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Spatial Dynamic Models with Short Panels: Evaluating the Impact of Home Purchase Restrictions on Housing Prices

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Abstract

Since the 2007 housing crisis in the United States, many countries have begun implementing various macroprudential policies to curb the ongoing rise in housing prices. As there is no clear consensus in the literature on the efficacy of these interventions, understanding their short-term impacts is crucial in informing future policy designs. Adapting a new econometric technique, we examine the short-term impact of home purchase restrictions in Singapore, accounting for the short panel nature of the data and the existence of dynamic, spatial, spatiotemporal, and unit-specific effects. Using quarterly housing data over 2012Q4-2014Q2, we find that public housing prices decrease by 3%-5% in the four quarters following policy implementation, but transaction volume does not change. These effects are likely driven by a decrease in the housing demand and the inelastic housing supply in the short run. We also show that models that ignore spatial and dynamic effects can overestimate policy effects.

Key words: Purchase restrictions; Housing prices; Spatial effects; Dynamic effects; Short panels

JEL Codes: C21; C23; R21; R38

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1. Introduction

Since the collapse of the housing sector in the United States in 2007, many countries have begun implementing various macroprudential policies to curb the rapid growth of housing prices.[1] Understanding the short-term effects of policies targeting housing prices is essential for guiding follow-up policy designs because a particular policy might not generate long-lasting impact and might be subject to future modifications based on its short-term effects. The short-term analysis of a policy in one country can also provide important lessons for other countries. However, housing prices are affected by factors other than those related to policies, such as spillover, temporal, spatiotemporal, and unit-specific effects. Therefore, in evaluating a policy's effects, it is important to acknowledge the existence of these factors. In addition, short-term analysis means that the panel used is short, which needs to be taken into account in formal analysis. This paper adapts a state-of-the-art econometric technique presented in: "*Unified M-estimation of fixed effects spatial dynamic models with short panels*" by Yang (2018, *J. of Econometrics*) to conduct a formal study of the short-term impact of home purchase restrictions in Singapore.

The policy under study is one by which the Singapore government requires permanent resident (PR) households to wait three years from the date of obtaining PR status before they can purchase resale public housing flats. The policy was announced and implemented on August 27, 2013. Figure 1 plots the housing price indices for Singapore's public and private housing markets. The public housing and private housing price indices show similar price trends until 2013Q2; subsequently, after policy implementation, differences between the two indices appeared. This pattern also suggests that prices reacted to the policy immediately because the public housing index was lower in 2013Q3 than in 2013Q2.

To formally evaluate the effects of this policy, we adopt a treatment-control strategy using private housing as a control group. We use a fixed-effects spatial dynamic panel data (FE-SDPD) model and estimate the model with a new method for the following reasons. First, the model takes into account spatial, temporal, spatiotemporal, and unit-specific effects.[2] These features of the housing market are well documented in existing studies (e.g., Case and Shiller, 1990; Brady, 2014). Second, evaluating the short-term impact of a policy necessitates the use

[1] For example, governments in Australia, Canada, China, Israel, New York, New Zealand, Singapore, Switzerland, and the U.K. have imposed restrictions on nonresidents' housing purchases, introduced higher taxes on nonresidents, restricted the number of housing units available for residents, or levied additional taxes if residents purchase more than one or two housing units.

[2] We use the terms "dynamic" and "temporal" interchangeably in this paper.

of a short panel, that is, panel data covering short time periods. However, short dynamic panel models are known to suffer from the well-known "initial values problem." We take advantage of the estimation approach recently developed by Yang (2018), as this approach provides consistent and asymptotically normal estimators for FE-SDPD models with short panels.

We find that the home purchase restriction created a negative effect on housing prices. In the four quarters after the policy's implementation, public housing prices decreased by approximately 3%-5%, relative to private housing prices. These results are consistent across models with different spatial terms and alternative spatial weight matrices and are also robust to placebo tests using random dates. Compared with our FE-SDPD model, models that ignore dynamic or spatial effects tend to overestimate the effect of the home purchase restriction. Although prices responded quickly and significantly, we do not find that the transaction volume in the public housing market declined. Possible mechanisms are the decreased demand induced by the purchase restriction that directly rendered new PRs ineligible to purchase resale public houses and the inelastic housing supply over a short period. Our findings suggest that purchase restrictions are effective in curbing housing prices when the supply is inelastic.

Our paper contributes to the literature on home purchase restrictions. The current literature has not reached a consensus on the effects of these policies. Most papers document that home purchase restrictions are effective in cooling down the market (Du and Zhang, 2015; Li and Xu, 2015; Li et al., 2017; Sun et al., 2017; Somerville et al., 2019), whereas a few papers show that purchase restrictions have the opposite effect (Zhou, 2016; Jia et al., 2018). We estimate the effects of purchase restrictions using a more general model, controlling for other factors potentially affecting housing prices, whereas other studies do not incorporate spatial or temporal effects in their models. In addition, although purchase restrictions have been adopted in several countries, existing studies disproportionally focus on China. This paper extends the literature by providing additional empirical evidence from Singapore. Our results are informative for governments in other countries where housing prices increase rapidly.

We also contribute to the literature on migration and housing. Permanent residency is an intermediate residential status between that of citizens and foreigners. Migrants are important for the economic success and sustainable development of countries such as the United States and Singapore. Researchers have examined the relationship between migration and the housing market (Mussa et al., 2017; Sharpe, 2019). Some papers have shown that immigration has a positive effect on average price growth (Saiz, 2007), whereas others have found that housing values grow relatively slowly in immigrant settlement districts because of natives moving away (Accetturo et al., 2014). There have been limited related studies on Singapore. Chia et al. (2017)

constructed a dynamic general equilibrium model and found that among the fundamental factors, residents and foreigners have contributed the most to housing price increases in Singapore. However, their paper did not distinguish PRs specifically. Li and Tang (2018) calibrated a similar model in which natives can upgrade from public to private housing and foreigners can choose to obtain permanent residency in order to purchase public housing. Their model suggests that both native population growth and foreign population growth generate housing price growth. We contribute to this literature by focusing on a specific group of migrants, i.e., PRs.

The remainder of this paper proceeds as follows. Section 2 discusses the institutional details in Singapore and the policy under study. Section 3 outlines the FE-SDPD model, its general estimation method, and the strategy for policy evaluation using this model. The data and summary statistics are provided in Section 4. The results, robustness checks, and discussion of mechanisms are presented in Section 5. Section 6 concludes the study.

2. Institutional Features and Policies in Singapore

2.1 Residential Property Market

In 2017, Singapore had a population of 5.61 million, including 3.44 million citizens, 0.53 million PRs, and 1.65 million foreigners.[3] There have been approximately 30,000 new PRs and between 15,777 and 22,100 new citizens each year since 2010. PRs and foreigners have limited access to residential properties.

Similar to the housing market in other economies such as Hong Kong and many European countries, the market in Singapore is characterized by both a public and a private sector. Specifically, residential properties in Singapore are grouped into three major categories: public housing, locally known as Housing and Development Board (HDB) flats; private non-landed properties (including condominiums and apartments); and private landed properties. Public housing accounts for approximately 73% of the overall housing stock.[4] The public housing market has two segments: new sales and resales. New public flats are heavily subsidized when purchased directly from the government but they entail many restrictions. In contrast, the resale market operates similarly to a laissez-faire marketplace in which the price is market-determined. Citizens can purchase any type of property, PRs have access to resale public flats and private

[3] The total might not add up due to rounding. The information is from the Yearbook of Statistics Singapore, 2018, https://www.singstat.gov.sg/-/media/files/publications/reference/yearbook_2018/yos2018.pdf.
[4] https://www.straitstimes.com/politics/parliament-hdb-flats-made-up-73-of-singapores-total-housing-stock-in-2016.

non-landed houses, and foreigners can purchase only private non-landed properties. New public flats are less expensive than resale flats in the same area, and private houses are the most expensive property type. Although the prices are lower, there are policies that restrict the supply and demand in the public housing sector. For example, to be eligible to purchase public flats, buyers must not own any property in Singapore or abroad. Specifically, if the buyers listed on a public flat application own a private property, either locally or overseas, they must dispose of all private properties before the purchase or within 6 months after the purchase of a public flat, and they are not eligible for subsidies when purchasing the public flat.[5]

In our study, private housing serves as a proper comparison group because it is difficult for a typical household that plans to purchase a public flat to switch to buying a private property within a short period. The price difference between private properties and public flats is high relative to the average household income. The area-adjusted average price in 2012—the year before the policy's implementation—was 4,707 Singapore dollars (SGDs) per square meter for a public flat or 39.84% of the average price for a private residential property, which was 11,816 SGDs per square meter.[6] According to the 2015 General Household Survey, the median monthly wage income of married couples was 7,602 SGD in 2010; therefore, their average annual salary was approximately 91,224 SGD. If a median-income couple wanted to purchase a 100-square meter private residential property instead of a public flat of the same size, the price difference based on the average price in 2012 would require them to work at least eight additional years if all the income is used for housing.[7] Comparing the additional years needed to accumulate the revenue to purchase a private residential property and the three years required by the policy to be eligible to purchase a public flat, new PR households would likely want to wait three years.[8]

PRs' demand for resale public flats accounts for a "disproportionate" share of the resale public housing market, relative to the percentage of PRs in the total number of residents eligible to purchase resale public flats (citizens and PRs). In 2012, PRs accounted for 14% of all

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[5] Source: https://www.hdb.gov.sg/cs/infoweb/residential/buying-a-flat/resale/eligibility-.

[6] The amount of $11,816 SGD is approximately equivalent to $9,456 USD as of 2012. In 2012, 1 USD equaled 1.249642 SGD, calculated from the daily exchange rate. We calculate the average price per square meter from the data that we subsequently introduce.

[7] If a couple borrowed the maximum of the 80% loan-to-value ratio (required by the government), then an additional two years of work would be required. However, the taxes due to the higher price of private properties would cost them additional years of work. PR households are required to pay 6% to 9% of the value of the property to the Inland Revenue Authority of Singapore within a few days of signing a housing contract. Furthermore, the debt-to-income ratios imposed by the government would prevent a household from obtaining a sufficient mortgage for a private house.

[8] If the household obtained the PR status before the policy implementation, they needed to wait less than three years to become eligible.

residents but purchased 6,636 public flats, representing 26% of the total transactions in the resale public housing market.[9] The reason is that (i) most citizens who qualify to buy new flats directly from the government choose to do so due to the heavily subsidized rate; additionally, (ii) PRs simply prefer resale public flats due to their huge price advantage over private properties, the affordability of public housing in Singapore relative to housing in their countries of origin, and the ownership premium over renting. Therefore, one would expect that once new PRs are denied the opportunity to purchase a public flat, public housing prices would decrease and/or the transaction volume would decline, depending on the elasticity of supply and demand.

For our analysis, we restrict the sample to the resale public housing and private non-landed residential markets, as these markets are accessible to both PRs and citizens. The new sales public housing market is not relevant to our policy study as it is not accessible to PRs; additionally, these data are not available from the government. We exclude private landed houses because PRs are usually not allowed to purchase landed properties.[10] Additionally, landed houses constitute a very small portion of the market—less than 5%—and are not frequently sold.

2.2 Home Purchase Restriction

The measure announced on August 27, 2013 is specific to the resale public housing market. Before the policy was introduced, an individual could purchase resale public housing once he/she obtained permanent residence. After this regulation went into effect, new PR households (i.e., those with no citizen owner) had to wait three years from the date on which they obtained permanent residency before they could buy a resale public flat. Here, the term "households" refers to all applicants and essential occupiers.[11] This measure applied to resale applications received at or after 5:30 p.m. on August 27, 2013. In other words, in a scenario in which both the applicant and his/her spouse were PRs, they would have to meet the 3-year residency period requirement before they became eligible to submit an application to buy a resale flat. The policy affected all new PRs who had held PR status for less than three years, as of the policy date, and who had not purchased a public flat. For example, if one of the applicants had held

[9] Source of population: https://www.strategygroup.gov.sg/docs/default-source/Population/population-in-brief-2012.pdf. The percentage of houses purchased by PRs is provided by the government.
[10] PRs who seek to purchase private landed property must apply for approval to the Singapore Land Authority. They are required to hold PR status for at least five years and be able to make an exceptional economic contribution to Singapore. Source: https://www.sla.gov.sg/Services/Restriction-on-Foreign-Ownership-of-Landed-Property.
[11] https://www.hdb.gov.sg/cs/Satellite?c=HDBArticle&cid=1383801213783&pagename=InfoWEB%2FHDBArticle%2FLetterKEOLayout.

PR status for one year as of August 27, 2013, the household needed to wait two additional years to become eligible.

It is worth discussing other policies related to the one that we are studying here. The housing market is frequently regulated by the Singapore government to ensure its steady and healthy growth. Beginning in September 2009, the government launched a series of cooling measures applying to both the public and private markets, but most of the measures were geared toward the private market.[12] Therefore, when evaluating the impact of the purchase restriction on the public housing market, one must be mindful of the possibility that there may be other regulations that have had negative impacts on this market, thus leading to an overestimation of the impact of the purchase restriction.[13] Specifically, one policy with immediate effects was announced on January 11, 2013. It required all PRs to pay the additional 5% buyer's stamp duty when buying their first property. Although this policy applies to both the private and public housing sectors, it is expected to affect public housing more than private housing, given that most PRs prefer to purchase public flats over private houses as their first property.[14] To address this concern, we use a short panel to isolate the effect of the additional buyer's stamp duty. We will discuss the sample period in detail in Section 4.

In addition to these discussions, we believe that housing prices have incorporated the effects of previous interventions. The market usually responds quickly to policy changes because the Singapore government typically announces and implements them unexpectedly and abruptly, as mentioned by Agarwal and Qian (2014, 2017). As discussed below, when we randomly choose dates (e.g., one year before policy implementation, one year after policy implementation, or two years after policy implementation) for our falsification tests, we do not observe the effect of dates a few quarters after the actual time of policy implementation. This fact may suggest that the market responds quickly to interventions.

3. Econometric Model and Method

[12] These include the seller's stamp duty, an additional buyer's stamp duty, the loan-to-value ratio limit, and the total debt servicing ratio. Although applied to both sectors, many of these interventions play a role only in the private housing market because the public housing sector has been strictly regulated since its establishment in the 1960s.

[13] In contrast, cooling measures with larger effects on the private housing market or affecting only the private sector may lead to an underestimation of the effect of the policy of interest, but these are less worrisome as a common practice in the field. Cooling measures with similar effects on both markets need not cause concern.

[14] The additional buyer's stamp duty of 5% is charged when PRs buy their first property, and 10% is charged when they purchase their second and subsequent residential properties. Only the rate of 5% plays a role in our study because new PRs must not own any property in order to be eligible to purchase a public flat.

3.1 Econometric Model

To evaluate the short-term impact of the purchase restriction imposed on new PRs purchasing public housing, we adopt a fixed-effects spatial dynamic panel data model and use a treatment-control strategy. The model is as follows:

$$y_{it} = \rho y_{i,t-1} + \lambda_1 \sum_{j=1}^{n} W_{1,ij} y_{jt} + \lambda_2 \sum_{j=1}^{n} W_{2,ij} y_{j,t-1} + \beta D_{it} + \gamma_i + \tau_{t^*} + u_{it}, \tag{1}$$
$$u_{it} = \lambda_3 \sum_{j=1}^{n} W_{3,ij} u_{jt} + \varepsilon_{it}, \quad i = 1, 2, \ldots, n, \ t = 1, 2, \ldots, T,$$

where y_{it} is the log of the floor-area-adjusted median housing price of unit i at time t. In our model and empirical analysis, the term "unit" means a spatial unit, not a housing unit.[15] In particular, unit i is a town-by-property combination (52 units with two types of properties in 26 towns). D_{it} equals 1 if unit i is subject to the purchase restriction at time t and 0 otherwise. Specifically, D_{it} takes the value of one *only when* public housing is concerned and $t \geq T_1$, where T_1 is the time when the purchase restriction was introduced. $\{\gamma_i\}$ are the unit-specific fixed effects (52 fixed effects). $\{\tau_{t^*}, t^* = 2, 3, 4\}$ denote the quarter-specific effects to capture seasonality (the first quarter is omitted). Seasonality in the real estate market is well documented in the literature (Ngai and Tenreyro, 2014).[16] $\rho y_{i,t-1}$ captures the temporal effects on prices. $\{\varepsilon_{it}\}$ are the idiosyncratic errors, assumed to be independent and identically distributed.

We use an FE-SDPD model for the following reasons. First, overwhelming evidence of spatial dependence in the housing market exists (Zhu et al., 2013; Brady, 2014; Cohen et al., 2016; Zhang et al., 2019; Cohen and Zabel, 2020). Second, a large body of the literature has shown that housing prices exhibit a temporal effect (Case and Shiller, 1990; Yavas and Yildirim, 2011; Moscone et al., 2014). A dynamic term or lagged dependent variable is used to capture this effect. Third, it is often impossible to observe all relevant explanatory variables in the data, and fixed-effects panel data models are widely used to control for omitted variable

[15] In other words, in this paper, the "unit" is different from the "housing unit."

[16] Ngai and Tenreyro (2014) showed that housing markets experience systematic above-trend increases in prices and transactions in the second and third quarters of each calendar year ("hot season") and below-trend decreases in the first and first fourth quarters ("cold season") in the United Kingdom and the United States. Sun et al. (2017) and Somerville et al. (2019) also controlled for seasonality in their models. Although Singapore does not have four seasons, its economic activities are highly subject to seasonal change. Cultural festivals and social customs are the reasons the Singapore government makes seasonal adjustments to macroeconomic data series. Source: https://www.singstat.gov.sg/-/media/files/publications/economy/ssnsep05-pg11-14.pdf.

bias.[17] Our FE-SDPD models can be applied to various topics involving spatial dependence, temporal effects, and unit-specific effects.[18]

One important feature of the FE-SDPD model is the spatial effects. Although the specific spatial forms in the true data generation process are unknown, the three types of spatial terms included in Model (1), i.e., the spatial lag effect, the space-time effect and the spatial error effect, are perhaps the three most popular forms of spatial interactions in the literature. The spatial lag term $\lambda_1 W_{1,ij} y_{jt}$ captures the spillover effects if the price of spatial unit i is affected by the current price of spatial unit j. The space-time term $\lambda_2 W_{2,ij} y_{j,t-1}$ captures the spillover effects if the price of spatial unit i is influenced by the previous price of spatial unit j. The spatial error term $\lambda_3 W_{3,ij} u_{jt}$ captures the spatial dependence in the disturbances. Ignoring spatial dependence in the dependent variable leads to biased estimates and inappropriate interpretations of the explanatory variable coefficients; ignoring spatial dependence in the disturbances leads to a loss of efficiency in the estimates (LeSage and Pace, 2009).

We do not adopt the spatial dynamic Durbin model for the following reasons. To model housing prices, a hedonic pricing model, which was proposed by Rosen (1974), has been widely used in the literature. According to the hedonic pricing model, internal and external characteristics should be included in the regression to determine housing prices, such as location, size, the number of rooms, the number of floors, and decorative elements. Because we use aggregate data, we are unable to use covariates at the housing unit level. Nonetheless, we are still able to capture the most important features that determine prices. The property type and location are likely the two most essential characteristics that affect housing prices in Singapore.[19] We use town-by-property fixed effects to capture the impact of property type and location. In addition, to mitigate the impact of size, we use the log of price per square meter to construct the dependent variable instead of the total price. In addition to location, property type, and size, we use quarter-specific fixed effects to capture seasonality, which affects housing prices.

[17] Qiu and Tong (2021) used a spatial difference-in-differences (DID) approach to evaluate the impact of light rail transit on property values, but they did not consider the temporal effects, the spatiotemporal effects, or the unobserved unit-specific effects. Jiang and Jin (2021) used a spatiotemporal dynamic panel data model and a quasi-maximum likelihood (QML) estimation to study the long-run effect of investor sentiment on stock return volatility, but their QML method is invalid for short-term analysis based on short panels, as discussed at the beginning of the paper.

[18] For example, it can be applied to fit the German wage curve as in Baltagi et al. (2012).

[19] The public housing prices are approximately 40% of the private housing prices. For properties within each sector, houses in mature towns are much more expensive than houses in other towns.

Another aspect of the FE-SDPD model is the definition of spatial weights. One can define neighboring spatial units based on contiguity (physical connectedness) or extend the definition based on distance. Specifically, we adopt four types of weights: common border, shared boundary, power distance, and exponential distance weights. For common border weights, the weight element $W_{r,ij}$ equals one if spatial units i and j share a common border and zero otherwise. For shared-boundary weights, the weight element $W_{r,ij} = l_{ij}$, where l_{ij} is the physical length of the boundary between towns where spatial units i and j are located. For distance weights, decay functions of distance are commonly used. The choices include the power distance ($W_{r,ij} = d_{ij}^{-\alpha}$), which becomes the inverse of the distance d_{ij} between spatial units i and j when $\alpha = 1$ or the inverse of the squared distance when $\alpha = 2$. Another choice is exponential distance weights, $W_{r,ij} = \exp(-\alpha d_{ij})$, and parameter values $\alpha = 0.01$ and $\alpha = 0.02$ are often used.

What is unique in our study is that the spatial unit is a town-by-property combination. We believe that public housing and private housing in the same town are also "neighboring housing" and influence each other. Consider spatial units i (public) and j (private) that belong to the same town, say A. We take $W_{r,ij} = 1$ for the common border spatial weights. For the l_{ij} in the shared boundary weights, we use the circumference of town A because these two spatial units share the entire town. For d_{ij} in the power distance or exponential distance weights, we use the minimum distance between town A and any other town. As a standard practice, all spatial weight matrices are row-normalized.

3.2 Estimation Method

We take the first difference of Model (1) to remove the town-by-property fixed effects, which yields the following formula:

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \lambda_1 \sum_{j=1}^{n} W_{1,ij} \Delta y_{jt} + \lambda_2 \sum_{j=1}^{n} W_{2,ij} \Delta y_{j,t-1} + \beta \Delta D_{it} + \Delta \tau_{t^*} + \Delta u_{it}, \quad (2)$$

$$\Delta u_{it} = \lambda_3 \sum_{j=1}^{n} W_{3,ij} \Delta u_{jt} + \Delta \varepsilon_{it}, \qquad i = 1, 2, \ldots, n, \; t = 2, \ldots, T.$$

To estimate Model (2), ordinary least squares (OLS) estimators are inconsistent; generalized method of moments (GMM) estimators are consistent but less efficient than maximum likelihood (ML) estimators (Gouriéroux et al., 2010). For ML estimation or quasi-maximum likelihood (QML) estimation of a dynamic panel data model covering short periods, the main difficulty lies in modeling the initial values of the endogenous variable, Δy_1. An incorrect treatment of the initial values will cause inconsistency and serious bias. The traditional way of handling this problem is to predict initial values using the observed values of the regressors (Hsiao et al., 2002; Su and Yang, 2015). However, this traditional strategy has some disadvantages. It assumes that the starting time of data generation, which is essentially unknown, is known; it uses a linear projection that may be misspecified; and it requires that the time-varying regressors are first-difference stationary, which may not hold.

To solve the problems with traditional estimation approaches, we use maximum-likelihood type estimation (M-estimation), which was developed by Yang (2018). The approach starts with conditional quasi-likelihood, with the initial differences Δy_1 being treated as if they are exogenous. The method then makes corrections to the conditional quasi-score functions. It turns out that the adjustments of the conditional quasi scores are free from the specifications of the distribution of initial differences, resulting in estimators that are free from the initial conditions. Compared with the previous methods that use predicted initial values (Hsiao et al., 2002; Elhorst, 2010; Su and Yang, 2015), Yang's method requires very limited knowledge about the process before data collection and a minimum set of assumptions.

The models and estimation methods in this paper are closely related to Yang (2018), but we extend Yang (2018) by applying his model and method in a difference-in-differences (DID) framework. The coefficient β in our model and the conventional DID method have the same interpretation. To illustrate our meaning, we consider a special case in which $\rho = \lambda_1 = \lambda_2 = \lambda_3 = 0$ and $T = 2$, as in Cameron and Trivedi (2005, Sec. 22.6). The model becomes $\Delta y_i = \beta \Delta D_i + \Delta\tau + \Delta\varepsilon_i$, where subscript t is dropped. Therefore, the "treatment effect" β can be estimated by an OLS regression of Δy on an intercept and the binary regressor, giving:

$$\hat{\beta} = \Delta\bar{y}^{\text{tr}} - \Delta\bar{y}^{\text{nt}},$$

where $\Delta\bar{y}^{\text{tr}}$ and $\Delta\bar{y}^{\text{nt}}$ are the sample averages of Δy_i for the treated and untreated observations, respectively. This estimator is similar to the DID estimator because the time difference is calculated separately for the treated and untreated groups; then, the difference in the time differences is estimated. For more details, see Cameron and Trivedi (2005, p. 769).

Compared with a simple DID model, our model incorporates dynamic, spatial, spatiotemporal, and unit-specific effects. In a situation in which temporal effects are present, excluding the dynamic term will lead to model misspecification. Allowing for dynamics in the underlying process could be crucial for obtaining consistent estimates of $\hat{\beta}$ on D_{it} or ΔD_{it}. Additionally, allowing for spatial dependence is essential, given the evidence of spatial spillovers in the housing market, as documented in the literature.

Another difference between our setting and the conventional DID method is that we do not have the dummy variable D_t for the following reasons. First, different from a simple DID model, we have a dynamic term. This lagged dependent variable captures the time effects to a large extent. Second, the use of a short-term panel ensures temporal homogeneity before and after the policy intervention. Both the private and public housing markets are unlikely to be subject to common shocks within a very short period, and therefore, D_t might be irrelevant.[20] Third, we do not have D_t to avoid a *dummy variable trap*—a scenario in which covariates are highly correlated. This issue stems from the correlation between D_t and the quarter dummies. It also stems from a high degree of correlation between $\varDelta D_t$ and $\varDelta D_{it}$. The following is an example of the sample that we use: two periods before and four periods after policy implementation.[21] The original time dummy and group-specific time dummy are as follows:

$$D_t{}^{tr,nt} = ((0,0,1,1,1,1)', (0,0,1,1,1,1)'), \text{ and } D_{it}{}^{tr,nt} = ((0,0,1,1,1,1)', (0,0,0,0,0,0)').$$

After the first difference, $D_t{}^{tr,nt}$ and $D_{it}{}^{tr,nt}$ become,

$$\Delta D_t{}^{tr,nt} = ((0,0,1,0,0,0)', (0,0,1,0,0,0)'), \text{ and } \Delta D_{it}{}^{tr,nt} = ((0,0,1,0,0,0)', (0,0,0,0,0,0)').$$

where the superscript denotes the treatment group and nontreatment group. Clearly, ΔD_t and ΔD_{it} are highly correlated. Therefore, we exclude D_t from the model to avoid the dummy variable trap.

Finally, we discuss a potential issue when using a treatment-control strategy. The stable unit treatment value assumption (SUTVA) implies that potential outcomes for spatial unit *i* are unrelated to the treatment status of other spatial units. Violations of the SUTVA assumption invalidate the identification of causal effects (Delgado and Florax, 2015; Chagas et al., 2016). We believe that this is not a concern in our context for the following reasons. The SUTVA assumption will be violated if new PRs are able to change the treatment status. The first possible scenario is that they are willing and able to purchase a private flat after the purchase restriction requiring them to wait three years to be eligible to purchase a public flat. In this case, private housing prices will be affected due to increased demand. However, as stated in Section 2, it is very difficult for a typical household to purchase private property, given the significant price difference between the two housing sectors. Another possibility is that new PRs become citizens and are not restricted by the purchase restrictions. However, according to the

[20] Another point is that, although the conventional DID method requires the assumption of parallel trends, this assumption is likely to be met because we focus on a very short period. We show such evidence in Figure 1. The public housing and private housing price indices show similar trends before the implementation of the purchase restriction.

[21] A sample of seven periods is involved in the main analysis, but only the dependent variable involves the initial period of data. All other covariates do not.

immigration policy, a person having spent two years as a PR could apply for citizenship, and the application takes six to twelve months to process. Therefore, even if an individual could successfully obtain citizenship, it takes a new PR at least two and a half years to become a citizen. Because of the time it takes to change from a PR to a citizen, the SUTVA is unlikely to be violated in our analysis.

4. Data

To conduct our analysis, we rely on three datasets. The first dataset we utilize consists of administrative data on all resale public flat transactions since January 1990 from the Singapore government's data sharing website.[22] The website provides information about the transaction times at the year-month level, resale prices, towns, streets, block numbers, flat types, flat models, sizes, floor ranges, and years of lease commencement.[23] The transaction time is the date of approval of resale transactions before March 2012. After March 2012, the transaction time is the date of registration for resale transactions. The gap between the two dates is a few weeks. We use samples from the period after this change in the data structure, except for one table in the placebo tests.

The second dataset is transaction-level data for all private residential transactions in Singapore since January 1, 1995 from the Real Estate Information System (REALIS) maintained by the Urban Redevelopment Authority of Singapore (URA).[24] The data contain information about transaction dates at the year-month-day level, transaction prices, housing unit attributes, and project attributes. We exclude transactions that occurred under an en bloc sales (collective sales) agreement because they are not conducted in a standard market and could thus bias our results.[25]

The third dataset contains the circumference of each town, the length of the common borders between towns, and the distance between towns obtained from ArcMap, a geographic information system (GIS) software. The map of Singapore comes from the government's website.[26] We use this geographic information to calculate our weight matrices.

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[22] Source: https://data.gov.sg/.

[23] The flat types include 1-room, 2-room, 3-room, 4-room, and 5-room flats, executive flats, and multigeneration flats. The flat models include standard models, improved models, and other models. Public housing has a 99-year leasehold.

[24] https://spring.ura.gov.sg/lad/ore/login/index.cfm.

[25] An en bloc sale refers to the sale of all housing units within a housing development to a single party or a consortium/joint venture. The price of housing bought through an en bloc sale is higher than the market price.

[26] https://services2.hdb.gov.sg/webapp/AA11EMAP/AA11PMainPage#.

Similar to many other recently developed estimation methods, Yang's (2018) method requires balanced panel data. Therefore, we aggregate transaction-level data into quarterly data for each town. We first compute the floor-area-adjusted price, which equals the transaction price divided by the corresponding floor area (square meters). Then, the median of the floor-area-adjusted prices of all the transactions within a quarter for each town is calculated. More detailed or frequent data, such as town-month-level data, will not provide us with a balanced panel because public houses are not frequently transacted.

Although we lose information at a detailed level by aggregating the data, aggregation should not be a significant concern. As mentioned earlier, the most important characteristic determining the prices within each housing sector is location, which we control for. In addition, public houses in Singapore are very homogeneous. The private non-landed housing within each residential project are also homogenous.[27] This homogeneity mitigates our concern about the information that we might lose, although we are unable to control for the differences across private housing projects.

In the main analysis, we use a sample of seven quarters from 2012Q4 to 2014Q2. The DID model requires at least two periods. A dynamic panel model requires one additional period for the initial value, and the seasonality of housing prices requires four additional quarters. We use 2012Q4 as the initial observation because the government implemented the purchase restriction in 2013Q3 as well as another related policy on January 11, 2013. If we use 2013Q1 as the initial observation, our key variable, D_{it}, would have only one quarter (2013Q2) before the purchase restriction was imposed. More importantly, the Yang (2018) method is robust to the initial value, and the key variable does not use the initial observation.[28] In addition to this sample period (2012Q4-2014Q2), we use another seven-quarter sample that excludes the time during which the policy was implemented (2012Q4-2013Q2 and 2013Q4-2014Q3), as a robustness check.

Table 1 shows the summary statistics at the town level for the floor-area-adjusted median price of both public and private housing two quarters before the policy and four quarters after the policy took effect. The public housing prices are approximately 40% of the private housing prices even before policy implementation. The price difference between public and private housing within the same town is mainly due to institutional features and structural attributes. In the model, we use town-by-property fixed effects to control for price heterogeneity between

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[27] A real estate project in Singapore includes hundreds or thousands of housing units.

[28] When using 2013Q1 as the initial observation, we obtain a significant coefficient for the policy variable of interest, but we prefer the sample used in the main analysis for obvious reasons.

public and private houses within the same town. All 26 towns experienced a decrease in public housing prices after the policy was announced, whereas only 14 out of 26 towns had a similar experience in the private market. At the national level, while private housing prices decreased by 0.04%, public housing prices decreased by 4.62%.

5. Results and Robustness Checks

5.1 Main Results

To demonstrate the advantage of our FE-SDPD model, we start with models that do not include dynamic and spatial terms. To estimate such a model, we use OLS estimation. Because the simple model does not require an initial value for the dynamic term, we start with the sample period of 2013Q1 to 2014Q2.

Given that the OLS method does not require a balanced panel, we first report the results based on the original transaction-level data in Table A1 in the Appendix.[29] Panel A reports the results using only public housing data after controlling for town fixed effects and seasonality. Panel B reports the results using both public housing and private housing, controlling for town-by-property fixed effects and seasonality. Column (1) in Panel A shows that public housing prices dropped by 4.59% immediately after the policy was implemented; column (1) in Panel B shows that public housing prices declined by 2.81% after policy implementation relative to private housing prices. A comparison of the two coefficients indicates that using only public housing data is likely to overestimate the cooling effect of the purchase restriction. In addition, we extend the sample up to three years after policy implementation. The estimated coefficient in the last column of Panel A becomes 9.51%, and that of Panel B becomes 6.21%, indicating that a simple model without dynamic and spatial terms is sensitive to sample selection. For other control variables, the results in both panels demonstrate that prices are higher in other quarters than in the first quarter.

We then show the results using aggregated data in Table A2, using quarterly data on both public and private housing at the town level, controlling for town-by-property fixed effects and seasonality. The coefficient for the "after policy" and the coefficient for the fourth calendar quarter become insignificant. This finding suggests that these two dummies might have strong correlations in the quarterly data. The interaction terms indicate that public housing prices dropped after the policy implementation, compared to private housing prices.

[29] The results of Table A1 and Table A2 are obtained using STATA.

However, the results from such a simple model are likely biased because they do not control for temporal effects and spatial dependence. We use our M-estimation method for all the following tables because the OLS method would bias the estimation of an FE-SDPD model. In addition, for models with spatial lags, the marginal effect is no longer the value of β. We follow LeSage and Pace (2009) and report the total impact.[30] While the inference methods regarding the total impact of the FE-SDPD model are not well developed, we obtain the standard errors of the total impact from 500 bootstrap samples.[31]

Using our FE-SDPD model, we first adopt an approach similar to an event study, separately estimating Model (1) using public and private housing. Columns (1)-(3) in Table 2 show the results using public housing data, and columns (4)-(6) present the results using private housing data. Columns (1) and (4) report the specification with the spatial lag term, columns (2) and (5) present it with the spatial error term, and columns (3) and (6) show it with the spatial lag and space-time terms. Panel A reports the estimates from the FE-SDPD model, and Panel B presents the total impact based on the coefficients in Panel A for models with spatial lags.[32]

Panel A in Table 2 shows that the coefficients on the policy dummy directly from the FE-SDPD model are significantly negative when using public housing data. The total impact in Panel B indicates that public housing prices dropped significantly by 3.52%-4.20% after policy implementation.[33] However, the coefficient for the policy dummy and the total impact are negative but insignificant when using private housing data. If people who initially planned to purchase public flats bought private houses instead, we would see that the private housing prices increased after the policy was implemented. This outcome suggests that new PR households did not immediately seek private houses as alternatives after the policy went into effect. Results in Table 2 support our next strategy using private properties as a control group.

For other covariates, the coefficient for the dynamic term indicates that prices in the private housing market have a statistically significant temporal effect. The pattern is consistent with

[30] In our FE-SDPD model, the total impact in the short run is measured by the average of all the elements of $(I_n - \lambda_1 W_1)^{-1}\beta$.

[31] The bootstrapping method is as follows. First, in each bootstrap sample, we treat the initial differences, Δy_1, the same as in the original data, but give a random shock ϵ_{it}, which follows a standard normal distribution, to the error term Δu_{it} from the second time period. Second, we sequentially obtain $\Delta y_2, \ldots, \Delta y_7$ based on equation (2). Third, we use our M-estimation to obtain the coefficients and then the total impact. Lastly, we obtain the bootstrapped standard error of the total impact from 500 samples. The standard errors of the total impact slightly change when we increase or decrease the sample number. We acknowledge that the proposed bootstrap method for standard error calculation needs a theoretical justification. This issue, together with the issue of theoretically improving the method of modeling the initial values in each bootstrap sample can be a topic of future research.

[32] We report the total impact of all models with spatial lags, except in Tables A3-A6 in the Appendix as these tables are already lengthy.

[33] The marginal effect is the same as the coefficient for the model without a spatial lag term in column (2).

that documented in prior studies. Given the presence of a temporal effect, this finding also indicates that excluding the dynamic term leads to model misspecifications.

Regarding spatial effects, the results support our argument that spatial dependence exists in the housing market. Specifically, the coefficients for the spatial lag term indicate positive spillover effects in the public housing market. An increase in the prices of public housing in one town drives up the prices of other housing in neighboring towns. In contrast, the spatial lag effect is insignificantly negative in the private housing market. A negative effect could occur when houses in two neighboring towns are competitors (Elhorst et al., 2012). For example, buyers purchasing houses in one town would decrease the demand for houses in neighboring towns. Because the negative coefficients are not statistically significant, we believe that the competition effect does not play an important role in the private housing market. The coefficients for the space-time lag are marginally significant and positive in column (6), indicating that the private housing prices in one town are positively affected by the lagged private housing prices in neighboring towns. The coefficients for the spatial error terms are insignificant.

Regarding the seasonality in the housing market, the coefficients for the second and third calendar quarters are significantly positive compared with the first quarter. These findings are consistent with those of Ngai and Tenreyro (2014), who document that housing markets experience systematic above-trend increases in prices in the second and third quarters of each calendar year in the United Kingdom and the United States. We provide similar evidence in Singapore.

The results in Table 3 and the subsequent tables use the sample from both housing markets, with two additional specifications. Column (4) shows the result of a model with a spatial lag term and a spatial error term, and column (5) presents the result of a model with all three spatial terms. The magnitude of the coefficients on the interaction term is from 3.12%-4.12%, but the total impact indicates that the prices of public housing compared with those of private houses declined significantly, by 3.39%-5.31%. A comparison of Panels A and B demonstrates that the effect of the policy incorporates some indirect impact that is also negative.

The coefficients on the dynamic term in all specifications are significantly positive, indicating temporal effects of prices in the housing market. The coefficients on the spatial lag terms in columns (4) and (5) are positively significant, suggesting positive spillovers between neighboring units (different properties within the same town or houses in neighboring towns regardless of the property type). The coefficient on the space-time term is marginally statistically significant in column (3), suggesting some evidence of spatiotemporal effects. The coefficients on the spatial error terms indicate that there is negative spatial dependence in the disturbances.

We then extend the sample period up to three years after the policy implementation, as shown in Table A3.[34] All of these results are similar to our earlier findings in Table 3. One possible reason for the similarity is that the affected PRs obtained PR status on different dates before August 2013 and gradually became eligible to purchase resale flats after the policy took effect.

Overall, the policy effect from a simple model is larger than that from the FE-SDPD model. This finding suggests that a simple model without controlling for the temporal effect or spatial dependence is likely to overestimate the policy effect. In addition, while the results from simple models are sensitive to the sample period, the policy effects from the FE-SDPD model are stable across different samples.

5.2 Robustness Checks

After the main analysis, we perform a series of tests to show the robustness of our results. First, we use three alternative weight matrices. The results using boundary weights, power distance weights, and exponential distance weights are shown in Tables 4, 5, and 6, respectively. When distance-based matrices are used, the economic interpretation of neighborhood effects is different from that when contiguity-based spatial weights are applied. However, we focus on the variable indicating the policy impact. The policy effects from Tables 4-6 are similar to those in Table 3 using common border weights. Under the alternative weight matrices, we further extend our analyses to cover longer sample periods, and the results, given in Table A4, are consistent with those in Table A3.

Second, we perform falsification tests by conducting the analysis using randomly chosen dates for the policy. Specifically, we choose 2012Q3 (one year before the policy implementation), 2014Q3 (one year after the policy implementation), and 2015Q3 (two years after the policy implementation) to study whether public housing prices change after these placebo dates. We did not choose earlier dates as placebo tests because the town of Punggol offered private housing beginning only in 2011Q3. The corresponding results of the three falsification tests are shown in Tables 7, 8, and 9. The specifications in each table are the same as those in Table 3. We also extend the sample for the placebo tests using 2014Q3 and 2015Q3 as random dates, shown in Tables A5 and A6 in the Appendix. We do not extend the sample

[34] Further extended samples are used, and once again similar results (available upon request) are obtained.

period for the falsification test using 2012Q3 as the placebo date because doing so would include the policy date. The falsification tests using the placebo dates yield null results, supporting our argument that the purchase restriction is responsible for the price decrease in the public housing market.

As another robustness test, we exclude the quarter during which the policy was implemented and extend the sample period by one quarter to maintain the minimum sample period that our method requires (2012Q4-2013Q2 and 2013Q4-2014Q3). The results in Table 10 are consistent with those in Table 3.

5.3 Discussion of Mechanisms

Finally, we discuss some possible mechanisms. Given the nature of the purchase restriction, one mechanism for the price decline is that the policy decreases demand in the public housing market by directly rendering new PRs ineligible to purchase houses. We then look at the supply side by examining the transaction volume. An ideal way to do so is to have information about buyers' residential status. Unfortunately, this information is not available at the individual or town level. Therefore, we use the transaction volume of houses purchased by both PRs and citizens. The results are presented in Tables A7-A9. We do not find that the total transaction volume in the public housing market significantly changed. This finding is similar to that of Sun et al. (2017) who evaluated home purchase restrictions in Beijing and found that in submarkets with a less elastic housing supply, the effects of purchase restrictions were greater on price and lesser on quantity.

There are some explanations for the significant change in housing prices but not for transaction volume. The first reason is the inelastic supply of resale public flats in the short run. Some institutional features explain this inelasticity. The land supply is inelastic given the limited land in Singapore, a city-state. When the land supply is limited, the housing supply could increase by increasing the building heights. However, it takes time to build new flats and to wait for them to enter the resale market. In addition, many policies restrict the supply of resale public flats. For example, owners of public housing are required to fulfill the minimum occupation period (MOP) of five years before they sell their flats.

The second reason is the small number of new PRs and their high willingness to pay for resale public flats. There have been only 30,000 new PRs each year since 2010, which is a small number compared to the number of all residents who are eligible to purchase resale public flats (4 million). Furthermore, new PRs are willing to pay a higher price for a resale public flat than citizens, as discussed in Section 2. Intuitively, this policy, which targets a small number of buyers who have a higher willingness to pay has significant effects on prices but not on the total transaction volume.

6. Conclusions

This paper investigates the short-term impact of a dramatic purchase restriction on housing prices in Singapore. Given that the policy is imposed on new PRs purchasing resale public flats, we use private houses as a control group. To evaluate the policy effect, we adopt a fixed-effects dynamic spatial panel model. To estimate our model, we use the M-estimation method developed by Yang (2018), which has many advantages over traditional methods. Our model and estimation method are attractive for other studies involving spatial dependence, temporal effects, unit-specific effects, and short-term analysis.

We find that, within a short time horizon after the purchase restriction went into effect, public housing prices declined by approximately 3%-5% relative to private housing prices. These results survive both robustness and falsification tests. We also show that models that ignore spatial and temporal effects can overestimate policy effects. In contrast to price, we do not find significant responses to the policy in the transaction volume. The inelastic supply of resale public flats, the small number of new PRs, and their high willingness to pay may explain our results.

Our findings are informative for policymakers. Many cities in the U.S., the U.K., China, and Singapore have been experiencing rapid housing price increases during the COVID-19 pandemic. Given the lessons learned in the 2000s that overheating in the housing market in the U.S. contributed to the global economic downturn from 2007 to 2009, the governments in the countries above may want to curb housing price increases. Our analysis indicates that demand-side purchase restrictions may be an appropriate policy.

There are several avenues for future research. First, it would be interesting to extend Yang's method to allow for unbalanced panel data. This extension would allow empirical studies to use transaction-level data. Second, we use a simple bootstrap method to calculate the standard errors of the total impact. Future work could consider developing better bootstrap methods for the inference of the total impact.

References

Accetturo, A., Manaresi, F., Mocetti, S., Olivieri, E., 2014. Don't Stand so close to me: The urban impact of immigration. *Regional Science and Urban Economics* 45, 45-56.

Agarwal, S., Qian, W., 2014. Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore. *American Economic Review* 104, 4205-30.

Agarwal, S., Qian, W., 2017. Access to home equity and consumption: Evidence from a policy experiment. *Review of Economics and Statistics* 99, 40-52.

Baltagi, B. H., Blien, U., Wolf, K., 2012. A dynamic spatial panel data approach to the German wage curve. *Economic Modelling* 29, 12-21.

Brady, R. R., 2014. The spatial diffusion of regional housing prices across US states. *Regional Science and Urban Economics* 46, 150-166.

Cameron, A. C., Trivedi, P. K., 2005. *Microeconometrics: methods and applications*. Cambridge University Press.

Case, K. E., Shiller, R. J., 1990. Forecasting prices and excess returns in the housing market. *Real Estate Economics* 18, 253-273.

Chagas, A. L., Azzoni, C. R., Almeida, A. N., 2016. A spatial difference-in-differences analysis of the impact of sugarcane production on respiratory diseases. *Regional Science and Urban Economics* 59, 24-36.

Chia, W. M., Li, M., Tang, Y., 2017. Public and private housing markets dynamics in Singapore: The role of fundamentals. *Journal of Housing Economics* 36, 44-61.

Cohen, J. P., Ioannides, Y.M., Thanapisitikul, W. W., 2016. Spatial effects and house price dynamics in the USA. *Journal of Housing Economics* 31, 1-13.

Cohen, J. P. and Zabel, J., 2020. Local house price diffusion. *Real Estate Economics* 48, 710-743.

Delgado, M. S., Florax, R. J., 2015. Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction. *Economics Letters* 137, 123-126.

Du, Z., Zhang, L., 2015. Home-purchase restriction, property tax and housing price in China: A counterfactual analysis. *Journal of Econometrics* 188, 558-568.

Elhorst, J. P., 2010. Dynamic panels with endogenous interaction effects when T is small. *Regional Science and Urban Economics* 40, 272-282.

Elhorst, J. Lacombe, D. J., Piras, G. (2012). On model specification and parameter space definitions in higher order spatial econometric models. *Regional Science and Urban Economics* 42, 211-220.

Gouriéroux, C., Phillips, P. C., Yu, J., 2010. Indirect inference for dynamic panel models. *Journal of Econometrics* 157, 68-77.

Hsiao, C., Pesaran, M. H., Tahmiscioglu, A. K., 2002. Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. *Journal of Econometrics* 109, 107-150.

Jia, S., Wang, Y., Fan, G. Z., 2018. Home-purchase limits and housing prices: Evidence from China. *The Journal of Real Estate Finance and Economics* 56, 386-409.

Jiang, S., Jin, X. (2021). Effects of investor sentiment on stock return volatility: A spatio-temporal dynamic panel model. *Economic Modelling*, 97, 298-306.

LeSage, J. P., Pace, R. K., 2009. *Introduction to spatial econometrics*. Chapman and Hall/CRC.

Li, V. J., Cheng, A. W. W., Cheong, T. S., 2017. Home purchase restriction and housing price: A distribution dynamics analysis. *Regional Science and Urban Economics* 67, 1-10.

Li, J., Xu, Y., 2015. Evaluating restrictive measures containing housing prices in China: A data envelopment analysis approach. *Urban Studies* 53, 2654-2669.

Li, X., Tang, Y., 2018. When natives meet immigrants in public and private housing markets. *Journal of Housing Economics* 41, 30-44.

Moscone, F., Tosetti, E., Canepa, A., 2014. Real estate market and financial stability in US metropolitan areas: A dynamic model with spatial effects. *Regional Science and Urban Economics* 49, 129-146.

Mussa, A., Nwaogu, U. G., Pozo, S., 2017. Immigration and housing: A spatial econometric analysis. *Journal of Housing Economics* 35, 13-25.

Ngai, L. R., Tenreyro, S., 2014. Hot and cold seasons in the housing market. *American Economic Review* 104, 3991-4026.

Qiu, F., Tong, Q. (2021). A spatial difference-in-differences approach to evaluate the impact of light rail transit on property values. *Economic Modelling*, 99, 105496.

Rosen, S., 1974. Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy* 82, 34-55.

Saiz, A., 2007. Immigration and housing rents in American cities. *Journal of Urban Economics* 61, 345-371.

Sharpe, J., 2019. Re-Evaluating the impact of immigration on the US rental housing market. *Journal of Urban Economics* 111, 14-34.

Somerville, C.T., Wang, L., Yang, Y., 2020. Using purchase restrictions to cool housing markets: A within-market analysis. *Journal of Urban Economics* 115, 103189.

Su, L., Yang, Z., 2015. QML estimation of dynamic panel data models with spatial errors. *Journal of Econometrics* 185, 230-258.

Sun, W., Zheng, S., Geltner, D. M., Wang, R., 2017. The housing market effects of local home purchase restrictions: Evidence from Beijing. *The Journal of Real Estate Finance and Economics* 55, 288-312.

Yang, Z., 2018. Unified M-estimation of fixed-effects spatial dynamic models with short panels. *Journal of Econometrics* 205, 423-447.

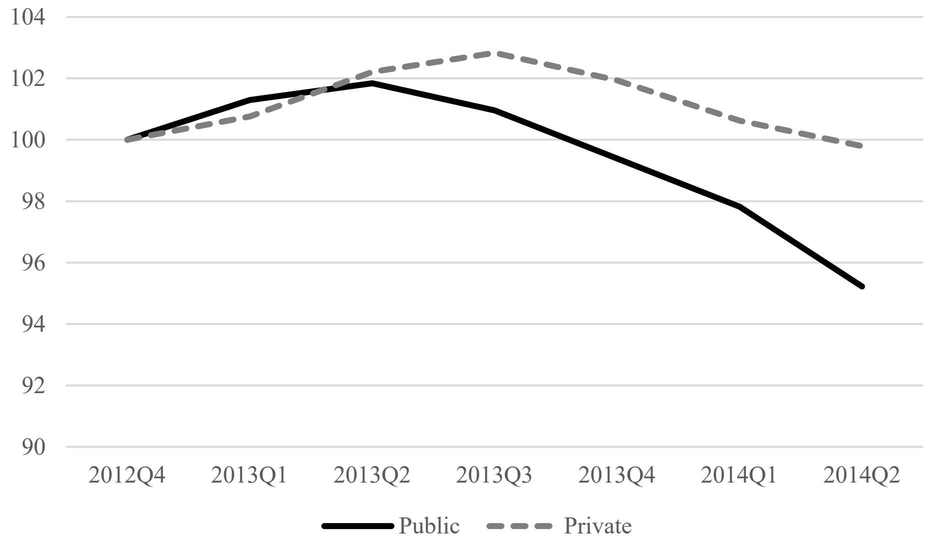
Yavas, A., Yildirim, Y., 2011. Price discovery in real estate markets: A dynamic analysis. *The Journal of Real Estate Finance and Economics* 42, 1-29.

Zhang, Y., Sun, Y., Stengos, T., 2019. Spatial dependence in the residential Canadian housing market. *The Journal of Real Estate Finance and Economics* 58, 223-263.

Zhou, Z, 2016. Overreaction to policy changes in the housing market: Evidence from Shanghai. *Regional Science and Urban Economics* 58, 26-41.

Zhu, B., Füss, R., Rottke, N.B., 2013. Spatial linkages in returns and volatilities among US regional housing markets. *Real Estate Economics* 41, 29-64.

Figure 1: Housing Price Indices, by Property Type



Note: The public housing price index is from the Singapore government's data sharing website, and the private housing price index is from Singapore's Real Estate Information System (REALIS). We use 2012Q4 as the reference quarter.

Table 1: Summary Statistics

Variable	Public housing prices				Private housing prices			
	Before policy		After policy		Before policy		After policy	
Sample	2013Q1-2013Q2		2013Q3-2014Q2		2013Q1-2013Q2		2013Q3-2014Q2	
Town	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Ang Mo Kio	5320.00	22.63	5038.25	160.03	11008.50	215.67	12737.92	1331.87
Bishan	5132.25	12.37	4887.75	143.56	13973.00	2129.81	13343.08	1087.98
Bishan	5754.75	78.14	5616.75	153.56	11927.25	457.14	14535.67	1702.29
Bukit Batok	4848.50	50.20	4569.58	192.60	12689.50	1463.00	11504.67	1107.84
Bukit Merah	6483.50	28.99	6210.58	153.77	19656.50	737.51	17368.25	1440.09
Bukit Panjang	4449.50	46.67	4239.33	237.33	12954.50	1478.56	12635.92	500.72
Bukit Timah	6393.25	66.82	6392.00	131.27	16512.25	1191.83	15346.67	1739.61
Central Area	6653.50	163.34	6518.92	450.34	23261.75	155.21	22880.33	867.72
Choa Chu Kang	4291.25	11.67	3960.50	185.60	8810.25	111.37	8881.25	378.75
Clementi	5674.00	169.00	5408.92	167.21	14359.00	1981.31	12531.58	794.97
Geylang	5433.50	17.68	5119.67	201.72	13994.00	190.92	13855.25	786.02
Hougang	4800.00	24.04	4539.67	144.38	10792.75	1656.40	13227.08	1379.06
Jurong East	4830.00	72.12	4618.42	142.38	8481.00	1074.10	10481.25	2679.02
Jurong West	4625.00	69.30	4400.83	187.80	11856.75	640.29	12505.42	1451.03
Kallang/Whampoa	5794.00	35.36	5487.75	116.22	14666.25	344.71	14964.08	1022.92
Marine Parade	6610.00	78.49	6379.17	231.00	16086.00	25.46	15832.08	403.78
Pasir Ris	4373.00	52.33	4126.67	111.20	10099.00	222.03	10657.92	210.37
Punggol	5345.75	117.03	4759.00	257.96	9377.75	608.47	9550.00	1487.57
Queenstown	6477.00	239.00	6407.75	175.02	16831.50	327.39	15411.08	1569.62
Sembawang	4504.75	34.29	4231.25	199.95	9016.00	59.40	9410.17	420.50
Sengkang	5028.25	111.37	4657.67	234.43	12389.50	72.83	11989.25	553.53
Serangoon	5211.00	144.25	5136.92	164.08	14524.00	2224.56	14097.92	1004.79
Tampines	4824.00	5.66	4632.25	125.90	11060.25	266.23	10846.67	710.72
Toa Payoh	5568.00	127.99	5265.33	141.07	14957.25	639.58	13381.67	204.72
Woodlands	4203.50	6.36	3993.83	144.73	9206.75	290.97	9307.17	230.12
Yishun	4610.00	70.71	4305.25	213.94	10326.75	1055.36	10805.33	551.91
National	5278.39	758.94	5034.77	811.42	13031.46	3567.95	13025.65	3128.09

Notes: Price is the floor-area-adjusted median price at the town-quarter level. "After policy" refers to the quarter during or after which the policy was implemented. For simplicity, we use "After policy" in all tables.

Table 2: Results for Public or Private Housing

	Public Housing			Private Housing		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Estimation from the FE-SDPD Model						
After policy	-0.0342	-0.0420	-0.0293	-0.0203	-0.0202	-0.0295
	(-7.23)	(-7.75)	(-2.91)	(-1.24)	(-1.59)	(-1.93)
Dynamic term	0.2449	0.2366	0.2316	0.3321	0.3612	0.3108
	(1.31)	(1.30)	(1.15)	(2.57)	(3.21)	(2.93)
Spatial lag	0.1645		0.1671	-0.1751		-0.1497
	(2.22)		(2.42)	(-1.09)		(-0.87)
Space-time			0.2359			0.3120
			(0.75)			(1.81)
Spatial error		0.1404			-0.2365	
		(1.42)			(-1.59)	
Second quarter	-0.0021	-0.0027	-0.0016	0.0639	0.0571	0.0678
	(-0.55)	(-0.60)	(-0.39)	(3.49)	(4.45)	(3.63)
Third quarter	0.0243	0.0308	0.0171	0.0712	0.0592	0.0579
	(3.79)	(4.31)	(1.11)	(1.81)	(2.17)	(1.40)
Fourth quarter	0.0108	0.0141	0.0056	0.0312	0.0239	0.0137
	(1.39)	(1.61)	(0.51)	(1.22)	(1.29)	(0.49)
Town fixed effect	YES	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy"						
Total impact	-0.0409		-0.0352	-0.0173		-0.0257
	[0.0104]		[0.0124]	[0.0210]		[0.0240]

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 3: Results for Public and Private Housing

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	-0.0381	-0.0400	-0.0412	-0.0312	-0.0343
	(-4.15)	(-5.45)	(-4.10)	(-5.23)	(-4.66)
Dynamic term	0.2832	0.3013	0.2785	0.3016	0.2756
	(2.70)	(3.02)	(2.72)	(3.03)	(2.63)
Spatial lag	-0.1218		-0.1021	0.4076	0.3538
	(-0.70)		(-0.49)	(2.94)	(2.19)
Space-time			0.3783		0.1336
			(1.71)		(0.74)
Spatial error		-0.2489		-0.7441	-0.6354
		(-1.39)		(-3.08)	(-2.26)
Second quarter	0.0288	0.0272	0.0324	0.0173	0.0199
	(2.90)	(3.87)	(3.17)	(3.56)	(3.14)
Third quarter	0.0445	0.0406	0.0303	0.0207	0.0197
	(1.79)	(2.51)	(1.02)	(1.46)	(1.16)
Fourth quarter	0.0163	0.0151	0.0017	0.0055	0.0029
	(1.19)	(1.51)	(0.10)	(0.71)	(0.30)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	-0.0339		-0.0374	-0.0527	-0.0531
	[0.0104]		[0.0130]	[0.0221]	[0.0308]

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 4: Robustness Checks – Length of Shared-Boundary Weights

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	-0.0366	-0.0385	-0.0397	-0.0364	-0.0382
	(-4.62)	(-5.32)	(-4.70)	(-5.30)	(-4.70)
Dynamic term	0.2787	0.2844	0.2809	0.2850	0.2745
	(2.70)	(2.91)	(2.69)	(2.76)	(1.09)
Spatial lag	-0.0721		-0.0604	0.2438	0.2124
	(-1.00)		(-0.76)	(1.37)	(0.13)
Space-time			0.1779		0.0855
			(1.45)		(0.72)
Spatial error		-0.1251		-0.3684	-0.3216
		(-2.06)		(-2.32)	(-1.82)
Second quarter	0.0274	0.0263	0.0287	0.0206	0.0220
	(3.09)	(3.41)	(3.11)	(2.73)	(2.56)
Third quarter	0.0417	0.0395	0.0348	0.0286	0.0274
	(1.95)	(2.26)	(1.57)	(1.47)	(1.39)
Fourth quarter	0.0147	0.0142	0.0082	0.0097	0.0077
	(1.17)	(1.29)	(0.64)	(0.97)	(0.80)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	-0.0342		-0.0374	-0.0482	-0.0486
	[0.0102]		[0.0119]	[0.0173]	[0.0218]

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 5: Robustness Checks – Power Distance Spatial Weights

	(1)	(2)	(3)	(4)	(5)	(6)
	Power = 1			Power = 2		
Panel A: Estimation from the FE-SDPD Model						
After policy × Public housing	-0.0326	-0.0395	-0.0307	-0.0324	-0.0353	-0.0290
	(-3.99)	(-5.86)	(-4.51)	(-4.49)	(-5.00)	(-4.27)
Dynamic term	0.2804	0.2842	0.3010	0.2784	0.2786	0.2919
	(2.69)	(2.82)	(2.73)	(2.62)	(2.75)	(2.68)
Spatial lag	0.1351		0.4064	0.1445		0.4314
	(0.69)		(2.28)	(1.02)		(2.60)
Spatial error		-0.2254	-0.7940		0.0147	-0.4902
		(-0.66)	(-1.45)		(0.08)	(-1.38)
Second quarter	0.0216	0.0263	0.0164	0.0212	0.0251	0.0152
	(2.44)	(3.85)	(2.58)	(2.54)	(2.94)	(2.33)
Third quarter	0.0317	0.0386	0.0194	0.0314	0.0378	0.0184
	(1.51)	(2.46)	(1.15)	(1.68)	(1.96)	(1.07)
Fourth quarter	0.0100	0.0142	0.0057	0.0098	0.0128	0.0051
	(0.80)	(1.43)	(0.68)	(0.82)	(1.06)	(0.55)
Town × Property fixed effect	YES	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"						
Total impact	-0.0377		-0.0518	-0.0379		-0.0509
	[0.0281]		[0.0433]	[0.0166]		[0.0302]

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 6: Robustness Checks – Exponential Distance Spatial Weights

	(1)	(2)	(3)	(4)	(5)	(6)
	Exponent = 0.01			Exponent = 0.02		
Panel A: Estimation from the FE-SDPD Model						
After policy × Public housing	-0.0331	-0.0395	-0.0312	-0.0321	-0.0353	-0.0301
	(-4.14)	(-5.96)	(-4.76)	(-4.52)	(-5.02)	(-4.98)
Dynamic term	0.2802	0.2846	0.3008	0.2788	0.2786	0.2917
	(2.70)	(2.81)	(2.72)	(2.63)	(2.73)	(2.66)
Spatial lag	0.1191		0.3969	0.1648		0.3892
	(0.58)		(2.20)	(0.94)		(2.53)
Spatial error		-0.2402	-0.8002		0.0161	-0.4243
		(-0.66)	(-1.33)		(0.07)	(-1.12)
Second quarter	0.0220	0.0263	0.0166	0.0207	0.0251	0.0162
	(2.45)	(3.89)	(2.63)	(2.40)	(2.93)	(2.50)
Third quarter	0.0325	0.0384	0.0199	0.0307	0.0378	0.0207
	(1.60)	(2.48)	(1.18)	(1.72)	(1.95)	(1.20)
Fourth quarter	0.0103	0.0144	0.0061	0.0093	0.0128	0.0060
	(0.82)	(1.46)	(0.75)	(0.77)	(1.05)	(0.66)
Town × Property fixed effect	YES	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"						
Total impact	-0.0375		-0.0517	-0.0384		-0.0493
	[0.0161]		[0.0433]	[0.0164]		[0.0280]

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 7: Placebo Tests – Using 2012Q3 as a Placebo Date

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	0.0110	0.0193	-0.0007	0.0030	0.0019
	(0.36)	(1.21)	(-0.00)	(0.00)	(0.00)
Dynamic term	0.6212	0.6913	0.5850	0.5501	0.5311
	(1.62)	(2.31)	(0.00)	(0.00)	(0.00)
Spatial lag	0.2694		0.2263	0.5081	0.4389
	(1.82)		(0.00)	(0.00)	(0.00)
Space-time			0.3383		0.1162
			(0.00)		(0.00)
Spatial error		0.1012		-0.4325	-0.3384
		(0.80)		(-0.00)	(-0.01)
Second quarter	0.0099	0.0157	0.0088	0.0057	0.0066
	(0.88)	(1.47)	(-0.00)	(-0.00)	(-0.00)
Third quarter	-0.0135	-0.0195	-0.0085	-0.0067	-0.0069
	(-0.75)	(-1.30)	(-0.00)	(-0.00)	(-0.00)
Fourth quarter	0.0103	0.0137	0.0157	0.0087	0.0107
	(0.79)	(1.06)	(-0.00)	(-0.00)	(-0.00)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	0.0150		-0.0009	0.0060	0.0033
	[0.0155]		[0.0188]	[0.0247]	[0.0294]

Notes: The sample period is from 2011Q4 to 2013Q2. The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B. The *t*-values close to zero in columns (3)-(5) in Panel A are likely the result of the coexistence of multiple spatial terms. Another reason might be that the Singapore government changed the data structure for transactions beginning in March 2012.

Table 8: Placebo Tests – Using 2014Q3 as a Placebo Date

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	-0.0151	-0.0130	-0.0123	-0.0099	-0.0163
	(-1.02)	(-0.85)	(-0.54)	(-0.28)	(-0.77)
Dynamic term	0.5540	0.5637	0.5672	0.5719	0.5810
	(2.98)	(3.53)	(2.51)	(2.36)	(1.95)
Spatial lag	-0.0834		-0.0680	0.1504	-0.5422
	(-0.35)		(-0.24)	(0.15)	(-1.84)
Space-time			0.1696		0.5613
			(0.31)		(0.53)
Spatial error		-0.1010		-0.2414	0.4031
		(-0.46)		(-0.24)	(1.40)
Second quarter	0.0137	0.0134	0.0161	0.0126	0.0232
	(1.42)	(1.49)	(1.30)	(1.42)	(1.13)
Third quarter	0.0048	0.0040	0.0036	0.0029	0.0047
	(0.33)	(0.29)	(0.22)	(0.17)	(0.20)
Fourth quarter	-0.0003	0.0002	0.0013	0.0009	0.0016
	(-0.02)	(0.02)	(0.10)	(0.08)	(0.08)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	-0.0140		-0.0115	-0.0116	-0.0106
	[0.0127]		[0.0139]	[0.0213]	[0.0243]

Notes: The sample period is from 2013Q4 to 2015Q2. The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 9: Placebo Tests – Using 2015Q3 as a Placebo Date

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	0.0006	0.0003	0.0020	0.0002	0.0020
	(0.07)	(0.03)	(0.23)	(0.03)	(0.18)
Dynamic term	0.1626	0.1641	0.1631	0.1640	0.1631
	(1.42)	(1.53)	(1.47)	(1.51)	(1.50)
Spatial lag	-0.1577		-0.1463	0.0501	-0.1471
	(-1.02)		(-0.83)	(0.08)	(-0.32)
Space-time			0.1033		0.1035
			(0.29)		(0.22)
Spatial error		-0.1627		-0.2153	0.0008
		(-1.10)		(-0.34)	(0.00)
Second quarter	0.0029	0.0022	0.0018	0.0020	0.0018
	(0.55)	(0.47)	(0.29)	(0.47)	(0.30)
Third quarter	-0.0161	-0.0142	-0.0181	-0.0136	-0.0181
	(-1.77)	(-1.67)	(-1.73)	(-1.22)	(-1.01)
Fourth quarter	-0.0212	-0.0183	-0.0214	-0.0173	-0.0214
	(-2.27)	(-2.68)	(-2.26)	(-1.53)	(-1.46)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	0.0005		0.0017	0.0002	0.0018
	[0.0070]		[0.0076]	[0.0111]	[0.0116]

Notes: The sample period is from 2014Q4 to 2016Q2. The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table 10: Robustness Checks – From 2012Q4 to 2014Q3 Excluding 2013Q3

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	-0.0354	-0.0385	-0.0379	-0.0318	-0.0315
	(-4.57)	(-5.57)	(-4.81)	(-2.88)	(-4.15)
Dynamic term	0.4756	0.4746	0.4667	0.4609	0.4633
	(4.43)	(5.20)	(4.06)	(3.65)	(4.25)
Spatial lag	-0.0580		-0.0428	0.3946	0.3993
	(-0.29)		(-0.17)	(1.38)	(1.88)
Space-time			0.2440		-0.0162
			(0.62)		(-0.05)
Spatial error		-0.1845		-0.6226	-0.6333
		(-0.92)		(-2.03)	(-2.71)
Second quarter	0.0285	0.0282	0.0308	0.0188	0.0185
	(2.82)	(3.58)	(3.01)	(2.58)	(2.79)
Third quarter	0.0000	0.0018	0.0019	0.0039	0.0038
	(0.00)	(0.24)	(0.19)	(0.66)	(0.58)
Fourth quarter	0.0049	0.0062	-0.0036	-0.0014	-0.0010
	(0.28)	(0.47)	(-0.13)	(-0.10)	(-0.06)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	-0.0335		-0.0363	-0.0526	-0.0525
	[0.0093]		[0.0099]	[0.0149]	[0.0242]

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B. The coefficient and the *t*-value for "Third quarter" are close to zero in column (1), likely the result of the selected sample and our extensive model, which incorporates many time effects.

Appendix

Table A1: Results of a Simple Model Using Transaction-Level Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample Period from 2013Q1 to	2014Q2	2014Q3	2014Q4	2015Q1	2015Q2	2015Q3	2015Q4	2016Q1	2016Q2
Panel A: Sample of Public Housing									
After policy	-0.0459***	-0.0558***	-0.0559***	-0.0673***	-0.0800***	-0.0864***	-0.0864***	-0.0911***	-0.0951***
	(-28.70)	(-37.96)	(-37.35)	(-46.65)	(-57.87)	(-63.34)	(-62.51)	(-66.93)	(-70.75)
Second quarter	-0.0028	-0.0028	-0.0029	0.0144***	-0.0056***	-0.0056***	-0.0056***	0.0039***	-0.0034**
	(-1.61)	(-1.59)	(-1.57)	(8.56)	(-3.70)	(-3.62)	(-3.60)	(2.72)	(-2.51)
Third quarter	0.0061***	-0.0127***	-0.0127***	0.0066***	0.0066***	-0.0099***	-0.0099***	0.0001	0.0003
	(2.79)	(-6.95)	(-6.81)	(3.87)	(3.79)	(-6.33)	(-6.25)	(0.10)	(0.19)
Fourth quarter	0.0213***	0.0263***	-0.0133***	0.0098***	0.0142***	0.0164***	-0.0035**	0.0076***	0.0086***
	(8.79)	(10.88)	(-6.59)	(5.48)	(7.79)	(8.91)	(-2.11)	(5.00)	(5.57)
Town × Property FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	23825	27978	32193	35942	40845	45343	49973	54108	59588
Adjusted R^2	0.580	0.585	0.582	0.585	0.586	0.591	0.590	0.591	0.590
Panel B: Sample of Both Private Housing and Public Housing									
After policy × Public housing	-0.0281***	-0.0357***	-0.0467***	-0.0499***	-0.0567***	-0.0550***	-0.0580***	-0.0582***	-0.0621***
	(-8.89)	(-12.01)	(-16.48)	(-18.10)	(-21.19)	(-21.16)	(-22.79)	(-23.08)	(-24.89)
After policy	-0.0155***	-0.0203***	-0.0141***	-0.0177***	-0.0230***	-0.0316***	-0.0293***	-0.0320***	-0.0329***
	(-6.33)	(-8.88)	(-6.37)	(-8.38)	(-11.51)	(-16.37)	(-15.42)	(-17.27)	(-18.21)
Second quarter	0.0235***	0.0234***	0.0229***	0.0293***	0.0181***	0.0175***	0.0168***	0.0216***	0.0160***
	(12.41)	(12.40)	(12.16)	(16.90)	(11.49)	(11.17)	(10.73)	(14.83)	(11.68)
Third quarter	0.0293***	0.0126***	0.0134***	0.0213***	0.0232***	0.0029*	0.0027	0.0081***	0.0085***
	(11.48)	(6.04)	(6.48)	(11.28)	(12.26)	(1.71)	(1.62)	(5.22)	(5.45)
Fourth quarter	0.0327***	0.0377***	0.0137***	0.0232***	0.0267***	0.0291***	0.0112***	0.0169***	0.0173***
	(12.19)	(14.33)	(6.16)	(11.82)	(13.63)	(14.96)	(6.41)	(10.51)	(10.75)
Town × Property FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	48328	54855	61588	67222	75759	84004	91435	98025	107386
Adjusted R^2	0.912	0.914	0.916	0.917	0.917	0.917	0.918	0.918	0.918

Notes: The dependent variable is the log of price per square meter for each transaction. The *t* statistics are reported in parentheses. Panel A reports the results using public housing data, and panel B reports the results using data from both markets. "After policy" is a dummy variable that takes the value of one if housing is transacted during or after September 2013. The transaction date in the original data is the year-month.

Table A2: Results of a Simple Model Using Data at the Town-Quarter Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample Period from 2013Q1 to	2014Q2	2014Q3	2014Q4	2015Q1	2015Q2	2015Q3	2015Q4	2016Q1	2016Q2
After policy × Public housing	-0.0380**	-0.0491***	-0.0557***	-0.0609***	-0.0674***	-0.0689***	-0.0706***	-0.0735***	-0.0772***
	(-2.31)	(-3.06)	(-3.60)	(-3.87)	(-4.13)	(-4.19)	(-4.39)	(-4.62)	(-4.93)
After policy	-0.0087	-0.0032	0.0001	0.0017	-0.0017	-0.0010	-0.0001	0.0003	-0.0008
	(-0.69)	(-0.25)	(0.01)	(0.14)	(-0.14)	(-0.08)	(-0.01)	(0.03)	(-0.07)
Second quarter	0.0259***	0.0259***	0.0259***	0.0270***	0.0181**	0.0181**	0.0181**	0.0194**	0.0150**
	(2.73)	(2.71)	(2.74)	(2.97)	(2.14)	(2.10)	(2.13)	(2.45)	(2.06)
Third quarter	0.0557***	0.0310***	0.0310***	0.0326***	0.0348***	0.0182**	0.0182**	0.0199**	0.0206**
	(4.42)	(2.89)	(2.93)	(3.44)	(3.52)	(2.00)	(2.02)	(2.43)	(2.54)
Fourth quarter	0.0293**	0.0293**	0.0121	0.0137	0.0159	0.0159	0.0036	0.0053	0.0060
	(2.33)	(2.31)	(1.15)	(1.45)	(1.61)	(1.58)	(0.40)	(0.64)	(0.74)
Town × Property FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	312	364	416	468	520	572	624	676	728
Adjusted R^2	0.981	0.981	0.982	0.980	0.979	0.978	0.979	0.979	0.979

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses. “After policy” is a dummy variable that takes the value of one if housing is transacted during and after 2013Q3.

Table A3: Results for Public and Private Housing across More Samples

	(1)	(2)	(3)	(4)	(5)
Sample / Variable			After policy × Public housing		
2012Q4 – 2014Q3	-0.0355	-0.0376	-0.0417	-0.0283	-0.0325
	(-4.70)	(-5.62)	(-4.28)	(-4.75)	(-4.81)
2012Q4 – 2014Q4	-0.0360	-0.0379	-0.0423	-0.0308	-0.0321
	(-4.98)	(-5.79)	(-4.65)	(-6.65)	(-5.17)
2012Q4 – 2015Q1	-0.0361	-0.0370	-0.0391	-0.0308	-0.0302
	(-4.44)	(-5.12)	(-4.30)	(-4.71)	(-4.19)
2012Q4 – 2015Q2	-0.0375	-0.0395	-0.0398	-0.0323	-0.0292
	(-3.81)	(-4.71)	(-3.45)	(-2.93)	(-3.61)
2012Q4 – 2015Q3	-0.0333	-0.0357	-0.0360	-0.0310	-0.0266
	(-3.72)	(-4.56)	(-3.61)	(-3.68)	(-3.91)
2012Q4 – 2015Q4	-0.0358	-0.0378	-0.0391	-0.0327	-0.0306
	(-4.27)	(-4.99)	(-4.20)	(-4.68)	(-4.55)
2012Q4 – 2016Q1	-0.0359	-0.0375	-0.0377	-0.0319	-0.0280
	(-4.36)	(-4.97)	(-4.24)	(-4.22)	(-4.01)
2012Q4 – 2016Q2	-0.0390	-0.0410	-0.0406	-0.0335	-0.0302
	(-4.80)	(-5.50)	(-4.60)	(-4.41)	(-4.39)
Dynamic term ρ	YES	YES	YES	YES	YES
Spatial lag λ_1	YES		YES	YES	YES
Space-time λ_2			YES		YES
Spatial error λ_3		YES		YES	YES
Seasonal effect	YES	YES	YES	YES	YES
Town × Property fixed effect	YES	YES	YES	YES	YES

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The t statistics are reported in parentheses.

Table A4: Result – Alternative Weights across More Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Weight	Boundary Length		Power Distance				Exponential Distance			
			Power = 1		Power = 2		Exponent = 0.01		Exponent = 0.02	
Sample/Variable	After policy × Public housing									
2012Q4–2014Q3	-0.0356	-0.0372	-0.0290	-0.0327	-0.0309	-0.0334	-0.0292	-0.0329	-0.0301	-0.0327
	(-4.96)	(-5.57)	(-4.46)	(-4.21)	(-4.73)	(-4.65)	(-4.48)	(-4.31)	(-4.68)	(-4.45)
2012Q4–2014Q4	-0.0363	-0.0379	-0.0307	-0.0340	-0.0344	-0.0323	-0.0310	-0.0343	-0.0318	-0.0342
	(-5.12)	(-5.78)	(-4.90)	(-4.75)	(-5.01)	(-5.01)	(-4.98)	(-4.95)	(-5.09)	(-5.00)
2012Q4–2015Q1	-0.0361	-0.0374	-0.0316	-0.0360	-0.0331	-0.0357	-0.0316	-0.0359	-0.0324	-0.0353
	(-4.34)	(-4.94)	(-3.90)	(-4.76)	(-4.09)	(-4.59)	(-3.91)	(-4.83)	(-4.05)	(-4.59)
2012Q4–2015Q2	-0.0382	-0.0403	-0.0315	-0.0382	-0.0338	-0.0379	-0.0315	-0.0382	-0.0329	-0.0374
	(-3.85)	(-4.60)	(-3.10)	(-4.34)	(-3.43)	(-4.27)	(-3.12)	(-4.49)	(-3.34)	(-4.31)
2012Q4–2015Q3	-0.0342	-0.0365	-0.0266	-0.0308	-0.0292	-0.0326	-0.0267	-0.0310	-0.0284	-0.0319
	(-3.69)	(-4.48)	(-2.85)	(-3.61)	(-3.32)	(-3.88)	(-2.90)	(-3.77)	(-3.24)	(-3.89)
2012Q4–2015Q4	-0.0369	-0.0386	-0.0301	-0.0339	-0.0325	-0.0356	-0.0302	-0.0342	-0.0318	-0.0351
	(-4.28)	(-4.95)	(-3.61)	(-3.97)	(-3.99)	(-4.34)	(-3.65)	(-4.12)	(-3.93)	(-4.32)
2012Q4–2016Q1	-0.0367	-0.0380	-0.0304	-0.0346	-0.0327	-0.0359	-0.0306	-0.0350	-0.0322	-0.0357
	(-4.28)	(-4.79)	(-3.61)	(-4.14)	(-3.99)	(-4.37)	(-3.70)	(-4.34)	(-3.98)	(-4.44)
2012Q4–2016Q2	-0.0404	-0.0416	-0.0332	-0.0382	-0.0360	-0.0397	-0.0334	-0.0386	-0.0354	-0.0395
	(-4.84)	(-5.37)	(-4.04)	(-4.56)	(-4.51)	(-4.94)	(-4.14)	(-4.78)	(-4.49)	(-5.00)
Dynamic term ρ	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Spatial lag λ_1	YES		YES		YES		YES		YES	
Spatial error λ_3		YES		YES		YES		YES		YES
Seasonal effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Town × Property FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses. Because of limited space, we report two specifications under each weight matrix.

Table A5: Placebo Tests – 2014Q3 as a Placebo Date across More Samples

	(1)	(2)	(3)	(4)	(5)
Sample			2013Q4 to 2015Q3		
After policy × Public housing	-0.0123	-0.0113	-0.0116	-0.0111	-0.0133
	(-1.09)	(-0.95)	(-0.93)	(-0.80)	(-0.98)
Dynamic term	0.5419	0.5437	0.5429	0.5439	0.5460
	(5.10)	(5.95)	(5.13)	(5.11)	(5.09)
Spatial lag	-0.0677		-0.0700	0.0182	-0.4457
	(-0.30)		(-0.31)	(0.05)	(-1.12)
Space-time			0.0642		0.3196
			(0.28)		(0.63)
Spatial error		-0.0744		-0.0901	0.3219
		(-0.36)		(-0.25)	(0.84)
Second quarter	0.0135	0.0131	0.0144	0.0130	0.0195
	(1.40)	(1.44)	(1.46)	(1.41)	(1.25)
Third quarter	-0.0035	-0.0031	-0.0033	-0.0030	-0.0052
	(-0.32)	(-0.31)	(-0.31)	(-0.30)	(-0.37)
Fourth quarter	-0.0010	-0.0005	-0.0003	-0.0004	-0.0009
	(-0.07)	(-0.04)	(-0.03)	(-0.03)	(-0.05)
Sample			2013Q4 to 2015Q4		
After policy × Public housing	-0.0185	-0.0179	-0.0172	-0.0163	-0.0192
	(-1.84)	(-1.60)	(-1.61)	(-1.38)	(-1.53)
Dynamic term	0.4322	0.4341	0.4349	0.4357	0.4365
	(5.64)	(6.00)	(5.68)	(5.69)	(5.66)
Spatial lag	-0.0182		-0.0283	0.1009	-0.2384
	(-0.09)		(-0.14)	(0.37)	(-0.70)
Space-time			0.1121		0.2316
			(0.64)		(0.75)
Spatial error		-0.0403		-0.1368	0.1962
		(-0.21)		(-0.51)	(0.57)
Second quarter	0.0122	0.0121	0.0138	0.0115	0.0167
	(1.39)	(1.40)	(1.50)	(1.47)	(1.24)
Third quarter	-0.0018	-0.0018	-0.0016	-0.0013	-0.0023
	(-0.18)	(-0.19)	(-0.15)	(-0.14)	(-0.20)
Fourth quarter	-0.0042	-0.0040	-0.0023	-0.0026	-0.0031
	(-0.36)	(-0.41)	(-0.20)	(-0.25)	(-0.23)
Town × Property fixed effect	YES	YES	YES	YES	YES

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses.

Table A6: Placebo Tests – 2015Q3 a Placebo Date across More Samples

	(1)	(2)	(3)	(4)	(5)
Sample			2014Q4 to 2016Q3		
After policy × Public housing	-0.0016	-0.0017	-0.0022	-0.0015	-0.0029
	(-0.20)	(-0.20)	(-0.28)	(-0.17)	(-0.39)
Dynamic term	0.1480	0.1463	0.1479	0.1482	0.1493
	(1.21)	(1.25)	(1.20)	(1.20)	(1.18)
Spatial lag	-0.1680		-0.1724	-0.2236	0.0579
	(-1.19)		(-1.17)	(-0.28)	(0.12)
Space-time			-0.0447		-0.0789
			(-0.15)		(-0.31)
Spatial error		-0.1607		0.0504	-0.2409
		(-1.13)		(0.07)	(-0.49)
Second quarter	0.0030	0.0024	0.0035	0.0032	0.0029
	(0.58)	(0.51)	(0.61)	(0.48)	(0.63)
Third quarter	-0.0050	-0.0045	-0.0044	-0.0052	-0.0031
	(-0.76)	(-0.72)	(-0.61)	(-0.63)	(-0.47)
Fourth quarter	-0.0209	-0.0178	-0.0208	-0.0219	-0.0164
	(-2.31)	(-2.66)	(-2.26)	(-1.41)	(-1.64)
Sample			2014Q4 to 2016Q4		
After policy × Public housing	0.0001	0.0000	0.0004	0.0000	0.0003
	(0.01)	(0.00)	(0.04)	(0.00)	(0.03)
Dynamic term	0.1724	0.1726	0.1728	0.1726	0.1727
	(1.50)	(1.56)	(1.55)	(1.52)	(1.54)
Spatial lag	-0.0617		-0.0602	-0.0110	-0.0327
	(-0.54)		(-0.49)	(-0.03)	(-0.76)
Space-time			0.0250		0.0194
			(0.08)		(0.06)
Spatial error		-0.0623		-0.0517	-0.0281
		(-0.55)		(-0.15)	(-0.25)
Second quarter	0.0026	0.0024	0.0024	0.0024	0.0023
	(0.50)	(0.46)	(0.39)	(0.46)	(0.39)
Third quarter	-0.0053	-0.0051	-0.0057	-0.0051	-0.0055
	(-0.80)	(-0.79)	(-0.75)	(-0.76)	(-0.70)
Fourth quarter	-0.0127	-0.0120	-0.0129	-0.0121	-0.0125
	(-1.62)	(-1.69)	(-1.54)	(-1.49)	(-1.50)
Town × Property fixed effect	YES	YES	YES	YES	YES

Notes: The dependent variable is the log of price. Price is the floor-area-adjusted median price at the town-quarter level. The *t* statistics are reported in parentheses.

Table A7: Results for Public Housing – Transaction Volume

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy	-0.0504	-0.0561	-0.0396	-0.0491	-0.0448
	(-0.77)	(-0.82)	(-0.65)	(-0.60)	(-0.70)
Dynamic term	0.0466	0.0451	0.0272	0.0469	0.0291
	(0.19)	(0.18)	(0.10)	(0.19)	(0.11)
Spatial lag	0.0850		0.0964	0.1032	-0.0444
	(1.50)		(1.42)	(0.35)	(-0.12)
Space-time			0.0763		0.0945
			(0.33)		(0.38)
Spatial error		0.0823		-0.0191	0.1429
		(1.41)		(-0.06)	(0.39)
Second quarter	0.2034	0.2212	0.2125	0.1996	0.2461
	(5.20)	(5.89)	(5.67)	(4.33)	(2.13)
Third quarter	0.1055	0.1162	0.0948	0.1032	0.1089
	(2.08)	(2.18)	(1.82)	(1.27)	(2.06)
Fourth quarter	0.0571	0.0623	0.0588	0.0559	0.0676
	(1.23)	(1.24)	(1.23)	(0.98)	(1.35)
Town fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy"					
Total impact	-0.0550		-0.0438	-0.0548	-0.0429
	[0.0559]		[0.0672]	[0.0620]	[0.0654]

Notes: The dependent variable is the log of transaction volumes at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table A8: Results for Private Housing – Transaction Volume

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy	-0.5178	-0.4791	-0.4572	-0.4788	-0.4572
	(-2.12)	(-2.33)	(-0.94)	(-1.43)	(-0.99)
Dynamic term	0.2829	0.2842	0.2809	0.2842	0.2809
	(1.62)	(1.74)	(1.64)	(1.64)	(1.64)
Spatial lag	-0.0510		-0.0388	0.0004	-0.0389
	(-0.61)		(-0.32)	(0.00)	(-0.54)
Space-time			0.0601		0.0601
			(0.16)		(0.15)
Spatial error		-0.0518		-0.0521	0.0001
		(-0.61)		(-0.18)	(0.00)
Second quarter	0.4768	0.4593	0.4952	0.4592	0.4953
	(3.00)	(2.88)	(3.25)	(2.18)	(2.98)
Third quarter	0.0635	0.0523	0.0289	0.0523	0.0289
	(0.27)	(0.24)	(0.09)	(0.21)	(0.09)
Fourth quarter	0.4013	0.3824	0.3993	0.3823	0.3993
	(1.99)	(1.97)	(1.93)	(1.56)	(2.04)
Town fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy"					
Total impact	-0.4927		-0.4401	-0.4790	-0.4401
	[0.2324]		[0.2551]	[0.2604]	[0.2638]

Notes: The dependent variable is the log of transaction volumes at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.

Table A9: Result for Public and Private Housing – Transaction Volume

	(1)	(2)	(3)	(4)	(5)
Panel A: Estimation from the FE-SDPD Model					
After policy × Public housing	0.1342	0.0944	0.3773	0.1565	0.3744
	(2.03)	(1.36)	(0.99)	(1.47)	(1.59)
Dynamic term	0.4308	0.4447	0.3412	0.4132	0.3454
	(3.96)	(4.07)	(3.03)	(4.03)	(3.10)
Spatial lag	0.1784		0.2122	0.4152	0.0693
	(1.56)		(0.55)	(1.54)	(0.11)
Space-time			0.4428		0.5016
			(1.03)		(2.08)
Spatial error		0.0832		-0.3445	0.1405
		(0.65)		(-1.11)	(0.34)
Second quarter	0.3681	0.4180	0.4733	0.2958	0.5332
	(4.12)	(4.56)	(5.56)	(2.87)	(3.20)
Third quarter	-0.1040	-0.1008	-0.1912	-0.0979	-0.2011
	(-0.95)	(-0.85)	(-1.17)	(-1.06)	(-1.54)
Fourth quarter	0.1209	0.1370	0.1753	0.1048	0.1978
	(0.96)	(1.01)	(1.48)	(1.02)	(1.50)
Town × Property fixed effect	YES	YES	YES	YES	YES
Panel B: Impacts of "After policy × Public housing"					
Total impact	0.1633		0.4789	0.2677	0.4023
	[0.1203]		[0.1627]	[0.2690]	[0.2504]

Notes: The dependent variable is the log transaction volumes at the town-quarter level. The *t* statistics are reported in parentheses in Panel A. The standard errors of the total impact are obtained from 500 bootstrap samples and are reported in brackets in Panel B.