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Epidemic shocks and housing price responses: Evidence from China's urban residential communities

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ABSTRACT

This paper evaluates the impact of the COVID-19 epidemic on the real estate market using a community-level panel dataset of 34 major cities in China. We find that the average housing price in communities with COVID-19 infections decreases by approximately 1.3% compared to communities with no confirmed cases. The economic implication is that homebuyers are willing to pay a premium equivalent to approximately 1.3% of the average housing price to avoid health risks. The response of real estate markets to epidemic shocks is heterogeneous in community and city characteristics. Dynamic analysis shows that the declines in home prices, transaction volumes, and rents are all short-lived, returning to their original development paths a few months after the epidemic shock. Public interventions such as community closures and quarantines may have contributed to the rapid recovery of the housing market, reducing the volatility of housing assets in the household sector.

1. Introduction

Coronavirus disease 2019 (COVID-19) is a new infectious disease that emerged in December 2019. It is contagious and has a long incubation period; thus, people are more likely to become infected with the virus if they live in an infected community than if they live in an uninfected community. The National Health Commission of China has reported national outbreak figures daily since January 11, 2020, and the local authorities have announced detailed information on the movement trajectories and residential locations of infected persons. Is people's risk aversion reflected in the prices of real estate markets? If real estate market prices are responsive to the risk of contracting illness during an epidemic, is this response heterogeneous? How have the dynamics of residential prices and transaction volumes evolved? This paper attempts to answer the above questions using price and transaction volume data for urban residential communities in China.

The COVID-19 epidemic provides a unique opportunity to measure housing market reactions to epidemic shocks. In this paper, we construct a difference-in-differences model with the announcement of infected communities as epidemic shocks. Because detailed information on infected communities is publicly available, we know the exact time and exact geographical location when a confirmed case is found in an infected community. Using the communities' latitude and longitude information, we employ nearest-neighbor matching and radius matching to obtain a control group consisting of uninfected communities, with an infected community as the centroid. From a real estate transaction platform (Fang.com), we obtained information on secondhand housing transactions at the community level in 34 major cities of China from May 2019 to June 2020. Using the variation in epidemic shocks in the time and space dimensions, we construct a hedonic price difference-in-differences model to explore the average treatment effects and heterogeneity of epidemic shocks on real estate sale prices. Furthermore, we investigate the dynamic responses of sale prices, transaction volumes and rents to epidemic shocks.

The empirical results indicate that the prices in the infected community decreased by approximately 1.3% compared to those of uninfected ones. Heterogeneity analysis shows that the characteristics of the community and city features affect the response of housing prices to epidemic shocks. These price shocks were only transitory and persisted in the first 3 or 4 months of an outbreak. Similarly, the transaction volumes dropped significantly due to the impact of the epidemic and returned to their previous trends after 3 or 4 months. The rental market analysis suggests that families with a higher ability to pay or with children are more averse to health risks. In addition, this effect was also short-lived. The rents returned to the previous trend after two periods. We highlight two important potential mechanisms of urban housing markets’

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response to the epidemic. First, reductions in housing demand due to the desire to avoid health risks resulted in reductions in housing prices, rents and transaction volumes immediately following an outbreak. Second, the rapid recovery in prices and transaction volumes highlights the role of urban public interventions when communities are exposed to the epidemic.

This paper falls into the extensive literature evaluating the effects of urban hazards on real estate values. Previous studies have focused on various hazards, including toxic waste sites (Kohlhase, 1991), cancer cluster (Davis, 2004), water and air pollution (Leggett and Bockstael, 2000; Smith and Huang, 1995; Chay and Greenstone, 2005), nuclear power plants (Clark and Allison, 1999; Folland and Hough, 2000), and crime (Hilafeldt and Mayock, 2010). Recently, there has been an explosion of relevant research. For instance, Pope (2008) found that a port noise disclosure reduced the value of homes in high-noise areas by 2.9 percent. Wisinger (2014) confirmed that housing values near registered chemical hazards were significantly lower than those in other areas. Currie et al. (2015) found that plant openings led to 11 percent declines in housing prices within a 0.5 miles. Grislain-Letréméry and Katossky (2014) showed that the impact of hazardous plants on housing values differed among three important French cities. Similarly, Nepal et al. (2020) found that the presence of an open drain in a neighborhood can reduce housing prices by 11%. Zhu et al. (2016) examined whether the 2011 Fukushima Nuclear Accident (FNA) changed the public’s attitudes toward nuclear energy, finding that land prices within 40 km of nuclear power plants dropped by approximately 18% one month after the accident, but this impact decreased over the long term. Chen et al. (2018) estimated that air pollution had a significantly negative impact on housing prices, and the willingness to pay for better air quality varied across different income groups.

Our work is also related to studies on the impact of natural disasters such as floods, fires, and earthquakes on housing prices. Rajapaksa et al. (2016) examined the impact of floods on property values, suggesting that property buyers are more responsive to the actual incidence of floods than the disclosure of information to the public on the risk of flooding. Sidla (2015) exploited the 1906 San Francisco Fire as an exogenous shock and found that the price of homes in high-noise areas within 0.5 miles. Grislain-Letréméry and Katossky (2014) showed that the impact of hazardous plants on housing values differed among three important French cities. Similarly, Nepal et al. (2020) found that the presence of an open drain in a neighborhood can reduce housing prices by 11%. Zhu et al. (2016) examined whether the 2011 Fukushima Nuclear Accident (FNA) changed the public’s attitudes toward nuclear energy, finding that land prices within 40 km of nuclear power plants dropped by approximately 18% one month after the accident, but this impact decreased over the long term. Chen et al. (2018) estimated that air pollution had a significantly negative impact on housing prices, and the willingness to pay for better air quality varied across different income groups.

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2. Background and theoretical considerations

2.1. The COVID-19 epidemic in China

On December 8, 2019, the first case of coronary pneumonia appeared in Wuhan, and the Wuhan Health Commission issued the “Urgent Notice on Reporting the Treatment of Unidentified Pneumonia” at the end of that year. On January 8, 2020, the novel coronavirus was preliminarily confirmed as the etiology of this epidemic. The National Health Commission (NHC) of China further strengthened its interdepartmental collaboration and began to develop specific measures to enhance the prevention and control of the epidemic. On January 11, 2020, the NHC first reported on the progress of unidentified viral pneumonia in Wuhan, the center of the epidemic. At this stage, there was a lack of effective preventive measures against the spread of the disease due to the public’s ignorance of the disease specifics and limited awareness of the epidemic.

Ten days after the NHC report, the outbreak spread from Wuhan City to other provinces. On January 23, 2020, according to the announcement of the epidemic prevention and control headquarters, buses, subways, ferries, and long-distance passenger transport in Wuhan suspended operations, and the airport and train stations were temporarily closed. To prevent the spread of the epidemic, the NHC issued the “Guidelines for Home Isolation Medical Observation” on February 5, 2020, which provided detailed guidance on infection prevention and control through home isolation. Local governments called on people to minimize their outdoor activities and to isolate themselves at home.

Local health commissions and the Centers for Disease Control and Prevention (CDC) synchronized notifications about cases in their regions through press conferences or their official websites, including the...
number of cases and the recently detailed movement trajectory of confirmed cases. Subsequently, information related to these outbreaks was quickly disseminated through newspapers, online media platforms, WeChat, etc. Many WeChat official accounts were updated daily with relevant information on the epidemic, and the public could access this information easily via WeChat on their mobile phones. In addition, some common mapping software programs in China, such as Baidu Maps and Tencent Maps, created maps of infected communities and kept them updated based on the most recent epidemic data provided by local health commissions. Therefore, once local authorities confirmed the infected communities studied in this paper, they made information available to the public at the same time.

Society paid a great deal of attention to the epidemic and gained more accurate knowledge of the means of disease transmission; thus, practical and scientific prevention and control measures were gradually taken by the population. In March 2020, there was a significant reduction in deaths (see the slope of the purple line in Fig. 1), and the cumulative cured cases also increased rapidly. The epidemic was effectively controlled in China in March 2020. In April, May, and June, the number of additional deaths and confirmed cases was very low (see Fig. 1), and the spread of the epidemic in China was almost completely contained, with Wuhan City ending its three-month blockade on April 8, 2020.

2.2. Theoretical considerations on the impacts of COVID-19 on property values

In this section, we discuss the possible impacts of COVID-19 on housing and rental prices, as well as the transaction volumes of second-hand homes.

When a confirmed case in a community is announced, potential homebuyers or tenants instinctively become risk averse due to health concerns, which leads to a decrease in home prices or rents in infected communities relative to uninfected communities. This is the primary hypothesis proposed in this paper.

Second, the above price responses may be very heterogeneous. Such heterogeneity is reflected not only in community characteristics but also in city features. Regarding community characteristics, the greater the population density of the community is, the greater the likelihood of being infected, reinforcing the decline in the willingness to pay caused by the epidemic shock, and the more significant the decline in housing prices. The better the amenities and public facilities around the community, the more resilient home prices and rents will be in the event of an epidemic shock. The heterogeneous response to epidemic shocks in communities with different average household income levels is somewhat ambiguous. On the one hand, the more upscale the community is, the more significant the decline in home prices because households with higher levels of income or wealth have a higher marginal valuation of life and are more sensitive to health risks. On the other hand, considering the quarantine measures implemented, high-end communities generally have a lower floor area ratio, lower population density, and greater independence among residences. Compared to that in low-end communities, home isolation in high-end communities is safer, more convenient, and effective in preventing epidemics. The more upscale the community is, the smaller the drop in home prices is likely to be. Which effect predominates remains an empirical question.

City features may also influence the price response of residential communities to epidemic shocks. First, the higher the city’s economic development level is, the more adequate the local government’s budget and staffing will be, the greater the city’s ability to implement epidemic prevention measures will, and the lower the likelihood that residents will be infected, which reduces the likelihood of residents being infected and mitigates the negative impact of the epidemic shock on housing prices. In addition, other things being equal, the stronger the demand for housing services in the city is, the more upward momentum there will be in residential prices, which will also mitigate the decline in prices due to the epidemic shock.

Third, we discuss the different forces that shape the dynamics of housing prices, transaction volumes and rents in the event of an epidemic shock. Under the impact of the epidemic, as we argued earlier, housing prices, rents and transaction volumes may be immediately affected by a downward adjustment; however, whether these adjustments are short-term or long-term will be influenced by a variety of factors. For example, timely and effective public intervention may shorten this adjustment process and prompt a rapid return to the original path of development. At the same time, fiscal and monetary policies to counter the impact of the epidemic may also create asset price appreciation expectations and trigger the involvement of speculative funds, thus creating a positive force to drive the gradual recovery of the real estate market. A detailed portrayal of the trajectory of changes in housing prices, rents and transaction volumes can provide a better understanding of the response mechanism of the real estate market to the epidemic shock, which is one of the key concerns of this paper.

Finally, we highlight the role of urban public interventions in governing the epidemic externality and shaping the housing market’s recovery trajectory. The novel coronavirus is highly contagious, and there are many negative externalities associated with its long incubation period. An infected person in the incubation period is a walking spreader of the virus. Government intervention is required to correct the negative externalities caused by the epidemic to promote social welfare. The Chinese government has taken decisive measures to control the epidemic; once a community is identified as infected, the community is immediately and wholly quarantined and observed for two weeks or more, limiting the spread of the epidemic from the infected community to adjacent neighborhoods and affecting the asset value of the surrounding community as little as possible. Furthermore, public intervention has served to stabilize the real estate market while curbing the negative externalities of the epidemic. The evolution of the epidemic itself and the introduction of public interventions together determine the trajectory of prices, rents and transaction volumes in the real estate market.

\[^2\text{For example, Wong (2008) found that housing with baseline prices one standard deviation below the mean suffered roughly half the price decline of those at the mean.}\]
3. Data and empirical strategy

3.1. Data sources

Community is a key concept in our study. In China, a community is a spatially contiguous complex managed by a single agent. In cities or towns, communities are generally enclosed by walls to form a separate residential area and are managed by a unified property management office or property committee. A community usually contains a number of buildings, and there are a number of households in a building. The definition of neighborhood is relatively flexible and generally refers to a geographic area that includes one or several adjacent communities as well as the surrounding environment.

We collected information about community characteristics, infected communities, and city features in 34 major cities in China. The community characteristics are obtained from one of China’s largest real estate transaction platforms, Fang.com, where we obtain monthly secondhand home transaction prices, rents, transaction volumes, and transaction time (monthly) for each community from May 2019 to June 2020. The other physical characteristics of communities, including the name, address, location (latitude and longitude), year built, landscaping ratio, floor area ratio, the total number of buildings and the total number of households in the community, are also from this website. Thus, we obtain 14 consecutive months of community-level secondhand housing market information for 34 cities.

Detailed information about the infected communities is common knowledge, as argued earlier. We obtained the name, address, and city of the infected communities and the date of infection (January 2020 to March 2020) from the Tencent Watchtower “infected communities” query platform. In this way, all communities that we identified from Fang.com can be characterized as infected or uninfected. We spatially match the above two kinds of communities using latitude and longitude information.

The city features are obtained from the China City Statistical Yearbook (2019), including GRP (yuan) per capita and the proportion of the urban employed population to the annual average population.

Regarding the transaction time we have collected from Fang.com, we would like to shed further light, as the identification of the transaction time will have a crucial impact on the setting of the model below. As we know, secondhand property transactions are different from those of ordinary consumer goods, and it will take longer to complete the closing process. In general, the buyer and seller first negotiate about the property transaction. If both parties reach the intention of making the deal, they will sign a contract of brokerage with the real estate transaction intermediary. Meanwhile, the buyer has to pay a certain deposit. The real estate transaction agent will then assist both parties in signing the property purchase and sale agreement, transferring the property and paying the relevant taxes and fees. If the seller still has an outstanding mortgage loan or if the buyer will use a mortgage loan to purchase a home, the transaction will take approximately one month to finalize, depending on the bank’s approval process.

After the successful closing of the transaction, the real estate broker will register the date when the brokerage contract was signed as the “transaction date” and other transaction information on the transaction platform (fang.com). That is, the registration of secondhand housing transactions tends to lag by roughly one month. In the context of this study, if an epidemic shock happens to occur during the time between the signing of the brokerage contract and the completion of the closing process, the buyer may breach the contract due to health risk aversion. In other words, the buyer may give up the deal and lose their deposit or start renegotiations with the seller, which means that the actual sold prices or the transaction volumes registered in this month may be lower. For example, assuming a confirmed case is detected in a community in February, homebuyers who signed brokerage contracts in January but have not yet completed their deals may default on their contracts due to health risk avoidance, which results in a decrease in both the volume and actual price of registered transactions in January in the infected community.

For the above reasons, we assume that the impact of the epidemic shock begins from period –1 (one month before the outbreak) in the analysis on housing prices and transaction volumes that follows. Unlike purchasing a home, the time to complete a rental transaction is relatively short. Therefore we assume that the impact of the outbreak begins from period 0 (the month of the outbreak) for the rental market. Subsequent empirical results also confirm the conjecture.

3.2. Selecting the control groups

To obtain counterfactuals for individuals in the treatment group (infected communities), it is necessary to find uninfected communities in the control group with characteristics similar to those of the treatment group. In addition to the presence of confirmed cases, other factors affecting housing prices should be as similar as possible in terms of both observable and unobservable characteristics, such as income, education, and other social environments. Therefore, we define similarity in terms of the geographic distance between communities and match the infected communities with uninfected ones in close proximity to identify the causal effects. This is done by setting a 750 m buffer zone centered on the infected community, and only matches within the buffer zone are allowed. Duplicate matches are not allowed. In this way, we successfully
match 725 infected communities, corresponding to 11,564 uninfected communities.

If a community has no transactions in one month, we consider the community’s monthly transaction volume to be 0. Some communities have very inactive housing markets and even no transactions during the period we studied. In the case of no transactions for 14 consecutive months, the average housing price of a community may be determined by referring to the transaction prices of neighboring communities, and the price may not accurately reflect the actual market situation of that community in that month. However, price information is an important basis for the analysis in this paper, and given that the secondhand housing market is linked to the rental market, we exclude infected communities with zero total transactions during the sample period when analyzing the impact of the epidemic on housing prices and rents. Ultimately, we successfully match 652 infected communities, corresponding to 9785 uninfected communities. Among them, 55 outbreaks occurred in January, 593 in February, and 4 in March. Unbalanced panel data on 10,437 communities for 14 months (May 2019–June 2020) are constructed, and the total number of observations is 130,807. We also remove infected communities with total transactions equal to 0 in the basis for our analysis, matching the infected communities with untreated communities.

Two matching methods are used to maximize the likelihood of similarity between the control and treatment groups, including nearest-neighbor matching and radius matching. The nearest-neighbor matching includes one-to-one and one-to-n (one-to-two and one-to-three) nearest-neighbor matching. As shown in Fig. 2a (left), C1 is an infected community, and A and B are the uninfected communities 582.80 m and 668.69 m away from C1, respectively. One-to-one nearest-neighbor matching uses the nearest community A as the counterfactual of C1. As shown in Fig. 2a (right), C2 is an infected community, and D, E, and F are the nearest three uninfected communities. The closest community D will be used as the counterfactual of C2 in the one-to-one nearest-neighbor matching, communities D and E will be selected as the counterfactual of C2 in the one-to-two matching, and D, E, and F will be chosen in the one-to-three matching procedure.

Table 1 presents the summary statistics for the communities that form the basis for our analysis, matching the infected communities with uninfected ones within a 750 m buffer zone. Descriptive statistics are reported separately by the type of community. “Infected=1” refers to 652 infected communities. “Infected=0” refers to 9785 uninfected ones within the 750 m buffer zone of each infected community.

Table 1 first presents descriptive statistics on the monthly transaction prices, transaction volumes, and rents for 3-bedroom homes at the community level before and after the treatment, respectively, and then presents summary statistics for the physical characteristics of the communities that did not change over time. In terms of the mean values in Table 1, it seems that there is no significant difference in the changes in sales prices between the infected and uninfected communities. The careful empirical analysis that follows shows that the treatment effects of epidemic shocks can only be clearly identified when a series of fixed effects affecting housing prices are controlled for. Due to the shock of the outbreak, the monthly transaction volumes and rental prices in all communities decreased after the outbreak, but the decrease was greater in the infected communities than in the uninfected communities. The average monthly transaction volumes and rents in the infected communities were significantly larger than those in the uninfected communities. A possible reason for this result is that communities with active market

Note: The first panel of Table 1 presents descriptive statistics for the average monthly transaction price, average monthly transaction volume, and average monthly rent of 3-bedroom homes in communities before and after the treatment respectively. With regard to sale prices and transaction volumes, “before” indicates that the transaction occurred before period −1, as we have explained in Section 3.1. The second panel presents summary statistics for the physical characteristics of the communities throughout the entire period.

Table 1
Summary statistics.

| Variable                     | Infected – 1 | Infected – 0 |
|------------------------------|--------------|--------------|
|                              | Mean         | S.d.         | Mean         | S.d.         |
|                              | Obs          |             | Obs          |             |
| Sale prices                  |              |              |              |              |
| (Monthly, yuan per sq.m.)    |              |              |              |              |
| before                       | 4241         | 31946.98    | 25912.01     | 65,831       | 32100.96    | 26818.51    |
| after                        | 3831         | 32028.27    | 27342.25     | 56,904       | 31992.72    | 28120.04    |
| Transaction volumes          |              |              |              |              |
| (Monthly, units)             |              |              |              |              |
| before                       | 5165         | 0.93        | 2.7          | 77,561       | 0.22        | 1.14        |
| after                        | 3963         | 0.72        | 2.85         | 59,429       | 0.21        | 1.21        |
| Rents                        |              |              |              |              |
| (Monthly, yuan per home)     |              |              |              |              |
| before                       | 4889         | 2859.36     | 3332.89      | 75,566       | 1963.05     | 3551.6      |
| after                        | 3183         | 2049.67     | 3274         | 47,169       | 1225.26     | 312.93      |

[5] In the rental analysis, the results support our main conclusions even when we do not remove the infected communities with 14 consecutive months of zero total transactions, as shown in Appendix Fig. 3a.

[6] The descriptive statistics for the rents of 1-bedroom homes and 2-bedroom homes can be seen in Appendix Tables 1a and 1b.
transactions have frequent population inflows and outflows and are more likely to have infected persons than other communities with less active markets. And there is no significant difference in the year built, land-scaping ratio, or floor area ratio between communities. The number of buildings and the number of households in the community are significantly higher in the infected communities than in the uninfected ones, which is consistent with intuition, as the probability of being infected is higher in more densely populated areas. The descriptive statistics for the 34 cities show that the mean values of gross regional product per capita and the proportion of the urban employed population to the annual average population are 104,119.2 (yuan) and 0.63 (%), respectively, as reported in Appendix Table 1d.

3.4. Empirical strategy

We are interested in the impact of the COVID-19 epidemic on housing prices, transaction volumes as well as rents. A hedonic property model is employed as follows:

\[ Y_{it} = \alpha + \beta \cdot \text{Infected}_i \cdot \text{Post}_{bt} + \theta \cdot T_i + \gamma_i \cdot t + \epsilon_{ibt} \]

\[ \text{Post}_{bt} = 1 \text{ if } t > m = -1, \text{ otherwise 0 in the case of prices or volumes analysis} \]

\[ \text{Post}_{bt} = 1 \text{ if } t >= 0, \text{ otherwise 0 in the case of rental analysis} \]

\[ (1) \]

\[ Y_{it} \text{ can be } \ln P_{it}, \text{ Volumes}_{it}, \text{ or } \ln R_{it}. \ln P_{it} \text{ is the natural logarithm of the monthly average of transaction price in community } i \text{ during month } t. \]

\[ \text{Volumes}_{it} \text{ is the monthly average transaction volume in community } i \text{ in month } t. \ln R_{it} \text{ is the natural logarithm of monthly average rental price in community } i \text{ during month } t. \text{ Infected}_i \text{ is an indicator set to 1 as long as a community has been infected, which is not time-varying. Post}_{bt} \text{ refers to the time- and buffer-varying indicator. In the analysis on housing prices and transaction volumes, as argued in Section 3.1, we assume the impact of the epidemic shock begins in period } -1 \text{ (one month before the actual time when the infected case is confirmed in buffer } b), \text{ therefore Post}_{bt} \text{ equals 1 after period } -1. \text{ And in the analysis of rents, Post}_{bt} \text{ is equal to one after the infected case is confirmed in buffer } b. \theta_i \text{ is the neighborhood fixed effect that controls for neighborhood characteristics that do not change over time. } T_i \text{ is the monthly fixed effect that absorbs common shocks from the time dimension. } \gamma_i \cdot t \text{ (interacting each buffer dummy } \gamma_i \text{ with the linear time trend } t) \text{ is a linear time trend for buffer } i \text{ with the linear time trend } t). \]

\[ \text{We would like to further clarify that this is a trend that is the same for both the treatment and the control observations within a specific buffer. Here, we are not removing the differential trends between treatment and control groups prior to testing for treatment effects. Rather we are relying on the event study (Model 3) to demonstrate parallel pre-trends.} \]

\[ \gamma_i \cdot t \text{ is buffer-by-month fixed effects (interacting each buffer dummy } \gamma_i \text{ with the monthly fixed effect } T_i), \text{ which accounts for the effects of the epidemic shock on housing prices in a given period. The meaning of other variables is the same as in Model (1).} \]

A key premise of the preceding analysis is that the common trend assumption holds, i.e., that the trends in housing prices, transaction volumes and rents in the infected communities will be the same as the trends in the uninfected ones. To simultaneously test the parallel trend hypothesis and analyze the dynamic impact of the epidemic on monthly housing prices, volumes and rents, we employ an event study by performing a regression on Model (3).

\[ Y_{it} = \alpha + \beta \cdot \text{Infected}_i \cdot \text{Post}_{bt} + \cdots + \beta_i \cdot \text{L}^8_i \cdot \text{Infected}_i + \theta_i \cdot T_i + \gamma_i \cdot t \cdot T_i + \epsilon_{ibt} \]

\[ (3) \]

We normalize the multiple shocks. Therefore, \(\beta\) is the estimate of the treatment (infected) interacted with a dummy for the m period before or after the epidemic shock, where \(m = \{-8,-7,-6,-5,-4,-3,-2,-1,0,1,2,3,4\}\). Additionally, \(\text{L}^8_i\) equals one for all months that are eight or more months before shock, while \(\text{L}^4_i\) equals one for all months that are four or more months after shock. When housing transactions took place exactly at time \(m\), \(\text{L}^0_i\) equals 1 and 0 otherwise. Because of the impact of the outbreak in period \(-1\), we use period \(-2\) as a benchmark. The \(-2\) period of the epidemic shock is excluded from the model, so the estimated coefficients represent the dynamic effect of the discount between infected and uninfected communities relative to the \(-2\) period. The meanings of the other variables are the same as those in Model (2).

4. Results and testing

4.1. Results

4.1.1. Event studies and tests for parallel trends

We first present event study graphs that motivate the following regression analysis. These graphs are derived from the estimation of Model (3). The figures plot the coefficients derived from the regression and their 95% confidence intervals. They provide an opportunity to assess the validity of the difference-in-differences approach that is based on the assumption of parallel trends prior to epidemic shocks.

Fig. 3a plots coefficients derived from the event study on housing prices. It supports the validity of the design, as there is little evidence of differential trends in prices between infected and uninfected communities preceding the COVID-19 outbreak. Consistent with the statement in section 3.1, we could see that the treatment effect shows a drop in the \(-1\) period in Fig. 3a, although statistically insignificant, indicating that the impact of the epidemic shock begins in period \(-1\). And we think that this drop is related to the transaction record registration system of the secondhand housing transaction platform. There is clear evidence that the COVID-19 epidemic leads to price declines in the first four months after the event began. In the fourth month after the outbreak, the difference between the average housing price change in the infected and uninfected communities decreased, suggesting that the impact of the outbreak on housing prices may be short-lived either because the outbreak was quickly and effectively contained and people found that the health risks in the infected communities could be avoided or because speculative capital stepped in, which caused the discount in the infected communities to disappear quickly.

Fig. 3b shows that there is little evidence of differential trends in transaction volumes between infected and uninfected communities before period \(-1\). For the same reasons mentioned above, the outbreak also results in a significant decline in transaction volume in period \(-1\). However, around four months after the epidemic shock, the transaction volumes in the infected communities largely returned to their original development path, which suggests that the impact of the epidemic shock on transaction volume was also short-lived. As in the analysis of housing price responses, in the following regressions on transaction volumes, we...
also assume that period $C_0$ is the time when the shock begins to have an effect on transaction volumes.

Fig. 3c indicates that there is little evidence of differential trends in rental prices between infected and uninfected communities preceding the COVID-19 outbreak. To ensure consistency with the analysis of prices and transaction volumes, Fig. 3c uses the $C_0$ period as a benchmark.

There is clear evidence that the COVID-19 epidemic led to rental price declines in the first two or three months after the event began, followed by a gradual recovery. In contrast to the dynamic effect of housing prices and transaction volumes by the epidemic shock, rental prices did not change significantly in the $C_0$ period,10 which may be because renting, unlike home purchases, has a relatively short time to complete the deal. Moreover, during the current period of the outbreak, there was no significant drop in rents in the infected communities, which was probably because there were very few new rental transactions in the month of the outbreak, and the guided rents of the communities announced by the rental transaction platform were calculated mainly based on the previously contracted prices. In addition, in the rental market, tenants often have to pay two or three months of rents at once at the transaction time, and the incumbent tenants could not exit immediately even if the epidemic hit the community.

4.1.2. Regression results

Table 2 presents the primary regression results of Models (1) and (2) using different matching methods. Columns 1–3 use nearest-neighbor matching, and columns 4–6 use radius matching. Panel A controls for buffer-liner time trends, and panel B controls for buffer-by-month fixed effects. The results show that the epidemic shock leads to an approximately 1.3% decrease in housing prices in infected communities. This finding is very similar to Wong’s (2008) estimate of the impact of the SARS shock on housing prices in Hong Kong, which shows that, on average, housing prices fell by 1.6% after the community spread of SARS was identified.

4.1.3. Heterogeneity analysis

The primary mode of transmission of the novel coronavirus is close person-to-person contact. It is reasonable to conjecture that the greater the population density in an infected community is, the greater the likelihood of being infected and the more significant the decline in housing prices. To test this idea, we use the number of households in a community as a proxy for population density and then rank the total number of households. Columns 1 and 3 in Table 3, Panel A, show the

Fig. 3. 3a Event study: The effect of the COVID-19 epidemic on housing prices. Notes: Fig. 3a shows the results for Model (3) using radius matching (550 m) methods.6 The dependent variable is housing prices (in logs). These are event study plots created by regressing housing prices on a full set of event time indicators interacted with an indicator for “infected”, buffer-by-month fixed effects, and community fixed effects. “Infected” is set to 1 as long as a community has been infected, which is not time-varying. Period $-2$ is chosen as a benchmark. Robust standard errors are clustered by buffer. Statistical significance is at the 5% level. Fig. 3b Event study: The effect of the COVID-19 epidemic on transaction volumes. Notes: Fig. 3b replicates Fig. 3a using transaction volumes as the dependent variable.7 Fig. 3c Event study: The effect of the COVID-19 epidemic on rents. Notes: Fig. 3c replicates Fig. 3a using rental prices of 3-bedroom homes8 as the dependent variable.9

6 Appendix Fig. 1 replicates Fig. 3a using radius matching (350 m) methods.
7 Appendix Fig. 2 replicates Fig. 3b using radius matching (350 m) methods.
8 Appendix Fig. 3b replicates the result of Model (3) using radius matching (550 m) methods but using the $-1$ period as a benchmark. The overall results are consistent with that in Fig. 3c.
9 Appendix Fig. 3c and d presents the event study graph for 1-bedroom and 2-bedroom homes, respectively. Rents for 1- and 2-bedroom homes were not affected by the epidemic.
10 Appendix Fig. 3e replicates Fig. 3c using radius matching (350 m) methods.
Table 2

The results for Models (1) and (2) using different matching methods.

|                  | (1) | (2) | (3) | (4) | (5) | (6) |
|------------------|-----|-----|-----|-----|-----|-----|
|                  | 1vs1| 1vs2| 1vs3| 350 m| 450 m| 550 m|
| Panel A          |     |     |     |      |      |      |
| Infected*Post    | −0.0201*** | −0.0123*** | −0.0105*** | −0.0131*** | −0.0132*** | −0.0129*** |
| (N, Community)   | (0.0039) | (0.0034) | (0.0033) | (0.0037) | (0.0034) | (0.0052) |
|                  | (N, Buffer) | 649 | 588 | 550 | 473 | 553 |
|                  | 14 | 14 | 14 | 14 | 14 | 14 |
|                  | 14,512 | 18,992 | 23,074 | 32,193 | 51,264 | 74,043 |
|                  | r2, a | 0.2077 | 0.1741 | 0.1667 | 0.1200 | 0.1105 | 0.0991 |
| Panel B          |     |     |     |      |      |      |
| Infected*Post    | −0.0204*** | −0.0127*** | −0.0107*** | −0.0140*** | −0.0142*** | −0.0137*** |
| (N, Community)   | (0.0039) | (0.0035) | (0.0034) | (0.0039) | (0.0036) | (0.0033) |
|                  | (N, Buffer) | 1058 | 1442 | 1783 | 2495 | 4036 |
|                  | 14 | 14 | 14 | 14 | 14 | 14 |
|                  | 12,722 | 17,652 | 21,872 | 31,085 | 50,259 | 73,176 |
|                  | r2, a | 0.9918 | 0.9927 | 0.9930 | 0.9926 | 0.9929 | 0.9928 |

Notes: Panel A and Panel B present the primary regression results for Model (1) and Model (2), respectively. The dependent variable in all regressions is housing values (in logs). Columns 1–3 use nearest-neighbor matching, corresponding to one-to-one, one-to-two, and one-to-three matching, respectively; columns 4–6 use radius matching, corresponding to 350 m, 450 m, and 550 m radii, respectively. Panel A controls the community fixed effects, monthly fixed effects and month fixed trend for buffers; Panel B controls for community fixed effects and buffers by month. Appendix Table 2 (Panel A) shows the results not controlling for any trend. N, Community, N, Buffer, and N, Month display information on the number of communities, the number of buffers used in the fixed effects, and the number of months for each specification, respectively. Robust standard errors are clustered by buffer.

* Statistical significance at 10%. ** Statistical significance at 5%. *** Statistical significance at 1%.

Table 3

Heterogeneity of housing price changes in different characteristics.

| Heterogeneity of housing price changes in | (1) | (2) | (3) | (4) |
|------------------------------------------|-----|-----|-----|-----|
|                                          |     |     |     |     |
|                                          | Up_25% | Lower_25% | Up_25% | Lower_25% |
| Panel A Community population density     | Infected*Post | −0.0125*** | −0.0111 | −0.0143*** | −0.0121 *** |
|                                          | (0.0046) | (0.0101) | (0.0050) | (0.0108) |
|                                          | N, Community | 409 | 689 | 394 | 671 |
|                                          | N, Buffer | 81 | 102 | 69 | 86 |
|                                          | N, Month | 14 | 14 | 14 | 14 |
|                                          | N | 5069 | 8712 | 4893 | 8490 |
|                                          | r2, a | 0.0844 | 0.1407 | 0.9944 | 0.9924 |
| Panel B Community income level           | Infected*Post | −0.0121** | −0.0181 | −0.0134** | −0.0192 |
|                                          | (0.0058) | (0.0116) | (0.0062) | (0.0128) |
|                                          | N, Community | 713 | 524 | 692 | 502 |
|                                          | N, Buffer | 121 | 108 | 100 | 91 |
|                                          | N, Month | 14 | 14 | 14 | 14 |
|                                          | N | 9050 | 6414 | 8766 | 6164 |
|                                          | r2, a | 0.0923 | 0.0616 | 0.9944 | 0.9822 |
| Panel C Cities GRP (per capita)          | Infected*Post | −0.0072 | −0.0291** | −0.0077 | −0.0346*** |
|                                          | (0.0047) | (0.0116) | (0.0050) | (0.0126) |
|                                          | N, Community | 1347 | 504 | 1298 | 481 |
|                                          | N, Buffer | 261 | 91 | 214 | 69 |
|                                          | N, Month | 14 | 14 | 14 | 14 |
|                                          | N | 17,134 | 6276 | 16,464 | 6010 |
|                                          | r2, a | 0.1502 | 0.0624 | 0.9876 | 0.9442 |
| Panel D Housing demand in the city       | Infected*Post | −0.0065 | −0.0203*** | −0.0068 | −0.0230*** |
|                                          | (0.0066) | (0.0066) | (0.0071) | (0.0071) |
|                                          | N, Community | 870 | 966 | 825 | 928 |
|                                          | N, Buffer | 175 | 171 | 141 | 135 |
|                                          | N, Month | 14 | 14 | 14 | 14 |
|                                          | N | 10,833 | 12,520 | 10,365 | 12,039 |
|                                          | r2, a | 0.1589 | 0.0951 | 0.9686 | 0.9894 |

Notes: This table reports regression coefficients from 16 separate regressions. The dependent variable in all regressions is housing values (in logs). All columns use radius matching (350 m radius). Columns 1 and 3 show subsamples of for upper 25% of the total number of households, the historical transaction prices of infected communities in July 2019, GRP per capita, and the proportion of the urban employed population to the annual average population, respectively; columns 2 and 4 show subsamples for the lower 25% of the above variables. Community fixed effects controlled in all model specifications. In addition, columns 1 and 2 include monthly fixed effects as well as time-liner trends for buffers, and columns 3 and 4 include buffer-by-month fixed effects. N, Community, N, Buffer, and N, Month display information on the number of communities, the number of buffers used in fixed effects, and the number of months for each specification, respectively. Robust standard errors are clustered by buffer.

* Statistical significance at 10%. ** Statistical significance at 5%. *** Statistical significance at 1%.
regression results from subsamples for the upper 25% (high density), while columns 2 and 4 report the results from the lower 25% subsamples (low density). From the results in Panel A of Table 3, the absolute value of the estimated results for the upper subsample is greater than that for the lower group (0.0125 > 0.0111; 0.0143 > 0.0120), and that for the lower group is not statistically significant. This shows that the greater the number of households in the infected community is, the more significant the price decline.

Generally, high-income people are more averse to health risks than low-income people. However, in terms of the implementation of quarantine measures, high-end communities are safer and more convenient. Therefore, compared with ordinary communities, whether high-end communities will have a higher or lower decline in housing prices due to the epidemic is uncertain. Table 3, Panel B is organized according to the historical transaction prices of infected communities in July 2019, and accordingly, the population is divided into the upper 25% and lower 25% subsamples. According to the results in Panel B of Table 3, compared with those in low-end communities, housing prices in high-end communities exhibit a smaller decline.

Do housing prices in different cities respond to epidemic shocks in different ways? Panels C and D of Table 3 report the heterogeneity of the price changes in terms of the city features. We use the 2018 GRP per capita and the proportion of the urban employed population to the annual average population to indicate the economic development level and housing demand of a city, respectively. Panel C in Table 3 shows that the higher the level of economic development in a city is, the smaller the decline in housing prices. Thanks to the more efficient implementation of epidemic prevention measures, the higher the economic development level is, the lower the housing price decline caused by the epidemic in that city. Panel D in Table 3 shows that the higher the proportion of the urban employed population is, the smaller the decline in housing prices. The heterogeneity analysis of housing price changes in terms of the living environment reported in Appendix Table 3 shows that access to rich education resources can alleviate the decline in housing prices.

### 4.2. Pseudo and robustness testing

**4.2.1. Pseudo testing**

If there is a spatial trend in housing prices, there may also be significant differences between infected and uninfected communities but not due to an epidemic shock, which poses a challenge for causal identification. The presence of a spatial trend can be tested by constructing spurious infected communities. Specifically, we assume that any other community within the 750 m buffer zone (excluding the real infected community) is a pseudo treated community, and the other community in the buffer zone (except the real infected community) is a control. We test whether the regression coefficients are significant using fake infected communities.

#### To avoid the effect of chance on the results, we also use other groups of fake infected communities, and the conclusions are consistent.
housing prices. The regression results are shown in Table 4. The regression coefficients are not significant, indicating that there is no spatial trend in housing prices and that the relative decline in housing prices estimated earlier is indeed due to epidemic shocks.

And then we further check whether there is spatial spillover of the infected community on neighboring communities. If the actual infected community has a spillover effect on the near uninfected ones, the nearest uninfected community will thus have a discount effect relative to other uninfected communities. Therefore, we use the nearest uninfected community to the actual treated as the fake treatment group, and other neighboring uninfected communities as the control group. The regression results are shown in Appendix Table 4. We find the coefficients are not significant, indicating that there is no spillover effect of the infected community on neighboring communities.

4.2.2. Robustness testing by redefining neighborhood similarity

To prove the robustness of the results, we also use historical housing price data for October 2019 to redefine neighborhood similarity. Specifically, we choose the uninfected community whose price was closest to the price of the infected community as the corresponding control group individual within a 750 m buffer zone of the infected community using one-to-one and one-to-two nearest-neighbor matching. The regression results for the above design are shown in Table 5, and the estimated coefficient (−1.1%) is very similar to the previous results in Table 3 (−1.3%). We can conclude that there is no evidence to support a systematic bias in the regression results in Table 3.

4.2.3. Robust test by using one-to-one matching

We relax the restriction that matches are allowed only within a radius of 750 m. In this way, every infected community can be matched with the nearest uninfected community, regardless of whether the distance is within 750 m. This avoids the problem of not being able to match within a radius of 750 m (this problem is caused by the large size of the community). Table 6 shows the regression results using one-to-one matching methods and different fixed effects. These results (−1.7%) are similar to the results (−1.8%) in the first column of Table 2 (1VS1 matching), indicating that the results are robust. Appendix Table 1d presents summary statistics for the sample constructed by one-to-one matching without the constraint of a 750 m radius.

5. Transaction volumes and rents

5.1. Transaction volumes

In this section, we examine the impact of epidemic shocks on the housing transaction volumes. Table 7 replicates Table 2 using transaction volumes as the dependent variable. The estimation results in Table 7 show that there are statistically significant declines in transaction volumes of the infected communities in all model specifications. The monthly transaction volumes in communities with COVID-19 infections decreased by approximately 0.24 compared to communities with no confirmed cases. Furthermore, the event study on transaction volumes (Fig. 3b) shows that the transaction volumes first dropped sharply due to the epidemic shock, but gradually recovered after a few months.

5.2. Rents

We then examine the response of the rental market to the epidemic shock. The natural logarithm of the guided rental price of 1-bedroom, 2-bedroom and 3-bedroom homes is used as the dependent variable in the regression on Models (1) and (2), and the results are shown in Table 8. The rental prices for one- and two-bedroom homes were not affected by the epidemic. The possible reason is that most of these renters are renting due to the convenience of their home to their place of work, which does not frequently change. Therefore, those people’s marginal willingness to pay has not changed. The results from event studies (see Appendix Fig. 3c and d) on the rental prices for one- and two-bedroom homes confirm the above findings. On the contrary, the effect on 3-bedroom rental prices is significantly negative (see Fig. 3c, Appendix Fig. 3a and b), probably because families with a higher ability to pay or with children are more risk averse.

6. Conclusion

The COVID-19 epidemic has had a profound multidimensional impact on economic and social activities around the world. This paper examines the impact of epidemic shocks on housing prices, transaction volumes and rents using data on real estate markets at the community level in China’s major cities. We perform spatial nearest-neighbor matching and radius matching between infected and uninfected communities with the aid of geographic information and construct a DID model accordingly.

The study finds that, on average, housing prices in infected communities decline by approximately 1.3% compared to uninfected communities. Heterogeneity analysis shows that the greater the infected community’s population density is, the greater the decline in housing prices. The decline in housing prices is greater in ordinary infected communities than in upscale communities. The higher the economic development level and the greater the demand for housing services in the city, the smaller the decline in housing prices caused by the epidemic shock. Event studies find that epidemic shocks cause economically and statistically significant but short-lived declines in housing prices, transaction volumes and rents, which may suggest that temporary public interventions, including community closure management and strict quarantine measures, inhibit the spread of the epidemic and thus effectively correct the negative externalities.

The findings of this paper not only contribute to the understanding of people’s avoidance of epidemic risks but also provide insights into the impact of ancient epidemic prevention and control measures, such as community quarantines, on social welfare.

Table 6

| Infected*Post | (1) | (2) | (3) |
|---------------|-----|-----|-----|
|               | −0.0189*** | −0.0178*** | −0.0196*** |
|               | (0.0033) | (0.0034) | (0.0035) |
| N Community   | 1673 | 1673 | 1602 |
| N Buffer      | 862  | 862  | 801  |
| N Month       | 14   | 14   | 14   |
| N             | 21,272 | 21,272 | 19,278 |
| r2,a          | 0.0218 | 0.1768 | 0.9898 |
| Community Fixed Effects | Y | Y | Y |
| Monthly Fixed Effects | N | Y | N |
| Buffer time trends | N | Y | N |
| Buffer by Month | N | N | Y |

Notes: Table 6 presents the regression results using 1VS1 nearest-neighbor matching (regardless of whether it is within the 750 m buffer). The dependent variable in all regressions is housing values (in logs). Column 1 controls for community fixed effects and monthly fixed effects; Column 2 controls for community fixed effects, monthly fixed effects and time trends for buffers; Column 3 controls for community fixed effects and buffers by month. Robust standard errors are clustered by buffer.

* Statistical significance at 10%. ** Statistical significance at 5%. *** Statistical significance at 1%.

12 The guided rental price is a forecast value based on the prices of homes that have recently been rented.
is the rental price (in logs) of 1-bedroom homes. The dependent variable in columns 3 and 4 is the rental price (in logs) of 2-bedroom homes. The dependent variable in columns 5 and 6 is the rental price (in logs) of 3-bedroom homes. Community matching, corresponding to 350 m, 450 m, and 550 m radii, respectively. Panel A controls the community fixed effects, monthly fixed effects and time trend for buffers; Panel B controls for community fixed effects and buffers by month. Appendix Table 2 (Panel B) shows the results without controlling for any trends. N_Community, N_Buffer, and N_Month display information on the number of communities, the number of buffers used in the fixed effects, and the number of months for each specification, respectively. Robust standard errors are clustered by buffer. * Statistical significance at 10%. ** Statistical significance at 5%. *** Statistical significance at 1%.

Table 7
The effect of the COVID-19 epidemic on the transaction volumes.

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|------------------|------|------|------|------|------|------|
|                  | LnR1 | LnR1 | LnR2 | LnR2 | LnR3 | LnR3 |
| Infected*Post    | 0.0047 | 0.0042 | 0.0011 | 0.0004 | -0.0139** | -0.0165** |
|                  | (0.0072) | (0.0089) | (0.0034) | (0.0041) | (0.0054) | (0.0072) |
| N_Community      | 214.5 | 1968 | 3093 | 2930 | 2524 | 2517 |
| N_Buffer         | 434 | 287 | 461 | 374 | 486 | 346 |
| N_Month          | 14 | 14 | 14 | 14 | 14 | 14 |
| N               | 26,935 | 19,045 | 29,822 | 28,115 | 26,552 | 24,745 |
| r²,a             | 0.1043 | 0.9855 | 0.9786 | 0.9959 | 0.9061 | 0.9937 |
| Community Fixed Effects | Y | Y | Y | Y | Y | Y |
| Monthly Fixed Effects | Y | N | Y | N | Y | N |
| Buffer time trends | Y | N | Y | N | Y | N |
| Buffer by Month   | Y | N | Y | N | Y | N |

Notes: This table reports regression coefficients from 6 separate regressions. All columns use radius matching (550 m radius). The dependent variable in columns 1 and 2 is the rental price (in logs) of 1-bedroom homes. The dependent variable in columns 3 and 4 is the rental price (in logs) of 2-bedroom homes. The dependent variable in columns 5 and 6 is the rental price (in logs) of 3-bedroom homes. Community fixed effects are controlled in all model specifications. Columns 1, 3, and 5 include monthly fixed effects and time trends for buffers. Columns 2, 4, and 6 include buffer-by-month fixed effects. N_Community, N_Buffer, and N_Month display information on the number of communities, the number of buffers used in the fixed effects, and the number of months for each specification, respectively. Robust standard errors are clustered by buffer. * Statistical significance at 10%. ** Statistical significance at 5%. *** Statistical significance at 1%.

Table 8
The effect of the COVID-19 epidemic on the guided rental price.

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|------------------|------|------|------|------|------|------|
|                  | LnR1 | LnR1 | LnR2 | LnR2 | LnR3 | LnR3 |
| Infected*Post    | 0.2400*** | -0.2242*** | -0.2480*** | -0.2467*** | -0.2539*** | -0.2661*** |
|                  | (0.0512) | (0.0518) | (0.0527) | (0.0512) | (0.0457) | (0.0459) |
| Control for buffer-liner time trends | N_Community | 1182 | 1542 | 1875 | 2583 | 4114 | 5912 |
|                  | N_Buffer | 649 | 588 | 550 | 473 | 553 | 594 |
|                  | N_Month | 14 | 14 | 14 | 14 | 14 | 14 |
|                  | N | 16548 | 21588 | 26250 | 36162 | 57596 | 82768 |
|                  | r²,a | 0.0858 | 0.9684 | 0.0953 | 0.0514 | 0.0474 | 0.0396 |
| Panel A Infected*Post | -0.2401*** | -0.2220*** | -0.2441*** | -0.2623*** | -0.2222*** | -0.2410*** |
|                  | (0.0514) | (0.0528) | (0.0542) | (0.0541) | (0.0480) | (0.0479) |
| Control for buffer-by-month fixed effects | N_Community | 1066 | 1445 | 1786 | 2506 | 4047 | 5857 |
|                  | N_Buffer | 533 | 491 | 461 | 396 | 486 | 539 |
|                  | N_Month | 14 | 14 | 14 | 14 | 14 | 14 |
|                  | N | 14924 | 20230 | 25004 | 35084 | 56558 | 81998 |
| r²,a             | 0.6645 | 0.6644 | 0.6639 | 0.5923 | 0.6189 | 0.6645 |

Notes: Panel A and Panel B present the primary regression results for Model (1) and Model (2), respectively. The dependent variable in all regressions is transaction volumes. Columns 1–3 use nearest-neighbor matching, corresponding to one-to-one, one-to-two, and one-to-three matching, respectively; columns 4–6 use radius matching, corresponding to 350 m, 450 m, and 550 m radii, respectively. Panel A controls the community fixed effects, monthly fixed effects and time trend for buffers; Panel B controls for community fixed effects and buffers by month. Appendix Table 2 (Panel B) shows the results without controlling for any trends. N_Community, N_Buffer, and N_Month display information on the number of communities, the number of buffers used in the fixed effects, and the number of months for each specification, respectively. Robust standard errors are clustered by buffer. * Statistical significance at 10%. ** Statistical significance at 5%. *** Statistical significance at 1%.

Author statement
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Declaration of competing interest
The authors have no conflicts of interest to disclose.

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Appendix A. Supplementary data
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