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Light at the end of the tunnel: The impacts of expected major transport improvements on residential property prices

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Abstract

Properties near public transportation systems are usually sold at a premium owing to the willingness of firms and people to pay for access to workplace and leisure. However, the economic impact of major infrastructure investments remains an empirical question plagued by identification issues. We investigate the economic impacts of a major transportation development project currently under construction in Hong Kong: the Tuen Mun–Chek Lap Kok tunnel, namely the effects on property prices of the expansion of the regional road network in the Greater Bay Area. We identify a significant accessibility premium well before the tunnel is completed. There is also a change in market structure of increased preference for residential property in areas closer to the tunnel, reflected by higher price appreciation. The findings help guide urban planning and public investment decisions, as well as the design and implementation of land value capture policy.

Keywords

Greater Bay Area, hedonic price models, housing, land use, planning, real estate, transport

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摘要

由于公司和个人愿意为临近工作场所和休闲场所付费，公共交通系统附近的物业通常有一个溢价。然而，重大基础设施投资的经济影响仍然是一个经验问题，受到各种识别的困扰。我们研究香港目前正在兴建的一项大型交通发展项目—屯门至赤腊角隧道的经济影响，即大湾区区域道路网络扩展对物业价格的影响。早在隧道竣工之前，我们就发现了显著的便利溢价。市场结构也发生了变化，人们更加青睐靠近隧道的地段的住宅，导致这些住宅升值更快。研究结果有助于指导城市规划和公共投资决策，以及土地价值获取政策的设计和实施。

关键词

大湾区、享乐价格模型、住房、土地使用、规划、房地产、交通

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Introduction

Accessibility to public transportation influences residential location choices, rents, as well as the overall organisation of economic activity (Redding and Turner, 2015). An improved transportation network can lead not only to increased land values (Knaap et al., 2001; Mohammad et al., 2013), house prices (Hamidi et al., 2016; Yang et al., 2019) and commercial property rents (Mohammad et al., 2013; Tchang, 2016) but also to fundamental changes in the economic, social and ecological environments of neighbourhoods (Chen et al., 2016; Credit, 2018; Wu, 2014).

Classical location theory posits that land and property values are higher in locations with better accessibility to desirable destinations, that is, where people experience improved 'ability to reach goods, services, activities or destinations' (Klaesson et al., 2015: 412). An 'accessibility premium' manifests itself as an increase in the prices of properties in proximity to new or improved transportation infrastructure (see, for example, the review in Hamidi et al., 2016; Mohammad et al., 2013). This premium is the net effect of the positive accessibility impact and adverse impact of negative externalities arising from the transportation, such as crime (Bowes and Ihlanfeldt, 2001), pollution (Kilpatrick et al., 2007) and noise (Theebe, 2004).

The generation of knowledge regarding the effects of such an accessibility premium can help guide urban planning and public investment decisions. Much of the academic interest is to provide evidence to support value capture schemes for financing transport investments (Smith and Gihring, 2006). However, reverse causality as well as the timing of people's expectations have bedevilled empirical identification in this field, particularly with respect to large-scale and high-prestige projects. Many previous studies have used cross-sectional data and simply ignore the before–after complications of this problem altogether (for a discussion, see e.g. Cao and Lou, 2018). Even when the research has taken a longitudinal perspective, peoples' expectations imply that one single and credible point of critical announcement is generally lacking.

We add to the empirical literature by an investigation of the economic impacts of the Tuen Mun–Chek Lap Kok tunnel ('the tunnel' hereafter) currently under construction in Hong Kong. The tunnel will provide a direct route from Tuen Mun, a residential district in the urban periphery, to the airport and the Hong Kong–Zhuhai–Macao Bridge. As a large-scale infrastructure project with a long construction period, the expected accessibility improvements may be capitalised into nearby residential prices well before its completion, according to the rational expectation hypothesis (Voith, 1991). The importance of understanding the impacts of the planned investment is underlined by its sheer size. The tunnel's cost to public funds of 44.8 billion HKD (approximately 4.4 billion GBP) motivates the estimation of the total value of the accessibility benefits, as reflected by the aggregate increase in property values.

We employ detailed data to assess whether residential property buyers are willing to pay a premium for proximity to the transportation development (i.e. the tunnel). The tunnel project went through three phases: the proposal, the official announcement and the construction period. Existing studies suggest that an accessibility premium should present in all three periods (Cao and Lou, 2018; Cho et al., 2020; Jayantha et al., 2015; Jung et al., 2016). However, it is unclear in which period the effect is strongest. To fill this gap in the literature we also assess the speed at which people capitalise future expectations into present property values. We use both continuous and discrete measurements of proximity to investigate the spatial variation of the accessibility premium. Based on existing theory and literature, we form four hypotheses to investigate how much of a premium the tunnel project generated during each of the three phases, and whether the project has caused a change in market structure, with increased preference for residential property in areas closer to the tunnel. We employ two empirical methods of analysis, a hedonic pricing model and repeat-sales indices, to analyse all private residential property transaction data within 20 km of the tunnel, occurring from April 2005 to October 2018.

This paper is organised as follows: the next section provides the background of the tunnel; section 'Analytical framework and testable hypotheses' outlines the analytical framework and derives testable hypotheses; section 'Empirical implementation' describes the empirical implementation and data; section 'Empirical findings' presents and discusses the results; section 'Policy implications' gives policy implications; section 'Conclusion' concludes the paper.

Background

The tunnel is a 9 km under-sea tunnel in Hong Kong currently under construction, due for completion in 2020. Figure 1 shows the location and surroundings of the tunnel. Upon completion, the tunnel will connect two parts of Hong Kong – New Territories and Lantau Island, which are geographically close but separated by water. Specifically, the tunnel will provide a direct route from Tuen Mun, a residential district in the urban periphery, to the Hong Kong Airport and the Hong Kong–Zhuhai–Macao Bridge (HKZMB). To illustrate the comparatively large accessibility improvements for residents in Tuen Mun (population about 500,000 and a land area of 85 km^2), the tunnel will cut the journey time to the airport and HKZMB from 30 minutes to 10 minutes and shorten travel distance by 22 km, compared with the existing route (grey route in Figure 1).

The tunnel is an important infrastructure development both locally and regionally, as it not only strengthens the transportation network of the Hong Kong Airport but also increases cross-boundary accessibility between the Greater Bay Area – Hong Kong, Zhuhai, Macau and Shenzhen, by reducing the time-travel distances between those nodes. Upon completion of the tunnel, Tuen Mun will be located at the apex of a new 'golden triangle' of the flow of people, goods, technology and expertise between Hong Kong and the Greater Bay Area, serving as a strategic intersection and gateway.

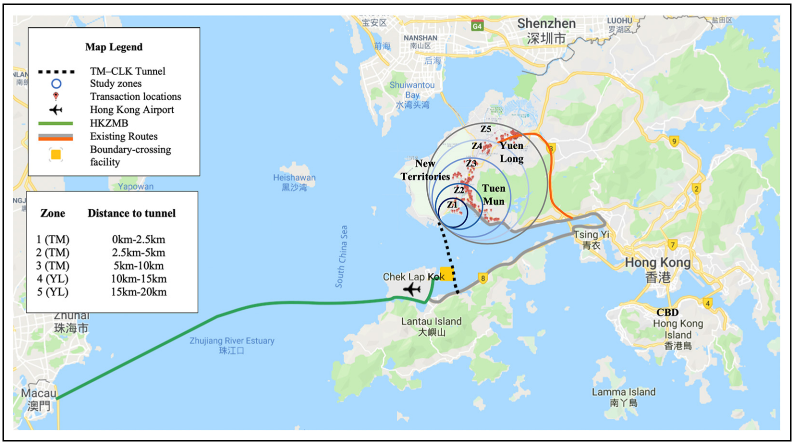

Figure 1. Map of study area.

The tunnel plan was published in the draft Outline Zoning Plan on 12 June 2009 and received official approval from the Legislative Council on 18 October 2011. Construction began on 7 June 2013. Originally scheduled to be completed in 2017, the project has been delayed by unforeseen ground conditions and the COVID-19 pandemic. It is expected to be completed by the end of 2020 at the earliest.

The need for the route was identified in the early 2000s. Currently, there is only one land route linking Hong Kong to the airport (grey line in Figure 1). In 2002 a similar route, proposed by the government, linking the New Territories to the Hong Kong Airport ('Route 10') was voted down by policymakers, with cost being one of the key concerns[1] as the existing route (Route 3) was already operating at a loss.[2] Since then, the existing route has suffered traffic disruption on multiple occasions. In 2008, the North Lantau Highway was blocked by landslides and flooding and similarly, in 2015, the Kap Shui Mun Bridge was closed for 2 hours after being hit by a vessel. Therefore, the tunnel is a much-needed and long-anticipated infrastructure. Moreover, the voting down of the proposal in 2002 demonstrates how political and policy decisions play an influential role in transportation planning.

In this study we employ data of all private residential property transactions within 20 km from the Northern entrance of the tunnel. This area corresponds to two residential districts in the New Territories; Tuen Mun (TM), the district closest to the tunnel, and Yuen Long (YL), the district further away from the tunnel. The area is categorised into zones of increasing distance bands, indicated by concentric zones in Figure 1.

Analytical framework and testable hypotheses

The positive relationship between accessibility and property values roots in classical location theory in urban economics. The bid-rent model (Alonso, 1964; Muth, 1969) explains rent in an urban context as a decreasing function of distance to the central business district (CBD). Housing and transport costs are jointly purchased: there is a trade-off where those paying higher prices for housing are compensated by lower travel costs. In efficient and well-functioning property markets, if the development of new transportation infrastructure increases the accessibility of a location, the effect should be capitalised into nearby property values as buyers bid up the prices for the preferred locations. This relationship can be summarised in equation (1).

$$V = f(S, L, T, D) + \varepsilon \tag{1}$$

where V is the value of a property, S is a set of structural characteristics, L is a set of location attributes, T is a set of variables representing the time of sale and D is a measurement of the distance to a particular transportation system.

The bid-rent model predicts that equation (1) is a decreasing function of D, or $\frac{\partial V}{\partial D} < 0$. The impact of transportation development and improvement on the economic, social and ecological environment of the affected neighbourhood can be estimated by examining the price changes over time. If the development or improvement of the transportation system improves accessibility in the neighbourhood, the effect will demonstrate itself in two ways. First, the value of $\frac{\partial V}{\partial D}$ will be smaller once the infrastructure is in place. Second, the value of $\frac{\partial V}{\partial D}$ will be smaller for properties that are closer to the transport system. Both cases suggest an improvement in the affected neighbourhood. The differences of $\frac{\partial V}{\partial D}$ between the 'before' and 'after' groups as well as the 'nearby' and 'away' groups of properties are the aggregated estimate of the accessibility premium.

The identification of the accessibility premium has two technical issues. First, when does the capitalisation of accessibility in property prices start? That is, how to identify the 'before' and 'after' groups? The impacts of transport investments vary depending on the timeframe of the project (McMillen and McDonald, 2004). Changes in property prices often occur after the announcement of the plans, prior to the actual opening of the transportation infrastructure – aligned with the rational expectations hypothesis (Muth, 1961). Some empirical evidence shows that about half of the accessibility effect materialises well before the opening of transportation developments (Hoogendoorn et al., 2019) and the highest increment of increase in house prices is found after solid financial commitment is made by government (Yen et al., 2018), that is, before construction starts. The tunnel project went through three phases: the proposal (from 22 June 2009 to 17 October 2011), the announcement (from 18 October 2011 to 06 June 2013) and the construction (from 07 June 2013 to present) periods. Therefore, we form the following testable hypotheses accordingly.

Hypothesis I: The tunnel project introduced an accessibility premium during the proposal, announcement and construction periods.

Hypothesis II: The tunnel's accessibility premium was not capitalised uniformly across the proposal, announcement and construction periods.

Second, where does the accessibility end, or how to determine the 'nearby' and 'away' groups? Determining the catchment area of a transportation system is largely an empirical issue, despite some de facto standards such as the half-mile distance adopted in the USA (Guerra et al., 2012). The choice of distance is more affected by transportation type than the density and size of the affected region (Debrezion et al., 2011; Shyr et al., 2013). The prevalent approach is to consider multiple bands of distances, such as 200–3000 m from the bus or subway stations (Diao et al., 2017; Im and Hong, 2018). For large cities in the USA and Canada, it is common to include properties that are more than 10 km away from rail stations (Dube et al., 2013; Welch et al., 2018). The tunnel is similarly expected to serve a large catchment area, as indicated in similar studies in the literature (Hoogendoorn et al., 2019; Yiu and Wong, 2005). Evidence also shows that the premium may vary considerably in strength and direction across space (Hyun and Milcheva, 2019; Ke and Gkritza, 2019). For example, the announcement of an urban development project in Seoul caused prices to appreciate for properties within a 1 km radius of the project site. However, apartments that were located around the project site but not in direct proximity suffered a relative loss resulting from the introduction of the project (Hyun and Milcheva, 2019). Consequently, we will test the following hypotheses by comparing property price changes among the five zones.

Hypothesis III: The tunnel project caused a change in market structure of increased preference for residential property in direct proximity to the tunnel, reflected by relatively higher price appreciation.

Hypothesis IV: The tunnel project caused a change in market structure of decreased preference for residential property located around but not in direct proximity to the tunnel, reflected by relatively lower price appreciation.

Empirical implementation

We use both a hedonic price model (Rosen, 1974) in a difference-in-difference (DID) framework and a repeat-sales method to test the hypotheses. Hedonic price modelling is an effective method to estimate the benefits arising from new transportation infrastructures (Gjestland et al., 2014). The hedonic DID framework allows a straightforward test of the difference between the treatment and control group as well as before and after the announcement. More importantly, this quasi-experimental approach effectively deals with the possible omission of important variables correlated with the accessibility premium (see, for instance, the discussion in Hyun and Milcheva, 2019: 24). This is particularly helpful for studies of urban development projects, for which omitted variable bias is often a concern because of the complexity and long project duration. In fact, the hedonic DID approach is the most commonly used method to estimate accessibility premium (see, for instance, Devaux et al., 2017; Dube et al., 2014; Hu, 2017; Im and Hong, 2018).

However, the conventional hedonic DID method can severely understate the standard deviation of the estimators when long time-series processes are involved (Bertrand et al., 2004). The preparation and construction of the tunnel project spanned a period of more than 10 years (i.e. from 2009 to present). It is likely that our hedonic DID models will over-reject the null hypothesis of no effect. We address this issue by dividing the 10 years event window into three phases: the proposal (3 years), the announcement (2 years) and the construction (5 years). We also used only 4 years before the proposal period as the control period. By estimating the accessibility premium in these shorter periods separately, the standard errors of the DID estimates are much less likely to be underestimated.

In addition, we use repeat sales methods to verify the DID estimations. Repeat-sales indices are constructed using only the data of properties that have transacted more than once over the sampling period. It is estimated by regressing the change in transaction prices of the same property on time dummies representing the two transaction periods. This matched-model methodology automatically controls for all time-invariant property attributes, including attributes that cannot be measured in the data set. Therefore, it can effectively resolve the omitted variable bias and mis-specification problems that are commonly encountered in hedonic price modelling. Of course, the repeat sales method has its own limitations.

Specifically, it cannot take into account changes in property attributes between sales. However, this is not an issue for our study because all properties included in our database are apartments in high-rise buildings, which usually do not have significant changes in housing attributes (particularly structural traits) over time.

Previous studies found that area, floor and age are significant in explaining property prices in Hong Kong (Jayantha et al., 2015; Yiu and Wong, 2005). We have included these variables in our hedonic models. The data set contains 116,494 observations, with approximately 40% of the properties transacting more than once over the 13-year period.[3] Table 1 summarises the descriptive statistics of the variables with their respective definitions, data sources and expected signs of coefficients based on theory and previous findings. The non-linear relationship between the dependent variables *Price* and *area*, *floor* and *age* was accounted for by incorporating their squared terms.

The semi-log functional form is used, with *ln*(*price*) as the dependent variable, which reduces the impact of extremities arising from positively skewed house prices. Distance to tunnel is modelled in two ways: in equation (2) distance is a continuous variable and in equation (3) distance is represented by five zones of increasing distance categories. This provides two alternative ways to test the first hypothesis.

$$\begin{aligned} \ln(price) &= \beta_0 + \beta_1 Area + \beta_2 Area^2 \\ &+ \beta_3 Floor + \beta_4 Floor^2 + \beta_4 Age \\ &+ \beta_5 Age^2 + \beta_6 HA + \beta_7 CBD \\ &+ \beta_8 MTR + \beta_9 Coast + \theta_1 Pro + \theta_2 Ann \\ &+ \theta_3 Con + \theta_4 Distance + \theta_5 Pro \cdot Distance \\ &+ \theta_6 Ann \cdot Distance + \theta_7 Con \cdot Distance \\ &+ \sum_{i=1}^{19} \gamma_i Year_i + \varepsilon \end{aligned} \tag{2}$$

Equation (2) examines whether the *Distance – ln*(*price*) relationship changes after the announcement. We use *Pro*, *Ann* and *Con* to indicate whether the property was transacted during the proposal, announcement and construction period, respectively. These three dummy variables are interacted with variables representing distance to tunnel, resulting in differences-in-differences estimators. *Hypothesis I* is true if θ_1, θ_2 and θ_3 are positive and statistically significant. *Hypothesis II* is true if θ_1, θ_2 and θ_3 are not identical. *Hypothesis III* is true if θ_5, θ_6 and θ_7 are negative and statistically significant. Owing to the continuous measurement of distance in equation (2), the test of *Hypothesis IV* is not straightforward. Instead, we use the interaction terms in equation (3) to test *Hypothesis IV*, as outlined below.

$$\begin{aligned} \ln(price) &= \beta_0 + \beta_1 Area + \beta_2 Area^2 \\ &+ \beta_3 Floor + \beta_4 Floor^2 + \beta_4 Age + \beta_5 Age^2 \\ &+ \beta_6 HA + \beta_7 CBD \\ &+ \beta_8 MTR + \beta_9 Coast + \theta_1 Pro + \theta_2 Ann \\ &+ \theta_3 Con + \sum_{j=2}^{5} \delta_j Zone_j \\ &+ \sum_{k=2}^{5} \vartheta_k (Pro * Zone_k), \\ &+ \sum_{l=2}^{5} \tau_l (Ann * Zone_l) \\ &+ \sum_{m=2}^{5} \varphi_m (Con * Zone_m), \\ &+ \sum_{i=2}^{14} \gamma_i Year_i + \varepsilon \end{aligned} \tag{3}$$

In equation (3), distance to tunnel is represented by five zones of increasing distance categories in Tuen Mun district (Zones 1–5). The reference category is Zone 1. *Pro*, *Ann* and *Con* capture the accessibility premium in Zone 1. The interaction terms are used to investigate whether accessibility premium varies among the five zones. The test of the first two hypotheses are the same as in

Table 1. Descriptive statistics (N = 116,494).

Variables		Source	Expected sign (+ /−)	Min	Max	Mean	SD
Dependent variable							
Logprice	Property transaction price (natural log transformed)	Land registry	NA[a]	12.43	18.90	14.71	0.73
Structural (S)							
Area	Saleable area in square feet	Land registry	+	185	4266	521.71	210.53
Floor	Floor level of the property unit	Land registry	+	1	71	15.11	11.39
Age	Time between year built and year of transaction	Land registry	−	0	59	14.95	10.63
HA	= 1 if built by the public sector housing authority and subsequently privatised; 0 otherwise	Housing authority	−	0	1	0.11	0.31
Locational (L)							
CBD	Driving distance to CBD (km)	Google distance API	−	19.2	40	32.29	3.62
MTR	= 1 if within 1 km walking distance to nearest mass transit rapid station; 0 otherwise	Google distance API	+	0	1	0.36	0.48
Coast	= 1 if within 1 km straight-line distance to the coast; 0 otherwise	Google distance API	+	0	1	0.12	0.33
Temporal (T)							
Pro	= 1 if transacted between 22 June 2009 and 18 October 2011 (project pronounce period); 0 otherwise.	Land registry	+	0	1	0.27	0.44
Ann	= 1 if transacted between 18 October 2011 and 7 June 2013 (announcement period); 0 otherwise.	Land registry	+	0	1	0.11	0.31

(continued)

Table 1. Continued

Variables		Source	Expected sign (+ /−)	Min	Max	Mean	SD
Con	= 1 if transacted after 7 June 2013 (construction period); 0 otherwise.	Land registry	+	0	1	0.34	0.47
Year 2000–year 2018	= 1 if transacted in 2000, 2001 … 2018, respectively; 0 otherwise	Land registry	+	0	1	NA	NA
Distance to tunnel (D)							
Distance	Distance to northern entrance of tunnel (km)	Google distance API	NA	1.8	18.4	9.95	4.76
Zone 1	= 1 if located within 0–2.5 km distance to northern entrance of tunnel; 0 otherwise	Google distance API	NA	0	1	0.04	0.19
Zone 2	= 1 if located within 2.5–5 km distance to northern entrance of tunnel; 0 otherwise	Google distance API	NA	0	1	0.13	0.34
Zone 3	= if located within 5–10 km distance to northern entrance of tunnel; 0 otherwise	Google distance API	NA	0	1	0.36	0.48
Zone 4	= if located within 10–15 km distance to northern entrance of tunnel; 0 otherwise	Google distance API	NA	0	1	0.22	0.42
Zone 5	= if located within 15–20 km distance to northern entrance of tunnel; 0 otherwise	Google distance API	NA	0	1	0.25	0.43

Note: [a]NA, not applicable.

equation (2). δ_j is used to test *Hypothesis III*. If the coefficient estimates of the interaction terms (i.e. ϑ_k, τ_l and φ_m) are negative, *Hypothesis III* is true. If the absolute value of ϑ_k, τ_l and φ_m are smaller for zones that are closer to the tunnel, *Hypothesis IV* is true.

We then estimate repeat sales price indices to verify the results from the DID analysis. Specifically, by assuming a linear specification, the price difference between a pair of repeat sales can be estimated by equation (4) below.

$$Price_i - Price_j = \delta_i Quarter_i - \delta_j Quarter_j + (\eta_i - \eta_j) Distance + \varepsilon, \tag{4}$$

where i and j denote the time of transaction, $Quarter_i$ is quarterly dummy variables that equals 1 if the transaction is recorded in the ith quarter, $i = 1, 2, \ldots 72$. *Price* and *Distance* are defined in Table 2. The distance to the tunnel, that is, variable *Distance*, remains the same over time for all properties included. However, η_i and η_j will differ if the tunnel project improve accessibility in the affected neighbourhood. Unfortunately, η_i and η_j are not individually identifiable in equation (4). We can only estimate accessibility premium over time through equation (5).

$$Price_i - Price_j = (\delta_i + \eta_i Distance) Quarter_i - (\delta_j + \eta_j Distance) Quarter_j + \varepsilon, \tag{5}$$

If the announcement of the tunnel project does not introduce any accessibility premium, then $\eta_i = \eta_j$ for all zones considered. The price indices will be very similar among the five zones. However, if the tunnel project does improve accessibility, η_i and η_j will get smaller during the three event periods in the affected neighbourhood. All else being equal, $Price_i - Price_j$ will be larger in affected areas if either or both of the two transactions occurred after the proposal date. As a result, price indices will show different patterns in affected and unaffected areas. The gap between price indices in affected and unaffected areas will show the development of the accessibility premium over time.

Repeat-sales indices are constructed for each of the five zones categorised in Figure 1. Zones 1 to 4 are treatment zones with decreasing treatment intensities in terms of tunnel proximity, while Zone 5 is the baseline zone. This approach allows us to compare the appreciation rates of an area affected by the transportation investment with a similar control area further away, using data from before and after the transport intervention, providing both cross-sectional and longitudinal comparison. To attribute the differences between the baseline and treatment zones to the impact of the tunnel, several assumptions need to hold: (1) the zones should be identical in all characteristics other than the proximity to the tunnel; (2) the price trends for all zones should be the same in the absence of the tunnel intervention; and (3) the zones cannot be differentially exposed to other interventions during the study period.

The study area fits the assumptions well. Naturally, properties located in the same residential district have greater comparability. Nevertheless, Tuen Mun and Yuen Long share many similarities, including land use, socioeconomic conditions, population trends and occupation composition. Both districts were developed using the same planning model of 'New Town' developments under the British colonial government in the 1970s, built in the urban periphery to accommodate increasing population growth. They are mixed-use but largely residential districts built around a town centre, connected by mass transit railway to the CBD. To the best of our knowledge, no other major exogenous changes have occurred that may have selectively affected one district but not the other during the study period. Moreover, the

Table 2. Model estimation summary.

	Model 1	Model 2	Model 3
	Continuous distance model (OLS)	Continuous distance model (MLM)	Zone model
Constant	13.3045***	13.4214***	13.2454***
Period dummies			
Pro	0.2013***	0.2000***	0.1951***
Ann	0.2894***	0.2934***	0.2161***
on	0.3603***	0.3587***	0.3027***
Distance to tunnel			
Distance	0.0115***	−0.0032***	
Zone 2			0.1350***
Zone 3			0.1086***
Zone 4			0.2282***
Zone 5			0.2208***
Interaction terms			
Pro × distance	−0.0063***	−0.0062***	
Ann × distance	−0.0132***	−0.0134***	
Con × distance	−0.0227***	−0.0225***	
Pro × Zone 2			−0.0180* *
Pro × Zone 3			−0.0413***
Pro × Zone 4			−0.0999***
Pro × Zone 5			−0.0599***
Ann × Zone 2			−0.0206* *
Ann × Zone 3			0.0166*
Ann × Zone 4			−0.1175***
Ann × Zone 5			−0.1224***
Con × Zone 2			−0.0400***
Con × Zone 3			−0.0709***
Con × Zone 4			−0.2749***
Con × Zone 5			−0.2802***
Structural			
Area	0.0022***	0.0022***	0.0022***

(continued)

Table 2. Continued

	Model 1	Model 2	Model 3
	Continuous distance model (OLS)	Continuous distance model (MLM)	Zone model
$Area^2$	−0.0000004***	−0.0000004***	−0.0000004***
Floor	0.0089***	0.0089***	0.0087***
$Floor^2$	−0.0001***	−0.0001***	−0.0001***
Age	−0.0308***	−0.0310***	−0.0307***
Age^2	0.0004***	0.0004***	0.0004***
HA	−0.2296***	−0.2093***	−0.2154***
Locational			
MTR	0.0555***	0.0574***	0.0588***
CBD	−0.0061***	−0.0061***	−0.0057***
Coast	0.1372***	0.1367***	0.1351***
Time dummies			
Year 2006	−0.0362***	−0.0329***	−0.0341***
Year 2007	0.0264***	0.0288***	0.0255***
Year 2008	0.1675***	0.1688***	0.1651***
Year 2009	0.1129***	0.1156***	0.1102***
Year 2010	0.3322***	0.3341***	0.3275***
Year 2011	0.5391***	0.5396***	0.5351***
Year 2012	0.7083***	0.7096***	0.7020***
Year 2013	0.8828***	0.8809***	0.8772***
Year 2014	0.9625***	0.9677***	0.9533***
Year 2015	1.1518***	1.1548***	1.1461***
Year 2016	1.1332***	1.1357***	1.1245***
Year 2017	1.3052***	1.3092***	1.2979***
Year 2018	1.4924***	1.4970***	1.4847***
Summary statistics	R^2 = 0.93758 Adjusted R^2 = 0.93757	Log likelihood = 34727.71 Wald $\chi^2(30) = 1550265$ *** LR = 2419.44***	R^2 = 0.93890 Adjusted R^2 = 0.93887

Notes: Zone 1 and the pre-proposal period are omitted in hedonic price models as the base category. Coefficient estimates of period dummies, zone dummies and their interaction terms are the difference between the omitted category and the corresponding included category.
$^*p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.

study area is in the periphery of Hong Kong, 30 km from the CBD; thus, house prices are sheltered from exogenous macroeconomic and industry-specific trends, avoiding the endogeneity between house prices and local employment growth (Stroebel and Vavra, 2019).

Because equation (5) does not estimate the value of η_i and η_j explicitly, we cannot use this model to test Hypotheses I and II directly. The model is primarily used to test Hypotheses III and IV. These two hypotheses are true if the price trends of the repeat-sales indices diverge after the proposal date, where the zones closer to the tunnel appreciate faster relative to the zones further away. Pre-proposal, the repeat-sales indices are expected to perform similarly for all zones and reflect the general trends of the wider Hong Kong residential property market.

Empirical findings

Hedonic price models

Table 2 presents the outputs of hedonic pricing models. Models 1 and 2 have the same specification but estimated by using OLS and multilevel regression (MLR) technique (Raudenbush and Bryk, 2002), respectively. MLR is often used when data are nested, for example, subway stations within districts (see, for example, Hou, 2017; Zolnik, 2020). By taking into account the variations of property prices within each neighbourhood, MLR results have more reliable coefficient estimates and standard errors. Model 2 is a two-level MLR model with *Zone* (= 1, 2, …, 5 for each of the five zones) as the second-level identifier. Both the log likelihood and the Wald χ^2 suggest that the model fits the data well. In addition, the LR test suggests a rejection of a linear model at the 1% level. Nevertheless, the coefficient estimates and standard errors are very similar between the OLS and the MLR models, with the only exception being variable *Distance*. In the OLS model the coefficient estimate of *Distance* is positive, whilst the MLR models return a much smaller and negative estimation. This is because the level variable (i.e. Zone) is highly correlated with *Distance*. The MLR approach is designed to separate these spatially correlated factors effectively such that the net effect of accessibility premium can be reliably estimated. This provides justification for us to use zone dummies in the zone model to further explore the variation of accessibility premium across different zones.

According to Model 2, the coefficient of *Distance* is -0.0032, meaning that the pre-proposal relationship between distance to tunnel and property price is negative; an increase of 1 km leads to a 0.32% decrease in price. After the project proposal was released, average property prices increased by 20%, 9.34% (i.e. 29.34%–20%) and 6.53% (i.e. 35.87%–29.34%) during the proposal, the announcement and the construction period, respectively. Moreover, the interaction term between the three period dummies and *Distance* are all negative and statistically significant. This indicates that house buyers are willing to pay a premium for proximity to the tunnel. Note that properties are sufficiently distant from the tunnel site to avoid negative externalities such as noise; the closest property is located 1.8 km from the tunnel. Moreover, the construction of the tunnel is located below ground level, which lessens nuisance impacts. These results offer support to Hypotheses I through III.

We further explore the identified accessibility premium by the zone model (e.g. Model 3). Before the announcement date, being close to the tunnel site was considered undesirable. The coefficient estimates of Zones 2 to 5 dummies are all positive, indicating that property prices in these zones are approximately 10.86% to 22.82% higher than that in Zone 1. This is consistent with what we found in Model 2. The three period dummies are inevitably highly correlated with their interaction terms. Therefore, their individual coefficient estimates could be biased. Fortunately, we are interested in the combined effect between these event variables and their interaction terms, which are not affected by multicollinearity issues. Specifically, we calculate accessibility premium in the proposal, the announcement and the construction periods in each of the five zones by using the coefficient estimates of the three event dummies and their interaction terms. The results are presented in three different formats in the first three panels in Table 3.

In Panel A, the cumulative accessibility premium was calculated by using the coefficient estimates from Model 3 directly. For Zone 1, the premium is the coefficient estimate of *Pro, Ann* and *Con*. This is because Zone 1 is the omitted category. For the other four zones, the accessibility premium is calculated by adding the coefficient estimates of *Pro, Ann* and *Con* and their corresponding interaction terms. For example, the accessibility premium for Zone 2 in the proposal period is $\hat{\theta}_1 + \hat{\vartheta}_2$, or $0.1951 - 0.0180 = 17.71\%$. In Panel B, the net accessibility premium in each period is calculated by calculating the difference between the cumulative premium of two adjacent periods for each zone. For example, the net accessibility premium for Zone 2 in the construction period is $26.27\% - 19.55\% = 6.72\%$. Because the length of the three periods are different (see Panel C), we also calculated quarterly accessibility premium based on Panel B. We found that the accessibility premium grew quickest during the proposal (or the unofficial announcement of the tunnel project) period. This is consistent with the findings in the literature, where infrastructure premiums were incorporated in property price before the construction of projects. The negative net accessibility premium and quarterly accessibility premium in Panels B and C suggest the structural change of the property market among the five zones. After the tunnel project was announced, local residents shifted their preference to properties that are closer to the tunnel site (i.e. Zones 1–3). Therefore, the attractiveness of Zones 4 and 5 decreased relatively. Note that the accessibility premium/discount reported in Panels A through C are estimated after controlling for annual price changes during the same period by using the time dummy variables in Models 2 and 3. The overall trend of property price changes during all three periods is increasing, as indicated by the positive and significant coefficient loadings of time dummies in Table 2.

Results in Panels A through C support all four hypotheses. The tunnel generated an accessibility premium to nearby properties (i.e. Zones 1–3), especially during the proposal period. However, for properties in Zones 4 and 5, there was actually a discount identified in the announcement and the construction periods. We conclude that the announcement of the tunnel project created an accessibility premium on nearby residential properties and caused a change in market structure of preference for residential property located at different vicinities of the tunnel site.

Repeat-sales analysis

We now proceed to further verify findings from hedonic price estimations by using the repeat-sales model results. The estimated indices are plotted in Figure 2. The accuracy and reliability of the repeat-sales indices in Figure 2 are supported by their consistency with the broader Hong Kong housing market price index and the general macroeconomic environment. The repeat-sales indices fell during the global financial crisis in 2008 and then recovered, with a steady upward trend since 2009. Before the tunnel proposal was released in the second quarter of 2009

Table 3. Accessibility premium and quarterly price index changes by zone and period.

Period	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
Panel A: cumulative accessibility premium					
Proposal (22 June 2009 to 18 October 2011)	19.51%	17.71%	15.38%	9.52%	13.53%
Announcement (18 October 2011 to 07 June 2013)	21.61%	19.55%	23.26%	9.86%	9.37%
Construction (07 June 2013 to 31 December 2018)	30.27%	26.27%	23.18%	2.78%	2.25%
Panel B: net accessibility premium in each period					
Proposal (22 June 2009 to 18 October 2011)	19.51%	17.71%	15.38%	9.52%	13.53%
Announcement (18 October 2011 to 07 June 2013)	2.10%	1.84%	7.89%	0.33%	−4.16%
Construction (07 June 2013 to 31 December 2018)	8.66%	6.72%	−0.08%	−7.08%	−7.11%
Panel C: quarterly accessibility premium					
Proposal (10 quarters)	1.91%	1.75%	1.53%	0.97%	1.36%
Announcement (6 quarters)	0.31%	0.27%	1.15%	0.05%	−0.64%
Construction (23 quarters)	0.37%	0.29%	−0.004%	−0.32%	−0.33%
Panel D: average repeat sales index value					
Pre-proposal (32 quarters)	109	107	112	106	106
Proposal (10 quarters)	147	143	142	137	133
Announcement (6 quarters)	182	178	178	166	160
Construction (23 quarters)	234	225	222	201	195
Panel E: quarterly repeat sales index changes					
Pre-proposal (32 quarters)	1.64%	1.51%	0.63%	1.04%	0.09%
Proposal (10 quarters)	4.51%	4.27%	4.45%	4.32%	3.99%
Announcement (6 quarters)	2.78%	2.76%	2.98%	2.08%	2.94%
Construction (23 quarters)	1.33%	1.17%	1.17%	1.05%	0.95%
Panel F: average repeat sales index value vs. Zone 1					
Pre-proposal (32 quarters)	–	−1.38	3.65	−2.69	−2.63
Proposal (10 quarters)	–	−4.79	−5.13	−10.37	−14.68*
Announcement (6 quarters)	–	−4.21	−4.07	−16.02**	−22.13***
Construction (23 quarters)	–	−8.79	−11.86*	−33.15***	−38.32***

Note: Panels A through C are calculated based on hedonic price estimations. Panels D through F are based on repeat sales estimations.
Panel F: two independent samples *t*-test calculated based on Panel D. * * *, * * and * indicate significance at the 1%, 5% and 10% level, respectively)

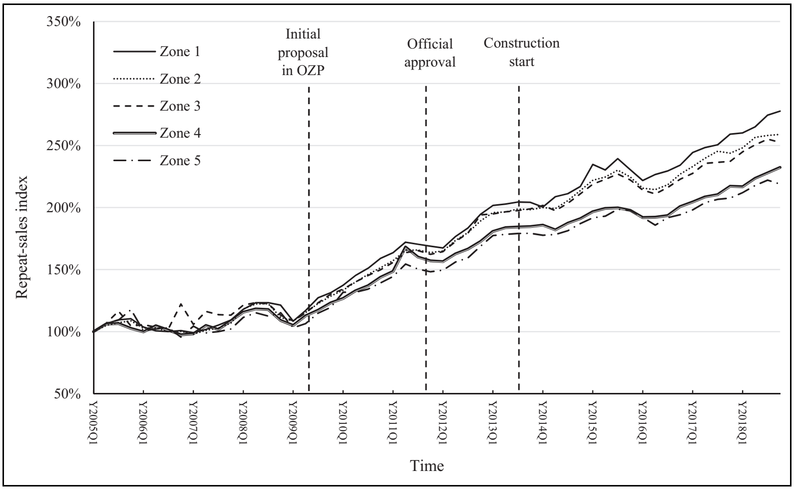

Figure 2. Repeat-sales indices.

(2005Q2–2009Q2), the indices performed similarly for all zones (see Panels D and E in Table 3). There is no significant difference at the 5% level between the indices of all zones during the pre-proposal period (see Panel F in Table 3). This is the evidence that the control and treatment groups chosen are appropriate.

After the tunnel proposal was released, the repeat-sales indices increased the most in the proposal period, followed by the announcement period, as indicated by the quarterly index changes in Panel E. On average, the quarterly index changes are around 4.31%, 2.71% and 1.14% during the proposal, the announcement and the construction period. This evidence supports Hypotheses I and II. Prices increased more rapidly for zones closer to the tunnel site than the zones further away, as evident from the larger index numbers for Zones 1 to 3 across the three periods in Panels D and E of Table 3. The *t*-tests indicate statistically significant mean differences between the indices during the post-proposal phases for Zones 1, 2 and 3 compared with zones 4 and 5 at the 5% level, but no significant mean differences between the indices for Zones 1 to 3. Clearly the market structure of properties in the affected areas has changed, with stronger preference towards apartments closer to the tunnel site. This evidence supports Hypotheses III and IV.

Policy implications

Residential value increases caused by transportation developments can be captured to recoup the costs of construction, using mechanisms such as betterment tax and accessibility increment contribution. The concept behind land value capture is to return to the community the benefit created by public investment but captured by property owners as windfall gains. Land value capture is not only an efficient and equitable source of funding (Ingram and Hong, 2012) but can also be a significant financial incentive for undertaking transportation investment (Xu and Zhang, 2016). This mechanism is plausible especially because Hong Kong is already familiar with transit-based land value capture, having used its application to finance the mass transit railway (Meakin, 1990). The accurate pricing of the impact of new transport development on property prices is useful to support the design and implementation of land value capture policy by determining the appropriate and acceptable level of value capture and boundary of the betterment catchment area. On the individual housing unit level, the hedonic pricing model can be used to distinguish the amount of price increase attributable to the transport development.

The increase in property value produced by the transportation development is an indicator of the economic value of the utility derived from increased accessibility to residents. Using the coefficient estimates from the hedonic regression model, we can estimate the size of the accessibility benefits. There are 137,477 private residential apartments in the Tuen Mun area (i.e. Zones 1–3). The average transaction price of these properties is 1,161,493 HKD during the pre-proposal period. The tunnel project increased the average property prices in this region by approximately 26% over 9 years, according to Model 3 results in Table 2. This translates to 42.4 billion HKD, which almost covers the 44.8 billion HKD construction cost entirely. This is the net effect of the expected transport improvement from the tunnel project in terms of changes in housing wealth in the private residential property market in the affected region. Note that this is in addition to the significant housing price appreciation (i.e. over 130% increase during the same period based on the coefficient estimates of *year2009* and *year2018*) resulting from other factors such as economic growth and inflation, which are captured by the time dummies in our regression models.

As virtually all land in Hong Kong is leasehold, owned by the government (see the discussion in Chiu, 2007), an alternative method of land value capture is the leasing of publicly owned land. The finding of expectation effects means that it is possible to finance the transportation infrastructure using the income of land sales in advance. The government can lease out land parcels nearby the planned transportation site to developers, as a mechanism to extract the value uplift for vacant land (Knaap et al., 2001; Yiu and Wong, 2005). The hedonic pricing estimates can be used to determine the accessibility premium to be included in land leases for affected areas.

Finally, the generation of knowledge regarding the effects of transportation developments on house prices helps guide urban planning and public investment decisions (Smith and Gihring, 2006). This study estimates that the tunnel generated a total economic value of 42.4 billion HKD in accessibility benefits even before its completion, representing nearly the full construction cost of 44.8 billion HKD. This value does not include the other long-term benefits that are expected to accrue when the tunnel becomes operational. The voting down of the earlier proposal in 2002 could potentially have been avoided if there was better knowledge of expected benefits for similar projects, which could have been leveraged to justify the public investment.

Conclusion

This paper sets out to examine the effects of major infrastructure projects on residential property prices and, specifically, to investigate whether the Tuen Mun–Chek Lap Kok tunnel project in Hong Kong introduced an accessibility premium in proximity to the tunnel. We find that the residential property market capitalised the expected accessibility benefits of the tunnel well before its opening. The accessibility premium is the largest during the proposal period. Moreover, the improvement of accessibility for residents in the urban periphery increases distributional equality, as it facilitates socio-spatial inclusion and mobility. These are positive urban planning outcomes from a transport justice perspective.

Our research contributes to the literature in two ways. On the technical front, we proposed an analytical framework that incorporates three phases of the tunnel project and five zones in the affected areas. This allows flexible and reliable identification of accessibility premiums across space and over time. This is a significant improvement over existing literature, where the temporal and spatial variations of transportation premiums are often studied in isolation. Second, we demonstrated how our findings can be used to support important decision-making in urban planning and development. Financing a large-scale transportation infrastructure project is challenging. Local authorities struggle to justify the costs during the proposal period and to recoup the vast expenses once the project starts. Hedonic price estimation of the accessibility premium can be used to justify public investment in similar projects in future. The finding of expectation effects demonstrates the possibility of financing similar transportation investments using land value capture in advance. This research has significant implications for both research and practice in urban planning and development.

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Notes

1. Hong Kong Highways Department (2002). Route 10 – North Lantau to Yuen Long Highway. Available at: https://www.legco.gov.hk/yr01-02/english/panels/tp/papers/tp1123cb1.pdf
2. *South China Morning Post* (2015). Alternative to Tsing Ma Bridge shot down years ago, Available at: https://www.scmp.com/news/hong-kong/education-community/article/1871798/alternative-tsing-ma-bridge-shot-down-years-ago
3. Properties that sold more than twice are treated as independent observations. For example, a unit which was resold three times is treated as two pairs of repeat-sales, matched as first–second transaction and second–third transaction.

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