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Research Paper

A 4D spatio-temporal approach to modelling land value uplift from rapid transit in high density and topographically-rich cities

Christopher D. Higgins[a,b,*]

[a] Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong
[b] Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong

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ABSTRACT

The land value uplift effects of rapid transit infrastructure provide evidence of willingness to pay for more sustainable forms of development and suggest a rationale for land value capture. The present research utilizes spatio-temporal methods in a quasi-experimental research design to examine changes in property values associated with pedestrian accessibility to the West Island Line heavy rail extension in Hong Kong. Several innovations in methods and techniques are proposed that respond to the econometric challenges involved in conducting research in high density, topographically-rich cities. Of these, the paper incorporates landscape topography throughout its estimation process, including the calculation of slope-aware measures of walkable accessibility on a 3D pedestrian network and proposes a new Spherical Distance Weights method for capturing horizontal and vertical spatial association among observations in 3D space. Finally, these weights are combined with measures of temporal distance for a 4D approach that accounts for relations among observations in space and time. Spatio-temporal difference-in-differences results reveal a significant change in the value of pedestrian access to the new transit stations of between 26% and 41% after opening. Interestingly, uplift occurred across both the new stations as well as for properties around the previous terminus, highlighting the network effects associated with changes in accessibility. Beyond demonstrating that rail transit is valued, these findings confirm the assumptions behind the city's Rail + Property value capture approach, suggesting it remains a viable model for sustainable finance and urbanism in other high-density and transit-oriented cities.

1. Introduction

In the spatial equilibrium framework established by Alonso (1964), Muth (1969), and Mills (1972), the value and development intensity of land at any location is partly an outcome of its accessibility, which is defined here as the ease with which one can travel between origins and destinations of value (Páez, Scott, & Morency, 2012). Consequently, a rapid transit project that reduces transportation costs and increases accessibility should, in theory, result in an increase in land prices and development intensity around station access points. Over the past 40 years, more than one hundred studies have sought to test this hypothesized relationship between urban rail transit, accessibility, and land value uplift (see Debrezion, Pels, and Rietveld (2007), Higgins and Kanaroglou (2016b), and Mohammad, Graham, Melo, and Anderson (2013) for reviews).

Despite being a mature topic, research in this area has recently been re-invigorated along several dimensions. For policy and planning, the existence of land value uplift around stations offers evidence of a transit project's larger benefits to society and suggests a willingness to pay for sustainable urbanism. From this, there has been a resurgence in interest in capitalizing on land value uplift through the use of land value capture (Cervero & Murakami, 2009; Suzuki, Murakami, Hong, & Tamayose, 2015; Zhao & Levinson, 2012) to offset the public costs of transit projects.

Moreover, recent research has benefitted from new theory, evidence, and innovations in methods and techniques used to better uncover the value of transit. This includes a shift to using walking time/network distance over Euclidean distance as a more behaviourally-relevant proxy for accessibility (Hess & Almeida, 2007); evidence of the value of not just transit accessibility, but transit-oriented development (TOD) in general (Bartholomew & Ewing, 2011); and, by extension, models that have revealed differences in land value uplift in heterogeneous station area TOD contexts (Atkinson-Palombo, 2010; Duncan, 2011a,b; Higgins & Kanaroglou, 2016a, 2018).

On the technical side, research has increasingly adopted the use of spatial econometrics (Anselin, 1988; Kelejian & Prucha, 1998, 1999,

* Address: Room ZS621, 6/F, South Wing, Block Z, 181 Chatham Road South, Hung Hom, Kowloon, Hong Kong.
E-mail address: christopher.d.higgins@polyu.edu.hk.

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2010; LeSage & Pace, 2009) to model spatial dependencies in real estate data and control for spatially-dependent omitted variables (Kuminoff, Parmeter, & Pope, 2010). Recent work has also seen innovations in spatio-temporal econometric methods (Dubé & Legros, 2013a,b) and an increase in the use of longitudinal data and quasi-experimental research methods to better isolate causal effects from new rapid transit (e.g. Diao, Leonard, & Sing, 2017; Devaux, Dubé, & Apparicio, 2017; Dubé, Des Rosiers, Thériault, & Dib, 2011; Dubé, Thériault, & Des Rosiers, 2013; Dubé, Legros, Thériault, & Des Rosiers, 2014). Related to this, longitudinal studies have detected anticipation or speculation effects that can begin as soon as a rapid transit project is announced (e.g. Knaap, Ding, and Hopkins (2001), Devaux et al. (2017), Dubé, Legros, and Devaux (2018); see Devaux et al. (2017) for a review).

Another recent strand of research has challenged the "horizontalism" that dominates contemporary urban geographic scholarship and the associated top-down, surficial, or planar cartographic gaze as the default representation of cities. In response, authors such as Graham and Hewitt (2012) and Harris (2014) argue that a more vertical, three-dimensional (3D), and volumetric frame of analysis is required to truly understand complex modern urban environments. In line with this argument, previous research has seen innovations in spatial econometrics that, in effect, extend the Alonso-Muth-Mills (AMM) model's concepts of bid-rent to vertical space by utilizing neighbourhood- and building-level weights (Sun, Tu, & Yu, 2005) and 3D spatial contiguity weights (Chen & Li, 2017).

The present paper combines these strands, and its novelty is derived from several aspects. First, this work employs state-of-the-art methods and approaches from previous research in planning and applied spatial econometrics. This includes calculating more behaviourally-relevant measures of pedestrian access to capture the land value uplift impacts associated with proximity to rapid transit; utilizing a spatio-temporal difference-in-differences (STDID) longitudinal study design to better isolate the impact of changes in rapid transit on land values; and estimating a disaggregate model that controls for different station area contexts.

Second, the paper also proposes three innovations of its own that respond to some econometric challenges that arise when conducting research in high-density and topographically-rich study areas. Of these, the paper is the first to incorporate landscape topography throughout the estimation process, including the calculation of slope-aware walkability and pedestrian accessibility. The paper also develops a new Spherical Distance Weights method for capturing spatial association in three-dimensions. It then combines its 3D weights with temporal weighting techniques for a new four-dimensional (4D) approach that accounts for relations among observations in space and time.

These techniques are applied to examine the property value impact of the West Island Line (WIL) extension of the Mass Transit Railway (MTR) in Hong Kong. The paper begins with a brief background on the project, followed by the development of the study's spatio-temporal methods. STDID model results show a significant change in the value of pedestrian access to different MTR stations over project phases. The paper concludes with a discussion of implications for research and planning practice.

2. Background

The WIL project is a 3-kilometre extension of the east–west Island Line on the MTR's heavy rail network in Hong Kong. Although versions of the WIL had been envisioned since MTR system planning began (Freeman & Partners, 1970), it was not until the early 2000 s that a proposal was put forward by the MTR to build the project. Consisting of three additional stops (Kennedy Town, Hong Kong University (HKU), and Sai Ying Pun), plans for the WIL underwent several revisions, with the final scheme presented in 2007, approved in early 2009, and construction beginning later that year. Kennedy Town and HKU stations opened on December 28, 2014, and Sai Ying Pun followed in March of 2015.

The cost of the extension is estimated to be HK$18.5 billion (USD $2.4 billion). In the past, the Hong Kong Government and the MTR have employed the Rail + Property (R + P) joint development model to offset the costs of constructing new heavy rail transit in the territory (Cervero & Murakami, 2009; Suzuki et al., 2015). This model of land value capture involves the Hong Kong Government granting land at "pre-rail" prices to the MTR, who in turn develops, leases, or disposes of this land at "post-rail" prices to recoup its costs. This recognition of, and capitalization on, the accessibility and land value benefits that new heavy rail transit projects can provide has been successful at offsetting costs (and sometimes creating a profit) for the MTR in the past. However, in the case of the WIL, the mature character of neighbourhoods around the new stations resulted in a lack of suitable opportunities for large-scale redevelopment. This led the Hong Kong Government to directly contribute HK$12.7 billion (USD$1.6 billion) to the project instead. Despite not utilizing the R + P model, the present study can still provide insight into the price increment that underpins the approach by estimating the difference between pre-rail and post-rail property prices in the Hong Kong context.

3. Data and methodology

3.1. Modelling approach

This research employs a STDID hedonic model to estimate the land value uplift effect associated with the opening of the WIL. Established by Lancaster (1966) and Rosen (1974), the hedonic model postulates that the total value of a good is the sum of the value placed on, or utility derived from, its constituent characteristics and that regressing these characteristics on the price of the good reveals their implicit price at equilibrium. The base technique employed to estimate the hedonic regression is the spatial autoregressive model proposed by Kelejian and Prucha (1998, 1999, 2010), which is extended here to include spatio-temporal weights. The model takes the form:

$$y = \alpha + \rho Wy + \beta M + \gamma H + \theta L + \tau Q + \varepsilon \tag{1}$$

$$\varepsilon = \lambda W\varepsilon + \mu \tag{2}$$

where y is a vector of log-transformed sale prices per square foot of net living area, α is a constant term; ρ and λ are scalar autoregressive parameters; W is the spatio-temporal weights matrix; Wy is the spatially- and temporally-lagged dependent variable; M is a vector of variables associated with the opening of the WIL extension; H is a vector of housing characteristics; L is a vector of locational characteristics; Q is a vector of quarterly dummies corresponding to the time of sale; β, γ, θ, and τ are parameters to be estimated; ε is the spatio-temporal autoregressive error term; $W\varepsilon$ is the spatially- and temporally-lagged error term; and μ is the independent and heteroskedastically distributed error term. The model is estimated using maximum likelihood with robust standard errors.

Difference-in-differences (DID) is a quasi-experimental technique that seeks to identify what are assumed to be causal effects associated with some change by modelling differences between a treatment group and a control group. The DID estimator assumes that in the absence of the change, any trends in the treatment group would be identical to the control group. The variables of interest associated with the WIL include:

$$\begin{aligned}\beta M = \beta_1 Walk + \beta_2 Station + \beta_3 Phase + \beta_4 (Station \times Walk)\\ + \beta_5 (Phase \times Walk) + \beta_6 (Phase \times Station)\\ + \beta_7 (Phase \times Station \times Walk)\end{aligned} \tag{3}$$

The parameter *Walk* captures each property's slope-aware walking time to the nearest MTR station, *Station* is a dummy variable that

Table 1
Treatment effects in the difference-in-differences approach.

	Control group	Treatment group	Group Difference
Project Phase 1	β_1	$\beta_1 + \beta_2 + \beta_4$	$\beta_2 + \beta_4$
Project Phase 2	$\beta_1 + \beta_3 + \beta_5$	$\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7$	$\beta_2 + \beta_4 + \beta_6 + \beta_7$
Project Phase Difference			**Difference-in-Differences**
Phase 2 Effect	$\beta_3 + \beta_5$	$\beta_3 + \beta_5 + \beta_6 + \beta_7$	$\beta_6 + \beta_7$

corresponds to whether the nearest MTR station is in the treatment group, and *Phase* is a dummy variable that corresponds to whether the property transaction took place after the treatment occurred. In a simple case with one control group (e.g. an existing MTR station), one treatment group (where a new MTR station opened), a pre-treatment time period or project phase (before the new station opened), and post-treatment project phase (after the new station opened), the interaction terms from Eq. (3) correspond to the estimated effects associated with the opening of the new station on the treatment group relative to the control (Table 1).

The present research extends this approach to consider four project phases and five station areas. The three direct treatment stations consist of the new WIL Kennedy Town, HKU, and Sai Ying Pun stations. For the control group, the networked nature of transit systems presents a conceptual challenge to the identification of "true" control sites. While the addition of new stations to the MTR network should result in increases in accessibility for locations around them, these changes also increase accessibility in existing stations by expanding available opportunities and the potential for reaching them across the whole network. However, in line with accessibility theory, the magnitude of this access benefit should decrease as time or distance from the new WIL opportunities increases.

In response, the WIL is evaluated against two pre-existing stations. The first is Sheung Wan station, which opened in 1986 and was the previous western terminus of the Island Line prior to the WIL project. The second is Chai Wan station, which opened in 1985 and serves as the eastern terminus of the Island Line. Because Sheung Wan is adjacent to the WIL, it seems likely that it too would benefit from increased access, making it a less than ideal choice as a control. In contrast, as travel time to Chai Wan is about 31 min on the MTR from Kennedy Town, the access benefits from the WIL should be more muted and stable over time in this context. As a result, Chai Wan is employed as the control station in the present study, while Sheung Wan is included in the treatment group.

For the project phases, the Pre-Announcement control phase is between Q1 2001 up until the Announcement phase in the fourth quarter of 2007 when final plans for the WIL were gazetted. After this, the Construction phase began in the third quarter of 2009 and continued until Kennedy Town and HKU stations opened on December 28, 2014 and Sai Ying Pun station opened in March of 2015. For the purposes of this research, the Opening phase is assumed to begin in the first quarter of 2015.

The central hypothesis being tested in this modelling framework is whether homebuyers eventually begin to place a higher value on their walking time to the nearest WIL station once station locations become known and finalized, begin construction, and ultimately open. To operationalize this hypothesis, each property's slope-aware walk time to the MTR is estimated as if their nearest station always existed. For some properties, this assumption means their closest station in the model is Sai Ying Pun when their closest functional station was Sheung Wan prior to the opening of the WIL. Nevertheless, this specification of a fixed walk time window around stations is intuitive for estimating when homebuyers anticipate and realize accessibility effects from the WIL in the DID framework as it captures if and when the property price gradient around stations aligns or re-orients to that hypothesized by the AMM model. Such an approach also implicitly controls for station area contextual heterogeneity in other unobserved characteristics such as amenities, TOD, urban design, and the urban spatial structure.

3.2. Data sources

Built on the slopes of a hilly to mountainous region, Hong Kong is a topographically-rich city. Compared to a flat plane, this landscape plays a fundamental role in informing the spatial processes under study. To account for topographical variation, the research utilizes a digital elevation model (DEM) captured at a spatial resolution of 2 m by the Hong Kong Government's Lands Department to establish base heights for features on the ground. The pedestrian network used for this study is derived from OpenStreetMap. To control for general neighbourhood trends, median monthly domestic household income was also collected from the Hong Kong Census and Statistics Department for 2001, 2006, 2011, and 2016, linearly interpolated into a quarterly time series (based on an assumed enumeration day in the 3rd quarter), and joined to Constituency Area small-level geographic boundaries.

Real estate transactions used in the present analysis were obtained from EPRC Limited, which records property transactions from Hong Kong's Land Registry. The sample consists of Agreements of Sale and Purchase for residential property within a 10-minute walk of the MTR stations in the study area. To ensure a quality sample of arm's-length transactions, observations were excluded if they lacked full data or if the purchasing party was a private limited company or Hong Kong's Urban Renewal Authority. Some properties around Chai Wan were sold under the government's home ownership scheme, which was suspended in 2003. These properties are traded at market value with the government subsidizing a set proportion of the purchase price and preliminary analysis revealed no systemic difference from other transactions in the sample. Finally, transactions falling within the top and bottom 0.01% of the distribution of sale prices (measured as the price per square foot of living space) were excluded. In total, the sample used for this research consists of 47,362 transactions that occurred between the first quarter of 2001 and the third quarter of 2017. More information on the characteristics of this sample can be found later in the paper.

3.3. 3D Topography, walkability, and accessibility

Although the calculation of network distances or walk time to stations is more behaviourally-relevant than Euclidean distance, previous work has been conducted under the assumption of a flat pedestrian plane and constant walking speed of between 1.3 and 1.4 m per second (4–5kph). At this speed, the average pedestrian covers a distance of 800 m in about 10-minutes, corresponding to the widely-used delineation of a transit station catchment area (Guerra, Cervero, & Tischler, 2013). However, although not problematic in more two-dimensional study areas, this planar approach will overstate (or understate) pedestrian accessibility in more three-dimensional, topographically-varied contexts. This is of course because walking speed is not constant with topography; setting aside individual ability, time pressure, and other factors, walking pace and speed varies with the slope or gradient of the pedestrian environment.

To account for the effect of varied topography on pedestrian accessibility, this research employs Tolber's "Hiking Function", which Tolber (1993) estimated empirically from data in Imhof (1950). The

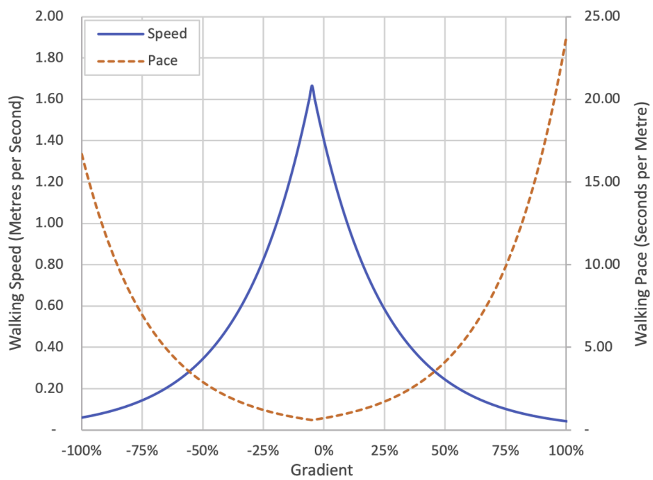

Fig. 1. Walking speed and pace by gradient per Tolber (1993) hiking function.

function takes the form:

$$v = 6e^{-3.5|m+0.05|} \tag{4}$$

where v is the velocity of travel measured in kilometres per hour and m is the gradient of the terrain. From this, walking velocity decreases exponentially as the topographical gradient of pedestrian paths increases. To return a pace of travel p measured in seconds per metre, the function can be rewritten as:

$$p = 0.6e^{3.5|m+0.05|} \tag{5}$$

Fig. 1 shows the change in pace and walking speed as the gradient of pedestrian paths increases. Per Tobler's function, changes in walking speed/pace are not directly proportional to changes in gradient/slope to account for different levels of effort involved in walking uphill or downhill. Tobler's function is offset so that a maximum walking speed of 1.67 m per second (6kph, or a pace of 0.6 s per metre) is achieved at a gradient of −5%, which corresponds to a slight downhill walk. On flat ground, walking speed is 1.4 m per second (5kph, or a pace of 0.71 s per metre).

To operationalize Tobler's hiking function, several steps were undertaken in a GIS environment using a custom Python tool available at (https://github.com/higgicd/3D_Network_Toolbox). First, pedestrian links were extracted from a 2D road centerline network. Second, additional pedestrian links corresponding to MTR station access tunnels, pedestrian bridges, plazas, staircases, internal building pathways, and shortcuts were added based on data from the Lands Department, OpenStreetMap, and manual audits, with no slope specified for particular links as appropriate. Third, each link was split into 10-metre segments (based on their 2D distance), and each segment's start- and end-point elevation and 3D distance were interpolated from the DEM. Fourth, each segment's 2D length and 3D start- and end-point elevation values were used to determine their average gradient. Fifth, the directional pace of travel p on each segment was calculated per Eq. (5). Finally, each pace of travel was multiplied by the 3D length of the segment to obtain slope- and direction-aware travel time cost attributes for all links in the pedestrian network. While this 3D network corresponds well to the topographically-rich pedestrian environment in the study area, additional edits to the network topology were required at the Belcher's housing estate near HKU to account for the lifts that connect the podium level to the shopping mall and streets beneath the towers.

Using Network Analyst in ArcGIS, estimated average pedestrian travel times on the 3D network were calculated based on the shortest path between building XYZ centroids (discussed below) and station entrance points (where stations passageways interface with the street). In this sense, it is assumed that when homeowners are implicitly pricing their accessibility to the MTR, they conceptualize the trip *to* the station from street level and are not including any additional vertical travel time that might occur within a building. Fig. 2 displays an overview of station locations and the estimated slope-aware walking time to each station from any building. For comparison, the extent of a flat-ground 10-minute pedestrian shed is shown as a dashed line in Fig. 2. Contrasted against the area covered when taking slope into consideration, the assumption of a 2D landscape results in an over-estimation of the pedestrian shed by 19% around the WIL, confirming that Hong Kong's topography plays an important role in defining pedestrian access within the study area. It should be noted that any properties that were closer to Central/Hong Kong station than Sheung Wan were dropped from the analysis so that the sample consists only of properties within a 10-minute walk of the 5 sample stations.

3.4. 3D spatial association

At the conceptual level, spatial dependence is a product of what is referred to as the first law of geography – that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). Consequently, it has long been recognized that the non-randomness of spatial dependence can impact the validity of regression coefficients estimated using ordinary least-squares, and in response, spatial econometric methods have been proposed to explicitly take such relationships into account (Anselin, 2010).

In the field of real estate, the economic behaviours that inform the data generating process exhibit spatial dependence (LeSage & Pace, 2009). For example, a spatial lag model specification is often justified based on the intuition that a home owner sets a price for their property based on not only the characteristics of their property, by also the transacted value of nearby comparable properties. Likewise, a spatial error term is often implemented to capture any measurement error or omitted variables that are assumed to be spatially-dependent. To specify the nature of these spatial relationships, a system of weights is used, of which Getis (2009) outlines three families: topological, based on contiguity among areal units; theoretical, based on some distance decline function; and empirical, based on a flexible system of weights extracted from the data.

3.4.1. Limitations of 2D weights in 3D space

The combination of a high-density built environment and a topographically-rich study area presents unique challenges for the application of spatial econometrics. For example, the typical workflow of the spatial analyst involves geocoding real estate transaction data based on the address of the property, returning the XY-coordinates of the sale. Next, a common theoretical approach to specifying a system of spatial weights involves calculating inverse Euclidean distances between observations in a two-dimensional Cartesian reference system:

$$d_{ij} = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \tag{6}$$

$$s_{ij} = \begin{cases} 1, & \text{if } d_{ij} = 0 \quad \forall\ i \neq j \\ d_{ij}^{-1}, & \text{if } d_{ij} \leq \bar{d} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where s_{ij} is the inverse distance d_{ij} between points i and j calculated from the X- and Y-coordinates of each point on a 2D plane. In practice, coincident points are typically assigned a d_{ij} equal to 1 to avoid division by zero. Because spatial autocorrelation declines with distance, the area of potential relations is often conceptualized as a circular buffer limited to any observations j that fall within some distance $\bar{d}$ of i. Decisions about the value of $\bar{d}$ are made based on theory or empirically by fitting a semivariogram. This latter approach results in what Getis (2009) refers to as a hybrid 'theoretical-empirical' weights matrix.

With single-detached homes on a flat plane, this specification of distance does not present an issue, as each point corresponds to a single

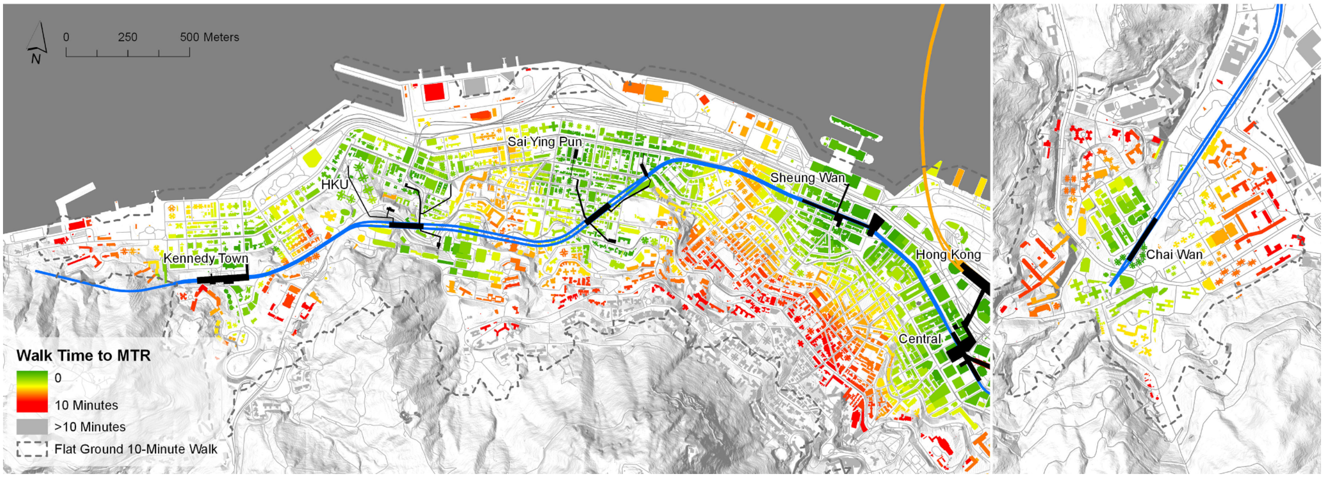

Fig. 2. Walk time to nearest MTR station.

sale. Spatial models can then be used to capture neighbourhood-level spatial dependence (or what Sun et al. (2005) refer to as the "neighbourhood effect"). However, when constructing a spatial weights matrix for a sample of sales in a high-density urban environment, multiple sales in a single building geocoded to the same XY-coordinates result in coincident points and spatial weights equal to 1 per Eq. (7). By representing 3D observations 2D space, this planar workflow only effectively weights transactions by distance if they occurred in neighbouring buildings, while all transactions inside the same building are given identical and maximum weight.

Extending the real estate data generating process to high-density residential contexts, it seems intuitive that, in addition to neighbourhood-level spatial effects, units in the same building share features in common, such as the presence of a lift or particular interior or exterior architectural attributes. Sun et al. (2005) refer to this as spatial dependence due to the "building effect". Recognizing the challenges associated with high-density contexts, Sun et al. (2005) propose the use of separate weights matrices to capture differences in neighbourhood- and building-level spatial dependence based on distance decay and transactions at the same XY coordinates respectively. Gelfand, Banerjee, Sirmans, Tu, and Ong (2007) adopt a similar approach and utilize multi-level models to account for building- and neighbourhood-level effects.

However, while these previous works incorporate binary building-level elements into their estimation process, it is argued here that such 2D approaches are incompatible with the geographic principle that near features are more related than distant ones in 3D space. For example, a unit on a high floor of a building might share more in common with other units on higher floors than lower floors, such as similar viewsheds, sun exposure, or longer vertical travel times. Likewise, a unit on a lower floor is likely to share more in common with other lower-floor units in the same or neighbouring buildings, such as higher levels of road-based particulate air pollution, noise, or shadows. The potential for such differences was recognized by Sun et al. (2005), and indeed, recent studies have explicitly examined the positive impact of factors such as elevation and floor height (Wong, Chau, Yau, & Cheung, 2011) and viewshed (Hui & Liang, 2016) on property prices in high-density markets.

Although a binary building-level effect can capture some elements of this 3D spatial dependence, the assumption of equal weight across all transactions within the same building is restrictive. As such, there is a rationale for broadening the conceptualization of spatial association to three dimensions, particularly when analyzing high-density built environments where the potential for spatial dependence extends to both the horizontal and vertical dimensions.

3.4.2. *Cube contiguity*

Building on recent advances in 3D geospatial technologies, one recent paper that has incorporated 3D measures of distance in the specification of spatial weights is the novel Cube Contiguity method proposed by Chen and Li (2017). Here, the authors conceptualize residential transactions in a tower as a series of cubes stacked upon one another and extend the concept of contiguity to 3D space by capturing each cube's nearest neighbours (which they specify to include up to three lags).

However, although it incorporates the potential for horizontal and vertical relations, the Cube Contiguity approach is limited by a simplified conceptualization of distance. According to Getis (2009), by limiting association to only spatial units with contiguous connections, contiguity weights risk omitting important spatial relationships that occur at greater distances. In response, Getis (2009, p. 407) argues that more theoretical approaches that employ distance weights "offer a considerable step forward over the use of contiguity matrices." Still, empirical weights are viewed as a better way to represent real-world spatial associations, though Getis states that a hybrid 'theoretical-empirical' approach that specifies distance weights based on an empirical semivariogram is a suitable compromise.

3.4.3. *Spherical distance weights*

In an effort to better capture spatial relationships in high-density housing markets, the present research proposes a Spherical Distance Weights method that extends the formulation of more general inverse distance weights in Eqs. (6)–(7) to 3D space. By utilizing X-, Y-, and Z-coordinates, this simple extension incorporates horizontal and vertical spatial distance:

$$d'_{ij} = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2 + (Z_i - Z_j)^2} \tag{8}$$

$$s'_{ij} = \begin{cases} 1, & \text{if } d'_{ij} = 0 \quad \forall\ i \neq j \\ d_{ij}{'}^{-1}, & \text{if } d'_{ij} \leq \bar{d} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

As with the circular buffer common in the 2D approach to distance weights, applying some cut-off distance $\bar{d}$ in the calculation of d'_{ij} in 3D space results in a spherical volume of potential spatial association among observations i and j.

Although the theoretical justification for adding Z-coordinates to the calculation of distance weights is strong, operationalizing Spherical Distance Weights with real estate transaction data in high-density urban environments presents some practical challenges related to data preparation. In the absence of detailed building information models, several steps were undertaken to associate real estate transactions with

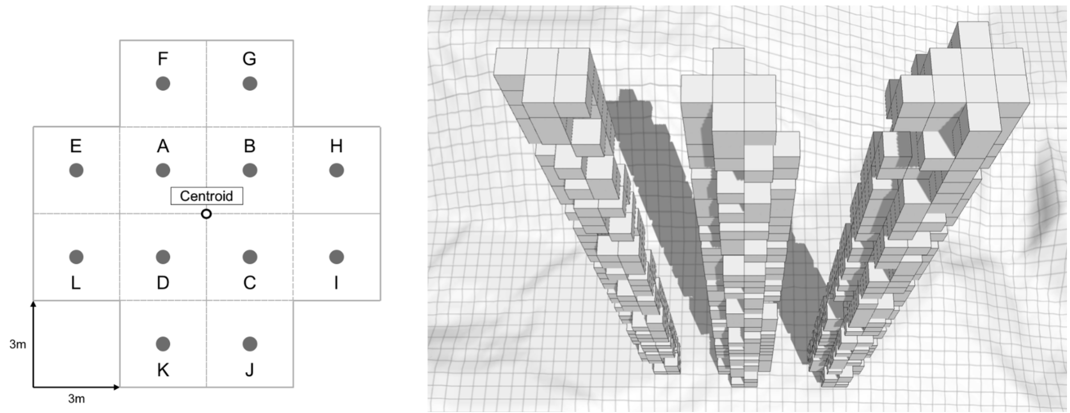

Fig. 3. Unit-offset grid (left) and combined unit-floor offset (right).

estimates of their location in 3D space.

3.4.3.1. Building centroid. First, transactions were geocoded based on their address and building name. For individual transactions, this process returns X- and Y-coordinates that roughly correspond to a building's centroid. Next, building centroid points are plotted in a GIS environment and their base ground height Z-coordinates are interpolated from the DEM. These two steps result in coincident building XYZ centroid points in 3D space, measured in metres.

3.4.3.2. Unit XY-offset. The second step involves offsetting base XY coordinates for individual units from the building centroid according to the 3 m by 3 m grid in the left panel of Fig. 3. Any numeric unit sequences are converted to alphabetic, and in total, 12 unit positions are considered. This layout fits the 'skinny' buildings of the Hong Kong study area well (only about 1.5% of all transactions had to be dropped from the analysis at this step, including transactions with unit labels that were missing, indeterminate, or greater than 'L'), but it can be tailored to other study areas with larger floor plans.

3.4.3.3. Floor Z-offset. Although the previous step separates transactions that occurred over different units, transactions of units with the same number or label on different floors are still coincident. To account for differences in elevation among floors in the same building, the total height of each floor is estimated according to Eq. (10).

$$h_{total} = h_{base} + (f_{adjust} \times 3) \tag{10}$$

Here, total floor height h_{total} is the building's base height h_{base} interpolated from the DEM plus the product of a transaction's adjusted floor number f_{adjust} and an estimated average building storey height of 3 m. Floor numbers are adjusted to account for tetraphobia and triskaidekaphobia in the sequencing of building floors common in Hong Kong, as this would lead to an overestimation of height for particular floors located after breaks in the numerical sequence. For example, if a floor's original number is 36, but the building omits floors 4, 13, 14, 24, and 34, the floor's number is adjusted to 31.

These three steps produce XYZ-coordinates that correspond to a series of regularly-spaced unit grid centroids layered by different floor heights. After converting the unit centroids to cubes for visualization, the end result in the right panel of Fig. 3 resembles the Cube Contiguity method proposed by Chen and Li (2017). However, the resulting spatial weights are based on 3D distances between cubic centroids rather than contiguity among cubic neighbours.

Next, inverse distances s'_{ij} between cubic centroids are calculated per Eqs. (8)–(9). In the present case, the hybrid 'theoretical-empirical' approach recommended by Getis (2009) is adopted, with the radius $\bar{d}$ of the sphere set at 300 m based on the estimation of an empirical semivariogram (Appendix 1). Pooling these s'_{ij} results in an $n \times n$ matrix S of spatial relations in three-dimensional space:

$$S = \begin{pmatrix} 0 & s_{12} & s_{13} & \cdots & s_{1N} \\ s_{21} & 0 & s_{23} & \cdots & s_{2N} \\ s_{31} & s_{32} & 0 & \cdots & s_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{N1} & s_{N2} & s_{N3} & \cdots & 0 \end{pmatrix} \tag{11}$$

Diagonal elements of S are set to zero, as no single observation can be a neighbour to itself. Note that observations in the sample are sorted chronologically considering the year, month, and day of sale to aid in the construction of temporal weights below. The resulting weighting scheme is more consistent with distance theory than the Cube Contiguity approach and more straightforward than specifying separate neighbourhood- and building-level matrices. Although this formulation omits a binary building-level indicator, the vertical morphology of the city means that proximate transactions within the same building will be afforded the greatest weight.

3.5. 4D spatio-temporal weights

Although the issue of spatial dependence has long been recognized, less attention has been paid to the temporal dimension associated with specifying spatial weights among observations collected over a period of time, such as real estate transactions (Dubé & Legros, 2013a,b). While spatial weights respond to Tobler's (1970, 2004) law about spatial association, the spatial weights matrix S is time-independent, weighting relations among observations that are spatially proximate, or *near*, but occurred at various times. In contrast, incorporating the time dimension on top of space responds to Miller's contention that it is "not just a matter of *where* you are, but also *when* you are (Miller, 2004, p. 287)." Accordingly, a system of spatio-temporal weights better draws a conceptual difference between things that are *related* versus just *near*.

Some recent research has incorporated temporal relations as a third dimension in their spatially-planar studies. To do so, a time index v corresponding to the sequential month of sale for each transaction is calculated. As in Dubé and Legros (2013b), v takes the form:

$$v_i = 12 \times (yyyy_i - yyyy_{min}) + mm_i \quad \forall\ i \tag{12}$$

where $yyyy_i$ and mm_i are the year and month of sale for observation i respectively and $yyyy_{min}$ is the earliest year of transactions in the sample. Next, the temporal distance t_{ij} between observations i and j is calculated:

$$t_{ij} = \begin{cases} (v_i - v_j)^{-\psi}, & \text{if } 0 < (v_i - v_j) \le \underline{v} \\ 1, & \text{if } v_i = v_j \quad \forall\ i \ne j \\ (v_j - v_i)^{-\omega}, & \text{if } 0 < (v_j - v_i) \le \bar{v} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where v_i is a time index corresponding to the sequential month of sale for transaction i, v_j is the index for transaction j, and $\underline{v}$ and $\bar{v}$ are cut-off temporal distances (which in this case are set to 12 and 6 respectively). With this month index, the relative temporal distance between transactions can be calculated to account for the "anchoring" of real estate asking prices relative to comparable sales and future expectations (Thanos, Dubé, & Legros, 2016). In that paper, the authors specify three separate weighting matrices that account for temporal distance relative to sales that occurred in the past, present, and future respectively. In the present case, relative temporal distance is estimated between transactions i and j that occurred in either the past $(0 < (v_i - v_j) \leq \underline{v})$, present $(v_i = v_j)$, or future $(0 < (v_j - v_i) \leq \bar{v})$ simultaneously. This single-matrix hybrid of the comparable past sales and speculative expectations approaches is similar to that in Dubé and Legros (2013a, 2013b). However, in contrast to Dubé and Legros (2013a) and Thanos et al. (2016) who consider either 6 or 12 months of temporal association in either direction respectively and set both ψ and ω to 1, this work assumes $\psi = 1$ and $\omega = 2$. This steeper discount on temporal associations up to 6 months in the future is done to reflect the inherent fuzziness of speculative expectations based on incomplete information compared to a record of sales that occurred over the previous 12 months.

Pooling these t_{ij} forms an $n \times n$ matrix T of temporal relations among observations:

$$T = \begin{pmatrix} 0 & t_{12} & t_{13} & \cdots & t_{1N} \\ t_{21} & 0 & t_{23} & \cdots & t_{2N} \\ t_{31} & t_{32} & 0 & \cdots & t_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ t_{N1} & t_{N2} & t_{N3} & \cdots & 0 \end{pmatrix} \tag{14}$$

As with matrix S, the diagonal of T is set to zero. With the sample sorted chronologically by each transaction's year, month, and day of sale, non-zero elements in the lower triangle of T reflect the weighted temporal distance t_{ij} between i and any past transactions j while the upper triangle of T reflects the weighted distance between i and future transactions j. Next, the spatio-temporal weights matrix W is calculated by taking the Hadamard product of the spatial weights matrix S and the temporal weights matrix T:

$$W = S \odot T = \begin{pmatrix} 0 & W_{12} & W_{13} & \cdots & W_{1N} \\ W_{21} & 0 & W_{23} & \cdots & W_{2N} \\ W_{31} & W_{32} & 0 & \cdots & W_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & W_{N3} & \cdots & 0 \end{pmatrix} \tag{15}$$

As a final step, the 4D spatio-temporal weights matrix W is standardized using a spectral transformation. It should be noted that there is some disagreement in the literature on weights standardization techniques. Kelejian and Prucha (2010) argue in favour of a spectral transformation over row-standardization, as row-stochastic scaling alters the structure of weights among observations and produces a matrix that cannot be re-scaled back to its un-normalized form. However, LeSage and Pace (2014, p. 245) are of the position that this "purely statistical" consideration neglects the data generating process used to justify the inclusion of spatial relations, which they argue is more consistent with row standardization. Still, Elhorst (2014) argues that when using inverse distance, row-standardization affects the economic assumptions behind the decay in relationships over space and can lead to the misspecification of distance weights. Moreover, the separate issue of missing data in the spatial weights matrix S from edge effects or boundary values remains unresolved. Although Anselin (1988) notes that, under the usual regularity conditions, the maximum likelihood estimator will return consistent estimates of spatial dependence with large samples, the impact of the additional edge effects that result from the imposition of temporal boundaries in W is under-studied.

3.6. Sample description

Table 2 displays descriptive statistics for the full sample. The average sale price over 2001 to 2017 was about HK$4.3 million and properties had an average size of almost 500 ft^2 of net living area. This corresponds to an average purchase price of HK$8,158 (US$1,043) per square foot of living space in the study area over this time period. Average slope-aware walk time to the nearest MTR entrance is approximately 4 min. Alternative log, negative exponential, squared, and gamma specifications of this variable were tested; however, the linear form ultimately provided the best balance between model fit, complexity, and interpretability. Other variables include the proportion of sales by station area and project phase, and the time of sale and characteristics of the property, such as the number of bedrooms or whether the property faces north (to control for any premiums associated with views of Victoria harbour).

Table 3 displays a more detailed breakdown of the proportion of property transactions in each station by project phase. Taken together, Fig. 4 provides a view of the assembled data in 3D space looking east from Kennedy Town station, highlighting the slope of the terrain, the distribution of transactions according to their walk time to the MTR, and their elevation and unit offset.

4. Model results

With 47,362 observations in the sample, the memory requirements of the $n \times n$ spatio-temporal weights matrix W made the estimation of a full model computationally infeasible. In response, five sub-samples were created by randomly drawing 50% of the transactions from the full sample, and the results in Tables 4 and 5 below correspond to averages across the five separate sub-sample models (full results for the five models can be found in Appendix 2). Both the spatio-temporal lag (ρ) and error terms (λ) were found to be significant, and the mean model fit is high at 0.884. Per LeSage and Pace (2009), the spatio-temporal specification means model results are understood in terms of direct (coefficients in Tables 4 and 5), indirect (spatial spillovers), and total effects (sum of the direct and indirect effects). However, based on Small and Steimetz (2012), it is argued here that the indirect spillover benefits of MTR accessibility are welfare-neutral, and as such, the focus of this section is on the direct effects only.

The variables corresponding to a property's characteristics in Table 4 indicate that properties sold for a higher value per square foot if they have more bedrooms or living/dining rooms, and premiums were also found if a property had a bay window, carpark space, flat roof or rooftop, clubhouse, pool, or faces north or north-west. In contrast, balcony space is a disamenity, perhaps seen by the market as a waste of valuable space. Older buildings sold at a discount, although this discount flattens over time, and no effect was seen for the terrace and north-east direction variables.

For the WIL, the base MTR Station Area context dummies in Table 4 capture interesting submarket effects along the corridor. Because of the interaction specification, these coefficients correspond to the average value of a property at a travel time to the MTR equal to zero in the different station areas in the first project phase relative to the Chai Wan reference. Average sale prices per square foot of living space for properties proximate to the Sheung Wan and HKU stations were about 10% and 5% more than properties around the Chai Wan control, while the insignificant effect for Sai Ying Pun and Kennedy Town suggests properties here were valued about the same as in Chai Wan in the pre-construction phase, all else being equal. The interaction of the station indicator variables with the project phases reveals that average prices vary over the station areas relative to Chai Wan, ranging from between 24% and 28% greater in the Announcement phase, 19% to 32% in the Construction phase, and 13% to 31% in the Opening phase.

Table 2
Sample descriptive statistics.

Variable	Mean (Prop.)	Std. Dev.	Min	Max.
Sale Price (HK$, thousands)	4,290.749	5,025.052	113.00	163,000.00
Net Area (ft^2)	493.765	248.626	155.000	7,395.000
Sale Price per Sq. ft. (Net, HK$)	8,158.354	5,738.219	336.8794	46,333.140
MTR Proximity				
Walking Time to Station (min)	3.998	2.033	0.147	9.988
Sales by MTR Station Areas				
Chai Wan	(0.115)		0	1
Sheung Wan	(0.085)		0	1
Sai Ying Pun	(0.337)		0	1
HKU	(0.224)		0	1
Kennedy Town	(0.239)		0	1
Sales by Project Phase				
Pre-Announcement	(0.469)		0	1
Announcement (2007 Q4)	(0.119)		0	1
Construction (2009 Q3)	(0.316)		0	1
Opening (2015 Q1)	(0.095)		0	1
Property Characteristics				
Balcony (0–1)	(0.131)		0	1
Bay Window (0–1)	(0.543)		0	1
Bedrooms (no.)	1.441	1.199	0	5
Building Age (years)	16.609	12.254	0	59
Carpark (0–1)	(0.024)		0	1
Club House (0–1)	(0.278)		0	1
Direction Facing: North (0–1)	(0.060)		0	1
Direction Facing: North-East (0–1)	(0.116)		0	1
Direction Facing: North-West (0–1)	(0.124)		0	1
Flat Roof (0–1)	(0.024)		0	1
Living Rooms/Dining Rooms (no.)	1.235	0.973	0	3
Pool (0–1)	(0.298)		0	1
Rooftop (0–1)	(0.019)		0	1
Terrace (0–1)	(0.000)		0	1
Unit Elevation (metres)	70.286	39.722	5.000	242.074
Neighbourhood Attributes				
Median Household Income (HK$1,000s)	28.021	12.508	14.000	91.586
Quarter of Sale				
Omitted for Brevity (0–1)				
n				47,362

Table 3
Proportion of sale transactions by MTR station and project phase.

	Chai Wan	Sheung Wan	Sai Ying Pun	HKU	Kennedy Town	Total
Phase 1: Pre-Announcement	0.050	0.039	0.158	0.110	0.111	0.469
Phase 2: Announcement	0.014	0.012	0.041	0.024	0.028	0.119
Phase 3: Construction	0.040	0.028	0.103	0.068	0.078	0.316
Phase 4: Opening	0.010	0.006	0.035	0.023	0.022	0.095
Total	0.115	0.085	0.337	0.224	0.239	1.000

These base station effects capture some heterogeneity in the context and desirability of different station areas over time and suggest that, overall, property prices in the treated submarkets accelerated at a much higher rate than that seen around Chai Wan. While these results offer an indication of general trends around the WIL, the key variables of interest consist of those associated with pedestrian accessibility to stations. To facilitate discussion, results for the Walk Time to MTR variables are pooled in Table 5 and interpreted according to the DID framework in Table 1. Marginal effects for each station are also plotted in Fig. 5.

First, in the Total Effects section, the Pre-Announcement MTR walk time for Chai Wan indicates that sale prices per square foot decreased by about 5.2% for every minute farther a property was from its nearest station entrance. This suggests that walkable proximity to the MTR was seen as an amenity in the control group prior to the WIL project. In contrast, the effect for the pre-existing Sheung Wan station is positive, with sale prices increasing by 1.2% as minutes from the station increase. This effect is opposite of that hypothesized and suggests that walkable proximity to the MTR was seen as a slight disamenity in this station area. Of the new stations in the Pre-Announcement phase, walk time is also positive for the Sai Ying Pun, HKU, and Kennedy Town stations at 1%, 0.7%, and 0.5% respectively. This is the hypothesized effect, as accessibility to the future stations should not be priced into property values prior to the announcement of the WIL project.

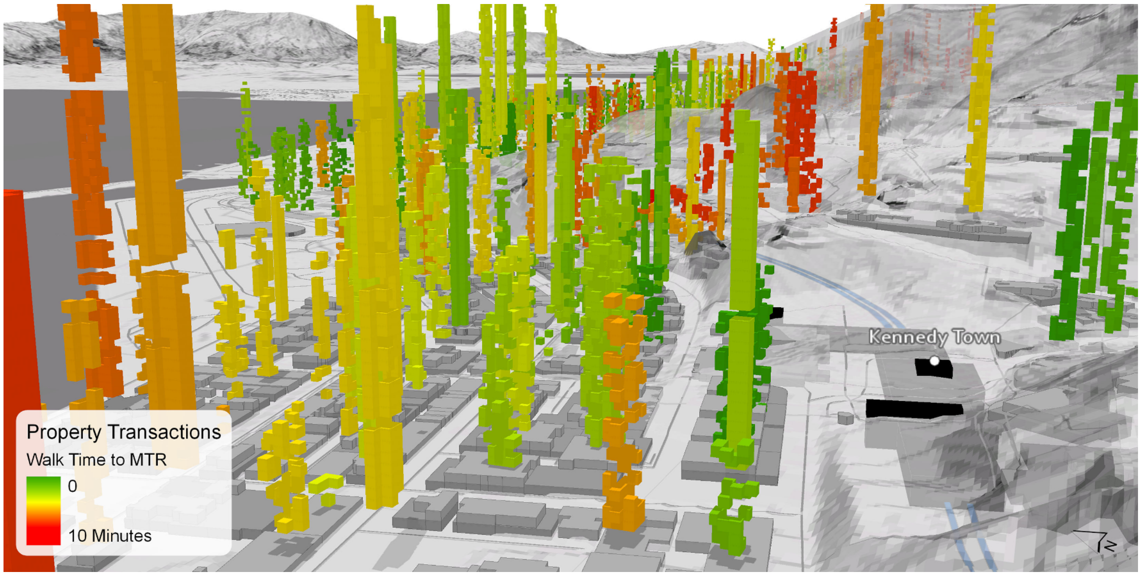

Fig. 4. View of sample transactions by walk time to the MTR.

After the announcement and gazetting of the WIL project in the fourth quarter of 2007, no change in the land value gradient is detected around the Chai Wan control station, nor around Sheung Wan and the future Sai Ying Pun and HKU stations. However, some speculative effects begin to be seen for properties that would be within walking distance of the announced Kennedy Town station. Here, the gradient changed to negative, with the total effect indicating every minute farther a property was located from the future station was associated with a price reduction of 1.5%. Over the construction phase, more evidence of the future MTR stations being priced into the land market is seen with walking distance to both Sai Ying Pun and Kennedy Town stations associated with a negative gradient. In the case of Kennedy Town, the walk time effect increased in magnitude, suggesting a higher value placed on anticipated accessibility to the upcoming station.

Finally, after opening, the walk time gradient for all treated stations becomes significantly negative. For the new WIL stations, results suggest that sale prices per square foot decrease by about 2%, 2%, and 4.1% for every minute farther a property is located from the Sai Ying Pun, HKU, and Kennedy Town stations respectively. For Sheung Wan, the price effect is also now negative, suggesting a discount of 3.3% for every minute farther a property is from the station.

Taking the first differences for individual stations in the Opening phase from the Pre-Announcement phase, STDID results show that the walk time gradient has decreased in absolute terms by 4.4%, 2.9%, 2.7%, and 4.6% in the Sheung Wan, Sai Ying Pun, HKU, and Kennedy Town station areas respectively, while the gradient in Chai Wan remained constant over time. Such results appear to confirm the hypothesis that pedestrian accessibility to the MTR became more valuable within the study area as the WIL project progressed. Consequently, for a property located 10-minutes away from the Sheung Wan, Sai Ying Pun, HKU, or Kennedy Town stations, the model estimates a decrease in value of 41.2%, 28.6%, 25.9%, and 39.8% respectively relative to a property located next to the station over the Pre-Announcement and Opening phases.

Still, the absolute magnitude of the price gradient in all treated stations is weaker than that seen around Chai Wan. For this station, properties located 10-minutes away from their nearest entrance were valued on average 41.6% less than those proximate to the station over all project phases. Nevertheless, the STDID results reveal a significant re-orientation of the property market towards the accessibility offered by the new stations after the WIL opened. In particular, the model finds evidence that the value of pedestrian access increased around all four treatment stations in the study area and that anticipatory effects were seen prior to the opening of the future Kennedy Town and Sai Ying Pun stations.

5. Discussion and conclusions

This research employed a quasi-experimental model to isolate the implicit capitalization of pedestrian accessibility to rapid transit into property values in Hong Kong. However, conducting research in a high-density, topographically-varied city presents some challenges for applied spatial econometrics. In response, the paper incorporated and developed several innovations in methods and techniques. This includes the creation of a 3D pedestrian network and the calculation of slope-aware measures of pedestrian accessibility. The spatial characteristics of a high-density property market also required the development of a new Spherical Distance Weights technique for capturing spatial dependence among observations in 3D space. These 3D weights were combined with measures of temporal distance and the resulting 4D approach is utilized within a STDID modelling framework to isolate longitudinal property price trends associated with the WIL extension of Hong Kong's MTR.

Results show that the opening of the western extension of the Island Line pushed up property values around the new stations and the line's previous western terminus relative to the eastern terminus control station. Moreover, model findings suggest that the market eventually oriented itself to the hypothesized walkability effect and began pricing pedestrian access to the MTR. There are significant differences in the timing of this effect, with speculation seen around the new Kennedy Town and Sai Ying Pun stations. Still, the greatest changes for all stations occurred after the WIL opened, with properties in buildings located 10-minutes away seeing price decreases that range from 25.9% to 41.2% relative to properties located next to station entrances.

In terms of extensions for research, this paper proposed several methodological innovations. First, the Spherical Distance Weights

Table 4
STDID model results (5-Model Mean).

Variable	Coefficient	Std. Err.
MTR Station Walk Time and Interactions		
Refer to Table 5		
MTR Station Areas (Pre-Announcement)		
Chai Wan	(reference)	
Sheung Wan	0.09974**	0.02789
Sai Ying Pun	0.04195	0.01841
HKU	0.05021*	0.02035
Kennedy Town	−0.02652	0.02088
*Project Phase * MTR Station Area*		
Pre-Announcement (All Stations)	(reference)	
Announcement * Chai Wan	(reference)	
Announcement * Sheung Wan	0.24984***	0.05776
Announcement * Sai Ying Pun	0.21230***	0.03743
Announcement * HKU	0.21969***	0.04186
Announcement * Kennedy Town	0.22204***	0.04342
Construction * Chai Wan	(reference)	
Construction * Sheung Wan	0.17912***	0.04287
Construction * Sai Ying Pun	0.25411***	0.02673
Construction * HKU	0.17615***	0.03020
Construction * Kennedy Town	0.28204***	0.03125
Opening * Chai Wan	(reference)	
Opening * Sheung Wan	0.21556**	0.07132
Opening * Sai Ying Pun	0.11931*	0.04356
Opening * HKU	0.12410*	0.04516
Opening * Kennedy Town	0.26815***	0.04985
Property Characteristics		
Balcony (0–1)	−0.03287***	0.00683
Bay Window (0–1)	0.01645**	0.00443
Bedrooms	0.01176*	0.00418
Building Age (years)	−0.03147***	0.00070
Building Age^2	0.00038***	0.00001
Carpark (0–1)	0.12646***	0.01186
Club House (0–1)	0.03315***	0.00711
Direction Facing: North (0–1)	0.02512***	0.00700
Direction Facing: North-East (0–1)	0.00314	0.00526
Direction Facing: North-West (0–1)	0.01103*	0.00507
Flat Roof (0–1)	0.10127***	0.00980
Living Rooms/Dining Rooms	0.01672**	0.00514
Pool (0–1)	0.04593***	0.00537
Rooftop (0–1)	0.06740***	0.01097
Terrace (0–1)	0.21177	0.12442
Unit Elevation (metres)	0.00247***	0.00005
Neighbourhood Attributes		
Median Household Income (HK$1,000 s)	0.00199***	0.00017
Quarter of Sale		
Omitted for Brevity (see Appendix)		
α	8.18642***	0.02440
ρ	0.00919***	0.00151
λ	4.17376***	0.02343
n	23,681	
Pseudo-R^2	0.8844	

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

technique extends Tobler's (1970, 2004) concept of spatial association to 3D space. This weighting system is more straightforward than the specification of separate neighbourhood- and building-level weights matrices used by Sun et al. (2005) and more consistent with distance theory than the Cube Contiguity approach proposed by Chen and Li (2017), particularly when an empirical semivariogram is used to specify spheres of potential spatial association. Given the potential for horizontal and vertical association among properties in a multi-storey built environment, such a 3D spatial weighting approach should be employed by any analyst utilizing spatial econometrics in high-density cities where bid-rent theory is more relevant to the value of built volume than that of land. Extending the Spherical Distance Weights to include a fourth temporal dimension works from Miller's (2004) distinction between "near" and "related" to better capture relationships that occurred in both 3D space and time.

Second, the use of Tobler's Hiking Function is a logical extension of the recent shift towards employing more behaviourally-relevant measures of network access over simple Euclidean distance. In the present case, comparisons with an assumed flat plane show that landscape topography has a significant impact on pedestrian accessibility, highlighting potential shortcomings associated with the horizontalism that dominates previous studies. As such, this approach should be employed to better capture how landscape affects access in other topographically-rich study areas where assumptions of planarity are unrealistic.

Nevertheless, while the 3D network methods result in a network that is more topographically-rich, representing the topologically complex pedestrian environment of cities like Hong Kong will remain challenging. Related to this, the paper considered walk times to the nearest station access point at street level, and with the offset in Tobler's function, it may be that premiums differ when considering the trip from the station. Research could also test for differences between trips to/from the internal parts of a station rather than their street interface. For example, both Sai Ying Pun and HKU stations feature extensive internal walkways, which could be impacting the magnitude of the results seen here if more value is placed on the total travel time to reach the station concourse rather than the station entrance. Direct specifications of network accessibility or alternative functional forms for walk time could also be used to estimate the relationship between access and property value.

Third, the paper's findings highlight an issue associated with determining a "true" control in quasi-experimental studies with interconnected network effects. In the case of rapid transit, increased accessibility offered by new station nodes inherently affects the accessibility of other stations on the transit network. This new supply of rapid transit may also affect other transit modes, such as by reducing the frequency or coverage of bus transit services. In the present case, large price changes were detected around the pre-existing Sheung Wan station after the WIL opened while trends in the more remote Chai Wan station area were stable, suggesting the latter is a more suitable choice as a control. Still, although the disaggregate model specification produces results that are sensitive to differences in uplift across individual stations, the models are not able to identify how station-area contextual factors are informing these differences.

Finally, for planning and policy, the significant value uplift seen after the opening of the WIL highlights the important role of the MTR in defining Hong Kong's accessibility and economic geography. But beyond contributing to the growing body of evidence that rapid transit is valued in general, the relevance of these findings for land value capture is particularly strong. The efficacy of Hong Kong's Rail + Property model of transit joint development is built on the difference between "pre-rail" and "post-rail" prices. While joint development was not pursued in practice along the WIL, an uplift increment of between 25.9% and 41.2% over the pre- and post-rail phases of the WIL project validates the model's key assumption. Still, such findings can also signal possible transit-induced gentrification effects (He, Tao, Hou, & Jiang, 2018), and further research into how land value uplift is affected by station area transit-oriented development contexts is required. But to echo the conclusions of Cervero and Murakami (2009), although the R + P model and the findings detailed here are informed by institutional advantages and the urban geographic/structural context of Hong Kong, it remains a viable model of sustainable finance and urbanism for other high-density and transit-oriented cities around the world.

Table 5
MTR access difference-in-difference results (5-Model Mean).

Variable	Chai Wan		Sheung Wan	Sai Ying Pun	HKU	Kennedy Town
MTR Walk Time						
Pre-Announcement	−0.05383***	+	0.06598***	0.06391***	0.06109***	0.05931***
	+		+	+	+	+
Announcement	0.00278	+	−0.00925	−0.01030	−0.01619	−0.02068*
Construction	0.00299	+	−0.00805	−0.02446**	−0.01405	−0.03563***
Opening	0.00914	+	−0.04537***	−0.02986**	−0.02760*	−0.04726***
Total Effect (> 95% C.I. only)						
Pre-Announcement	−0.05383		0.01215	0.01008	0.00726	0.00547
Announcement	−0.05383		0.01215	0.01008	0.00726	−0.01521
Construction	−0.05383		0.01215	−0.01438	0.00726	−0.03016
Opening	−0.05383		−0.03322	−0.01978	−0.02035	−0.04178
Difference from Pre-Announcement						
Pre-Announcement	–		–	–	–	–
Announcement	0.00000		0.00000	0.00000	0.00000	−0.02068
Construction	0.00000		0.00000	−0.02446	0.00000	−0.03563
Opening	0.00000		−0.04537	−0.02986	−0.02760	−0.04726
Difference from Chai Wan						
Pre-Announcement	–		0.06598	0.06391	0.06109	0.05931
Announcement	–		0.06598	0.06391	0.06109	0.03862
Construction	–		0.06598	0.03946	0.06109	0.02367
Opening	–		0.02062	0.03406	0.03349	0.01205
Difference-in-Differences						
Pre-Announcement	–		–	–	–	–
Announcement	–		0.00000	0.00000	0.00000	−0.02068
Construction	–		0.00000	−0.02446	0.00000	−0.03563
Opening	–		−0.04537	−0.02986	−0.02760	−0.04726

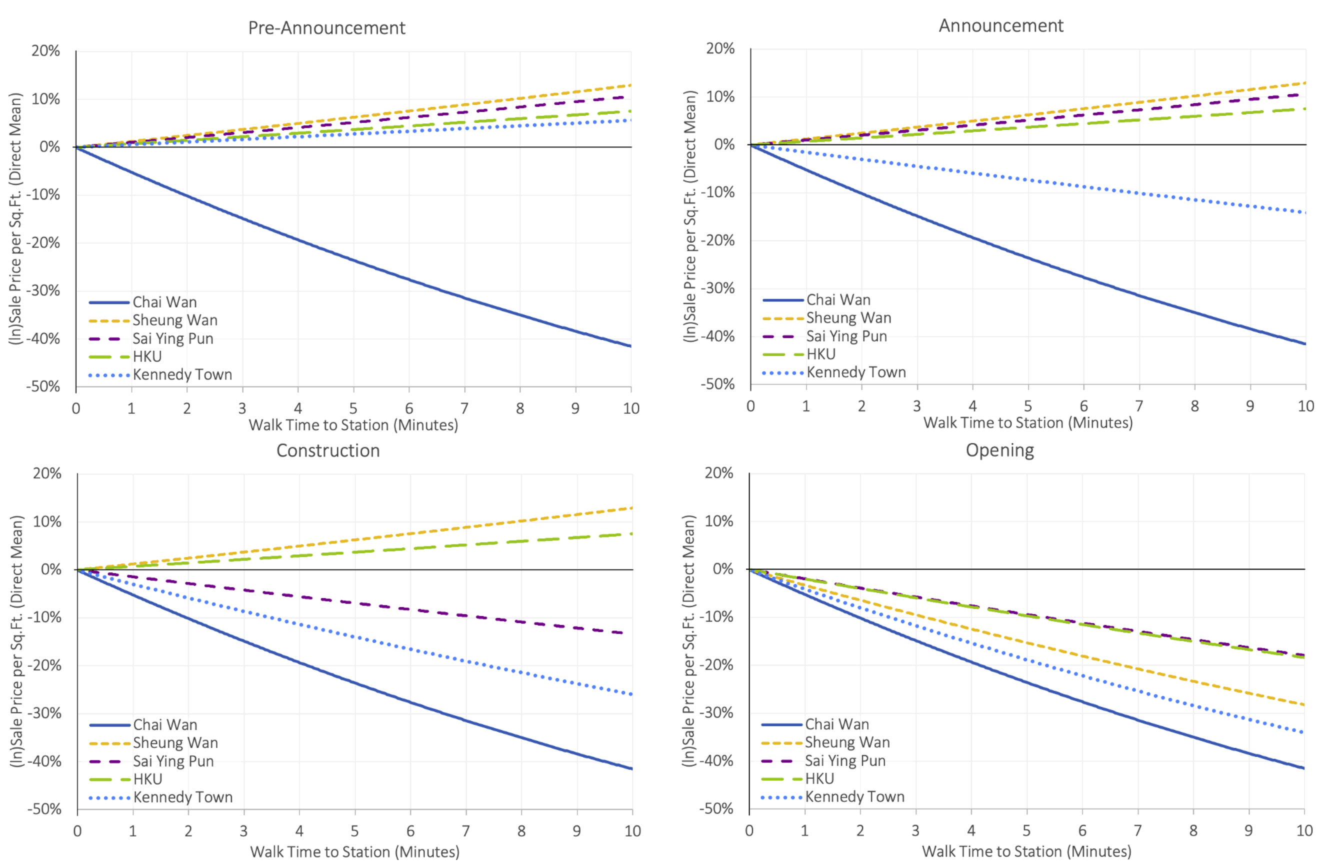

Fig. 5. Estimated walk time marginal effect.

Acknowledgement

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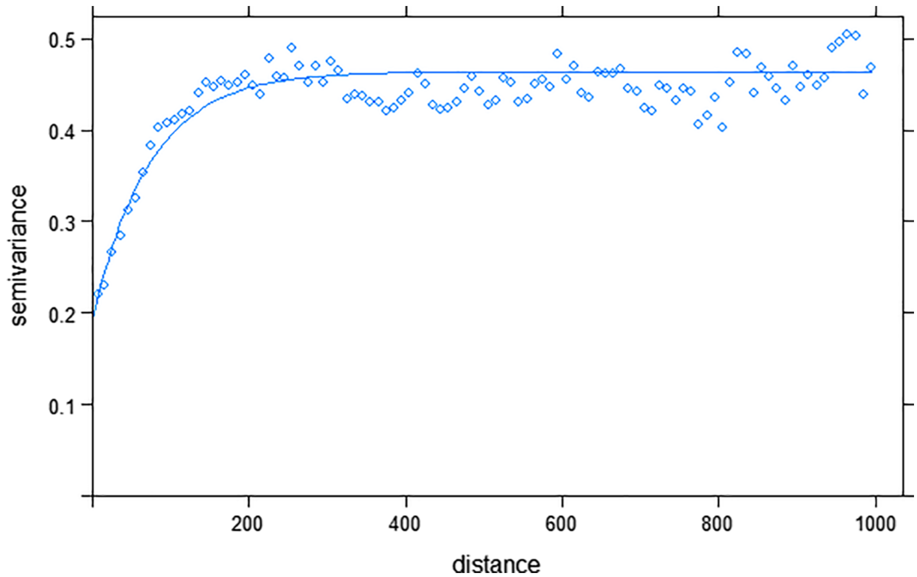
Appendix 1. Empirical Semivariogram fit to 3D Transactions



Based on the results of the semivariogram, the range of spatial autocorrelation in the sample is determined to largely be contained within a distance of 300 m.

Appendix 2. Full 5-Model STDID Results

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
MTR Proximity					
Walking Time to Station (min)	−0.05409***	−0.05233***	−0.05439***	−0.05540***	−0.05295***
MTR Station Areas					
Chai Wan			(*reference*)		
Sheung Wan	0.09398**	0.11010***	0.07289*	0.10934***	0.11237***
Sai Ying Pun	0.03936*	0.05609**	0.02518	0.03987*	0.04925**
HKU	0.04542*	0.03234	0.05604**	0.05636**	0.06086**
Kennedy Town	−0.02287	−0.02602	−0.03748	−0.02291	−0.02332
Project Phase					
Pre-Announcement			(*omitted*)		
Announcement			(*omitted*)		
Construction			(*omitted*)		
Opening			(*omitted*)		
*MTR Proximity * MTR Station Area*					
Walk Time * Chai Wan			(*reference*)		
Walk Time * Sheung Wan	0.06943***	0.06334***	0.06949***	0.06615***	0.06152***
Walk Time * Sai Ying Pun	0.06472***	0.06011***	0.06543***	0.06714***	0.06217***
Walk Time * HKU	0.06239***	0.06591***	0.05897***	0.06048***	0.05769***
Walk Time * Kennedy Town	0.05848***	0.06044***	0.05999***	0.06023***	0.05740***
*MTR Proximity * Project Phase*					
Walk Time * Pre-Announcement			(*reference*)		
Walk Time * Announcement	−0.00034	0.00208	0.00610	0.00711	−0.00106
Walk Time * Construction	0.00322	−0.00007	0.00427	0.00458	0.00295
Walk Time * Opening	0.00944	0.00402	0.01172	0.00856	0.01195
*Project Phase * MTR Station Area*					
Pre-Announcement * Chai Wan			(*reference*)		
Pre-Announcement * Sheung Wan			(*reference*)		
Pre-Announcement * Sai Ying Pun			(*reference*)		
Pre-Announcement * HKU			(*reference*)		
Pre-Announcement * Kennedy Town			(*reference*)		
Announcement * Chai Wan			(*reference*)		
Announcement * Sheung Wan	0.27491***	0.29553***	0.28751***	0.22844***	0.16283**

Announcement * Sai Ying Pun	0.21295***	0.19787***	0.21819***	0.23579***	0.19668***
Announcement * HKU	0.21846***	0.26542***	0.22486***	0.19674***	0.19299***
Announcement * Kennedy Town	0.20420***	0.23138***	0.26265***	0.20155***	0.21041***
Construction * Chai Wan			(*reference*)		
Construction * Sheung Wan	0.19231***	0.16079***	0.18657***	0.18626***	0.16965***
Construction * Sai Ying Pun	0.29843***	0.19254***	0.26827***	0.28114***	0.23017***
Construction * HKU	0.16939***	0.21380***	0.16376***	0.17926***	0.15457***
Construction * Kennedy Town	0.27125***	0.27909***	0.29577***	0.29439***	0.26970***
Opening * Chai Wan			(*reference*)		
Opening * Sheung Wan	0.29330***	0.19686**	0.20059**	0.16617*	0.22087**
Opening * Sai Ying Pun	0.10975*	0.09011*	0.11814**	0.12756**	0.15097***
Opening * HKU	0.09976*	0.12970**	0.13807**	0.10713*	0.14583**
Opening * Kennedy Town	0.25160***	0.24691***	0.31405***	0.26098***	0.26721***
*Project Phase * MTR Station Area * Walk Time*					
Pre-Announcement * Chai Wan * Walk Time			(*reference*)		
Pre-Announcement * Sheung Wan * Walk Time			(*reference*)		
Pre-Announcement * Sai Ying Pun * Walk Time			(*reference*)		
Pre-Announcement * HKU * Walk Time			(*reference*)		
Pre-Announcement * Kennedy Town * Walk Time			(*reference*)		
Announcement * Chai Wan * Walk Time			(*reference*)		
Announcement * Sheung Wan * Walk Time	−0.01513	−0.01441	−0.01456	−0.00959	0.00742
Announcement * Sai Ying Pun * Walk Time	−0.00660	−0.00513	−0.01169	−0.02029**	−0.00779
Announcement * HKU * Walk Time	−0.01765	−0.02810**	−0.01787	−0.01175	−0.00557
Announcement * Kennedy Town * Walk Time	−0.01408	−0.02298*	−0.02830**	−0.01891*	−0.01914*
Construction * Chai Wan * Walk Time			(*reference*)		
Construction * Sheung Wan * Walk Time	−0.01184	−0.00420	−0.00924	−0.01006	−0.00490
Construction * Sai Ying Pun * Walk Time	−0.03111***	−0.01126*	−0.02740***	−0.03129***	−0.02123***
Construction * HKU * Walk Time	−0.01299	−0.02452***	−0.01165	−0.01403*	−0.00707
Construction * Kennedy Town * Walk Time	−0.03463***	−0.03579***	−0.03790***	−0.03769***	−0.03216***
Opening * Chai Wan * Walk Time			(*reference*)		
Opening * Sheung Wan * Walk Time	−0.05874***	−0.04425***	−0.04238***	−0.03559**	−0.04588***
Opening * Sai Ying Pun * Walk Time	−0.02935***	−0.02482**	−0.02446**	−0.03298***	−0.03767***
Opening * HKU * Walk Time	−0.02340*	−0.03126**	−0.02334*	−0.02703**	−0.03299**
Opening * Kennedy Town * Walk Time	−0.04527***	−0.04490***	−0.05212***	−0.04668***	−0.04730***
Property Characteristics					
Balcony (0–1)	−0.02396***	−0.04594***	−0.02667***	−0.03391***	−0.03387***
Bay Window (0–1)	0.01944***	0.01130*	0.02016***	0.01237**	0.01900***
Bedrooms	0.00980*	0.01182**	0.00871*	0.01079*	0.01769***
Building Age (years)	−0.03066***	−0.03212***	−0.03092***	−0.03145***	−0.03218***
Building Age^2	0.00038***	0.00038***	0.00037***	0.00037***	0.00040***
Carpark (0–1)	0.13819***	0.12975***	0.12332***	0.11496***	0.12605***
Club House (0–1)	0.03370***	0.03448***	0.03379***	0.03391***	0.02990***
Direction Facing: North (0–1)	0.02885***	0.02160**	0.02790***	0.02428**	0.02295**
Direction Facing: North-East (0–1)	0.00088	0.00417	0.00173	0.00646	0.00245
Direction Facing: North-West (0–1)	0.01017*	0.01515**	0.00986	0.01188*	0.00810
Flat Roof (0–1)	0.11726***	0.09067***	0.10785***	0.09186***	0.09873***
Living Rooms/Dining Rooms	0.01952***	0.01666**	0.01976***	0.01691**	0.01074*
Pool (0–1)	0.05495***	0.04235***	0.04558***	0.04205***	0.04471***
Rooftop (0–1)	0.05507***	0.06743***	0.08529***	0.05823***	0.07098***
Terrace (0–1)	0.13301	0.37512**	0.54225**	−0.11202	0.12051
Unit Elevation (metres)	0.00249***	0.00243***	0.00246***	0.00252***	0.00244***
Neighbourhood Attributes					
Median Household Income (HK$1,000s)	0.00185***	0.00205***	0.00195***	0.00212***	0.00196***
Quarter of Sale					
2001 Quarter 1			(*reference*)		
2001 Quarter 2	−0.05579**	−0.04757*	−0.05952**	−0.07796***	−0.07163***
2001 Quarter 3	−0.10246***	−0.07611***	−0.10201***	−0.11019***	−0.07086***
2001 Quarter 4	−0.08436***	−0.08949***	−0.07381**	−0.12474***	−0.09740***
2002 Quarter 1	−0.07624**	−0.06769**	−0.07771**	−0.10709***	−0.08259***
2002 Quarter 2	−0.12004***	−0.10570***	−0.10903***	−0.13465***	−0.09759***
2002 Quarter 3	−0.16202***	−0.15047***	−0.14271***	−0.15824***	−0.16962***
2002 Quarter 4	−0.26731***	−0.24417***	−0.27520***	−0.30843***	−0.23651***
2003 Quarter 1	−0.25131***	−0.25524***	−0.25082***	−0.26915***	−0.23227***
2003 Quarter 2	−0.28553***	−0.28299***	−0.26711***	−0.29943***	−0.29848***
2003 Quarter 3	−0.25932***	−0.24281***	−0.25353***	−0.27763***	−0.24769***
2003 Quarter 4	−0.20569***	−0.19212***	−0.20001***	−0.21096***	−0.19028***
2004 Quarter 1	−0.10571***	−0.05598**	−0.08325***	−0.10759***	−0.06092**
2004 Quarter 2	−0.02550	−0.01065	−0.02034	−0.02347	−0.01647
2004 Quarter 3	0.00500	0.01239	0.01301	−0.03712	0.00058
2004 Quarter 4	0.06158**	0.06772**	0.06832**	0.03412	0.07184***
2005 Quarter 1	0.15884***	0.17722***	0.15568***	0.14824***	0.14921***
2005 Quarter 2	0.18645***	0.18442***	0.17162***	0.16122***	0.14980***
2005 Quarter 3	0.24041***	0.20711***	0.22005***	0.19614***	0.20552***
2005 Quarter 4	0.24690***	0.22581***	0.23729***	0.22556***	0.20645***
2006 Quarter 1	0.26131***	0.26287***	0.25406***	0.22865***	0.25772***
2006 Quarter 2	0.27781***	0.29557***	0.30240***	0.26089***	0.26870***
2006 Quarter 3	0.28180***	0.28359***	0.28110***	0.25467***	0.26697***
2006 Quarter 4	0.28441***	0.30581***	0.30917***	0.27365***	0.29854***

2007 Quarter 1	0.32684***	0.35095***	0.36469***	0.34645***	0.33601***
2007 Quarter 2	0.41302***	0.41718***	0.41709***	0.39949***	0.39252***
2007 Quarter 3	0.45147***	0.45602***	0.44336***	0.42776***	0.43628***
2007 Quarter 4	0.39977***	0.38917***	0.37713***	0.36128***	0.38711***
2008 Quarter 1	0.52071***	0.53161***	0.50375***	0.48955***	0.52432***
2008 Quarter 2	0.56847***	0.54973***	0.52313***	0.52838***	0.54579***
2008 Quarter 3	0.53255***	0.50906***	0.48533***	0.51487***	0.51979***
2008 Quarter 4	0.34771***	0.38016***	0.33538***	0.32831***	0.35227***
2009 Quarter 1	0.34951***	0.35408***	0.38108***	0.36101***	0.37822***
2009 Quarter 2	0.46867***	0.47136***	0.45964***	0.45030***	0.45594***
2009 Quarter 3	0.58235***	0.60122***	0.58053***	0.54890***	0.56789***
2009 Quarter 4	0.63114***	0.63341***	0.61936***	0.58478***	0.60981***
2010 Quarter 1	0.75464***	0.68788***	0.73494***	0.70381***	0.68050***
2010 Quarter 2	0.73124***	0.73950***	0.72325***	0.71087***	0.73278***
2010 Quarter 3	0.76967***	0.79137***	0.76365***	0.74134***	0.76437***
2010 Quarter 4	0.83655***	0.86092***	0.85270***	0.80499***	0.84157***
2011 Quarter 1	0.92608***	0.93830***	0.92462***	0.91419***	0.92819***
2011 Quarter 2	0.94458***	1.00047***	0.97198***	0.96520***	0.96636***
2011 Quarter 3	0.94232***	0.98146***	0.94658***	0.94867***	0.96105***
2011 Quarter 4	0.96688***	0.95566***	0.96143***	0.92336***	0.98529***
2012 Quarter 1	1.00876***	1.03630***	1.02435***	0.99338***	1.00833***
2012 Quarter 2	1.08421***	1.09348***	1.10209***	1.06192***	1.06809***
2012 Quarter 3	1.10457***	1.15127***	1.10933***	1.08780***	1.12270***
2012 Quarter 4	1.17936***	1.19176***	1.17863***	1.13982***	1.16857***
2013 Quarter 1	1.21747***	1.26013***	1.21546***	1.19947***	1.23735***
2013 Quarter 2	1.22296***	1.28691***	1.24287***	1.21752***	1.24970***
2013 Quarter 3	1.19712***	1.26634***	1.19826***	1.21257***	1.24350***
2013 Quarter 4	1.18760***	1.23391***	1.20996***	1.19474***	1.18155***
2014 Quarter 1	1.20077***	1.20407***	1.16983***	1.19043***	1.18742***
2014 Quarter 2	1.21680***	1.25829***	1.27181***	1.23952***	1.25377***
2014 Quarter 3	1.26477***	1.28196***	1.27203***	1.24528***	1.25292***
2014 Quarter 4	1.28592***	1.32268***	1.29843***	1.29325***	1.32348***
2015 Quarter 1	1.50129***	1.49220***	1.50230***	1.49149***	1.45260***
2015 Quarter 2	1.42737***	1.46080***	1.40841***	1.44881***	1.40312***
2015 Quarter 3	1.49113***	1.51514***	1.44672***	1.49056***	1.45332***
2015 Quarter 4	1.42717***	1.43245***	1.36412***	1.41686***	1.37380***
2016 Quarter 1	1.35230***	1.33628***	1.29368***	1.32075***	1.34439***
2016 Quarter 2	1.31985***	1.43646***	1.34410***	1.36258***	1.32580***
2016 Quarter 3	1.40514***	1.45025***	1.38363***	1.39946***	1.40507***
2016 Quarter 4	1.49114***	1.53743***	1.45236***	1.49341***	1.44657***
2017 Quarter 1	1.49371***	1.49618***	1.43727***	1.49804***	1.47647***
2017 Quarter 2	1.53709***	1.58675***	1.49762***	1.51383***	1.53936***
2017 Quarter 3	1.50722***	1.57955***	1.48994***	1.54434***	1.56356***
α	8.17067***	8.18908***	8.17734***	8.19900***	8.19599***
ρ	0.01087***	0.00585***	0.01181***	0.01147***	0.00594***
λ	5.51206***	3.18978***	3.97644***	4.45493***	3.73557***
n	23,681	23,681	23,681	23,681	23,681
Pseudo-R^2	0.8860	0.8830	0.8807	0.8843	0.8880

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

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