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Effect of COVID-19 lockdowns on city-center and suburban housing markets: Evidence from Hangzhou, China

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ABSTRACT

In 2020, governments worldwide enforced lockdowns to contain the spread of COVID-19, severely impeding aspects of daily life such as work, school, and tourism. Consequently, numerous economic activities were affected. Before the COVID-19 outbreak, city-center housing markets in areas surrounding popular tourist attractions performed better than did suburban housing markets because of the output of the tourism industry. This study examines the changes in the performance of city-center and suburban housing markets in regions with popular tourist attractions after the lockdown. Specifically, the dynamics of city-center and suburban housing markets in Hangzhou, where West Lake is located, and the changes in the information transfer between these housing markets after the lockdown are explored. Transaction data from January 1, 2019 to September 30, 2020 are used to perform analysis, in which adjusted housing prices and asking prices are employed to measure market performance and sellers’ pricing strategies, and transaction volume and time on the market are used to measure market liquidity and transaction frequency. The results reveal that the effects of lockdowns differ between city-center and suburban housing markets. After the lockdown, a substantial structural change is observed in the suburban housing market; the volatility risk of housing prices decreases substantially, causing an increase in transaction premiums. Housing prices and transaction volume increase in the city-center housing market after the lockdown; this is possibly because of the influence from the overall housing market boom. In addition, because sellers raise their asking prices and the transaction time is extended, the sellers in the city-center housing market are particularly influenced by the disposition effect. This leads to a reversal in the lead–lag relationship between the city center and suburban housing markets in terms of informativeness. Specifically, before the lockdown, the city-center market transfers information to the suburban market, but after the lockdown, the suburban market transfers information to the city-center market. The COVID-19 pandemic has changed the world in many aspects; this paper finds that it will also change the development pattern of the real estate market in different locations.

1. Introduction

The COVID-19 pandemic has had a significant impact worldwide. The rapid spread of the pandemic has prompted governments in

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several countries to impose lockdowns to contain the spread of infection. Compared to the SARS pandemic in 2003, the COVID-19 pandemic has inflicted greater and longer-lasting damage to the global economy. The damage to the economy has partially been caused by lockdowns, which governments have enforced as a last resort. Although lockdowns effectively contain the spread of COVID-19, they strongly affect daily life. Lockdowns have affected nearly all economic activities in cities and forced citizens to continue their economic activities remotely, including work, school, and tourism. Remote work and schooling have become necessary to mitigate the damage to industries. However, the prohibition of tourism causes major economic damage to the tourism industry and tourist attractions, which can in turn spread to other industries in a domino effect. This study investigates the effect of COVID-19 lockdowns on housing markets in areas near tourist attractions (i.e., city centers) and their surrounding regions (i.e., suburbs). The performance of housing markets in touristic and nontouristic areas is compared as a preliminary analysis of whether COVID-19 lockdowns have caused a structural change in the regional economy of tourist attractions.

This study targets West Lake and examines the dynamics of the city-center and suburban housing markets in Hangzhou, China, in addition to exploring changes in information transmission during the COVID-19 lockdown. West Lake, a major historical and cultural attraction in China featuring famous scenery, has facilitated the development of tourism and high economic output for the center of Hangzhou, particularly for Xihu District. Therefore, housing prices in the city center are considerably higher than those in the suburbs, which are relatively far from West Lake. Studies have examined the meaning of the cultural landscape of West Lake (Zhang & Taylor, 2020; Zhang, 2017), tourism behavior in Hangzhou (Qian, 2015; Tang et al., 2020), the effect of West Lake on housing prices in the surrounding areas (Wen et al., 2014; Wen & Tao, 2015; Wen et al., 2017), the behavior of housing prices in Hangzhou (Wen & Xiao, 2017; Wen et al., 2018; Wen et al., 2017), and the effect of tourism on housing prices in Hangzhou (Zhang et al., 2019). In this study, touristic and nontouristic areas are compared to provide preliminary insight into the effect of COVID-19 lockdowns on housing markets near tourist attractions.

Some studies have shown that the impact of COVID-19 in China is enormous. Using data from Chinese publicly listed firms, Jie et al. (2021) document the COVID-19 impact on firm investment. Fang et al. (2021) propose that China’s foreign direct investment is affected by the COVID-19 pandemic and faces unprecedented risks and challenges. Several studies have investigated the effect of COVID-19 lockdowns. Bradley et al. (2020) establish a choice theory–based equilibrium model for labor markets during a pandemic that comprises variables such as the heterogeneity of productivity, age, and ability to work at home. According to the model, the spread of pandemics and lockdowns affect labor markets considerably; the duration of lockdowns affects workers’ decisions to work from home and the number of job openings in companies. In an examination of a large number of samples of workforces in Europe, Pfeiffer et al. (2020) report that COVID-19 and the associated lockdowns inflicted a tremendous amount of damage to the European economy and that the subsidies proposed by the European Union, such as short-term work allowances, mitigated only one quarter of the damage.

Because lockdowns affect work and income, they also affect consumer behavior. Pichler et al. (2020) report that total economic output and consumption in the United Kingdom 2 months after the COVID-19 lockdown were 27% lower than those before the lockdown. The three industries most severely affected were the retail industry, the restaurant and hotel industry, and activities in the service industry related to entertainment. Coibion et al. (2020) conduct a survey with more than 10,000 respondents on the effect of COVID-19 lockdowns on household expenditures and expectations of economic performance. The respondents note a decrease in their income and wealth by an average of US$5293 and US$33,482, respectively, due to the COVID-19 pandemic. In addition, their total expenditure decreases by 31%, with the most substantial decreases being in travel expenses and clothing purchases. Moreover, families in districts with the earliest lockdowns are the most severely affected. Decreases in travel expenses affect the tourism industry. Exploring the effect of COVID-19 lockdowns on the Greek labor market, Betcherman et al. (2020) identify the tourism industry as the industry most severely affected by the lockdowns.

The aforementioned findings demonstrate the impact of COVID-19 lockdowns on the economy, income, labor markets, and consumer behavior, particularly those associated with tourism. No study has investigated whether COVID-19 lockdowns affect housing markets surrounding tourist attractions. Therefore, this study examines changes in the performance of city-center and suburban housing markets associated with tourist attractions after the lockdown. Housing market performance and transaction frequency are measured by using four variables: transaction price, asking price, transaction volume, and time on the market. The results indicate that seller strategies in the city-center housing market change considerably and involve a disposition effect after the lockdown, and that

![Fig. 1. Housing price index of Hangzhou.](image-url)
suburban housing prices rise substantially, with reduced volatility risks. Thus, COVID-19 lockdowns at the tourism level cause a spillover effect on housing markets.

2. Background and literature review

2.1. Housing markets in Hangzhou

Qian (2015) note that Hangzhou, one of the oldest cities in China, has transitioned into a highly developed metropolis. Hangzhou is a major economic center in the Pearl River Delta. High development in Hangzhou has caused a tremendous rise in housing prices. Fig. 1 presents a time series chart of housing prices in Hangzhou provided by the National Bureau of Statistics of the People’s Republic of China; the figure indicates a nearly double increase in housing prices from 2005 to 2020.

West Lake, located in downtown Hangzhou, holds meaning to China as a critical cultural landscape (Zhang et al., 2017) because it has facilitated the flourishing of the tourism industry in Hangzhou. The central districts of Hangzhou, namely Shangcheng, Xiaocheng, Xihu, Gongshu, Jianggan, and Binjiang districts, are some of the earliest-developed areas in Hangzhou. The suburban areas are Yuhang and Xiaoshan districts (see Fig. 2).

Studies have investigated the characteristics of housing prices in Hangzhou. Wen et al. (2018) adopt a conventional feature model for housing price and the component regression method to explore the effect of new railroads on housing prices. The empirical results reveal that neighboring subway stations affect housing prices significantly; housing prices in areas within 2 km of a station are 2.1–6.1% higher than those in the areas far from stations. Wen and Xiao (2017) analyze residential information in Hangzhou in 2015 to examine the spatial effect of waterscapes on housing prices and discover that the accessibility of the Grand Canal affects housing prices considerably; for each 1% distance away from the canal, the price of a house decreases by 0.016%.

The aforementioned findings reveal that transportation and scenery are major factors affecting housing prices in Hangzhou. In terms of the factors affecting housing prices in different districts of Hangzhou, tourism is the most commonly discussed factor. In an analysis of the effect of West Lake on housing prices, Wen et al. (2014) employ 649 sets of residential data in 2011 to create a housing price feature model that involves the use of spatial regression analysis to identify the spatial effect of urban lakes on housing prices according to the heterogeneity of direction and distance. The results reveal that West Lake exerts a positive spillover effect on housing price; for each 1% increment of distance away from West Lake, the price of a house decreases by 0.159%. Wen and Zhang (2015) use the data on Hangzhou to create a feature model comprising factors such as residential structure, neighborhood, location, and scenery to evaluate the positive effects of different types of scenery on housing prices. The empirical results reveal that West Lake, Qiantang River, parks, mountains, rivers, and lakes strongly influence housing prices, indicating that urban residents are willing to pay higher housing prices to protect these natural environments. For each 1% increment of distance away from West Lake, the price of a house decreases by 0.229%. Wen et al. (2015) collect residential data from six administrative districts in Hangzhou from 2003, 2008, and 2011 to create a conventional feature price model and a spatial model to analyze the effect of the city center on housing price dynamics in Hangzhou. The results indicate that Hangzhou has three city-center structures and that the city center influences housing prices considerably. In particular, West Lake plays a critical role in the spatial structure of housing prices; a notable increase between 2003 and 2011 is observed in the effect of proximity to West Lake, the most influential factor on housing prices.

The aforementioned findings indicate that tourism is a major factor affecting the housing market in Hangzhou. Numerous studies have demonstrated the impact of COVID-19 lockdowns on regions, industries, and economic activities associated with tourism and travel. Therefore, this study examines the effect of COVID-19 lockdowns on housing markets associated with tourist attractions.

2.2. Effect of COVID-19 on Hangzhou

On January 21, 2020, the first case of COVID-19 infection in Hangzhou was reported. In response, the government of Zhejiang Province, in which Hangzhou is located, declared a Level 1 major public health emergency 2 days after the report. On January 28, 19 new cases were reported in Hangzhou, constituting the highest number of cases reported in a single day at the time. Subsequently, the effects of COVID-19 on Hangzhou began to expand. On February 23, the centrally located Gongshu district became the first district to institute “closed-off management,” or a lockdown. In addition, all public transportation in Yuhang District, a suburban district near West Lake, was suspended.

On February 4, 2020, a key date in the control of the pandemic, 10 measures were implemented to prevent and control the pandemic, and all villages, communities, and administrative units in Hangzhou entered closed-off management. That day, on which nine new cases of COVID-19 were reported, lockdowns began in Hangzhou. The pandemic in Hangzhou was effectively controlled after that day because the number of newly diagnosed cases reported each day did not exceed 10. Subsequently, to satisfy the needs of citizens and companies for work and production, the Hangzhou city government issued permissions to the first group of enterprises to resume operations on February 10. The second group of enterprises were permitted to resume operations on February 15, at which time more than 40,000 enterprises had resumed operations, and the majority of production activity in Hangzhou resumed. On March 2, the Zhejiang Province government adjusted the major public health emergency from Level 1 to Level 2.

Although the COVID-19 control measures in Hangzhou have gradually been relaxed, no country, including China, has completely overcome the crisis caused by the COVID-19 pandemic. The impact of the pandemic has exceeded that of the severe acute respiratory syndrome (SARS) pandemic in 2002 in terms of scope, severity, and duration. Several studies have explored this impact. Chopra and Mehta (2022) explore the contagious effects of the COVID-19 pandemic on the Asian stock markets. Ludvigson et al. (2020) and Sharif et al. (2020) analyze the possible impact of COVID-19 on the macroeconomy. Baker et al. (2020), Al-Awadhi et al. (2020), and
Albuquerque et al. (2020) have explored the effect of COVID-19 on the financial market. Kozlowski et al. (2020), Alon et al. (2020), Bick et al. (2020), Blundell et al. (2020), and Kramer and Kramer (2020) have investigated the changes in human society caused by COVID-19. Nakamura and Suzuki (2021) discover the effect that COVID-19 has had on labor markets and the intentions to migrate from developing countries.

Studies have explored the measures implemented by governments in response to the COVID-19 pandemic (Ashraf, 2020; Figari & Fiorio, 2020; Rowthorn, 2020). Several studies have investigated the effect of COVID-19 lockdowns on government policies (Beck & Wagner, 2020; Fadinger & Schymik, 2020). Few studies have explored the effect of COVID-19 on housing markets because gathering housing market data within a short amount of time is difficult, and no study has examined the effect of lockdowns on tourist attractions. Therefore, this study investigates the effect of COVID-19 lockdowns on housing markets in areas near tourist attractions (i.e., city centers) and their surrounding regions (i.e., suburbs) to contribute to the field of research.

3. Samples

The data used in this study are acquired from Beike, an online platform that publishes housing transaction data on a daily basis. The company that provides the data, ke.com, is the first real estate agency in China to be listed by the New York Stock Exchange. Because of its economies of scale, the market share of ke.com in the real estate transactions in Hangzhou has increased consistently, and it has acquired several local real estate transaction agencies in Hangzhou. Therefore, the housing transaction data provided by Beike are sufficiently numerous to accurately represent the housing market in Hangzhou.

This study analyzes transaction data from January 1, 2019, to September 30, 2020 on eight districts, namely the central Shangcheng, Xiacheng, Xihu, Gongshu, Jianggan, and Binjiang districts and the suburban Yuhang and Xiaoshan districts. The total number of data sets is 36,259, of which 1510, 1931, 4871, 3110, 5838, 1524, 14,108, and 3367 data sets are from Shangcheng, Xiacheng, Xihu, Gongshu, Jianggan, Binjiang, Yuhang, and Xiaoshan districts, respectively.

This paper uses the variables of each housing transaction data set, which comprises total housing price (CN¥10,000), total asking price (CN¥10,000), time on the market (days), and other housing price characteristics such as residential area (m²), number of

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bathrooms, rooms, and halls, and floor location. In order to make graphs to illustrate the situation of each day’s housing market transactions, this paper calculates the average unit price each day to obtain the average housing price (HP) and the total trading number each day in the area to get the transaction volume (Vol). And for empirical model tests, this paper uses housing price characteristics to estimate the adjusted housing price (AHP) and the adjusted asking price (ALHP) based on transaction data. A description of all used variables is listed in Table 1.

Studies have discussed seller trading strategies by comparing two types of housing price: the seller’s offering price and the actual trading price (Beracha & Seiler, 2014; Deng et al., 2022), which are thus used in the present study for analyses. Early research on seller pricing strategies, such as Horowitz (1992), has revealed sellers’ tendency to set the offering prices higher than their reservation prices, which causes the final trading prices to be lower than the offering prices. This phenomenon is also observed in the present study data; for example, the average offering price in the Shangcheng District is higher than the average trading price by 37% (CN¥10,000).

To compare the transactions in the city-center and suburban housing markets, daily average unit price (per m²; Fig. 3) and daily accumulated transaction volume (i.e., number of transactions; Fig. 4) in the city center and the suburbs are calculated. In Fig. 3(a), HPc and HPs represent the average unit price in the city center and the suburbs, respectively. According to the figure, both the average unit housing price and its daily change are considerably higher in the city center than in the suburbs. The calculation for each data period reveals that the average housing price per m² is higher in the city than in the suburbs by CN¥14,000 (i.e., by 53%). Therefore, location strongly influences the Hangzhou housing market.

In Fig. 3(b), Volc and Vols represent transaction volume in the city center and suburbs, respectively. The data reveal zero transactions from January 23 to February 19, 2020, a period in which Chinese New Year occurred and the lockdown began on February 4. The figure indicates an increase in transaction volume in both areas after the lifting of the lockdown. Before the enforcement of the lockdown, transaction volume is considerably higher in the city center than in the suburbs. After the lifting of the lockdown, for most of the data periods, transaction volume is higher in the suburbs than in the city center. This indicates that more transactions are performed in the suburban housing market than in the city-center housing market after the lockdown.

Fig. 3 reveals the trend of average housing price before and after the coronavirus disease 2019 (COVID-19) outbreak. However, this housing price trend is not necessarily due to the COVID-19 pandemic because housing prices are affected by various factors, and housing estates traded at different times also vary in terms of characteristics. Some studies have employed the raw trading data of housing estates to investigate how the COVID-19 outbreak has affected the housing market. Nevertheless, controlling the effects of housing characteristic and trading time differences on housing prices for a rigorous estimation of the actual influence of COVID-19 is challenging. Yang and Zhou (2022) used average housing prices to discuss the effect of COVID-19 on housing prices in the Yangtze river delta region in China, without controlling housing quality or trading time differences. Studies have employed the difference-in-difference method (Qian et al., 2021) or nonparametric estimation (Zhao, 2020) to examine housing price changes before and after the COVID-19 outbreak.

Cheung et al. (2021) and Huang et al. (2021) filter raw price data with hedonic housing price models to establish time series data of housing price and thereby observe housing price changes over time. This approach is also adopted in the present study because it, despite requiring a large sample of trading data, allows for a comprehensive examination of housing price changes over time before and after the pandemic. In addition, similar to other studies on housing prices in Hangzhou (Wen & Zhang, 2015; Wen et al., 2014, 2018; Wen et al., 2017; Wen et al., 2015), this study uses a hedonic model to estimate the data and control specific factors. The hedonic model that this paper used to obtain the fitted price to construct the time series data is as follows:

$$THP_i = a_0 + a_1 \text{area} + a_2 \text{bathroom} + a_3 \text{room} + a_4 \text{hall} + a_5 \text{floor} + \epsilon_i$$  \hspace{1cm} (1)

where Total housing price (THP) is designated as the dependent variable, and the area of a residential building (area), number of bathrooms (bathroom), rooms (room), and halls (hall), and the floor of the residential space (floor) are the housing price feature variables used for estimation.

Housing characteristics vary across locations, and thus studies have highlighted the need to divide a single housing market into several submarkets for different regions (Costello et al. 2019; Lisi, 2019). According to the studies, because of the nature of the submarkets, one unique housing price feature model is implemented for each district in this paper. After the models for each district are created, the total estimated price of each residential building is calculated. The estimated price of the ith residential building is calculated as follows:

$$E[THP_i] = \hat{a}_0 + \hat{a}_1 \text{area} + \hat{a}_2 \text{bathroom} + \hat{a}_3 \text{room} + \hat{a}_4 \text{hall} + \hat{a}_5 \text{floor},$$  \hspace{1cm} (2)

The estimated price is subtracted from the actual transaction price to obtain the transaction premium of the ith residential building after the housing price feature variables are controlled, as shown in the following equation:

$$AHP_i = THP_i - E[THP_i]$$  \hspace{1cm} (3)

where AHP represents the adjusted housing price, which is regarded as the transaction premium. If $AHP_i > 0$, then the actual transaction price is a relative premium (i.e., higher than the estimated price); if $AHP_i < 0$, then the actual transaction price is a relative discount (i.e., lower than the estimated price). In the subsequent empirical analyses, housing price is estimated by using AHP rather than the original prices. The asking prices are also estimated by using (1), and the asking price premiums (i.e., adjusted asking price) are calculated by using (3).
Table 1
Descriptions of the variables.

| Variable                     | Definition                                                                 | Source                                      |
|------------------------------|---------------------------------------------------------------------------|---------------------------------------------|
| Total housing price (THP)    | The total transaction price of the house (CN¥10,000)                       | The housing transaction data from Beike     |
| Total asking price (TLHP)    | Total asking price of the house (CN¥10,000)                               |                                             |
| Time on the market (DOM)     | The time the house remains on the market (days)                            |                                             |
| Residential area (area)      | House size (m²)                                                           |                                             |
| Number of bathrooms (bathroom) | Total number of bathrooms                                                 |                                             |
| Rooms (room)                 | Total number of rooms                                                     |                                             |
| Halls (hall)                 | Number of living rooms                                                    |                                             |
| Floor location (floor)       | Number of floors                                                          |                                             |
| The average housing price (HP) | Obtained by calculating the average unit price each day                   |                                             |
| The transaction volume (Vol) | Obtained by calculating the total trading number each day                 |                                             |
| The adjusted housing price (AHP) | (1) Using the housing price feature variables to estimate total housing price |
|                              | (2) The estimated price is subtracted from the actual transaction price to obtain the adjusted housing price, i.e., the transaction premium of the \( i \)th house |                                             |
| The adjusted asking price (ALHP) | (1) Using the housing price feature variables to estimate asking housing price |
|                              | (2) The estimated price is subtracted from the actual asking price to obtain the adjusted asking price, i.e., the asking price premium of the \( i \)th house |                                             |

![Graph of Housing prices](image1)

(a) Housing prices

![Graph of Trading volumes](image2)

(b) Trading volumes

Fig. 3. Housing prices and Trading volumes.

4. Empirical results

Table 2 displays the simple statistics of the housing market data, which are constituted of variables including transaction premium (AHP), asking price premium (ALHP), time on the market (DOM), and transaction volume (Vol). These variables are calculated...
separately for the city center and the suburbs. Transaction volume is calculated as the number of transactions performed in a district each day, and the other variables are defined as the daily mean values in each district. After the days with zero transactions are excluded from the data, a total of 589 data sets are obtained.

Table 2 also lists the mean variable values before and after the lockdown. The verification statistics indicate a considerable increase in all variables after the end of the lockdown; specifically, \( AHP, ALHP, DOM, \) and \( Vol \) for both the city center and the suburbs increase substantially. In contrast to the deterioration of most financial markets due to the COVID-19 pandemic,\(^2\) an increase in housing prices and transaction volume is observed in the housing market. Therefore, the effect of COVID-19 on the housing market is unique and must be further investigated. Table 2 presents the sequential nature of the variables. The results of a unit root test indicate that the variables are stationary.

Table 3 presents the changes in city-center and suburb transaction price in Hangzhou after the lockdown. The effect of the lockdown on transaction price and their volatility risk is examined through measurement of heterogeneous volatility by using the generalized autoregressive conditional heteroscedasticity (GARCH) model, which is defined as follows:

\[
\begin{align*}
AHP_{t,i} & = \beta_0 + \beta_1 AHP_{t-1,i} + \beta_2 \text{Dummy} + \epsilon_{t,i} \\
\epsilon_{t+i} | \Omega_{t-i} & \sim N(0, \sigma_{t,i}^2) \\
\sigma_{t,i}^2 & = \gamma_0 + \gamma_1 \epsilon_{t-1,i}^2 + \gamma_2 \sigma_{t-1,i}^2 + \gamma_3 \text{Dummy}
\end{align*}
\]

where \( \text{Dummy} \) indicates the dummy variable for the lockdown (1 indicates time after February 4, and 0 indicates the time before this date). Eq. (4.1) is a mean equation used to examine the effect of the lockdown on transaction premium, and (4.3) is a variance equation used to verify the effect of the lockdown on the volatility of the premium.

According to Table 3, transaction premium and volatility risk in the city center are only self-correlated and did not exhibit significant structural change after the lockdown. Transaction premium in the suburbs is also autocorrelated. However, notable structural changes are observed in transaction premium and volatility risk in the suburbs after the lockdown. The mean equation shows that transaction premium is strongly affected by the dummy variable, with a coefficient of 3.58. This indicates that the average transaction premium increases by CN¥35,800 after the lockdown with the other conditions remaining unchanged. Volatility is considerably influenced by the dummy variable, with a negative coefficient, indicating that the volatility risk of the adjusted housing prices decreases substantially after the lockdown. Accordingly, although housing price and transaction volume in both the city center and the suburbs increase after the lockdown, the satisfactory performance of the city-center housing market may be the result of influence from the overall market. A structural change in the suburban housing market after the Hangzhou lockdown is observed; volatility risk decreases substantially, leading to an increase in transaction premium.

The difference in asking price between the city-center and suburban housing markets is also explored. Table 4 displays the results of the GARCH model estimation with asking price premium as the dependent variable. Neither market is affected by the lockdown in terms of asking price volatility. However, after the lockdown, a structural change in asking price is observed; asking price premiums increase substantially in both the city center and the suburbs. As the mean equation in Table 4 demonstrates, asking price in the city center is strongly affected by the dummy variable, with its premium increasing by CN¥63,700; the asking price premium in the suburbs increases by only CN¥33,900 after the lockdown. Because asking price is adjusted by the control variables, the increase in asking price

\(^2\) According to Al-Awadhi et al. (2020), the daily increase in number of COVID-19 diagnoses and the total number of deaths caused by COVID-19 exert a strong negative effect on the stock income of all companies in the Chinese stock market. Albuquerque et al. (2020) report that the COVID-19 outbreak and subsequent lockdowns could lead to an unprecedented stock market collapse and suggest that investors adjust their stock investment to favor environmental and social firms. Ali et al. (2020) describe a contagion effect whereby global stock markets plunge after the outbreak of COVID-19.
asking price is caused by the other variables or by changes in sellers' strategies. For example, Genesove and Mayer (2001) analyzed the trading data in the Boston housing market to achieve relatively favorable transaction prices. Studies have reported that sellers in housing markets tend to increase asking price to avoid losses, thereby increasing time on the market. Negative impact, the increase in asking price represents a disposition effect consistent with the behavior of loss aversion (Engelhardt, 2003). Studies have also examined the relationship between asking price strategies and the time on the market; this may influence the relationship between asking price and the other transaction variables.

Table 4 presents the causal relationship among the four transaction variables, which can be used to determine whether the structural change in asking price is caused by the other variables or by changes in sellers’ asking price strategies. According to Table 5, sellers’ asking price strategies are a major factor affecting transaction price in the city center. A lead-lag model is employed to address the structural change in asking price, where the dependent variable is the adjusted asking price in the city-center housing market and the suburban housing market, respectively. Number in parenthesis is the p-value. The symbol * * represents statistically significant at 1% levels.
relationship between asking price and transaction premium before the lockdown is observed; transaction premium is also affected by the transaction volume. Transaction volume can be used as an alternative variable to liquidity. Therefore, as Table 5 shows, before the lockdown, transaction premium in the city center is affected by asking price strategies and market liquidity. Market transactions are also influenced by asking price strategies. In other words, sellers adjust their pricing strategies dynamically. After the lockdown, a substantial structural change is observed in housing transactions in the city center.

### Table 4
Estimations for the changes in the adjusted listing prices after the lockdown.

| Mean Equation | $\text{ALHP}_{it-1}$ | Mean Equation | $\text{ALHP}_{it-1}$ |
|---------------|-----------------------|---------------|-----------------------|
| $\text{DOM}$  | 0.1986 * **           | $\text{DOM}$  | 0.2138 * **           |
|               | [4.9871]              |               | [4.6383]              |
| $\text{Dummy}$| 6.3680 * **           | $\text{Dummy}$| 3.3937 * **           |
|               | [2.9864]              |               | [2.2808]              |
| $\text{Constant}$ | -5.1977 * **      | $\text{Constant}$ | -3.5318 * **      |
|               | [-3.8042]             |               | [-3.9849]             |

Notes: $\text{ALHP}_{it-1}$ and $\text{ALHP}_{it}$ denote the adjusted asking prices in the city-center housing market and the suburban housing market, respectively. $\text{Dummy}$ denotes the dummy variable for the lockdown (1 indicates time after February 4, and 0 indicates the time before this date). Number in bracket is t-statistic. The symbols * * * and * * * represent statistically significant at the 1% and 5% levels, respectively.

### Table 5
The causal relationship among the four transaction variables.

| The city-center housing market | Before the lockdown (N = 373) | After the lockdown (N = 214) |
|--------------------------------|-------------------------------|------------------------------|
| Null Hypothesis                | $F$-statistic | p-value | Null Hypothesis | $F$-statistic | p-value |
| $\text{AHP}_t \rightarrow \text{ALHP}_t$ | 4.7725 * ** | 0.0090 | $\text{AHP}_t \rightarrow \text{ALHP}_t$ | 1.2724 | 0.2823 |
| $\text{ALHP}_t \rightarrow \text{AHP}_t$ | 6.9664 * ** | 0.0011 | $\text{ALHP}_t \rightarrow \text{AHP}_t$ | 2.7952 | 0.0634 |
| $\text{DOM}_t \rightarrow \text{ALHP}_t$ | 0.1491 | 0.8616 | $\text{DOM}_t \rightarrow \text{ALHP}_t$ | 4.4554 * ** | 0.0127 |
| $\text{ALHP}_t \rightarrow \text{DOM}_t$ | 0.3207 | 0.7259 | $\text{ALHP}_t \rightarrow \text{DOM}_t$ | 3.4393 * ** | 0.0339 |
| $\text{Vol}_t \rightarrow \text{ALHP}_t$ | 2.5058 | 0.0830 | $\text{Vol}_t \rightarrow \text{ALHP}_t$ | 0.7710 | 0.4639 |
| $\text{ALHP}_t \rightarrow \text{Vol}_t$ | 0.5650 | 0.5689 | $\text{ALHP}_t \rightarrow \text{Vol}_t$ | 0.0270 | 0.9734 |
| $\text{DOM}_t \rightarrow \text{AHP}_t$ | 0.3985 | 0.6716 | $\text{DOM}_t \rightarrow \text{AHP}_t$ | 4.6474 * * | 0.0106 |
| $\text{AHP}_t \rightarrow \text{DOM}_t$ | 0.3879 | 0.6788 | $\text{AHP}_t \rightarrow \text{DOM}_t$ | 1.4973 | 0.2261 |
| $\text{Vol}_t \rightarrow \text{AHP}_t$ | 7.0227 * ** | 0.0010 | $\text{Vol}_t \rightarrow \text{AHP}_t$ | 0.8349 | 0.4354 |
| $\text{AHP}_t \rightarrow \text{Vol}_t$ | 0.1123 | 0.8938 | $\text{AHP}_t \rightarrow \text{Vol}_t$ | 0.0139 | 0.9862 |
| $\text{Vol}_t \rightarrow \text{DOM}_t$ | 2.8169 | 0.0611 | $\text{Vol}_t \rightarrow \text{DOM}_t$ | 7.2784 * ** | 0.0009 |
| $\text{DOM}_t \rightarrow \text{Vol}_t$ | 1.4081 | 0.2459 | $\text{DOM}_t \rightarrow \text{Vol}_t$ | 1.2432 | 0.2906 |

| The suburban housing market | Before the lockdown (N = 373) | After the lockdown (N = 214) |
|--------------------------------|-------------------------------|------------------------------|
| Null Hypothesis                | $F$-statistic | p-value | Null Hypothesis | $F$-statistic | p-value |
| $\text{AHP}_t \rightarrow \text{ALHP}_t$ | 0.6026 | 0.5479 | $\text{AHP}_t \rightarrow \text{ALHP}_t$ | 2.4940 | 0.0850 |
| $\text{ALHP}_t \rightarrow \text{AHP}_t$ | 1.8489 | 0.1589 | $\text{ALHP}_t \rightarrow \text{AHP}_t$ | 2.6784 | 0.0710 |
| $\text{DOM}_t \rightarrow \text{ALHP}_t$ | 3.0042 | 0.0508 | $\text{DOM}_t \rightarrow \text{ALHP}_t$ | 1.0185 | 0.3629 |
| $\text{ALHP}_t \rightarrow \text{DOM}_t$ | 1.5889 | 0.2055 | $\text{ALHP}_t \rightarrow \text{DOM}_t$ | 0.0731 | 0.9296 |
| $\text{Vol}_t \rightarrow \text{ALHP}_t$ | 1.1199 | 0.3274 | $\text{Vol}_t \rightarrow \text{ALHP}_t$ | 2.1741 | 0.1163 |
| $\text{ALHP}_t \rightarrow \text{Vol}_t$ | 0.9652 | 0.3819 | $\text{ALHP}_t \rightarrow \text{Vol}_t$ | 0.2200 | 0.8027 |
| $\text{DOM}_t \rightarrow \text{AHP}_t$ | 4.2725 * * | 0.0146 | $\text{DOM}_t \rightarrow \text{AHP}_t$ | 0.9450 | 0.3903 |
| $\text{AHP}_t \rightarrow \text{DOM}_t$ | 1.5167 | 0.2208 | $\text{AHP}_t \rightarrow \text{DOM}_t$ | 0.2838 | 0.7532 |
| $\text{Vol}_t \rightarrow \text{AHP}_t$ | 1.6837 | 0.1871 | $\text{Vol}_t \rightarrow \text{AHP}_t$ | 2.9816 | 0.0529 |
| $\text{AHP}_t \rightarrow \text{Vol}_t$ | 0.5022 | 0.6056 | $\text{AHP}_t \rightarrow \text{Vol}_t$ | 0.0989 | 0.9058 |
| $\text{Vol}_t \rightarrow \text{DOM}_t$ | 0.0901 | 0.9138 | $\text{Vol}_t \rightarrow \text{DOM}_t$ | 0.4630 | 0.6301 |
| $\text{DOM}_t \rightarrow \text{Vol}_t$ | 0.5544 | 0.5749 | $\text{DOM}_t \rightarrow \text{Vol}_t$ | 0.4894 | 0.6137 |

Notes: $\text{AHP}_t$, $\text{ALHP}_t$, $\text{DOM}_t$, and $\text{Vol}_t$ (i = c,s) denote the adjusted housing prices, the adjusted asking prices, days on market, and volumes in the city-center housing market and the suburban housing market, respectively. The symbols * * * and * * represent statistically significant at the 1% and 5% levels.
information lag. Asking price premium and market liquidity both influence time on the market, and asking price is affected by time on the market. In addition time on the market influences transaction premium.

Table 5 demonstrates that no dynamic adjustments occur in asking price strategies in the suburbs. Before the lockdown, only time on the market influences transaction premium. No information lead–lag relationship between these transaction variables after the lockdown is observed. Asking price strategies are dynamically adjusted in the city center, and these adjustments strongly affect the other market variables. Moreover, structural changes in asking price strategies after the lockdown are observed. Fig. 4 presents the information transfer among the variables, which further demonstrates the changes in the city-center housing market after the lockdown. After the lockdown, the influence of asking price strategies on time on the market increases considerably, causing information lag in transaction price.

As Tables 4 and 5 and Fig. 4 show, the asking price strategies of the sellers in the city-center housing market are informative. After the lockdown, the influence of asking price strategies on time on the market increases considerably, causing information lag in transaction price. This phenomenon does not occur in the suburban housing market. Thus, differences between changes in the city-center and suburban housing markets lead to changes in their informativeness.

The vector autoregression–multivariate GARCH model is applied to evaluate the relationship between the transaction variables of the city-center housing market and those of the suburban housing market to compare their informativeness. The correlation between these variables in terms of average performance and volatility and their information lead–lag relationship is investigated. With $Y_t$ as the transaction variable, the model is calculated as follows:

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \epsilon_t$$

(5.1)

$$\epsilon_t \sim \text{N}(0, H_t)$$

(5.2)

$$H_t = \Phi C + A \epsilon_{t-1}' \epsilon_{t-1} A + B H_{t-1} B$$

(5.3)

where $\epsilon_t$ and $H_t$ represent the residual and variance matrices, respectively. The data from before and after the lockdown are used in the estimation. Table 6 presents the data from before the lockdown. The correlation among the four transaction variables (i.e., transaction premium, asking price premium, time on the market, and transaction volume) in the city-center and suburban housing markets is explored. Table 6 lists the estimation results, which are used to examine the causal relationship between the variables of the two housing markets and identify their transaction informativeness. Table 7 displays the examination results.

According to Tables 6 and 7, in terms of causality in mean, the city-center housing market is more informative than the suburban market before the lockdown. This is because the city-center and suburban housing markets exhibit a causal relationship of mutual

| Variables | AHP <sub>t</sub> | ALHP <sub>t</sub> | DOM <sub>t</sub> | Vol <sub>t</sub> |
|-----------|----------------|----------------|---------------|------------|
| Mean model: $Y_t$ | | | | |
| $Y_{t-1}$ | 0.1628 | 0.0010 | 0.0490 | 0.2521 | -0.1099 | 0.0578 | 0.4761 | 0.0000 |
| $Y_{t-1}$ | 0.1051 | 0.1388 | 0.1261 | 0.1218 | 0.0101 | 0.8399 | 0.2629 | 0.0000 |
| $\text{Constant}$ | -4.0867 | 0.0004 | -4.4780 | 0.0006 | 135.2744 | 0.0000 | 6.6164 | 0.0000 |
| Mean model: $Y_t$ | | | | |
| $Y_{t-1}$ | 0.0768 | 0.0306 | 0.0441 | 0.1826 | 0.1291 | 0.0026 | 0.2030 | 0.0000 |
| $Y_{t-1}$ | 0.0775 | 0.1111 | 0.0672 | 0.1703 | 0.1233 | 0.0305 | 0.4968 | 0.0000 |
| $\text{Constant}$ | -3.2349 | 0.0001 | -4.1957 | 0.0000 | 77.4116 | 0.0000 | 5.2504 | 0.0000 |
| C(1, 1) | 15.0036 | 0.0000 | 19.3187 | 0.0000 | 14.7482 | 0.0000 | -0.2689 | 0.7888 |
| C(2, 1) | 1.1970 | 0.5942 | 4.3950 | 0.0192 | 16.0033 | 0.0000 | -4.4272 | 0.0000 |
| C(2, 2) | 0.1000 | 0.0000 | < 0.0002 | 0.0006 | 0.4535 | 0.0000 | 0.2095 | 0.0108 |
| A(1, 1) | -0.0533 | 0.3131 | 0.2864 | 0.0006 | 0.4535 | 0.0000 | 0.2095 | 0.0108 |
| A(1, 2) | 0.2383 | 0.0000 | -0.0260 | 0.6653 | 0.2090 | 0.0025 | -0.2182 | 0.0015 |
| A(2, 1) | -0.4737 | 0.0000 | -0.8321 | 0.0000 | -0.0764 | 0.2592 | 0.1522 | 0.1283 |
| A(2, 2) | 0.3467 | 0.0000 | 0.1837 | 0.0635 | 0.4353 | 0.0000 | 0.5981 | 0.0000 |
| B(1, 1) | 0.6299 | 0.0000 | 0.3492 | 0.0000 | -0.7341 | 0.0000 | -0.9446 | 0.0000 |
| B(1, 2) | -0.2426 | 0.0001 | -0.6119 | 0.0000 | 0.4482 | 0.0001 | -0.0965 | 0.5664 |
| B(2, 1) | 0.3611 | 0.0000 | 0.4068 | 0.0017 | 0.3841 | 0.0037 | 1.0108 | 0.0000 |
| B(2, 2) | 0.6456 | 0.0000 | 0.2576 | 0.0286 | 0.4196 | 0.0005 | 0.7308 | 0.0000 |

Notes: AHP, ALHP, DOM, and Vol (i = c, s) denote the adjusted housing prices, the adjusted asking prices, days on market, and volumes in the city-center housing market and the suburban housing market, respectively. Number in bold denotes statistically significant at 5% level. The estimated model can be described as follows.

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \epsilon_t \sim \text{N}(0, H_t)$$

where $\epsilon_t$ and $H_t$ represent the residual and variance matrices, respectively.
feedback only in transaction volume, which denotes market liquidity. However, the city-center housing market outperforms the suburban market in terms of information regarding transaction premium and time on the market. In terms of information transfer of market volatility, the two markets mutually influence each other for all variables.

Tables 8 and 9 present the correlation and causal relationships between the four transaction variables in the city-center and suburban housing markets according to the data from after the lockdown. The two markets mutually influence each other for all variables in terms of information transfer of market volatility; however, in terms of causality in mean, the suburban market is more informative than the city-center market after the lockdown. This is because the suburban market outperforms the city-center market in terms of information response on transaction volume, which denotes market liquidity. The city-center housing market, which exhibits abundant information on transaction premium and time on the market before the lockdown, does not outperform the suburban market in terms of these variables after the lockdown. This is consistent with the results in Tables 4 and 5 and Fig. 4, which demonstrate that the transaction prices in the city-center market became less informative after the lockdown. Accordingly, sellers in the city center adjust their asking price strategies after the lockdown; in response to the negative impact of the pandemic, they raise price levels and in turn extend the time on the market. Consequently, the information response of the liquidity of the city-center market is slower than that of the suburban market.

5. Conclusion

Several countries have imposed lockdowns to prevent the spread of COVID-19, severely inhibiting daily life. Because of lockdowns, tourism has been prohibited or limited, causing major economic damage to the tourism industry and tourist attractions. This study explores the structural changes in the city-center and suburban housing markets of Hangzhou, China, in which the West Lake tourist attraction is located, after the COVID-19 lockdown.

Four variables are used to measure market performance and transaction frequency, namely transaction price, asking price, days on market, and transaction volumes. Tables 7 and 8 present the correlation and causal relationships between the four transaction variables in the city-center and suburban housing markets according to the data from before and after the lockdown.

| Variable: AHP | Null Hypothesis | $\chi^2(n)$ | F-Statistic | p-value |
|---------------|----------------|-------------|-------------|---------|
| Causality in mean | $AHP_i \rightarrow AHP_s$ | 4.6762 * * | 0.0306 |
| | $AHP_i \rightarrow AHP_s$ | 2.1915 | 0.1388 |
| Causality in variance | $AHP_i \rightarrow AHP_s$ | 46.2362 * ** | 0.0000 |
| | $AHP_i \rightarrow AHP_s$ | 39.8481 * ** | 0.0000 |
| | $BEKK$ cross effects | 101.1983 * ** | 0.0000 |
| Variable: ALHP | Null Hypothesis | $\chi^2(n)$ | F-Statistic | p-value |
| Causality in mean | $ALHP_i \rightarrow ALHP_s$ | 1.7766 | 0.1826 |
| | $ALHP_i \rightarrow ALHP_s$ | 2.3937 | 0.1218 |
| Causality in variance | $ALHP_i \rightarrow ALHP_s$ | 208.1846 * ** | 0.0000 |
| | $ALHP_i \rightarrow ALHP_s$ | 122.2586 * ** | 0.0000 |
| | $BEKK$ cross effects | 451.5543 * ** | 0.0000 |
| Variable: DOM | Null Hypothesis | $\chi^2(n)$ | F-Statistic | p-value |
| Causality in mean | $DOM_i \rightarrow DOM_s$ | 9.0696 * ** | 0.0026 |
| | $DOM_i \rightarrow DOM_s$ | 0.0408 | 0.8399 |
| Causality in variance | $DOM_i \rightarrow DOM_s$ | 27.3137 * ** | 0.0000 |
| | $DOM_i \rightarrow DOM_s$ | 17.0925 * ** | 0.0002 |
| | $BEKK$ cross effects | 161.9653 * ** | 0.0000 |
| Variable: Vol | Null Hypothesis | $\chi^2(n)$ | F-Statistic | p-value |
| Causality in mean | $Vol_i \rightarrow Vol_s$ | 21.4577 * ** | 0.0000 |
| | $Vol_i \rightarrow Vol_s$ | 22.0449 * ** | 0.0000 |
| Causality in variance | $Vol_i \rightarrow Vol_s$ | 10.8386 * ** | 0.0044 |
| | $Vol_i \rightarrow Vol_s$ | 98.8271 * ** | 0.0000 |
| | $BEKK$ cross effects | 280.1419 * ** | 0.0000 |

Notes: $AHP_i, ALHP_i, DOM_i,$ and $Vol_i$ ($i = c, s$) denote the adjusted housing prices, the adjusted asking prices, days on market, and volumes in the city-center housing market and the suburban housing market, respectively. The symbols * ** and * * represent statistically significant at the 1% and 5% levels.
After the rigorous estimations using the housing price feature model and the submarket (i.e., district) data, the daily data sequences on transaction volume, and time on the market. This study uses 36,259 transaction data sets from September 2019 to September 2020. 

Notes: Estimations for VAR-MGARCH model (after the lockdown).

Table 8

| Variables | AHP<sub>i,t</sub> | p-value | ALHP<sub>1,i</sub> | p-value | DOM<sub>i</sub> | p-value | Vol<sub>i</sub> | p-value |
|-----------|-----------------|---------|-------------------|---------|----------------|---------|-------------|---------|
| Mean model: Y<sub>t</sub> | | | | | | | |
| Y<sub>1,t-1</sub> | 0.2540 | 0.0001 | 0.3024 | 0.0128 | -0.0779 | 0.3056 | 0.3866 | 0.0000 |
| Y<sub>1,t-1</sub> | -0.0023 | 0.9814 | -0.0089 | 0.9335 | -0.0628 | 0.4596 | 0.0407 | 0.0000 |
| Constant | -3.6437 | 0.0472 | -4.0419 | 0.0037 | 138.4257 | 0.0000 | 5.2934 | 0.0000 |
| Mean model: Y<sub>i</sub> | | | | | | | |
| Y<sub>1,t-1</sub> | 0.0706 | 0.0740 | 0.0344 | 0.3818 | 0.0758 | 0.1778 | 0.0994 | 0.0653 |
| Y<sub>1,t-1</sub> | 0.0107 | 0.8735 | 0.0351 | 0.5501 | -0.1001 | 0.1473 | 0.7266 | 0.0000 |
| Constant | -2.8888 | 0.0481 | -2.2382 | 0.0501 | 102.5578 | 0.0000 | 2.9614 | 0.0007 |
| C(1, 1) | 14.3298 | 0.0000 | 20.1906 | 0.0000 | 14.0617 | 0.2479 | 0.6679 | 0.6521 |
| C(2, 2) | -3.2376 | 0.1421 | -5.4883 | 0.0000 | 8.6211 | 0.2373 | 4.1324 | 0.0000 |
| A(1, 1) | -0.0000 | 0.9999 | 0.0000 | 0.9999 | 5.1749 | 0.8717 | <0.0000 | 0.9999 |
| A(1, 2) | 0.185 | 0.0656 | 0.5437 | 0.0000 | 0.5356 | 0.0000 | 0.2074 | 0.0107 |
| A(2, 1) | 0.1901 | 0.0000 | -0.0645 | 0.1180 | 0.2949 | 0.0002 | -0.2815 | 0.0002 |
| A(2, 2) | -0.4752 | 0.0019 | -0.8526 | 0.0000 | 0.0705 | 0.5347 | 0.3936 | 0.0002 |
| B(1, 1) | 0.2729 | 0.0001 | 0.1946 | 0.0118 | 0.2552 | 0.0425 | 0.7734 | 0.0000 |
| B(1, 2) | 0.6524 | 0.0000 | -0.0831 | 0.0000 | 0.5126 | 0.0179 | 0.9949 | 0.0000 |
| B(2, 1) | -0.0886 | 0.1041 | 0.2945 | 0.0000 | -0.5841 | 0.0542 | 0.2386 | 0.0060 |
| B(2, 2) | 0.4167 | 0.0008 | 0.5617 | 0.0000 | -0.7667 | 0.0074 | -0.4318 | 0.0000 |
| B(2, 2) | 0.8900 | 0.0000 | 0.8327 | 0.0000 | -0.2143 | 0.5499 | 0.4414 | 0.0000 |

Notes: AHP<sub>i</sub>, ALHP<sub>1</sub>, DOM<sub>i</sub>, and Vol<sub>i</sub> (i = c, s) denote the adjusted housing prices, the adjusted asking prices, days on market, and volumes in the city-center housing market and the suburban housing market, respectively. Number in bold denotes statistically significant at 5% level. The estimated model can be described as follows.

\[ Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \epsilon_t, \epsilon_t \sim N(0, H_t) \]

\[ H_t = \Sigma + \Gamma \epsilon_{t-1} \epsilon_{t-1}' + \Delta + \Omega H_{t-1} \]

where \( Y_t \) denotes the variable vector, \( \epsilon_t \) and \( H_t \) represent the residual and variance matrices, respectively.

transaction volume, and time on the market. This study uses 36,259 transaction data sets from September 2019 to September 2020. After the rigorous estimations using the housing price feature model and the submarket (i.e., district) data, the daily data sequences on the city-center and suburban housing markets are created by incorporating the four variables. The raw data are processed to examine the effect of COVID-19 on housing markets.

Because of the flourishing tourism industry and high economic value of the central districts of Hangzhou, such as Xihu District, housing prices in the city center are considerably higher than those in the suburban districts, which are relatively far from West Lake. Nevertheless, this study indicates that suburban housing prices increase substantially after the lockdown, and their volatility risk decrease. In the city-center housing market, because of the notable disposition effect from the sellers, only asking price exhibits a structural change. Therefore, the COVID-19 lockdown exerts a spillover effect, which is originated from the tourism industry and may have led to a decrease in the difference between the city-center and suburban housing markets in terms of housing price.

Further examination reveals that the asking price strategies implemented in the suburban housing market are not dynamically adjusted. Therefore, no noticeable disposition effect is detected in this market. In the city-center housing market, before the lockdown, transaction premium is influenced by asking price strategies and market liquidity, and market transactions influence asking price strategies; this indicates that sellers dynamically adjust their pricing strategies. After the lockdown, transaction premium in the city center begins to lag in information. Because the sellers increases asking prices substantially and thus extends the time on the market, although the transaction prices increase, information lag occurred for these prices.

The difference in the disposition effects may have affected the informativeness of the city-center and suburban housing markets. Therefore, this study investigates the transaction informativeness of the city-center and suburban housing markets after the COVID-19 lockdown. According to the results, the city-center market outperforms the suburban market in terms of transaction informativeness before the lockdown; by contrast, the suburban market outperforms the city-center market after the lockdown. The effect of the COVID-19 lockdown on housing markets near tourist attractions (city center) and their surrounding areas (suburbs) is examined to identify the structural changes in the local economy of these attractions after the lockdown. Future research should examine this topic from other perspectives to identify the appropriate response to the COVID-19 outbreak. Specifically, the results of this paper provide the following contributions and recommendations:

1. Following the COVID-19 outbreak, a large number of studies have investigated the influences of the pandemic from an urban perspective. For example, Liu (2020) and Hamidi et al. (2020) discussed why COVID-19 viruses spread more easily in some cities than in others. Regions are subjected to varying levels of influences by the pandemic; the regional economies may also be affected to various degrees and recover at different speeds due to differences in their local industries (Hayakawa & Keola, 2021). The present study explores the effect of the COVID-19 outbreak on Hangzhou. Such exploration has also been conducted in various cities, including Milan, Italy (Tricarico & Vidovich, 2021), Portland, USA (Figuiozzi & Unnikrishnan, 2021), and Lisbon, Portugal (Batalha et al., 2022). Research on China has predominantly been focused on Wuhan (e.g., Kong et al., 2022; Xu et al., 2022). Although Hangzhou has been used as an example by Li et al. (2021) to discuss the effects of COVID-19 on housing prices, they examine only the relationship between...
to COVID-19 their study on 12 international megacities, Liang et al. (2021) find that rental prices in these cities have been negatively impacted due to the changes of their housing markets.

Tourism is also among the most severely hit industries during the COVID-19 pandemic (Coibion et al., 2020; Lee et al., 2019). In Hangzhou, the postpandemic changes of the tourism industry is of particular importance and requires continuous attention.

Studies discussing the influences of COVID-19 on different cities vary in terms of their topics because of the heterogeneity among cities. For Hangzhou, the postpandemic changes of the tourism industry is of particular importance and requires continuous attention. Tourism is also among the most severely hit industries during the COVID-19 pandemic (Coibion et al., 2020; Lee et al., 2019). In their study on 12 international megacities, Liang et al. (2021) find that rental prices in these cities have been negatively impacted due to COVID-19's severe hit to the travel industry and particularly that travelers have tended to rent properties in the suburbs rather than downtowns. Ever since the lockdown in Hangzhou, the housing market performance in its tourist hotspots has differed from that of other regions. This finding implies that the COVID-19, through its effect on Hangzhou’s tourism industry, also affects other markets in the city. The local government may have to pay additional attention to the effect of the tourism industry, if it remains unrestored, on the citizens’ income and housing properties. Owners of downtown housing properties may bear the brunt of the pandemic because it has a particularly large adverse effect on the fluidity and informativeness of downtown housing market, which forces these owners to sell their properties within a short period of time. Such a situation has also been observed in other tourist attractions; for example, Batalha et al. (2022) focus their study on Lisbon, a tourist-intensive city, and reveal a negative effect of COVID-19 on the prices of downtown short-term rentals. Accordingly, local governments in tourist areas should pay attention to how well the tourism industry has recovered as well as changes in the housing market.

Table 9
Granger causality (after the lockdown).

| Variable: $AHP$ | $\chi^2(n)$ | $F$-Statistic | $p$-value |
|-----------------|-------------|---------------|-----------|
| Null Hypothesis | $AHP_i \rightarrow AHP_j$ | 3.1929 | 0.0740 |
| Causality in mean | $AHP_i \rightarrow AHP_j$ | 0.0005 | 0.9814 |
| Null Hypothesis | $AHP_i \rightarrow AHP_j$ | 17.9847 ** | 8.9924 ** | 0.0001 |
| Causality in variance | $AHP_i \rightarrow AHP_j$ | 14.7722 ** | 7.3861 ** | 0.0006 |
| BEKK cross effects | $AHP_i \rightarrow AHP_j$ | 38.2809 ** | 7.6562 ** | 0.0000 |
| Variable: $ALHP$ | $ALHP_i \rightarrow ALHP_j$ | $\chi^2(n)$ | $F$-Statistic | $p$-value |
| Causality in mean | $ALHP_i \rightarrow ALHP_j$ | 0.7648 | 0.3818 |
| Causality in variance | $ALHP_i \rightarrow ALHP_j$ | 0.0070 | 0.9335 |
| Null Hypothesis | $ALHP_i \rightarrow ALHP_j$ | 1144.6718 ** | 572.3359 ** | 0.0000 |
| Causality in variance | $ALHP_i \rightarrow ALHP_j$ | 67.6676 ** | 33.8338 ** | 0.0000 |
| BEKK cross effects | $ALHP_i \rightarrow ALHP_j$ | 2154.3567 ** | 430.8713 ** | 0.0000 |
| Variable: $DOM$ | $DOM_i \rightarrow DOM_j$ | $\chi^2(n)$ | $F$-Statistic | $p$-value |
| Causality in mean | $DOM_i \rightarrow DOM_j$ | 1.8156 | 0.1778 |
| Causality in variance | $DOM_i \rightarrow DOM_j$ | 0.5470 | 0.4596 |
| Null Hypothesis | $DOM_i \rightarrow DOM_j$ | 23.2431 ** | 11.6216 ** | 0.0000 |
| Causality in mean | $DOM_i \rightarrow DOM_j$ | 7.6940 * | 3.8470 * | 0.0213 |
| Causality in variance | $DOM_i \rightarrow DOM_j$ | 93.5959 ** | 10.7192 ** | 0.0000 |
| BEKK cross effects | $DOM_i \rightarrow DOM_j$ | $\chi^2(n)$ | $F$-Statistic | $p$-value |
| Causality in mean | $Vol_i \rightarrow Vol_j$ | 3.3973 | 0.0653 |
| Causality in variance | $Vol_i \rightarrow Vol_j$ | 23.1834 ** | 0.0000 |
| Null Hypothesis | $Vol_i \rightarrow Vol_j$ | 14.1566 ** | 7.0783 ** | 0.0000 |
| Causality in mean | $Vol_i \rightarrow Vol_j$ | 49.1842 ** | 24.5921 ** | 0.0000 |
| Causality in variance | $Vol_i \rightarrow Vol_j$ | 38.2809 ** | 23.3514 ** | 0.0000 |
| BEKK cross effects | $Vol_i \rightarrow Vol_j$ | $\chi^2(n)$ | $F$-Statistic | $p$-value |

Notes: $AHP_i$, $ALHP_i$, $DOM_i$, and $Vol_i$ ($c = s$) denote the adjusted housing prices, the adjusted asking prices, days on market, and volumes in the city-center housing market and the suburban housing market, respectively. The symbols *** and ** represent statistically significant at the 1% and 5% levels.

3. The effect of urban population density on COVID-19 spread has been verified in several studies (e.g., Almagro & Sabouri, 2020; Li et al., 2016). In Hangzhou, the housing market performance in its tourist hotspots has differed from that of other regions. This finding implies that the COVID-19, through its effect on Hangzhou’s tourism industry, also affects other markets in the city. The local government may have to pay additional attention to the effect of the tourism industry, if it remains unrestored, on the citizens’ income and housing properties. Owners of downtown housing properties may bear the brunt of the pandemic because it has a particularly large adverse effect on the fluidity and informativeness of downtown housing market, which forces these owners to sell their properties within a short period of time. Such a situation has also been observed in other tourist attractions; for example, Batalha et al. (2022) focus their study on Lisbon, a tourist-intensive city, and reveal a negative effect of COVID-19 on the prices of downtown short-term rentals. Accordingly, local governments in tourist areas should pay attention to how well the tourism industry has recovered as well as changes in the housing market.
their housing prices are affected by lockdowns, indicating a convergence of their housing prices. Gupta et al. (2021) state in their recent study in the United States that the differences among regional housing prices will continue to decrease, suggesting a flattening effect of COVID-19 on housing prices. A flattening effect is also observed in the present study’s investigation into the Chinese housing market. According to Gupta et al. (2021), such a flattening effect prompts the need to reevaluate housing prices and thus considerably affects housing market investments. Given the observed convergence between downtown and suburb housing prices in Hangzhou, the present study recommends that investors and governments in China stay aware of the potential flattening effect of COVID-19 on the Chinese housing market.

Data Availability

The authors do not have permission to share data.

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