The Spill-over Effects of Urban Village Removal on Nearby Home Values in Beijing

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Abstract

Chengzhongcun (urban villages) is a typical type of informal housing in which rural migrants stay in Chinese cities. High crime rates, inadequate infrastructure and services, and poor living conditions are just some of the problems in urban villages that threaten public security and management. With the growing demand of local residents for better urban environment and more land for new construction, city governments seek to remove such informal housing sites.

As urban villages are being woven into the modern urban landscapes, one interesting question is to ask how these villages removal are valued by the nearby urban dwellers. Given that urban villages' removal is really a big investment, how can we measure its benefit? In other words, what are the spill-over effects of these villages' removal on the changes of urban housing values nearby? This paper seeks to measure this spill-over effect in Beijing.

Our research is based on a geo-coded micro data set of resale housing transactions in Beijing. The sample size is more than 24 thousands during the period from 2006 to 2011. We have the geo-coded urban village database containing each village's name, location and removal time. We also obtain a unique micro survey data on 50 villages conducted in September 2008, which provide us the details of villages' area, rural migrants' income and their degree of dis-harmony against neighboring urban residents, which are measured by the extent of discrimination and income gap.

To examine the premium effect, we first use a DID-Hedonic model specification to examine the mean difference in difference effect and its time trend of urban villages' removal on surrounding housing prices, for each wave of removal in Beijing. Then, we explore the heterogeneity of this effect on basic of micro data from 2008 Beijing Urban Village Survey accounting for a village's size, existed duration, security risky and its degree of disharmony. Finally, taking into account of two concerns that may affect our empirical analysis, first is that all locations near urban villages do have rapid housing price growth rates even without villages' demolition and second is that the choice of which urban villages to be removed made by municipal government maybe not completely random, we employ two sub-sample strategies including propensity score matching method for robustness test.

Considering that the empirical studies on urban villages' removal and housing value changes are still very few in China, this paper based on micro data sets from Beijing will have some contribution on this topic. Our findings show that, both two waves of villages' removals have significant positive spill-over effects on nearby housing price changes, and this effect is stronger for larger, older, or villages with more degree of dis-harmony. The results have some policy implications regarding city planning and management. More thoughts are also needed for the other side of the coin – the living condition change of those rural migrants who are displaced during this process.

Key words: *urban villages' removal, housing value changes; spill-over effect; difference in difference*

1. Introduction

China has experienced rapid and unprecedented urban growth with massive rural-urban migration, since its economic reform and other “open door” policies in the late 1970s. From 1978 to 2012, the share of urban population increased from 17.9% in 1978 to 52.6% in 2012 (National Bureau of Statistics, 2008, 2010, 2012). Rural-urban migration is responsible for almost 70 percent of the nation’s urban population growth (Zhang and Song, 2003). According to Rural Migrant Workers Monitoring reported by the National Bureau of Statistics, there are 163 millions of rural workers left home and work in cities in 2012, which accounting for 12 percents of total population and nearly one third of the world’s floating population as estimated by United Nations.

Such rapid urbanization has triggered dramatic change in the spatial and social landscapes of Chinese cities. One of the most prominent imprints of rural-urban migrants is urban villages which is a kind of compressed settlements and also named “villages within cities”[1] because they were previous farming villages and now are surrounded or otherwise encroached upon by urban expansion (Zhang and Song, 2003; Song et al., 2008). One result of China’s massive rural migration is the enormous demand for inexpensive and accessible housing in urban area. However, most rural migrants are excluded from the formal housing market because of unaffordable high price in “commodity housing” market and access restrictions for public housing

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1 Referred as *“ChengZhongCun”* in Chinese; also translated as “villages amid the city”, “villages encircled by the city,” and “urban villages” (e.g., Zhang et al., 2003; Wu, 2007; Tian, 2008). For the sake of simplicity, hereafter, we use the term “urban villages” to refer to it in this paper.

caused by *hukou* (household registration). Those rural migrants most commonly live in employer-provided housing such as factory dorms or choose to rent rooms in urban villages. According to Zheng et al. (2009), urban villages actually represent a match between migrants' demand for cheap housing and the supply of low-cost housing in villages encroached upon by urban expansion.

Urban villages bring significant negative externalities to adjacent communities as well as the whole city. Because of the lack of public services and urban management, urban villages are usually in poor condition: buildings are overcrowded; public facilities are inadequate and poorly maintained; high crime rates and poor living conditions (Zhang, 2002; Song and Zenou, 2012). Together with very high population density, these have caused problems such as potential public security threat, congestion and environmental pollution (Liu and Liang, 1997; Zhang et al., 2003). Despite of those negative externalities, many city governments chosen to tolerant their existence. As a type of low-cost housing provided by the market, urban villages have greatly reduced the labor cost of manufacturing and low-skill service industries, and thus effectively stimulated the economic growth of the cities with labor-intensive industries.

However, as a city further grows, two forces push the city government to remove those urban villages within its urban boundary. First, with urban residents' rising demand for better quality of life and the environment, urban villages' negative externalities will significantly hurt nearby residents' utility, and thus will be negatively capitalized into land values nearby to a larger extent. Therefore, removing those urban villages will generate larger social benefit, which will be captured by the rise of land values at adjacent places. Land sale revenue is a major component of the local government's fiscal revenue, so the local government will have a stronger intensive to remove those urban villages if the removal can bring in higher land sale income. Second, as a city's industrial composition transits from labor-intensive to skill-intensive industries, the labor demand for low-skilled workers will decrease, and thus the contribution of urban villages to the urban economy will diminish. Comparing the benefit and cost urban villages bring to its city, the city government will make the trade-off and choose to remove them.

In this paper, we estimate the sizes of urban villages' negative externality and also the positive spillover effect of their removal on nearby communities. As a common practice, we use housing value and its change to measure such externalities. To be more precise, we collect two micro data sets. One data set includes all the existing urban villages in 2007 in Beijing, and their later condition (removed or not, if yes, the year of removal). We have the information of each urban village's exact location (geo-coded), size (number of dwellers), income gap and a measure of the social interaction frequency between migrant workers in the village and the surrounding urban residents in the formal housing sector. The other data set contains 24 thousand micro housing resale records during 2006 to 2011, including exact location (geo-coded), transaction price and date, the housing unit's physical and community attributes. Combining these two data sets together, we estimate the level and difference-in-difference (DID) specifications of hedonic housing price model, from which we find significant negative externality of urban village and significant positive spill-over effect of its removal on nearby communities' housing prices. We also look into the heterogeneity of those effects. Not surprisingly, we find that larger and older urban villages and those that are less integrated into surrounding communities (with larger income gap and weaker interaction frequency) have a larger spillover effect on nearby housing values after their removal. Finally, we use propensity score method to control for the possible selection bias in the removal of urban villages, and find that our findings are robust.

The paper unfolds as follows. In the next section we introduce the two waves of urban village removal and housing market in Beijing. In Section 3, we present our empirical models and results of testing urban villages' negative externality and their removal's positive spillover effect on nearby housing values and changes. The heterogeneity of those effects and the robustness check using propensity score method are discussed in section 4. Section 5 concludes.

2. Removal of urban villages, housing transactions and urban residents in Beijing

2.1 Urban villages and their removal process in Beijing

Because urban villages are not formally considered part of the urban economy—and thus excluded from urban statistics collection—information about their number and spatial distribution is not publicly available (Zheng et al. 2009). On the basic of urban villages' information collected in this paper, what we sure is that during our research period, from 2006 to 2011, Beijing has experienced two waves of removal of urban villages, first is before 2008 Beijing Olympic Games and 104 villages have been removed, second were since 2010 and 50 bigger villages named "key villages" removed. What's more, there are 214 villages left, which means these villages are always exist during our research period. The spatial distribution of these urban villages is shown in Figure 1.

insert Fig.1 about here

As for the two waves of removal for Beijing urban villages have experienced, the first wave was conducted as a part of preparation for the 2008 Beijing Olympic Games, and thus most of these projects were concentrated around the Olympic venues (for example the newly-built Olympic Park in Haidian District) and some well-known scenic spots, such as *Houhai Lake* and *Qianmen Street*. The second wave was launched since 2010, and its target is to promote integrated development of urban and rural area in Beijing, according to official claims.

It should be emphasized that removed villages during the two different periods have some systematic differences. During the first wave, removed urban villages are relatively small-size and almost located within the 4^{th} ring road of Beijing, which are really very close to city center. However, during the second wave, the size of 50 key villages are much larger and they locates more distant from city center, most of them scatter between 4th and 5th ring road and some are out of 5th ring road. As reported by the government, these 50 key villages were distributed in nine districts and 33 *jiedao*s, and the total area of 50 key villages is 85.3 square kilometers, with 214 thousands native people and more than 1 million migrants live in. Thus, another interesting research question is the difference in effect between two types of urban villages' removal, from the prospective of housing market. We then collect some detail information for each village from several sources.

More precisely, as for the e first wave for urban villages' removal before Beijing 2008 Olympic Games, the data is collected from the Beijing Municipal Commission of Development and Reform (hereinafter referred to as BMCDR). We find the information from website of BMCDR, where lists public notices for any urban village removal project as an approval of environmental improvement project. Using a keyword search method[2], we collect all the related projects' information, including name of the project, location, sometime is its spatial boundary, area[3] and the time of this approval issued, which we use to judge the time for this removal project. After excluding villages which size is obviously too small, taking 5000 square meters as selection criteria, we finally have 104 villages that were removed before 2008

[2] We have searched for "urban villages" (which in Chinese is *chengzhongcun*) and "environmental improvement", and record key information displayed in that project. One example for this can find in: http://www.bjpc.gov.cn/jggs/200906/t413222.htm.

[3] Unfortunately, not all these projects have this information and some are so small that we delete them from dataset.

Olympic Games and geo-coded them through GIS.

As for the second wave for urban villages' removal since 2010, the is from a name list of the key urban villages to be renovated from 2010, which was first issued by urban government at July, 2009[4]. This name list only provide their names and in which *jiedao* but not contain any details, we have geo-coded locations for these 50 villages through geography information system. It is worth to mention that, these 50 key villages were selected from integrated multi-dimensional reasons, such as dirty sanitary environment, poor social security and order, and the sense of security of surrounding residents is very low. Thus, this second wave of urban villages' removal is conducted together by Beijing Municipal Public Security Bureau, Municipal Commission of Housing and Urban-Rural Development, Administration for Industry and Commerce, Municipal Health Bureau and Municipal Bureau of City Administration. According to government public information, it is said that these renovation projects are aiming at promoting urban-rural development, quality of social security and environmental sanitation. But as we conducted interviews with urban planners from Beijing Municipal Commission of Urban Planning, a direct cause is the ***Uighur riots*** happened in Urumqi on 5th July, 2009. There is concern that some analogous public security problems may emerge where a large number of migrants live together, especially in Beijing, capital of the nation. So urban villages with the largest number of migrants without urban or rural *hukou* in Beijing, were chosen to

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[4] Which can be found at : http://zhengwu.beijing.gov.cn/gzdt/bmdt/t1067032.htm.

constitute the 50 key villages. Although we do not have detail information about number of migrants for each village, but public reports from official media (Xinhua Net) indicate that a remarkable common feature of these key urban villages is they all have a large migrant-native ratio and were considered to be the most difficult ones to removal.

Besides, there are many villages that have not been removed at the end of 2011, a name list of these villages are gained from land use status survey of Beijing Municipal Institute of City Planning and Design. As can be seen in Figure 1, this third kind of villages are almost scattered outside of 4^{th} or even 5^{th} ring road. Some villages should better be called as urban villages beside the city area rather than urban villages in the city, the word *city* to the metropolitan built-up area of Beijing. Using *Sogou Map (http://map.sogou.com/)* and GIS, we have geo-coded these 214 urban villages.

Last but not least, special emphasis is needed for introducing a special micro survey of 50 Beijing urban villages. In order to explore the heterogeneity of different villages' removal on nearby home values, we employ a special survey data of 50 urban villages and 756 migrants in Beijing conducted in September 2008 will provide useful information for our study. It was a questionnaire survey conducted in September 2008 and administered by Beijing Municipal Institute of Urban Planning and Design and Tsinghua University's Institute of Real Estate Studies. It should be emphasized that, in that survey, a two-stage sampling method was employed (Zheng et.al. 2009). In the first stage, 50 urban villages were selected randomly, and in the second stage, 15–20 migrants were we selected in each of the 50 urban villages. Thus we believe this survey data can be a suitable subsample for study in this paper, although we do not have details for every urban village. 43 out of the total 50 surveyed villages were located within the research area of this study, and 8 villages out of the 43 had been removed during the second wave.

On the basic of this unique micro survey data, we can obtain some interesting features of these villages which will help us in-depth analysis of the heterogeneity of urban villages' removal on housing value changes. For example, as we know since when have the migrants lived in current village, which may reflect how long this village has been existed. And the answers about migrants' feeling of being discriminated against by urban residents can be regarded as an indicator of interaction between these two groups of people. In addition, there are area and monthly income of migrants for each village. What's more, these valuable micro data of villages will also provide a basis for the analysis on probability of each village's being removed in propensity score method.

2.2 Housing transactions and urban residents in Beijing

To investigate how housing price responds to a nearby event of urban village removal, we obtain a unique micro data set of 24410 housing resale transactions (after data cleaning) in 2338 residential complexes located inside 5th Ring Road from 2006 to 2011 in Beijing (see Figure 1). This unique dataset of micro samples of Beijing stock housing transactions is authorized by China Data Center, Tsinghua University, and is provided by “*WoAiWoJia*” (www.5i5j.com), the second largest broker in Beijing with a market share of about 10 percent. The detail information includes project name, location, transaction time, price, and physical features such as area, age, floor, orientation, and degree of decoration, etc. Taking housing samples around the second wave villages for example, the average housing price before removal for homes located less than 1000 meters from a village is 12017 *yuan* per square meter, while the average price is 13317 *yuan* per square meter for homes further from these villages, which indicates the negative externality urban villages impose on nearby homes. We will do regression analysis to control for other variables to obtain a more precise measure of this price discount.

As the interaction of urban villages’ migrants and their neighboring urban residents is a very important dimension of our study, we also employ a micro dataset of urban residents from 2010 Urban Household Survey in Beijing, which is conducted by the National Bureau of Statistics. There are totally more than 30 thousands urban households, we have located these households using their *Juweihui* (namely neighborhood committee, which is the most basic unit of urban management) code. A number of 15510 households are within our research area and their reported average monthly income is about 6000 *yuan.* Combining this information and the survey data of migrants in urban villages, we can gain the income gap between migrants and their urban neighbors.

3. The spill-over effects of urban village and its removal on nearby home values

We posit that these urban villages have negative effect on surrounding property values, and thus removal of these villages will improve housing values nearby. We use hedonic techniques to examine whether the negative effects and its removal are capitalized in residential property price. Our unit of analysis is a residential property sample i in project j in quarter t, and the research area is within 5^{th} Ring Road of Beijing, as mentioned above.

First, we use basic Hedonic price regression to examine both the mixed effect of urban villages' existence and removal on nearby home values through 2006 to 2011, and the pure static effect of urban villages' existence on housing units' price when all these villages are still existed. Second, we set up a DID-Hedonic model to test the effect of urban villages' removal on housing units' price change. Then, taking into account of one concern that all locations near urban villages do have rapid housing price growth rates, we using subsample of housing units around all these urban villages to redo the regressions and confirm our research findings.

3.1 Basic hedonic analysis for testing mixed and static effect

Basic empirical model specification

Equation (1) reports the basic hedonic pricing equation for housing units:

$$log\, P_i = \beta_0 + \varphi_t + \beta_1 * Dummy\_in_i + \boldsymbol{\beta_i} * \boldsymbol{X_{ij}} + \varepsilon_i \qquad (1)$$

where P_i is the sale price of housing unit i as average price per m^2, β_0 is a constant, $Dummy\_in_i$ is a dummy variable that indicate whether a housing unit's distance to its closest village is less than **1000 meters** and the error term is denoted by ε_i. It is worth to mention that, as we have known the removal name list for two waves of urban villages, we can recalculate $Dummy\_in_i$ for different time period. In the above regression equation we also control for quarter fixed effect φ_t and X_{ij}, a vector of time-invariant attributes as our controlled variables. To be more precise, we include the following categories of control variables: location variables, amenities including both public goods and private goods, and physical property features.

Firstly, ***location*** is of the most importance for determining housing price, given the monocentric spatial structure of Beijing, the CBD area (*jianguomen*) is the main employment center (Zheng&Kahn,2008), and other areas such as *yayuncun*, *zhongguancun* and *jinrongjie* are some important sub-centers.

Secondly, ***amenities*** are also known have high influence for housing value, because they will directly determine the quality of life for around households. We include four kinds of important urban public services, namely subway stations, hospitals, schools and parks. What's more we also control for the accessibility of shopping for each housing unit, using distance from housing unit to the nearest shopping mall.

Finally, the ***physical property features*** of housing, such as area, number of bedroom and drawing room, floor of total floor, age, orientation and the degree of decoration, etc. are widely known as key factors for housing price. Thanks to our unique micro transactions dataset of second-hand houses in Beijing, we can control all these variables.

In this stage, controlling for other influential factors mentioned above, we can capture the effect of urban villages on the surrounding housing units' price, so what we are most interested is the sign and significance of β_1, which we expect to be significantly negative.

The main independent variables used in empirical study are shown in Table 1.

insert Table 1 about here

Results of urban villages and housing value

The results of our first stage analysis are provided in Table 2 with robust t-statistics in parentheses, standard errors are clustered by project. The R^2 indicates that our model can explain 72% of the variation in housing price. Most of the coefficients have expected signs. As limited by space of this article, we only report estimated coefficients which we are most interested in and some of the key control variables.

insert Table 2. about here

Basic Hedonic regression results

In column (1), we estimate a significant negative price gradient of -0.020 with respect to the distance from CBD. This means that each 1 kilometer further from city center would result in about 2% decrease in housing price. As for other location variables of distance to job sub-centers, the coefficients are all significantly negative, meaning that *zhongguancun*, *jinrongjie* and *yayuncun* all have positive impact on housing price, with the influence in descending order.

We also control for the amenities, both public and private services that determine one location's quality of life. The subway, which provides great travel convenience for residents' daily life in Beijing, and one of the most concerned public goods in hedonic housing price analysis by scholars, is very significant as expected. When a housing unit is located 10% nearer to one subway station, its price will increase about 0.17%. Besides, primary schools and parks are also have significant impact on housing price, while the coefficients of distance to the closest hospital is not significant, although its robust t-statistics are relatively large. The sign of park is negative but hospital is positive, we believe this just reflects that residents are willing to live near a park as a green open space for relax, but prefer to live relatively away from hospitals because of its unlucky. As for private services, negative signs of *d_shop* indicate that housing price fall with the distance from shopping centers. It is necessary to mention that convenient shopping services nearby are always cared by Chinese households. Housing price increases by nearly 0.18% when its distance to the closest shopping center decreases 10%.

We then turn to the estimated results for property physical features. Recall that the unit of measurement for housing price is *yuan* per square meters, as expected, space of a house is positively related to unit price. Houses with more parlors do have higher price, 1 more parlor will lead to about 0.03% increase in housing price. In contrast, the number of bedrooms is less important after controlling for total space and number of parlors, its sign is positive but not significant. As expected, negative sign of area indicates that larger house always have lower unit price.

It is very interesting to mention that our results discover significantly quadratic relationships between housing age, floor and housing price. The relationship for housing price and housing age is U-shape with turning point at approximately 23 years for housing age, the range of housing age of our data is form 1 to 40 years. That is to say for relatively new houses less than 23 years, housing age has negative effect on housing price as normal; while for the rest older houses more than 23 years, the relationship is reverse. We infer this is because of omitted variables caused by the spatial structure of Beijing's metropolitan built-up area and housing market, many old houses before housing reform and high quality public goods are both located within 3rd ring of Beijing. However, we do not have data on the quality of all these public goods, and maybe omit some other location variables, these will result in U-shape relation between housing age and price. While the relationship of floor and price is inverted U-shaped and the peak is at nearly 20^{th} floor, this is accord with our common sense in the market, the most expensive houses of a multilayer residential building lie in a bit higher than the middle floor, and in our samples, the range of floor is from 1 to 39.

The mixed and static effect of urban villages on nearby home value

In column (2), we introduce *Dummy_in* into the regression, in order to test the mixed effect both of urban villages' existence and of their removal on adjacent housing samples' price. Recall that the variable *Dummy_in* is changing with time from 2006 to 2011, so that it captures both the static effect for those housing units whose value of *Dummy_in* is constant, and the dynamic effect for those housing units around removed villages in this model. This causes some changes for other control variables[5]. The significantly negative coefficient of *Dummy_in* indicates that whether a housing unit is locate less than 1000m to an urban village, its price will be 0.03% lower than their counterparts outside. This proves that mixed effect of urban village on neighboring housing price is negative and quiet significant at 1% level. We could infer that residents in Beijing are not willing to live near urban villages.

In column (3), we substitute *dv* with a dummy variable *dummy_in* which takes the value of 1 only if a house is located less than 1000 meters to an urban village, this sphere of influence is exactly how we define our experiment group and control group in DID-Hedonic model specification in equation (2). As we expected, this variable is significantly negative at 1% level with the value of -0.0275, revealing that the price of housing units in our experimental group is 0.02% lower than these in control group.

It is also very interesting to compare the differences between different waves of urban

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[5] We have noticed that the significance of *d_yayuancun* changing. This may be a reflection of the spatial correlation of distribution of some urban villages and *yayuancun* area in *Beijing*, *Yayuancun* area is very close to Olympic Park of Beijing, while this area gathered a lot of villages to be demolished before 2008 Olympic Games.

villages. In column (4), we use sub-samples in 2006 and 2007, which is the only period that these urban villages were existed simultaneously, to test this differences. We control for the distance to other villages, which have never been removed from 2006 to 2011, and focus on the coefficients of $dummy\_in_1$ and $dummy\_in_2$. Both of the two coefficients are negative and statistically significant at 5% level. While the differences in coefficients indicate that, urban villages removed in the second wave may have stronger negative effect on nearby housing price during the year of 2006 and 2007. Estimated coefficient of $dummy\_in_1$ is -0.0375, which means that if one house is located within 1000 meters of a village removed before 2008 Olympic Games, its price drops 0.037% compared to the ones outside. While the estimated coefficient of $dummy\_in_2$ is -0.0418, relatively bigger than former, revealing that if a house is near a village removed in 2010, its price drops about 0.042% compared to the ones outside. That is to say urban villages removed in the second wave have stronger negative effect than villages of the first wave, and the difference is nearly 11.5%. We believe this is because villages in second wave always have larger size and number of migrants live in.

3.2 DID-hedonic analysis for testing dynamic effect

In the second stage, we set up a DID-Hedonic model to analysis how the price of housing units near urban villages changes after receiving an exogenous shock, the removal of its vicinal urban village. Then use sub-samples of housing units around these villages to check our empirical findings.

DID-Hedonic model specifications

Equation (2) reports the general setup of a DID-Hedonic pricing equation for housing units:

$$log\ P_i=\beta_0 + \varphi_t + \beta_2 * dummy_{in_1} + \beta_3 * dummy_{in_1} * demo_1$$

$$+ \beta_4 * dummy\_in_2 + \beta_5 * dummy\_in_2 * demo_2$$

$$+\boldsymbol{\beta_i} * \boldsymbol{X_{ij}} + \varepsilon_i \qquad (2)$$

With all else variable remain the same as in equation (1), the dummy variable *dummy_in* indicates that whether a housing unit sample is near a removed urban village, to be more accurate, whether within **1000 meters** of that village. This dummy variable distinguishes our experimental group, housing units within 1000 meters around one urban village which is about to be removed, and the control group, housing units outside 1000 meters of an removed urban village. The subscript 1 is for housing units who are located within 1000 meters of an urban village removed in the first wave, before Beijing 2008 Olympic Games. Similarly, the subscript 2 is for housing units within the spatial influential sphere of urban villages removed in the second wave, since 2010.

We also create a breakpoint dummy variable *demo* which takes the value of 0 before removal and turn to be 1 after that, indicating that whether this shock has happened or not. Here the subscripts 1 and 2 are also corresponding to be affected by urban villages' removal in different time periods as above. We use this variable to capture the difference before and after the shock. However, as we have controlled every quarter fixed effect by φ_t , which are linear correlate with *demo*, so that *demo* needs not to show up in the regression.

In fact, the interaction term of $dummy\_in$ and $demo$ is what we are most interested in at this stage, since their coefficients, β_3 and β_5, will reflect the difference in difference effect on housing price caused by urban villages' removal. Because $dummy\_in * demo$ captures not only the difference of the housing transaction units' price inside vs. outside the spatial sphere of influence of urban villages, but also the difference before vs. after the shock. We expect β_3 and β_5 to be significantly positive, which means that the removal of urban villages do increase the neighboring housing units' transaction price. It is also very interesting to compare absolute values of these two coefficients, and try to find out what kind of removal of urban villages can generate greater external effects for housing market.

There is a concern that all the houses near urban villages do have a faster growth rate for housing price through our research period, because these locations could be regarded as just in property price depressions where housing price will grow faster naturally, even without removal of urban villages.

In order to deal with this potential problem, we employ these housing units around urban villages which have always existed throughout our analysis period as our new control group. This means that we use a sub-sample of housing units within 1000 meters of any urban village for further confirmation of our empirical results. The control group is no longer housing transactions away from 1000 meters of a removed village, but turn to be housing transactions near an always existing village since 2006 to 2011.

Results of urban villages' removal and dynamics in nearby housing value

We now test whether removal of urban villages will promote faster housing price growth for neighboring houses, employing the difference in difference model specification based on equation (2). Table 3 reports the results of the DID-Hedonic regression, with the full sample results shown in column (1) and results of subsamples in different time period for first and second wave villages are shown in column (2) and (3), respectively. We control for quarter fixed effects, and standard errors are clustered by project as in above regression.

*** insert Table 3. about here***

In Column (1), results based on full sample show that the two variables indicating experimental groups ($dummy\_in_1$ and $dummy\_in_2$) are both statistically significant at 5% and 10% level respectively with negative signs. Both two interaction terms ($dummy\_in_1*demo_1$ and $dummy\_in_2*demo_2$) what we are most interested have significant positive signs at 5% level, which confirm our hypothesis that removal of urban villages resulting in higher housing price in peripheral area. In the first wave before 2008 Olympic Games, removal of these urban villages increase housing price within a radius of around 1000 meters by 0.045%, and in the second wave since 2010, this premium of neighboring housing price is about 0.032%. To our surprise, as for removal's difference in difference effect in housing price, the villages removed in the first wave have greater influence on neighboring housing prices increase.

We then use four groups of sub-samples in different time periods to verify our findings in column (1). Note that when we test for second-wave villages separately, the first-wave villages have been removed and should not be considered. Column (2) shows the results for testing effect caused by first-wave villages' removal alone, and the time period is from the start of 2006 to the end of 2008. The estimated coefficient for $dummy\_in_1*demo_1$ is 0.0439, very close to the result of 0.445 in column (1). As for the effect of second-wave urban villages, the time period is from the start of 2009 to the end of 2011, these results are in column (3). Compared to 0.0327 in column (1), estimated coefficients for $dummy\_in_2*demo_2$ is 0.0316, which is not so much difference. In a word, the difference in difference analysis provides evidence that removal of urban villages do improve surrounding housing price. The mean increase rate in housing price affected by first wave of removed villages is 0.04%, and the value is 0.03% for those affected by the second wave removed villages. We consider this is because the location differences of these two kinds of villages, these villages in the first wave located nearer to city center, where land resources are more scarcity, and larger number of people with higher income who care more about their living environment.

Considering the concern that all the houses near urban villages do have a faster housing price growth rate, we now change our control group by just using housing samples within 1000 meters of any urban village to check the robustness of findings in DID-Hedonic models. Results are listed in column (4) and column (5) of Table 3. The results on mean effects of difference in difference are still hold for the two waves of removal, with estimated coefficients are 0.0404 for housing units affected by the first wave of removal, and 0.0330 for those affected by second wave. These two coefficients are very stable and remain almost the same as compared with results from the former analysis.

4. The heterogeneity of this spill-over effect

4.1 Model specifications for investigating heterogeneity

Then, we turn to investigate the heterogeneity of this effect, and focus on the features of a village, its interaction with surrounding urban area and the gap between them. As for villages' details, we make full use of what we got from 2008 micro survey, and construct a series of variables to capture the different characteristics of each village.

The variable *Varea* represents a village's area, *Living_Months* is the median number of months has a migrant lived in this current village, *Case* is a ratio of security cases happened in past half year as answered by the migrants[6]. It is worth mentioning that we also have variables to characterize the degree of disharmony for one village and its urban neighbor area. There is a question about how often a migrant feels being

[6] In the questionnaire, we asked whether there were security cases in past half year, and we calculate the ratio of migrants who answered yes on the total number of migrants in one village.

discriminated against by urban residents, and we generate *Feel* to reflect the ratio of people answers *"very often"* or *"sometimes"* in one village. What's more, on the basic of migrants' monthly income, we employ the micro data of urban householdes from 2010 Urban Household Survey in Beijing to construct a new variable *Income_gap* dividing neighboring urban residents' income by migrants' income of an urban village. We use *Income_gap* as a reflection of the income gap between one urban village's migrants and their urban residents' neighbors.

As in equation (3), we include a new interaction term using $dummy\_in_2 * demo_2$ and Z_k, which represent *village k*'s characteristic as mentioned above, and $\boldsymbol{\beta_8}$ are what we are most interested at this stage.

$$log\ P_i = \beta_0 + \varphi_t + \beta_4 * dummy\_in_2 + \boldsymbol{\beta_8} * dummy\_in_2 * demo_2 * \boldsymbol{Z_k} + \beta_i * X_{ij} + \varepsilon_i \qquad (3)$$

4.2 Results of the heterogeneous spill-over effect

Empirical findings are shown in Table 4, as we select out housing transactions near the surveyed villages and limit research period from 2009 to 2011, the sample size is quite smaller but the R^2 is still large with the value of 0.643. Recall that 8 out of 43 villages were removed in the second wave and others are always existed in this period.

*** insert Table. 4 about here ***

In column (1), the basic DID effect is significantly positive as before with an even larger value at 0.052 (as compared to the estimated coefficient with value of 0.032 in column (5) of Table 3). However, what we are interested in column (1) is not the difference, but credible results for exploring heterogeneity. The interaction term of *Dummy_in2*demo2* with a village's area in column (2), and its migrants' median living months in column (3) are both significantly positive. This indicates that removal of larger or older villages will lead to higher premium in housing value. While a village's security situation in column (4) is positive but not statistically significant.

As for the degree of disharmony for one village and its urban neighbor area, the estimated effect for the feeling of being discriminated against, interaction term with *Feel* in column (5) and income gap, interaction term with *Incgap* in column (6) are both positive and significant at 5% and 1% level, respectively. These findings suggest that the more disharmony of one village and its urban neighbor area, the more premium in housing value when this villages is removed.

5. Robustness check using propensity score method

5.1 Propensity score method for endogenous selection

There is a concern that choices of which urban villages to be removed maybe not completely random, urban government may choose village with more potential in housing price increase to be removed earlier. Here comes the endogenous problem in our analysis, which means our findings of the effect maybe biased. In this case, the propensity score method (Rosenbaum and Rubin, 1983) would be helpful. This method is good at measuring the average treatment effect on the treated (which is the so called *ATT* in related literature) by finding out the really comparable samples or to what extent they are comparable.

The first stage is to run a probability model for the removal of urban village, on the basic of the results, we can predict the probability of removal for each village and use this predicted probability as the propensity score.

Because that the features of urban villages themselves may be highly influential for the removal decisions made by the government, we employ the 43 villages out of 2008 micro survey, which have detail information, as a special sub-sample of villages applying propensity score method analysis. We set up a Probit model in first stage to analysis one village's probability to be removed as in equation (4).

$$\textit{Removal status of village}_k = \beta_0 + \boldsymbol{\beta_{k1}} * \boldsymbol{Z_k} + \boldsymbol{\beta_{k2}} * \boldsymbol{X_k} + \varepsilon_i \qquad (4)$$

The variable on the left hand side is a dummy variable representing whether *village*$_k$ will be removed later or not. $\boldsymbol{Z_k}$ which is on the right hand side is a vector of the urban village's features itself we got from the survey, such as village's size, security situation, the income gap and the degree of interaction between migrants in villages and their urban residents neighbor. $\boldsymbol{X_k}$ is a vector of other location variables such as the distance from one villages to city center and the closest subway station.

The second stage is to find out which villages are really similar enough as for their propensity scores and investigate the difference in difference effect just in their surroundings. What we expect are villages with similar values of propensity scores while some of them have been removed and others have not. Thus we can overcome the selection problem to some extent by examining the effect of villages' removal on housing price changes just around these villages. It should be noted that, if we find out 5 groups of villages within each villages have similar propensity scores, then we will control for group fixed effects when check the DID effect using housing samples near these selected villages.

5.2 DID results checked using matched villages based on PSM

The first stage is to run a probability model for urban village's removal, empirical results of this Probit model as mentioned in equation (4) are provided in column (1) of Table 5. What's surprising is that most of urban village's features and location variables have no significant effect on its removal status, even for the degree of disharmony (*Feel* or *Income_gap*), village's existed time or its location in the city (as measured by distance to city center or closest subway station). The area and security status of a village has positive sign and relatively high t-statistics, although these coefficients are not significant. Two variables that are significant in this stage are the average income of one village's rural migrants and its peripheral urban neighbors, although the relative income gap itself is not significant. We believe these two income variables embody some unobserved location convenience valued by migrants and urban residents. It must be emphasized that the probit model in propensity score analysis is not to explore what factors have significant effect on the shock, but to control potential variables to get comparable samples in the second stage.

*** insert Table. 5 about here ***

On the basic of results in column (1), we use the predicted probability as the propensity score and find pairs of villages that have similar scores, indicating that they are comparable. We got a total of 18 not removed but comparable villages for 7 of 8 removed villages, and divide these 25 villages into 4 groups according to their propensity scores, while the other villages are dropped. What we care about is whether this DID effect is still significant within each groups, after including group fixed effect for the sub-sample housing units.

Column (2) of Table 5 displays the final results. The estimated coefficient of *Dummy_in2*demo2* are still significantly positive, with the value of 0.087, a much larger effect than we have gained from basic DID-Hedonic analysis. This proves that, the effect of urban villages' removal on nearby home value increase is significant presence, accounting for the endogenous selection problems.

6. Conclusion

Urban villages in Chinese cities can be considered as a product not only of China's recent rapid urbanization associated with massive rural-urban migration but also of the persistent rural-urban division existing even within the urban boundary. They have many negative effects such as potential public security threat and poor sanitary conditions, due to the lack of urban public services and management. Urban villages have made significant contribution to the growth of those cities with labor-intensive industries, as they greatly reduced rural migrant workers' housing cost and thus their labor cost. However, such benefits have started to decrease, especially in big cities, as those cities are switching to skill-intensive industries and the demand for low-skilled workers shrinks, and the high-skilled workers' demand for better quality of life and the environment is also rising. This is the rationale behind local governments' decision to remove those urban villages.

The contribution of our paper is to quantitatively measure the externalities of urban villages and their removal on nearby formal housing communities. We find that, an average urban village caused about 0.04% housing price discount in nearby communities before 2008, while the removal of this urban village triggered a 0.03% to 0.04% housing price growth in those communities during 2006 to 2011. This positive spillover effect has big heterogeneity – the removal of larger, older urban villages, and those villages that have a bigger income gap and weaker interaction with nearby residents shows a significant larger spillover effect.

The above empirical findings support local governments' and local residents' (in formal housing sector) rationale behind the removal of urban villages, but this is just one side of the coin. After the removal of urban villages, the rural migrant workers originally stayed in those villages are displaced and pushed further out to the remote suburban areas. This phenomenon has been documented in the United States by scholars such as Brueckner and Rosenthal (2009) but we know of no studies investigating such patterns in LDC cities. Those poor people do not leave Beijing because they can find jobs here, but they have to commute longer distances from the city fringe to work places[7]. To mitigate this problem, the Beijing municipal government has built a limited number of public affordable housing projects near suburban subway stops. But, during the last ten years, only the poor households with Beijing local *hukou* were eligible to such subsidized public housing. An optimistic signal is that recently Beijing municipal government started to offer a small amount of public housing to rural migrant workers. The "New Urbanization" strategy proposed by the new Central Government aims to provide those rural migrants in cities with equal accessibility to job opportunities, public services and social security, and turn them into real urban residents. Under this strategy more urban policies are expected to be implemented which will offer those rural migrants with more urban opportunities.

[7] According to the 2008 Survey data, among 744 migrants who answered the question whether they will leave Beijing if his or her current village were removed by urban government, there are only 55 respondents said yes, less than 7.5 percent.

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Appendix

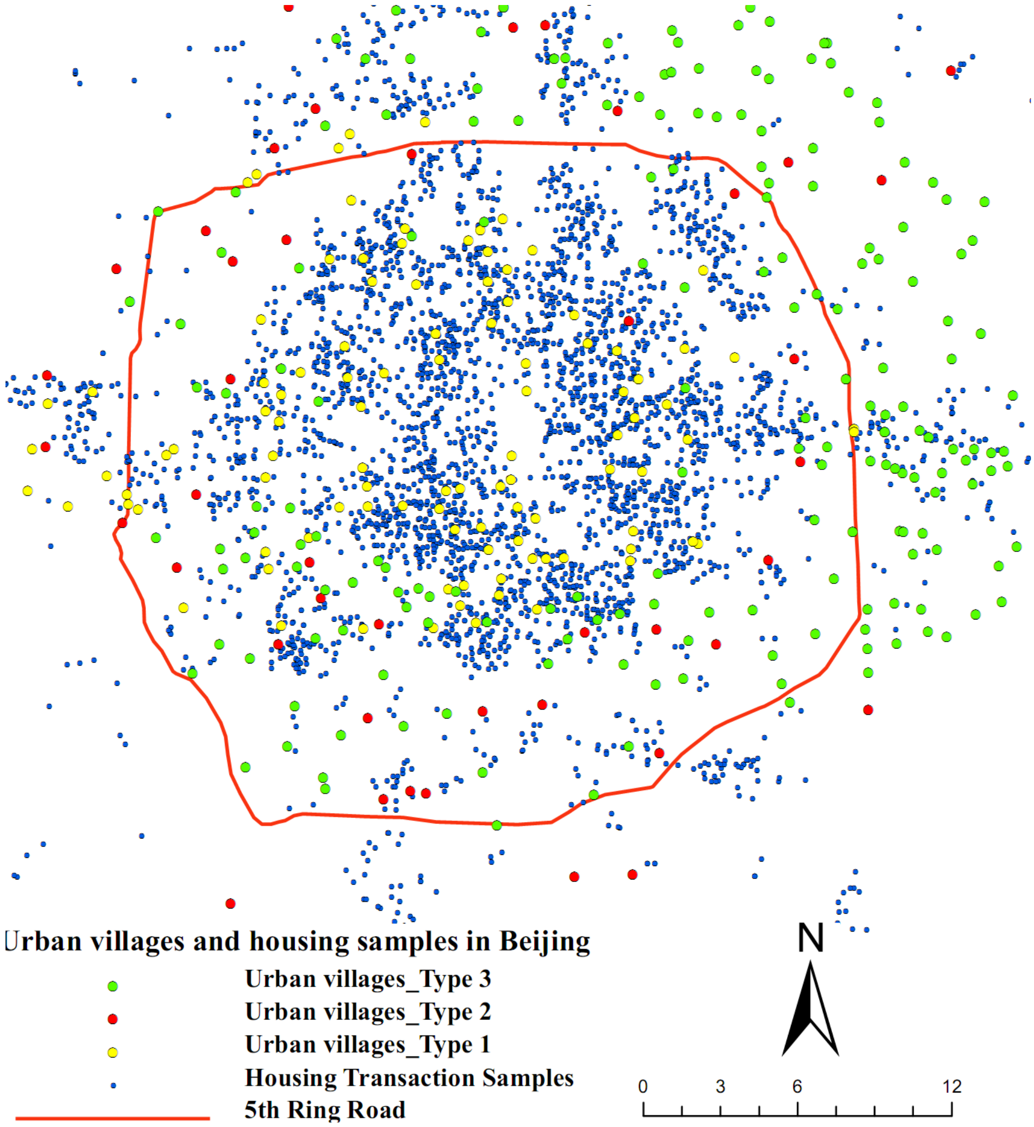

Fig. 1. Spatial Distribution of Urban Villages and Housing Samples in Beijing

Table 1. Descriptive Statistics

Variable	Definition	Obs.	Mean	Std. Dev.
1. Basic				
Log(HP)	Log average price of a residential housing unit (Yuan per square meter)	24410	9.66	0.45
Din	Binary,1==the housing unit' distance to a village is less than 1000 meters,0==otherwise. ***dynamic variable***	24410	1452.09	962.39
Dv3	A residential unit's distance to the closet villages which always exist from 2006 to 2011, in meter, static variable	24410	1642.06	1025.16
Din1	Binary,1==the housing unit' distance to a village removed in first wave is less than 1000 meters,0==otherwise.	24410	0.36	0.48
Din2	Binary,1==the housing unit' distance to a village removed in second wave is less than 1000 meters,0==otherwise.	24410	0.09	0.28
Demo1	Quarterly dummy,1==housing unit is sold after first wave of removal, 0==otherwise	24410	0.81	0.40
Demo2	Quarterly dummy,1==housing unit is sold after second wave of removal, 0==otherwise	24410	0.36	0.48
2.Locaion				
D_CBD	A residential unit's distance to CBD, in km, static variable	24410	8.39	3.49
D_jrj	A residential unit's distance to *jinrongjie*, in km, static variable	24410	9517.30	3667.94
D_zgc	A residential unit's distance to *zhongguancun*, in km, static variable	24410	13323.71	5137.56
D_yyc	A residential unit's distance to *yayuancun*, in km, static variable	24410	10097.13	4996.19
D_sub	A residential unit's distance to closest subway station, in m, ***dynamic variable***	24410	1967.45	1877.49
3.Amenity				
D_school	A residential unit's distance to closest primary school, in m, static variable	24410	3082.28	2172.66
D_park	A residential unit's distance to closest park, in m, static variable	24410	1956.32	1070.03
D_hospital	A residential unit's distance to closest hospital, in m, static variable	24410	2371.70	1878.57
D_shop	A residential unit's distance to closest shopping center, in m, static variable	24410	1712.30	1368.23

Table 1. Descriptive Statistics (continued)

Variable	Definition	Obs.	Mean	Std. Dev.
4. Features of 2008 surveyed urban villages				
Varea	A village's area, in hectare	43	12.75	2.46
Month	Median months of migrants has lived in one village, in month	43	30.37	14.89
Case	Ratio of security cases happened in past half year in one village, %	43	18.27%	14.32%
Vinc	Migrants' median monthly income in one village, in yuan	43	2706.80	390.82
Vrent	A village's monthly rent, in yuan per square meter	43	25.92	8.36
Live_sta	A village's average degree of living facilities, whether migrants have some of 8 kinds of basic living facilities[8] in their house	43	3.03	0.49
Inc_jwh	Urban residents' median monthly income in a village's closest *Juweihui*, in yuan	43	6423.92	2348.03
Incgap	Income gap between one urban village's migrants and their urban residents' neighbors, the latter divided by the former	43	2.08	0.86
Feel	Ratio of migrants who feel of being discriminated by urban residents in one village, %	43	39.55%	14.24%
5.Housing physical features				
Age	A residential unit's housing age, in year	24410	11.83	6.20
Total_floor	A residential unit's total floor of its building	24410	17.22	8.18
Floor	A residential unit's floor	24410	9.16	6.66
Area	A residential unit's total space, in square meter	24410	87.21	40.27
Parlour	Number of a residential unit's parlours	24410	1.21	0.42
Bedroom	Number of a residential unit's bedrooms	24410	1.93	0.95
Decoration	Dummy, indicate the degree of a residential unit's decoration	24410	2.96	1.01
Orientation	Dummy, indicate the orientation of a residential unit	24410	5.02	2.75
6.Time Trend				
Time_Q	Quarterly time trend, 2006q1-2011q2=1,2,3,…,24			
Time_1	Quarterly time trend after first wave removal			
Time_2	Quarterly time trend after second wave removal			

[8] These are electricity, natural gas, running water, heater, TV, refrigerator, air conditioning, and water heater.

Table 2. The effect of urban villages' existence on nearby home value

	(1)	(2)	(3)
Time period	**2006-2011**	**2006-2011**	**2006-2007**
Dependent variable	*Log(HP)*	*Log(HP)*	*Log(HP)*
Log(dv)			
Dummy_in		-0.0275***	
		(-3.051)	
Dummy_in1			-0.0375**
			(-2.084)
Dummy_in2			-0.0418**
			(-2.252)
Log(dv3)			0.0052
			(0.527)
d_CBD	-0.0204***	-0.0203***	-0.0252***
	(-9.406)	(-9.506)	(-7.431)
Log(d_jrj)	-0.0797***	-0.0767***	-0.0204
	(-3.703)	(-3.587)	(-0.505)
Log(d_yyc)	-0.0201**	-0.0151	-0.0000
	(-2.176)	(-1.596)	(-0.003)
Log(d_zgc)	-0.1806***	-0.1811***	-0.2175***
	(-10.732)	(-10.596)	(-7.428)
Log(d_sub)	-0.0173**	-0.0201***	-0.0060
	(-2.446)	(-2.915)	(-0.426)
Log(d_school)	-0.0181*	-0.0170*	-0.0233*
	(-1.911)	(-1.809)	(-1.944)
Log(d_park)	-0.0127*	-0.0109	-0.0128
	(-1.709)	(-1.486)	(-1.002)
Log(d_hospital)	0.0099	0.0083	0.0128
	(1.182)	(1.008)	(1.016)
Log(d_shop)	-0.0185***	-0.0168***	-0.0208*
	(-2.970)	(-2.678)	(-1.929)

Table 2. Continued

parlour	0.0347***	0.0339***	0.0207*
	(5.092)	(4.960)	(1.807)
room	0.0001	0.0002	-0.0008
	(0.029)	(0.047)	(-0.164)
area	-0.0010***	-0.0010***	-0.0006***
	(-5.300)	(-5.307)	(-2.632)
age	-0.0234***	-0.0234***	-0.0402***
	(-8.513)	(-8.418)	(-10.629)
age2	0.0005***	0.0005***	0.0009***
	(7.068)	(6.981)	(9.140)
floor	0.0039***	0.0039***	0.0033*
	(3.138)	(3.121)	(1.649)
floor2	-0.0001**	-0.0001**	-0.0001
	(-2.070)	(-2.043)	(-0.997)
total_floor	-0.0001	-0.0001	0.0011
	(-0.172)	(-0.168)	(1.154)
Constant	12.2021***	12.1503***	12.0282***
	(72.379)	(71.637)	(36.061)
Quarter fixed effects	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes
Observations	24410	24410	4727
R-squared	0.722	0.722	0.599

Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3. The effect of urban villages' removal on nearby home values' dynamic

	(1)	(2)	(3)	(4)	(5)
				Sub-samples around urban villages	
Time period	***2006-2011***	***2006~2008***	***2009-2011***	***2006-2011***	***2006-2011***
Dependent variable	***Log(HP)***	***Log(HP)***	***Log(HP)***	***Log(HP)***	***Log(HP)***
Dummy_in1	-0.0504**	-0.0417**		-0.0359**	
	(-2.488)	(-2.411)		(-2.003)	
Dummy_in2	-0.0257*		-0.0220		-0.0104
	(-1.879)		(-1.479)		(-0.637)
*Dummy_in1*demo1*	**0.0445****	**0.0439****		**0.0404****	
	(2.261)	**(2.554)**		**(2.313)**	
*Dummy_in2*demo2*	**0.0327****		**0.0316****		**0.0330***
	(2.346)		**(2.227)**		**(1.939)**
d_CBD	-0.0207***	-0.0237***	-0.0189***	-0.0215***	-0.0270***
	(-9.570)	(-7.447)	(-8.945)	(-9.738)	(-6.443)
Log(d_jrj)	-0.0828***	-0.0428	-0.0990***	-0.0572**	0.0169
	(-3.866)	(-1.254)	(-4.707)	(-2.374)	(0.528)
Log(d_yyc)	-0.0166*	-0.0055	-0.0253***	-0.0371***	0.0194
	(-1.729)	(-0.418)	(-2.657)	(-2.605)	(0.805)
Log(d_zgc)	-0.1846***	-0.2032***	-0.1720***	-0.1873***	-0.2975***
	(-10.785)	(-7.659)	(-10.254)	(-9.283)	(-9.708)
Log(d_sub)	-0.0179**	-0.0095	-0.0215***	-0.0114	-0.0121
	(-2.564)	(-0.818)	(-3.221)	(-1.392)	(-1.203)
Log(d_school)	-0.0181*	-0.0306***	-0.0160	-0.0249***	-0.0086
	(-1.887)	(-2.629)	(-1.514)	(-2.759)	(-0.508)
Log(d_park)	-0.0144*	-0.0099	-0.0140*	-0.0134	-0.0255
	(-1.792)	(-0.883)	(-1.804)	(-1.467)	(-1.473)
Log(d_hospital)	0.0095	0.0119	0.0094	0.0040	-0.0111
	(1.177)	(1.047)	(1.077)	(0.451)	(-0.672)
Log(d_shop)	-0.0179***	-0.0199**	-0.0172***	-0.0258***	-0.0554***
	(-2.776)	(-2.184)	(-2.652)	(-3.597)	(-4.288)
Constant	12.2762***	12.0482***	13.4855***	13.5183***	12.6491***
	(69.464)	(47.232)	(80.807)	(68.445)	(43.433)
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Housing physical features	Yes	Yes	Yes	Yes	Yes
Observations	24410	7093	17317	14612	5902
R-squared	0.722	0.603	0.602	0.729	0.747

Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. Heterogeneity of DID effects using 2008-survey-village

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	***Log(HP)***	***Log(HP)***	***Log(HP)***	***Log(HP)***	***Log(HP)***	***Log(HP)***
Dummy_in2	-0.0122	-0.0143	-0.0044	0.0022	-0.0101	-0.0143
	(-0.757)	(-0.876)	(-0.252)	(0.107)	(-0.544)	(-0.793)
*Dummy_in2*demo2*	0.0520***					
	(3.118)					
*Dummy_in2*demo2*Varea*		**0.0041*** **				
		(3.456)				
*Dummy_in2*demo2*Month*			**0.0016** **			
			(2.443)			
*Dummy_in2*demo2*Case*				**0.1170**		
				(1.195)		
*Dummy_in2*demo2*Feel*					**0.1301** **	
					(2.297)	
*Dummy_in2*demo2*Incgap*						**0.0229*** **
						(2.650)
Log(dv3)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.359)	(1.368)	(1.362)	(1.364)	(1.277)	(1.259)
D_CBD	-0.0255***	-0.0254***	-0.0254***	-0.0255***	-0.0253***	-0.0252***
	(-7.294)	(-7.260)	(-7.276)	(-7.287)	(-7.257)	(-7.218)
Log(d_jrj)	-0.0330	-0.0326	-0.0317	-0.0311	-0.0354	-0.0374
	(-0.607)	(-0.601)	(-0.581)	(-0.569)	(-0.653)	(-0.689)
Log(d_yyc)	-0.0616**	-0.0615**	-0.0621**	-0.0611**	-0.0629**	-0.0619**
	(-2.102)	(-2.102)	(-2.125)	(-2.083)	(-2.153)	(-2.118)
Log(d_zgc)	-0.1793***	-0.1791***	-0.1793***	-0.1792***	-0.1774***	-0.1766***
	(-6.148)	(-6.156)	(-6.152)	(-6.148)	(-6.122)	(-6.106)
Log(d_sub)	-0.0339***	-0.0341***	-0.0338***	-0.0342***	-0.0347***	-0.0352***
	(-3.098)	(-3.113)	(-3.086)	(-3.108)	(-3.165)	(-3.210)
Log(d_shop)	-0.0335***	-0.0338***	-0.0344***	-0.0342***	-0.0348***	-0.0344***
	(-2.954)	(-2.983)	(-3.002)	(-2.959)	(-2.998)	(-2.988)
Constant	13.3420***	13.3411***	13.3483***	13.3315***	13.3661***	13.3578***
	(25.697)	(25.726)	(25.764)	(25.523)	(25.807)	(25.744)
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Housing physical features	Yes	Yes	Yes	Yes	Yes	Yes
Other amenity variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6599	6599	6599	6599	6599	6599
R-squared	0.643	0.643	0.643	0.643	0.643	0.643

Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Results of propensity score method analysis

Stage I Probit		***Stage II DID-Hedonic***	
	(1)		(2)
VARIABLES	*D_Removal*	VARIABLES	Log(HP)
Vinc	0.002**	*Dummy_in2*	-0.0721
	(2.243)		(-1.463)
Month	0.003	*Dummy_in2*demo2*	0.0869**
	(0.147)		(2.380)
Vrent	-0.016	*D_CBD*	0.0001**
	(-0.442)		(2.572)
Case	3.506	*Log(d_jrj)*	0.0286*
	(1.336)		(1.877)
Live_sta	-0.740	*Log(d_yyc)*	0.6068***
	(-0.906)		(3.528)
Varea	0.173	*Log(d_zgc)*	0.2538**
	(1.110)		(2.494)
Inc_jwh	0.000*	*D_CBD*	-0.2221**
	(1.840)		(-2.371)
D_CBD	0.000	*Log(d_sub)*	-0.0245
	(1.233)		(-0.944)
Log(d_sub)	0.138	*Log(d_school)*	0.0755
	(0.792)		(1.587)
		Log(d_park)	-0.2733**
			(-2.073)
		Log(d_hospital)	-0.2328***
			(-5.337)
		Log(d_shop)	-0.0913**
			(-2.168)
		Group fixed effects	***Yes***
		Quarter fixed effects	Yes
		Housing physical features	Yes
Constant	-10.734**	Constant	8.0389***
	(-2.301)		(4.739)
Observations	43	Observations	856
Pseudo R-squared	0.335	R-squared	0.762

z-statistics in parentheses of Column (1), Robust t-statistics in parentheses of Column (2);

*** p<0.01, ** p<0.05, * p<0.1