Does market sentiment push up China's housing prices? - An empirical study based on the data of 45 mainstream cities in China

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Abstract: This paper reports a series of empirical tests that scrutinised the potential effect of market sentiment on China's housing prices at the city level. The analyses employed unbalanced panel data from 45 large- and medium-sized cities in China for the period of 2011 to 2017. We first constructed the housing market sentiment index using principal component analysis, following which the index was applied in a system GMM estimation to analyse its impact. The results of the dynamic GMM estimation indicated that market sentiment plays a significant role in increasing housing prices in the 45 selected cities. Subsequently, general fixed effect regressions, placebo tests, and Poisson regressions were performed to test the robustness of the dynamic GMM estimation results. All the robustness checks confirmed the positive impact of market sentiment on housing prices. Additionally, we investigated the moderating effects of mobile network coverage, wage rate, and education on the positive relationship between market sentiment and housing prices. It was revealed that mobile network coverage has a positive moderating effect on this link, while wage rate and education have negative moderating effects. Lastly, this study explored the heterogeneity of market sentiment's effect on housing prices, concluding that although this effect is positive in both first- and second-tier cities, it is significantly stronger in first-tier cities. The research findings are useful for the Chinese government in regulating housing prices by stabilising market sentiment.

Keywords: market sentiment; housing prices; system GMM; moderating effect; China.

1. Introduction

Since the capitalisation of housing distribution in 1998, China's housing prices have been experiencing a dramatic rise; this phenomenon has aroused widespread concern among academics. Mainstream notions, such as economic growth (Wang and Zhang, 2014; Zhang *et al.,* 2016), urbanisation (Wang *et al.,* 2017a), and China's land policy (Wang *et al.,* 2017b), partly explain the reasons for rising housing prices from the standpoint of traditional economics theory. However, it is not enough to rely solely on this theory — which is based on the market efficiency hypothesis and the complete rationality hypothesis — to justify fluctuating housing prices (Lai and Order, 2010). In all likelihood, China's housing market is not efficient and home-buyers and real estate developers are not completely rational (Shen and Liu, 2004). In the day and age of the Internet, where information is abundant and communication is convenient, market participants can access prodigiously vast quantities of information anytime and anywhere. On that note, terms such as "*Riguangpan*[1]" and "panic-buying houses" appear frequently in recent Chinese internet news reports and on social media[2], which may boost the irrational sentiment of potential home-buyers. Specifically, the aforementioned terms that frequently emerge in media portrayals of the housing market may make home-buyers firmly believe that China's housing market is in a state of short supply and housing prices cannot possibly fall in a short space of time. These beliefs may increase noise trading and subsequently lead to the herding effect.

In addition to the media's sensational reports on China's housing market, several observable housing market factors may also contribute to the irrational sentiment of potential home-buyers. For example, since the beginning of this century, the annual housing turnover in China has increased significantly, with an average annual growth rate of nearly 12%[3]. The sharp rise in housing turnover can be easily perceived by potential home-buyers, as they tend to find that more people around them have taken the action of purchasing houses. Taking this into consideration along with the excessive exaggeration of China's housing shortage by the media, the

[1] "Riguangpan" is a vivid description of a scene in which all houses for sale are sold out on the opening day, marking the boom of China's housing market.
[2] The Baidu search engine generates about 5,650,000 results for the search term "riguangpan" and 4,720,000 results for the search term "panic-buying houses".
[3] Data on annual housing turnover in China was obtained from the CEInet Statistics Database. The annual growth rate was calculated by the authors.

irrational sentiment of potential home-buyers is likely to be intense. As buyers believe more firmly that the contradiction between supply and demand in China's housing market is acute and that housing prices in China will continue to rise, noise trading and the herding effect may exacerbate further. These effects, in turn, increase the demand for housing and drive up China's housing prices. Further, home-buyers' noise trading and herding behavior may trigger the sentiment of real estate developers. Specifically, the irrational rush purchasing of home-buyers can strengthen developers' beliefs that China's housing market is a seller's market, which encourages them to buy land wantonly for real estate investment. Supporting this concept, Yang et al. (2020) found that with the boom in home purchasing in China, local land transaction volume has expanded sharply over this century. The rapid expansion of land demand positively impacts the rise of land prices, which is an important cost of real estate development that stimulates the corresponding rise of housing prices. In summation, market sentiment may contribute to China's high housing prices. In line with this, Shiller (2005) argued from the perspective of behavioural economics that human desires can play an important driving role in the property market. Clayton *et al.* (2009) elaborated on this by explaining how the abnormal deviation of house pricing is caused by sentiment. Their view is that features like weak liquidity, high segmentation, and the inability to short-sell in the housing market have weakened the ability of market regulation to correct mispricing.

Due to the inability to quantify sentiment as well as a lack of data, the effect of housing market sentiment on housing prices has garnered little attention from researchers. As such, only a few studies have empirically investigated the influence of housing market sentiment on fluctuations in housing prices (Jin *et al*., 2014; Wang and Hui, 2017; Hui *et al*., 2017; Lam and Hui, 2018; Usta, 2021)[4]. Of these studies, only Hui *et al*. (2017) investigated the correlation between housing market sentiment and fluctuating housing prices in the Chinese mainland, particularly in Shanghai City. However, the sharp rise in housing prices is not unique to Shanghai; it is a common phenomenon throughout China[5]. Additionally, the sentiment proxies Hui *et al*. (2017) utilised in their study were based on lagged market data, meaning that the sentiment index they constructed was lagging (Hui *et al*., 2018). Therefore, our study aimed to investigate 45 large- and medium-sized cities in China as well as to incorporate big data from the Internet into the framework of our housing market sentiment index to improve its immediacy. Notably, as many potential home-buyers or investors scour the internet for market information, the Baidu index (*BI*) was included in the construction of our housing market sentiment index. By December 2020, the number of Internet users in China had touched 989 million, with an Internet penetration rate of more than 70%. The search engine Baidu boasts the highest utilisation rate at nearly 80% (CNNIC, 2021). Therefore, the frequency of searches containing housing-price-related keywords in Baidu can be interpreted to reflect the degree of attention given by potential home-buyers to the housing market.

Since 2019, the China Business Network has categorised Chinese cities into five tiers as per their level of development. In particular, first-tier cities and second-tier cities in China exhibit great differences in social development, which are reflected in Figure 1. Figure 1(a) shows these cities' per capita GDP (GDP) and wage rate (Wage), which measure their economic development from the national macro perspective and the employee micro perspective, respectively. According to Figure 1(a), the per capita GDP and wage rate of first-tier cities are significantly higher than those of second-tier cities, implying that the former have a more developed economy than the latter. In addition to economic level, China's first-tier cities are also substantially better than second-tier cities in other aspects of social development, which are reflected in Figure 1(b). Figure 1(b) describes the differences between the two tiers of cities in terms of mobile network coverage (MNC) and education level (Edu)[6]. As can be seen in the figure, not only do the levels of mobile network coverage and education in China's first-tier cities surpass those of second-tier cities, but the gap between both tiers also appears to be

[4] Jin *et al*. (2014) drew their sample from the United States; Wang and Hui (2017) and Lam and Hui (2018) drew their samples from Hong Kong; Hui *et al*. (2017) drew their sample from Shanghai; Usta (2021) drew their sample from Turkey.

[5] The average growth rate of housing prices in the Chinese mainland's 31 provincial regions from 1999 to 2018 was 463%, while Shanghai's alone was 686%. Although the growth rate in Shanghai is higher than the average in China, it is not the highest. Jiangxi (730%) and Shaanxi (694%) both reached higher rates than Shanghai. The data on provincial housing prices was derived from the CEInet Statistics Database, while the growth rates of housing prices were calculated by the authors.

[6] MNC is expressed by the number of mobile phone users. Edu is expressed by the number of college students per 10 thousand people.

widening. In addition, there are several differences in both city tiers' housing markets, as depicted by their housing prices, housing supply, and housing demand performances in Figure 2[7]. First, the housing prices in first-tier cities are higher than those in second-tier cities, and the housing price gap between the two tiers of cities is gradually widening. Second, the HD curves of both first- and second-tier cities are above their corresponding HS curves, indicating that the housing markets in both tier cities are in short supply. Third, both housing supply and housing demand in first-tier cities are higher than those in second-tier cities, and in general, housing demand in both tiers of cities has been expanding, especially before 2017. However, it is surprising that despite the continuous spike in housing demand, housing supply in the two tiers of cities has tended to stabilise; this may be due to restrictions on land supply by the Chinese government (Liu et al., 2018). In summary, the housing market in China's first-tier cities is certainly 'hotter' than that in second-tier cities, as indicated by the higher housing prices and greater housing supply and demand in first-tier cities. As such, in order to regulate the overheated housing market, the central government of China has introduced housing purchase restriction policies, including restrictions on outsiders' purchase of houses, on the purchase of a second house, and on the availability of housing loans. Nonetheless, this policy is not mandatory; local governments can exercise their own discretion as to whether or not to implement housing purchase restriction policies. They are also free to decide how strongly the policies are implemented based on their own conditions. Consequently, perhaps because the housing market in China's first-tier cities is fiercer, housing purchase restriction policies are much more forcefully and strictly implemented in first-tier cities than in second-tier cities.

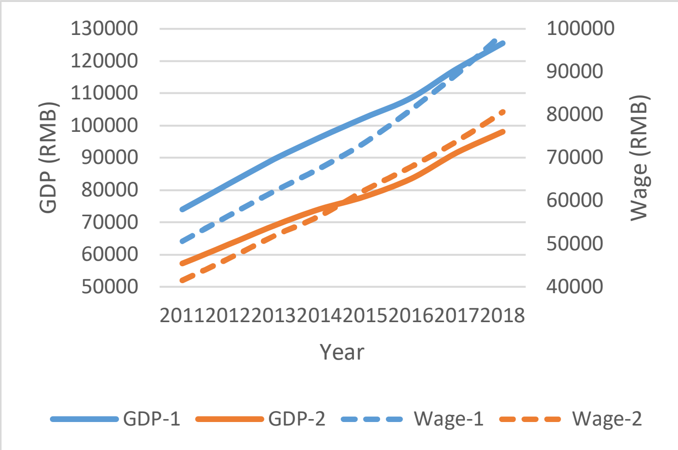
As explained earlier, the frequent media portrayals of China's hot housing market may boost sentiment in China's housing market, which in turn pushes up China's housing prices. As such, the availability of media information is an important basis for the mechanism through which market sentiment affects China's housing prices. In view of people's habit of obtaining media information through the mobile Internet, mobile network coverage may have a moderating effect on the relationship between market sentiment and housing prices in China. Next, motivated by the finding of Kim *et al*. (2018) that education can significantly enhance individual economic rationality and the quality of economic decision-making, we believe that education may also have a moderating effect on the sentiment–price link in China's housing market. Finally, based on the consumption function theory, Hamburger (1955) explicated that consumption and investment are determined by consumers' expectation of their lifetime spending power; wage rate is an appropriate proxy to characterise this expectation. As such, wage rate may affect house purchase decisions of home-buyers. Therefore, this study empirically explored the moderating effects of mobile network coverage, education, and wage rate on the positive relationship between market sentiment and housing prices in China. In addition, as mentioned earlier, there are vast differences between China's first- and second-tier cities in terms of mobile network coverage, education level, and wage rate. This implies that market sentiment may have divergent effects on housing prices in first- and second-tier Chinese cities. Taking this possibility into account, we also examined the heterogeneity of the relationship between market sentiment and housing prices across first- and second-tier cities[8].

The possible marginal contributions of this study are as follows. First, our research extended the sample to 45 large- and medium-sized cities in China, covering almost all the country's first- and second-tier cities. Thus, our conclusions are applicable to most mainstream cities in China. Second, we incorporated Internet big data, i.e., the Baidu Index, in constructing the market sentiment index of China's housing market, which improves the immediacy of the constructed index. Third, we investigated the moderating roles of mobile network coverage, inhabitant education level, and wage rate in the impact of market sentiment on China's housing prices. Finally, we examined the difference in this impact between first- and second-tier cities in China.

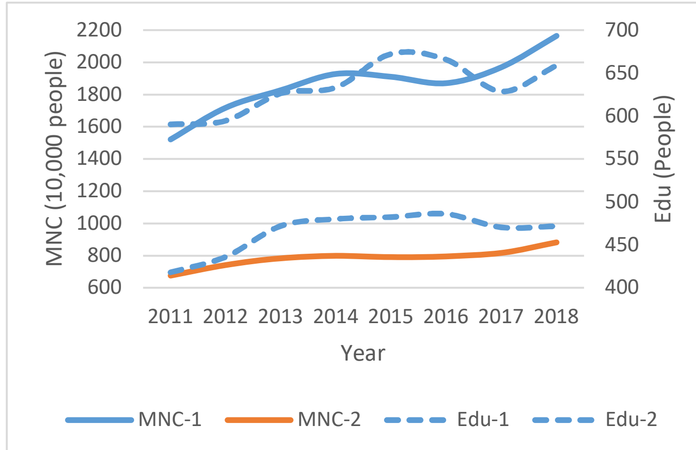
The remainder of this paper is presented in four sections. Section 2 reviews previous relevant studies; Section 3 contains data and methodology details; Section 4 presents and deliberates on the empirical outcomes; and lastly, Section 5 concludes the findings and

[7] Housing supply is expressed by floor space of completed housing. Housing demand is expressed by commercial housing sales by floor area.
[8] The list of the first- and second-tier cities is presented in Table A1 of the Appendix.

puts forward policy recommendations.



(a)



(b)

Figure 1 Social development indicators of China's first- and second-tier cities from 2011 to 2018

Note: GDP-1, Wage-1, MNC-1, and Edu-1 refer to the per capita GDP, wage rate, mobile network coverage, and education level of China's first-tier cities, respectively; GDP-2, Wage-2, MNC-2, and Edu-2 refer to the per capita GDP, wage rate, mobile network coverage, and education level of China's second-tier cities, respectively.

(Data sources: China real estate information network; The statistical yearbooks of cities)

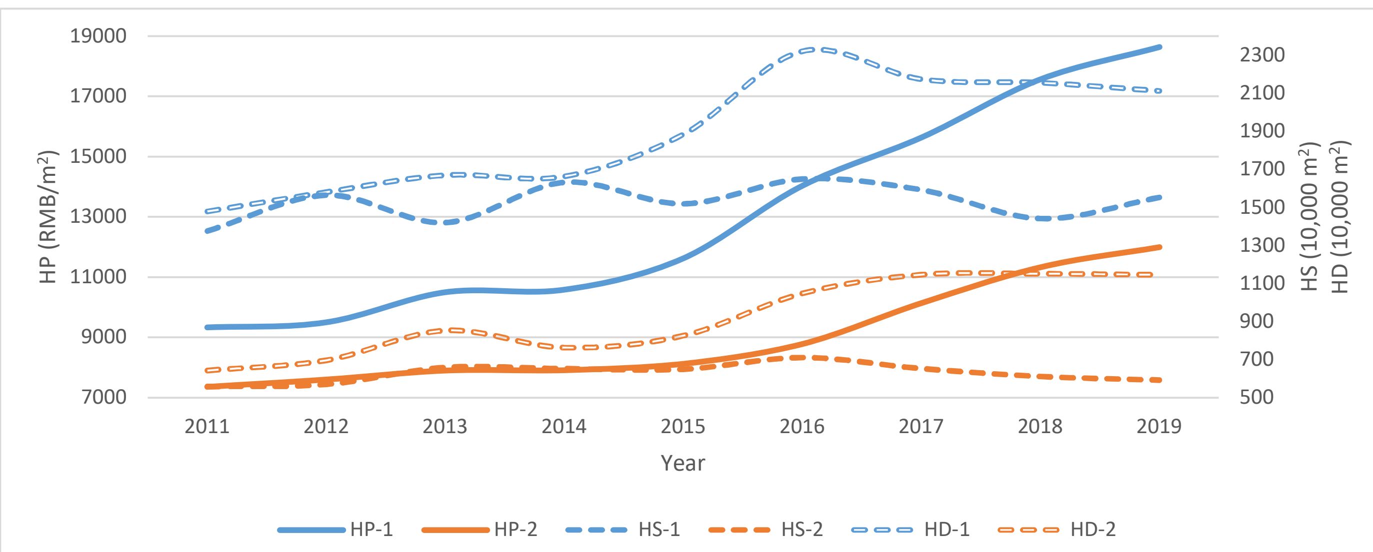


Figure 2 Housing market indicators of China's first- and second-tier cities from 2011 to 2019

Note: HP-1, HS-1, and HD-1 refer to housing prices, housing supply, and housing demand in China's first-tier cities, respectively; HP-2, HS-2, and HD-2 refer to housing prices, housing supply, and housing demand in China's second-tier cities, respectively.

(Data sources: China real estate information network; The statistical yearbooks of cities)

2. Literature Review

2.1 Construction of Sentiment Index

Although there are only a few published papers on market sentiment in the housing market, there are plenty of in-depth studies on investor sentiment in the financial market. There are three methods of constructing an index of investor sentiment in the financial market: the direct proxy measurement method, the indirect proxy measurement method, and the composite indirect proxy measurement method. The direct proxy measurement method involves directly collecting data on investors' expectations of the financial market through a survey questionnaire. To analyse the impact of investor sentiment on the share market under this method, the "investors intelligence" indicator by Clarke and Statman (1998) and Fisher and Statman (2000) is deployed. However, using the direct proxy measurement method to construct an investor sentiment index is contingent on sample size, geographical distribution, and subjective factors (Groves, 2004). Alternatively, the indirect proxy measurement method refers to the use of indirect proxies to quantify investor sentiment. These proxies typically reflect investor sentiment to some extent, such as odd-lot sales to purchases ratio, discounts on closed-end funds, and net mutual fund redemptions (Neal and Wheatley, 1998). Both the direct and indirect proxy measurement methods select only one proxy to measure investor sentiment, which is potentially biased. As such, a sentiment index constructed via the direct or indirect proxy measurement methods may fail to accurately and comprehensively quantify investor behaviour and psychology. Following this line of thought, Baker and Wurgler (2006) pioneered the formulation of the investor sentiment index through the composite indirect proxy measurement method. Their approach builds the index by first selecting multiple indirect sentiment proxies at the same time and then extracting principal components of the selected proxies through principal component analysis (PCA). By incorporating multiple proxies simultaneously, the constructed investor sentiment index effectively mitigates bias and covers as many sentiment factors as possible. Accordingly, investor sentiment indices developed using the composite indirect proxy measurement method provide a more comprehensive description of investor sentiment. For this reason, most researchers use this method to construct investor sentiment indices (Chen *et al.,* 2010; Chong *et al.,* 2017; Kim *et al.,* 2019; Jokar and Daneshi, 2020).

Hui *et al*. (2017) were the first to use Baker and Wurgler's (2006) composite indirect proxy measurement method in the housing market, wherein they chose indirect proxies from different categories (e.g., land market, stock market, and capital market) before employing PCA to build sentiment indices. Since then, Hui *et al*. (2018), Lam and Hui (2018), and Dong *et al.* (2021) have constructed similar sentiment indices in the housing market. However, as almost all the indirect proxies were based on lagged market data, the housing market sentiment indices created via the composite indirect proxy measurement method may be lagging behind (Hui *et al.,* 2018). Conversely, using Internet big data to measure market sentiment is forward-looking, as its immediacy effectively alleviates delays (Da *et al.,* 2015). In this regard, the Baidu Index is a type of Internet big data published by Baidu Inc. which reports the search frequency of specific keywords. Since Baidu is the most popular search engine in China (CNNIC, 2021), the Baidu Index naturally became the first choice of researchers to measure market sentiment in China. For example, Fang *et al.* (2020) used the Baidu Index to measure investor sentiment and study its effect on the volatility of China's stock prices. Nevertheless, relying on Internet big data as the sole proxy with which to measure market sentiment is not only biased but lacks rigorous scientific backing. Therefore, we combined the composite indirect proxy measurement method created by Baker and Wurgler (2006) with Internet big data by not only selecting indirect proxies such as new housing sale volume (*NHS*), second-hand housing sale volume (*SHS*), new housing floor space under construction (*NHFSC*), the volume of land purchased by real estate enterprises (*LPV*), the transaction number of residential land (*RLTN*), and land premium rate (*LPR*), but also incorporating the Baidu Index (*BI*) to construct the sentiment index in the housing market through PCA.

2.2 The Effect of Market Sentiment on Housing Prices

Researchers have analysed the relationship between market sentiment and housing prices through different empirical methods. Some studied the causal relationship between market sentiment and housing prices (Wang and Hui, 2017; Usta, 2021). For instance, Wang and Hui (2017) used an integrated renormalised partial directed coherence (renormalised PDC) method to study the causality between market sentiment housing prices, rent prices, and the volume of house trading in Hong Kong. Their study concluded that market sentiment has the most significant impact on house prices in Hong Kong. Usta (2021) conducted a series of causality tests (T-Y) and found that market sentiment affects housing prices in Turkey by manipulating the supply of houses. Other researchers have studied the specific quantitative relationship between market sentiment and house price fluctuation (Jin *et al.,* 2014; Hui *et al*., 2017; Lam and Hui, 2018). Among them, Jin *et al.* (2014) studied American housing price patterns between 1998 and 2008, which was during the US real estate bubble and deflation. They concluded that irrational market sentiment has not only a significant impact on American housing prices but a negative impact on future housing prices. This is contrary to a study by Hui *et al*. (2017) which found that in the short term, developer and buyer-seller sentiments positively impact the rise in housing returns in Shanghai. In the long run, their findings showed that stronger developer sentiment still leads to higher housing returns while buyer-seller sentiment is negatively correlated with housing returns in Shanghai, whereby stronger buyer-seller sentiment diminishes the growth rate of housing prices. However, it remains unclear if an increase in buyer-seller sentiment can lead to a decline in Shanghai's housing prices.

Through a review of the existing literature, we find that almost all extant studies recognise market sentiment as a key factor affecting housing price fluctuation. However, whether market sentiment has a positive or negative impact on housing prices has not been agreed upon, which may be due to the different samples selected by different researchers. To date, Hui *et al*. (2017) remains the only study to investigate fluctuations in housing prices in Mainland China. Even so, as Hui *et al*. (2017) only investigated one mainland city, i.e., Shanghai, it is uncertain if their findings apply to most cities in the Chinese mainland. Moreover, as mentioned earlier, the proxies adopted by Hui *et al*. (2017) were all based on lagged market data, which may have caused their sentiment index to fall behind. Therefore, our study did not only investigate multiple cities but also incorporated the Baidu Index as a sentiment proxy in conjunction with indirect proxies to construct our sentiment index.

2.3 Hypothesis

It is not unreasonable to assume that due to limited market information and the inadequate cognitive ability of market participants, participants in China’s housing market may have merely partial rationality (Shen and Liu, 2004). However, most market participants are overly confident in their decision-making abilities as well as in the accuracy of their acquired information, especially when market sentiment is positive (Frank, 1935; Fischhoff *et al*., 1977). Unfortunately, such overconfidence results in home-buyers overestimating the returns on their houses and making more frequent house purchasing decisions than they would if they were completely rational (Benos, 1998, Odean, 1998). Supporting this, Leowenstein *et al.* (2001) argued that positive sentiment tends to encourage market participants to make optimistic judgments and decisions. Therefore, positive market sentiment may increase demand in the housing market, and consequently, drive up housing prices. In addition, because of the serious information asymmetry in China’s housing market, frequent media reports of "*Riguangpan*" and "panic-buying houses" may strengthen the sentiment that China's housing prices will continue to rise, thereby leading to more noise trading and herd behaviour. In turn, noise trading and herd behaviour increase demand in the housing market, followed by the price of housing in China. This is corroborated by Kuang *et al.*’s (2020) study, which found that media reports contribute to fluctuating housing prices in China. Therefore, based on the above analysis, we put forward our first hypothesis.

HP1: Market sentiment has a positive effect on housing prices in China.

As an important source of housing market information for home-buyers, the mobile network may have a moderating effect on the impact of market sentiment on China's housing prices. Specifically, a more developed mobile network means that media coverage of China's hot housing market and the irrational opinions on the housing market shared on social media are more accessible to market participants. This makes it easier for market sentiment to spread among potential home-buyers, causing higher noise trading and a stronger herding effect. As such, a developed mobile network may strengthen the impact of market sentiment on China's housing prices. As far as China is concerned, the development of mobile networks in different cities is not balanced, such that the level of mobile network coverage in China’s first-tier cities far exceeds that in second-tier cities (Li and He, 2015). Based on the above analysis, we proposed hypothesis HP2a.

Wage and education may also have moderating effects on the relationship between market sentiment and China's housing prices. A higher wage rate often means richer and stronger purchasing power (Chiu, 1996). As such, people with high wages are less likely to worry that they cannot afford a house despite rising house prices. This means that in spite of high market sentiment and the expectation that housing prices may continue to rise, people with high wages are not expected to buy houses irrationally. Therefore, in cities with higher average wage rates, there would be less irrational purchase decisions caused by market sentiment. As for education, Kim *et al.* (2018) found that education can significantly enhance individuals' economic rationality and quality of economic decision-making, which means that people with a higher education level are less prone to making irrational house purchase decisions influenced by market sentiment. Thus, the housing market in cities with more educated residents may have less noise trading and a weaker herding effect. Overall, wage and education are likely to have negative moderating effects on the impact of market sentiment on China's housing prices. As previously stated, the wage rates and education level of residents in China's first-tier cities are both higher than those in second-tier cities. Therefore, in line with the above analysis, this paper put forward hypothesis HP2b.

HP2a: Market sentiment has a more significant impact on housing prices in China's first-tier cities than second-tier cities.

HP2b: Market sentiment has a less significant impact on housing prices in China's first-tier cities than second-tier cities.

3. Methodology & Data

This study intended to investigate the effect of market sentiment on housing prices in China. To achieve this objective, we first constructed the sentiment index for every city using PCA, then applied the constructed sentiment index to the dynamic GMM estimation to scrutinise whether market sentiment influences housing prices.

3.1 Construction of Sentiment Index for Housing Market

The sentiment index in the housing market constituted the explanatory variable in this paper, and had to be constructed via PCA. The preliminary sentiment index ($Sentiment_{it}^{*}$) was developed as follows.

$$\begin{aligned} Sentiment_{it}^{*} &= \beta_1 rlNHS_{it} + \beta_2 rlNHS_{i,t-1} + \beta_3 rlSHS_{it} + \beta_4 rlSHS_{i,t-1} + \beta_5 rlNHFSC_{it} + \beta_6 rlNHFSC_{i,t-1} + \beta_7 rlLPV_{it} \\ &+ \beta_8 rlLPV_{i,t-1} + \beta_9 rlRLTN_{it} + \beta_{10} rlRLTN_{i,t-1} + \beta_{11} rLPR_{it} + \beta_{12} rLPR_{i,t-1} + \beta_{13} lBI_{it} \end{aligned} \tag{1}$$

Upon constructing $Sentiment_{it}^{*}$, a correlation analysis between $Sentiment_{it}^{*}$ and all the proxies (except lBI_{it}) was performed. In each group of a proxy and its lag[9], the one which had a stronger correlation with $Sentiment_{it}^{*}$ was selected for the second PCA along with lBI_{it} to construct the final sentiment index ($Sentiment_{it}$).

Next, we introduce the reasons for selecting the indicators and discuss how they were constructed into a comprehensive sentiment index. The following six underlying indicators were chosen to build the sentiment index of China's housing market: 1. *NHS*, 2. *SHS*, 3. *NHFSC*, 4. *LPV*, 5. *RLTN,* and 6. *LPR*. While the first two indicators reflect the sentiment of home-buyers in the housing market, the last four indicators reflect the sentiment of developers.

As the above six underlying indicators were all based on lagged market data, we included *BI* (i.e., a type of Internet big data that captures the frequency of searches containing housing-price-related keywords) as another underlying indicator in the hopes of improving the immediacy of our constructed index. China has high Internet penetration and the Baidu search engine has a high usage rate; thus, including the frequency of Baidu searches containing housing-price-related keywords may, to an extent, reflect the degree of attention given by potential home-buyers to the housing market. Therefore, in this paper, *BI* was regarded as another proxy for

[9] For example, $rlNHS_{it}$ and $rlNHS_{i,t-1}$ form a group, and so on.

building the sentiment index. *BI* data is available through the certified website of the Baidu index[10]. Participants in the housing market can obtain housing price information by searching different keywords, such as "city + housing prices" and "city + housing for sale". Compared to "city + housing for sale", searching the keywords "city + housing prices" to attain house price information is more direct and efficient because the former's results include some information unrelated to housing prices, such as housing sales contracts and housing sales dispute news. As such, the search volume of the keywords "city + housing prices" is much higher than that of "city + housing for sale", which is reflected in the *BI* data. Taking Beijing as an example, the *BI* of "Beijing housing prices" is 1419, but that of "Beijing housing for sale" is only 79. Furthermore, the *BI* values of "housing for sale" for some cities involved in this study (e.g., Yangzhou, Yantai, Zhuhai, etc.) were unavailable because of their insufficient search volume. Therefore, we used the *BI* of the key words "city + housing prices" as the proxy variable of *BI*. By inputting the keywords "city + housing prices", for example "Beijing housing prices", the *BI* data of the corresponding city and year were immediately retrieved.

NHS and *SHS* were selected to represent the sentiment of home-buyers in the housing market. Housing sales volume can reflect the active level of the housing market. When market activity rises continuously, noise dealing and herd behaviour may occur. Accordingly, as irrational home purchases increase, irrational sentiment in the housing market grows. This is corroborated by the work of Hui and Wang (2014), who found that market sentiment impacts investor-initiated transactions. Housing can be categorised as either new or second-hand. As such, our study simultaneously investigated both *NHS* and *SHS* to measure the sentiment of home-buyers. The data was collected from China's real estate statistics yearbooks, cities' statistical yearbooks, and cities' statistical communiqué in corresponding years.

In this paper, the indicators *NHFSC*, *LPV*, *RLTN*, and *LPR* were chosen to signify the sentiment of real estate developers. This is because the investment strength of real estate developers is associated with their sentiment, seen in both the land market and the housing market. When real estate companies are optimistic about the housing market, they tend to increase the quantity of land reserves and speed up the pace of new housing constructions. As such, *NHFSC*, *LPV,* and the number of residential land transactions will rise. Conversely, when they are wary of the housing market, they may reduce the quantity of land reserves and slow down the construction of new housing. Accordingly, *NHFSC*, *LPV,* and the number of residential land transactions will decline. It is also noteworthy that China auctions its land use rights. Optimistic real estate developers believe that housing prices will continue to rise and are thus inspired to bid for land. During land auctions, enthusiasm among developers can affect each other, resulting in herd behaviour, higher transaction prices, and eventually, an increased premium rate. Furthermore, the belief that housing prices are on the uptrend increases developers' reservation price when purchasing land use rights, which in turn, increases the premium rate. On the contrary, when real estate developers are pessimistic about the housing market, their lack of enthusiasm to bid for land will decrease the reservation price of land and thereby drop the premium rate. Based on the above analysis, we posit that *NHFSC*, *LPV*, *RLTN,* and *LPR* can signal the sentiment of real estate developers.

According to Hui *et al.* (2018) and Lam and Hui (2018), because the above six indicators[11] include the effects of macroeconomic fundamentals, these effects need to be eliminated prior to constructing the sentiment index. This was achieved by adopting the six indicators as explained variables and GDP and CPI as explanatory variables for the regression analysis. Subsequently, we utilised the residuals as the six sentiments' proxies: $rlNHS_{it}$, $rlSHS_{it}$, $rlNHFSC_{it}$, $rlLPV_{it}$, $rlRLTN_{it}$, and $rLPR_{it}$. Equation (2) shows the regression model that was used.

$$Y_{it} = \alpha + \beta_1 \ln GDP_{it} + \beta_2 CPI_{it} + \mu \tag{2}$$

In Equation (2), *Y* represents the six indicators, GDP is the real GDP with 2011 as the base year, CPI is the consumer price index with

10 The website address is http://index.baidu.com/v2/index.html#/.
11 The six indicators are *NHS*, *SHS*, *NHFSC*, *LPV*, *RLTN* and *LPR*.

2011 as the base year, i and t are the city and year respectively, α is the intercept term, β_1 and β_2 are the coefficients, and μ is the error term. Moreover, the six indicators[11] and GDP were processed using logarithm before the regression to reduce the effects of heteroscedasticity. In accordance with Lam and Hui (2018), we considered the possible lag of the six indicators[11] in reflecting market sentiment; therefore, we took the lag values of the six indicators[11] as the explained variables and used the same method to extract residuals as six more sentiment proxies: $rlNHS_{i,t-1}$, $rlSHS_{i,t-1}$, $rlNHFSC_{i,t-1}$, $rlLPV_{i,t-1}$, $rlRLTN_{i,t-1}$, and $rLPR_{i,t-1}$. Similarly, to decrease the effects of heteroscedasticity for *BI*, its logarithm (lBI_{it}) was taken. So, a total of 13 sentiment proxies were used in PCA to build the sentiment index for every city. Next, the constructed sentiment index was employed to examine the effect of market sentiment on housing prices.

3.2 Effects of Market Sentiment on Housing Prices

The objective of this study was to explore the possible impact of market sentiment on housing prices in China. Housing price is the dependent variable and sentiment in the housing market is the main explanatory variable in this paper. We derived the control variables as per the supply and demand framework of the housing market. In theory, both the supply (H^S) of and demand (H^D) for housing can influence housing prices, as shown in Equation (3) (Usta, 2021). With regards to the supply side, housing construction cost, the scale of new and second-hand houses on sale, and credit funds may affect housing prices. Housing demand, on the other hand, is affected by credit funds, income, user cost, and population (Maisel, 1949; Stevenson, 2008). Based on the above analysis and in accordance with Wang *et al.* (2017a), we selected land transfer price (*LTP*), the floor space of completed housing (*FSHC*), and credit funds (*CF*) as control variables from the perspective of H^S, which was expressed as Equation (4). We further selected credit funds (*CF*), the permanent population (*PP*), disposable income per capita (*PCDI*), and the urbanisation rate (*UR*) as control variables from the perspective of H^D, which was formulated as Equation (5). Derived from the demand and supply equations, the basic reduced form of the house price function associated with market sentiment was expressed as Equation (6).

$$HP = f(H^S, H^D) \tag{3}$$

$$H^S = f(LTP, FSHC, CF) \tag{4}$$

$$H^D = f(CF, PP, PCDI, UR) \tag{5}$$

$$HP = f(Sentiment, LTP, FSHC, CF, PP, PCDI, UR) \tag{6}$$

The variables are discussed in more detail below:

Housing price (HP): Housing prices was the dependent variable in this study. The data of housing prices was taken as the annual average price of urban commercial housing at the city level for 45 selected cities from 2011 to 2017. The data was acquired from China's real estate information network, which is organised by the State Information Centre of China.

Sentiment: The sentiment index in the housing market was the main variable of interest in this study. We independently constructed and calculated the sentiment index using PCA.

Land transfer price (LTP): Land transfer cost is one of the main costs of housing construction, such that the increase in land transfer price will trigger a corresponding rise in housing construction costs as well as in housing prices. Supporting this notion, Kim (2005) found that the rapid growth of land price was one of the main reasons for the spiral increase of house prices in South Korea during the period of 1987 to 2003. Therefore, this study included *LTP* as a control variable with a positive expected sign. The data of land transfer price was taken as the annual transaction price of land use rights transferred through auctions imposed by the government, which was also obtained from China's real estate information network.

Floor space of completed housing (FSHC): The floor space of completed housing is, to large extent, a measure of housing supply. Its changes can thus cause an unfavourable effect on housing prices. If there exists plenty of unsold floor space of completed housing without sufficient demand for it, the excess supply will put downward pressure on housing prices. Therefore, a negative association is expected between the floor space of completed housing and housing prices, which is consistent with the finding of Jiang and Zhu (2021). Consequently, this study included *FSHC* as a control variable. The data for floor space of completed housing in this study was the annual sum of the construction area of housing that had been completed in accordance with design requirements, identified to meet completion acceptance standards, and could be officially handed over for use. The data came from the statistical yearbooks of cities.

Credit funds (CF): Credit funds can affect both the supply and demand of housing. On the one hand, credit support enhances the purchase ability of potential home-buyers and thus increases demand in the housing market. Higher demand then generates a positive impact on housing prices. Supporting this, Kelly et al. (2018) empirically confirmed the positive relationship between credit funds and housing prices. On the other hand, credit support can also stimulate an increase in housing supply by easing the financing constraints of real estate developers, which then has a negative impact on housing prices (Davis and Zhu, 2011). As such, we took *CF* as a control variable in the analysis framework, though the sign of its estimated coefficient was uncertain. The data of credit funds was derived from the loan balance of financial institutions at year-end, which were obtained from China's real estate information network.

Permanent population (PP): Population is one of the main variables in housing demand. Since shelter is a basic need for humans, increases in population lead to increases in housing demand. Potepan (1994) found that inter-metropolitan migration causes changes in housing prices and higher net migrations in metropolises hike up housing prices by increasing the number of permanent residents. As a fundamental factor for demand in the housing market, the growth of the permanent population may explain the rise in China's housing prices (Wang and Zhang, 2014). Therefore, *PP* was selected as a control variable in our model. The data of permanent population was represented by the number of people who live at home for more than six months in a year. This data was acquired from the statistical yearbooks of cities.

Disposable income per capita (PCDI): According to the theory of demand, an increase in consumers' income will lead to an increase in the demand for normal goods. As houses are normal goods with a high income elasticity of demand, higher income per capita stimulates higher demand for housing, which in turn promotes the rise of housing prices. Supporting this, Wang and Zhang (2014) found that increased wage income drives up housing prices. Hui *et al.* (2016) further stated that inter-generation wealth transfer raises housing prices. Therefore, we concluded that changes in the disposable incomes of home-buyers may impact housing prices. As such, we incorporated *PCDI* as a control variable in this study. The data of disposable income per capita was taken as the income of households per capita for the purpose of final expenditure and savings, which was obtained from cities' statistical yearbooks.

Urbanisation rate (UR): Urbanisation rate is the share of the urban population in the total population. Urbanisation increases the demand for urban housing, which promotes a rise in housing prices. Supporting this, Wang *et al*. (2017a) noted a significant positive correlation between the extent of urbanisation and housing prices. Therefore, we included *UR* as a control variable. The data for urbanisation rate was the proportion of the urban population in the total population, which came from cities' statistical yearbooks.

The panel data in this research covered 45 cities involving 19 first-tier and 26 second-tier cities in China from 2011 to 2017[12]. The list of the cities is presented in Table A1 of the Appendix. Table 1 presents the descriptive statistics of the full sample.

Table 1

Descriptive statistics of full sample

Variable Name	Measurement	Mean	Standard Deviation	Min	Max	Expected sign

[12] Four second-tier cities were excluded from the analysis due to a lack of Baidu Index data.

HP	RMB per metre square	8,923.00	4,910.16	4,462.01	41,939.64	
Sentiment		0.56	0.15	0.08	1.05	+
LTP	RMB per metre square	4,068.93	6,050.42	500.03	64,509.14	+
FSHC	10 thousand square metres	1,035.34	782.61	33.17	5,055.73	-
CF	100 million RMB	12,460.40	10,945.88	1,295.48	63,382.50	+/-
PP	10 thousand persons	869.58	535.20	156.80	3,075.00	+
PCDI	RMB	34,971.43	9,104.49	15,953.00	62,595.74	+
UR	Ratio	0.69	0.13	0.37	1.00	+

3.3 Empirical Methodology

We collected panel data on 45 cities for the period ranging from 2011 to 2017 to study the relationship between market sentiment and housing prices. To decrease the effects of heteroscedasticity, the explained variable *HP* and several control variables, such as *LTP*, *FSHC*, *PP,* and *PCDI,* were processed with a logarithm. According to Nickell (1981), as a benchmark regression model, the fixed effect model can provide a reasonable series of static estimation results. However, static estimation does not take into account endogenous problems that may be caused by a correlation between housing prices and market sentiment. This may result in biased estimation results. Therefore, to solve the problem of endogeneity, we followed Arellano and Bond's (1991) suggestion to use System GMM, wherein the lagged value of the explained variable is added as an instrumental variable in the panel data model to gauge endogeneity. Finally, the benchmark regression of this research was established as follows:

$$Ln(HP_{it}) = \alpha_0 + \alpha_1 Ln(HP_{i,t-1}) + \alpha_2 Sentiment_{it} + \beta Z_{it} + \varepsilon_{it} \tag{7}$$

In Equation (7), $HP_{i,t-1}$ is the lagged value of the explained variable, Z represents a series of control variables which may influence housing prices, and ε_{it} is the error term.

In order to test the robustness of the benchmark regression, a series of robustness checks were conducted, namely the general fixed effect model, placebo test, and Poisson model. The general fixed effect model is shown as Equation (8).

$$Ln(HP_{it}) = \alpha_0 + \alpha_1 Sentiment_{it} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{8}$$

In Equation (8), μ_i and ν_t are the fixed effects for city and time, respectively. Other variables have the same connotation as those in Equation (7). If the results of the fixed effect model show a positive correlation between market sentiment and China's housing prices, the placebo test should be conducted, as the positive correlation may only be a placebo effect stemming from undetected limitations in the research design. Refering to Cornaggia and Li (2019), we extracted the sentiment index data of all samples and randomly assigned the data to each sample before re-regressing Equation (8). If the positive correlation between market sentiment and China's housing prices is a placebo effect, the processed market sentiment and China's housing prices should still be significantly positively correlated. Moreover, the variables in the general panel fixed model follow a normal distribution (Wen *et al.*, 2018). To check the robustness of the baseline regression results under the condition of multiple distribution, the Poisson model as shown in Equation (9) was used. In Equation (9), all the variables have the same connotation as those in Equation (7).

$$HP_{it} = \alpha_0 + \alpha_1 Sentiment_{it} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{9}$$

3.4 Moderating Effects

To test whether mobile network coverage, wage rate, and education affect the impact of market sentiment on China's housing prices, we added these three variables and their interactions with sentiment into Equation (7), as presented in Equations (10), (11), and (12).

$$Ln(HP_{it}) = \alpha_0 + \alpha_1 Ln(HP_{i,t-1}) + \alpha_2 Sentiment_{it} + \alpha_3 (MNC_{it} * Sentiment_{it}) + \alpha_4 MNC_{it} + \beta Z_{it} + \varepsilon_{it} \tag{10}$$

$$Ln(HP_{it}) = \alpha_0 + \alpha_1 Ln(HP_{i,t-1}) + \alpha_2 Sentiment_{it} + \alpha_3 (Wage_{it} * Sentiment_{it}) + \alpha_4 Wage_{it} + \beta Z_{it} + \varepsilon_{it} \tag{11}$$

$$Ln(HP_{it}) = \alpha_0 + \alpha_1 Ln(HP_{i,t-1}) + \alpha_2 Sentiment_{it} + \alpha_3 (Edu_{it} * Sentiment_{it}) + \alpha_4 Edu_{it} + \beta Z_{it} + \varepsilon_{it} \tag{12}$$

In Equations (10), (11), and (12), *MNC* refers to mobile network coverage, which was expressed by the number of mobile phone users. *Wage* means wage rate, while *Edu* refers to inhabitant education level, which was proxied by the number of college students per 10 thousand people. Other variables represent the same connotations as above. The data for *MNC*, *Wage,* and *Edu* were derived from China's real estate information network and the statistical yearbooks of cities.

4. Empirical Findings and Discussion

4.1 Housing Market Sentiment Index

The sentiment index was constructed using PCA. The Bartlett test and Kaiser-Meyer-Olkin (KMO) test were first conducted on the 13 sentiment proxies; their outcomes are shown in Table 2. As can be seen from the results, the Bartlett test value was highly significant, and a strong correlation was found between the sentiment proxies. The KMO test result of 0.714 indicated that a factor analysis may be useful with this dataset. Therefore, it was reasonable to conduct PCA on the 13 proxies to separate the common components. The results of the PCA are shown in Tables 3 and 4. The first three factors, or principal components, reported an Eigen value greater than one (>1) and explained almost 80% of the total variance. As such, we selected the first three principal components to construct the preliminary sentiment index ($Sentiment_{it}^*$). Equation (13) shows the $Sentiment_{it}^*$ equation that was constructed.

$$\begin{aligned} Sentiment_{it}^* &= 0.0908 rlNHS_{it} + 0.0861 rlNHS_{i,t-1} + 0.0942 rlSHS_{it} + 0.0903 rlSHS_{i,t-1} + 0.0768 rlNHFSC_{it} \\ &+ 0.0704 rlNHFSC_{i,t-1} + 0.0947 rlLPV_{it} + 0.0783 rlLPV_{i,t-1} + 0.0271 rlRLTN_{it} + 0.0109 rlRLTN_{i,t-1} + 0.1017 rLPR_{it} \\ &+ 0.1001 rLPR_{i,t-1} + 0.1257 lBI_{it} \end{aligned} \tag{13}$$

Table 2

Bartlett Test of Sphericity and Kaiser-Meyer-Olkin Measure of Sampling Adequacy

Chi-square	Degrees of freedom	p-value	Kaiser-Meyer-Olkin
15911.981	78	0.000	0.714

Table 3

*Sentiment** - total variance explained

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.36194	48.94	48.94	6.36194	48.94	48.94
2	2.4958	19.20	68.14	2.4958	19.20	68.14
3	1.59569	12.27	80.41	1.59569	12.27	80.41
4	0.690248	05.31	85.72			
5	0.541144	4.16	89.88			
6	0.530554	4.08	93.96			
7	0.373957	2.88	96.84			
8	0.294984	2.27	99.11			
9	0.0802025	0.62	99.73			
10	0.0334427	0.26	99.98			
11	0.00204096	0.02	100			

Table 4

*Sentiment** - principal components (eigenvectors)

Variables	Comp1	Comp2	Comp3
$rlNHS_{it}$	0.3912	0.0435	-0.0838
$rlNHS_{i,t-1}$	0.3864	0.0594	-0.1335
$rlSHS_{it}$	0.3862	0.0819	-0.0939
$rlSHS_{i,t-1}$	0.3822	0.0963	-0.1361
$rlNHFSC_{it}$	0.3852	-0.0618	-0.0567
$rlNHFSC_{i,t-1}$	0.3783	-0.0466	-0.1142
$rlLPV_{it}$	-0.0087	0.5417	0.1233
$rlLPV_{i,t-1}$	-0.0389	0.5325	0.0599
$rlRLTN_{it}$	-0.0962	0.4151	-0.1028
$rlRLTN_{i,t-1}$	-0.1172	0.4320	-0.2163
$rLPR_{it}$	0.1073	-0.0078	0.6370
$rLPR_{i,t-1}$	0.1039	0.0158	0.6015
lBI_{it}	0.2529	0.1907	0.2964

Upon the construction of $Sentiment^{*}_{it}$, a correlation analysis of all the proxies (except lBI_{it}) with $Sentiment^{*}_{it}$ was performed. The results of the correlation analysis are presented in Table 5. The ones which had a stronger correlation with $Sentiment^{*}_{it}$ in each group of a proxy and its lag[13] ($rlNHS_{it}$, $rlSHS_{it}$, $rlNHFSC_{it}$, $rlLPV_{it}$, $rlRLTN_{it}$, and $rLPR_{it}$) were then selected for the second PCA, together with lBI_{it}. The results of the second PCA are presented in Tables 6 and 7.

Table 5

The correlation coefficients between $sentiment^{*}_{it}$ and 13 sentiment proxy variables

Variables	$rlNHS_{it}$	$rlNHS_{i,t-1}$	$rlSHS_{it}$	$rlSHS_{i,t-1}$	$rlNHFSC_{it}$	$rlNHFSC_{i,t-1}$
CC	0.8484***	0.8411***	0.8704***	0.8652***	0.7478***	0.7338***
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Variables	$rlLPV_{it}$	$rlLPV_{i,t-1}$	$rlRLTN_{it}$	$rlRLTN_{i,t-1}$	$rLPR_{it}$	$rLPR_{i,t-1}$
CC	0.4681***	0.3854***	0.1232*	0.0586	0.2941***	0.2920***
P-value	0.0000	0.0000	0.0668	0.3853	0.0000	0.0000

Table 6

Final Sentiment - total variance explained

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.43562	49.08	49.08	3.43562	49.08	49.08
2	1.52603	21.80	70.88	1.52603	21.80	70.88
3	1.06388	15.20	86.08	1.06388	15.20	86.08
4	0.538752	7.70	93.78			
5	0.385348	5.50	99.28			
6	0.0492574	0.70	99.98			

[13] For example,, $rlNHS_{it}$ and $rlNHS_{i,t-1}$ form a group, and so on.

7	0.00110482	0.02	100

Table 7

Final Sentiment - principal components (eigenvectors)

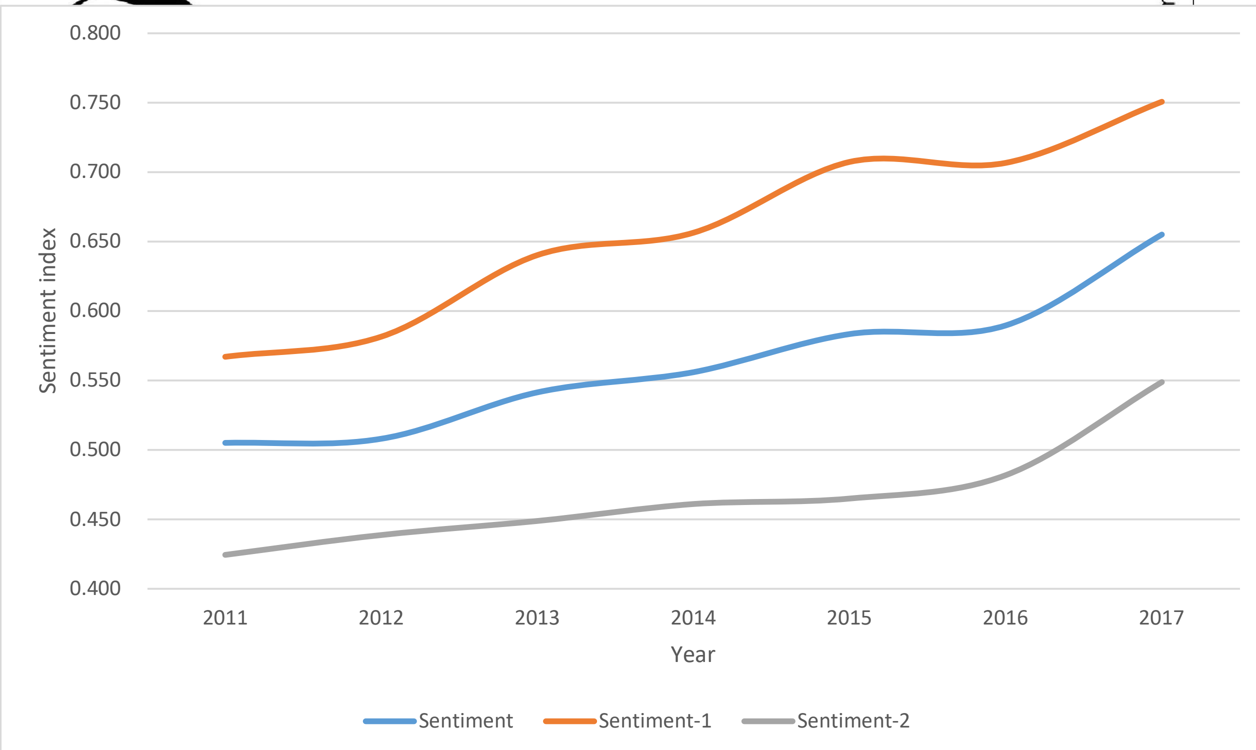
Variable	Comp1	Comp2	Comp3
$rlNHS_{it}$	0.5246	0.0146	-0.1964
$rlSHS_{it}$	0.5198	0.059	-0.2046
$rlNHFSC_{it}$	0.5096	-0.1103	-0.1705
$rlLPV_{it}$	-0.0082	0.7156	0.0474
$rlRLTN_{it}$	-0.1361	0.6315	-0.2457
$rLPR_{it}$	0.1698	0.0413	0.8566
lBI_{it}	0.3841	0.2674	0.3067

Based on the results of the second PCA, the first three principal components were chosen to construct the final sentiment index ($Sentiment_{it}$). Equation (14) shows the final $Sentiment_{it}$ equation that was developed. Equation (14) was then used to calculate the sentiment index of the 45 sample cities between 2011 and 2017.

$$\begin{aligned} Sentiment_{it} &= 0.1307rlNHS_{it} + 0.1370rlSHS_{it} + 0.1050rlNHFSC_{it} + 0.1523rlLPV_{it} + 0.0455rlRLTN_{it} \\ &+ 0.2073rLPR_{it} + 0.2255lBI_{it} \end{aligned} \quad (14)$$

Figures 3 and 4 depict the housing market sentiment index calculated using Equation (14). Figure 3 shows the housing market sentiment index of the 45 sample cities involved in this study, including 19 first-tier cities and 26 second-tier cities, from 2011 to 2017. Specifically, the blue curve labelled Sentiment, the orange curve labelled Sentiment-1, and the gray curve labelled Sentiment-2 in Figure 3 show the average sentiment indices of the 45 cities, the 19 first-tier cities, and the 26 second-tier cities respectively. First, in general, the sentiment index of the 45 cities increased year by year from 2011 to 2017, especially after 2016, which can be observed from the steeper curve during the period of 2016 to 2017. Coincidentally, China's housing prices not only maintained a rising trend year by year from 2011 to 2017, but also increased dramatically after 2016 due to the excessively lenient real estate and monetary policies implemented by the Chinese government in 2016 (Su et al., 2018). The synchronous change of the sentiment index and China's housing prices seems to imply a positive correlation between housing market sentiment and housing prices. Second, the curve of Sentimental-1 is above that of Sentimental-2, which indicates that market participants are more interested in the housing market of China's first-tier cities than in that of second-tier cities. Different from Figure 3, which describes the average sentiment index of the cities, Figure 4 intuitively presents the housing market sentiment of each city involved in this study in 2015 on a map of China[14]. In Figure 4, we used colour to represent housing market sentiment, wherein a darker colour symbolises stronger market sentiment. As seen in Figure 4, most first-tier cities are marked with deeper colours than second-tier cities on the map. This reveals that housing market sentiment in first-tier cities is generally higher than that in second-tier cities, which is consistent with Figure 3.

[14] We should have presented 2017's results; however, due to missing data on some cities in 2016 and 2017, we presented 2015's results.



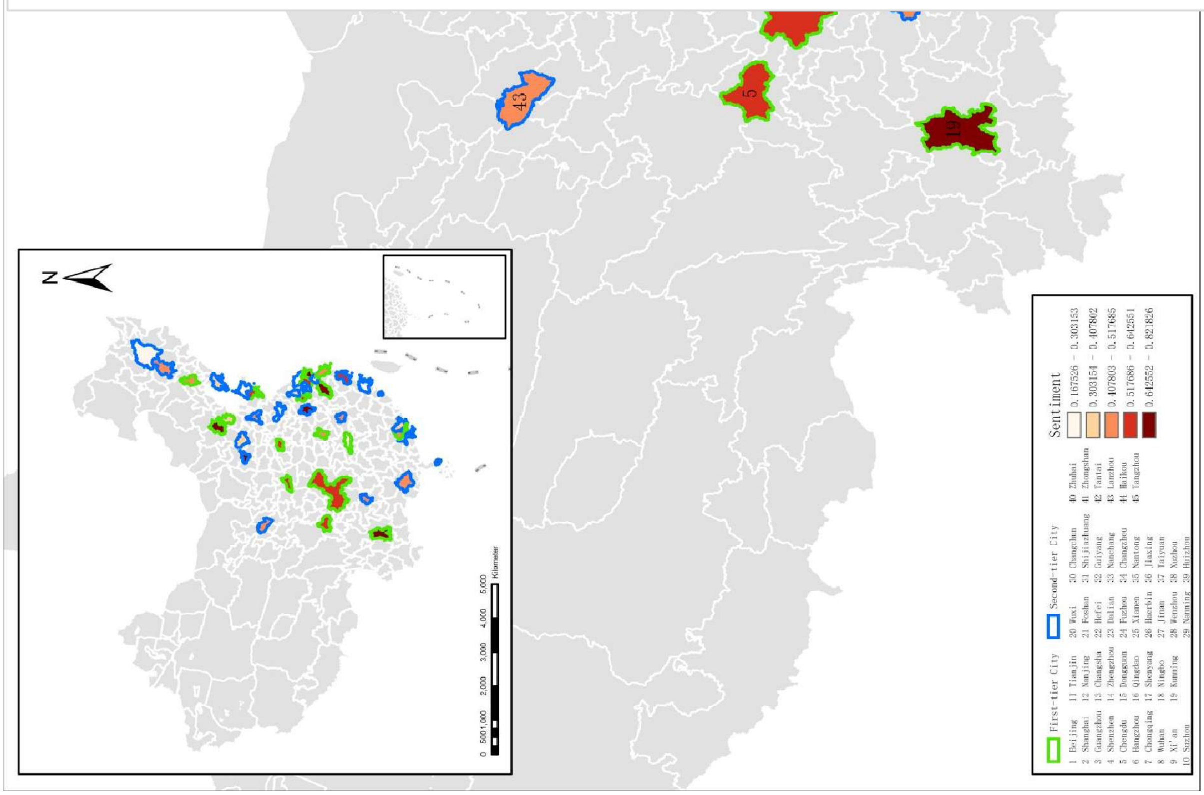


Figure 3 The average sentiment index in the 45 cities, first-tier cities, and second-tier cities from 2011 to 2017

Figure 4 The sentiment index of the sample cities in 2015

4.2 Relationship between Market Sentiment and Housing Prices

Next, utilising the constructed housing market sentiment index, we estimated the effect of market sentiment on housing prices.

Columns I and II in Table 8 depict the empirical outcomes of this effect; Column I reports the impact excluding all control variables, while Column II assimilates control variables to ascertain the relationship. The results show that in both columns, the Sargan test was not significant at the 10% level, indicating that the instrumental variable was effective and posed no problem of over-identification. In addition, AR (1) was significant at the 5% level, whereas AR (2) was not significant at the 10% level; thus, the error term was not auto-correlative and the dynamic panel data model was reasonable.

The estimated coefficients of *Sentiment* reported by Columns I and II in Table 8 were both positive and significant at the 1% level. This signifies that market sentiment has a favourable impact on the increase in housing prices in China, verifying the validity of Hypothesis 1. In other words, China's high housing prices have been partly driven by housing market sentiment in recent years. In addition, the coefficients of both $HP_{i,t-1}$ were positive and significant at the 1% significance level, which indicates that cities with high housing prices in the present tend to have higher housing prices in the future as well. This finding is consistent not only with Wang et al.'s (2018) research but also with Jo and Kim's (2014) proposition that price inertia exists in the housing market.

As for the control variables, with the exception of *UR*, all the variables obtained statistically significant coefficients with signs that were in line with expectations. First, we predicted that the migration of the population from rural to urban areas increases the demand for urban housing and so pushes up housing prices. *UR* was thus expected to obtain a statistically significant positive coefficient. However, interestingly, the coefficient obtained by *UR* was not statistically significant, meaning that urbanisation has no significant impact on housing prices in these 45 cities, possibly due to China's low-quality urbanisation. Specifically, the large number of migrant workers from the countryside has contributed to China's urbanisation process. Even so, most of the migrant workers rent in basements, urban villages, and urban fringe areas where few urban aborigines live; dozens even share a single house (Zhou, 2016). In other words, the large-scale migrant worker population from the countryside only makes China's urbanisation develop statistically, but has no substantial impact on the demand for urban housing in the country. This is a reminder to the Chinese government to pay attention to the quality of urbanisation in addition to its quantity, so as to promote the deep integration of migrant workers into cities (Wei et al., 2018). Second, among all the control variables, *PP* recorded the largest estimation coefficient, indicating that high housing demand is the main reason for the rise of housing prices in China. Supporting this, Lin et al. (2018) pointed out that population is the most important factor affecting China's housing demand. In addition, the estimated coefficient obtained by *CF* was positive and significant at 1% significance level, which seems to imply that in China, credit support's positive effect on housing prices via higher potential home-buyer purchasing power is stronger than its negative effect on housing prices via looser financing constraints for real estate developers. The positive relationship between credit funds and housing prices can also be explained from another perspective. According to Zhou et al. (2020), credit development is an important factor in promoting economic growth, which is often accompanied by the growth of residents' income. As mentioned earlier and empirically supported in Table 8, residents' income has a positive impact on housing prices. As such, there is a statistically positive correlation between credit funds and housing prices.

To test the robustness of the benchmark regression results, the general fixed effect model, placebo test, and Poisson regression were conducted. The estimation results are presented in Columns III to VIII of Table 8. The results show that whether excluding or including control variables, the impact of market sentiment on China's housing prices is still positive at the 1% significance level, both in the general fixed effect model (Columns III and IV) and the Poisson model (Column VII and VIII); this is consistent with the benchmark regression results. The results of the placebo test are shown in Columns V and VI of Table 8. The regression results exhibit that the coefficients of *Sentiment* in Columns V and VI were not only statistically insignificant, but also very different from the fixed effect regression results. This finding suggests that the positive relationship between market sentiment and China's housing prices as concluded by the fixed effect model was not a placebo effect.

Table 8

Baseline regression results and robustness checks

	Baseline regression		Robustness checks					
	GMM		Fixed effect		Placebo effect		Poisson model	
	I	II	III	IV	V	VI	VII	VIII
$Sentiment_{it}$	0.364***	0.344***	0.541***	0.304***	0.076	-0.019	0.691***	0.373***
	(136.78)	(10.13)	(13.05)	(6.12)	(1.05)	(-0.70)	(6.14)	(5.92)
$Ln(LTP_{it})$		0.033**		0.061***		0.096***		0.064***
		(2.12)		(2.65)		(3.83)		(2.94)
$Ln(FSHC_{it})$		-0.042***		-0.079***		-0.098***		-0.098***
		(-3.02)		(-3.69)		(-3.78)		(-3.10)
$Ln(CF_{it})$		0.020***		0.020***		0.043**		0.013***
		(3.19)		(3.06)		(2.37)		(3.39)
$Ln(PP_{it})$		0.227*		0.755**		1.315***		1.226***
		(1.95)		(2.32)		(3.45)		(3.45)
$Ln(PCDI_{it})$		0.145***		0.223***		0.183*		0.156***
		(2.75)		(2.88)		(1.90)		(5.68)
UR_{it}		-0.090		-0.078		-0.071		-0.038***
		(-0.72)		(-0.81)		(-0.63)		(-4.08)
Constant	-0.211***	-1.200*	5.446***	-0.601	8.511***	-2.068		
	(-3.86)	(-1.66)	(20.11)	(-0.33)	(18.00)	(-0.97)		
$Ln(HP_{i,t-1})$	0.762***	0.527***						
	(95.46)	(8.62)						
Observations	222	210	263	240	263	245	263	240
R-squared			0.435	0.704	0.000	0.512		
city FE			YES	YES	YES	YES	YES	YES
year FE			YES	YES	YES	YES	YES	YES
Sargan test	0.517	0.546						
AR(1)	0.019	0.037						
AR(2)	0.676	0.671						

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

4.3 Further analysis

4.3.1 The analysis of moderating effects

In this part, we regressed Equations (10), (11), and (12) to verify the possible moderating effects of mobile network coverage, wage rate, and education on the relationship between market sentiment and China's housing prices. The regression results are shown in Table 9. The findings of the Sargan tests and AR tests suggest that the estimated models are reliable. Column I reports the estimation results of the moderating effect of mobile network coverage. It was observed that the estimated coefficient of *Sentiment* was positive at the 1% significance level, whereby the conclusion that market sentiment has a positive impact on China's housing prices is not changed by the interaction term $MNC_{it}*Sentiment_{it}$. The estimated coefficient of the interaction term $MNC_{it}*Sentiment_{it}$ was positive at the 5% significance level, confirming the positive moderating effect of mobile network coverage. Specifically, with wider mobile network coverage, the positive impact of market sentiment on China's housing prices is enhanced. Columns II and III report the estimation outputs of the moderating effects of wage rate and education, respectively. The results show that after the interaction terms

$Wage_{it}*Sentiment_{it}$ and $Edu_{it}*Sentiment_{it}$ were added, market sentiment still promotes the rise of China's housing prices, while the negative estimated coefficients of the two interaction terms indicate that wage rate and education both have negative moderating effects on the sentiment–price relationship in China's housing market. More precisely, with higher levels of residents' education and wage, the positive effect of market sentiment on China's housing prices will diminish. However, the coefficient of the interaction term $Edu_{it}*Sentiment_{it}$ was only -0.001, highlighting that the negative moderating effect of education is not strong.

Table 9

The impact of market sentiment on housing market with interactions

	I	II	III
$Sentiment_{it}$	0.327***	0.537***	0.152***
	(6.78)	(14.11)	(6.82)
$MNC_{it} * Sentiment_{it}$	0.232***		
	(7.63)		
$Wage_{it} * Sentiment_{it}$		-0.318***	
		(-3.89)	
$Edu_{it} * Sentiment_{it}$			-0.001***
			(-8.16)
$Ln(LTP_{it})$	0.015***	0.012***	0.008***
	(3.25)	(5.06)	(6.78)
$Ln(FSHC_{it})$	-0.037***	-0.017***	-0.008
	(-3.11)	(-3.78)	(-0.91)
$Ln(CF_{it})$	0.029**	0.035***	-0.011
	(2.21)	(3.21)	(-0.85)
$Ln(PP_{it})$	0.480***	0.256**	0.057*
	(5.00)	(2.53)	(1.68)
$Ln(PCDI_{it})$	-0.058	-0.031	0.110***
	(-0.73)	(-0.55)	(3.50)
UR_{it}	-0.096	-0.113	-0.008
	(-0.21)	(-0.53)	(-0.60)
$Ln(MNC_{it})$	0.022***		
	(4.93)		
$Ln(Wage_{it})$		-0.085***	
		(-9.80)	
$Ln(Edu_{it})$			0.000***
			(8.18)
Constant	0.370	0.149***	-1.175**
	(0.75)	(3.22)	(-2.34)
$Ln(HP_{i,t-1})$	0.427***	0.467***	0.978***
	(6.96)	(7.92)	(13.27)
Observations	210	210	210
Sargan test	0.701	0.423	0.711
AR(1)	0.032	0.049	0.037
AR(2)	0.671	0.739	0.712

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

4.3.2 Comparison of first- and second- tier cities

Compared with second-tier cities, China's first-tier cities have higher mobile network coverage, wage rates, and inhabitant education levels. On the one hand, the moderating effects of network coverage (positive), wage rate (negative), and education (negative) on the impact of market sentiment on China's housing prices are not completely consistent. On the other hand, there may be other moderating variables that have not been detected. As such, it remains difficult to draw a direct conclusion on whether market sentiment has a stronger positive effect on housing prices in China's first- or second-tier cities. To determine the existence of variances in this effect across the city tiers, we divided the 45 cities into two sub-samples: first- and second-tier cities. We first used the same method to construct the sentiment indices of first-tier cities ($Sentiment_{it}^{f}$) and second-tier cities ($Sentiment_{it}^{s}$). Equations (15) and (16) show the $Sentiment_{it}^{f}$ and $Sentiment_{it}^{s}$ formulas, respectively.

$$Sentiment_{it}^{f} = 0.1811rlCHT_{it} + 0.1822rlSHT_{it} + 0.1816rlCHNC_{it} + 0.0434rlLA_{i,t-1} - 0.0998rlLTN_{i,t-1} + 0.2001rLPR_{i,t-1} + 0.2087BI_{it} \tag{15}$$

$$Sentiment_{it}^{s} = 0.1552rlCHT_{i,t-1} + 0.1762rlSHT_{i,t-1} + 0.1556rlCHNC_{i,t-1} + 0.1409rlLA_{it} + 0.0376rlLTN_{it} + 0.1747rLPR_{it} + 0.1988BI_{it} \tag{16}$$

After obtaining the sentiment index data for the two city tiers, we conducted empirical analysis separately on the first- and second-tier cities, the outcomes of which are shown in Table 10. Columns I and III report the impact of market sentiment on housing prices in first- and second-tier cities, respectively, excluding all control variables, while Columns II and IV incorporate the control variables to ascertain the relationship. Columns V and VI are the regression results of the full sample for reference. Since the sub-sample contained fewer cities, system GMM was not suitable for use in the heterogeneity analysis. As a result, system GMM was replaced with the fixed effect model for the comparison of first- and second- tier cities.

According to Table 10, the estimated coefficients of *Sentiment* reported by all columns were positive and significant at the 1% level. This shows that market sentiment has a favourable impact on housing prices in first-tier as well as second-tier cities, which once again proves the robustness of the benchmark regression results. In addition, regardless of the inclusion of the control variables, the estimated coefficients obtained by *Sentiment* for the first-tier cities were larger than those for the second-tier cities. That is, compared with second-tier cities, market sentiment has a stronger positive effect on housing prices in first-tier cities, affirming the validity of HP2a.

There are also several differences in the impact of the control variables on housing prices between China's first- and second-tier cities. First, in terms of *LTP*, whether from the perspective of the marginal effect or statistical significance, *LTP* has a stronger impact on housing prices in first-tier cities, which may be explained as a result of unbalanced development. Specifically, cities in China consist of several districts with uneven levels of development, despite the fact that all the districts belong to the same city. More importantly, compared to China's first-tier cities, the gap among districts is much larger in second-tier cities. Different from first-tier cities, where higher land prices are caused by the general rise in land prices in most districts, the main driver of land prices in second-tier cities may only be increases in land prices in a few relatively developed districts. As such, in China's second-tier cities, the significant rise in housing prices stemming from rising land prices may only occur in a few districts with relatively good development. According to Guo and Wang (2021), there is a significant positive spatial autocorrelation in housing prices. In other words, although the rise in land prices can significantly stimulate rising housing prices in relatively well-developed districts in second-tier cities, this positive effect may be limited by the low housing prices in their adjacent districts. Consequently, the positive effect of rising land prices on housing prices in second-tier cities tends to be weaker than that in first-tier cities.

Second, according to the coefficients acquired for *FSHC* in Columns II and IV in Table 10, we can see that although *FSHC* has an inhibitory effect on housing prices in both first- and second-tier cities in China, this effect is more significant in first-tier cities.

Evidently, compared to second-tier cities, the increase in housing supply has a stronger inhibitory effect on housing prices in China's first-tier cities, which is likely because of strict housing purchase restriction policies in first-tier cities. Specifically, as mentioned earlier, China's first-tier cities have stricter housing purchase restrictions than second-tier cities, including higher access thresholds for housing purchase by external populations as well as various restrictions on the purchase of second housing by local families. Therefore, although the housing market in first-tier cities is more attractive to potential home-buyers, the existence of strict housing purchase restriction policies qualifies only a small number of people to buy housing there. Simply put, the effective demand in first-tier cities' housing market is restrained by their strict housing purchase restriction policies. However, housing purchase restriction policies in second-tier cities are relatively loose, which mitigates the possibility of housing demand being constrained by such policies. Overall, when housing supply increases by the same proportion, housing prices in first-tier cities may decline more than those in second-tier cities.

Third, although *PP* has a positive impact on housing prices in both first- and second-tier cities, this impact is much weaker in first-tier cities, which may also be due to their strict housing purchase restriction policies. As these policies render some people ineligible to buy a house, there may not be a substantial increase in housing demand despite a larger population size. As such, the positive impact of population size on housing prices in first-tier cities may be weakened. Finally, *PCDI* has a positive impact on housing prices in second-tier cities as expected, but surprisingly does not have a significant impact on housing prices in first-tier cities. We explained earlier that housing prices in China's first-tier cities are much higher than those in second-tier cities. In view of this, a small increase in residents' income may not help them cope with extremely high housing prices in first-tier cities, and thus may not have a substantive impact on housing demand in these cities. Therefore, *PCDI* does not demonstrate a significant statistical relationship with housing prices in first-tier cities.

Table 10

The impact of market sentiment on housing prices (Sub-sample)

	First-tier cities		Second-tier cities		Full-sample	
	I	II	III	IV	V	VI
$Sentiment_{it}$	0.655***	0.385***	0.423***	0.196***	0.541***	0.304***
	(11.29)	(5.10)	(7.38)	(3.11)	(13.05)	(6.12)
$Ln(LTP_{it})$		0.094***		0.007**		0.061***
		(3.11)		(2.21)		(2.65)
$Ln(FSHC_{it})$		-0.136***		-0.062**		-0.079***
		(-3.20)		(-2.57)		(-3.69)
$Ln(CF_{it})$		0.019**		0.022***		0.020***
		(2.14)		(3.95)		(3.06)
$Ln(PP_{it})$		0.780**		2.016**		0.755**
		(2.05)		(2.13)		(2.32)
$Ln(PCDI_{it})$		0.062		0.203***		0.223***
		(0.61)		(3.56)		(2.88)
UR_{it}		-0.066		1.318		-0.078
		(-0.63)		(1.54)		(-0.81)
Constant	4.704***	1.039	6.155***	-8.224	5.446***	-0.601
	(11.93)	(0.50)	(17.08)	(-1.57)	(20.11)	(-0.33)
Observations	129	122	134	118	263	240
R-squared	0.539	0.727	0.329	0.769	0.435	0.704
city FE	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES

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

5. Conclusion

5.1 Summary of findings and policy implications

This paper employed dynamic GMM estimation, the fixed effect model, placebo test, and Poisson model to gauge the impact of market sentiment on housing prices in 45 large- and medium-sized Chinese cities from 2011 to 2017. Urbanisation, population, income, and other indicators that may affect housing prices were adopted as control variables in the models, so as to more closely characterise the impact of market sentiment on housing prices. The empirical outcomes indicate that market sentiment has a positive impact on housing prices in the 45 cities. By incorporating interactions into the models, this study also empirically examined the possible moderating effects of mobile network coverage, wage rate, and education on this relationship. The empirical results show that a broader mobile network coverage reinforces the positive impact of market sentiment on housing prices, while better wage rates and higher inhabitant education levels weaken this positive impact. In addition, according to the empirical results of the main model, the control variables *LTP*, *CF*, *PP,* and *PCDI* exert positive effects on housing prices, while the control variable *FSHC* can significantly hamper housing prices. Lastly, the study explored first-tier and second-tier cities as two distinct sub-samples to estimate the heterogeneity of market sentiment's influence on housing prices, revealing that the effect is significantly stronger in first-tier cities.

The findings of this study offer some references for the Chinese government to regulate housing prices. First, in view of the stimulating effect of market sentiment on China's housing prices, the Chinese government may try to quantify and publish sentiment in the housing market on a regular basis in addition to setting an alarm value. This would build participants' rational knowledge of the current housing market and promote home-buyers' and developers' rational decision making. Second, in view of the heterogeneity of the positive effect of market sentiment on housing prices across different cities, when setting alarm values, it is necessary to vary from city to city according to the situation on the ground. Third, as the excessive exaggeration of China's housing market by the media can rouse market sentiment, the Chinese government may reduce information asymmetry in the housing market by guiding media agencies towards publishing objective and fair reports of the housing market while avoiding excessive exaggeration of housing prices. Fourth, in view of the negative moderating effects of wage rate and education on the sentiment–price relationship in the housing market, the Chinese government should strive to continuously improve residents' levels of salary and education. Fifth, the positive relationship between land prices and housing prices shows that it may be necessary for the Chinese government to control land prices. More specifically, as high market sentiment may incite developers' enthusiasm for land acquisition and thus promote land prices, the Chinese government may set quotas on land areas purchased by developers in each period to avoid land prices being bid up. In addition, since land price plays a much stronger role in promoting the housing prices in the first-tier cities than in the second-tier cities, it should be easier to achieve obvious results in the first-tier cities by controlling land price to regulate house price. Finally, considering the positive impact of credit funds on housing prices, the Chinese government should limit the credit funds flowing into the housing market.

5.2 Limitations and recommendations for future study

Although we tried our best to execute this empirical study precisely, there are still some limitations that cannot be solved at present; nevertheless, they provide directions for future research. First, to improve the immediacy of the constructed housing market sentiment index, the Baidu Index was incorporated into the index's construction framework. However, the representativeness of the Baidu Index as a proxy variable largely depends on the keywords used in searches, because in addition to our chosen keywords "city + housing prices", other keywords searched online can also secure house price information. While we attempted several different keywords and justified the keywords "city + housing prices" in our study, there may still be other keywords that we failed to identify. Therefore, future research can use the Baidu Index with other keywords to quantify housing market sentiment. Second, this paper empirically examined the moderating effects of mobile network coverage, wage rate, and education on the relationship between market sentiment and housing prices. However, there may still be other moderating variables that have yet to be recognised, indicating an area for exploration in future studies. Finally, we were limited by the availability of data, as the sample period of this study was just from 2011 to 2017. If the data can be updated, future scholars can extend this research to generate more current implications.

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Appendix

Table A1

List of the sample cities analysed in this study

First-tier cities		Second-tier cities	
1	Beijing	20	Wuxi
2	Shanghai	21	Foshan
3	Guangzhou	22	Hefei
4	Shenzhen	23	Dalian
5	Chengdu	24	Fuzhou
6	Hangzhou	25	Xiamen
7	Chongqing	26	Haerbin
8	Wuhan	27	Ji'nan
9	Xi'an	28	Wenzhou
10	Suzhou	29	Nanning
11	Tianjin	30	Changchun
12	Nanjing	31	Shijiazhuang
13	Changsha	32	Guiyang
14	Zhengzhou	33	Nanchang
15	Dongguan	34	Changzhou
16	Qingdao	35	Nantong
17	Shenyang	36	Jiaxing
18	Ningbo	37	Taiyuan
19	Kunming	38	Xuzhou
		39	Huizhou
		40	Zhuhai
		41	Zhongshan
		42	Yantai
		43	Lanzhou
		44	Haikou
		45	Yangzhou