COVID-19 effects on property markets: The pandemic decreases the implicit price of metro accessibility

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ARTICLE INFO

ABSTRACT

The metro (or underground railways) has become a backbone in the transit systems of many cities. It has numerous externalities, such as ameliorating traffic congestion and enhancing nearby property prices. Previous studies extensively focused on the relationship between metro accessibility and property prices and obtained various interesting findings and enriched practical implications. However, this relationship in the era of the coronavirus disease 2019 (COVID-19) and other epidemic shocks has not been investigated. Based on a unique property transaction dataset (including tens of thousands of transactions stretching from 2018 to 2020) in Chengdu, China, this study develops a battery of hedonic pricing models and difference-in-differences models to decipher the time-varying relationship between metro accessibility and residential property prices. The results show that the implicit price of metro accessibility modestly decreases in COVID-19, which can be explained by the declining role of the metro. In other words, the price gap between proximate and distant properties is narrowed, and the property price gradient is flattened. Specifically, the price elasticity of distance to the metro is − 0.024 before COVID-19, but it turns to − 0.018 during the pandemic. The relative price of properties within 500 m from metro stations to those farther away (500 m − 3 km) decreases by 15.4% during the pandemic. Additionally, COVID-19 does not jeopardize property prices in Chengdu. Furthermore, the decrease in metro access premiums may be short-lived and only persisted for several months or years. The plausibility and robustness of the core findings have been confirmed through alternative treatment groups, alternative model specifications, and placebo tests.

1. Introduction

Shaping travel demand, reducing the number of car trips, and establishing an accessible and rider-friendly transit system are now crucial transport planning objectives (Cervero and Kockelman, 1997). The importance of the metro (or underground railway) system, which is characterized by large capacity, astonishing velocity, high frequency, and great efficiency, has long been emphasized (Cui and Nelson, 2019; Lin et al., 2021a; Lin et al., 2021b), particularly for cities facing dramatic population growth and economic prosperity. The metro has become a backbone in the transit systems of many cities (primarily large cities). At the end of 2021, 188 cities in 62 countries or regions established their metro system, and the operating mileage was 18,952.29 km (Han et al.,

2022).

As a typical public good (or social good, collective good), the metro has various benefits. The most discernable and fundamental benefit is the reduction in commute time or the enhancement of transport accessibility. Other benefits include but are not limited to saving land, ameliorating traffic congestion and delays, decreasing carbon dioxide emissions and air pollution, shaping the urban expansion pattern, promoting the compact development mode, reducing the social exclusion of disadvantaged groups, improving quality of life and human health, stimulating the urban economy, and enhancing property prices in catchment areas (Chen et al., 2022; Jin et al., 2022; Wen et al., 2021).

The relationship between accessibility to transit (e.g., metro, light rail, and commuter rail), which generally describes how easy a resident

can access the transit service, and property prices is a long-studied topic with profound practical implications and strong policy relevance (So et al., 1997; Yang et al., 2020a). In theory, in most cases, transit accessibility should have a positive impact on property prices (or rents). The reason is as follows. Most residents are eager to live in communities with a high level of transit accessibility from the perspective of convenience and quality of life. Empirically, the interaction between transit accessibility and property prices has been widely documented in a voluminous body of the existing literature (Debrezion et al., 2007; Wu et al., 2020).

As of the end of 2019, the coronavirus disease 2019 (COVID-19) outbreak spread swiftly. The outbreak soon hit the world profoundly and became a global pandemic in March 2020, devastating people's livelihoods. Evidently, the pandemic places serious disruptions to all aspects of society, such as building use (Valdenebro et al., 2021), unemployment (Bauer and Weber, 2021), financial asset market (Sène et al., 2021), and property market (Yang and Zhou, 2022). For example, many policy measures, such as social distancing, community closure, shutdown orders, mandatory quarantine, and "stay-at-home" orders, have been initiated to decrease urban mobility and prevent virus transmission in numerous countries, such as China.

The connection between transit accessibility and property prices is likely to be altered by COVID-19 because transit gets less important in residents' daily life, evidenced by drastically declining transit ridership. For example, in Chengdu, China, the daily metro ridership in 2020 is 13.8% less than that in 2019. In the first half of 2020, the number is at the near-term low of 32.0%. In addition to mandatory quarantine, other causes of the waning role of transit include the negative perception of transit (high perceived infection risk) (Abdullah et al., 2021; Beck and Hensher, 2020; Eisenmann et al., 2021).

This study aims to examine the property market impacts of COVID-19, mainly focusing on the implicit price of metro accessibility. The conceptual framework of this study is shown in Fig. 1. We suspect that the implicit price of metro accessibility is decreased by the COVID-19 pandemic. In other words, the price gap between proximate and distant properties is narrowed, and the property price gradient is flattened. The reason is that the attractiveness of the metro considerably goes down (especially in the initial stage of the pandemic), so residents (homo economicus) are unwilling to pay so much for metro accessibility.

To this end, based on the 2-year property transaction data stretching from 2019 and 2020 in Chengdu, China, a few multilevel hedonic pricing models and difference-in-differences (DID) models are developed to scrutinize the time-varying relationship between metro accessibility and residential property prices (i.e., housing values). Results from several robustness checks—including alternative treatment groups, alternative model specifications, and placebo tests (falsification tests)—verify the plausibility and credibility of our core findings. The contributions of this paper include the following: (1) enriching COVID-19 research that is now dominated by public health and medical work and augmenting the COVID-19 economic impact assessment arena; (2) analyzing the influence of metro accessibility on the property market (in terms of prices) in the COVID-19 era. To our knowledge, this study is the first to analyze COVID-19-induced changes in the price premiums of transit accessibility; (3) comparing the differences of price premiums

attributed to metro accessibility in periods before and during COVID-19; and (4) pointing out an innovative research direction (studying the effects of pandemic shocks such as COVID-19 on the implicit prices of particular property attributes).

The remainder of this paper is organized as follows. Section 2 provides a review of studies documenting either rail transit impacts or COVID-19 impacts on property prices. Section 3 introduces the study area (Chengdu) and property transaction price data utilized for empirical analysis. Section 4 introduces the methodologies: the hedonic pricing model and DID model. Section 5 reveals the empirical modeling outcomes. Section 6 winds up the paper and determines avenues for further research.

2. Literature review

2.1. Property price impacts of rail transit

A huge body of the literature has evaluated the impacts of rail transit, including metro, light rail, and commuter rail, on property prices. It obtains a relatively consistent conclusion that rail transit positively influences property prices in its adjacent regions, although a handful of research counters the argument and questions the view (Du and Mulley, 2007; Tian et al., 2017; Wagner et al., 2017; Zhong and Li, 2016).

Table 1 provides a review of selected studies. With regard to property category, residential properties (housing) have aroused the greatest scholarly attention. Moreover, most previous studies were carried out in the West (e.g., the U.S. and Europe), possibly due to a long history of rail transit in the region. Most of, though not all, the studies concentrated on the holistic influences of rail transit accessibility on property prices to gain a general picture. Interested readers can refer to Debrezion et al. (2007), Mohammad et al. (2013), Higgins and Kanaroglou (2016), Ingvardson and Nielsen (2018), and Wu et al. (2020) for systematic reviews or meta-analysis of the related literature.

2.2. COVID-19 impacts on property prices

Studies on the effects of COVID-19 on property prices (more broadly, property market responses to COVID-19) fall into the stream of research assessing the impacts of urban hazards or disasters on property prices (Folland and Hough, 2000; Francke and Korevaar, 2021; Kohlhase, 1991; Liu and Tang, 2021). To date, only a modicum of property valuation research focused on the COVID-19 context (D'Lima et al., 2022).

Several studies investigated the holistic effect of COVID-19 on property prices in various places. Based on nonparametric estimation, Zhao (2020) concluded that COVID-19 does not harm property prices in U.S. contexts. Yiu (2021) observed considerable rebounds in property prices in numerous developed countries after the COVID-19 outbreak. Yang and Zhou (2022) examined the influence of COVID-19 on housing prices in the Yangtze River Delta region (China) and showed that the effects of COVID-19 vary in first-, second-, and third-tier cities. Tomal and Marona (2021) demonstrated that property rents decreased by approximately 9% in Krakow, Poland. Oyedeji (2020) revealed that the prices and rents of properties substantially reduced in Lagos, Nigeria, during the COVID-19 pandemic.
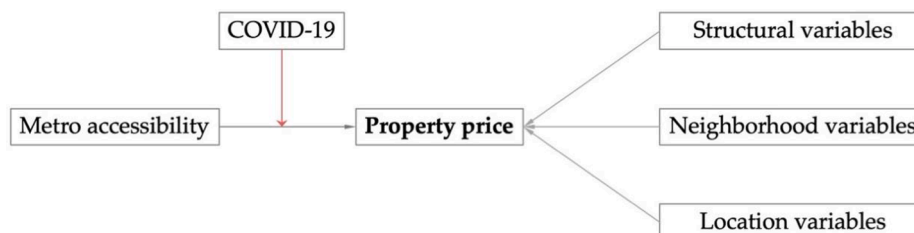

Fig. 1. The conceptual framework of this study.

Table 1
Selected studies on property price impacts of rail transit.

Reference	Study area	Property type	Samples	Method	Key finding
Damm et al. (1980)	Washington, D.C., the U.S.	Residential & Retail	286 single-family properties, 771 multi-family properties, and 353 retail properties	Hedonic pricing model	The metro impact is more pronounced on retail establishment prices than on single- and multi-family housing prices.
Gatzlaff and Smith (1993)	Miami, the U.S.	Residential	912 properties	Repeat-sales model and hedonic pricing model	Property prices are weakly influenced by the metro system announcement.
So et al. (1997)	Hong Kong, China	Residential	1234 properties	Hedonic pricing model	Metro accessibility is positively associated with property prices.
Bowes and Ihlanfeldt (2001)	Atlanta, the U.S.	Residential	22,388 properties	Hedonic pricing model	Price premiums offered by rail transit vary considerably, depending on access to downtown and the neighborhood-level median income.
Armstrong and Rodríguez (2006)	Eastern Massachusetts, the U.S.	Residential	1860 single-family properties	Hedonic pricing model and spatial lag model	Properties located in areas with a commuter rail station have an approximately 10% higher value uplift than those outside the areas.
Debrezion et al. (2011)	Amsterdam, Rotterdam, Enschede	Residential	40,326 properties in Amsterdam, 17,772 in Rotterdam, and 5,997 Enschede	Hedonic pricing model	Price premiums stemming from rail transit vary across cities.
Shyr et al. (2013)	Hong Kong, Taipei, and Kaohsiung, China	Residential	5291 properties in Hong Kong, 4068 in Taipei, and 2999 in Kaohsiung	Hedonic pricing model	Price premiums offered by metro accessibility are biggest in Kaohsiung and smallest in Hong Kong.
Kim (2016)	Beijing, China	Residential	3385 underground properties	Hedonic pricing model	Metro accessibility is positively associated with underground property rents.
Dai et al. (2016)	Beijing, China	Residential	2964 properties	Hedonic pricing model	Metro transfer stations produce larger price premiums than regular (or non-transfer) stations.
Xu et al. (2016)	Wuhan, China	Commercial	676 properties	Spatial econometric model	The metro access premiums are 16.7% within 100 m of stations and 8.0% within 100–400 m of stations.
Diao et al. (2017)	Singapore	Residential	21,954 properties	Spatial DID model	A new metro line increases property prices within 600 m of stations by approximately 8.6%, relative to the price of the property farther away from the metro.
Tian et al. (2017)	Salt Lake County, Utah, the U.S.	Residential	4274 properties	Spatial econometric model and multilevel hedonic pricing model	Property prices are insignificantly affected by light rail accessibility.
Pilgram and West (2018)	Minneapolis, Minnesota, the U.S.	Residential	Thousands of properties	DID model	The estimate of price premiums attributed to metro accessibility varies, depending on the control group and "after" period choice.
Camins-Esakov and Vandegrift (2018)	Bayonne, New Jersey, the U.S.	Residential	140 repeat-sale properties	Linear regression model	The extension of a light rail line has an insignificant impact on annual price appreciation.
Mulley et al. (2018)	Sydney, Australia	Residential	1522 properties	Geographically weighted regression model	The light rail exerts a larger impact in the suburbs than in the city center.
Yen et al. (2018)	Queensland, Australia	Residential	19,561 properties	DID model	The announcement of the light rail boosts property prices in the catchment area.
Li (2018)	Xi'an, China	Residential	1359 properties	Hedonic pricing model	Properties located 300–1200 m from metro stations have the highest premium.
Yang et al. (2020b)	Shenzhen, China	Residential	722 communities	Hedonic pricing model	Metro transfer stations provide greater premiums than regular (or non-transfer) stations. The metro has a greater effect in the suburbs than in the urban area.

In a departure from research focusing on the holistic COVID-19 effect, a few studies analyzed the COVID-19 effects on the implicit price of particular property attributes (e.g., location, community-level COVID-19 infection, and gated community), many of which are not commonly used in traditional hedonic modeling. Gupta et al. (2021) pointed out a decreasing property price (or rent) differential between city centers and outskirts in most U.S. metropolitan areas. Moreover, they suggested that such a price (or rent) differential is more evident in places with prevalent "working-at-home" patterns, regulated property markets, and inelastic property supply. That is, the authors identified the flattening of the bid-rent curve (or land price gradient) (Alonso, 1964), but it is place-varying. In addition, Liu and Tang (2021) and Qian et al. (2021) used the DID model to confirm that communities with confirmed COVID-19 cases are priced lower than others, keeping all else equal. They illustrated that in China, the price gap is 1.3%−2.5% but only persists for a few months. Moreover, Li et al. (2021a) suggested that in China, gated communities have a heightened "security zone" function because of stringent access controls imposed by the government in the era of COVID-19. Thus, the authors argued that gated communities experience a value uplift in the

COVID-19 era. Their hedonic modeling results in Beijing confirmed the argument and identified an increase of 2% in property prices for such communities, compared with open communities.

2.3. Thrust of this study

As the above shows, numerous studies investigated the interaction between rail transit accessibility and property prices (or rents) in various contexts, particularly in the West. Moreover, the COVID-19 effects on housing markets have been examined in a small number of very recent studies, largely published in 2021 and 2022. However, the "metro-property price" (more broadly, "transit-property price") relationship has not been revealed in the era of COVID-19 and previous epidemic shocks. To our knowledge, this study is the pioneer to do so, filling research gaps.

3. Study area and data

3.1. Study area

Chengdu (alternatively romanized as Chengtu) (Fig. 2) is the study area. Chengdu is a sub-provincial city and the capital of Sichuan Province, a landlocked province in Southwest China. It neighbors Ya'an to the west, Meishan to the south, Ziyang to the southeast, Deyang to the northeast, and Ngawa Tibetan and Qiang Autonomous Prefecture to the northwest. Chengdu is a megacity, the core of the Chengdu – Chongqing (Cheng – Yu) Urban Agglomeration, a crucial central city (*guojia zhongxin chengshi*) in West China designated by the State Council, a national high-tech industrial base, a trade and logistics center, and a transportation and communication hub in Southwest China. It is enticingly known as "Rong City" and "Jin'guan City." It was recognized by UNESCO (United Nations Educational, Scientific, and Cultural Organization) as a City of Gastronomy.

In 2020, the city had jurisdiction over twelve districts, three counties, and five county-level cities. The total area was 14,335 km², accommodating 20.94 million permanent residents (sixth-largest in China). Its gross domestic product (GDP) was 1771.67 billion yuan, an increase of 4.0% over the previous year at comparable (constant) prices.

Chengdu opened its first metro line (Line 1) on September 27, 2010, making it the 12th Mainland Chinese city with a metro system. As of the end of 2020, it had a total of 12 metro lines (Lines 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 17, and 18), totaling 518.5 km. Furthermore, Chengdu is ranked fourth in terms of total mileage in China, exceeded only by Shanghai, Beijing, and Guangzhou. In Chengdu, metro trips account for over 50% of transit trips made by city residents now (https://www.xinhuanet. com/2020–12/18/c_1126878095.htm).

3.2. Data and variables

The transaction price is the best and most fundamental indicator of the market value of properties. Traditionally, complete and open accessible housing data in China are not delivered to the general public. Put simply, obtaining the data on actual property transactions from either the government or property agencies is difficult, though not impossible. As such, the asking prices of properties, which are perceived to be highly correlated with transaction prices, are often used in traditional Chinese property valuation studies. Fortunately, in recent years, reliable transaction price data can be observed from several property agencies (e.g., Lianjia, Beike, and Anjuke), increasing the accuracy of property valuation research and the plausibility of its findings.

This study aims to evaluate the differences, between the treatment and control groups, in the changes in property prices that occur over time. Two periods—"before (the treatment)" and "after (the treatment)"—are needed. Therefore, property transaction price data during 2018 and 2020 are collected from two leading housing agency websites in Mainland China, namely Lianjia (*cd.lianjia.com*) and Beike (*cd.ke. com*). Property samples transacted between 2019 and 2020 are used in the main analysis, whereas those transacted in 2018 are solely utilized in placebo tests.

The sampling process is as follows. First, we removed samples outside the 3-km buffer of metro stations to obtain a high-quality dataset for the subsequent metro-corridor analysis. The choice of the distance threshold (3 km) is informed by the existing literature (Chu et al., 2021; Salon et al., 2014; Yazdanifard et al., 2021; Zhao and Ke, 2021). Second, the metro inauguration often uplifts property prices within the catchment area. Therefore, we excluded the samples within the 3-km buffer of "new" metro stations opened during 2018–2020 to eliminate the effects of "new" lines on the implicit price of metro accessibility and acquire a "cleaner" dataset. Finally, a total of 88,504 property transaction samples clustered in 3790 residential complexes were left for the subsequent analysis. Their spatial distribution is shown in Fig. 2.

Apart from the transaction price, we collected other attributes of the property samples, including structural variables (e.g., floor area and the number of bedrooms), neighborhood variables (e.g., floor area ratio), and the geographical location (coordinates) of the residential complex. By using Geographic Information Science (GIS) analysis techniques (Li et al., 2021b; Li et al., 2021c; Liu et al., 2019; Liu et al., 2018), we calculated location variables (e.g., the distance to the city center) for DID analysis.

Table 2 shows the definition and unit of variables included in this study. The dependent variable is the transaction price. Regarding the explanatory variable, we use the distance to the closest metro station or a distance-based dummy variable to assess metro accessibility. Besides, following previous hedonic studies (Cui and Gu, 2021; Cui et al., 2018; Yang et al., 2020c), we selected 14 control variables. These variables comprehensively capture the structural, neighborhood, and location attributes of the property. Notably, apart from the traditional city center (which is also the geometric center), an emerging city center, namely Financial City, is considered in assessing the property's location variables. Financial City, a high-end financial center, serves as the CBD (central business district) of Chengdu now. Furthermore, the floor information, which describes the level (height) relative to the building of the property, is directly provided by the housing agency websites.

Table 3 displays the summary statistics of all the variables.

4. Methodology

4.1. Hedonic pricing model

Hedonic pricing models assume that the price of a commodity is the summation of component prices (or hedonic prices, implicit prices, shadow prices) of a set of the commodity's attributes (Rosen, 1974). They often regress the property price (or its natural logarithm form) onto a battery of observable hedonic characteristics of the property, such as gross floor area, green space ratio, neighborhood amenities, and access to the city center (Xiao et al., 2017; Ye et al., 2019; Zhao and Ke, 2021). Hedonic characteristics are generally categorized into three groups, namely structural (micro-level), neighborhood (meso-level), and location (macro-level). The traditional hedonic pricing model can be written as follows:

$$PRICE = \beta_0 + \sum_k \beta_k X_k + \varepsilon, \tag{1}$$

where *PRICE* represents the property price; β_0 is the constant term; X_k is the k-th property attribute; β_k is the corresponding coefficient of X_k; and ε is the error term.

The underlying assumption of the traditional hedonic pricing model, which is the so-called ordinary least square (OLS) model, is that the residuals are uncorrelated with each other. However, in the context of China, properties are usually spatially nested in a residential complex. That is, properties within the same residential complex may share similar unobserved attributes, thereby leading to the problem of correlated residuals. The OLS model ignores such a spatially nested data structure and may misestimate the standard error of coefficients. As a result, the genuinely insignificant variables may be improperly estimated to be significant (Snidjers and Bosker, 1999; Yang et al., 2021a), making researchers obtain wrong conclusions. To tackle such a problem, we introduce the multilevel modeling approach into this study:

$$PRICE = \beta_0 + \sum_k \beta_k X_k + u + \varepsilon, \tag{2}$$

where u is the random term of the residential complex, and it follows the normal distribution with the mean of zero; and other terms are the same as in **Eq. 1**. In contrast with **Eq. 1**, **Eq. 2** allows the intercept to vary across residential complexes, capturing the unobserved attributes that the OLS model fails to control.

To analyze the effects of metro accessibility on property prices, we employed the following multilevel double-log hedonic pricing model:
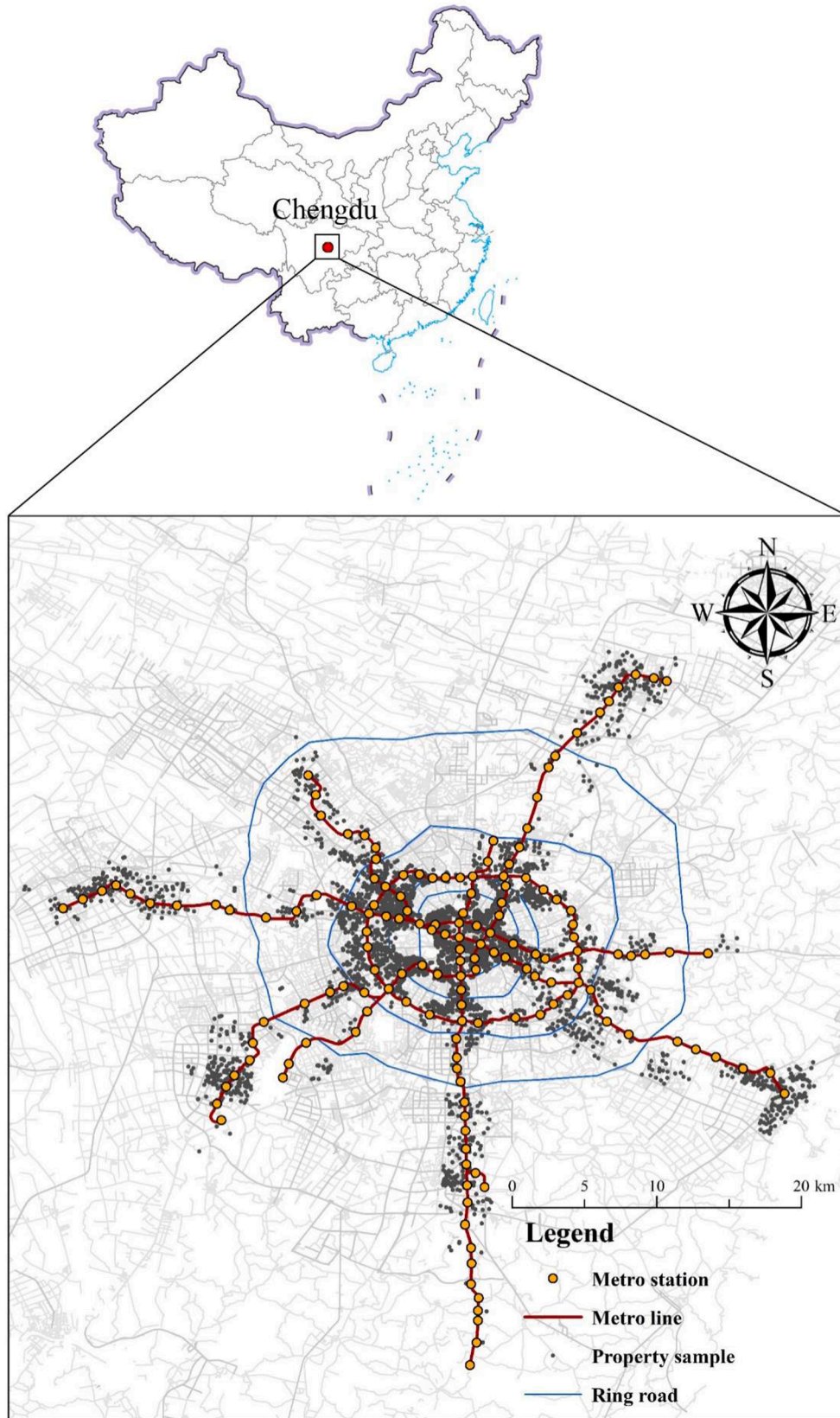
Fig. 2. Location of the study area and transacted property samples.

Table 2
Definitions and units of variables.

Variable	Description	Unit	Level[a]
Dependent variable			
PRICE	–	10^4 yuan	–
Independent variable			
DIST2STATION	Distance from the centroid of the residential complex to the closest metro station	m	Level 2
PROMIXITY_500M	Dummy variable, 1 for a property located within 500 m of metro stations, and 0 otherwise	–	Level 2
AGE	Age of the residential complex	year	Level 2
LOW_FLOOR	Dummy variable, 1 for a property on the low floor, and 0 otherwise (Dropped as the reference group)	–	Level 1
INTERMEDIATE_FLOOR	Dummy variable, 1 for a property on the intermediate floor, and 0 otherwise	–	Level 1
HIGH_FLOOR	Dummy variable, 1 for a property on the high floor, and 0 otherwise	–	Level 1
SOUTH_ORIENTATION	Dummy variable, 1 for a property with rooms facing south, and 0 otherwise	–	Level 1
AREA	Gross floor area	m^2	Level 1
LIVING_ROOM_0&1	Dummy variable, 1 for a property with zero or one living room, and 0 otherwise (Dropped as the reference group)	–	Level 1
LIVING_ROOM_2+	Dummy variable, 1 for a property with two living or more rooms, and 0 otherwise	–	Level 1
BEDROOM_1	Dummy variable, 1 for a property with one bedroom, and 0 otherwise (Dropped as the reference group)	–	Level 1
BEDROOM_2	Dummy variable, 1 for a property with two bedrooms, and 0 otherwise	–	Level 1
BEDROOM_3	Dummy variable, 1 for a property with three bedrooms, and 0 otherwise	–	Level 1
BEDROOM_4+	Dummy variable, 1 for a property with four or more bedrooms, and 0 otherwise	–	Level 1
BATHROOM_0&1	Dummy variable, 1 for a property with zero or one bathroom, and 0 otherwise (Dropped as the reference group)	–	Level 1
BATHROOM_2+	Dummy variable, 1 for a property with two or more bathrooms, and 0 otherwise	–	Level 1
FAR	Floor area ratio of the residential complex	–	Level 2
GREEN	Green space ratio of the residential complex	–	Level 2
DIST2TIANFU	Distance from the centroid of the residential complex to Tianfu Square (traditional city center)	m	Level 2
DIST2FINANCIAL	Distance from the centroid of the residential complex to Financial City (high-end financial center, as an emerging city center)	m	Level 2
POST_COVID	Dummy variable, 1 for a property transacted after the COVID-19 outbreak (February 2020), and 0 otherwise	–	Level 1

Note: [a] Levels 1 and 2 denote the property level and residential complex level, respectively. They are crucial in multilevel modeling.

$$lnPRICE = \beta_0 + \alpha lnDIST2STATION + \sum_k \beta_k X_k + u + \varepsilon, \qquad (3)$$

where *lnPRICE* is the natural logarithm of the property price; *lnDIST2STATION* is the natural logarithm of the distance to the closest metro station; α is the coefficient of interest, representing the property

price gradient near metro stations; X_k is the *k*-th control variable (in the natural logarithm form, except for dummy variables); β_k is the corresponding coefficient of X_k; and other terms are defined as above. We can have an initial understanding of the influences of the pandemic on the implicit price of metro accessibility by comparing α estimated from the samples before and after the COVID-19 outbreak.

4.2. DID model

The DID model is an appropriate and effective approach to identify the effects of an exogenous shock (e.g., the outbreak of COVID-19) and attenuate the endogeneity problem induced by the hedonic pricing model. Fig. 3 illustrates the basic idea of DID models.

In the DID model, samples are divided into two groups, namely the treatment and control groups. The treatment group is assumed to be directly exposed to the exogenous shock. By contrast, the control group should not be affected, thereby providing a counterfactual scenario. Causal effects could be estimated by comparing the differences between the changes in the treatment and control groups before and after the exogenous shock. Specifically, in this study, we take the properties within the 500-m buffer zone of metro stations as the treatment group and others as the control group. The choice of the distance threshold (500 m) is informed by previous studies (Mohammad et al., 2017; Sharma and Newman, 2018; Zhao et al., 2018). The multilevel DID hedonic pricing model can be written as follows:

$$ln(PRICE) = \beta_0 + \alpha_1 POST\_2020M2 \times PROMIXITY\_500M + \alpha_2 POST\_2020M2$$
$$+ \alpha_3 PROMIXITY\_500M + \sum_k \beta_k X_k + u + \varepsilon, \qquad (3)$$

where *POST_2020M2* (i.e., *POST_COVID*) is a dummy variable that equals one for samples transacted after February 2020 (the outbreak of COVID-19 in Mainland China) and zero otherwise; *PROMIXITY_500M* is a dummy variable that equals one for the property within the 500-m buffer of metro stations and zero otherwise; α_1, the coefficient of the interaction term, is the parameter of predominate interest. We expect it to be significantly negative, indicating that COVID-19 decreases the property price near metro stations; and other terms are defined as above.

In the traditional DID model, the treatment variable is binary. In this study, we also utilize a DID model with a continuous treatment variable to analyze COVID-19 effects on the property price gradient near metro stations:

$$lnPRICE = \beta_0 + \gamma_1 POST\_2020M2 \times lnDIST2STATION + \gamma_2 POST\_2020M2$$
$$+ \gamma_3 lnDIST2STATION + \sum_k \beta_k X_k + u + \varepsilon, \qquad (5)$$

where γ_1 is the coefficient of primary interest; γ_2 and γ_3 are the coefficient of the COVID-19 time dummy and *lnDIST2STATION*; and other variables are as defined as above. We expect it to be positive, which indicates that COVID-19 decreases the property price gradient near metro stations.

5. Results

A pair-wise correlation analysis is conducted for collinearity detection before hedonic modeling. Fig. 4 shows the results. It illustrates the absence of the collinearity problem in our data and ensures the statistical power of the regression models and the precision of the estimated coefficients.

5.1. Baseline results

We estimated four baseline models to decipher the relationship of metro accessibility with property prices before and during COVID-19. First, we develop two multilevel double-log hedonic pricing models

Table 3
Summary statistics of variables.

| Variable	Mean	St. D.	Min	25%	50%	75%	Max
PRICE	140.68	76.18	6	94	124	166	1800
DIST2STATION	843.27	575.70	7.46	444.95	702.48	1035.37	2996.55
PROMIXITY_500M	30.5%	–	0	–	–	–	1
AGE	8.31	6.07	0	4	7	11	55
LOW_FLOOR	25.7%	–	0	–	–	–	1
INTERMEDIATE_FLOOR	35.3%	–	0	–	–	–	1
HIGH_FLOOR	39.0%	–	0	–	–	–	1
SOUTH_ORIENTATION	26.8%	–	0	–	–	–	1
AREA	86.85	31.89	13	67	84	98	727
LIVING_ROOM_0&1	52.4%	–	0	–	–	–	1
LIVING_ROOM_2+	47.6%	–	0	–	–	–	1
BEDROOM_1	13.4%	–	0	–	–	–	1
BEDROOM_2	41.2%	–	0	–	–	–	1
BEDROOM_3	38.8%	–	0	–	–	–	1
BEDROOM_4+	6.6%	–	0	–	–	–	1
BATHROOM_0&1	70.8%	–	0	–	–	–	1
BATHROOM_2+	29.2%	–	0	–	–	–	1
FAR	3.51	1.39	0.20	2.52	3.5	4.2	12.41
GREEN	0.33	0.10	0.00	0.30	0.30	0.38	0.87
DIST2TIANFU	10,325.58	6214.16	245.21	5375.49	8473.73	15,877.43	27,959.67
DIST2FINANCIAL	12,573.15	5978.53	255.74	8156.13	11,525.57	15,316.52	30,478.88
POST_COVID	55.3%	–	0	–	–	–	1
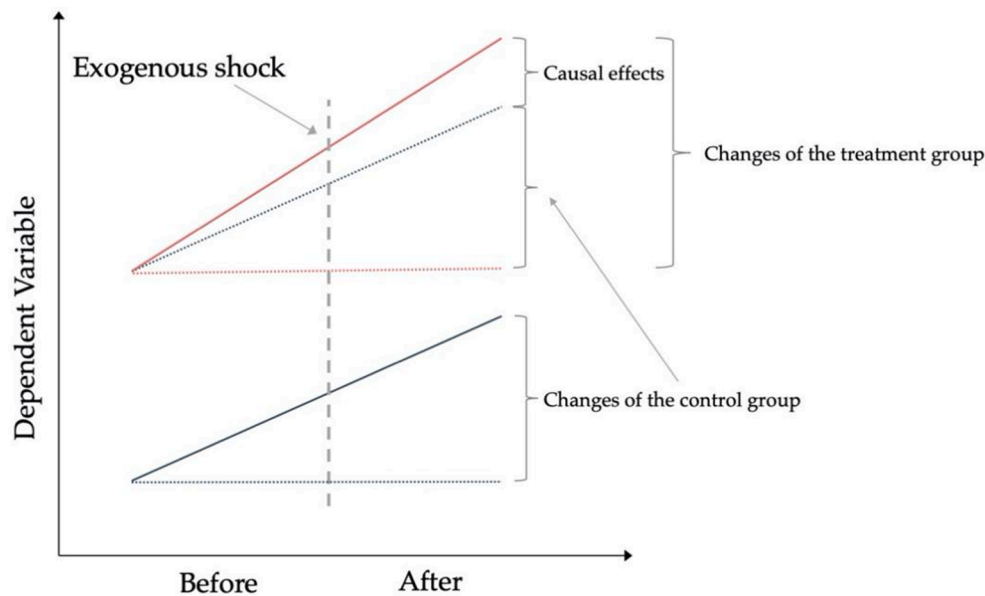
Fig. 3. Graphical illustration of the DID model.

(Models 1 and 2) to assess the relationship before and during COVID-19. Then, we pool the 2019 and 2020 property data and calculate a (traditional) DID model (Model 3) and a DID model with a continuous treatment variable (Model 4) to scrutinize the dynamic relationship between metro accessibility and property prices. Table 4 shows the results of the four baseline models.

Regarding the random effects, the variances of *u* (level-two errors), *Var(COMPLEX)*, are all significant in four baseline models (The 95% confidence interval does not cover zero). This finding shows the effectiveness of the residential-complex-varying intercept and justifies the use of the multilevel modeling approach.

The performance of the control variables largely agrees with our expectations and previous property valuation studies. First, gross floor area, number of living rooms, number of bedrooms, number of bathrooms, and south-facing orientation are all positively associated with property prices, whereas age is negatively related to property prices. Second, two neighborhood variables, namely floor area ratio and green

space ratio, positively affect property prices. Third, proximity to two city centers, Tianfu Square (city center) and Financial City (high-end financial center), is positively correlated with property prices. The price elasticity of proximity to Tianfu Square (around 0.23) is modestly higher than that of proximity to Financial City (around 0.17), indicating that the traditional city center plays a more prominent role in determining property prices. Last, the floor level affects property prices in a non-linear manner. Interestingly, compared with low- and high-floor properties, those on the intermediate floor have 0.8%−0.9% higher prices. A possible reason is that the intermediate floor simultaneously possesses the merits of both the low floor (convenient transportation and safety) and the high floor (few noises and wide views). Furthermore, the coefficient of the variable *POST_COVID* is either positive or insignificant. We do not find any evidence supporting that COVID-19 harms property prices in the Chinese city, which contrasts with studies in many western cities (Oyedeji, 2020; Tomal and Marona, 2021).

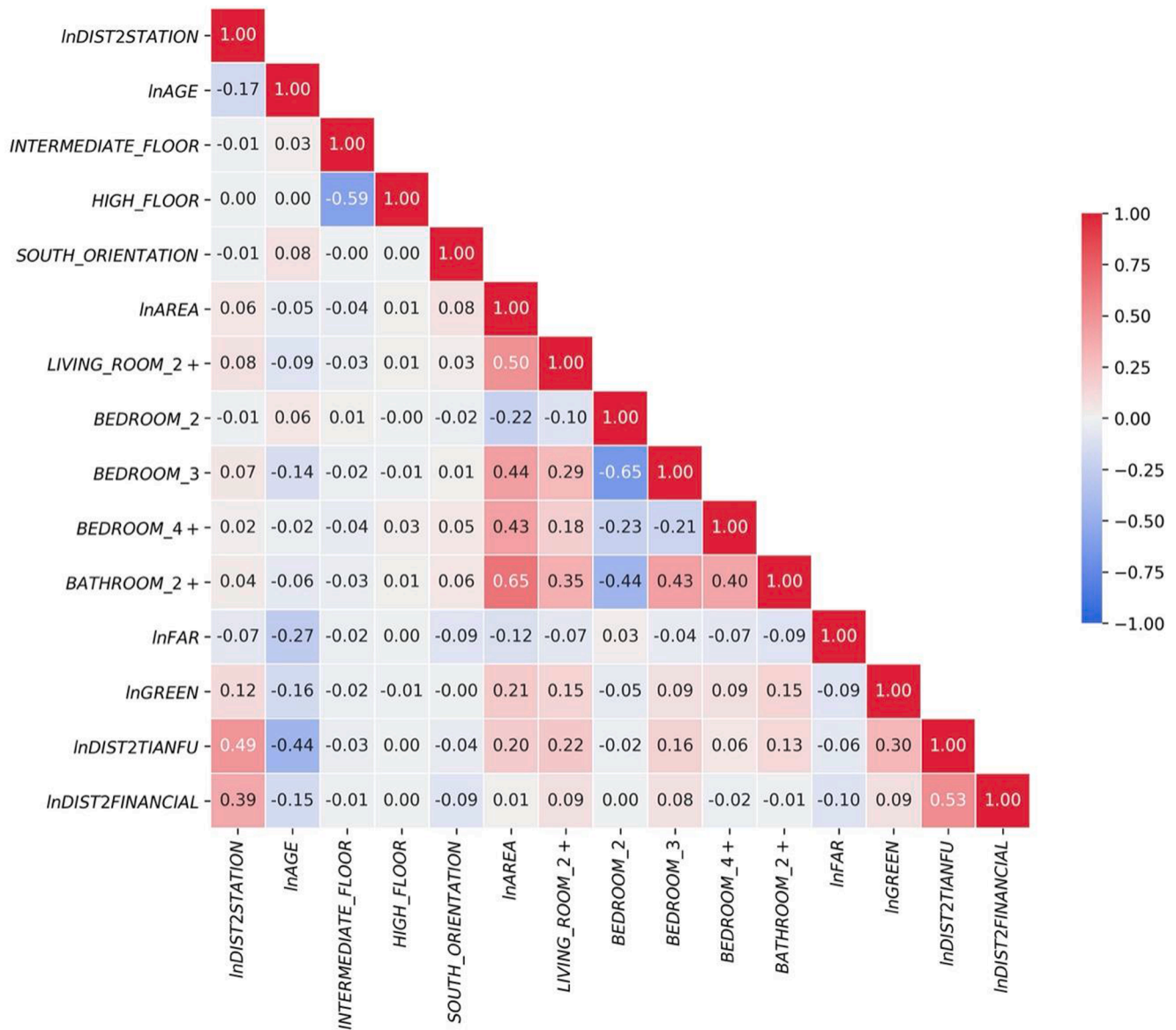The primary interest of this study is the moderating effects of COVID-

Fig. 4. Correlation matrix of the independent variables.

19 on property prices near metro stations. First, in the four baseline models, the coefficients of primary interest are all significant. As for the sign and magnitude, Models 1 and 2 separately present the property price gradient near metro stations before and after the COVID-19 outbreak. As expected, COVID-19 notably flattens the elasticity of the distance to the closest metro station, which is indicated by the observation that the absolute value of the coefficient of *lnDIST2STATION* is much lower in Model 2 than in Model 1 (0.016 versus 0.031). Furthermore, the DID modeling results confirm the above findings. Specifically, in Model 3, properties immediately adjacent to metro stations (within the 500-m buffer) have a 2.6% (0.026) price premium before COVID-19. However, such a premium significantly diminishes to 2.2% (=0.026–0.004) by the pandemic. In other words, the relative price of properties within 500 m from metro stations to properties farther away (500 m − 3 km) decreases by 15.4% (=0.004/0.026) in the pandemic. In addition, in Model 4, the moderating effects of COVID-19 on

lnDIST2STATION is 0.006, which means that the effects of *lnDIST2-STATON* decrease from − 0.024 to − 0.018 (=−0.024 + 0.006) during COVID-19. In a nutshell, our baseline model results indicate that COVID-19 significantly reduces the property price premium offered by metro accessibility.

5.2. Dynamic effects

With the rapid development of effective treatments and vaccines, the pandemic has been effectively contained. To test how the effects of COVID-19 on the implicit price of metro accessibility vary in time, we estimate the following multilevel DID hedonic pricing models separately:

Table 4
Baseline results.

Variable	Model 1: Pre-COVID model (Jan. 2019 − Jan. 2020) N = 32,271		Model 2: During-COVID model (Feb. 2020 − Dec. 2020) N = 39,917		Model 3: DID model (Jan. 2019 − Dec. 2020) N = 72,188		Model 4: DID model with a continuous treatment variable (Jan. 2019 − Dec. 2020) N = 72,188	
	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic
lnDIST2STATION	**−0.031*****	−4.48	**−0.016****	−2.29			**−0.024*****	−3.63
PROMIXITY_500M					0.026**	3.05		
POST_COVID					0.049***	51.42	0.011	1.46
POST_COVID × lnDIST2STATION							**0.006*****	5.08
POST_COVID × PROMIXITY_500M					**−0.004****	−2.17		
lnAGE	−0.246***	−30.89	−0.289***	−37.50	−0.275***	−37.50	−0.276***	−35.57
INTERMEDIATE_FLOOR	0.009***	5.63	0.008***	6.18	0.008***	7.77	0.008***	7.76
HIGH_FLOOR	0.003**	1.99	0.001	0.62	0.001	0.89	0.001	0.89
SOUTH_ORIENTATION	0.006***	4.16	0.006***	5.25	0.006***	6.72	0.006***	6.73
lnAREA	0.818***	158.48	0.824***	193.71	0.819***	246.12	0.8129***	246.12
LIVING_ROOM_2+	0.005**	3.45	0.05***	4.43	0.005***	5.69	0.005***	5.74
BEDROOM_2	0.101***	31.60	0.107***	40.64	0.103***	50.27	0.103***	50.32
BEDROOM_3	0.153***	37.15	0.170***	50.34	0.161***	60.95	0.162***	60.99
BEDROOM_4+	0.201***	34.63	0.217***	45.71	0.208***	55.89	0.208***	55.93
BATHROOM_2+	0.025***	11.19	0.016***	9.09	0.020***	13.98	0.020***	14.01
lnFAR	0.057***	5.97	0.053***	5.92	0.049***	5.69	0.049***	5.68
lnGREEN	0.096***	9.68	0.078***	9.53	0.083***	10.46	0.082***	10.42
lnDIST2TIANFU	−0.216***	−31.09	−0.235***	−35.71	−0.232***	−37.53	−0.230***	−36.84
lnDIST2FINANCIAL	−0.165***	−17.72	−0.172***	−18.45	−0.172***	−19.40	−0.171***	−19.29
Constant	5.260***	52.16	5.465***	56.97	5.289***	60.72	5.431***	59.63
Random effects								
	Estimate	95% Conf. Interval	Estimate	95% Conf. Interval	Estimate	95% Conf. Interval	Estimate	95% Conf. Interval
Var(COMPLEX)	0.050	[0.047, 0.053]	0.057	[0.054, 0.060]	0.055	[0.052, 0.058]	0.055	[0.052,0.058]
AIC	−44,172		−63,080		−111,143		−111,166	
BIC	−44,021		−62,925		−110,959		−110,982	

Note: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.
[a] Coefficients of interest are shown in bold.
[b] We tried to replace the single dummy variable, *POST_COVID*, with a set of calendar-year-month dummies (capturing year-month fixed effects). The model results are highly stable. Hence, we only use a dummy variable instead of a set of dummy variables in our baseline models for brevity. Related modeling results can be obtained from the corresponding author upon reasonable request.
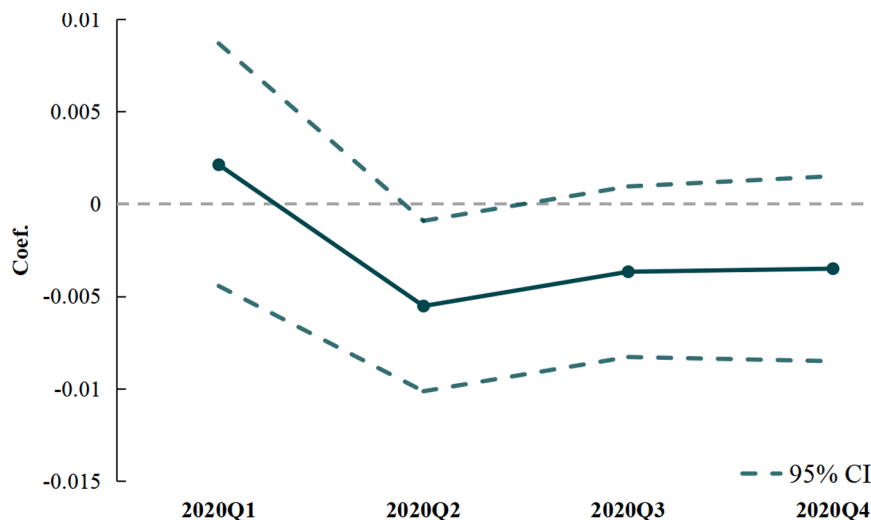

Fig. 5. Temporally dynamic effects estimated from the DID model. *Note:* The coefficients of $Q_i\_2020 \times PROMIXITY\_500M$ (i = 1, 2, 3, 4) are shown. The above figure shows that the coefficients are mostly negative. It indicates that the relative price of properties adjacent to the metro station has reduced, suggesting a decrease in the implicit price of metro accessibility in 2020Q2, 2020Q3, and 2020Q4.

$$\ln(PRICE) = \beta_0 + \alpha_1 Q1\_2020 \times PROXIMITY\_500M + \alpha_2 Q2\_2020 \times PROXIMITY\_500M + \alpha_3 Q3\_2020 \times PROXIMITY\_500M + \alpha_4 Q4\_2020 \times PROXIMITY\_500M + \alpha_5 PROXIMITY\_500M + \sum_k \beta_k X_k + \delta + u + \varepsilon, \tag{6}$$
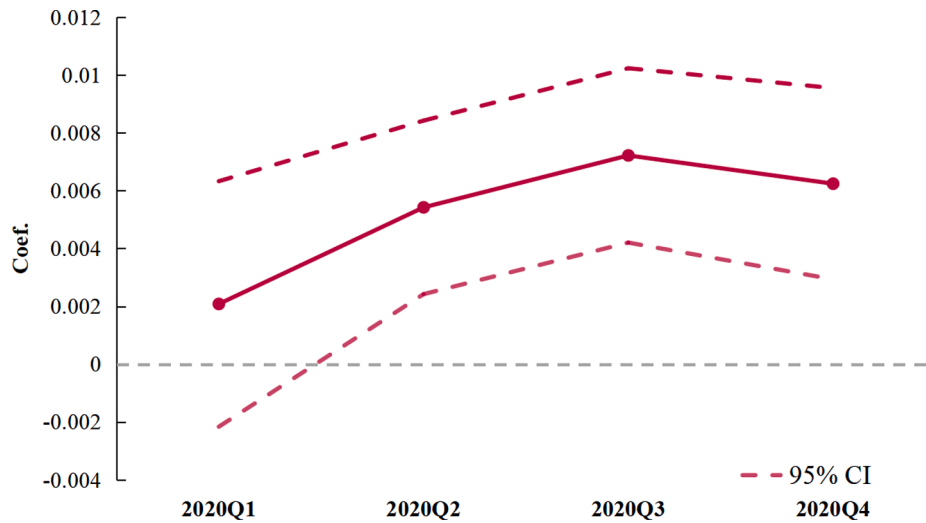
Fig. 6. Temporally dynamic effects estimated from the DID model with a continuous treatment variable. *Note:* The coefficients of $Q_i\_2020 \times lnDIST2STATION$ ($i = 1$, 2, 3, 4) are shown. The above figure shows that the coefficients are positive, indicating a decrease in the implicit price of metro accessibility in the four quarters of 2020.

$$\ln(PRICE) = \beta_0 + \alpha_1 Q1\_2020 \times lnDIST2STATION + \alpha_2 Q2\_2020 \times lnDIST2STATION + \\ \alpha_3 Q3\_2020 \times lnDIST2STATION + \alpha_4 Q4\_2020 \times lnDIST2STATION \\ + \alpha_5 lnDIST2STATION + \sum_k \beta_k X_k + \delta + u + \varepsilon$$

(7)

where $Q1\_2020$, $Q2\_2020$, $Q3\_2020$, and $Q4\_2020$ are four dummy variables, representing the first, second, third, and fourth quarters of 2020; δ is a set of calendar-year-month dummies; and other terms are the same as in **Eq. 4** and **Eq. 5**. β_1, β_2, β_3, and β_4 are the coefficients of interest, reflecting the temporally dynamic effects of COVID-19.

Fig. 5 and Fig. 6 depict the coefficients of interest obtained through estimating **Eq. 6** and **Eq. 7**, respectively, with the pooled samples of 2019 and 2020. The results of the DID model (**Eq. 6**) (see Fig. 5) reveal

that the moderating effect of COVID-19 on the property price immediately adjacent to metro stations is insignificant in the first quarter of 2020. Then, the effects turn significantly negative in the second quarter of 2020. After that, the effects become slightly insignificant but still have negative signs. These observations indicate that the price premiums stemming from metro accessibility decrease during COVID-19 and provide weak evidence supporting that the COVID-19-induced decrease in the price premiums only persists for a few months and may evaporate finally.
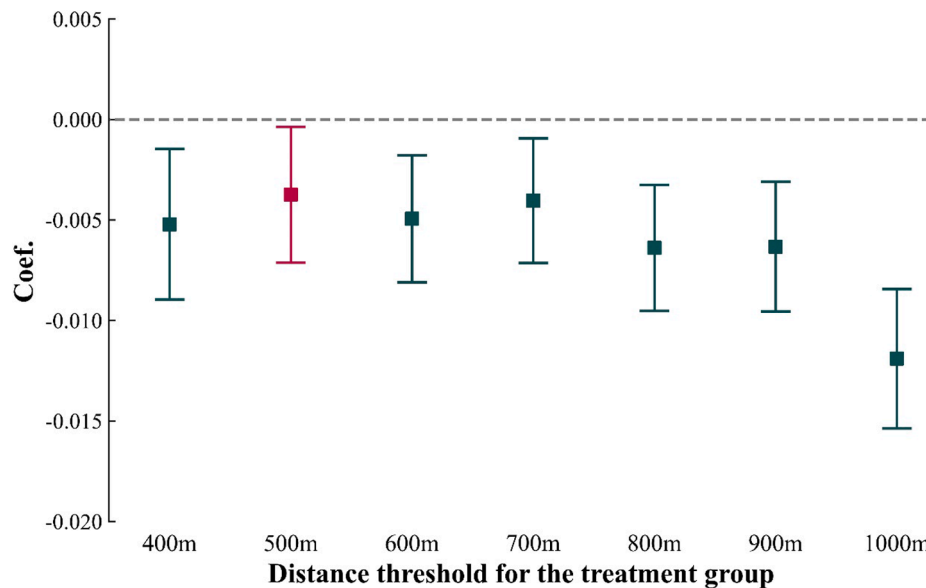

Fig. 7. Distance threshold sensitivity test results. *Note:* Baseline results are marked red.

Table 5
Robustness check results: Alternative model specifications.

Variable	Model 5: DID model (Dependent variable = price per square meter) (Jan. 2019 − Dec. 2020) N = 72,188		Model 6: DID model with a continuous treatment variable (Dependent variable = price per square meter) (Jan. 2019 − Dec. 2020) N = 72,188		Model 7: DID model incorporating fixed effects (Dependent variable = price per square meter) (Jan. 2019 − Dec. 2020) N = 72,188		Model 8: DID model with a continuous treatment variable incorporating fixed effects (Dependent variable = price per square meter) (Jan. 2019 − Dec. 2020) N = 72,188	
	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
POST_COVID × PROMIXITY_500M	−0.003*	−1.72			−0.004*	−2.00		
POST_COVID × lnDIST2STATION			**0.005***	4.44			**0.005***	4.73
PROMIXITY_500M	0.025***	2.91						
lnDIST2STATION			−0.021***	−3.14				
POST_COVID	0.049***	49.83	0.014*	1.91				
lnAGE	−0.275***	−37.55	−0.276***	−37.58				
INTERMEDIATE_FLOOR	0.007***	6.50	0.007***	6.49	0.007	7.17	0.007***	7.16
HIGH_FLOOR	0.000	0.31	0.000	0.30	0.001	0.92	0.001	0.92
SOUTH_ORIENTATION	0.006***	5.95	0.006***	5.96	0.006***	6.15	0.006***	6.16
lnFAR	0.048***	5.65	0.048***	5.65				
lnGREEN	0.072***	9.07	0.071***	9.03				
lnDIST2TIANFU	−0.237***	−38.45	−0.236***	−37.82				
lnDIST2FINANCIAL	−0.163***	−18.46	−0.163***	−18.36				
Constant	4.572***	53.18	4.698***	52.21	0.422***	485.56	0.402***	96.06
Random effects								
	Estimate	95% Conf. Interval	Estimate	95% Conf. Interval				
Var(COMPLEX)	0.055	[0.052, 0.057]	0.055	[0.052,0.057]				
Fixed effects								
Residential-complex fixed effects					Yes		Yes	
Calendar-year-month fixed effects					Yes		Yes	
AIC	−107,124		−107,141		−126,755		−126,775	
BIC	−106,995		−107,021		−126,709		−126,729	

Note: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.
Coefficients of interest are shown in bold.

Fig. 6 shows the coefficients of *lnDIST2STATION* in different quarters by estimating **Eq. 7**. In the first quarter of 2020, the effects of COVID-19 on the property price gradient near metro stations are insignificant. Then, the effect increases and becomes significant in the second and third quarters of 2020. Interestingly, the significantly positive effects begin to decrease in the fourth quarter of 2020.

5.3. Robustness checks

We perform three types of robustness checks to verify the effectiveness of our core empirical findings. First, one may argue that the DID model results rest with the choice of the treatment group. Therefore, we conduct a distance threshold sensitivity test to check the robustness of our DID model results over different treatment group choices. Specifically, we re-estimate **Eq. 4** (Model 3) with different distance thresholds (400 m, 600 m, 700 m, 800 m, 900 m, and 1000 m), which range from 400 m to 1000 m, for the treatment group. Fig. 7 displays the coefficient of the variable *POST_2020M2 × PROMIXITY_i (i = 400 m, 500 m, 600 m, 700 m, 800 m, 900 m, 1000 m)*, which is of predominant interest. We can observe that all the coefficients are significantly negative. Such consistent evidence enhances the plausibility of our baseline results.

Second, we adopt an alternative model specification by using the price per square meter as the dependent variable (Models 5 and 6) to reduce the dominant role and confounding effects of the gross floor area (or size) on the gross price of a property as much as possible. Then, we employ two DID models with binary and continuous treatment variables incorporating residential-complex and calendar-year-month fixed effects to absorb the time-invariant characteristics of residential complexes and common shocks in the property market (Models 7 and 8). Table 5 shows the results. As expected, the coefficients of interest are significant, and their signs and magnitudes are highly consistent with the baseline results.

Third, we conduct a placebo test by shifting the studied time window back one year (supposing that the COVID-19 outbreak happened one

year earlier, February 2019) and re-estimate the corresponding DID models with the property samples transacted between 2018 and 2019. If the effects of the falsified COVID-19 are significant, then the implicit price of metro accessibility may have periodic changes (also called seasonality), and our baseline results may be unreliable.

Table 6 offers the placebo test results. Both of the coefficients of interest are insignificant, which means that no periodic changes in the implicit price of metro accessibility occur during the same time period in 2019. This observation indicates that our core findings are not driven by seasonality, augmenting their plausibility.

6. Conclusions and discussion

The relationship of rail transit with property prices in normal periods has been widely investigated in various contexts. However, such a relationship has not been analyzed in COVID-19 or other epidemic-stricken periods. This study argues that the pandemic may reduce metro access premiums. In light of this, this study develops several econometric methods to test our hypothesis based on tens of thousands of property transaction data in Chengdu, China. The results offer strong evidence backing our argument. Various robustness checks have confirmed their plausibility. To our knowledge, this study is the pioneer of such a research topic. In a departure from studies focusing on the property market's responses to COVID-19 (e.g., holistic effect on property price, rent, transaction volume, turnover rate, or liquidity), this study specifically analyzes COVID-19-induced changes in the implicit price of particular property attributes, enriching the existing literature.

An oft-discussed and hot-debated issue highly related to land/property price premiums is value capture. In other words, how to let residents squeeze partial or whole value from infrastructure allocation (e.g., metro service provision) can be explored in the years to come. The implementation of value capture schemes is often perceived to be significant, timely and enormously, but today's China does not have mature or applicable value capture approaches (e.g., property tax)

Table 6
Robustness check results: Placebo test.

Variable	Model 9: DID model (Jan. 2018 – Dec. 2019) N = 46,628		Model 10: DID model with a continuous treatment variable (Jan. 2018 – Dec. 2019) N = 46,628	
	Coef.	*t*-statistic	Coef.	*t*-statistic
POST_FALSIFIED_COVID × PROMIXITY_500M	**0.004**	0.88		
POST_FALSIFIED_COVID × lnDIST2STATION			**0.002**	0.55
PROMIXITY_500M	0.017*	1.72		
lnDIST2STATION			−0.027***	−3.64
POST_FALSIFIED_COVID	−0.035***	−15.18	−0.044***	−2.45
lnAGE	−0.234***	−28.07	−0.236***	−28.22
INTERMEDIATE_FLOOR	0.009***	3.85	0.009***	3.85
HIGH_FLOOR	0.004*	1.84	0.004*	1.84
SOUTH_ORIENTATION	0.004*	1.85	0.004*	1.84
lnAREA	0.795***	105.79	0.794***	105.78
LIVING_ROOM_2+	0.016***	7.13	0.016***	7.15
BEDROOM_2	0.010***	21.47	0.010***	21.50
BEDROOM_3	0.147***	24.30	0.148***	24.32
BEDROOM_4+	0.200***	23.32	0.201***	23.34
BATHROOM_2+	0.019***	23.32	0.019***	5.74
lnFAR	0.063***	6.34	0.063***	6.29
lnGREEN	0.087***	8.69	0.088***	8.72
lnDIST2TIANFU	−0.201***	−28.16	−0.198***	−27.32
lnDIST2FINANCIAL	−0.169***	−17.51	−0.168***	−17.43
Constant	5.056***	49.08	5.199***	48.34
Random effects				
	Estimate	95% Conf. Interval	Estimate	95% Conf. Interval
Var(COMPLEX)	0.053	[0.050, 0.056]	0.052	[0.049, 0.056]
AIC	−13,138		−13,146	
BIC	−12,963		−12,971	

Note: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Coefficients of interest are shown in bold.

because of institutional barriers. However, implementing any such scheme is not without political resistance. City governments may need to initiate and conduct small-scale experiments in carefully selected regions (Yang et al., 2020b). Moreover, value capture schemes worldwide are often time-constant (fixed). This study concludes that price premiums attributed to metro accessibility are time-varying (decreased by COVID-19). Therefore, time-varying value capture schemes are suggested, indicating that government agencies should adjust the scheme details at set time intervals.

Although weak, Fig. 5 and Fig. 6 provide evidence supporting that the decrease in metro access premiums may be short-lived and only persisted for several months or years. Metro access price premiums may gradually return to normal levels as time goes on. The underlying logic is the rebound of metro ridership and the vanishing negative perception of transit, triggered by the cancellation of mobility restriction measures (e. g., quarantine order and decline in metro frequency) and the resumption of normal urban life.

This study is not immune from limitations. First, the metro inauguration has not only a local effect on property price (e.g., uplifting property prices within the catchment areas) but also a regional (or network) effect on the property market (He, 2020). The former can be termed the "to-transit accessibility effect," whereas the latter can be interpreted as the "by-transit accessibility effect" (Yang et al., 2020a). This study exclusively explores the time-varying to-transit accessibility effect. The by-transit accessibility effect that may also be time-varying can be scrutinized in further research. Second, this study pre-specifies a functional form to describe the relationship between property prices and hedonic variables. Using more flexible machine-learning techniques

is recommended to delve deeper into the complex relationship (Liu et al., 2021; Lu et al., 2022; Yang et al., 2021b).

CRediT authorship contribution statement

Linchuan Yang: Conceptualization, Data curation, Visualization, Writing – original draft, Project administration, Funding acquisition. **Yuan Liang:** Conceptualization, Investigation, Software, Writing – original draft, Methodology, Visualization. **Baojie He:** Writing – review & editing. **Yi Lu:** Writing – review & editing. **Zhonghua Gou:** Writing – review & editing.

Declaration of Competing Interest

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

Acknowledgements

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