by Han and Park (2014), the absence of external variables like government

[10] Such an issue does not affect our main results and contributions to the literature. Even if we ignore the government intervention or other possible extern shocks, our results clearly show that the GARCH effect is pervasive in our sample and different volatility model specifications such as the GARCH, EGARCH, and GARCH-M models appear in different cities and in different regions. In other words, the result of such a significant geographical disparity still holds.

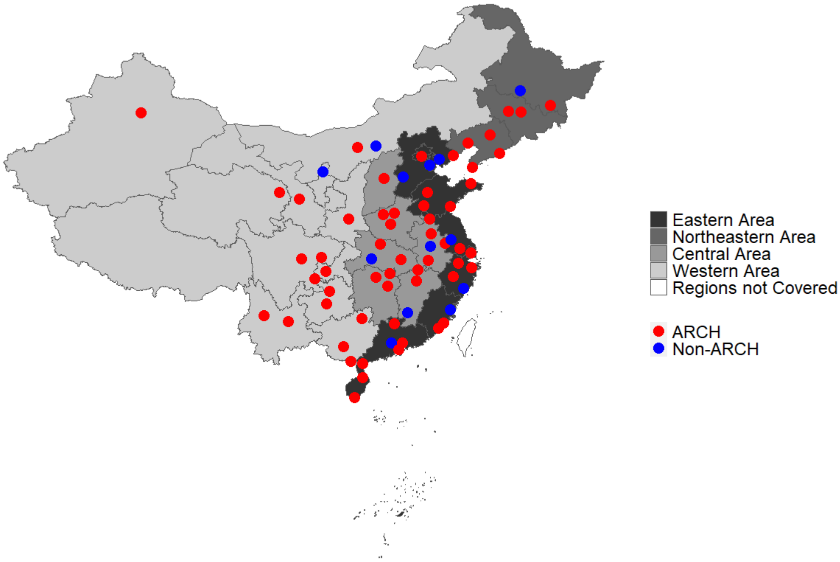

Figure 2. The geographical distribution of cities with versus without GARCH effects in house price volatility, 70 cities

Table 3. Volatility model specification for the 57 cities with GARCH effects

City	Alpha	Beta	Specification	City	Alpha	Beta	Specification
Eastern Area (21 cities)				Central Area (13 cities)			
Beijing	1.0000***	0.00	AR(0)-IGARCH(1,1)	Taiyuan	0.0103	0.9185***	AR(1)-GARCH(1,1)-M
	(45.4609)	NA			(1.2527)	(45.0853)	
Shanghai	0.8669***	0.1331	AR(0)-IGARCH(1,1)	Nanchang	0.1318	0.7662	AR(1)-EGARCH(1,1)
	(26.6191)	NA			(1.4603)	(6.6087)	
Nanjing	0.7718***	0.2282	AR(0)-IGARCH(1,1)	Zhengzhou	0.2809***	0.6598***	AR(1)-EGARCH(1,1)-M
	(16.2125)	NA			(19.7230)	(18.1150)	
Hangzhou	0.9486***	0.0514	AR(0)-IGARCH(1,1)	Wuhan	0.0706	0.8004***	AR(0)-EGARCH(1,1)
	(21.9451)	NA			(0.5203)	(14.6600)	
Ningbo	0.1139**	0.8628***	AR(1)-GARCH(1,1)	Changsha	0.9157***	0.0843	AR(0)-IGARCH(1,1)
	(2.3224)	(18.1003)			(15.7580)	NA	
Xiamen	0.623	0.377	AR(0)-IGARCH(1,1)	Bengbu	0.7002	0.2998	AR(0)-IGARCH(1,1)
	(5.7855)	NA			(8.2125)	NA	
Jinan	0.1438*	0.7675***	AR(1)-EGARCH(1,1)	Anqing	0.1324	0.8200***	AR(1)-EGARCH(1,1)-M
	(1.8264)	(9.0708)			(1.3201)	(16.1178)	
Qingdao	0.5974***	0.0792	AR(1)-GARCH(1,1)	Jiujiang	0.0950***	0.8651***	AR(1)-GARCH(1,1)-M
	(2.9867)	(0.8449)			(2.8191)	(24.1342)	
Shenzhen	0.7577***	0.2423	AR(0)-IGARCH(1,1)	Luoyang	0.1591**	0.7971***	AR(1)-GARCH(1,1)-M
	(14.8947)	NA			(1.9770)	(11.3461)	
Haikou	0.5606***	0.4394	AR(0)-IGARCH(1,1)	Pingdingshan	0.2791***	0.6605***	AR(0)-GARCH(1,1)-M
	(13.8023)	NA			(13.6170)	(16.3549)	
Qinhuangdao	0.0241*	0.9507***	AR(1)-GARCH(1,1)-M	Xiangfan	0.0902	0.8713***	AR(1)-EGARCH(1,1)
	(1.7567)	(54.6521)			(0.9885)	(16.8038)	
Wuxi	0.8803***	0.1197	AR(0)-IGARCH(1,1)	Yueyang	0.7543***	0.2457	AR(0)-IGARCH(1,1)
	(13.2405)	NA			(11.5413)	NA	
Xuzhou	0.6165***	0.3835	AR(0)-IGARCH(1,1)	Changde	0.1541*	0.8136***	AR(1)-GARCH(1,1)
	(9.1198)	NA			(1.8575)	(10.3054)	
Jinhua	0.8682	0.1318	AR(0)-IGARCH(1,1)	Western Area (16 cities)			
	(6.1085)	NA		Nanning	0.3311***	0.6584***	AR(1)-GARCH(1,1)
Quanzhou	0.0595	0.7965	AR(1)-EGARCH(1,1)		(3.0163)	(8.3871)	
	(0.6469)	(7.9191)		Chengdu	0.5628***	0.4011	AR(1)-GARCH(1,1)

End of Table 3

City	Alpha	Beta	Specification	City	Alpha	Beta	Specification
Yantai	0.0034	0.9127***	AR(1)-EGARCH(1,1)		(3.6682)	(4.0125)	
	(0.0348)	(21.8032)		Guiyang	0.0665	0.8733***	AR(0)-EGARCH(1,1)
Jining	0.6032	0.3968	AR(0)-IGARCH(1,1)		(0.6239)	(20.1685)	
	(8.0821)	NA		Kunming	0.8680***	0.1320	AR(0)-IGARCH(1,1)
Huizhou	0.0594	0.9231***	AR(0)-EGARCH(1,1)		(13.1678)	NA	
	(0.6906)	(28.6261)		Chongqing	0.0348	0.9067***	AR(0)-EGARCH(1,1)
Zhanjiang	0.8149***	0.1851	AR(0)-IGARCH(1,1)		(0.4239)	(26.4321)	
	(9.9787)	NA		Xi'an	0.8229***	0.1771	AR(0)-IGARCH(1,1)
Shaoguan	0.0516	0.8831***	AR(1)-EGARCH(1,1)		(15.6953)	NA	
	(0.5074)	(15.392)		Lanzhou	0.7510***	0.249	AR(0)-IGARCH(1,1)
Sanya	0.7568***	0.2432	AR(0)-IGARCH(1,1)		(10.1543)	NA	
	(18.6177)	NA		Xining	0.1205***	0.8538***	AR(1)-GARCH(1,1)-M
Northeastern Area (7 cities)					(3.0496)	(29.2665)	
Shenyang	0.0211	0.9612***	AR(1)-GARCH(1,1)-M	Urumqi	0.7256***	0.2744	AR(0)-IGARCH(1,1)
	(1.4552)	(59.2319)			(8.5720)	NA	
Dalian	0.1923***	0.7920***	AR(1)-GARCH(1,1)-M	Baotou	0.0286**	0.8670***	AR(1)-GARCH(1,1)-M
	(3.7674)	(25.0242)			(2.3601)	(23.2509)	
Changchun	0.1676	0.6097	AR(1)-EGARCH(1,1)	Guilin	0.1121	0.7461	AR(1)-EGARCH(1,1)
	(1.5017)	(7.3555)			(0.9937)	(8.2828)	
Dandong	0.0731	0.8739***	AR(1)-EGARCH(1,1)	Beihai	0.6477***	0.3523	AR(0)-IGARCH(1,1)
	(0.7971)	(18.9498)			(8.9963)	NA	
Jinzhou	0.2896***	0.6961***	AR(1)-GARCH(1,1)	Luzhou	0.0000	0.9601***	AR(1)-GARCH(1,1)-M
	(3.0208)	(10.0608)			(0.0000)	(60.6671)	
Jilin	0.6802	0.3198	AR(0)-IGARCH(1,1)	Nanchong	0.8492***	0.1508	AR(0)-IGARCH(1,1)
	(6.8506)	NA			(13.6559)	NA	
Mudanjiang	0.1751**	0.8053***	AR(1)-GARCH(1,1)	Zunyi	0.1061	0.8546***	AR(1)-EGARCH(1,1)
	(1.9739)	(10.4253)			(1.2265)	(17.2441)	
				Dali	0.2083***	0.7766***	AR(1)-GARCH(1,1)
					(3.1209)	(16.0155)	

Notes: t statistics are in parentheses. *, **, and *** denote the significant level of 10%, 5%, and 1%, respectively.

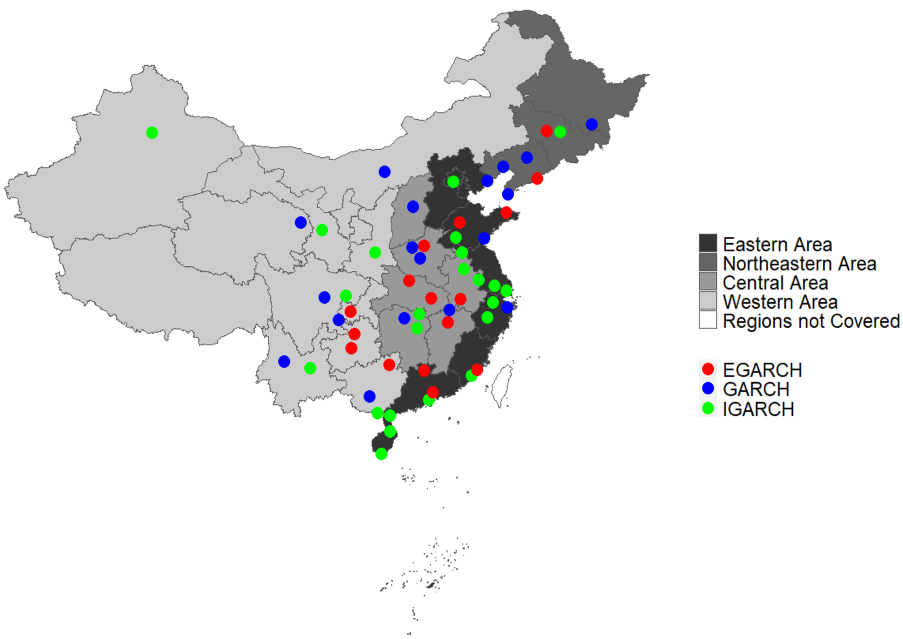

Figure 3. The geographical distribution of the selected best-fitted volatility model specifications, 57 cities

intervention in the volatility modeling might lead to the observation of the persistent IGARCH type of volatility. The shock that occurs in cities with GARCH effects, especially those with IGARCH effects, tends to be permanent (Gil-Alana et al., 2014). Therefore, the government should pay special attention to these IGARCH cities and control the severe fluctuations of the house prices.

Third, the other selected best-fitted volatility model specifications, particularly for that one with the GARCH in mean effects, also show the significant disparity in geographical distribution and among city hierarchy groups. Among the 12 cities that chose the GARCH in mean specifications, only Qinhuangdao is from the Eastern area; and the other 11 cities are relatively lower hierarchy cities with a less developed economy.

In summary, based on the results of the McLeod-Li test and the best-fitted volatility model selection, we observe two important and interesting facts: (1) the GARCH effect is quite pervasive in Chinese city-level housing markets; (2) geographical disparity and disparity among city hierarchy groups have been identified both in whether there is a GARCH effect for each city and in the best-fitted volatility model specifications.

4. Determinants of the house price volatility

This section uses the two-way fixed effects model to investigate what factors affect house price volatility in China. The basic regression described in Section 2 is given by: $Volatility_{it} = \alpha_0 + \beta X_{it} + city + time + \varepsilon_{it}$, where $Volatility_{it}$ is the volatility pattern indicator with the values of 0, 1, and 2 for no-GARCH effect, GARCH effect with conventional GARCH(1,1) or EGARCH(1,1) specification, and GARCH effect with IGARCH specification for each of the 70 cities, respectively. The vector X_{it} is the specific factor(s) that may affect house price volatility, including amenities of the community, amenities of consumption, demographic and economic factors, education and healthcare amenities, and weather and environmental factors. City-fixed and time-fixed effects are captured by the *city* and *time* variables as year dummies, respectively. The term α_0 is the constant intercept, and ε_{it} is the error term. Following Yang and Zhou (2013) and Yang et al. (2018), we next run a simple regression to investigate the statistically significant factors, and then conduct a multiple regression, as the detected significant variables may highly correlate with each other.

First, we examine the impact of four community amenities factors on the volatility pattern and the volatility value, because the low-cost and convenient transportation attracts people and firms to agglomerate in cities (Glaeser et al., 2001) and shorter commuting times may also increase demand for housing units located in city suburbs (Baum-Snow, 2007). In this analysis, we consider the area of paved roads, length of the highway, number of public vehicles, buses and trolley buses, and rental vehicles as four key factors. The regression results show that all variables except the number of public transportations significantly affect the volatility pattern (column A of Table 4) and that all variables except the length of the highway significantly affect the volatility value (column A of Table 5).

Second, we examine the impact of the amenities of consumption on the volatility pattern and its value respectively, which further identifies the effects of the scale of the catering trade, the number of star hotels, and the scale of the wholesale and retail trade. Glaeser et al. (2001) propose that cities are so attractive to live in large part because they are fantastic consumption centers. Nevertheless, our results illustrate that only the number of star hotels is significant at a 5% level for the volatility pattern (column B of Table 4).

Third, we examine the impact of demographic and economic factors on the volatility pattern and its value. Earlier studies on the intercity housing markets find that demographic and economic factors highly correlate with the spillover effects of house price volatility (Miao et al., 2011; Yang et al., 2018, 2021). We use the measure of population, population growth, unemployment rate, number of employees, local government income of tax, local government expenditure, government revenue, GDP growth, city GDP per capita, city GDP, and average wage as major proxies of demographic and economic factors. The regression results reveal that population growth, unemployment rate, local government revenue, and average wage significantly affect the volatility pattern (column C of Table 4), and that population growth, unemployment rate, local government income of tax, government revenue, city GDP per capita, and GDP growth are the significant variables in affecting the volatility value (column C of Table 5).

Fourth, we examine the impact of education and healthcare amenities, including the number of schools (primary, secondary, and higher education institutions), the corresponding numbers of teachers and enrolled students, and the number and size (measured by the number of beds) of hospitals and health centers. All these variables significantly affect the house price volatility pattern (column D of Table 4), and almost all of these variables also significantly affect the volatility value per se (column D of Table 5).

Fifth, we examine the impact of weather and environmental factors. We consider average temperature, precipitation, sunshine time, area of gardens and green spaces, and air quality measured by PM2.5 because air pollution has significantly affected Chinese migration interests (Qin & Zhu, 2018). The results reveal that precipitation and the area of gardens and green spaces significantly affect the volatility pattern (column E of Table 4), and that sunshine time and the area of gardens and green spaces are the two significant variables in affecting the volatility value (column E of Table 5).

Finally, we conduct a multiple regression for all the detected significant variables at a 5% significance level, to explore the relatively more important factors further as in Yang and Zhou (2013) and Yang et al. (2018). For the detected significant variables on the volatility pattern,

Table 4. Determinants of the house price volatility pattern

Variable	A	B	C	D	E	F
	Communication	Consumption	Demographic and economic	Education healthcare	Environment	Multiple regression
AP	0.3497***					2.7497***
	(82.627)					(376.6482)
HW	–0.4447***					0.3984
	(583.2901)					(–40.1634)
PT	0.2674					
	(–6.4165)					
RV	–0.5322***					–1.8729***
	(317.1808)					(82.0201)
CT		–0.1223				
		(–1.4341)				
SH		0.2158***				4.1095***
		(41.8169)				(1000.7777)
WR		0.1232*				
		(2.8051)				
PO			–0.4082			
			(–4.7184)			
PG			0.0394***			–0.1060
			(19.0286)			(–27.7122)
UR			–0.0954***			–0.1229
			(90.3914)			(–29.6435)
EP			–0.0813			
			(–21.7079)			
GT			–0.3553			
			(–12.9789)			
GE			–0.0007			
			(–21.6953)			
GR			0.8968***			–0.7454
			(16.7619)			(–9.4717)
GG			0.0037			
			(–18.4629)			
GC			–0.7040			
			(0.8587)			
CG			–0.2992			
			(–10.372)			
AW			0.4353**			1.1350
			(6.1888)			(–26.4875)
TH				0.6688***		4.5864***
				(59.7502)		(240.1033)
TS				–1.8808***		–10.2605***
				(219.2829)		(641.0008)
TP				0.626***		–2.9010
				(17.7251)		(2.4034)
SHI				–0.5118***		–0.0020
				(41.0884)		(–60.8557)
SP				0.5748***		–0.5652
				(40.6353)		(–60.6362)
SSS				0.3591***		0.8798
				(10.5984)		(–45.823)

End of Table 4

Variable	A Communication	B Consumption	C Demographic and economic	D Education healthcare	E Environment	F Multiple regression
BH				0.6400***		3.8079***
				(145.4777)		(373.1749)
HI				–0.2973***		–5.3652***
				(37.2649)		(469.6295)
PS				–0.4020***		1.9738***
				(186.7325)		(248.1672)
SS				0.7263***		3.4036***
				(62.2793)		(115.0172)
HP				–0.7801***		0.6285
				(400.4562)		(–19.2456)
AT					–0.0167	
					(2.3213)	
PC					0.1285***	0.0554
					(7.4737)	(–51.8562)
SUN					0.2274*	
					(3.4346)	
GRE					0.3180***	–0.8514***
					(53.7119)	(48.0372)
PM2.5					0.1128	
					(–6.9367)	
Observations	9228	6636	8586	9234	1063	2985
McFadden	0.0488	0.0100	0.0488	0.0594	0.0329	0.5481

Notes: Detailed information on the explanatory variables is given in Table A1 and A2 of the Appendix. *t* statistics are in parentheses. *, **, and *** denote the significant level of 10%, 5%, and 1%, respectively.

Table 5. Determinants of the house price volatility per se

Variable	A Communication	B Consumption	C Demographic and economic	D Education healthcare	E Environment	F Multiple regression
AP	11.6724***					11.8529***
	(5.5431)					(5.2311)
HW	–13.5352					
	(–1.6294)					
PT	12.8567***					23.5505***
	(4.979)					(8.1612)
RV	–13.3422***					–18.7669***
	(–5.4347)					(–6.9901)
CT		2.1344*				
		(1.7458)				
SH		–2.6201				
		(–1.1034)				
WR		1.9078				
		(0.4798)				
PO			–34.1308			
			(–0.9601)			
PG			2.264***			1.5705***
			(4.411)			(3.9175)
UR			2.5711***			–3.1869***
			(3.5571)			(–5.9917)

End of Table 5

Variable	A	B	C	D	E	F
	Communication	Consumption	Demographic and economic	Education healthcare	Environment	Multiple regression
EP			3.8664			
			(0.4732)			
GT			27.6386***			19.6767***
			(2.9722)			(3.7251)
GE			0.5026			
			(0.0723)			
GR			12.8359**			–12.4261*
			(2.3274)			(–1.817)
GG			0.1173			
			(0.9589)			
GC			147.7721***			10.0082
			(3.4777)			(1.3643)
CG			–181.8202***			–33.9906***
			(–4.0822)			(–3.8068)
AW			–47.0298***			–14.3256
			(–3.6145)			(–1.4985)
TH				14.0952*		
				(1.7397)		
TS				–30.6637***		–20.1015***
				(–2.6009)		(–4.2923)
TP				1.9558		
				(0.1545)		
SHI				17.7823**		4.1501
				(2.1776)		(1.0348)
SP				–10.0984**		–5.218
				(–2.2788)		(–1.0043)
SSS				–2.0633		
				(–0.8202)		
BH				–0.5882		
				(–0.1554)		
HI				–7.1199**		16.0609*
				(–1.965)		(1.7415)
PS				–8.0977***		8.6172***
				(–4.2215)		(2.9985)
SS				8.3814		
				(0.93)		
HP				–3.3134**		4.4967***
				(–2.051)		(4.2738)
AT					0.0231	
					(1.1182)	
PC					–0.146*	
					(–1.689)	
SUN					–1.0579***	0.3628
					(–3.02)	(0.5417)
GRE					1.0833**	0.2118
					(1.967)	(0.0889)
PM2.5					–0.122	
					(–0.3343)	
Observations	7482	5340	6936	7368	773	2609
R^2	0.0033	0.0002	0.0305	0.0066	0.0098	0.0896

Notes: Detail information on the explanatory variables is given in Table A1 and A2 of the Appendix. *t* statistics are in parentheses. *, **, and *** denote the significant level of 10%, 5%, and 1%, respectively.

the multiple regression results show that the significant determinants are amenities of communications, amenities of consumption, education and healthcare amenities, and weather and environmental factors (column F of Table 4). The detected significant variables on the volatility value now turn out to be amenities of communications, demographic and economic factors, and education and healthcare amenities (column F of Table 5). In other words, the multiple regression results indicate that both the house price volatility pattern and the volatility value per se are significantly affected by fundamentals-based factors.

Given our multiple regression results, education and healthcare amenities can impact house price volatility in various ways.[11] Column F of Table 4 shows that the number of teachers in higher institutes does increase the house price volatility significantly, the same applies to the number of primary schools and the number of secondary schools. The intuition behind these results is straightforward. The presence of a higher number of teachers in higher institutes can lead to neighborhood development and improvements in infrastructure and amenities. While this can initially increase the desirability of the area and drive up house prices, it can thus lead to higher volatility. Similarly, a higher number of primary and/or secondary schools often attract a large number of students from outside the local area. It can lead to a greater influx of students and consequently, a higher demand for housing in the surrounding area. This increased demand can drive up prices and lead to more volatility in the housing market. However, our findings suggest that the number of teachers in secondary schools and the number of high institutes will decrease the house price volatility. Unlike professors or faculty members, the teachers in secondary schools may not purchase a house in the neighborhood rather than choose to rent a local house initially. This diversification can reduce the overall volatility in the market. The establishment of high institutes often leads to the development of accompanying amenities and infrastructure, such as restaurants, retail stores, and public transportation. These improvements can increase the desirability of the area and make it more attractive for potential homeowners, supporting stable house prices and reducing volatility. Regarding the impact of amenities on house price volatility, we find that the number of beds in hospitals and healthcare centers significantly increases the volatility. The presence of well-equipped healthcare facilities, including hospitals and healthcare centers, can enhance the attractiveness of a location. Access to quality healthcare services is often a consideration for homebuyers, and areas with better healthcare infrastructure may experience higher demand, potentially increasing house prices and volatility.

[11] Here, we focus on the important factors: education and healthcare amenities. The detailed explanation of how other significant variables affect house price volatility can be required upon authors.

5. Conclusions

Our study is the first to investigate the house price volatility in Chinese 70 and medium and large-sized cities from 2005 to 2019. We document several novel findings of China's housing market. There exists a significant GARCH effect in 57 cities, among which 23 cities show a persistent volatility pattern. Interestingly, a significant geographical disparity appears both in the distribution of cities with or without the GARCH effect and in the distribution of the best-fitted volatility specification for each of the 57 cities. Furthermore, our results show that both the house price volatility pattern and the associated volatility value per se are mainly determined by fundamental factors, especially education and healthcare amenities.

Our findings shed light on China's house price volatility pattern, providing valuable information to policymakers. We find that there exists a high degree of volatility persistence in 23 cities, which could cause a disturbance in house prices and even induce a large scale of default in the mortgage. This fact should draw policymakers' attention to monitoring the house price patterns of those cities. Further research would be fruitful to examine whether and how the home-purchase restriction policies mitigate the volatility in China's house price return.

Acknowledgements

The authors would like to thank Professor Jian Yang for suggesting the basic idea of this paper and for his continuous assistance in its preparation.

Funding

This work was supported by the National Natural Science Foundations of China under Grant No. 72001119 & No. 72103105, the National Social Science Fund of China under Grant No. 23CJY036, and the Asia Research Center in Nankai University under Grant No. AS2114 & No. AS2301.

Author contributions

ZY was responsible for the design and development of the data analysis. XL was responsible for data collection and analysis. ZY, XL, and YL were responsible for data interpretation. ZY, XL, and YL wrote the first draft of the article.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Alexander, C., & Lazar, E. (2006). Normal mixture GARCH(1,1): Applications to exchange rate modelling. *Journal of Applied*

Econometrics, *21*(3), 307–336. https://doi.org/10.1002/jae.849

Brandt, L., & Rawski, T. G. (Eds.). (2008). *China's great economic transformation*. Cambridge University Press. https://doi.org/10.1017/CBO9780511754234

Bai, C., Li, Q., & Ouyang, M. (2014). Property taxes and home prices: A tale of two cities. *Journal of Econometrics*, *180*(1), 1–15. https://doi.org/10.1016/j.jeconom.2013.08.039

Bardhan, A., Edelstein, R. H., & Kroll, C. (2014). *Housing market stability in China and the potential for global contagion* (Fisher Center Working Papers). https://escholarship.org/content/qt6409t2kt/qt6409t2kt.pdf

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, *122*(2), 775–805. https://doi.org/10.1162/qjec.122.2.775

Begiazi, K., & Katsiampa, P. (2019). Modelling UK house prices with structural breaks and conditional variance analysis. *The Journal of Real Estate Finance and Economics*, *58*, 290–309. https://doi.org/10.2307/2951764

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T., Patton, A. J., & Wang, W. (2016). Daily house price indices: Construction, modeling, and longer-run predictions. *Journal of Applied Econometrics*, *31*(6), 1005–1025. https://doi.org/10.1002/jae.2471

Campbell, J. Y., & Cocco, J. F. (2003). Household risk management and optimal mortgage choice. *The Quarterly Journal of Economics*, *118*(4), 1449–1494. https://doi.org/10.1162/003355303322552847

Chan, S., Han, G., & Zhang, W. (2016). How strong are the linkages between real estate and other sectors in China? *Research in International Business and Finance*, *36*, 52–72. https://doi.org/10.1016/j.ribaf.2015.09.018

Chang, C. C., Huang, W. Y., & Shyu, S. D. (2012). Pricing mortgage insurance with asymmetric jump risk and default risk: Evidence in the US housing market. *The Journal of Real Estate Finance and Economics*, *45*, 846–868. https://doi.org/10.1007/s11146-011-9307-2

Chen, M. C., Chang, C. C., Lin, S. K., & Shyu, S. D. (2010). Estimation of housing price jump risks and their impact on the valuation of mortgage insurance contracts. *Journal of Risk and Insurance*, *77*(2), 399–422. https://doi.org/10.1111/j.1539-6975.2009.01326.x

Chivakul, M., Lam, M. W. W., Liu, X., Maliszewski, W., & Schipke, M. A. (2015). *Understanding residential real estate in China*. International Monetary Fund. https://doi.org/10.5089/9781484337066.001

Cotter, J., Gabriel, S., & Roll, R. (2015). Can housing risk be diversified? A cautionary tale from the housing boom and bust. *The Review of Financial Studies*, *28*(3), 913–936. https://doi.org/10.1093/rfs/hhu085

Cotter, J., & Stevenson, S. (2006). Multivariate modeling of daily REIT volatility. *The Journal of Real Estate Finance and Economics*, *32*, 305–325. https://doi.org/10.1007/s11146-006-6804-9

Coulson, N. E., & Tang, M. (2013). Institutional and demographic influences on the presence, scale and geographic scope of individual Chinese real estate investment. *Regional Science and Urban Economics*, *43*(2), 187–196. https://doi.org/10.1016/j.regsciurbeco.2012.12.001

Crawford, G. W., & Fratantoni, M. C. (2003). Assessing the forecasting performance of regime-switching, ARIMA and GARCH models of house prices. *Real Estate Economics*, *31*(2), 223–243. https://doi.org/10.1111/1540-6229.00064

Deng, Y., Girardin, E., & Joyeux, R. (2018). Fundamentals and the volatility of real estate prices in China: A sequential modelling strategy. *China Economic Review*, *48*, 205–222. https://doi.org/10.1016/j.chieco.2016.10.011

Dolde, W., & Tirtiroglu, D. (1997). Temporal and spatial information diffusion in real estate price changes and variances. *Real Estate Economics*, *25*(4), 539–565. https://doi.org/10.1111/1540-6229.00727

Dolde, W., & Tirtiroglu, D. (2002). Housing price volatility changes and their effects. *Real Estate Economics*, *30*(1), 41–66. https://doi.org/10.1111/1540-6229.00029

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, *50*(4), 987–1007. https://doi.org/10.2307/1912773

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. *Econometrica: Journal of the Econometric Society*, *55*(2), 391–407. https://doi.org/10.2307/1913242

Fang, H., Gu, Q., Xiong, W., & Zhou, L. A. (2016). Demystifying the Chinese housing boom. *NBER Macroeconomics Annual*, *30*(1), 105–166. https://doi.org/10.1086/685953

Fei, P., Ding, L., & Deng, Y. (2010). Correlation and volatility dynamics in REIT returns: Performance and portfolio considerations. *The Journal of Portfolio Management*, *36*(2), 113–125. https://doi.org/10.3905/JPM.2010.36.2.113

Garriga, C., Hedlund, A., Tang, Y., & Wang, P. (2021). Rural-urban migration and house prices in China. *Regional Science and Urban Economics*, *91*, Article 103613. https://doi.org/10.1016/j.regsciurbeco.2020.103613

Germaschewski, Y. (2023). House price volatility in China: Demand versus supply. *Economic Inquiry*, *61*(1), 199–220. https://doi.org/10.1111/ecin.13112

Gil-Alana, L. A., Barros, C., & Peypoch, N. (2014). Long memory and fractional integration in the housing price series of London and Paris. *Applied Economics*, *46*(27), 3377–3388. https://doi.org/10.1080/00036846.2014.929630

Glaeser, E., Huang, W., Ma, Y., & Shleifer, A. (2017). A real estate boom with Chinese characteristics. *Journal of Economic Perspectives*, *31*(1), 93–116. https://doi.org/10.1257/jep.31.1.93

Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, *1*(1), 27–50. https://doi.org/10.1093/jeg/1.1.27

Gong, Y., Boelhouwer, P., & de Haan, J. (2016a). Interurban house price gradient: Effect of urban hierarchy distance on house prices. *Urban Studies*, *53*(15), 3317–3335. https://doi.org/10.1177/0042098015608090

Gong, Y., de Haan, J., & Boelhouwer, P. (2020). Cross-city spillovers in Chinese housing markets: From a city network perspective. *Papers in Regional Science*, *99*(4), 1065–1085. https://doi.org/10.1111/pirs.12512

Gong, Y., Hu, J., & Boelhouwer, P. J. (2016b). Spatial interrelations of Chinese housing markets: Spatial causality, convergence and diffusion. *Regional Science and Urban Economics*, *59*, 103–117. https://doi.org/10.1016/j.regsciurbeco.2016.06.003

Han, H., & Park, J. Y. (2014). GARCH with omitted persistent covariate. *Economics Letters*, *124*(2), 248–254. https://doi.org/10.1016/j.econlet.2014.05.016

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, *20*(7), 873–889. https://doi.org/10.1002/jae.800

Holmes, M. J., & Grimes, A. (2008). Is there long-run convergence among regional house prices in the UK? *Urban Studies*, *45*(8), 1531–1544. https://doi.org/10.1177/0042098008091489

Hossain, B., & Latif, E. (2009). Determinants of housing price volatility in Canada: A dynamic analysis. *Applied Economics*, *41*(27), 3521–3531. https://doi.org/10.1080/00036840701522861

International Monetary Fund. (2011). *Global economic prospects and policy challenges*. https://www.imf.org/external/np/g20/pdf/070911.pdf

Kim, W., & Linton, O. (2011). Estimation of a semiparametric IGARCH(1,1) model. *Econometric Theory*, *27*(3), 639–661. https://doi.org/10.1017/S0266466610000435

Leamer, E. E. (2007). *Housing is the business cycle* (NBER Working Paper No. 13428). https://www.nber.org/system/files/working_papers/w13428/w13428.pdf

Lee, C. L., & Reed, R. G. (2014). The relationship between housing market intervention for first-time buyers and house price volatility. *Housing Studies*, *29*(8), 1073–1095. https://doi.org/10.1080/02673037.2014.927420

Li, J., Wei, Y., & Chiang, Y. H. (2020). Bubbles or cycles? Housing price dynamics in China's major cities. *International Journal of Strategic Property Management*, *24*(2), 90–101. https://doi.org/10.3846/ijspm.2019.11535

Liu, C., & Xiong, W. (2018). *China's real estate market* (NBER Working Paper No. 25297). https://doi.org/10.3386/w25297

McLeod, A. I., & Li, W. K. (1983). Diagnostic checking ARMA time series models using squared-residual autocorrelations. *Journal of Time Series Analysis*, *4*(4), 269–273. https://doi.org/10.1111/j.1467-9892.1983.tb00373.x

Mian, A., & Sufi, A. (2015). *Household debt and defaults from 2000 to 2010: Facts from credit bureau data* (Working Paper No. 21203). National Bureau of Economic Research. https://doi.org/10.3386/w21203

Mian, A., Sufi, A., & Trebbi, F. (2015). Foreclosures, house prices, and the real economy. *The Journal of Finance*, *70*(6), 2587–2634. https://doi.org/10.1111/jofi.12310

Miao, H., Ramchander, S., & Simpson, M. W. (2011). Return and volatility transmission in US housing markets. *Real Estate Economics*, *39*(4), 701–741. https://doi.org/10.1111/j.1540-6229.2010.00303.x

Miles, W. (2008). Volatility clustering in US home prices. *Journal of Real Estate Research*, *30*(1), 73–90. https://doi.org/10.1080/10835547.2008.12091211

Miles, W. (2011). Long-range dependence in US home price volatility. *The Journal of Real Estate Finance and Economics*, *42*, 329–347. https://doi.org/10.1007/s11146-009-9204-0

Miller, N., & Peng, L. (2006). Exploring metropolitan housing price volatility. *The Journal of Real Estate Finance and Economics*, *33*, 5–18. https://doi.org/10.1007/s11146-006-8271-8

National Development and Reform Commission. (2016). *The 13th Five-Year Plan for Economic and Social Development of the People's Republic of China*. https://en.ndrc.gov.cn/policies/202105/P020210527785800103339.pdf

Nelson, D. B. (1990). Stationarity and persistence in the GARCH(1,1) model. *Econometric Theory*, *6*(3), 318–334. https://doi.org/10.1017/S0266466600005296

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of The Econometric Society*, *59*(2), 347–370. https://doi.org/10.2307/2938260

Nong, H., Yu, Z., & Li, Y. (2023). *Is the gray rhino coming? Dynamic transmission of financial shocks between real estate companies and banks in China* (Working paper). Nankai University.

Peng, Z., Yu, Z., & Nong, H. (2020). Inter-type investment connectedness: A new perspective on China's booming real estate market. *Global Economic Review*, *49*(2), 186–204. https://doi.org/10.1080/1226508X.2020.1744465

Piazzesi, M., & Schneider, M. (2016). Housing and macroeconomics. *Handbook of Macroeconomics*, *2*, 1547–1640. https://doi.org/10.1016/bs.hesmac.2016.06.003

Qin, Y., & Zhu, H. (2018). Run away? Air pollution and emigration interests in China. *Journal of Population Economics*, *31*(1), 235–266. https://doi.org/10.1007/s00148-017-0653-0

Ren, Y., Xiong, C., & Yuan, Y. (2012). House price bubbles in China. *China Economic Review*, *23*(4), 786–800. https://doi.org/10.1016/j.chieco.2012.04.001

Rogoff, K. S., & Yang, Y. (2020). *Peak China housing* (Working Paper No. 27697). National Bureau of Economic Research. https://doi.org/10.3386/w27697

Song, Z., & Xiong, W. (2018). Risks in China's financial system. *Annual Review of Financial Economics*, *10*, 261–286. https://doi.org/10.1146/annurev-financial-110716-032402

Su, C. W., Cai, X. Y., Qin, M., Tao, R., & Umar, M. (2021). Can bank credit withstand falling house price in China? *International Review of Economics* & *Finance*, *71*, 257–267. https://doi.org/10.1016/j.iref.2020.09.013

The State Council of China. (2014). *National new-type urbanization plan*. https://english.www.gov.cn/policies/policy_watch/2014/08/23/content_281474983027472.htm

Tsai, I. C., Chen, M. C., & Ma, T. (2010). Modelling house price volatility states in the UK by switching ARCH models. *Applied Economics*, *42*(9), 1145–1153. https://doi.org/10.1080/00036840701721133

Tsai, I. C., & Chiang, S. H. (2019). Exuberance and spillovers in housing markets: Evidence from first-and second-tier cities in China. *Regional Science and Urban Economics*, *77*, 75–86. https://doi.org/10.1016/j.regsciurbeco.2019.02.005

Webb, R. I., Yang, J., & Zhang, J. (2016). Price jump risk in the US housing market. *The Journal of Real Estate Finance and Economics*, *53*, 29–49. https://doi.org/10.1007/s11146-015-9518-z

Wong, S. K., Yiu, C. Y., Tse, M. K. S., & Chau, K. W. (2006). Do the forward sales of real estate stabilize spot prices? *The Journal of Real Estate Finance and Economics*, *32*, 289–304. https://doi.org/10.1007/s11146-006-6803-x

Wu, F., Chen, J., Pan, F., Gallent, N., & Zhang, F. (2020). Assetization: The Chinese path to housing financialization. *Annals of the American Association of Geographers*, *110*(5), 1483–1499. https://doi.org/10.1080/24694452.2020.1715195

Wu, J., Deng, Y., & Liu, H. (2014). House price index construction in the nascent housing market: The case of China. *The Journal of Real Estate Finance and Economics*, *48*, 522–545. https://doi.org/10.1007/s11146-013-9416-1

Wu, J., Gyourko, J., & Deng, Y. (2012). Evaluating conditions in major Chinese housing markets. *Regional Science and Urban Economics*, *42*(3), 531–543. https://doi.org/10.1016/j.regsciurbeco.2011.03.003

Wu, J., Gyourko, J., & Deng, Y. (2016). Evaluating the risk of Chinese housing markets: What we know and what we need to know. *China Economic Review*, *39*, 91–114. https://doi.org/10.1016/j.chieco.2016.03.008

Xu, X., & Zhang, Y. (2022). Contemporaneous causality among one hundred Chinese cities. *Empirical Economics*, *63*(4), 2315–2329. https://doi.org/10.1007/s00181-021-02190-5

Yang, J., Li, M., & Yu, Z. (2022). *Low-frequency vs high-frequency housing price spillovers in China* (Working Paper). University of Colorado Denver.

Yang, J., Tong, M., & Yu, Z. (2021). Housing market spillovers through the lens of transaction volume: A new spillover index approach. *Journal of Empirical Finance*, *64*, 351–378. https://doi.org/10.1016/j.jempfin.2021.10.003

Yang, J., Tong, M., & Yu, Z. (2023). Can volume be more informative than prices? Evidence from Chinese housing markets. *Review of Quantitative Finance and Accounting*, *61*, 633–672. https://doi.org/10.1007/s11156-023-01161-4

Yang, J., Yu, Z., & Deng, Y. (2018). Housing price spillovers in China: A high-dimensional generalized VAR approach. *Regional Science and Urban Economics*, *68*, 98–114. https://doi.org/10.1016/j.regsciurbeco.2017.10.016

Yang, J., Yu, Z., Jia, Y., & Ma, J. (2017). *Transmission of financial shocks among China's financial institutions* (Working Paper No. 2017/4). The People's Bank of China (PBC).

Yang, J., Yu, Z., & Ma, J. (2019). China's financial network with international spillovers: A first look. *Pacific-Basin Finance Journal*, *58*, Article 101222. https://doi.org/10.1016/j.pacfin.2019.101222

Yang, J., & Zhou, Y. (2013). Credit risk spillovers among financial institutions around the global credit crisis: Firm-level evidence. *Management Science*, *59*(10), 2343–2359. https://doi.org/10.1287/mnsc.2013.1706

Zhou, J., & Kang, Z. (2011). A comparison of alternative forecast models of REIT volatility. *The Journal of Real Estate Finance and Economics*, *42*, 275–294. https://doi.org/10.1007/s11146-009-9198-7

Zhou, Y., & Haurin, D. (2010). On the determinants of house value volatility. *Journal of Real Estate Research*, *32*(4), 377–396. https://doi.org/10.1080/10835547.2010.12091292

Zhu, B., Füss, R., & Rottke, N. B. (2013). Spatial linkages in returns and volatilities among US regional housing markets. *Real Estate Economics*, *41*(1), 29–64. https://doi.org/10.1111/j.1540-6229.2012.00337.x

Zimmer, D. M. (2015). Time-varying correlation in housing prices. *The Journal of Real Estate Finance and Economics*, *51*, 86–100. https://doi.org/10.1007/s11146-014-9475-y

Appendix

Table A1. Description of variables used in further investigation of the determinants

Variables	Abbreviation	Definition
Area of Paved Road	AP	Log value of Area of Paved Road
Length of Highway	HW	Log value of Length of Highway
No. of Public Transit Vehicle Bus and Trolley Bus	PT	Log value of No. of Public Transit Vehicle Bus and Trolley Bus
No. of Rental Vehicle	RV	Log value of No. of Rental Vehicle
Catering Trade	CT	Log value of Catering Trade
No. of Star related hotels	SH	Log value of No. of Star related hotels
Wholesale and Retail Trade	WR	Log value of Wholesale and Retail Trade
Population	PO	Log value of Population
Population Growth	PG	Log value of Population Growth×100
Unemployment Rate	UR	Unemployment/(Employee + Unemployment)×100
No. of Employees	EP	Log value of No. of Employees
Government Revenue Tax	GT	Log value of Government Revenue Tax
Government Expenditure	GE	Log value of Government Expenditure
Government Revenue	GR	Log value of Government Revenue
GDP Growth	GG	Log value of GDP Growth×100
City GDP per capita	GC	Log value of City GDP per capita
City GDP	CG	Log value of City GDP
Average Wage	AW	Log value of Average Wage
No. of Teachers in Higher Institutes	TH	Log value of No. of Teachers in Higher Institutes
No. of Teachers in Secondary Schools	TS	Log value of No. of Teachers in Secondary Schools
No. of Teachers in Primary Schools	TP	Log value of No. of Teachers in Primary Schools
No. of Enrolled students in Higher Institutes	SHI	Log value of No. of Enrolled students in Higher Institutes
No. of Enrolled students in Primary Schools	SP	Log value of No. of Enrolled students in Primary Schools
No. of Enrolled students in Secondary Schools	SSS	Log value of No. of Enrolled students in Secondary Schools
No. of Beds in Hospitals and Healthcare centers	BH	Log value of No. of Beds in Hospitals and Healthcare centers
No. of High Institutes	HI	Log value of No. of High Institutes
No. of Primary Schools	PS	Log value of No. of Primary Schools
No. of Secondary Schools	SS	Log value of No. of Secondary Schools
No. of Hospitals and health care centers	HP	Log value of No. of Hospitals and health care centers
Climate Average Temperature	AT	Raw data of Temperature in a Certain City
Climate Precipitation	PC	Log value of Climate Precipitation
Climate Sunshine	SUN	Log value of Climate Sunshine
Area of Garden and Green	GRE	Log value of Area of Garden and Green
Air Quality PM2.5	PM2.5	Log value of Air Quality PM2.5

Data source: CEIC

Table A2. Summary statistics of variables used in further investigation of the determinants

	GRE	AP	AW	CT	GC	CG	GG
Mean	9.0584	3.2017	10.5835	2.4382	10.7107	5.5652	12.3113
Median	8.9676	3.1600	10.6315	2.4510	10.7680	5.6024	11.8347
Std	1.0402	0.9082	0.4705	1.0483	0.6482	1.0123	6.8119
Skewness	0.6702	0.1709	–0.2231	–0.0300	–0.4160	–0.0893	–0.5907
Kurtosis	3.1573	2.4679	2.3865	2.6088	2.8435	2.7824	10.3474
	GT	GE	GR	HW	PT	RV	BH
Mean	9.6325	10.4353	9.9376	9.3288	0.7701	1.5553	10.0831
Median	9.6158	10.4315	9.9112	9.4088	0.7793	1.5872	10.0989
Std	1.2831	1.0389	1.2214	0.6996	1.0599	1.0401	0.7154
Skewness	0.1674	0.1856	0.1499	–0.5290	0.0655	0.1645	–0.2144
Kurtosis	2.8369	3.3118	2.8581	5.7434	2.2337	2.6041	4.0571
	EP	SHI	SP	SSS	HI	HP	PS
Mean	6.9704	4.9870	5.9304	5.6537	2.6589	5.4485	6.4900
Median	6.8773	4.8331	6.0219	5.7205	2.5649	5.4992	6.5425
Std	1.1844	1.0885	0.6068	0.5901	1.0665	0.6395	0.7573
Skewness	0.3242	–0.1090	–0.2635	–0.3297	–0.0300	–0.2490	–0.0150
Kurtosis	2.4960	2.1717	3.4313	4.2739	1.8248	5.1882	2.9459
	SS	SHI	TH	TP	TS	URE	PG
Mean	5.6043	4.2359	2.1336	3.0422	3.0361	3.5963	1.0511
Median	5.6870	4.1897	1.8969	3.0951	3.1113	3.5142	0.7548
Std	0.5822	0.6909	1.1323	0.5857	0.5977	0.7465	2.0667
Skewness	–0.4469	0.4805	–0.0480	–0.3490	–0.5195	–0.1926	3.2355
Kurtosis	3.8701	3.8650	2.0931	3.8849	4.3688	4.9744	53.9075
	PO	WR	PM2.5	AT	PC	SUN	UR
Mean	8.6063	4.4133	3.7536	14.3277	3.5631	4.9942	4.5143
Median	8.7603	4.4259	3.7377	16.3000	3.8795	5.1216	4.5425
Std	0.6469	1.1386	0.5004	10.7432	1.5501	0.5566	3.2459
Skewness	–0.5794	–0.1872	0.1169	–0.6520	–1.0377	–1.9970	3.1817
Kurtosis	4.8140	3.0221	2.8631	2.7649	4.2068	9.9294	40.4470

Data source: CEIC