Private land use for public housing projects: The Influence of a Government Announcement on Housing Markets in Hong Kong

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A B S T R A C T

Insufficient land supply and housing shortage limit the development in Hong Kong. To tackle such obstacles, the Hong Kong government launched a new housing initiative in June 2018, that is, to reallocate private housing sites for public housing in East Kowloon. Yet, the initiative may give rise to two important questions: (1) how does this initiative affect the housing searching behaviour in the housing market; and (2) in what way should the new public housing be developed, if it is to be compatible with the host neighborhood - by the public sector, or with the participation of the private sector. Little is known about the possible impacts of such an initiative.

To fill this research gap, this paper adopts an improved spatial econometric model by incorporating spatial and temporal information to explore the above two questions. Our results indicate that (1) the announcement of the initiative leads to a 5% change in time-on-market for private housing in East Kowloon; (2) people in private property prefer more to live near public housing developed by the private sector. These findings somehow echo the invasion theory of urban change: Neighborhood changes in private housing areas will spill-over to adjacent urban areas.

Keywords:
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Land use policy
Search behavior
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1. Introduction

For years, private property price in Hong Kong skyrocketed to an unimaginable level of 382.6 in May 2018 (set the basis of 100 in the year 1999), a rise of over 300% over the last 18 years. In contrast, one official report from the Statistical department of Hong Kong reveals that the average income level increased only 20% from 2011 to 2018, which is far behind the rising speed of private property price. On comparing the aforementioned two vital statistics to the other well-developed cities worldwide such as Sydney, San Francisco, and Tokyo, Hong Kong tails the above cities with the lowest ratio of average household income level to average private property price, suggesting that people in Hong Kong tops the other well-developed cities for the housing unaffordability issue.

Housing difficulties are not just in private property, but also in public housing. According to Hui et al. (2018), the shortage of public rental housing supply gives rise to the waiting time even extend to an average level of 5.5 years. To tackle such deficiencies, the Hong Kong government launched a new housing initiative in June 2018; that is, to reallocate private housing sites for public housing in East Kowloon (Legislative Council of The Hong Kong (LEGCO), 2018). Yet, the initiative may give rise to two important questions: (1) how does this announcement of the housing initiative affect the homebuyers' search behavior in the housing market, and (2) in what way should the new public housing be developed, if it is to be compatible with the host neighborhood − by the public sector (i.e. homeownership scheme, hereafter HOS), or with the private sector participation scheme (PSPS). Little is known about the possible impacts of such an initiative. Details of HOS and PSPS are addressed in section 2.

From the perspective of behavior research in housing and land use literature, the answers to the above two questions provide new angles to understand buyers' search behavior and predict home purchase behavior. First, the announcement of the new housing initiative is the signal to bring about some changes in the neighborhood area. The exploration of the first question enables us to understand how people respond to the new housing initiative in terms of housing search behavior. Second, for most of the residents in Hong Kong, they could hardly vote on or influence the new housing initiative making. However, they could vote with their feet by choosing to live close to or far from affordable housing in predicting the impact of this new housing initiative on buyers' purchase behavior. The answer to the second question, before massively enforcing the new housing initiative, not only is a timely and increasingly important policy topic but also helps the policymakers promote and execute this and other new housing initiatives.

In general, the changes in the neighborhood area are one kind of invasion, in which inner zones/areas expand outward as the overall development of the city continues (Burgess et al., 1925 citied in Naik et al., 2015). Such changes in urban and land use literature are called invasion theory (Naik et al., 2015). There is a dearth of empirical research to test the invasion theory in urban, housing and land use literature due to the time of "invasion" in the invasion theory is not easy to identify. The announcement of the new housing initiative in Hong Kong provides an excellent setting for testing this issue. For this purpose, the empirical study in the following part covers two pillars. The first pillar is to investigate the impact of the announcement of the new housing initiative on housing search behavior. In the housing and land use literature, housing search behavior is often measured by time-on-market (TOM), which refers to the duration of time it takes until it is sold (Carrillo and Williams, 2019). The second pillar is to employ previous housing transaction records to identify the way new public housing should be developed. How is such housing development compatible with the host neighborhood? This outlines some hidden patterns of home purchase behavior towards the new housing initiative. In the existing literature, home purchase behavior is often considered by the proxy-willingness to pay.

This paper is related to the literature about how housing-related policy affects TOM. Tucker et al. (2013) considered the influence of Massachusetts' policy on TOM where the policy prohibits home sellers from resetting the properties' days on market through relisting. Liang et al. (2018) studied the impact of new residential stamp duty on TOM. Related to another stream of literature, this paper explores the spillover effects on the neighborhood of public housing development. Albright et al. (2013) investigated the spillovers of opening the affordable housing on the proximate crime rate, property value, taxes in Mount Laurel, New Jersey. Diamond and McQuade (2019) studied the spillovers of properties supported by the Low Income Housing Tax Credit. To our best knowledge, our paper is the first trial to address the above two issues in one study: (1) the impacts of housing policy on TOM, and (2) the influence of the public housing development on the neighborhood.

The structure of this paper is organized as follows. Following a brief introduction, Section 2 presents an overview of the land use, housing situation and Home Ownership Scheme in Hong Kong. Section 3 reviews relevant literature. Sections 4 and 5 discuss the research method and the study area, data and selected variables respectively. Sections 6 presents the results and findings, followed by concluding remarks in Section 7.

2. Overview of the land use, housing situation, and Home Ownership Scheme in Hong Kong

2.1. Overview of land use and housing situation in Hong Kong

The city of Hong Kong lies in the southern part of China. The total land area is 1,106 km^2, of which about 24% (i.e. 268 km^2) and 4% (i.e. 43 km^2) are existing built-up areas and areas under planning studies respectively (Hong Kong Planning Department (HKPD), 2016). The remaining land area (i.e. 72% of the total land) is left for green and reservation (Hong Kong Planning Department (HKPD), 2016). By referring to the recent demographical report from the Hong Kong government, the population is around 7,524,100 (Census and Statistics Department (CSD), 2019). In other words, the average population density of Hong Kong is about 6,802 persons/km^2 on a territorial scale. If only the built-up areas are considered, the average population density is, surprisingly, as high as 28,075 persons/km^2.

In realizing the dense population and limited land resources for city development, the Hong Kong government plays an important role to optimize land use for different purposes (i.e. private and public uses). On one hand, the government holds the rights of total control over land supply and land use. According to Lai (1993), the Hong Kong government disposes of land for commercial, industrial and private residential by competitive auction. On the other hand, the land is free allocated by the government for public uses (Lai, 1993). One of the typical land allocations for public use is the public housing development. To make good use of limited land resource, public housing follows the pattern of high-rise and high-density development. The Hong Kong Housing Authority is responsible for the design, development and facilities management of the public housing in Hong Kong (Hong Kong Housing Authority (HKHA), 2019). The public housing in Hong Kong comprises public rental housing and subsidized sales flats (i.e. the Home Ownership Scheme). The eligibility to apply for public rental housing and homeownership scheme is subject to limits or cut-off points for monthly income and personal assets (Wang and Cao, 2017).

According to the updated statistics from the Transport and Housing Bureau (Transport and Housing Bureau (THB), 2018), there were about 2.775 million permanent living quarters in Hong Kong at the end of March 2018. It consists of 1.221 million (45.4%) public housing units (i.
e. 0.815 million public rental housing units and about 0.405 million subsidized sale flats) and about 1.554 million (53.7%) private housing units. About 44.7%, 54.6% and 0.7% of the population were accommodated in public permanent housing, private permanent housing, and temporary housing respectively in 2018. More importantly, another statistical report from the Rating and Valuation Department (Rating and Valuation Department (RVD), 2018) figures out that the vacancy rate of private property moves steadily from 3.7% in 2009 to 4.3% in 2018, indicating a rigid demand and low supply in the private housing market.

Currently, the high-rise and high-density development in Hong Kong has inevitably generated some serious problems. For one thing, the method of disposal leads to high land prices, which further fuels the ever-rising property price and consequently makes Hong Kong's property amongst the most expensive in the world (Sito and Li, 2017). For another, it engenders the waiting times of 5.5 years for general applicants, and the single elderly applicants had to wait for almost three years (Vetter, 2019).

To resolve the housing problems, the Hong Kong government adopts both long-term and short-term land use strategies and housing polices. In the long-run, the government intends to supply 450,000 homes covering both public and private sectors within the next 10 years to meet demand. However, the long-term housing policy cannot be well executed without sufficient land supporting. In the short run, by contrast, the government launched a new housing initiative (June 2018). That is, to reallocate private housing sites for public housing in East Kowloon with an aim to supply about 10,600 public housing units by the end of 2022 (Legislative Council of The Hong Kong (LEGCO), 2018).

2.2. Home Ownership Scheme (HOS) and the Private Sector Participation Scheme (PSPS) in Hong Kong

The Home Ownership Scheme (HOS) and the Private Sector Participation Scheme (PSPS) were introduced in the late 1970s by the Hong Kong Government (Lau, 2005).

Under the HOS, it consists of the construction of flats and sale to eligible households/applicants by the Hong Kong Housing Authority (HKHA) (La Grange, 1998). Eligible applicants are mainly tenants living in public rental housing (Hong Kong Housing Authority (HKHA), 2020). To ensure the flats under HOS are affordable to target applicants/groups, the sales price of the HOS flats is set as below the estimated market price by some discount (e.g. from 20% to 50%). If the owner of HOS flat would like to sell or re-mortgage the flat, the discount is needed to repay the HKHA as a proportion of the market value of the flat (La Grange, 1998).

The PSPS is a complementary scheme of HOS (Lau, 2005). Under the PSPS, the HKHA takes advantage of the resources from the private sector/developer to design, build, and manage flats for sale to eligible households (La Grange, 1998). In this sense, the PSPS is a public-private partnership scheme that involves both the public and private sectors. The private developers would shoulder all capital costs, which includes a land premium paid in the tender process for the right to the PSPS development. The public sector procures a great number of the PSPS flats from the private sector at a guaranteed price, for resale to eligible households (La Grange, 1998). The scheme had been attractive to some developers in that they could benefit from selling the non-domestic units of the PSPS project (Lau, 2005).

From the 1970s to the early 2000s, there were 206,408 HOS flats and 97,824 PSPS flats completed, providing affordable housing to one million people (Lau, 2005). However, the HOS and the PSPS were ceased from 2003 onwards (Chiu, 2010). Until 2011, the Hong Kong government rebooted the HOS to tackle the problem of housing affordability resulting from soaring housing prices (Wang and Cao, 2017).

3. Literature Review

This section has two parts. The first part addresses the overview of search behavior in housing markets, while the second part focuses on the link between affordable housing and private property value. The organization of these two parts enables to form research hypotheses, which helps explore the two aforementioned research questions.

3.1. Search behavior in housing markets: An Overview

In studying the search behavior in housing markets, it is ideal to have direct information such as search costs from buyers, multiple rounds of bargaining between sellers and buyers and information on property market conditions (Turnbull and Sirmans, 1993). In Hong Kong, information on search costs and bargaining process could not be accessed, because neither are they documented by property agents' companies nor the Hong Kong government. Therefore, the measurement of search behavior relies on the information of market conditions, which is termed as Time on the market (TOM) or days on the market. It well reflects the total number of days the property listed on the active market before the transaction agreement is made between buyers and sellers.

In the literature, housing search behavior is often considered the relationship between TOM and housing transaction price, which has long been investigated by researchers (for example, Miller, 1978; Zuehlke, 1987; Haurin, 1988; Kalra and Chan, 1994; Forgey et al., 1996; Kramer, 1999; Ong and Koh, 2000; Knight, 2002; Merlo and Ortalo-Magne, 2004; Li, 2004; Hui et al., 2012; Haurin et al., 2013; Khezr, 2015; McGreal et al., 2016; Liang et al., 2018). In the following part of the review, the selected papers are from the perspective of the determinants of TOM, which is by no means exhaustive.

Forgey et al. (1996) discovered that the longer marketing period often associated with the higher sales price. Kramer (1999) summarized the home sellers' strategy in response to different market conditions. When the housing markets boom, home sellers will not set a high price in order to have a short marketing period. But in the case of the market goes down, the sellers are unlikely to readjust the sales price if they consider that the market reverts from bottom to boom. Hui et al. (2012) investigated how overpricing properties affect the marketing period. Their findings suggested that overpricing would effectively maximize home sellers' returns and TOM can be explained by economic conditions. By the same token, Khezr (2015) showed that the overpricing of properties leads to a longer marketing period.

In addition to the housing transaction price, housing characteristics in previous studies are used as the special determines to explain TOM. Haurin (1988) delineated that the marketing time of the property is determined by the unusual structural attributes of a property. This demonstrates that TOM is larger if the properties equipped with unusual characteristics (Kalra and Chan, 1994). Ong and Koh (2000) showed that the properties located on lower floors tend to have a longer marketing period in Singapore. Li (2004) found that TOM may not be well explained by some structural attributes such as a number of bedrooms, private enclosed space. However, he argued that properties located on higher floors and with convenient parking space lead to shorter TOM. Haurin et al. (2013) used a proportional hazards model to express TOM as the set of household characteristics and the price appreciation variables. By considering the property sales record on a quarterly basis from 2002 to 2009 in Belfast of the UK, their findings suggested that home sellers' search behavior switches to an auction-like process when housing markets rise. Huang (2017) examined the impacts of housing attributes and environmental variables on TOM of sub-divided units in Hong Kong. By harnessing a two-stage least square method, the author showcased that tenants of sub-divided units are less sensitive in the negative impact of TOM on rent.

Very limited studies explain TOM by covering the spatial and temporal effects of the housing characteristics. The exceptions are some recent studies (e.g. McGreal et al., 2016; and Liang et al., 2018). McGreal et al. (2016) examined the spatial effects of TOM on property markets in Adelaide, Australia. By adopting the space-time model via a two-stage least square (2SLS) technique, they found that the cycle parameter has a greater influence on TOM than property price. They further disclosed that GDP is the main driver for TOM. If GDP climbed up by 1%, then TOM would reduce by 4.4 days. Liang et al. (2018) pointed out that TOM can also be explained by reinforcement of new stamp duty. On employing 4,921 housing transaction records from 2013 to 2017 in Hong Kong, their empirical analysis was to test the theory proposed by McGreal et al. (2009): "*if buyers' options are more limited and search is restricted within well-defined neighborhoods, then TOM should be shortened*". Their findings supported the theory of McGreal et al (2009).

In summary, a rich set of literature studied home search behavior in terms of TOM in the U.S., U.K. and western markets, yet very few concerned the impact of housing policy on TOM. In the following part of the empirical research, this paper intends to investigate the effect of the announcement of the new housing initiative on housing search behavior. On reviewing the search behavior in housing markets, we have our first hypothesis:

H1: The marketing period (expressed by TOM) of private property is reduced in the East Kowloon district after the announcement of the new housing initiative.

3.2. Linkage between affordable housing and the private property value:
An Overview

This section addresses the linkage between affordable housing and private property value. It will use the term "affordable housing" instead of "public housing", which is inspired from the file of "*Legislative Council Panel on Housing and Panel on Development Government's New Initiatives on Housing*" (Legislative Council of The Hong Kong (LEGCO), 2018). It states: "…*We have been working hard to allocate sites for public housing, including some sites that were originally intended for private housing. To better meet the need for more* ***affordable housing***…"

Many studies endeavored to explore the relationship between public/affordable housing and proximately neighborhood private estate value. There was no consensus agreement as regards the impact of affordable housing on private estate value. Previous studies found that the positive, negative and even mixed effects on private estate value (Ellen et al. 2007; Freeman and Botein, 2002).

According to a study conducted by Nguyen (2005), the extent or degree to which the neighborhood private estate values are affected depends on some specific factors of affordable housing. They are, namely, the design and management of affordable housing, compatibility between affordable housing and the host neighborhood.

Cummings and Landis (1993) pointed out that the quality and design of the affordable housing structure is a very important factor for property values locating in proximity. In their study, a cross-section based hedonic model was used for considering six affordable housing sites. They discovered that private estate values do not change significantly if they are close to these six affordable housing sites. They provided possible explanations that the design of affordable housing matches the building style of the neighborhood private estates, in terms of scale, size, and amenities. Briggs et al. (1999) aimed to detect the quality and design of the structure that may decline the proximately private estate values. Their study examined ex-ante and ex-post of affordable housing development through linear regression analysis. However, they found that the results were statistically insignificant, indicating that there are no harmful effects on private estate values. A possible explanation is that the newly built affordable housing would not lower the property value if they are well designed and developed.

As for the second factor-compatible between affordable housing and host neighborhood, Lee et al. (1999) compared the detrimental effects of affordable housing on private property value in the suburban and urban areas in Philadelphia. They found a 35% drop in private property value in the suburban. Similarly, Galster et al. (1999) investigated affordable housing (known as Section 8 in U.S.) on private estate sales price in Baltimore, U.S. by using the hedonic model. They argued that affordable housing would bring about positive effects, provided that they were located in the vicinity of the white neighborhood community. Ellen and Voicu (2006) explored the spillover effects of affordable housing on neighborhood areas in New York City. They found that the property value in the proximate

areas experienced positive impacts from the nonprofit affordable housing. They also discovered that the magnitude of the positive impact was positively associated with the non-profit project size. On the other hand, Deng (2011) examined how affordable housing financed and supported by the Low-Income Housing Tax Credit (LIHTC) program affected neighborhood. By selecting over 5,000 new housing units between 1990 and 2007 in Detroit, he found that half of the LIHTC program had improved the socioeconomic status while the rest of the neighborhood fell behind.

Albright et al. (2013) investigated the impact of opening the affordable housing on the proximate crime rate, property value, taxes in Mount Laurel, New Jersey. They demonstrated that the opening of affordable housing was not associated with changes in crime rate, property value, and taxes. Their findings suggested that affordable housing can indeed be developed in an affluent suburban community. One recent research carried out by Davison et al. (2017) explored the relationship between affordable housing and surrounding private estate value in Australia. By adopting a mixed-method, they found that the proximity to affordable housing only has slightly (or trivial) effects on neighboring property values. Diamond and McQuade (2019) proposed a non-parametric estimation method to study the spillover effects of properties financed by Low-Income Housing Tax Credit (LIHTC) on neighborhood communities. On considering a large data sample around 2,458,000 low-income housing units that located in 129 counties, their interesting findings showed that (1) LIHTC development enabled to revitalize low-income neighborhoods and lift up property price by 6.5%. In contrast, (2) LIHTC development in the high-income community would induce the property price drop by 2.5%, which attracted low-income households.

To recap, there has been a rich set of literature as regards the impact of affordable housing on neighborhood private estate value. However, most of these studies have focused on the U.S., Australia and a dearth of such research can be seen in Hong Kong with the exception conducted by Lau (2018). The impact of affordable housing on private estate value has been largely overlooked in Hong Kong. Without carefully considering this issue, it would give rise to a lot of problems, such as long-time negotiation for the compensation because of potential adverse effects (or depreciation effects) on the neighboring property value. As such, it would hamper the enforcement of any new housing initiatives and bring about the ineffective arrangement and solution for tackling the housing problem for the public. In this regard, it leads to our second and third hypotheses:

H2: Benefit (in terms of sales property price) among private property is positively associated with the distance to the homeownership scheme (HOS) public housing.

H3: The design and development of public housing projects by following the private sector participation scheme (PSPS) are compatible with the neighborhood housing area.

4. Data

4.1. Sample data

In this research, 4,890 second-hand sales records of private property in Hong Kong were collected from local property agent's website "591. com" for empirical study, of which 3300 and 1590 private property sales records are observed before and after the announcement of the new housing initiative (June 2018) respectively. The collection from the "591.com" is because only this agent's website documents the information of TOM and housing transaction price. Using this set of sample data from one source would be able to minimize the variability among different agents. The time span of the sample data covering 30 months from August 2016 to Jan 2019. This set of sample data covers the whole territory of Hong Kong (i.e., Hong Kong Island, Kowloon, and New Territory). In order to minimize the market inflation effects, each housing price is deflated by dividing the private domestic price index from the Rating and Valuation Department of Hong Kong (Rating and Valuation Department (RVD), 2020). In so doing, the price level of the data sample can adjust to the level in August 2016. The distribution of the collected sample is shown in Fig. 1.

4.2. Selected Variables

Three groups of attributes are considered in this study: namely, structural attributes, neighborhood attributes, new housing initiative related attributes (Table 1). The first group of attributes includes basic information on the housing units as age, size, floor and a number of living rooms of the property. Age is often pondered as the key structural variable in previous studies (Boussauw et al., 2014; Tian et al., 2017). In a similar vein, size is also the structural variable that has been widely considered to control the variability of properties (Hui and Liang, 2016; Huang, 2017; Liang et al., 2018). The apartment located on the higher floor is positively related to the property value (Hui et al., 2007). Apart from the above three variables, the number of living rooms is often used as a control variable. Previous studies show that the apartment of more living rooms should have higher property value (Hui et al., 2007; Li et al., 2016).

Neighborhood attributes refer to the proximity of such amenities as community centers, parks, hospitals, public transport (mass transit railway [MTR]), and education service provision facilities (e.g., primary, secondary schools) and urban renewal projects (i.e., redevelopment projects and rehabilitation projects). Accessibility to the community centers allows the residents in Hong Kong to enjoy the convenience of public services (Hui et al., 2018; Liang et al., 2018). Parks here indicates the shortest distance to the parks. Previous studies show that the park is attractive to the residents (Hui et al., 2007; Chen and Jim, 2010; Hui and Liang, 2016). Hospitals in this research refer to the accessibility to the nearest hospital. In the existing urban and housing literature, the hospital is some kind of semi-obnoxious facility (Peng and Chiang, 2015; Hui et al., 2018), which may generate both desirable and undesirable effects on the public. A user-friendly urban railway system plays a crucial role for residents. The efficiency of urban transit and railway system could mostly resolve and relieve the urban traffic congestion problem. Many studies suggest that there are positive capitalization effects of easy access to the railway service on housing price (Ahlfeldt and Wendland, 2009; Debrezion et al., 2011; Duncan, 2011). Education service denotes as the shortest distance to the primary school. The existing housing literature document a rich set of studies on considering the capitalization effect of education district on housing value (Nguyen-Hoang and Yinger, 2011; Wen et al., 2017; Choy and Li, 2017; Wen et al., 2019). In Hong Kong, a number of private residential buildings confront with the problem of aging (Wong, 2017, citied in Hui et al., 2018), which will generate some potential safety issue (e.g. building collapse) to the public (Ng, 2017, cited in Hui et al., 2018). Therefore, Redevelopment and Rehabilitation are employed as control variables for empirical studies. The information about the "distance to nearest" attributes have been collected from the website of the Lands Department of Hong Kong.

The final group of attributes (e.g., new housing initiative related attributes), comprises eight attributes. Policy refers to the cases where the transaction of private properties happened after the announcement of the new housing initiative. EK is short for East Kowloon in which the Hong Kong Government intends to reallocate more private housing sites for public housing. The two attributes Policy and EK play important roles to explain how the new housing initiative affects housing search behavior. These two variables are used to test Hypothesis 1.

Another two important variables are the PSPS and HOS, which are the acronyms for the private sector participation scheme and homeownership scheme respectively. The choice of these two variables is due to PSPS and HOS are used for capturing the development and design pattern of sales public housing. More

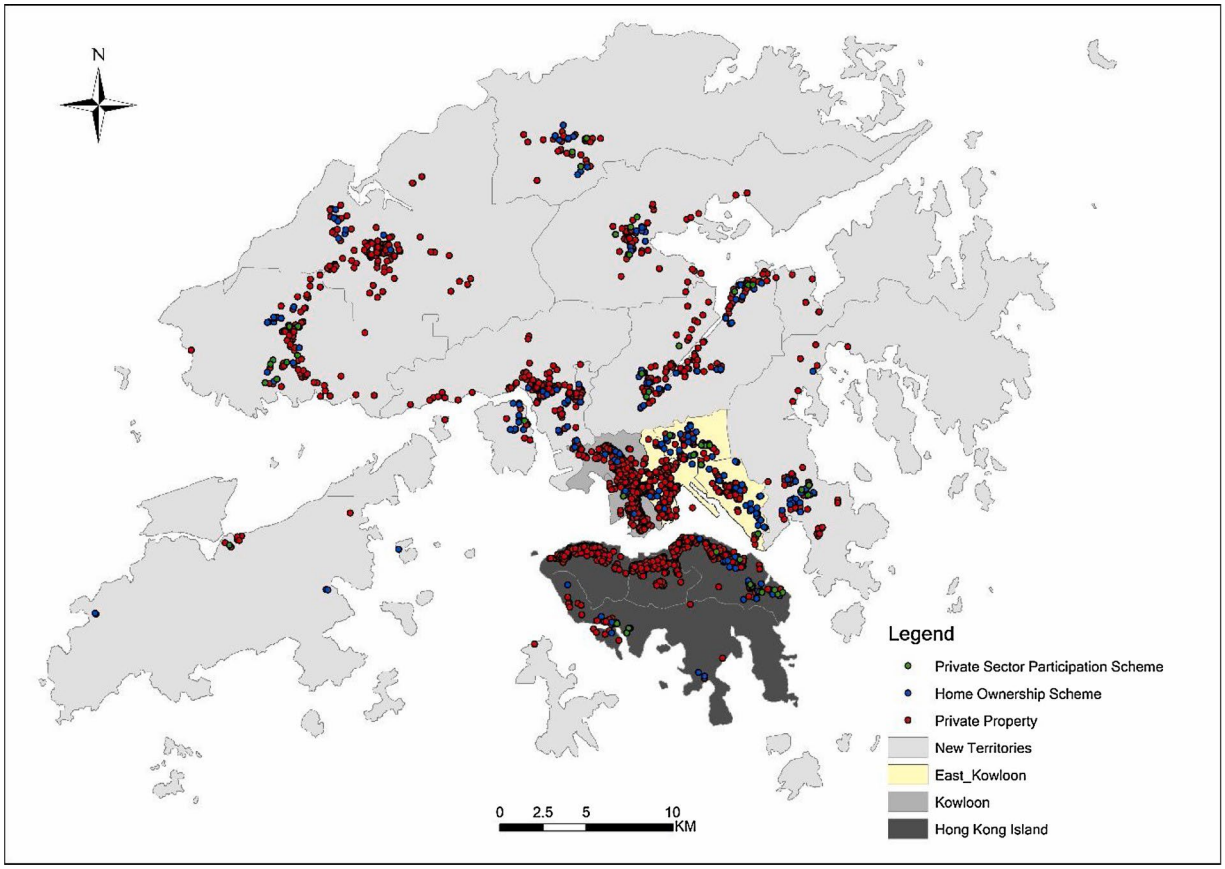

Fig. 1. Distribution of public housing (PSPS and HOS) and private properties in Hong Kong.

specifically, the development and design pattern of PSPS projects follow the private developers' style, while HOS adopts the traditional design and development from the Hong Kong Housing Authority. The consideration of PSPS and HOS allows us to predict the home purchase behavior in response to the new housing initiative. For such purpose, HOS and PSPS are the key variables to test Hypotheses 2 and 3 respectively.

The attribute Hit is the number of times the information of the private property has been browsed on the agent's website before it is sold out. The variable Hit is the proxy to explore the housing search behavior.

NT, KL and HK are three district control variables, which are short for the properties located at New Territories, Kowloon, and Hong Kong Island, respectively. The New Territories are treated as the baseline district, and HK and KL are utilized as two dummy variables to indicate the location of the sold property on Hong Kong Island and in Kowloon, respectively. The descriptive statistics of the selected attributes are grouped in Table 1. The 'distance to nearest' attributes in Table 1 is calculated by the use of ArcGIS@10.2.

5. Research Method

5.1. Spatial models

To study the impact of the new housing initiative on housing behavior, this research employs two spatial economic models through inspired by the previous studies (Dube and Legros, 2016´ ; Hui and Liang, 2016; Huang, 2017; Liang et al., 2018; Diamond and McQuade, 2019). Both of these two models boast with the linear forms:

$$TOM = f(\text{Structure}, \text{Neighborhood}, \text{Initiative}, \text{Spatial}, \text{Price}_{asking}) \quad (\Delta)$$

$$\text{Price}_{transaction} = g(\text{Structure}, \text{Neighborhood}, \text{Initiative}, \text{Spatial}) \quad (\Omega)$$

The first one (Δ) is called the TOM model, which is the linear function of a series of attributes. Structure, Neighborhood, Initiative, Spatial, Price_{asking} stand for the determinants of TOM, which are determined by structural attributes of the property, accessibility to the neighborhood amenities (or dis-amenities), the new housing initiative, spatial interaction and the asking price of the property. The utilization of the (Δ) enables us to investigate the people's housing search behavior responding to the new housing initiative. The second model (Ω) is the pricing model, which is also the linear function of a series of attributes. Structure, Neighborhood, Initiative, Spatial in function *g* hold the same

Table 1

Summary of Variables and Descriptive Statistics.

Variables	Description	Unit	Mean	Standard Deviation	N
Price	Transaction price of apartment Asking Price	HKD/m^2	156,458.39	135,016.42	4890
	Asking price of apartment	HKD/m^2	164,996.52	158,722.18	4890
TOM	Time-on-market of the property	Days	31.42	23.85	4890
Structural Attributes					
Rooms (C)	Number of bedrooms in the apartment Size (C) Size		2.34	1.28	4890
of the apartment (m^2)		Counts Square Meters	46.83	24.68	4890
Floor (C)	The floor on which the apartment is located	Counts	21.25	10.78	4890
Age (C)	Age of building or apartment	Years	27.32	14.53	4890
Neighborhood Attributes					
Community (C)	The distance to the nearest community center	100 meters	3.45	4.14	4890
Park (C)	The distance to the nearest park	100 meters	7.31	6.69	4890
Hospital (C)	The distance to the nearest public hospital	100 meters	6.49	6.52	4890
MTR (C)	The distance to the nearest entrance of MTR station	100 meters	7.76	8.29	4890
Primary (C)	The distance to the nearest primary school	100 meters	13.35	17.43	4890
Secondary (C)	The distance to the nearest secondary school	100 meters	14.59	14.89	4890
Redevelopment	The distance to the nearest redevelopment projects (C)	100 meters	45.82	54.59	4890
Rehabilitation (C)	The distance to the nearest urban rehabilitation projects	100 meters	44.82	52.55	4890
New Housing Initiati	**ve Related Attributes**				
PSPS (H3)	The distance to the nearest public housing that belongs to private sector participation scheme (PSPS)	100 meters	20.64	20.10	4890
HOS (H2)	The distance to the nearest public housing that belongs to the homeownership scheme (HOS)	100 meters	6.86	8.24	4890
Policy⁑ (H1)	If the transaction of the property performed after the announcement of the new housing initiative	1 or 0	0.32	0.47	4890
EK (H1)	If the property is located in East Kowloon (Areas of private housing site for public housing)	1 or 0	0.19	0.39	4890
Hit (C)	The number of times that the property has been visited through an online platform before the transaction	Counts	266.79	566.28	4890
NT (Ref)	If the property is located in New Territories	1 or 0	0.41	0.49	4890
KL (C)	If the property is located in Kowloon	1 or 0	0.40	0.49	4890
HK (C)	If the property is located in Hong Kong Island	1 or 0	0.19	0.39	4890

Note: (Ref) refers to the variable is selected as a reference to avoid dummy trap in the empirical analysis.

⁑ There are 3300 and 1590 private property sales records are observed before and after the announcement of the new housing initiative (June 2018) respectively. (C) refers to the control variable in the empirical study in the following context. H1, H2, and H3

indicate that the variables are used to test hypotheses 1, 2 and 3 respectively.

meaning as that in function *f*. The consideration of (Ω) allows us to answer in what way the new public housing should be developed if it is to be compatible with the host neighborhood - by the public sector, or with the participation of the private sector.

To be specific, the mathematical form of the TOM model and pricing model are presented as Equations (1) and (2) below:

$$\ln(TOM) = \rho_{TOM} W \ln(TOM) + \beta_0 + X_{Structural}\beta_{Structural} + X_{Neighborhood}\beta_{Neighborhood} + X_{PSPS}\beta_{PSPS} + X_{HOS}\beta_{HOS} + X_{District}\beta_{District} + X_{policy}\beta_{policy} + X_{EK}\beta_{EK} + X_{policy*EK}\beta_{policy*EK} + \vartheta\beta_{\vartheta} + \varepsilon \quad (1)$$

$$\ln(\text{Price}) = \rho_{price} W \times \ln(\text{Price}) + \alpha_0 + X_{Structural}\alpha_{Structural} + X_{Neighborhood}\alpha_{Neighborhood} + X_{PSPS}\alpha_{PSPS} + X_{HOS}\alpha_{HOS} + X_{District}\alpha_{District} + \mu \quad (2)$$

where the Price in Equation (2) is the transaction price of the property, TOM denotes time-on-market (dependent variable). $X_{Structural}$, $X_{Neighborhood}$, are the variables of housing structural attributes and neighborhood attributes. X_{PSPS}, X_{HOS}, X_{policy}, X_{EK}, $X_{District}$ and $X_{policy*EK}$ are the variables of new housing initiative related attributes. α_0, $\alpha_{Structural}$, $\alpha_{Neighborhood}$, α_{PSPS}, α_{HOS}, $\alpha_{District}$, β_0, $\beta_{Structural}$, $\beta_{Neighborhood}$, β_{PSPS}, β_{HOS}, $\beta_{District}$, β_{policy}, β_{EK}, $\beta_{policy*EK}$, and β_θ are coefficients corresponding to Equations (1) and (2). ε and μ are error terms of Equations (1) and (2). ε and μ measure spatial dependence of transaction price and TOM. W is the spatial weight matrix. The definition of the spatial weight matrix is specified in the next section. α_{PSPS}, α_{HOS}, $\alpha_{District}$, β_{PSPS}, β_{HOS}, β_{policy}, β_{EK}, and $\beta_{policy*EK}$ are of particular interest, because they are termed as a set of important indicators to investigate the impact of the new housing initiative on housing behavior.

It is noted that ϑ in (1) is used as a proxy variable to consider the above-market price (Anglin et al. 2003; Hui et al., 2012), which enables us to investigate how the degree of overpricing (i.e., the discrepancy between the initial asking price and expected housing transaction price) affects TOM. Accordingly, θ is defined as follows:

$$\theta = \ln(\text{Price}_{asking}) - E[\ln(\text{Price}_{asking})]$$

where the $\ln(\text{Price}_{asking})$ refers to the natural log of the initial asking price, $E[\ln(\text{Price}_{asking})]$ is denoted as expected housing transaction price. The model of $E[\ln(\text{Price}_{asking})]$ is shown as equation (3):

$$E[\ln(\text{Price}_{asking})] = \gamma_0 + X_{Structural}\gamma_{Structural} + X_{Neighborhood}\gamma_{Neighborhood} + X_{PSPS}\gamma_{PSPS} + X_{HOS}\gamma_{HOS} + X_{District}\gamma_{District} \quad (3)$$

The variables $X_{Structural}$, $X_{Neighborhood}$, X_{PSPS}, X_{HOS}, and $X_{District}$ are identical as (1) and (2). γ_0, $\gamma_{Structural}$, $\gamma_{Neighborhood}$, γ_{PSPS}, γ_{HOS}, and $\gamma_{District}$ are coefficients corresponding to (3).

It is worth mentioning that model (1) used in this study needs not to consider the instrumental variables (IV). The use of IV arises from the problem of endogeneity when the transaction price and TOM are used on both sides of the empirical equation simultaneously (Benefield et al., 2014; Liang et al., 2018). In this paper, the employment of ϑ and TOM in Equation (1) is distinguished from endogenous scenarios mentioned by Benefield et al. (2014) and Liang et al. (2018). The reason is very simple. ϑ is considered as the function of the initial asking price set by the home sellers, where they do not have prior knowledge about the marketing period of the property. As such, from the angle of the timeline of housing search behavior, TOM would be affected by ϑ, but ϑ cannot affect TOM.

5.2. Spatial Weighting Matrix

In order to consider the spatial pattern, a spatial weighting matrix plays a crucial role in exploring the spatial spillover effects (Amaral et al., 2014; Gu et al., 2017). The spatial weighting matrix in this study is based on the recent work of Dube and Legros (2014)′ , where each element w_{ij} in the spatial weighting matrix, W_0 is defined as

$$w_{ij} = \begin{cases} \left(\frac{1}{d_{ij}} \times \frac{1}{\Delta t_{ij}}\right), & \text{if } i \neq j \text{ and } 0 < t_i < t_j \\ 0, & \text{others} \end{cases}, \quad (4)$$

where d_{ij} is the distance between location i and location j, Δt_{ij} is defined as $t_j - t_i$, which is the time span between time j and i. Thus, w_{ij} addresses the strength of the potential interaction between the $i-th$ and j-th housing observations provided that the property transaction at location j takes place later than that at location i ($t_i < t_j$). The spatial weighting matrix defined in Equation (4) incorporated spatial and temporal information that has no cut-off points.

One necessary step called normalized spatial weight matrix needs to be performed after defining the spatial weighting matrix such that all weights/elements in the matrix range between 0 and 1. Accordingly, TOM and housing transaction price in the above spatial econometric models (1) and (2) can be interpreted as the weighted average of neighboring TOM and transaction price (Anselin, 1988). More specifically, the normalization procedure in this paper follows the method proposed by Kelejian and Prucha (2010). This is to reproduce the normalized spatial weighting matrix by dividing the maximum eigenvalue φ_{max} of original spatial weighting matrix W_0. In the mathematical presentation, it is shown as Equation (5), as follows:

$$W = \frac{1}{\phi_{max}} W_0 \quad (5)$$

Using (5) not only allows to overcome the misspecification problem of simple row normalization when estimating spatial coefficients (Elhorst, 2014) but also enables us to examine the economic interpretation of distance decay (Elhorst, 2001).

6. Results and findings

6.1. Model selection

The statistical results are reported in Tables 2 ~ 5, by use of MATLAB@2016a. The statistical results include TOM models (Table 2) and pricing models (Table 3). The results of two TOM models in Table 2 are close, where R^2 of two TOM models are around 33%. Likewise, the estimated coefficients of two pricing models (i.e., OLS and SAR model) are similar in Table 3. The explanatory power of models, as reflected by the R^2 value, is around 52%.

By use of the spatial model selection technique of Hui and Liang (2016), a series of robust tests have been carried out in order to choose the legitimate model for analysis. The results of TOM models and pricing models are shown in Tables 2 and 3 respectively. In Table 2, it is straightforward to see that all the tests, including Moran's I statistic, LM lag test, LM error test, LM lag robust test, and LM error robust test, are statistically significant. By referring to Hui and Liang (2016), Liang et al.

Table 2
Summary Statistics of TOM Models.

Variables	Model 1 (OLS)			Model 2 (SAR TOM Model)		
	Coefficient	t-stat	p-value	Coefficient	t-stat	p-value
Intercept	− 1.3716***	− 4.1874	0.0000	− 1.5098***	− 4.6217	0.0000
θ (Theta)	0.2778***	7.7319	0.0000	0.2799***	7.8109	0.0000
Structural Attributes						
Rooms	0.0336*	2.2654	0.0235	0.0325*	2.2053	0.0274
Size	0.1106*	2.3608	0.0183	0.1153*	2.4686	0.0135
Floor	0.0057***	5.1314	0.0000	0.0058***	5.2272	0.0000
Age	0.1026***	6.1806	0.0000	0.1029***	6.2234	0.0000
Neighborhood Attributes						
Community	− 0.0332	− 1.6561	0.0977	− 0.0299	− 1.5026	0.1329
Park	− 0.0030	− 0.1309	0.8958	− 0.0046	− 0.2026	0.8394
Hospital	0.0183	0.8626	0.3884	0.0195	0.9239	0.3555
MTR	− 0.0552**	− 3.1941	0.0014	− 0.0533**	− 3.1013	0.0019
Primary	− 0.0025	− 0.1307	0.8959	− 0.0021	− 0.1112	0.9114
Secondary	− 0.0306	− 1.5728	0.1158	− 0.0314	− 1.6230	0.1046
Redevelopment	− 0.0406**	− 2.5976	0.0094	− 0.0355*	− 2.2826	0.0224
Rehabilitation	0.0219	1.8006	0.0718	0.0207	1.7120	0.0868
New Housing Initiative Related Attributes						
PSPS	0.0406**	2.7403	0.0062	0.0429**	2.9022	0.0038
HOS	0.0009	0.0629	0.9497	− 0.0008	− 0.0508	0.9595
Policy	− 0.6402***	− 19.1168	0.0000	− 0.6221***	− 18.6368	0.0000
EK	0.0593	0.8737	0.3823	0.0547	0.8078	0.4192
Policy*EK	− 0.1417**	− 2.6684	0.0076	− 0.1306*	− 2.4676	0.0136
Hit	0.4819***	44.8875	0.0000	0.4836***	45.1789	0.0000
KL	− 0.0230	− 0.4234	0.6721	− 0.0393	− 0.7256	0.4680
HK	− 0.0540	− 1.1138	0.2654	− 0.0634	− 1.3117	0.1895
Rho				0.1019***	26.1634	0.0000
R^2	0.3311			0.3318		
Moran's I test		9.6726***	0.0000			
LM-Lag test					18.8204***	0.0000
LM-Error test					10.3497**	0.0013
LM-Lag Robust test					13.0754***	0.0000
LM-Error Robust test					4.6047*	0.0319
N	4890			4890		

Note: *p <0.05, **p <0.01, ***p <0.001. SAR TOM Model is short for Spatial Autoregressive TOM Model.

Table 3
Summary Statistics of Pricing Models.

Variables	Model 3 (OLS)			Model 4 (SAR Pricing Model)		
	Coefficient	t-stat	p-value	Coefficient	t-stat	p-value
Intercept	2.8556***	23.5973	0.0000	2.8925***	23.5045	0.0000
Structural Attributes						
Rooms 0.0579*** 9.8856 0.0000 0.0582*** 9.9221 0.0000 Size 0.6092*** 36.8366 0.0000 0.6076*** 36.4868 0.0000 Floor 0.0032*** 7.1633 0.0000 0.0031*** 7.1171 0.0000 Age − 0.0933*** − 14.7475 0.0000 − 0.0929*** − 14.6555 0.0000						
Neighborhood Attributes						
Community 0.0047 0.5918 0.5540 0.0037 0.4736 0.6357 Park − 0.0394*** − 4.2809 0.0000 − 0.0389*** − 4.2280 0.0000 Hospital 0.0074 0.8823 0.3776 0.0073 0.8742 0.3819 MTR − 0.0302*** − 4.6231 0.0000 − 0.0311*** − 4.7501 0.0000 Primary 0.0022 0.2855 0.7752 0.0021 0.2709 0.7864 Secondary − 0.0012 − 0.1541 0.8775 − 0.0009 − 0.1123 0.9106 Redevelopment − 0.0364*** − 6.0013 0.0000 − 0.0381*** − 6.2124 0.0000 Rehabilitation 0.0026 0.5318 0.5948 0.0029 0.6172 0.5371						
New Housing Initiative Related Attributes						
PSPS − 0.0016 − 0.2762 0.7824 − 0.0022 − 0.3673 0.7133 HOS 0.0677*** 11.2939 0.0000 0.0683*** 11.3893 0.0000 KL 0.0934*** 5.0068 0.0000 0.0963*** 5.1209 0.0000 HK 0.2359*** 12.6315 0.0000 0.2385*** 12.7111 0.0000						

Rho				0.1482***	5.7749	0.0000
R^2	0.5217			0.5221		
Moran's I test		11.1715***	0.0000			
LM-Lag test					8.3390**	0.0039
LM-Error test	3.1294 0.0769 LM-Lag Robust test	8.8974** 0.0029				
LM-Error Robust test					3.6879	0.0548
N	4890			4890		

Note: *p <0.05, **p <0.01, ***p <0.001. SAR Pricing Model is short for Spatial Autoregressive Pricing Model.

(2018), the most suitable model can be selected by comparing the greater statistics between LM lag robust test and LM error robust test. Hence, it is easy to identify that the LM lag robust statistic (13.0754, Table 2) is greater than the LM error robust statistic (4.6047, Table 2), indicating that the SAR TOM model is recognized as the best fit for the data analysis in the following subsections.

Table 3 indicates that the Moran's I statistic is significant with high statistical value 11.1715, showing strong evidence for spatial autocorrelation in housing transaction prices. Then we move on to conduct the Lagrange multiplier (LM) lag test and LM error test. The results show that the LM lag test is statistically significant at 8.3390, while the LM error test is not significant. Therefore, the SAR pricing model is selected as a reasonable choice for the following empirical analysis (Hui and Liang, 2016).

The estimation results of the SAR TOM model and SAR pricing model in Tables 2 and 3 do not reflect the spatial spillover effects. The spatial spillover effects are some kind of estimated results based on model results (Elhorst, 2014; LeSage and Pace, 2009). The following section will explain the specific results and analysis of such effects.

6.2. Spillover effects and Total effects

As indicated by LeSage and Pace (2009) that interpretations of the estimated results of spatial models should concentrate on direct, indirect (or spillover) and total effects because 'the change in a single observation (region) associated with any given explanatory variable will affect the region itself (a direct impact) and potentially affect all other regions indirectly (an indirect impact)'. Total effects are the results of the sum of direct and spillover effects (Hui et al., 2018; Liang et al., 2018). In fact, the indirect, direct effects and total effects are some kind of estimated results based on model results, where the detailed mathematical derivation and formula can be referred to LeSage and Pace (2009) and Elhorst (2014). In other words, the results of direct, indirect and total effects share the same total variability (R^2) as the statistical result of the spatial model (i.e. R^2 Table 2 and Table 4 for TOM model are identical, R^2 in Table 3 and Table 5 for pricing model are the same). To save space, only spillover (indirect) effects and total effects are reported in Tables 4 and 5.

It is straightforward to see that ϑ (Theta) is significant with a positive coefficient (0.3124, Table 4). Using ϑ as the above-market price to explore the degree to which the difference between the initial asking price and expected selling price affects TOM. The significant coefficient shows that setting the initial asking price higher by the homeowners in the private property market may result in a longer TOM, which is in line with the findings of Hui et al. (2012).

6.2.1. Structural attributes

6.2.1.1. SAR TOM model. All the variables of structural attributes in the TOM model are significant (Table 4). The significant coefficients of Rooms and Size show that the property with more room may result in longer marketing time, so as a larger sized flat. The seller of the large- sized property intends to set a high list price in the market, which would not be sold out in a short time. The positive sign of the coefficient of Age (= 0.1135 Table 4) shows that the age of the property positively associates with the TOM. More interestingly, the spillover effect of Age (= 0.0116, Table 4) illustrates that TOM would extend by 1.16% if the neighboring property is one year older. The properties situated on a high floor require a longer TOM as the statistical result is 0.65% (Table 4). The spillover effect of Floor (= 0.0007 in Table 4) displays that tall buildings in Hong Kong are not uncommon and therefore the housing sellers long for a good return by listing their property at a high price. From homebuyers' perspective, however, the result indicates that they will keep on searching more available housing units on high floors until they find one suitable. As a result, the neighboring property located on a high floor may result in a longer TOM.

6.2.1.2. SAR Pricing model. Similar to the SAR TOM model, all variables in the structural attributes are detected to be significant (Table 5). A small part of the total effects is from the spillover effects, which echoes

Table 4
Spatial Spillover Effects and Total Effects of SAR TOM Model.

Variables	Spillover (Indirect) Effects			Total Effects		
				Coefficient		
Coefficient		t-stat	p-value		t-stat	p-value
θ (Theta)	0.0318***	7.6164	0.0000	0.3124***	7.9321	0.0000
Structural Attributes Rooms						
	0.0038*	2.2463	0.0247	0.0373*	2.2667	0.0234
Size	0.0128*	2.4461	0.0145	0.1261*	2.4496	0.0143
Floor	0.0007***	5.1534	0.0000	0.0065***	5.2539	0.0000
Age	0.0116***	5.9336	0.0000	0.1135***	6.1524	0.0000
Neighborhood Attributes						
Community	− 0.0033	− 1.4814	0.1386	− 0.0328	− 1.4813	0.1386
Park	− 0.0007	0.2597	0.7951	− 0.0069	− 0.2588	0.7958
Hospital	0.0021	0.8479	0.3964	0.0209	0.8533	0.3935
MTR	0.0060**	− 3.0327	0.0024	0.0589**	− 3.0592	0.0022
Primary	− 0.0004	− 0.1883	0.8506	− 0.0041	− 0.1903	0.8491
Secondary	− 0.0034	− 1.5862	0.1128	− 0.0342	− 1.5927	0.1112
Redevelopment	− 0.0041*	− 2.2439	0.0249	− 0.0402*	− 2.2563	0.0241
Rehabilitation	0.0024	1.7662	0.0774	0.0236	1.7767	0.0756
New Housing Initiative Related Attributes						
PSPS	0.0048**	2.8273	0.0047	0.0478**	2.8657	0.0042
HOS	− 0.0001	− 0.0094	0.9924	− 0.0002	− 0.0093	0.9926
Policy	− 0.0704***	− 14.8023	0.0000	− 0.6913***	− 19.3349	0.0000
EK	0.0058	0.7675	0.4427	0.0574	0.7674	0.4429
Policy*EK	− 0.0146*	− 2.4516	0.0143	− 0.1439*	− 2.4742	0.0133
Hit	0.0548***	20.9831	0.0000	0.5382***	44.9219	0.0000
KL	− 0.0044	− 0.6936	0.4879	− 0.0432	− 0.6952	0.4869
HK	− 0.0072	− 1.3532	0.1760	− 0.0716	− 1.3546	0.1756

Note: *p <0.05, **p <0.01, ***p <0.001. SAR TOM Model is short for Spatial Autoregressive TOM Model.

Table 5
Spatial Spillover Effects and Total Effects of SAR Pricing Model.

Variables	Coefficient	t-stat	p-value		t-stat	p-value
	Spillover (Indirect) Effects			**Total Effects**		
				Coefficient		
Structural Attributes						
Rooms	0.0008***	8.7959	0.0000	0.0575***	10.1022	0.0000
Size	0.0009***	13.8394	0.0000	0.0599***	34.7875	0.0000
Floor 0.00005*** 7.7747 0.0000 0.0037*** 7.2043 0.0000 Age − 0.0014*** − 8.8269 0.0000 − 0.0918*** − 14.2490 0.0000						
Neighborhood Attributes						
Community − 0.0001 − 0.3927 0.6945 0.0038 0.4932 0.6218 Park − 0.0006*** − 5.7148 0.0000 − 0.0378*** − 4.2525 0.0000 Hospital − 0.0001 − 0.6722 0.5015 0.0070 0.8215 0.4114 MTR − 0.0005*** − 4.6567 0.0000 − 0.0306*** − 4.7687 0.0000 Primary − 0.0003 − 0.2430 0.8079 0.0022 0.2823 0.7776						
Secondary	0.0002	0.1491	0.8815	0.0012	0.1553	0.8766
Redevelopment − 0.0006*** − 5.7034 0.0000 − 0.0375*** − 6.3405 0.0000 Rehabilitation − 0.0004 − 0.5259 0.5989 0.0029 0.5979 0.5498						
New Housing Initiative Related Attributes						
PSPS − 0.0003 − 0.3315 0.7403 − 0.0020 − 0.3454 0.7297 HOS 0.0010*** 10.8135 0.0000 0.0671*** 11.5783 0.0000 KL 0.0014*** 5.6864 0.0000 0.0948*** 5.0176 0.0000						
HK	0.0034***	10.8013	0.0000	0.2348***	12.9748	0.0000

Note: *p <0.05, **p <0.01, ***p <0.001. SAR Pricing Model is short for Spatial Autoregressive Pricing Model.

with previous studies (LeSage, 2015; Hui and Liang, 2016; Hui et al., 2018 and Liang et al., 2018). For instance, the spillover effects of Rooms, Size, Floor and Age contribute 1.39% (= 0.0008/0.0575), 1.50% (= 0.0009/0.0599), 1.41% (= 0.00005/0.0037) and 1.53% (=-0.0014/-0.0918) to their total effects respectively (Table 5). The coefficient of 0.0575 (Rooms, Table 5) suggests that more rooms in a flat need the homebuyers to pay more. The significant result of Size with a positive coefficient of 0.0599 (Table 5) tells a similar story. The spillover effect of Age shows that the home buyers in the focal property would have a 0.14% discount if the neighboring properties are one year older (Table 5). The total effect of age is significant with a negative sign (-0.0918, Table 5), implying that people in Hong Kong are willing to pay a premium of 9.18% for a newer property. Living on a high floor attracts a price premium around 0.37% (0.0037, Table 5), with the spillover effects almost trivial (0.00005 in Table 5), exhibiting that a preference for a high floor amongst neighboring residents exerts trivial positive effects on the sales of the focal flat. The significant coefficient of the spillover effect of Floor echoes with that of Hui et al. (2018) that tall buildings are common in Hong Kong and living on higher floors is always more attractive, due to possibly enjoying a better view from heights.

6.2.2. Neighborhood attributes

6.2.2.1. SAR TOM model. It is so surprising to see that only two variables, namely MTR and Redevelopment are detected to be significant (Table 4). The spillover effects of two significant variables contribute roughly 10.19% to the total effects respectively (i.e. 0.006/0.0589 = 0.10186, MTR; -0.0041/-0.0402 = 0.10199, Redevelopment, Table 4). The positive coefficient of MTR (0.0589, Table 4) illustrates that TOM would be reduced by 5.89% if the entrance of MTR station is 100 meters nearer, which strengthens the point that MTR is regarded as the primary choice for the residents

to commute and local travel (Hui et al., 2018; Liang et al., 2018). The negative coefficient sign of Redevelopment (-0.0402 in Table 4) reveals that the TOM is negatively associated with the distance to the redevelopment projects. This is due to the property located in the vicinity of the redevelopment project that would have a higher opportunity to be redeveloped. It may indicate that the property itself is aged and waiting to be redeveloped (Hui et al., 2018).

6.2.2.2. SAR Pricing model. Only three out of eight variables are significant. They are, namely, Park (-3.78%, Table 5), MTR (-3.06%, Table 5) and Redevelopment (-3.75%, Table 5). These significant results show that private property residents enjoy living proximately to green space, public transport (MTR) and redeveloped urban areas. The spillover effects of these three variables are all significant, contributing 1.58% (= -0.0006/-0.0378, Park, Table 5), 1.63% (= -0.0005/-0.0306, MTR, Table 5), and 1.60% (= -0.0006/-0.0375, Redevelopment,
Table 5) to the corresponding total effects. Living close to an urban green area (i.e., Park) is attractive to many people, as it allows them to have more exposure to the natural environment (Miller, 1997; Jim & Chen 2006; Hui et al., 2007). The magnitude of the coefficient of MTR (-3.06%, Table 5) indicates that people in Hong Kong prefer to pay 3.06% more to reside in the vicinity to the entrance of MTR station. The negative coefficient of Redevelopment indicates that residents in Hong Kong are more likely to live in an urban regeneration area as redevelopment projects refresh old buildings in decay urban districts and upgrade a better living environment for residents nearby.

6.2.3. New housing initiative related attributes

The coefficients of the new housing initiative attributes are of particular interest in this study. The statistical results of the SAR TOM model shed light on home searching behavior in response to the new housing initiative, while the estimation results in the SAR pricing model aim to predict the home purchasing behavior as a result of the new housing initiative.

6.2.3.1. SAR TOM model. The results of the new housing initiative related attributes are shown in Table 4, where four out of eight variables are found to be significant. They are, namely, PSPS, Policy, Policy*EK and Hit (Table 4). Nearly 10.15% of the spillover effects of these four significant variables come from the total effects.

Hit refers to the number of times the information of property has been viewed via the internet or the smartphone before it is sold. The positive coefficient of Hit (0.5382, Table 4) implies how popularity in the markets — the higher the scale of the variable Hit, the longer TOM. A possible explanation is due to the buyers may discover some unfavorable aspects of property (Liang et al., 2018) such that the statistics of Hit may well remind potential buyers whether they should think twice before making a decision.

On comparing the results of PSPS and HOS (Table 4), private properties located near the public housing developed by private developers have higher liquidity. The spillover effect (0.0048 in Table 4) demonstrates that closer to PSPS public housing declines the marketing period of focal/subject private property by 0.48%.

The estimation results of Policy (-0.6913, Table 4) and Policy*EK (-0.1439, Table 4) portray the impact of the announcement of the new housing initiative on search behavior in Hong Kong's housing markets, which support the first hypothesis (H1). The negative coefficients of both Policy and Policy*EK support the invasion theory. This means that the launch of the new housing initiative-reallocating private land use for public housing is a signal of changing the host neighborhood in the private housing areas. And it will positively spill over to the adjacent urban areas. The announcement of the new initiative may bring about some uncertainty to the private housing areas in the area of East Kowloon. Home sellers may intend to move out to other housing areas by quickly selling the property. In this regard, the marketing period of private property is captured to be declined by 14.39%. The spillover effects of Policy and Policy*EK also reveal that the transaction of private housing in the neighborhood after the announcement of the new housing initiative would reduce the TOM of subject private property. From the perspective of homebuyers, this finding echoes with that of a recent study by Liang et al., 2018. The upcoming new housing and land use arrangement leads the buyers to have limited options in their search behavior.

6.2.3.2. SAR Pricing model. Only three variables, namely, KL, HK, and HOS are detected to be statistically significant in the SAR pricing model (Table 5). The spillover effects of these three variables contribute around 1.4% of the total effects. The significance of KL and HK indicates that people in Hong Kong are more willing to purchase properties in Kowloon and Hong Kong Island as the business service centers/facilities are clustered in both areas. There are more job opportunities with shorter commuting time to work. The positive coefficient of HOS (0.0671, Table 5), which follows the prediction of the second hypothesis (H2). The results 5 show that if the public housing which is developed by the Hong Kong government is 100 meters nearer, the transaction price will drop by 6.71%. In other words, people in Hong Kong are willing to pay 6.71% more to stay far away from HOS. This result is remarkably different from previous studies (Cummings and Landis, 1993; Briggs et al., 1999; Davison et al., 2017). A possible explanation is due to the design pattern of HOS is incompatible with that of private housing nearby. It is easy to identify a HOS block by its distinctive physical appearance. Such incompatibility of HOS is likely to be seen as an intruder, which may ruin and poison the amenities in the host neighborhood.

On the contrary, the insignificance of PSPS well supports the third hypothesis (H3): The design and development of public housing projects by following the private sector participation scheme (PSPS) are more compatible with the neighborhood housing area. The results of PSPS may provide a good solution for this issue. In a nutshell, PSPS is the public housing projects, but funded and developed by private companies. They oversaw the designs of the PSPS and the whole project development. In doing so, the pattern of design and development of PSPS projects are not so much different from private housing, making them more compatible with the neighborhood. The estimation results of HOS and PSPS showcase some hidden patterns of housing purchase behavior in Hong Kong. This provides useful information for urban planners, housing and land use policy-makers to bring forth their new housing initiative in Hong Kong.

7. Conclusions

This paper aims to study the impact of the announcement of the new housing initiative, i.e. reallocating the private sites for public housing projects and housing behavior. Our major findings are: (1) the announcement of the new housing initiative leads to a 5% change in time-on-market for private housing in East Kowloon (first hypothesis). (2) people in private property prefer more to live near public housing developed by the private sector, i.e. PSPS (second and third hypotheses). These two findings somehow echo with invasion theory in the urban and housing literature that neighborhood changes in private housing areas will positively spill-over to adjacent urban areas.

More importantly, the first findings are in line with the housing search theory of McGreal et al. (2009). The new housing initiative in the short run may help increase the supply of public housing in Hong Kong, implying that the Hong Kong government is on the right track to meet the high demand for housing. However,

if the new housing initiative is massively carried out in the city of Hong Kong, the result of the TOM model suggests that the initiative will probably drive out the residents/new homebuyers in the local host neighborhood. It will also bring about reverse gentrification effects on the neighbourhood. The Hong Kong government should carefully review the impact of reallocating private housing sites for public housing. Relying on a single land resource to sustain the long-term housing supply might be risky. Therefore, Hong Kong should seek out more available land resources to supply public housing in the long-run.

The contributions of this study to housing and land use literature are in several ways. First, the impact of reallocating private housing sites for the public project on housing behavior is hardly seen in the housing and land use literature. The investigation of the effects of the new housing initiative on people's housing behavior is from the two angles: (1) how does this initiative affect the housing search behavior in the housing market? (2) in what way should the new public housing be developed, if it is to be compatible with the host neighborhood - by the public sector, or with the participation of the private sector? The deliberation of the first question allows us to understand how people respond to the new housing initiative in terms of housing search behavior. The investigation of the second question provides us some hints to predict the people's purchase behavior in response to the initiative. Second, the exploration of the two issues enables us to test the invasion theory in housing and land use literature mentioned by Naik et al. (2015), which is overlooked in the existing housing and land use literature. Third, this paper adopts the improved spatial econometric models (i.e., pricing model and TOM model) by incorporating spatial and temporal information for empirical analysis. Last but not least, this empirical study provides important implications for academics and policy-makers alike, not only in Hong Kong but also for similar high rise, high-density cities elsewhere.

The limitation of this research lies in the following dimensions, which encompass potentially fruitful directions for future research. First, this study only discloses the impact of the announcement of the new housing initiative on the housing market. The true impact after the public housing projects are developed in private property areas should be further investigated, if data were available. Second, the new housing initiative is not the only way to solve the problem of the housing shortage. The Hong Kong government endeavors to solve this problem by taking on more different strategies. This could have provided a new direction for research. Future studies should analyze and compare the impact of different housing initiatives on the neighborhood community, other than the one we did here. **CRediT authorship contribution statement**

Cong Liang: Conceptualization, Software, Formal analysis, Writing - original draft, Writing - review & editing, Funding acquisition. **Eddie C. M. Hui:** Writing - review & editing, Resources. **Tsz Leung Yip:** Methodology, Formal analysis, Funding acquisition. **Yaoxuan Huang:** Software, Resources, Visualization, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2020.1050 67.

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