Understanding the Spatial Impact of COVID-19: New insights from Beijing after one year into post-lockdown recovery

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Abstract This paper studies the spatial impact of COVID-19 pandemic through the lens of intra-city population and house rent changes in Beijing, China. Drawing on multiple geospatial data sets, we find that the pandemic has flattened the housing bid-rent curve in Beijing, which corroborates existing literature mainly based on cities in developed countries. Through regression analysis and spatial equilibrium modelling, we identify key mechanisms of the flattened bid-rent curve and the accompanying decentralisation of residents. First, workplace population change, particularly in central Beijing, seems to be the main factor contributing to the resident population and house rent changes. Second, we find no significant evidence on the spatial impact from remote working, as the share of remote working in Beijing appears low after about one year recovery. This finding contrasts to existing studies where remote working has been perceived as the main driver for urban spatial structure change in a developed country context. Third, through a novel method for quantifying locational preference changes, it is found that the observed decentralisation trend in Beijing, ceteris paribus, may also be associated with increased (decreased) preference for living in suburban (central) locations. However, the preference change for central locations is marginal, hence providing an early rebuttal of the 'demise of centres' proposition.

JEL Codes: R00, E24

Key Words: COVID-19, agglomeration, urban spatial structure, equilibrium model

1 Introduction

There has been growing research investigating the spatial impacts of COVID-19 in cities. Several recent papers have documented a changing trend of decentralisation in the U.S. cities: during the pandemic, residents have been relocating from the dense metropolitan areas to the less dense periphery (Althoff et al., 2020; Coven et al., 2020; Glaeser et al., 2020; Haslag and Weagley, 2021) and this migration pattern has reflected in the housing market as a flattening of bid-rent gradients (Gupta, et al., 2021; Liu and Su, 2021; Rosenthal et al., 2021). The bid-rent functions are typically downward sloping to reflect the greater value of the city centre relative to the suburbs. However, the COVID-19 pandemic has flattened the bid-rent relationship by attracting residents and possibly firms to relocate from central areas to suburbs, which causes higher appreciation rates of house prices and rents in the suburbs. The flattening of the bid-rent curve seems a symbolic feature in terms of the pandemic impact on housing market in cities.

There is also a large and growing literature examining the long-term impact of remote working on cities, mainly using data from U.S. cities (Behrens et al., 2021; Brueckner et al., 2021; Brynjolfsson et al., 2020; Delventhal and Parkhomenko, 2021; Delventhal et al., 2020), and joined by some evidence from the United Kingdom (De Fraja et al., 2021), Australia (Lennox, 2020) and Germany (Alipour et al., 2020). Some of the key variables in these studies include the varying share of remote/flexible workers across sectors and occupations, the split between on-site and remote working and the associated change in commuting cost (Coven et al., 2020; Gupta et al., 2021; Delventhal and Parkhomenko, 2020). A general finding is that remote/flexible working may lead to residents migrating away from cores and into suburbs due to reduced commuting cost, resulting reduced agglomeration effect in cores, and consequently the decline (increase) of house prices in cores (suburbs). It seems that long-term remote/flexible working provides a plausible explanation to the observed bid-rent curve changes.

Two significant research gaps can be identified. Firstly, existing studies examining the spatial-economic impact of the pandemic have been mainly focused on cities in developed countries, whereas pandemic studies for developing countries have been mainly focused on the instant change of mobility (Kraemer et al., 2020; Nouvellet et al., 2021) and transmission factors (Baud et al., 2020) at early waves of COVID-19. Few papers examine the spatial impact of the pandemic into the recovery stage. The significance of studying the spatial impact of COVID-19 in developing countries, notably China, lies in the following two aspects, 1) most affected cities in China ended city-wide lockdown around the middle of 2020 and have been actively engaging in post-pandemic recovery since then, thus providing a unique source of information for examining the lasting impact of the pandemic and informing fast, just and green recovery strategies for other cities; and 2) the share of remote/flexible working renders much lower in low-to-middle income countries due to their distinct economic and occupational structure (Dingle and Neiman, 2020; Gottlieb et al., 2020; Saltiel, 2020) and cultural characteristics. The distinct context thus requires research for identifying factors and mechanisms in relation to the flattening of the bid-rent curve beyond remote/flexible working.

Secondly, given the wide evidence on the flattening of the bid-rent curve for houses, few studies provide all-round explanations on why the flattening trend. The lack of causal investigation relates to a number of analytical and data challenges. For example, employment loss may directly affect housing demand hence prices, while residents may respond to income changes and housing price signals through relocation. The endogeneity of housing prices and the location choice of residents complicates the analysis of the bid-rent curve change. In addition, conventional data sources such as annual population/employment surveys can hardly capture the dynamic population and price changes induced by the pandemic. Online open source data (e.g. property listing website, location-based services data) open up new frontiers for probing the pandemic impact in cities, which is further catalysed by the lived experience of using online services during the lockdown.

To address the research gaps, this paper examines the spatial impact of the pandemic in Beijing through the lens of resident/workplace population and house rents. The novelty of this study lies in the following aspects. Firstly, it makes use of data from a wide range of novel sources, including rent data from a leading domestic real estate agency, movement data from mobile phone data and large-scale location-based services (LBS) data. The multi-source data enables a data cross-validation exercise. Secondly, Beijing is ahead of most major cities in the world in terms of embarking on post-pandemic recovery (city-wide lockdown lifted in May 2020). A study of Beijing is expected to generate early and timely insights for gauging the magnitude of spatial impact on cities incurred by the pandemic. Lastly, the paper presents a new analytical strategy that combines regression analysis with spatial equilibrium model and demonstrates its capability in understanding the nexus of population, employment and housing rents through a case study of Beijing.

Our descriptive analyses find that Beijing has experienced a sizable loss of resident population (-14%) and workplace population (-16%), comparing March 2021 with March 2019, and a modest trend of decentralisation of residents from central locations to suburbs. The trend of flattening bid-rent curves is also confirmed in Beijing by estimating the rent-distance relationship using a hedonic model with a range of property-/time-specific variables controlled for.

Reduced-form regression and spatial equilibrium model are used to explain why the bid rent curve has flattened in Beijing. The regression results show statistically positive association between workplace population change and the change in the slope of the bid-rent curve. That is, central locations which saw higher workplace population loss experienced higher rental reductions from 2019 to 2020. Considering the limitations of regression analysis in handling circular causality between house rents and resident population, a spatial equilibrium model is developed, which features a logit discrete choice model for residential location choice and endogenous house rents. Specifically, the model is calibrated for 2019 using observed employment-residence location choices and house rents. The calibrated model is then used to predict the spatial distribution of residents and rents for 2021, based on observed employment changes from 2019 to 2021. Housing stock and transport accessibility is assumed to be supply-side constraints, which remain constant between 2019 and 2021. The model predictions are then compared with the observed data.

The model tests show that the model assuming constant locational preference (2019-based) could well predict the change of employed residents and house rents in 2021, which suggests that aggregate employment change (higher % decrease in the centre than in the suburbs) seems to be the main cause of the flattening of the bid-rent curve. Our analysis into the discrepancy between the modelled and the observed suggests that the flattening may also involve locational preference changes in central and/or suburban locations in Beijing. We further quantify the potential locational preference changes through estimating a residual attractiveness term in the discrete choice model and find that the change of location preference for central Beijing is marginal. This finding contradicts the recent speculation of 'demise of city centres' due to drastically reduced preference for central locations.

Our paper connects to two lines of wider literature. First, it is built on extensive research on agglomeration which considers the benefits of spatial concentration (e.g. Ahlfeldt and Pietrostefani, 2019; Combes and Gobillon, 2015; Puga, 2010; Rothenal and Strange, 2004, 2020). A key tool used in this literature to examine the agglomeration effects is the bid-rent curve, which relates real estate prices to distance. Albouy et al. (2018) identify cross-sectional variation in the estimates of the bid-rent relationship across metropolitan areas. Based on the same analysis scale, Liu et al. (2018) focus on the vertical agglomeration effect and find a steep relationship between rents and height of the building. Our lens narrows to the intracity bid-rent curve, and by tracking its shift over time, we can estimate the spatial impact of the pandemic at a higher level of granularity.

Second, it ties well to research evaluating the impact of pandemics on the real estate market. The cholera outbreak in the London Broad Street of 1854 has caused persistent negative effects on the housing price in the affected area (Ambrus et al., 2020). By studying the plague in the 17th century of Amsterdam and the cholera in the 19th century of Paris, Francke and Korevaar (2020) document transitory declines of residential housing prices and rents. Similar patterns are observed in Canada and Hong Kong during the SARS pandemic in 2003 (Ouazad, 2020; Wong, 2008). Among the recent studies that examine the impact of COVID-19, Gupta, et al. (2021), Liu and Su (2021) and Liu and Tang (2021) investigate residential housing and Ling et al. (2020) and Rosenthal et al. (2021) focus on commercial real estate. Our work complements this strand of literature with early evidence from Beijing, a major city in a developing country that is nearly one year into post-pandemic recovery.

The rest of the paper is organized as follows: Section 2 describes our data, and Section 3 provides descriptive analysis of the spatial change of population and the shift of the house rent gradient incurred by the pandemic. Section 4 and Section 5 explore the factors and mechanisms of the bid-rent curve change in Beijing, using a regression model and a spatial equilibrium model, respectively. Conclusions and implications are discussed in Section 6.

2 Data

To enable a comprehensive and consistent investigation of the spatial impact of the COVID-19 pandemic in Beijing, we have compiled datasets from a wide range of sources (see Table 1). First, for capturing the *jiedao*[3]-level change of resident population and workplace population from 2018 to 2021, we leverage novel data sources such as the location-based services (LBS) data obtained from Baidu

[3] The smallest statistical unit in China. The total number of *jiedao* is different from the office figure because some *jiedao* in the Tongzhou Sub-centre are subdivided according to the masterplan.

map and mobile phone signal data from China Unicom. The resident and workplace population are inferred based on the longest place of stay at daytime and nighttime in a three-month observation period, respectively. For processing the residence location and workplace, land-use and Point of Interests data were used as additional sources of data[4].

Table 1 List of data input

Data	**Data source**	**Spatial-temporal resolution**
Population & Employment		
Resident population (persons)	Location-based services (LBS) data from Baidu map	Jiedao level in Beijing, monthly from Jan. 2018 to Mar. 2021
	Mobile phone signal data from China Unicom	Jiedao level in Beijing, 2019
	Micro data from the 6th Census	Jiedao level in Beijing, 2010
	Beijing Statistical Yearbook	District level in Beijing, 2019
Workplace population (persons)	The same as those for resident population, except the 6th Census data	
Employment	Micro data from the Third Economic Census in Beijing	Jiedao level in Beijing, 2013
	Beijing Statistical Yearbook	City level in Beijing, 2019
Housing		
House rents (Yuan/m^2 p.a.)	Lianjia, a leading domestic real estate agency	Transaction level in Beijing from Jan. 2018 to Dec. 2020
Housing stock (m^2)	Historical model data provided by local planning authority	Jiedao level in Beijing, 2018
Transport		
Origin-destination commuting flow	Mobile phone signal data from China Unicom	Inter-/intra-zonal, 2018
Travel time and distance	Retrieved from Baidu map, based on morning peak time traffic on a typical workday	Inter-/intra-zonal, retrieved in March 2019
Income & Housing expenditure		
Workplace wage (as a weighted average of sectoral wages) (Yuan p.a.)	Beijing Statistical Yearbook	City-level average sectoral wage by broad industry group, 2019; further adjusted according to district-level average income
Average disposable income* (Yuan p.a.)	Beijing Municipal Bureau of Statistics	City-level average, quarterly, from 2019Q1 to 2021Q1
Share of expenditure on housing in disposable income** (%)	Beijing Statistical Yearbook	City-level average, 2019

Notes: * For defining the price level in the spatial equilibrium model. ** Used as initial parameter input for calibrating the base-year (2019) spatial equilibrium model, subject to endogenous refinement according to the observed house rent data for 2019.

[4] Note that the processing of LBS and mobile phone data was conducted by domestic data providers and collaborators, and the authors do not have access to the raw tracking data.

Compared with official statistics which are often spatially aggregated and at yearly intervals, these novel data sources feature high spatial-temporal resolution, subject to implicit sampling biases (Wan et al., 2017). We validate the LBS data and the mobile phone data by comparing them with the most recent (2019) district-level population statistics from official sources as well as *jiedao*-level data from historical census (see Appendix A). Overall, the quality of the population data derived from LBS and mobile phone data seem satisfactory, and the mobile phone data feature higher goodness of fit than the LBS data.

Second, the prevalence of online property listing websites in China provides a novel data source on house price dynamics. House rents data are obtained from Lianjia.com, the largest real estate agency in Beijing that accounts for approximately 70% of the market share (Guo and Qu, 2019). The dataset covers detailed residential rentals in Beijing that occurred between 2018 and 2020, which include rent date and price and comprehensive physical characteristics (i.e., building age, size, floor, orientation, decoration, number of rooms, property fee, green ratio, and size of the residential community). Locational features such as the distance to the city centre, public transport, park, shopping malls and the number of fitting clubs, hospitals and public education resources nearby are collected based on maps embedded in Lianjia.com. One limitation of the Lianjia data is the relatively low sampling rate in suburban areas, as most of the rents collected are concentrated in central areas in Beijing. The spatial distribution of the rent data is presented in Appendix Figure B1 and summary statistics are provided in Appendix Table C1.

Third, this study combines statistical model analysis with spatial equilibrium modelling. For calibrating the spatial equilibrium model, we also collect data on transport, income, and housing expenditure for Beijing. Data input for the spatial equilibrium model will be discussed in Section 5.2 shortly.

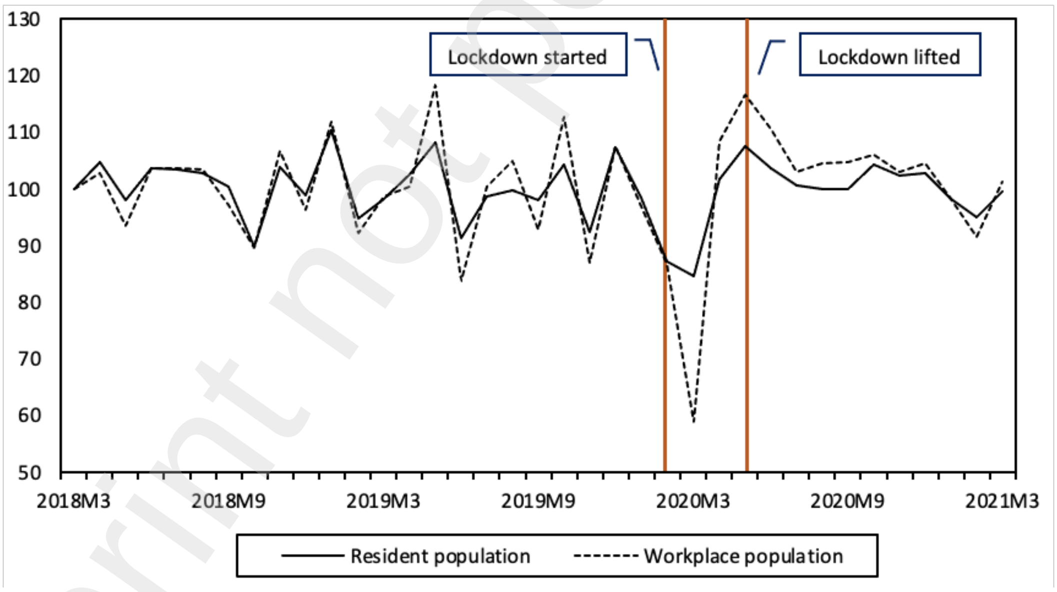
3 Descriptive analysis: Change of population and house rents

This section examines the spatial change of 1) resident and workplace population, and 2) house rents in Beijing from March 2018 to March 2021. The analysis starts from 2018, as it enables an explicit comparison between pre- and post-pandemic Beijing. The population data are derived from the LBS data, and the house rents data are sourced from the largest real estate agency in China (Lianjia).

3.1. Change of population

Resident and workplace population in Beijing dived to a historical low in March 2020. The relative reduction based on March 2019 is 26.1% and 16.1% for resident and workplace population, respectively. Figure 1 presents the relative change of city-wide population in Beijing from March 2018 to March 2021 based on the LBS data, using the population in March 2018 as 100. From 2018 to the end of 2019, resident and workplace population in Beijing have been broadly stable. The fluctuation of population is mostly attributable to seasonal differences and national holidays in May and October. The outbreak of COVID-19 in Beijing was first recorded in middle January 2020, followed by city-wide travel restrictions and other lockdown measures imposed in February[5]. Both resident and workplace population hence reduced to a historical low in March 2020.

Figure 1 Relative change of population in Beijing: Mar. 2018–Mar. 2021 (Population in Mar. 2018 = 100)



[5] The outbreak of COVID-19 occurred right before the Chinese New Year holiday when migrant workers usually return to their hometowns. According to the move-out index and move-in index provided by Baidu (see Appendix Figure B2), in 2019 most of the migrant population returned to Beijing after the new year celebration, but this did not occur in 2020.

Lockdown in Beijing was lifted (marked by the reopening of schools and the lift of inter-city travel ban) at the end of May 2020. Both resident and workplace population have been bouncing back since then. Note that the lift of lockdown in Beijing followed a phased and place-based approach, where people from surrounding cities in Greater Beijing city region were allowed to enter Beijing earlier than those from outside of Greater Beijing, which may explain the early population recovery between March and May in 2020.

In terms of post-lockdown recovery, resident and workplace population in Beijing recovered to 24.4 million and 11.3 million in March 2021, 13.8% and 15.4% lower than March 2019 level, respectively. The loss of the workplace population (2.2 million) is less than that of the resident population (3.9 million) in absolute terms, albeit higher in relative terms. It should be noted that the total number of COVID-19 deaths till May 2020 was only 8 according to official statistics[6], hence COVID-19 death was unlikely to be a direct cause of population loss.

It would be important to note that the loss of workplace population is not equivalent to employment loss. The change of workplace population consists of two components, i) net job loss, and ii) absent workers possibly engaging in remote/flexible working. Evidence from an online survey of local renters in March 2021 (sample size: 967, conducted by the same authors) suggests that the percentage of remote/flexible working in Beijing is likely to be low (<10%). The implication is that, assuming a 10% share of remote/flexible working in Beijing, the actual city-wide job loss would be 6.1% (16.1%-10%) after 10 months into post-lockdown recovery from May 2020.

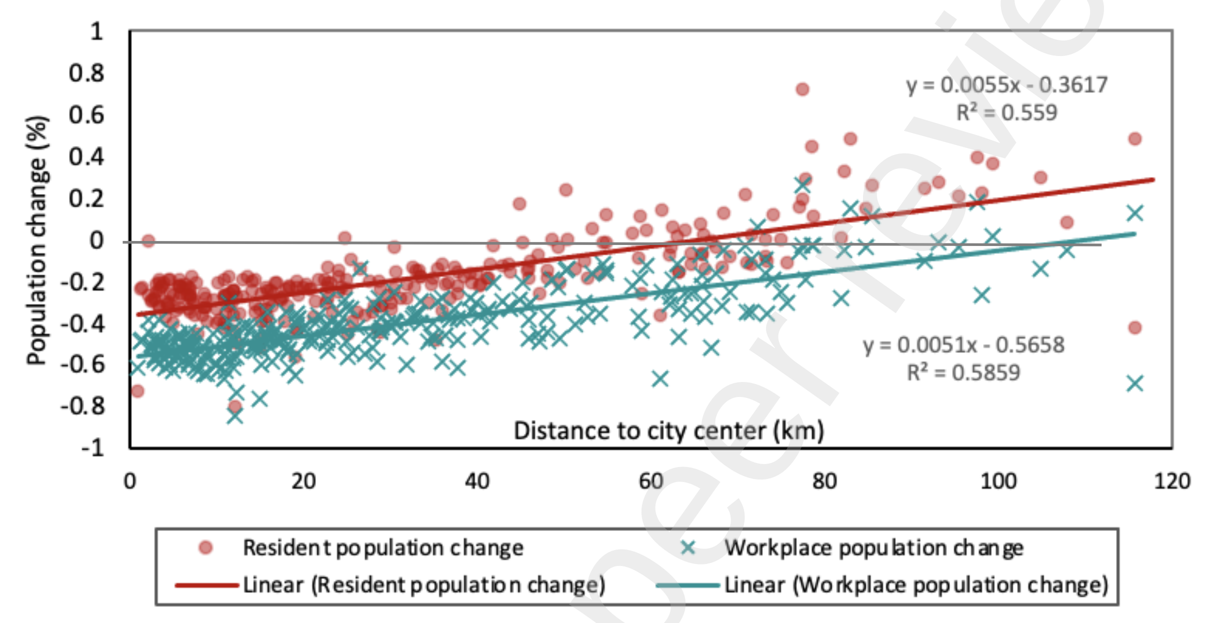
Across the city, we find uneven population changes both during and after the pandemic[7]. Figure 2 shows the percentage change of *jiedao*-level population from March 2019 to March 2020 with respect to the distance to the city centre (i.e. Tian'anmen Square). In the first wave, virtually all locations in Beijing experienced loss of workplace population, while some suburban locations saw net increase of residents, despite the city-wide reduction of resident population. In terms of the spatial pattern of change, reduction in central locations tends to be much higher, in relative terms, than in suburban locations. The elasticity of population change with respect to the distance from the city centre is similar for both resident and workplace population, which is around 0.005, indicating 1 km away from the city

[6] Beijing Municipal Health Commission (2020): http://wjw.beijing.gov.cn/wjwh/ztzl/xxgzbd/gzbdyqtb/202005/t20200526_1908549.html

[7] Map of population changes at the *jiedao* level can be found in Appendix Figure B3.

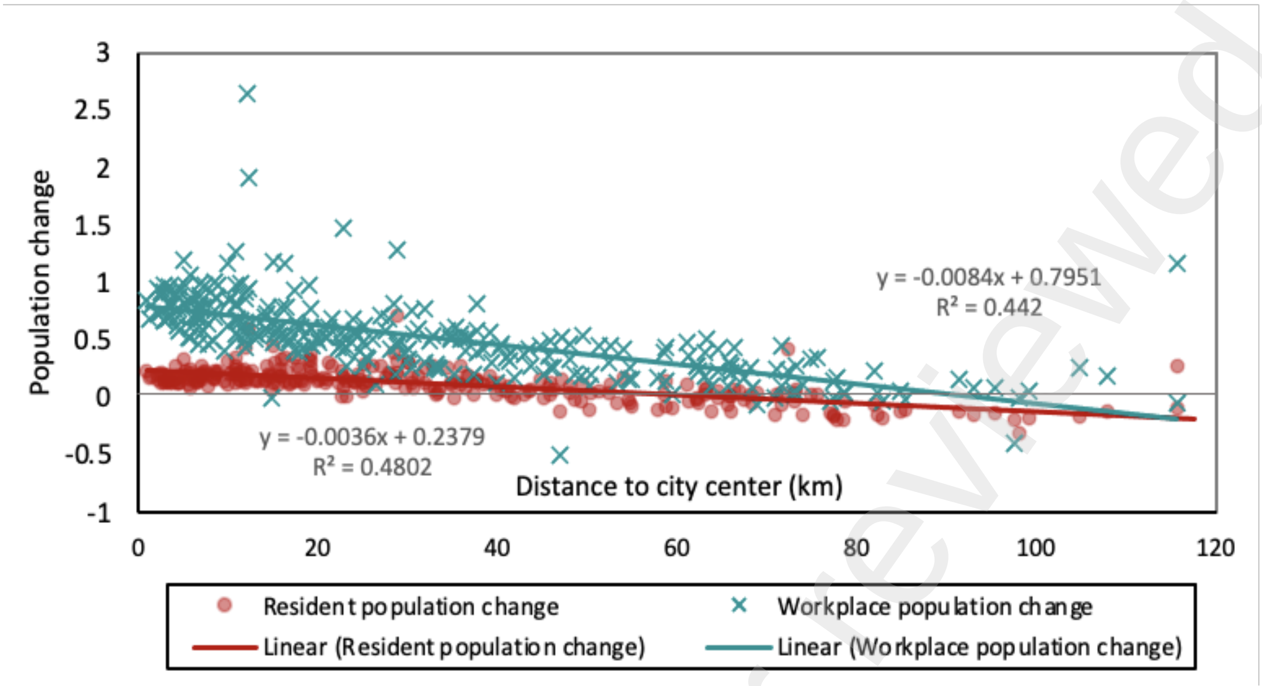
centre is associated with an additional 0.6% reduction of population. As a verification exercise, we have also examined the relative change of population during March 2018 – March 2019 (see Appendix Figure B4). The finding suggests that the positive correlation between population change and distance to the centre was unique, and hence most likely to be an effect of the pandemic.

Figure 2 The change of resident and workplace population with respect to the distance to city centre (Tian'anmen Square) (Mar. 2020 vs Mar. 2019)



In terms of post-lockdown recovery, return to work seems more effective in central locations than that in suburban locations. Figure 3 shows the percentage change of *jiedao*-level population from March 2020 to March 2021 against the distance from the city centre. The slope of both resident and workplace population has turned negative, indicating a faster rate of recovery in central locations than in far suburbs. We also find that the elasticity of workplace population recovery with respect to distance to the centre is significantly higher than that of resident population. Specifically, 1 km closer to the city centre is associated with an additional 0.36% and 0.84% increase of resident and workplace population, respectively.

Figure 3 The change of resident and workplace population with respect to the distance to city centre (Tian'anmen Square) (Mar. 2021 vs Mar. 2020)



3.2. Change of residential bid-rent curve

In this section, we examine the relationship between house rents and the distance to the city centre, namely, the bid-rent curve, and the slope change of the bid-rent curve in Beijing in the wake of the COVID-19 pandemic. Specifically, inspired by Gupta et al. (2021) who identified flattened bid-rent curves in US cities due to the pandemic, we would like to test whether a similar 'flattening' trend of bid-rent curve would present in Beijing in a developing country context. The reason for considering house rents instead of sale prices is that house rents usually reflect short-term equilibrium in the housing market (Ouazad, 2020). It is also our intention to provide early evidence on the wider social impact in post-pandemic cities from the lens of housing affordability, as renters tend to be more vulnerable than homeowners due to tenure insecurity and potentially precarious employment status (Wu, 2006).

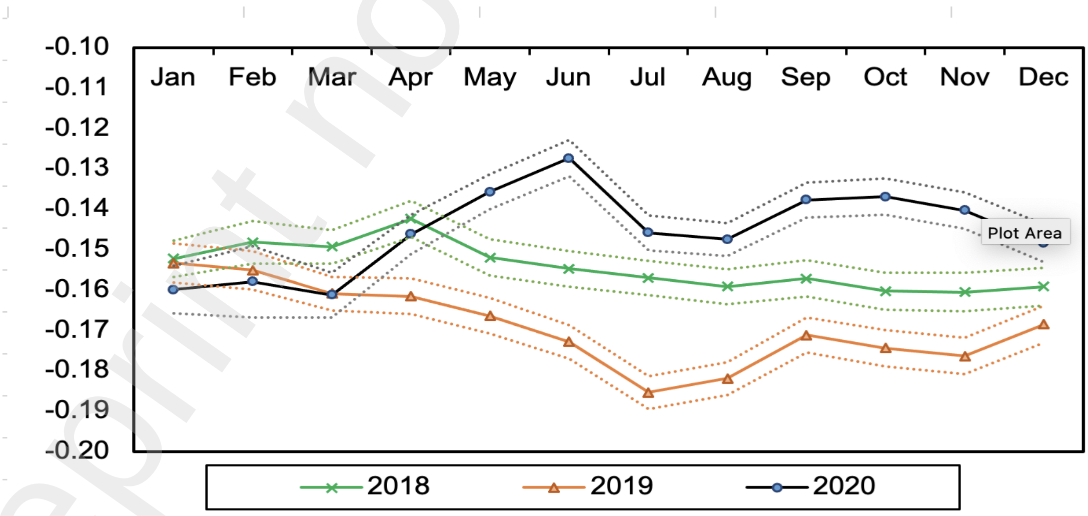
The traditional monocentric theory of cities suggests that rents in the city centre should be higher than in the suburbs because of proximity to workplaces, better amenities, and limited land supply (Gupta et al., 2021). However, this long-standing pattern may reduce owing to the pandemic-induced decline (increase) in demand for houses in core (suburban) locations. We measure the bid-rent curve by a hedonic pricing model with physical property attributes controlled. The equation is specified as below:

$$log\ (Y_{i,t}) = \beta_1 log\ (Distance_i) + \beta_{2,t} log\ (Distance_i) * \varphi_t + \lambda' X_{i,t} + \omega_i + \varphi_t + \varepsilon_{it} \qquad (1)$$

$Y_{i,t}$ is the rent of unit i at time t. $Distance_i$ is a continuous variable measuring the Euclidean distance to the city centre of Beijing (i.e., Tian'anmen Square) from unit i, and φ_t denotes the year times month fixed effects. $X_{i,t}$ is a set of hedonic variables controlling for the physical features of the property. ω_i denotes the business district[8] fixed effects and ε_{it} is the error term. β_1 measures the rent gradient against the distance from the city centre in the base month (January 2018), and $\beta_{2,t}$ captures the monthly rent gradient relative to the base month, which is of interest in the following analysis.

The estimated values of $\beta_{2,t}$ are illustrated in Figure 4[9]. From 2018 to 2019, the rent gradient in Beijing became steeper, indicating that house rents in central locations have been growing faster than those in suburbs. In terms of seasonal difference, the rent gradient tends to decrease from the first quarter to the last quarter. However, house rent gradient in 2020 shows a significant upward shift in the slope since March 2020, implying flattening of the bid-rent curve indeed. This suggests that rents in central locations decreased faster than those in suburbs in face of the pandemic. The rent gradient reached the highest (-0.124) in June 2020, compared with -0.171 in June 2019 and -0.155 in June 2018. The rent gradient has started to decline, reverting to historical trend, since June 2020, but the year-end gradient remains significantly higher than that in 2019 and 2018.

Figure 4 Monthly rent gradients in Beijing: 2018-2020



[8] It is defined by Lianjia and is smaller than the *jiedao* unit.
[9] Detailed hedonic model results are provided in Appendix Table C2.

4 Why flattened curve – Regression analysis

In this section, we attempt to explain the flattened bid-rent curve in Beijing by using a reduced-form regression. Our main hypothesis is that central locations which see higher workplace population loss would experience higher rental reduction. Focusing on workplace population changes, rather than resident population, aims to explore a direct link between the spatial distribution of employment loss and rent gradient change. Also, it could help to circumvent the possible circular causality between rent changes and resident population changes via household relocation.

To test the hypothesis, we develop a series of three regression models. For Model (1), The year-on-year change of rents at the *jiedao* level is used as the dependent variable and the average distance to the city centre as the independent variable. We choose *jiedao* as the spatial unit of analysis, which is consistent with the measurement of population changes. The rent data are collected for three years between 2018 and 2020, covering 193 out of 335 *jiedao* in Beijing. According to the distinct stages of COVID-19 development in Beijing, we divide the year of 2020 into two halves, namely the first half (January-June) covering the outbreak and the city-wide lockdown in Beijing, and the second half (July-Dec) for post-lockdown recovery. The year-on-year change of semi-annual average rents are calculated accordingly as the dependent variable. Note that the observed house rents are mostly likely to be sampled from properties of distinct physical characteristics. To control the potential bias caused by heterogeneity of properties, a hedonic price model is developed to correct the observed rents with property physical attributes controlled for (see Appendix D for details).

Model (2) and Model (3) are proposed to examine whether the workplace population changes have an impact on the rent gradient. Specifically, Model (2) presents a regression with the workplace population changes as the only explanatory variable and rent changes as the dependent variable. The residuals of Model (2) are then used in Model (3) as the dependent variable, regressed on the same set of explanatory variables in Model (1). The hypothesis is that the positive relationship between rent changes and the distance should decrease from Model (1) to Model (3), as part of the correlation is captured by the workplace population changes as per Model (2).

Regression results are reported in Table 2[10]. As shown in column (1), we find a significantly negative association of the year-on-year semi-annual rent changes with the distance from the city centre in the base period, namely, the first half of 2019, which also sustains into the second half of 2019. The negative distance-rent relationship turns positive in 2020, which confirms the flattening of the bid-rent curve. The distance-rent relationship becomes stronger in the second half of 2020 (i.e. 0.0526) compared with the first half (i.e. 0.0321). In column (2), we find a significantly positive impact of workplace population changes on rent changes. In other words, locations with lower workplace population changes would experience lower house rent decline. In column (3), regression residuals from Model (2) are used as the dependent variable. By comparing results in column (1) and (3), we find a notable decline of the distance-rent relationship in both halves in 2020 after controlling the influence of workplace population changes on rent changes. This suggests that the distance-rent relationship can be partially explained by workplace population changes.

Table 2 Regression results on the year-on-year change of semi-annual rents

	(1)	(2)	(3)
	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
log(Distance)	-0.0194*** (0.0046)		-0.0153*** (0.0047)
log(Distance)*D(Jul. – Dec. 2019)	-0.0025 (0.0065)		-0.0074 (0.0066)
log(Distance)*D(Jan. – Jun. 2020)	0.0321*** (0.0067)		0.0216*** (0.0068)
log(Distance)*D(Jul. – Dec. 2020)	0.0526*** (0.0064)		0.0431*** (0.0065)
Year-on-year change of workplace population		0.1619*** (0.0096)	
D(Jul. – Dec. 2019)	-0.0249 (0.0607)		0.0480 (0.0617)
D(Jan. – Jun. 2020)	-0.3775*** (0.0626)		-0.2005*** (0.0636)
D(Jul. – Dec. 2020)	-0.5807*** (0.0600)		-0.4341*** (0.0610)
Constant	0.2196*** (0.0432)	-0.0017 (0.0020)	0.1562*** (0.0440)
Observations	606	606	606
Adjusted R-squared	0.4603	0.3169	0.1824

Notes: D(Jul. – Dec. 2019), D(Jan. – Jun. 2020), and D(Jul. – Dec. 2020) are three dummy variables used to indicate different time periods of observations. The dependent variable in the first two columns is the year-on-year semi-annual rent changes and the dependent variable in column (3) is the residuals based on regression results in column (2). Only *jiedao* with over 50 rentals in each of the semi-annual periods are included in the regression. Standard errors in parentheses. ***, **, and * denotes statistical significance at the 1%, 5% and 10% level, respectively.

[10] The summary statistics are provided in Appendix Table C3.

We also test the impact of remote/flexible working on the flattened bid-rent curve. Recall our own housing tenant survey finding (see Section 3.1, page 10), the ratio of remote working in Beijing appears low. Nonetheless, as suggested by literature (Dingle and Neiman, 2020), remote working may be significant for some knowledge-intensive sectors, which tend to concentrate in the city centre. Thus, the spatial concentration of high-skill jobs may be related to the bid-rent curve change. To test this hypothesis, we follow Gupta et al. (2021) to connect the rent change with the share of knowledge-intensive jobs, which include the professional technical service, monetary and financial services, and software and information technology services. However, as shown in Table 3, we observe a significantly positive relationship between the rent change and the pre-pandemic share of knowledge-intensive jobs, which does not change with the pandemic. That is, places with higher share of knowledge-intensive jobs would experience larger rent increases. This positive relationship is contrary to the findings of Gupta et al. (2021). We also find that, when the influence of knowledge-intensive jobs is controlled, the distance-rent relationship sees only negligible changes. Hence, the flattened bid-rent curve is less likely to be caused by the role of remote working.

Table 3 Results on the impact of the share of knowledge-intensive jobs (*JobRatio*) on rent changes

	(1)	(2)	(3)
	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
JobRatio	0.0563*** (0.0162)	0.0850*** (0.0257)	
JobRatio*D(Jul. – Dec. 2019)		-0.0317 (0.0363)	
JobRatio*D(Jan. – Jun. 2020)		-0.0454 (0.0363)	
JobRatio*D(Jul. – Dec. 2020)		-0.0463 (0.0361)	
log(Distance)			-0.0183*** (0.0045)
log(Distance)*D(Jul. – Dec. 2019)			-0.0025 (0.0064)
log(Distance)*D(Jan. – Jun. 2020)			0.0324*** (0.0066)
log(Distance)*D(Jul. – Dec. 2020)			0.0528*** (0.0063)
D(Jul. – Dec. 2019)		-0.0448*** (0.0068)	-0.0253 (0.0595)
D(Jan. – Jun. 2020)		-0.0727*** (0.0069)	-0.3805*** (0.0614)

D(Jul. – Dec. 2020)		-0.0847***	-0.5821***
		(0.0067)	(0.0590)
Constant	-0.0225***	0.0289***	0.2249***
	(0.0030)	(0.0049)	(0.0424)
Observations	606	606	606
Adjusted R-squared	0.0179	0.3877	0.4697

Notes: D(Jul. – Dec. 2019), D(Jan. – Jun. 2020), and D(Jul. – Dec. 2020) are three dummy variables used to indicate different time periods of observations. The dependent variable in the first two columns is the year-on-year semi-annual rent changes and the dependent variable in column (3) is the residuals based on regression results in column (1). Only *jiedaos* with over 50 rentals in each of the semi-annual periods are included in the regression. Standard errors in parentheses. ***, **, and * denotes statistical significance at the 1%, 5% and 10% level, respectively.

To summarise, the regression analysis confirms the flattening of the bid-rent curve for rental houses in Beijing and one important channel of impact is the pandemic-induced workplace population changes, for the loss of workplace population would reduce the housing demand within the labour catchment area. As our regression model suggests minimal impact of flexible/remote working, it seems reasonable to argue that employment change is a significant factor that contributes to the flattened bid-rent curve.

However, the regression analysis has its limitations. Firstly, the analysis is primarily focused on workplace population, while the nexus of resident population, workplace population and rent changes is not yet disentangled. In particular, the circular causality around rents (i.e. rents being not only the *effect* of demand changes, but also the *cause* of household relocation) remains a major issue to be addressed. Secondly, the setting of Model (2) (rents changes regressed on workplace population changes) implicitly assumes that the workplace population change would only affect the same zone (*jiedao*), but not the wider labour catchment area. This is against the observed commuting pattern in Beijing, where an average worker would commute over 12km for work (BTRC, 2015). It is likely that the loss of workplace population in one location would affect the housing demand across the wider commuting catchment area in metropolitan Beijing. Lastly, the flattening of the bid-rent curve, in theory, could be attributed to locational preference changes, even in absence of employment change. For example, an increase of preference for suburban locations over central locations could lead to rent decline (rise) in the centre (suburbs).

As a response to the above caveats and considerations, we present a spatial equilibrium modelling approach in the next section, which is expected to unravel the nexus of resident population, workplace population and rent changes.

5 Why flattened curve – Spatial equilibrium modelling

To complement the regression analysis, this section presents a purpose-built spatial equilibrium model for further investigating the flattening of the bid-rent curve. The spatial equilibrium model features a multinomial logit model for residential location choice with endogenous house rents subject to exogenous housing stock constraints. The use of spatial equilibrium model complements the regression analysis on the following aspects. Firstly, endogenous house rents enable the simulation of household relocation as a response to price signals, hence addressing the circular causality issue in regression analysis. Secondly, the residential location choice model based on exogenous employment input would capture the impact of employment loss on the housing market across the wider commuting catchment area, rather than the workplace zone alone. Thirdly, a novel modelling method is proposed for gauging the magnitude of possible locational preference changes in Beijing.

The model is initially calibrated for the base year 2019, where observed spatial distribution of employed residents, workers, commuting pattern and house rents at *jiedao* level are used as calibration inputs. The calibrated model is then used to 'predict' the spatial distribution of employed residents and house rents for 2021, using observed 2019-2021 workplace population change as a key input. The predicted spatial distribution of residents and house rents are compared with the observed data for 2021 (both resident and rent data available till March 2021).

5.1 The model

We follow established urban economic models (Anas and Liu, 2007), employing a multinomial logit model for residential location choice, subject to housing market equilibrium conditions. The probability of employed residents working at location j choosing to live in zone i is defined as:

$$P_{i|j} = \frac{S_i e^{V_{i|j}}}{\sum_m (S_m e^{V_{i|j}})} \tag{2}$$

$$V_{i|j} = \beta_1 d_{ij} + \beta_2 \, ln \, ln \, (h_i) \, + E_{i|j} \tag{3}$$

where S_i is the total housing floorspace at zone i, correcting the bias introduced by the uneven sizes of zones in the model (Ben-Akiva and Lerman, 1985); $V_{i|j}$ is the observable locational utility for living in zone i, given workplace j. The design of the utility function $V_{i|j}$ considers the classic trade-off between travel disutility of commuting (d_{ij}) and endogenous house price (h_i), and a composite attractiveness term ($E_{i|j}$) that is unobserved by modellers but could be empirically estimated using observed location choice data. β are coefficients to be estimated. Compared with conventional multinominal logit model applications, the incorporation of $E_{i|j}$ captures the residual attractiveness of location i additional to the interaction between d_{ij} and h_i, and hence serves as a proxy for residential location preference for zone i given workplace j. $E_{i|j}$, once calibrated using base-year observed data, will be retained as a constant in forecast runs.

We further define $d_{ij}^f = a_f c_{ij}^f + (1 - a_f)\, ln\, ln\, c_{ij}^f\ - a_f$ as a log-linear travel disutility function following Daly and Zachary (1978), where $c_{ij} = g_{ij} + w_j t_{ij}$ is the generalised commuting cost between zone i and j including both monetary cost (g_{ij}) and value of time (w_j is the wage at workplace j and t_{ij} is the travel time). Modern city regions tend to have a commuting catchment of 50+km and a travel disutility function that is linear to travel time/distance may underestimate the travel demand for long-distance commuting. The use of log-linear travel disutility thus would better capture the non-linear travel demand elasticity at city-region level (Jin et al., 2013; Wan et al., 2021).

Based on the output of the location choice model, the next step is to calculate the aggregate housing demand at zone i and then solve the equilibrium house rent (h_i). We first calculate the number of employed residents (ER) at zone i as:

$$ER_i = \sum_j P_{i\,|j} J_j \tag{4}$$

The average budget constraint (Ω_i) for residents at zone i as the average annual wage income weighted by $P_{i|j}$, net of commuting costs, is then defined as:

$$\Omega_i = \sum\nolimits_j \frac{(W_j - 2Dc_{ij}w_j)P_{i|j}J_j}{\sum_m P_{i|m}J_m} \tag{5}$$

where W_j is the average annual wage at workplace j, which is exogenous input; w_j is the hourly wage at j derived from W_j; D=250 is the average annual number of workdays and $2D$ indicates the annual number of commuting trips, assuming two trips per workday; the J_j is the number of employed workers at workplace j; and $\sum_m P_{i|m}J_m$ is the total number employed residents at zone i. This gives the zonal total expenditure on housing (M_i):

$$M_i = \sum\nolimits_f \Omega_i \gamma_i (\sum\nolimits_m P_{i|m}J_m) \tag{6}$$

where $\gamma_i \in (0,1)$ is a coefficient measuring the average share of income spent on housing[11] at zone i. Assuming housing market clearing, the average house rent at residence zone i (h_i) can be then calculated as $h_i = \frac{M_i}{S_i}$, where S_i is the total housing floor space in zone i, which is an exogenous stock constraint. The exogenous housing stock represents the inertia-prone nature of housing supply and can be updated in model forecasts as a policy variable. The housing equilibrium condition entails housing market clear at all zones simultaneously, through home location adjustment of utility-maximizing residents. Following the tradition of computable equilibrium models, h_i is solved in an iterative manner (see Figure 5).

Figure 5 Algorithm of the spatial equilibrium model

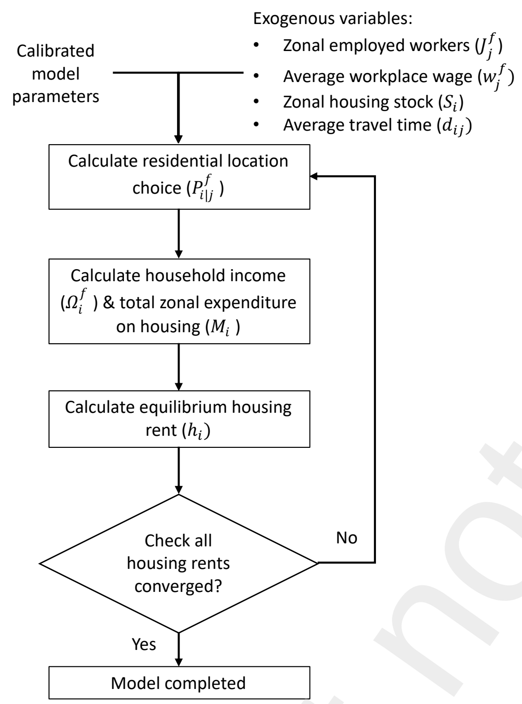
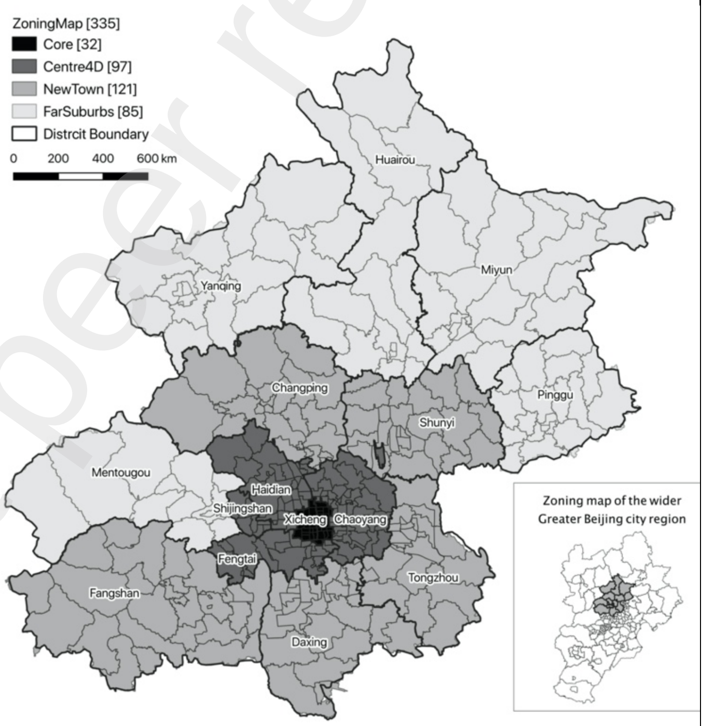


Figure 6 Zoning map for Beijing and the Greater Beijing city region



In terms of model segmentation, the empirical model for Greater Beijing consists of 476 model zones, among which 335 zones represent *jiedao* in Beijing and 141 zones represent the wider areas outside Beijing in the Greater Beijing city region (see the zoning map in Figure 6). The coverage of the wider

[11] According to the definition of local statistics in Beijing, expenditure on housing includes house rent (imputed rent for owner-occupiers), utilities and property management fees.

city region enables the modelling of inter-city commuting and migration. The model has one composite type of housing and one composite type of employed residents due to data availability.

5.2 Data input and assumptions

The data input for model calibration (2019) and forecast (2021) are summarized in Table 4 at the district level. For the base year (2019) model calibration, zonal average expenditure on housing (γ_i), location utility function coefficients (β) and the zonal residual attractiveness term ($E_{i|j}$) will be empirically estimated based on observed zonal employed residents (ER), workplace population, average house rent, housing stock, labour wage and travel time matrix. The inter-zonal travel time is based on the quickest journey time sampled for a typical Tuesday at 8am from a leading domestic online map service. The intra-zonal travel time is estimated by modellers based on the geographical size of the zone and knowledge on local travel. Note that the observed zonal ER, workplace population and the associated commuting flow are processed from the mobile phone data for 2019. The use of mobile data for 2019 fills a major data gap in terms of jiedao-level population and employment statistics in Beijing. However, the mobile phone data are available for 2019 only, and the population data for 2021 is based on the LBS data.

For the 2021 prediction, the zonal employment data are derived based on the change of workplace population obtained from the LBS data series. According to the LBS data series, overall Beijing saw a 15.4% decrease of workplace population from March 2019 to March 2021. In terms of the spatial distribution of the decrease, central locations tend to experience a higher percentage of reduction than far suburbs (also see early analysis in Section 3). Within the broad location groups, the distribution is also uneven. For example, Chaoyang district has seen a 20.5% reduction in workplace population, compared with a 13.2% reduction in Haidian district. No conclusive reasons could be provided at this stage due to limited data, but it could be postulated that such difference is associated with the local sectoral structure and the socio-economic status of residents: Chaoyang featured a relatively high level of manufacturing jobs, contrast to the concentration of knowledge-intensive, high-skill jobs in Zhongguancun in Haidai.

It should be noted that the 2021 model prediction is based on the following assumptions: 1) zonal housing stock remains the same as in 2019; 2) the share of housing expenditure in total income remains the same at zonal level as in 2019; 3) zonal wage grows in a pro rata manner according to official statistics on income growth; specifically, average disposable income in Beijing increased from 67,756 Yuan in 2019 to 68,273Yuan in 2020 based on 2019 price level (adjusted using official year-end consumer price index (CPI)); the latest official statistics show that 2021Q1 saw an increase of 9.4% (based on constant price) on disposable income; disposable income for 2021 model forecast is thus set as 74,691 Yuan; 4) inter- and intra-zonal travel time and cost remains the same as 2019 level, which is based on the fact that all capacity restrictions for metro, bus and taxi in Beijing have been lifted since July 2020[12]; 5) despite the modelling capability to simulate inter-city migration, we exogenously control the total number of employed residents in Beijing for 2021 according to the observed total from the LBS data (10.15 million); note that controlling this boundary condition would not affect the intra-city residential location choice modelling; and finally 6) all variables for areas outside Beijing in the Greater Beijing city region remain the same as in 2019.

Table 4 Overview of input data for model calibration (2019) and forecast (2021)

	2019 (Input for Calibration)				**2021 (Input for Forecast)**	
	ER ('000)	Emp. ('000)	House Rent (Yuan/m^2 p.a.)	Labour Wage (Yuan p.a.)**	Emp. ('000)	%Diff_Emp 2021 vs 2019
Core*	**998**	**1,745**	**1,418**	**81,663**	**1,485**	**-14.9%**
Dongcheng	417	754	1,473	74,291	624	-17.2%
Xicheng	581	991	1,382	87,271	861	-13.2%
Centre4D	**5,261**	**6,646**	**1,084**	**68,577**	**5,539**	**-16.7%**
Fengtai	1,151	1,096	872	54,910	924	-15.6%
Chaoyang	1,967	2,660	1,167	70,016	2,113	-20.5%
Haidian	1,817	2,568	1,183	73,233	2,230	-13.2%
Shijingshan	326	323	815	66,078	271	-15.9%
NewTown	**4,747**	**3,425**	**605**	**63,053**	**2,920**	**-14.8%**
Daxing	1,093	1,010	542	67,160	874	-13.4%
Fangshan	689	455	503	56,225	399	-12.4%
Changping	1,255	786	731	62,811	646	-17.9%
Tongzhou	993	598	600	55,696	535	-10.6%
Shunyi	715	576	567	69,225	467	-18.9%
FarSuburbs	**1,129**	**895**	**435**	**59,044**	**807**	**-9.8%**
Miyun	271	216	433	60,276	199	-8.0%
Pinggu	245	190	404	53,449	180	-5.2%
Yanqing	196	173	351	48,949	149	-13.9%
Huairou	232	198	491	64,555	166	-15.8%

[12] http://cn.chinadaily.com.cn/a/202007/24/WS5f1b73b6a310a859d09da10c.html.

Mentougou	186	119	507	71,253	114	-4.4%
Grand Total	**12,135**	**12,711**	**863**	**68,214**	**10,751**	**-15.4%**

Notes: *Input data is reported at the district level and the 16 districts were grouped into four broad areas based their proximity to the city centre; **After tax and before deducting commuting cost (c_{ij}).

5.3 Model prediction results

5.3.1 Prediction results of employed residents

We first present the comparison between the predicted and observed number of employed residents in Beijing in 2021. Overall, the predictions show a high-level goodness of fit with the observed residents at district level, which indicates that employment change between 2019 and 2021 (which is exogenous to the model) seems to be the main cause of the resident population change, subject to aforementioned model assumptions. Specifically, as shown in Table 5, district-level prediction errors remain below 5% in most districts and a few fall between 5% and 10%. The predictive capability of the model can be further examined by comparing the elasticity of ER between the modelled and the observed (see Figure 7). The elasticity of ER is the change of ER (endogenous) relative to the change of employment (exogenous). It complements the percentage difference (%Diff.) measure, as it shows the elasticity of the model free from the magnitude of input change. The elasticity comparison shows a strong linear correlation between the modelled and observed, except a few districts in Far Suburbs.

Table 5 Comparison of spatial distribution of employed residents (ER) in Beijing (2021) - Modelled vs Observed

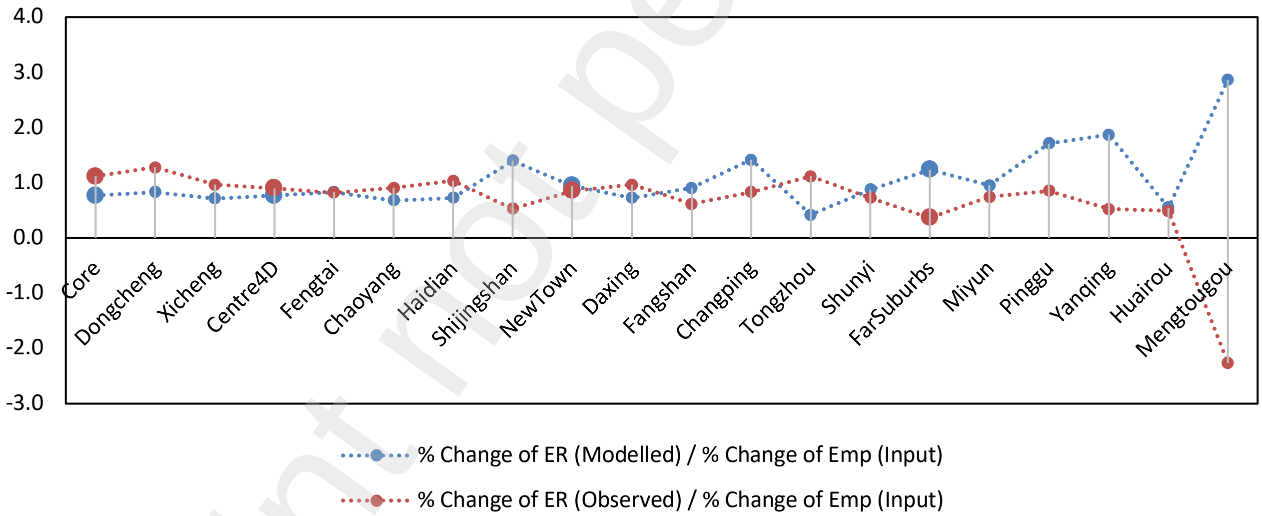
	ER - Modelled* ('000)	**ER - Observed ('000)**	**%Diff. - Modelled/Observed-1**
Core	**857**	**831**	**3.1%**
Dongcheng	352	325	8.2%
Xicheng	505	507	-0.5%
Centre4D	**4,504**	**4,452**	**1.2%**
Fengtai	988	1,003	-1.5%
Chaoyang	1,639	1,600	2.4%
Haidian	1,596	1,570	1.6%
Shijingshan	281	299	-6.1%
NewTown	**4,126**	**4,146**	**-0.5%**
Daxing	946	944	0.2%
Fangshan	609	636	-4.3%
Changping	1,083	1,069	1.3%
Tongzhou	882	881	0.1%

Shunyi	606	616	-1.7%
FarSuburbs	**1,021**	**1,079**	**-5.4%**
Miyun	246	255	-3.3%
Pinggu	229	234	-1.9%
Yanqing	172	181	-5.0%
Huairou	200	215	-6.9%
Mengtougou	173	205	-15.7%
Grand Total	**10,508***	**10,508**	**0.0%**

Notes: * Modelled based on residual attractiveness term $E_{i\,|\,j}$ estimated and retained from 2019.

In terms of the spatial pattern of discrepancies, we find that the model overestimates the total employed residents (ER) in the Core and Centre4D by 3.1% and 1.2%, respectively. At the same time, the model underestimates ER living in New Towns and Far Suburbs by 0.5% and 5.4%, respectively. The opposite direction of prediction discrepancies in central and suburban districts appears to reflect the widely claimed 'decentralisation' trend incurred by the pandemic, where suburban locations attract residents from central locations, resulting in reduced (increased) population in city cores (suburbs).

Figure 7 Relative change of employed residents (ER) in Beijing 2021 - Modelled vs Observed



Notes: An elasticity value close to one suggests a proportional change of district-level ER relative to employment change. Mentougou appears to be an outlier. According to the LBS data, employed residents in Mentougou increased around 10% despite a 4.4% employment decrease, hence a negative elasticity of -2.26. One plausible explanation of the negative elasticity is the low sampling rate of LBS data in Mentougou, which is in rural Beijing. Nonetheless, this potential data error is unlikely to alter the main findings of the study due to the small population size of Mentougou (around 1.5% of total population in Beijing).

The decentralisation trend implies a reduced preference for central locations and/or increased preference for suburban locations. To gauge the magnitude of the potential change of locational preference, we propose a novel method by estimating $E_{i|j}^{2021}$ for 2021, which reflects the absolute changes of utility required for reproducing the observed district-group level distribution of residents in Beijing in 2021. Table 6 presents each utility component in the locational utility function $V_{i|j}$, including the newly estimated $E_{i|j}^{2021}$. For aggregating each utility component across location alternatives, *logsum* method (Ben-Akiva, 1974; Train, 2003, p. 95) is applied, which accounts for the choice effect and hence is a standard method for utility aggregation in discrete choice. Travel time (d_{ij}) and $E_{(j)}^{2019}$ remain the same between 2019 and 2021, while the house rents $ln\ (h_i)$ are endogenous in the 2021 model. Also, all utility components across locations have been adjusted to have zero mean. Note that this adjustment does not change the logit probability, because the numerical level of utility is irrelevant in the logit function and 'only differences in utility matter' (Train, 2009, p. 24). The ranking of d_{ij} and $ln\ ln\ (h_i)$ across the four location groups indicates that central districts in Beijing have better transport accessibility but lower housing affordability than New Towns and Far Suburbs.

Our interest lies on the value of $E_{i|j}^{2021}$. Recall that $E_{i|j}^{2019}$ represent pre-pandemic locational preferences net of the trade-off between transport and house cost, and a positive (negative) value means that the base-year model without $E_{i|j}^{2019}$ would underestimate (overestimate) the number of employed residents in that particular location. The newly estimated $E_{i|j}^{2021}$ would capture the changes of locational preference in 2021, net of the endogenous change of transport and house rents. Specifically, the Core would see a reduction of utility by 0.07, while the utility of living in Far Suburbs would increase by 0.14, such that the model would reproduce the observed data. It confirms that the observed decentralisation trend could be explained by aggregate locational preference changes in Beijing. In terms of relative change (see last column in Table 6), the percentage change of locational preference (that is, the sum of all utility components) is under 10% for all location groups, except for Far Suburbs. It should be noted that potential preference changes and possibly increasing data errors in less developed areas may jointly contribute to the discrepancy in Far Suburbs. Thus, the numerical increase of preference for Far Suburbs needs to be interpreted with caution, and to be verified when additional data become available.

Taken together, despite the confirmed trend of 'decentralisation' in Beijing, a structural change of locational preferences in Beijing, in particular for central locations, seems an exaggeration. The reduction of locational preference for central districts in Beijing appears marginal. This finding contradicts the speculation of ‘demise of city centres’ due to drastically reduced preference for central locations. However, residential location preference change could be significant at local level, as demonstrated by the discrepancy in Far Suburban districts.

Table 6 Quantifying the potential change of locational preference by $E_{i|j}^{2021}$

Panel A: 2019						
	d_{ij}	$ln\ (h_i)$	$d_{ij} + ln\ (h_i)$	$E_{i\|j}^{2019}$		Total_2019*
Core	0.51	-1.12	-0.61	-0.33		-0.94
Centre4D	0.18	-0.60	-0.41	1.50		1.09
NewTown	-0.25	0.69	0.43	-0.24		0.20
FarSuburbs	-0.44	1.03	0.59	-0.94		-0.34
Mean	*0.00*	*0.00*	*0.00*	*0.00*		*0.00*
S.D.	*0.43*	*1.03*	*0.60*	*1.05*		*0.86*

Panel B: 2021							
	d_{ij}	$ln\ (h_i)$	$d_{ij} + ln\ (h_i)$	$E_{i\|j}^{2019}$	$E_{i\|j}^{2021}$	Total_2020**	%Diff. (Total_2020/Total_2019-1)
Core	0.51	-1.12	-0.61	-0.33	-0.07	-1.02	7.5%
Centre4D	0.18	-0.59	-0.40	1.50	-0.05	1.06	-3.1%
NewTown	-0.25	0.69	0.44	-0.24	-0.03	0.18	-9.0%
FarSuburbs	-0.44	1.01	0.57	-0.94	0.14	-0.22	-35.7%
Mean	*0.00*	*0.00*	*0.00*	*0.00*	0.00	0.00	
S.D.	*0.43*	*1.02*	*0.59*	*1.05*	0.10	0.86	

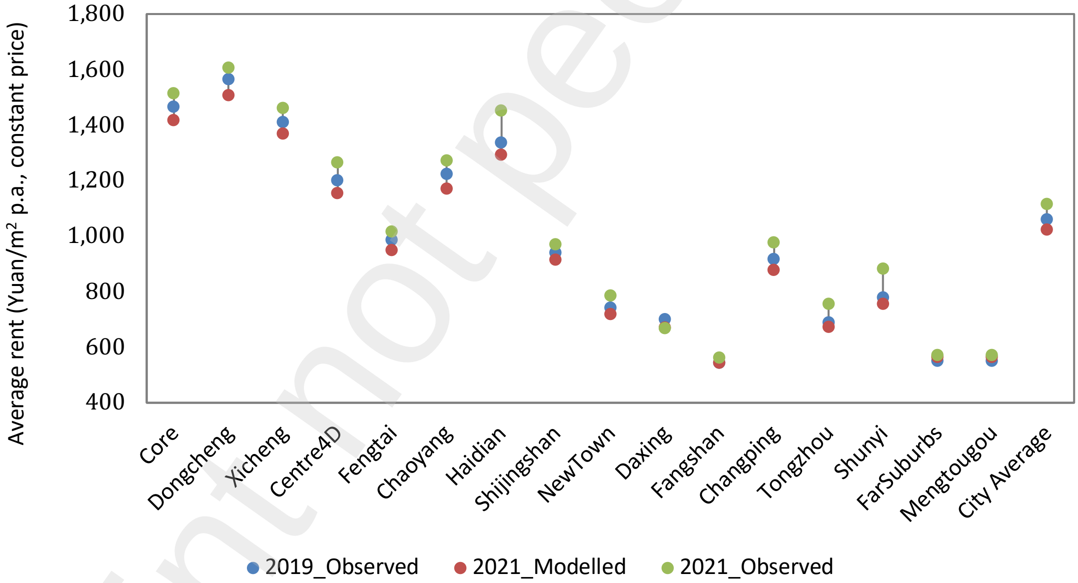
Notes: *Total_2019 = $d_{ij} + ln\ (h_i) + E_{i|j}^{2019}$; ** Total_2020 = $d_{ij} + ln\ (h_i) + E_{i|j}^{2019} + E_{i|j}^{2021}$.

5.3.2 Prediction results of house rents

As a validation exercise, we further examine the predicted house rents with the observed data. The observed house rent data in 2021 were collected from Lianjia in March 2021. All rent data are adjusted to constant price based on official CPI data. Note that the observed rental data for 2021 are not used in model prediction. Overall, we find a good fit of predicted house rents with observed rents in Beijing ($R^2 = 0.99$, see notes in Figure 8). The predictability of rents suggests that, under spatial equilibrium, there are no indications of ‘demise of city centres’ in Beijing, as the overall rent pattern remains stable from 2019 to 2021. Note that the 2021 observed rent data is the listing rent data in March which cover only 94 *jiedao* (mainly central and New-Town districts) in Beijing, the comparison is thus based on the 94 *jiedao* only.

Based on the limited rent data for 2021, Figure 8 shows that the 2021 rents are consistently higher than those in 2019 despite a strong linear correlation, while the modelled rents for 2021 are generally lower than the 2019 level. The increase of house rents in Beijing seems counterintuitive, given the 13.1% loss of employed residents from 2019-2021 according to the LBS data. The negative impact of population loss on house rent is partially compensated by the income increase (9.4% from 2019 to 2021 according to official statistics); but the combined effect would still suggest a decrease of average house rent by around 5%, which is broadly in line with the change of modelled equilibrium rents from 2019 to 2021 (3.5%).

Figure 8 Comparison of district-level average house rent in Beijing: 2019 Observed vs 2021 Modelled vs 2021 Observed



Notes: districts without 2021 observed rents excluded. Regression results: $(2021\_Observed) = 0.86 * (2021\_Modelled) + 22.686$, $R^2 = 0.99$, $S.E. = 39.2$, $Obs. = 12$.

The counterintuitive increase of house rents in Beijing in 2021 may be attributed to a combination of the following factors, (i) smaller sample size of the 2021 rent data hence bigger sampling biases and errors; (ii) additional inflation of house rents that is unaccounted by the official CPI data[13]; and (iii) the income growth as reported by the official statistics is not geographically evenly distributed and may concentrate in certain locations (e.g. Haidian and Shunyi), possibly as a result of employer-led initiatives for incentivising employees to return to work. However, the hypothesis is not yet verified due to lack of granular income data.

5.4. Summary

To conclude the model-based analysis, we use an established residential location choice model coupled with housing market equilibrium to predict the spatial distribution of employed residents and house rents in 2021 Beijing, and compare predictions with the observed data for March 2021, 10 months into the recovery since the lockdown was lifted in May 2020. Overall, the predicted spatial distribution of residents and average house rents in Beijing show a high level of goodness of fit with the observed data at the district level, confirming that the change of employment is the main cause for the observed change of residents in Beijing. No structural change of house rent pattern has been observed after 10 months post-lockdown recovery. Such stability is captured and explained by the two-way interaction between house rents and household residential (re-)location choices. Nonetheless, the pattern of model prediction errors implies a certain level of locational preference changes in Beijing. To gauge the magnitude of possible locational preference changes, a novel method is proposed where an additional set of residual attractiveness term $E_{i|j}^{2021}$ is estimated. We find marginal changes of locational preference for central locations in Beijing, which refutes the hypothesis of a structural change in terms of residential location choice preference in post-pandemic Beijing. The observed rising house rents in central Beijing corroborates existing literature that post-pandemic recovery is likely to widen the disparity in income, productivity, and housing affordability across the city (Florida et al, 2021). This finding may have important policy implications for spatial planning professionals, as proactive and timely planning interventions would be required to contain the widening disparity.

[13] The house price index from official local statistics confirms a surge of house price (mainly second-hand houses) by around 9% (nominal price) from March 2019 to March 2021. By contrast, the housing expenditure item in the CPI data has been virtually constant during the same period.

6 Conclusion

This paper examines the spatial impact of the COVID-19 pandemic through regression analysis and spatial equilibrium modelling. The analysis leverages a range of novel data sources on population and house rents in Beijing. As Beijing has been engaging in post-lockdown recovery since May 2020, the study provides early and timely evidence on the impact of the pandemic through the lens of resident/workplace population change and the associated effects on local housing market. The complementary use of regression analysis and spatial equilibrium model helps to address the circular causality between residential (re-)location and house rent changes. In addition, a novel analytical method for estimating the locational preference change has been proposed. The empirical findings and proposed methodology are expected to contribute to the wider literature on post-pandemic impact studies. Key findings are summarised below.

Firstly, the pandemic has caused a flattening of the house bid-rent curve in Beijing by putting downward pressure on house rents in the city centre, which corroborates existing evidence of flattened bid-rent curves mainly in cities in developed countries. Second, existing literature tends to attribute the flattening to flexible/remote working in a developed country context. By contrast, we find that workplace population change seems to be the main factor in Beijing, as the share of flexible/remote working in Beijing is perceivably low. Thirdly, in terms of locational preference change, our model-based analysis implies decreased (increased) preference for central (suburban) locations in Beijing, albeit the magnitude of change for central locations is marginal. The *ad hoc* finding refutes the wide speculation of the 'demise of city centres'.

On the generality of findings, it should be noted that our analysis is essentially city- and time-specific and based on a particular set of modelling assumptions (see Section 5.2), subject to possible data biases. On the one hand, Beijing may indeed differ from major cities in the Global North due to its socio-political and cultural character. On the other hand, it implies that the longer-term propensity for remote/flexible working might be exaggerated in literature, at least for cities in developing countries. If remote/flexible working is indeed behaviourally, socially and economically favourable and proved to be so, proactive policy support may be necessary for its longevity. Despite the distinct context of Chinese cities, we believe that the study of Beijing after nearly one year into post-lockdown recovery could make a timely contribution to the international endeavour of post-pandemic recovery.

In terms of implications for future research, firstly, a continuous monitoring of population and housing market changes in Beijing is expected to provide a useful and much-needed reference for other cities that are at an earlier stage of post-pandemic recovery. Second, our study demonstrates that the emerging data sources such as the location-based services and online housing/job listing website will play a unique and perhaps indispensable role in capturing the nuanced socio-economic changes across locations, sectors, and population groups in post-pandemic cities. Our lived experience of online working and living may not only catalyse, but also necessitate the incorporation of new digital data sources with conventional statistics. It is thus critical to develop transferable and scalable methods for processing and validating the big data. Third, established spatial economic models provide robust analytical tools for identifying 'structural changes' through purposely designed scenario tests. Through comparing model predictions and the observed data, early signs of possibly disruptive or unfavourable changes could be detected, which would then enable pre-emptive policy interventions to be considered. Our study of Beijing is nothing but an early attempt to this end. Much remains to be done.

7 References

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Understanding the Spatial Impact of COVID-19：New insights from Beijing after one year into post-lockdown recovery

Online Appendices

Appendix A Validation of population data derived from two big data sets

Appendix B Supplementary figures

Figure B1 The spatial distribution of house rentals in Beijing

Figure B2 Beijing move-out and move-in index between Jan. and Mar.: 2019 vs 2020

Figure B3 The population change at the *jiedao* level in Beijing

Figure B4 The change of resident and workplace population with respect to the distance to city centre (Tian'anmen Square) (Mar. 2019 vs Mar. 2018)

Appendix C Supplementary tables

Table C1 Summary statistics of house rentals

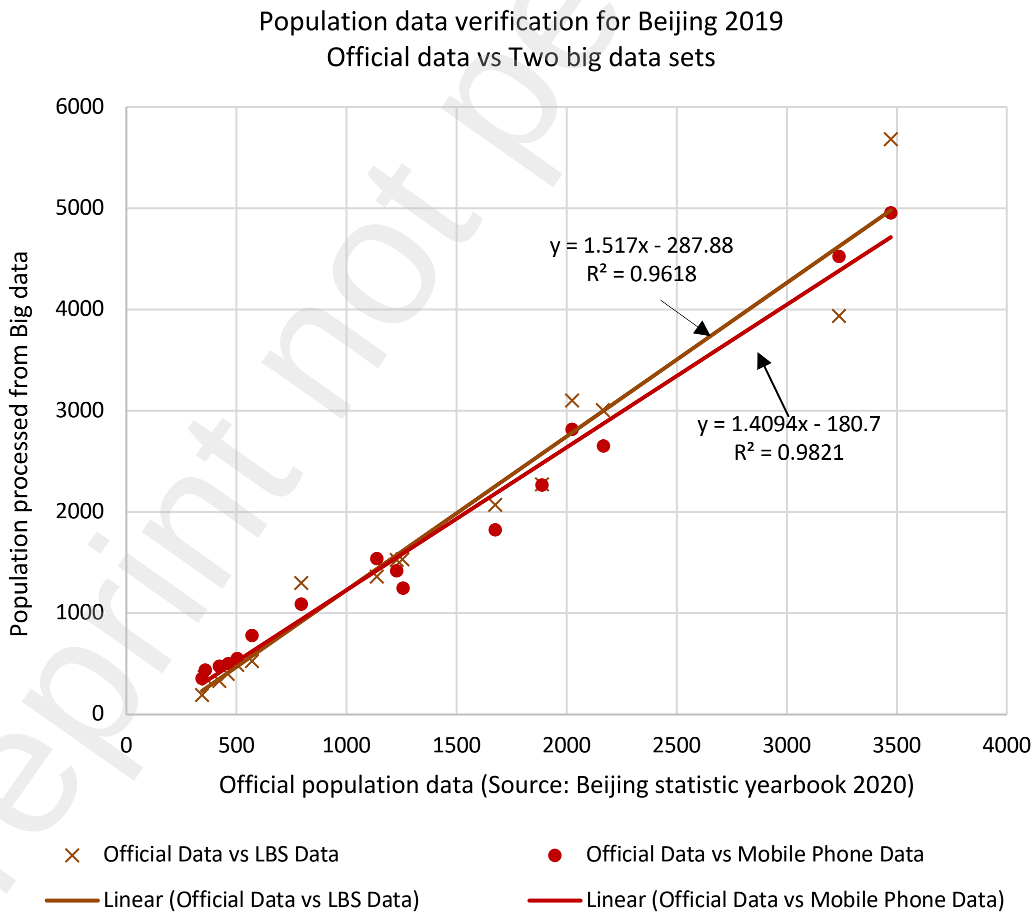
Table C2 Hedonic pricing results for equation (1)

Table C3 Summary statistics of variables in the regression model presented in Table 2

Appendix D The calculation of year-on-year change of semi-annual average rents

Appendix A Validation of population data derived from two big data sets

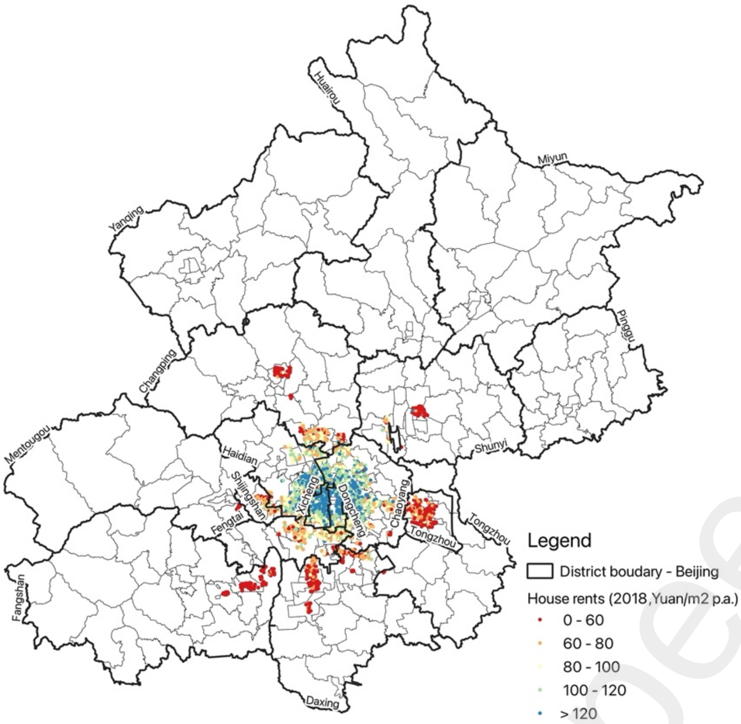
The validation of the resident population data derived from the location-based services (BLS) data and the Mobile Phone data is based on 2019, which is the latest official population statistics. In terms of absolute level of population, it should be noted that the LBS data report 28.8 million resident population in Dec 2019 and the Mobile Phone data report 27.7 million. By contrast, official statistics report 21.5 million year-end resident population in 2019. The difference could be attributed to the following factor. The official population statistics consider only usual residents who live in Beijing for no less than 6 months, including both local (i.e. those with Hukou) and migrant (i.e. those without Beijing Hukou) population. Short-term business visitors and other floating population are thus excluded. However, the LBS data and the Mobile Phone data cover all service users in Beijing based on a 3-month observation period, therefore the reported higher total population would include both usual residents and relatively temporary population. Despite the difference in total population, there is a strong statistical correlation between the two big data sets and the official data in terms of district-level population as reported in the figure below.



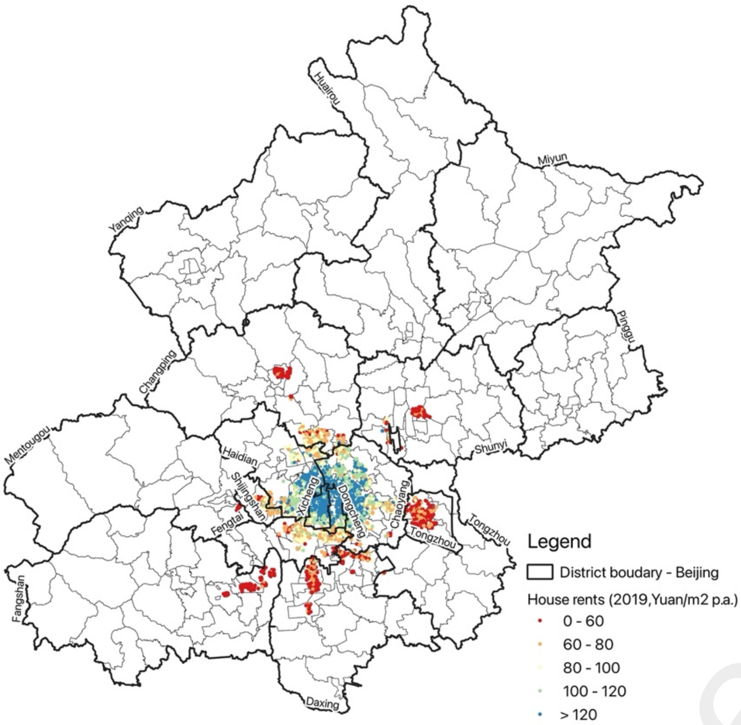
Appendix B Supplementary figures

Figure B1 The spatial distribution of house rentals in Beijing

a. 2018:



b. 2019:


Huairou
Miyun
Yanqing
Pinggu
Changping
Shunyi
Mentougou
Haidian
Shijingshan
Xicheng
Dongcheng
Chaoyang
Fengtai
Tongzhou
Fangshan
Daxing
Legend
District boudary - Beijing
House rents (2019,Yuan/m2 p.a.)
0 - 60
60 - 80
80 - 100
100 - 120
> 120

c. 2020:

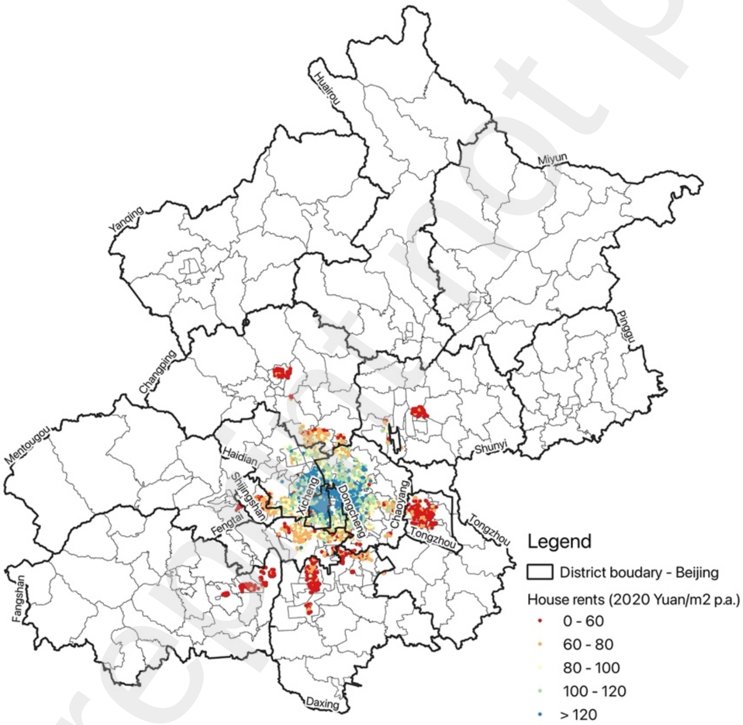
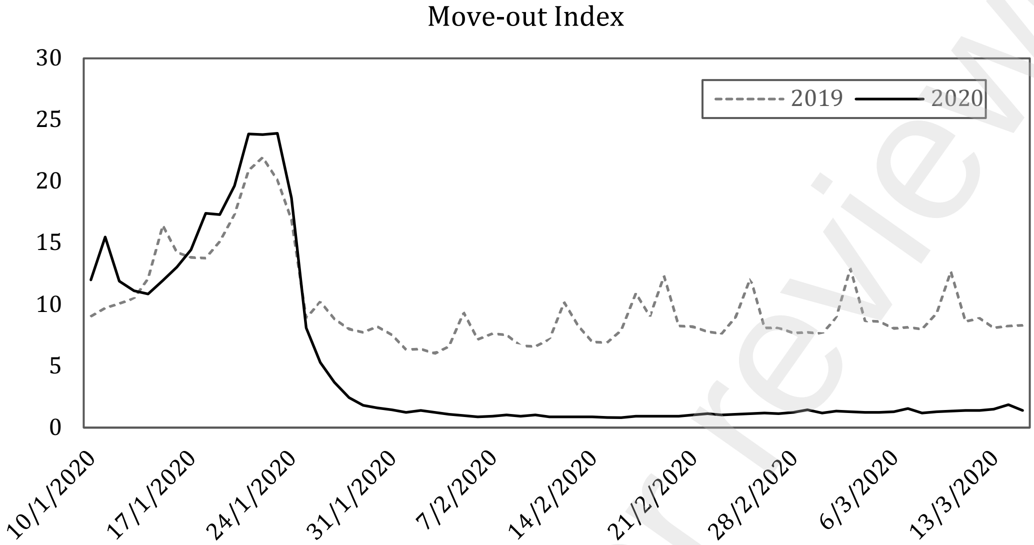

Huairou
Miyun
Yanqing
Pinggu
Changping
Shunyi
Mentougou
Haidian
Shijingshan
Xicheng
Dongcheng
Chaoyang
Fengtai
Tongzhou
Fangshan
Daxing
Legend
District boudary - Beijing
House rents (2020 Yuan/m2 p.a.)
0 - 60
60 - 80
80 - 100
100 - 120
> 120

Figure B2 Beijing move-out and move-in index between January and March: 2019 vs 2020 (Source: Baidu)



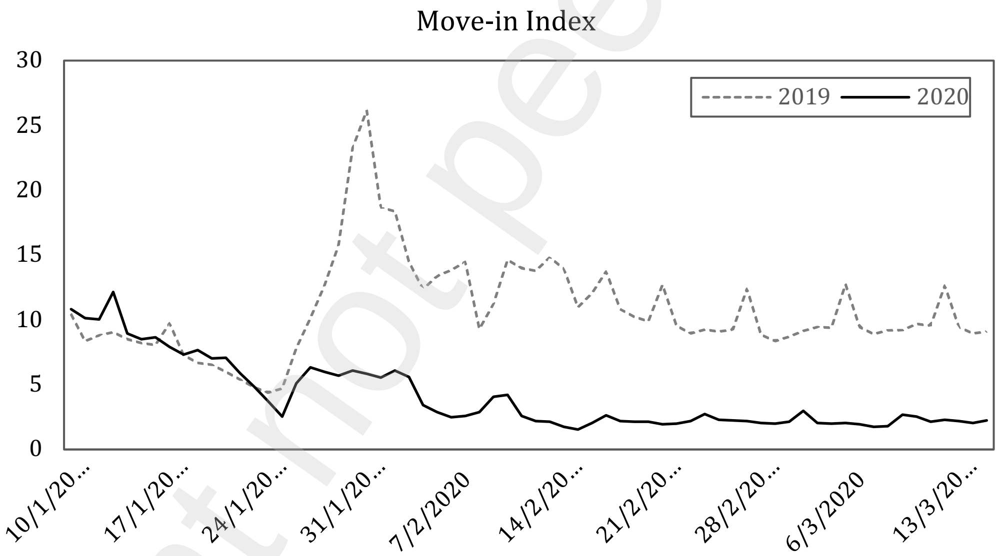
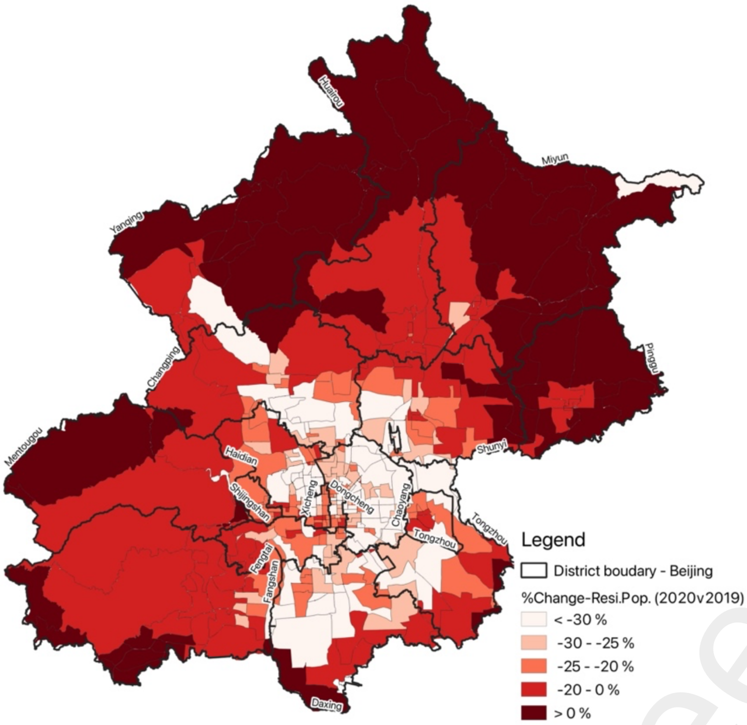
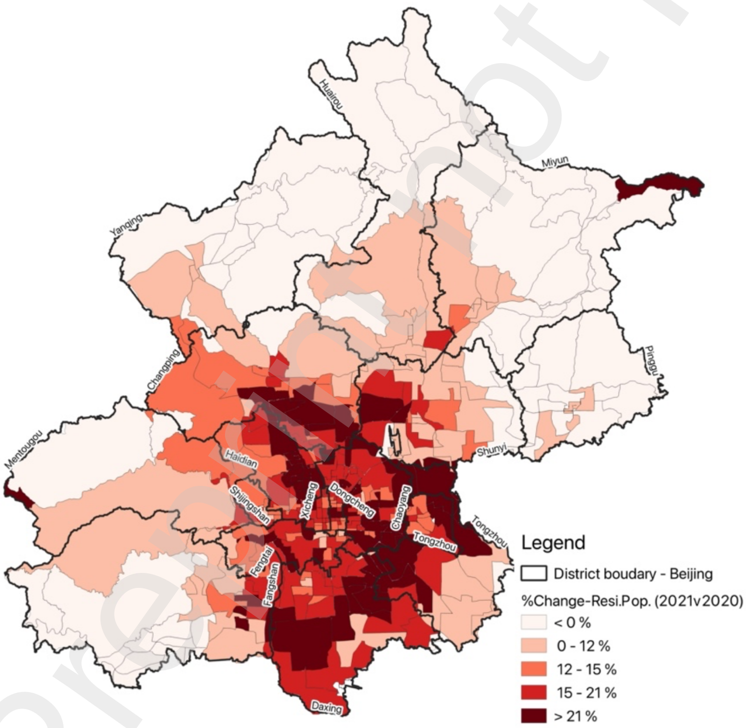


Figure B3 The population change at *jiedao* level in Beijing

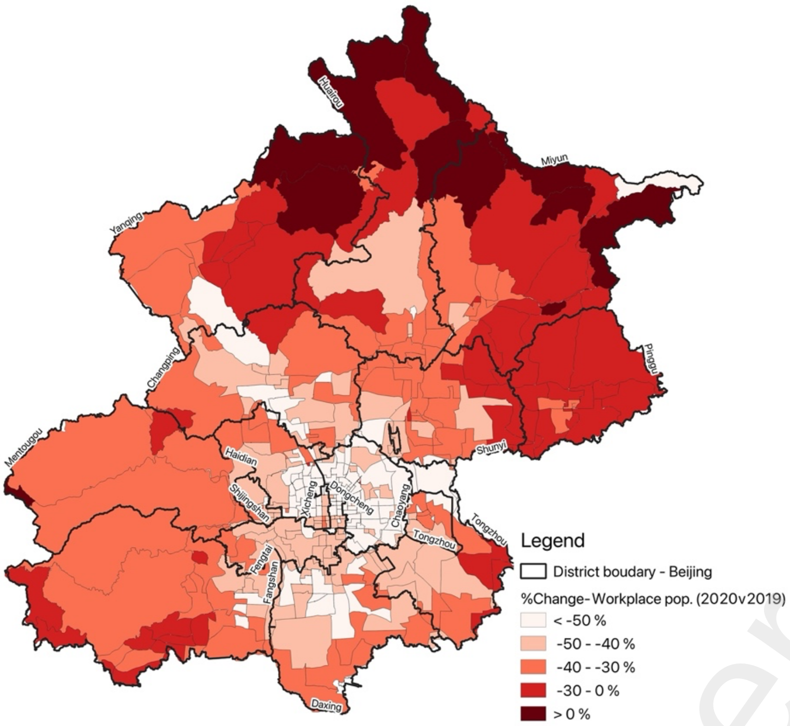
a. Resident population: March 2020 vs March 2019



b. Resident population: March 2021 vs March 2020



c. Workplace population: March 2020 vs March 2019



d. Workplace population: March 2021 vs March 2020

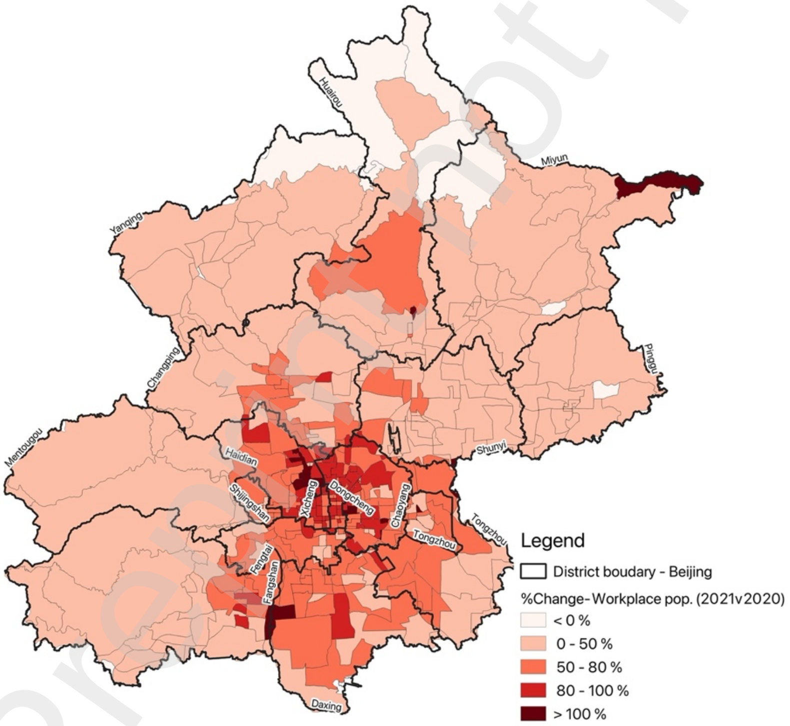
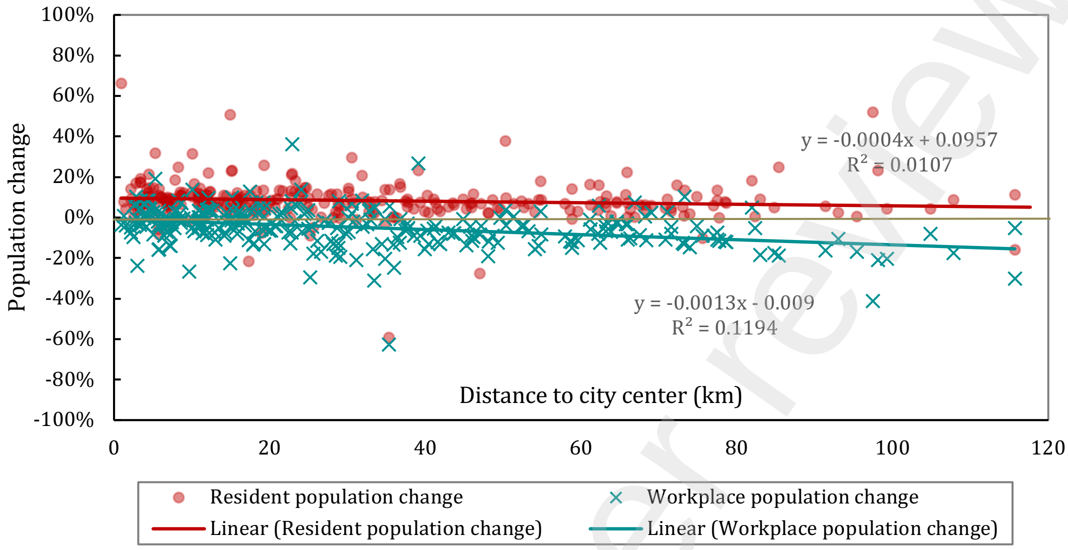


Figure B4 The change of resident and workplace population with respect to the distance to city centre (Tian'anmen Square) (March 2019 vs March 2018)



Appendix C Supplementary tables

Table C1 Summary statistics of house rentals

Variable	**2018** (obs. 104,965)	**2019** (obs. 128,541)	**2020** (obs. 166,210)
	Mean	Mean	Mean
monthly rent	6,736	6,627	6,233
unit rent	90	90	87
building age	18.96	18.87	19.23
gross floor area	78.08	77.20	75.51
floor	7.70	7.72	7.77
south orientation	0.64	0.66	0.65
number of rooms	1.84	1.84	1.81
no of houses in the same residential community	1,967	1,981	2,025
property fee	1.87	1.85	1.89
high green ratio	0.38	0.37	0.36
mtr within 0.5km	0.21	0.23	0.25
bus within 0.5km	0.53	0.55	0.56
park within 1km	0.65	0.65	0.67
mall within 1km	0.55	0.56	0.58
no of fitting clubs within 2km	4.87	4.86	4.86
no of hospitals within 2km	7.26	7.21	7.26
no of primary schools within 2km	4.23	4.18	4.22
no of high schools within 2km	3.92	3.87	3.92
distance to the city centre	12,271	12,533	12,213

Table C2 Hedonic pricing results for equation (1)

	(1)	(2)
	Coeff.	S.E.
Distance to city centre	-0.1522***	(0.0045)
Distance to city centre*2018 Feb	0.0040	(0.0052)
Distance to city centre*2018 Mar	0.0029	(0.0042)
Distance to city centre*2018 Apr	0.0098**	(0.0045)
Distance to city centre*2018 May	0.0002	(0.0045)
Distance to city centre*2018 Jun	-0.0025	(0.0044)
Distance to city centre*2018 Jul	-0.0048	(0.0042)
Distance to city centre*2018 Aug	-0.0069	(0.0043)
Distance to city centre*2018 Sep	-0.0049	(0.0045)
Distance to city centre*2018 Oct	-0.0081*	(0.0046)
Distance to city centre*2018 Nov	-0.0083*	(0.0048)
Distance to city centre*2018 Dec	-0.0069	(0.0047)
Distance to city centre*2019 Jan	-0.0011	(0.0048)
Distance to city centre*2019 Feb	-0.0029	(0.0048)
Distance to city centre*2019 Mar	-0.0087**	(0.0042)
Distance to city centre*2019 Apr	-0.0094**	(0.0044)
Distance to city centre*2019 May	-0.0141***	(0.0044)
Distance to city centre*2019 Jun	-0.0206***	(0.0042)
Distance to city centre*2019 Jul	-0.0331***	(0.0041)
Distance to city centre*2019 Aug	-0.0297***	(0.0041)
Distance to city centre*2019 Sep	-0.0189***	(0.0043)
Distance to city centre*2019 Oct	-0.0222***	(0.0044)
Distance to city centre*2019 Nov	-0.0241***	(0.0045)
Distance to city centre*2019 Dec	-0.0162***	(0.0045)
Distance to city centre*2020 Jan	-0.0077	(0.0058)
Distance to city centre*2020 Feb	-0.0057	(0.0089)
Distance to city centre*2020 Mar	-0.0090*	(0.0055)
Distance to city centre*2020 Apr	0.0060	(0.0048)
Distance to city centre*2020 May	0.0165***	(0.0044)
Distance to city centre*2020 Jun	0.0248***	(0.0045)
Distance to city centre*2020 Jul	0.0064	(0.0043)
Distance to city centre*2020 Aug	0.0048	(0.0041)
Distance to city centre*2020 Sep	0.0145***	(0.0043)
Distance to city centre*2020 Oct	0.0153***	(0.0044)
Distance to city centre*2020 Nov	0.0119***	(0.0045)
Distance to city centre*2020 Dec	0.0038	(0.0047)
Physical property features	Y	
Business district fixed effects	Y	
Year and month fixed effects	Y	
Observations	399,716	
R-squared	0.8698	

Notes: Physical property features include age, age^2, gross floor area, gross floor area^2, floor, floor^2, south orientation, number of rooms, decoration status, number of houses in the same residential community, property fee, green ratio, access to bus, park, shopping mall and MTR, the number of fitting clubs within 2km, the number hospitals within 2km, the number of primary schools within 2km and the number of high schools within 2km. Standard errors are reported in parentheses. ***, **, and * denotes statistical significance at the 1%, 5% and 10% level, respectively.

Table C3 Summary statistics of variables in the regression model presented in Table 2

Variables	No	Mean	SD	Min	Max
Jan. – Jun. 2020					
Year-on-year change of semiannual rents	148	-0.039	0.043	-0.340	0.108
Year-on-year change of workplace population	148	-0.318	0.067	-0.483	-0.116
Jul. – Dec. 2020					
Year-on-year change of semiannual rents	159	-0.051	0.056	-0.247	0.218
Year-on-year change of workplace population	159	-0.190	0.067	-0.426	0.058
Jan. – Jun. 2019					
Year-on-year change of semiannual rents	148	0.039	0.041	-0.161	0.169
Year-on-year change of workplace population	148	0.169	0.101	-0.212	0.603
Jul. – Dec. 2019					
Year-on-year change of semiannual rents	152	-0.009	0.060	-0.133	0.082
Year-on-year change of workplace population	152	0.0003	0.037	-0.189	0.228
JobRatio	159	0.119	0.140	0.000	0.714
log(Distance)	159	9.318	0.747	7.203	10.531

Notes: the number of observations is slightly different in each period because of the rental number filter.

Appendix D The calculation of year-on-year change of semi-annual average rents

We measure the year-on-year change of semi-annual average rents as below:

$$\log (Y_{i,t}) = \alpha_1 T_i * S_i + T_i + S_i + \lambda' X_{i,t} + \varepsilon_{it}$$

$Y_{i,t}$ is the rent of unit *i* at time *t*, T_i denotes the year fixed effects, and S_i represents the *jiedao* of unit *i*. X_{it} is a set of hedonic variables controlling for the physical features of the property. ε_{it} is the error term. α_1 reports the rent change in each *jiedao* relative to the base year.

We calculate the year-on-year change of semi-annual rents for four time periods, namely, the first half (January-June) of 2019, the second half (July-December) of 2019, the first half (January-June) of 2020, and the second half (July-December) of 2020. They are generated by using different subsamples of rentals. For example, we use the subsample of rentals occurred in the first half of 2019 and 2020 to generate the rent change in the first half of 2020.