INTERNATIONAL REAL ESTATE REVIEW

2026 Vol.29 No. 1: pp. 121 – 147

Decoupling the Effect of Land Depreciation on the Construction of Residential Property Price Indices

Lennon H.T. Choy
University of Hong Kong, Hong Kong, People's Republic of China,
Email: lennonchoy@hku.hk

Winky K.O. Ho[*]
Hong Kong Polytechnic University, Hong Kong, People's Republic of China,
Email: winky.ho@polyu.edu.hk

Unreliable property price information can lead to misallocation of land use and inefficient utilization of scarce resources. Traditional hedonic pricing models estimated by using ordinary least squares (OLS) commonly include property age as an explanatory variable, which implicitly assumes that both land and building structures depreciate over time. However, recent research argues that residential property price indices (RPPIs) should separate the depreciation of the building structure from the land component. Under this view, property age should only interact with the structural characteristics of the building, not the land. This paper estimates RPPIs by using both a standard time dummy hedonic price model and a modified version that adjusts for structural quality by interacting age with building features. Using a dataset of 451,894 observations, we find that the standard model tends to produce a downward bias in periods of mild price variation and an upward bias during periods of large price fluctuations. Finally, we compare our estimated indices with those published by the local government. The results show that turning points, price peaks, and troughs are largely consistent across both sets of indices.

Keywords

Land depreciation, Property age, RPPIs, Biases

---

[*] Corresponding author

DOI: https://doi.org/10.53383/100418

1. Introduction

Accurate and timely residential property price information is essential for the effective functioning of real estate markets. In response, many countries have developed and published different types of residential property price indices (RPPIs). Examples include Denmark (Holmgaard, 2016), Jamaica (Langrin and Moulton, 2016), Japan (Shimizu et al., 2010; Furuta et al., 2021), Malta (Ellul et al., 2019), the Netherlands (Statistics Netherlands, 2013), the United Kingdom (Halifax, 2022; HM Land Registry, 2022), and the United States (U.S.; Diewert et al., 2010; S&P Dow Jones Indices LLC, 2022). In particular, the National Association of Realtors in the U.S. publishes a widely used index for existing single–family homes based on transactions conducted by its member realtors across major metropolitan areas.

A residential property serves both as a place of residence and a vehicle for wealth accumulation for homeowners and investors. However, no two properties are exactly alike (Case & Quigley, 1991), and in the context of escalating property prices and housing shortages, buyers and sellers face increasing uncertainty in decision–making. Case and Shiller (1987) emphasize that housing price indices serve as useful benchmarks for individuals to assess their real wealth. Furthermore, such indices are instrumental for policymakers in designing effective land and housing policies.

Traditional hedonic pricing models typically include property age as an explanatory variable, thus implicitly assuming that both land and building structures depreciate over time (Sia, 2022). However, more recent research argues that this assumption is flawed. Instead, the depreciation effect should be attributed solely to the building structure, not the land (Diewert et al., 2010; De Haan and Diewert, 2013; Rambaldi et al., 2016; Xu et al. 2018). If this distinction is not made, the resulting indices cannot accurately reflect price changes while holding housing characteristics constant. Consequently, such indices fail to capture the true price movement of the same home sold at different points in time. Estimation bias that arise from variations in housing quality further undermines the reliability of standard RPPI methodologies. Nevertheless, De Haan and Diewert (2013) contend that these biases can be mitigated by explicitly removing the land depreciation component.

This study aims to estimate constant quality RPPIs that exclude land depreciation by using the constant quality time dummy hedonic price index (CQTDHPI) approach proposed by De Haan and Diewert (2013). We compare our CQTDHPI results with indices derived from the standard time dummy hedonic price index (TDHPI) model, as well as the official indices published by the Rating and Valuation Department (RVD) of The Government of the Hong Kong Special Administrative Region (SAR). Using a comprehensive dataset of “selected popular residential developments” in Hong Kong (as identified by the

RVD), this research offers a modest yet meaningful contribution toward the development of more accurate, consistent, and policy–relevant RPPIs.

This paper is structured as follows. Section 2 reviews the literature on the methodologies for constructing various types of RPPIs. Section 3 outlines the methodology for constructing the constant quality housing price index (CQTDHPI), which incorporates quality adjustments for building age, and explains how to estimate the annual net depreciation rate. Sections 4 and 5 describe the dataset and present an exploratory data analysis by using graphical and other visualization techniques to highlight key characteristics. Section 6 discusses the empirical results in detail and offers policy recommendations. Section 7 elaborates on the broader policy implications of developing quality–adjusted price indices. Finally, Section 8 concludes with a summary of the main findings.

2. Literature Review

Residential properties are characterized by a diverse array of features, including square footage, age, number of floors, views, orientation, school district, location, and proximity to local rail services. These characteristics may change over time due to factors such as depreciation, view-obstructing new constructions, or the establishment of new transit stations. The existing literature has sought to address biases associated with changes in housing quality by employing methods that can be broadly categorized into three groups.

The first category, repeated sale price indices (RSPIs), originates from the foundational work of Bailey et al. (1963). This method estimates RSPIs for residential properties that have been transacted at least twice within a specified time period, with the use of time dummies. The dependent variable is defined as the logarithmic difference in property prices between the first and second sales, with time dummy values set to –1, 1, or 0, depending on the timing of the sales. While this method facilitates straightforward price estimations and allows for control of quality changes in housing characteristics (Cannaday et al. 2005; Chau et al. 2005a; Wong et al. 2012; 2018), it has significant drawbacks, including a substantial reduction in the number of observations and potential sample selection bias, as noted by Gatzlaff and Haurin (1997) and Steele and Goy (1997). Furthermore, the assumption that the error term is independent of the time elapsed between consecutive sales has been critiqued.

Subsequent developments in RSPIs have attracted considerable scholarly interest, with various adaptations proposed. For instance, Case and Shiller (1987) improve on the work of Bailey et al. (1963) by suggesting that the variance should vary with the time interval between sales. They introduce the “weighted repeat–sales indices”, which assign a higher weight to properties with shorter intervals between transactions. However, this modification still wrestles with issues related to reduced sample sizes. Shiller (1991) advocates for an arithmetic average of the repeated sales method over the geometric average, and recommends a value–weighted, equally–weighted, or interval–weighted approach based on context. Nagaraja et al. (2011) introduce the autoregressive index, which utilizes the entire dataset of housing transactions and applies different weights according to the frequency of transactions. This approach allows for the estimation of autoregressive price indices across various geographical levels.

A critical concern regarding RSPIs has been raised by Clapp and Giaccotto (1992), who find that the repeat–sales sample often comprises lower–end properties of generally inferior quality, thus leading to the potential of a "lemon bias". This is particularly relevant as first–time and younger buyers are more likely to purchase these lower–end residences before upgrading as their financial situations improve.

The second major approach is the time dummy hedonic method. In this method, observed housing expenditure, typically expressed in natural logarithm, is modelled as a function of various housing characteristics and time dummies that correspond to sale dates. The coefficients estimated for each housing feature indicate percentage changes in property prices for one–unit changes in those features, thus allowing for the calculation of RPPIs from the time dummy coefficients. Recent studies, such as De Haan and Diewert (2013) and Diewert et al. (2015), have sought to isolate the effects of land depreciation from property prices by positing that land does not depreciate alongside building structure and noting that larger properties generally incur higher depreciation and maintenance costs.

The third category encompasses hybrid models, first proposed by Case and Quigley (1991), which merge the repeat sales method with hedonic price modelling to utilize a full sample of housing transactions. This methodology jointly estimates data from repeated sales of unchanged and improved properties alongside single sales (see also Wallace and Meese (1997)). Alternative versions of hybrid models have been advanced by Knight et al. (1995) and Clapp and Giaccotto (1998).

To identify the most suitable methodology for estimating RPPIs, Case et al. (1991) compare RPPIs derived from hedonic pricing, weighted repeat sales, and hybrid approaches. Their findings indicate that the hedonic method suffers from model specification bias and inefficiency, with even greater biases apparent in the weighted repeat sales method. Ultimately, their study concludes that the hybrid model offers superior performance, thus effectively addressing many of the issues encountered by the other methods. In our study, we utilize the methodology proposed by De Haan and Diewert (2013), which aims to exclude the effect of land depreciation when employing the time dummy hedonic price method. Our research focuses on this approach to estimate quality–adjusted

RPPIs, which ensures that the influence of land depreciation is absent in our estimated equations.

3. Model Specification

Following the methodology proposed by De Haan and Diewert (2013), the price P_i^t of a residential property i at time t is modelled as a function of a fixed set of K housing characteristics, measured by quantity z_{ik}^t. This relationship is expressed through the time dummy hedonic price model as shown in Equation (1):

$$ln(P_i^t) = \beta_0 + \sum_{k=1}^{K} \beta_k z_{ik}^t + \sum_{\tau=1}^{T} \delta^\tau D_i^\tau + \varepsilon_i^t \qquad (1)$$

In this model, β_0 denotes the intercept, while β_k represents the coefficients associated with K housing features. D_i^τ is a time dummy variable that equals one if property i is transacted in period τ, and zero otherwise. The coefficients δ^τ capture the effect of time on property prices. If there are T time periods, only $(T-1)$ dummy variables are included in the regression, as one period (e.g., $t = 0$) is used as the reference (base) period and therefore omitted to avoid perfect multicollinearity.

The model uses the natural logarithm of prices, a common transformation in real estate price modelling, since property prices tend to follow a log–normal distribution (Diewert, 2003; De Haan and Diewert, 2013; Silver, 2014; De Haan and Krsinich, 2018). To eliminate heteroskedasticity in the error terms, several authors (Diewert, 2003; Diewert et al., 2009; De Haan and Krsinich, 2018) recommend the use of a log–linear specification. This formulation also allows the incorporation of time dummies, which makes it possible to isolate the time effect on residential property values. In practice, Equation (1) can be estimated by regressing the logarithm of property prices on a set of physical, environmental, and locational attributes, along with time dummy variables. The coefficients on the time dummies provide a direct measure of the temporal changes in market prices (Silver and Heravi, 2007).

More recently, a growing body of literature has advocated for the further refinement of quality–adjusted RPPIs by explicitly separating land and structure components. Specifically, age should only interact with a building structure in a multiplicative form (Diewert et al., 2015; Rambaldi et al., 2016). There are at least two reasons for this specification. First, land does not depreciate over time. Second, within the same residential building, a more expensive structure typically implies a larger floor area. Larger units are subject to higher depreciation effects and generally incur higher maintenance costs as they age, compared to smaller units in the same development.

To isolate the effect of land on property prices, we specify the following regression equation:

$$ln(P_i^t) = \beta_0 + \sum_{k=1}^{K} \beta_k z_{ik}^t + \gamma S_i^t + \theta A_i^t S_i^t + \sum_{\tau=1}^{T} \delta^\tau D_i^\tau + \varepsilon_i^t \qquad (2)$$

where z_{ik}^t denotes the vector of housing characteristics excluding structural and age–related variables and S_i^t is the age of the residential property. The coefficient γ measures the effect of the building structure, while θ captures the interaction effect between age and structure. Under this specification, the land component is excluded, which allows us to focus solely on the structural depreciation of the property.

Equation (2) is the hedonic regression model used to estimate the effects of various housing characteristics (excluding land) on property prices, specifically focusing on building structure and its interaction with age. Equation (3) uses the estimated coefficient $\hat{\theta}$ from Equation (2) to calculate the net depreciation rate σ. This is done by applying the estimated coefficient $\hat{\theta}$ to a typical or average building structure $\hat{S}_i^t$ and an average building age $\hat{N}$. Hence, Equation (2) is used to estimate how building age (via the interaction term $A_i^t S_i^t$) affects log prices while Equation (3) then transforms this estimated effect into a net depreciation rate (in percentage terms) for a representative property.

Based on the estimated $\beta_0, \beta_k, \gamma, \theta$ and δ^τ, the second step involves calculating the net depreciation rate for selected, commonly traded residential developments by using:

$$\sigma = 1 - e^{\hat{N}\cdot\hat{\theta}\cdot\hat{S}_i^t} \qquad (3)$$

This net depreciation rate does not reflect the standard accounting concept of age–based depreciation. Instead, it measures 'a net depreciation rate; i.e., a gross depreciation rate less the rate of renovations and decisions to the structure (De Haan and Diewart, 2013, p.82).

The final step involves calculating both the standard and quality–adjusted RPPIs by applying the transformation $100 \cdot e^{\hat{\delta}^\tau}$ for each time dummy coefficient. Mathematically, Equation (4) shows why the exponential of the estimated time dummy coefficient corresponds to the price index:

$$PI^{0,t} = \frac{\hat{P}_i^t}{\hat{P}_i^0} = e^{\ln(\hat{P}_i^t)-\ln(\hat{P}_i^0)} = e^{\hat{\delta}^\tau} \qquad (4)$$

In the base period (e.g., July 1999), the price index is normalized to 100. For any subsequent period t (e.g., May 2000), the price index is calculated by using $100 \cdot e^{\hat{\delta}^{May\,2000}}$. This involves taking the exponential of the estimated coefficient for the corresponding time dummy and scaling it by 100. By repeating this process for all time periods, we construct a full time series of the RPPI.

Since the RPPI reflects changes in the market value of a residential property with constant quality characteristics z_{ik},, it inherently adjusts for variations in structural features and incorporates property age as part of the model. As a result, the RPPI captures price changes that are net of quality adjustments over time.

4. Data Definitions and Sources

In this study, we examine model misspecification in the standard time dummy hedonic price model by applying the model to a dataset that consists of all private housing estates classified as “selected popular residential developments” by the RVD of the Hong Kong SAR Government. The dataset covers the period of January 1997 to May 2021 and consists of 451,894 pooled cross–sectional observations. These residential developments are situated across the three main geographic regions of Hong Kong: Hong Kong Island, Kowloon, and the New Territories. Examples of such developments include Les Saisons, Robinson Place, Sham Wan Towers, South Horizons, Taikoo Shing, The Belcher’s, Sorrento, The Hermitage, YOHO Midtown, and YOHO Town (see Rating and Valuation Department (2022)).

The dataset contains disaggregated transaction–level data, including building name, location, transaction date, occupation permit date, total consideration, gross floor area, and other property attributes (e.g., whether the property was transacted with a carpark). These records are collected by the Hong Kong government and compiled by a private company, the EPRC. However, some entries are excluded from the final dataset due to missing or incorrect values, such as records with missing property prices or inconsistencies. Additionally, transactions recorded with zero consideration—typically gifts between family members—are also removed to maintain data quality.

The primary objective of this study is to estimate and compare two hedonic pricing models: the standard time dummy hedonic price model (Equation 5) and the constant quality time dummy hedonic price model (Equation 6). These models are specified as follows:

$$\begin{aligned} ln(P_i^t) &= \beta_0 + \beta_1 GFA_i^t + \beta_2 AGE_i^t + \beta_3 FL_i^t + \beta_4 CP_i^t + \beta_5 MTR_i^t \\ &+ \beta_6 E_i^t + \beta_7 S_i^t + \beta_8 W_i^t + \beta_9 N_i^t + \beta_{10} NE_i^t + \beta_{11} SE_i^t + \beta_{12} SW_i^t \\ &+ \beta_{13} URBAN_i^t + \sum_{i=1}^{293} \delta_i D_i^\tau + \epsilon \end{aligned} \tag{5}$$

$$\begin{aligned} ln(P_i^t) &= \beta_0 + \beta_1 GFA_i^t + \beta_2 ZZ_i^t + \beta_3 FL_i^t + \beta_4 CP_i^t + \beta_5 MTR_i^t \\ &+\beta_6 E_i^t + \beta_7 S_i^t + \beta_8 W_i^t + \beta_9 N_i^t + \beta_{10} NE_i^t + \beta_{11} SE_i^t + \beta_{12} SW_i^t \\ &+\beta_{13} URBAN_i^t + \sum_{i=1}^{293} \delta_i D_i^\tau + \epsilon \end{aligned} \tag{6}$$

where P_i^t is the total consideration (price) of residential property *i* in period *t*, measured in Hong Kong dollars.

GFA_i^t denotes the gross floor area of property *i*, including areas such as penthouses, bay windows, and balconies.

AGE_i^t is the age of the property, calculated as the time difference (in years) between the date of the occupation permit and the transaction date.

ZZ_i^t represents the interaction between building structure and property age (i.e., structure × age).

FL_i^t is the floor level on which property *i* is located.

CP_i^t is the number of carpark spaces transacted with property *i*.

MTR_i^t is a dummy variable equal to 1 if the walking distance from property *i* to the nearest Mass Transit Railway (MTR) station is 10 minutes or less; 0 otherwise.

$E_i^t, S_i^t, W_i^t{}_i, N_i^t, NE_i^t, SE_i^t, SW_i^t$ and NW_i^t represent dummy variables for the directional orientation of the property, with 1 indicating that the property faces a given direction, and 0 otherwise. Northwest is omitted as the reference category.

$URBAN_i^t$ is a dummy variable set to 1 if the property is located in either Hong Kong Island or Kowloon; 0 otherwise.

D_i^τ is a set of monthly time dummy variables from January 1997 to May 2021. The dummy for July 1997 is excluded, which serves as the baseline period, thus resulting in 292 time dummies.

5. Exploratory Data Analysis

Through graphical and other data visualization presentations, investigators can use an exploratory data analysis to analyze data sets to outline their major features. The objectives of an exploratory data analysis are to answer research questions, test assumptions and generate hypotheses for further analysis. Figure

1 presents a correlation matrix that shows the linear relationship between each variable. The matrix shows that *LP* is moderately correlated with *GFA* (0.6), and *ZZ* (0.4), thus suggesting larger floor areas, and floor areas x age are associated with higher prices. Other features, such as car park (*CP*) (0.3) and floor level *(FL*) (0.1) have weaker correlations, thus implying that the presence of car parks and higher floor levels may slightly increase property prices.

Orientation variables (*E*, *S*, *W*, etc.) have a negligible correlation with *LP*, which is generally below ± 0.07, thus indicating limited influence. The *URBAN* variable is positively correlated with *LP* (0.3), while *NT* has a negative correlation (–0.3), which reflects potential geographic price differences. The inter–feature correlations reveal a moderately negative correlation between *AGE* and *FL* (–0.3), which suggests that newer buildings are more likely to have higher floor levels. *GFA* and *CP* are also moderately correlated (0.4), which may reflect the impacts of floor space on number of carparks. Overall, *GFA*, *ZZ*, and *URBAN* appear to be the most relevant predictors of price, while multicollinearity is generally low, with few high inter–feature correlations.

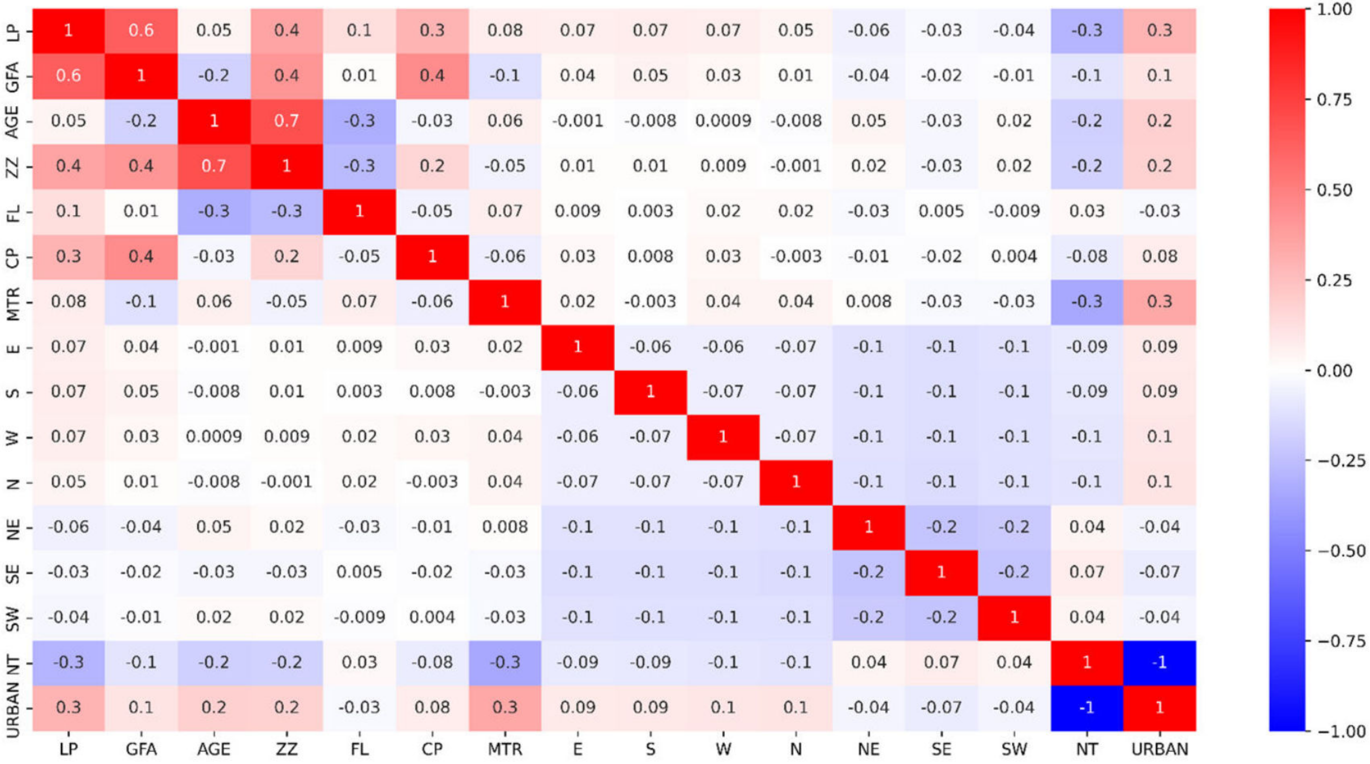
Furthermore, Table 1 presents a summary of the descriptive statistics of the variables used in this study. Descriptive statistics are a brief description that summarizes a specific data set, which can be either a representation of the whole population or a sample of a population. The table provides descriptive statistics for a dataset of 451,895 observations across several variables. The dependent variable *LP* has a near–normal distribution (skew = 0.4) with a mean of 15.1 and low dispersion (std = 0.7). Key predictors like gross floor area (*GFA*) and *ZZ* show right–skewed distributions (skew = 3.9 and 5.2), thus indicating a long tail of large properties. *AGE* is more symmetrically distributed, while *CP*, though mostly zeros, shows a sharp right skew (7.0), which suggests a rare but impactful presence.

The orientation indicators (*E*, *S*, *W*, etc.) and *URBAN* are binary variables, and mostly centred around low means, thus implying that only a small proportion of properties face each direction or are in urban areas. The large standard deviations and skewness values for several features (e.g., *ZZ*, *CP*) suggest potential outliers or long–tailed distributions, which may require transformation or robust modelling. Overall, the dataset appears to be rich, with both continuous and binary features, and thus suitable for regression tasks.

6. Results and Discussion

This section presents the empirical results based on the full sample of "selected popular residential developments" in Hong Kong. Specifically, Table 2 reports the estimation outcomes by using Newey–West heteroscedasticity– and autocorrelation–consistent (HAC) standard errors and covariance. The table includes coefficient estimates with robust standard errors, measures of

Figure 1 **Correlation Matrix**



	LP	GFA	AGE	ZZ	FL	CP	MTR	E	S	W	N	NE	SE	SW	NT	URBAN
LP	1	0.6	0.05	0.4	0.1	0.3	0.08	0.07	0.07	0.07	0.05	-0.06	-0.03	-0.04	-0.3	0.3
GFA	0.6	1	-0.2	0.4	0.01	0.4	-0.1	0.04	0.05	0.03	0.01	-0.04	-0.02	-0.01	-0.1	0.1
AGE	0.05	-0.2	1	0.7	-0.3	-0.03	0.06	-0.001	-0.008	0.0009	-0.008	0.05	-0.03	0.02	-0.2	0.2
ZZ	0.4	0.4	0.7	1	-0.3	0.2	-0.05	0.01	0.01	0.009	-0.001	0.02	-0.03	0.02	-0.2	0.2
FL	0.1	0.01	-0.3	-0.3	1	-0.05	0.07	0.009	0.003	0.02	0.02	-0.03	0.005	-0.009	0.03	-0.03
CP	0.3	0.4	-0.03	0.2	-0.05	1	-0.06	0.03	0.008	0.03	-0.003	-0.01	-0.02	0.004	-0.08	0.08
MTR	0.08	-0.1	0.06	-0.05	0.07	-0.06	1	0.02	-0.003	0.04	0.04	0.008	-0.03	-0.03	-0.3	0.3
E	0.07	0.04	-0.001	0.01	0.009	0.03	0.02	1	-0.06	-0.06	-0.07	-0.1	-0.1	-0.1	-0.09	0.09
S	0.07	0.05	-0.008	0.01	0.003	0.008	-0.003	-0.06	1	-0.07	-0.07	-0.1	-0.1	-0.1	-0.09	0.09
W	0.07	0.03	0.0009	0.009	0.02	0.03	0.04	-0.06	-0.07	1	-0.07	-0.1	-0.1	-0.1	-0.1	0.1
N	0.05	0.01	-0.008	-0.001	0.02	-0.003	0.04	-0.07	-0.07	-0.07	1	-0.1	-0.1	-0.1	-0.1	0.1
NE	-0.06	-0.04	0.05	0.02	-0.03	-0.01	0.008	-0.1	-0.1	-0.1	-0.1	1	-0.2	-0.2	0.04	-0.04
SE	-0.03	-0.02	-0.03	-0.03	0.005	-0.02	-0.03	-0.1	-0.1	-0.1	-0.1	-0.2	1	-0.2	0.07	-0.07
SW	-0.04	-0.01	0.02	0.02	-0.009	0.004	-0.03	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	1	0.04	-0.04
NT	-0.3	-0.1	-0.2	-0.2	0.03	-0.08	-0.3	-0.09	-0.09	-0.1	-0.1	0.04	0.07	0.04	1	-1
URBAN	0.3	0.1	0.2	0.2	-0.03	0.08	0.3	0.09	0.09	0.1	0.1	-0.04	-0.07	-0.04	-1	1

Table 1 **Descriptive Statistics**

	Count	Mean	Std	Min	25%	50%	75%	Max	Skew
P	451,895	15.1	0.7	13.5	14.5	15	15.6	19.5	0.4
GFA	451,895	786.8	367.2	231	580	696	872	12889	3.9
AGE	451,895	13.7	10.2	0	5.3	12	20.5	52.6	0.7
ZZ	451,895	10,482.7	10,631.9	1.3	3948.7	8506.1	13,787.8	673,354.3	5.2
FL	451,895	19.7	14.1	1	8	17	28	81	0.9
CP	451,895	0	0.2	0	0	0	0	11	7
MTR	451,895	0.6	0.5	0	0	1	1	1	-0.6
E	451,895	0.1	0.2	0	0	0	0	1	3.8
S	451,895	0.1	0.2	0	0	0	0	1	3.6
W	451,895	0.1	0.2	0	0	0	0	1	3.7
N	451,895	0.1	0.2	0	0	0	0	1	3.5
NE	451,895	0.2	0.4	0	0	0	0	1	1.8
SE	451,895	0.2	0.4	0	0	0	0	1	1.5
SW	451,895	0.2	0.4	0	0	0	0	1	1.7
NW	451,895	0.2	0.4	0	0	0	0	1	1.5
URBAN	451,895	0.4	0.5	0	0	0	0	1	0.3

goodness–of–fit, and diagnostic statistics. All of the explanatory variables are statistically significant at the 1% level and exhibit the expected signs.[1] The adjusted R^2 values across the six model specifications range from 0.839 to 0.860, thus indicating a strong overall fit for both the full sample and subsamples.

Across all of the models, a larger gross floor area and higher floor level are consistently associated with price premiums. In contrast, property age (or its interaction with structure, denoted by *ZZ*) exhibits a negative coefficient, which suggests depreciation over time. Some counterintuitive results are also observed. For instance, the coefficient for proximity to an MTR station is negative in the *URBAN* subsample. This can be explained by the presence of high–end developments in urban areas (Hong Kong Island and Kowloon) that are intentionally located in quieter, more exclusive neighbourhoods without immediate access to MTR stations. Residents in these areas, typically upper– or upper–middle–class, may prioritize privacy and a peaceful environment over transit convenience and prefer to travel by private vehicle. Similarly, the negative coefficient for CP in the NT subsample may be attributed to the limited number of transactions that involve carparks in this region. Of the 261,194 property transactions, only 2.10% (5,924) include the sale of one or more carparks. This small proportion likely introduces statistical noise, which may account for the unexpected negative sign.

Based on the results in Column (b) of Table 2, the annual net depreciation rate for selected popular residential developments can be estimated by using Equation (3). Assuming the same residential property is transacted twice with an age difference of *N* years, the annual depreciation rate, σ, is calculated as:

$$\sigma = 1 - e^{\widehat{\theta} \cdot \hat{s}_i^t} \tag{7}$$

To calculate the annual net depreciation rate, we set $N = 1$, thus reducing Equation (3) to Equation (7). By inserting the estimated coefficient $\widehat{\theta} = -8.52 \cdot 10^{-6}$ for *ZZ* and the sample mean $\bar{S}_i^t = 786.8$square feet, the estimated annual depreciation rate is approximately 0.67% for these developments.

To construct RPPIs for Hong Kong, we calculate the monthly index values for the full market and two subsamples by using parameters from the log–linear models in Equations (5) and (6). Figure 2 shows the indices generated by the standard TDHPI and CQTDHPI, alongside the official government price index for the same group of developments. Figures 3 and 4 show similar indices for the urban and NT subsamples, respectively. All indices are normalized to July 1999 = 100, with the government index rescaled accordingly.

---

[1] Due to space limitations, the estimates and robust standard errors for 292 time dummies are not shown in Table 2. They can be provided upon request.

Table 2 **Regression Results**

	a. Hong Kong (TDHPI Model)	b. Hong Kong (CQTDHPI Model)	c. Urban Area (TDHPI Model)	d. Urban Area (CQTDHPI Model)	e. New Territories (TDHPI Model)	f. New Territories (CQTDHPI Model)
β_0	14.5682* (0.008)	14.5237* (0.009)	15.0559* (0.012)	15.0089* (0.012)	14.5815* (0.013)	14.5307* (0.013)
GFA_i^t	0.0012* (0.000)	0.0014* (0.000)	0.0013* (0.000)	0.0014* (0.000)	0.0012* (0.000)	0.0013* (0.000)
AGE_i^t	–0.0111* (0.000)		–0.0099* (0.000)		–0.0110* (0.000)	
ZZ_i^t		–0.000* (0.000)		–0.000* (0.000)		-0.000* (0.000)
FL_i^t	0.0036* (0.000)	0.0044* (0.000)	0.0034* (0.000)	0.0042* (0.000)	0.0034* (0.000)	0.0041* (0.000)
CP_i^t	0.0435* (0.009)	0.0094* (0.002)	0.0702* (0.009)	0.0731* (0.010)	–0.1457* (0.018)	–0.2105* (0.019)
MTR_i^t	0.1031* (0.001)	0.1020* (0.001)	–0.0402* (0.002)	–0.0462* (0.002)	0.1697* (0.002)	0.1775* (0.001)
E_i^t	0.0907* (0.002)	0.0907* (0.002)	0.0972* (0.003)	0.0988* (0.003)	0.0879* (0.003)	0.0879* (0.004)
S_i^t	0.0766* (0.002)	0.0756* (0.002)	0.0739* (0.003)	0.0725* (0.003)	0.0679* (0.003)	0.0712* (0.003)

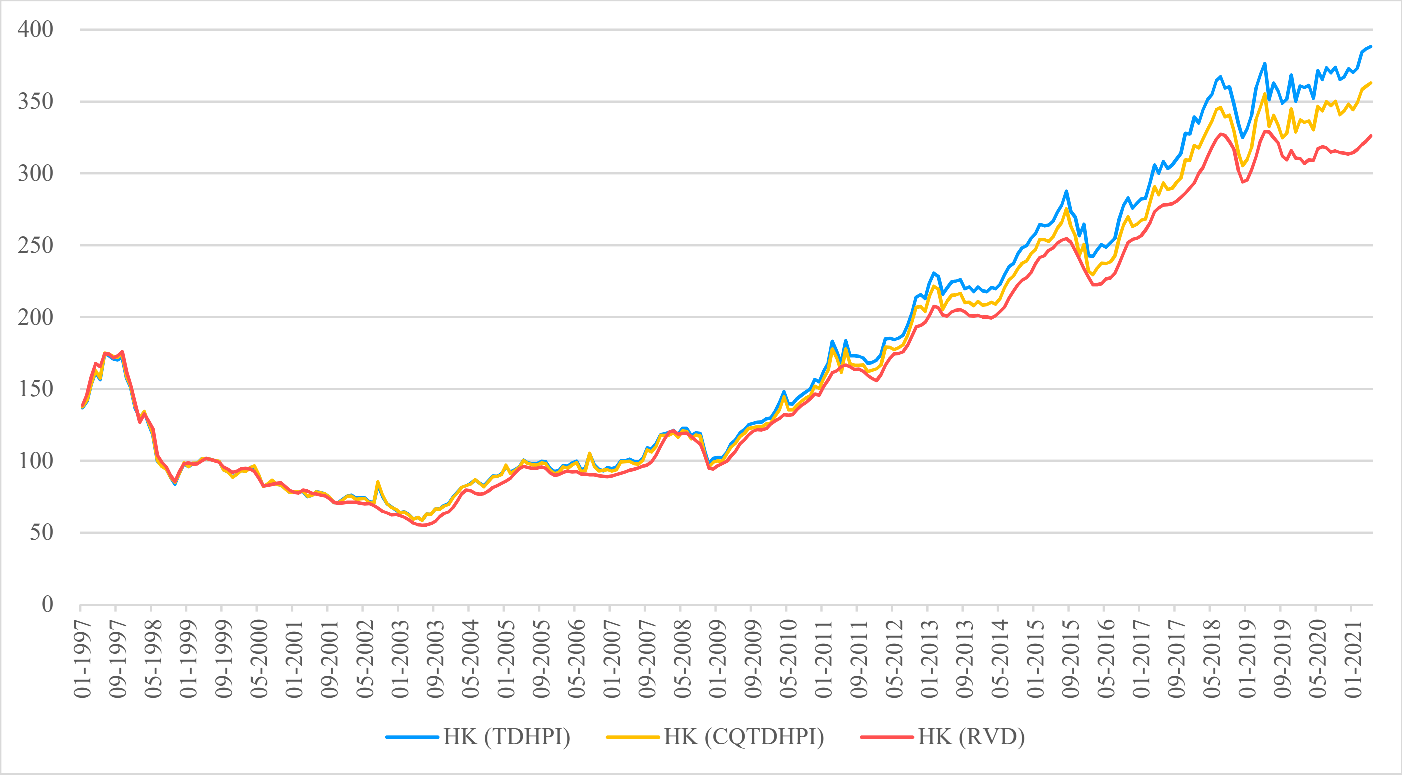
(Continued…)

(Table 2 Continued)

	a. Hong Kong (TDHPI Model)	b. Hong Kong (CQTDHPI Model)	c. Urban Area (TDHPI Model)	d. Urban Area (CQTDHPI Model)	e. New Territories (TDHPI Model)	f. New Territories (CQTDHPI Model)
W_i^t	0.0853*	0.0841*	0.0952*	0.0919*	0.0605*	0.0647*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
N_i^t	0.0484*	0.0517*	0.0674*	0.0688*	0.0256*	0.0322*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
NE_i^t	0.0071*	0.0032*	0.0184*	0.0165*	0.0034*	–0.0001*
	(0.001)	(0.001)	(0. 002)	(0.002)	(0.002)	(0.002)
SE_i^t	0.0245*	0.0266*	0.0235*	0.0242*	0.0211*	0.0237*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
SW_i^t	0.0162*	0.0155*	0.0149*	0.0170*	0.0140*	0.0133*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$URBAN_i^t$	0.4313*	0.4066*				
	(0.002)	(0.001)				
R^2	0.853	0.848	0.860	0.856	0.845	0.839
Adjusted R^2	0.853	0.848	0.860	0.856	0.845	0.839
F-statistic	3729	3382	1416	1278	2325	2078
Prob (F-statistic)	0.00	0.00	0.00	0.00	0.00	0.00
Log-Likelihood	–70,040	–78,034	–18,833	–21,259	–33,811	–38,467
AIC	140,700	156,700	38,280	43,130	68,230	77,540
Observations	451,894	451,894	190,700	190,700	261,194	261,194

Notes: Figures in the parentheses are the robust standard errors; * indicates statistically significant at 1 percent confidence level.

Figure 2 **Monthly Price Indices of Time Dummy Hedonic Price Model, its Modified Version and RVD (Hong Kong)**



As shown in Figure 2, the TDHPI and CQTDHPI closely align during the period of 1997–2008, with minimal price differentials. However, from 2009 onwards, the two indices begin to diverge. The TDHPI remains below the CQTDHPI until February 2002 but consistently exceeds the CQTDHPI thereafter through to May 2021. This pattern indicates a downward bias in the standard index during periods of modest price fluctuations and an upward bias during periods of more pronounced market shifts.

Figures 3 and 4 support these findings. In urban areas, both indices track closely until 2008. The TDHPI remains below the CQTDHPI until December 2004 and then consistently rises above the CQTDHPI from January 2005 through to May 2021. In the NT, both indices follow a similar trajectory until March 2005. The TDHPI is slightly lower than the CQTDHPI until July 2004 and surpasses the CQTDHPI from August 2004 onward. Overall, the standard and modified indices across the three groups reveal consistent trends.

We also compare the CQTDHPI with the official government indices in Figures 2 to 4. These comparisons show that the two sets of indices closely track each other until the early 2000s or 2007, after which differences emerge. Notably, the official indices are consistently lower than the CQTDHPI. While this might suggest a downward bias in the official indices, we refrain from making that conclusion for several reasons. The consistent gap between the CQTDHPI and the official RVD indices where the RVD indices are systematically lower from the early 2000s or 2007 and onward, can be attributed to several methodological and data–related differences.

First, the two indices employ fundamentally different approaches to quality adjustment. The CQTDHPI applies a hedonic regression model with the total transaction price (in logs) as the dependent variable and controls for key structural, locational, and temporal characteristics, such as the *GFA*, *GFA* × *AGE*, and other relevant attributes. This allows the model to directly isolate price changes over time while controlling for heterogeneity across properties. In contrast, the RVD indices use a valuation–based approach, where adjustments are made by using rateable values which are the estimates of annual rental income determined at a reference date and supplemented by the judgment of professional valuers (Chau et al. 2005b). This indirect method may not capture transaction–level nuances or rapid market changes as effectively as the regression–based hedonic model.

Second, the RVD indices exhibit a consistent one–month lag relative to the CQTDHPI, as shown in Figures 2, 3 and 4. This lag likely results from the reliance of the RVD on valuation inputs, which are reviewed periodically and may not immediately reflect emerging market conditions. Consequently, the RVD indices tend to understate price growth during upswings and may overstate prices during downswings, which, over time, contributes to a persistent gap below the CQTDHPI.

Figure 3 Monthly Price Indices of Time Dummy Hedonic Price Model, its Modified Version and RVD (Urban Area)

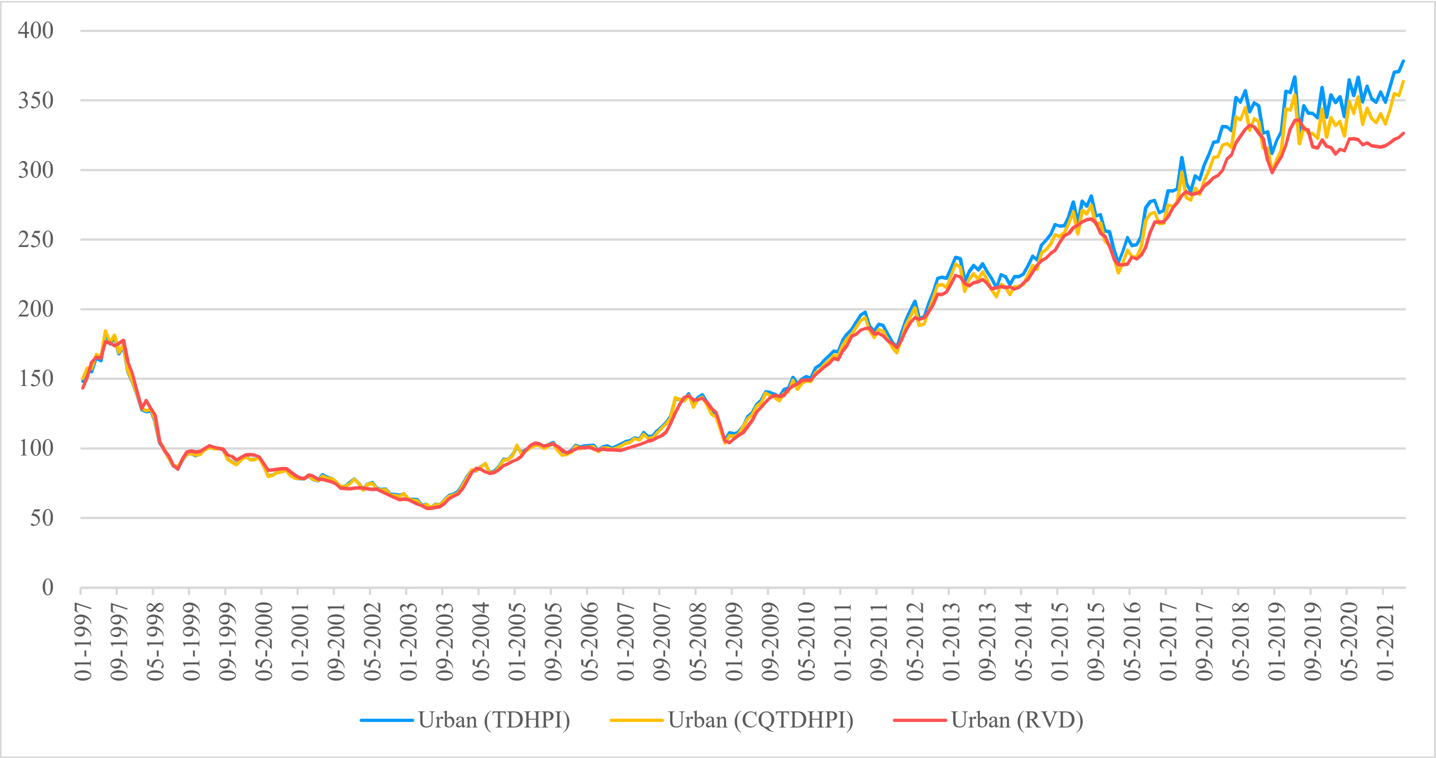
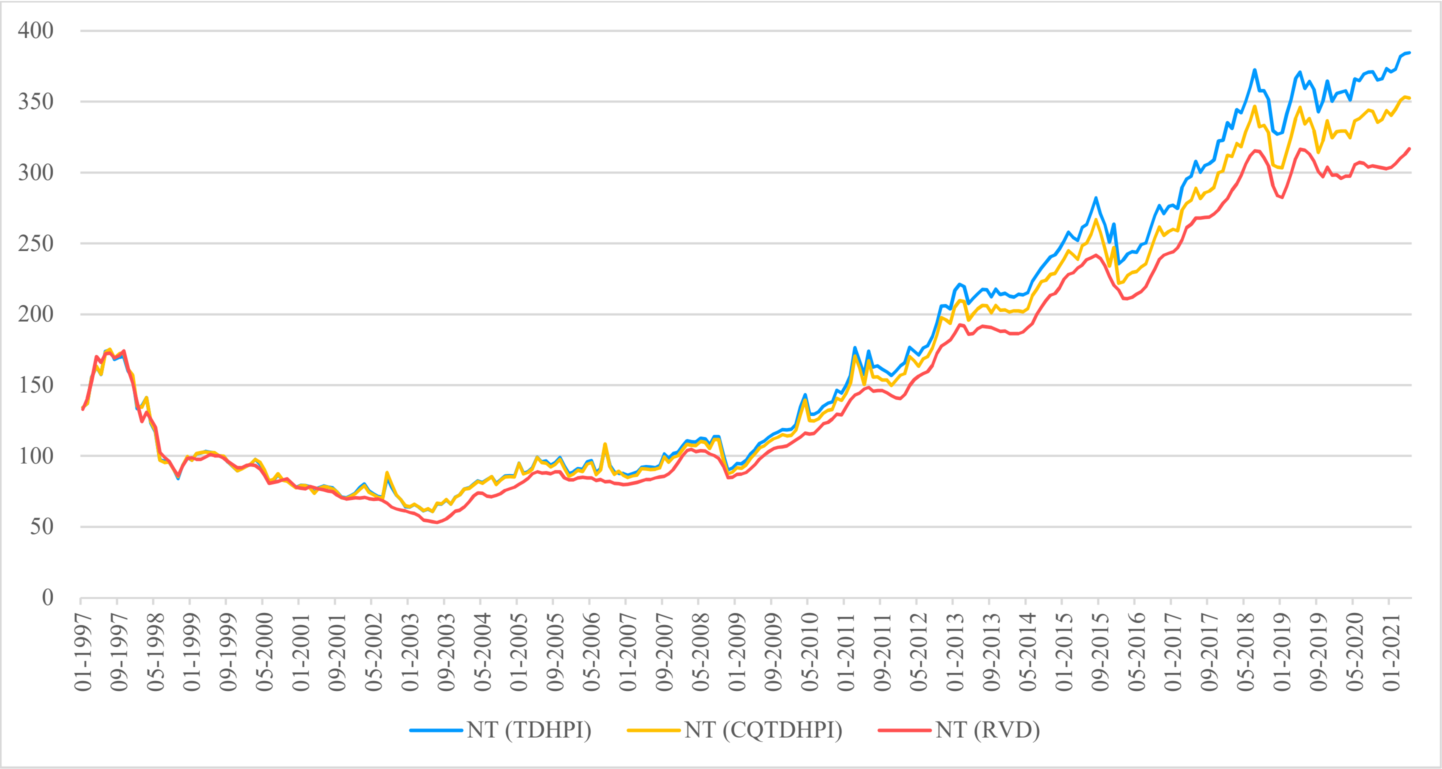


Figure 4 Monthly Price Indices of Time Dummy Hedonic Price Model, its Modified Version and RVD (NT)



Third, differences in data coverage may also play a role. While the CQTDHPI is based on a detailed dataset of transaction records, the index still contains data gaps. In contrast, the RVD database is likely more comprehensive, possibly including a complete record of property transactions. The RVD indices tend to report lower overall price levels because they include a broader range of transactions, particularly lower–priced properties such as small flats, older buildings, and units in less active areas. In contrast, the CQTDHPI, based on a cleaner but narrower dataset, often excludes these lower–end sales due to data filtering, which can unintentionally bias the indices upward. As a result, the CQTDHPI may reflect larger price growth, while the RVD indices present a more moderated view of the market by capturing the full spectrum of property transactions.

Moreover, the hedonic model specifications differ in complexity and granularity. The CQTDHPI likely benefits from a more flexible and detailed specification, including interaction terms and finer–grained location or property features. These allow for more accurate adjustments for quality differences over time. By contrast, the RVD model may adopt more aggregated variables, which can result in less precise estimates.

Lastly, the use of rateable values as the basis for quality adjustment in the RVD indices introduces an anchoring effect. Since rateable values are periodically updated and based on a notional rental income rather than current transaction prices, they can lag behind real–time market conditions. This valuation inertia further contributes to the RVD indices being consistently below our transaction–based CQTDHPI, especially during periods of rapid market appreciation.

While both indices aim to measure residential property price trends in Hong Kong, differences in methodology, particularly in quality adjustment, speed of incorporating new information, and dataset coverage, help to explain why the RVD indices have consistently tracked below the CQTDHPI since the early 2000s or 2007. Nevertheless, the turning points and directional trends in both sets of indices are broadly consistent, although the official series sometimes lags behind our results by about one month.

The fact that the turning points and directional trends in both indices are broadly consistent suggests that they share a common sensitivity to the underlying market dynamics. Despite methodological differences, both indices appear to capture major shifts in the residential property market, such as those driven by changes in interest rates, economic conditions, or housing policies (Leung and Tang, 2015; Wong and Ho, 2017). This indicates that they are both grounded in actual transaction data and effectively reflect the broader economic signals that influence property prices.

This consistency also points to the robustness of the price trend signals produced by each index. Even if the indices differ in their levels or volatility, their alignment in timing and direction reinforces the credibility of those trends. When both sets of indices show a turning point, such as a shift from price growth to decline, it strengthens the case that a real market change has occurred, not just a statistical artifact of one particular methodology.

Finally, the relationship between the two sets of indices highlights a broader trade–off in index construction between responsiveness and stability. The CQTDHPI appears to incorporate new information more rapidly, thus capturing market shifts in near real time. In contrast, the RVD index may place greater emphasis on stability and smoothing, which can result in a more measured response to short–term fluctuations. Despite these differences, the convergence in their directional trends underscores the value of both sets of indices as complementary tools for tracking and understanding movements in the residential property market.

7. Policy Implications

Reliable housing price indices are essential tools for informing public policy. They provide critical data on housing market conditions, and support decisions related to affordability, taxation, urban planning, and economic stability. Affordable housing initiatives, for instance, rely on these indices to identify regions that are facing cost burdens and to design targeted programs (Johnson, 2015; Molinsky and Airgood–Obrycki, 2018; Waters and Wernham, 2023). Price indices also reveal regional trends, thus enabling policymakers to intervene, such as applying rent controls or subsidies, when affordability worsens. Moreover, indices allow for ongoing evaluation of such policies by tracking changes in housing prices and affordability over time. This monitoring supports policy adjustments and ensures that objectives are met.

From a financial stability perspective, housing price indices help to identify risks such as speculation or bubbles, thus enabling proactive measures like tightening lending standards (Zhu, 2014; Biljanovska, 2023; Maclennan et al., 2023). Central banks also use them to guide monetary policy by adjusting interest rates in response to market fluctuations. Accurate indices support fair property taxation (Lenoe et al., 2018; OECD, 2022), which affects local government revenue and budgeting. In urban planning, indices reveal housing demand trends, which informs infrastructure investment and land use strategies (Glaeser et al., 2005; Glaeser and Gyourko, 2018; Tang and Ho, 2014; 2015).

They are also vital in identifying gentrification and displacement, which enable protective policies for vulnerable groups. Socially, housing price data help to address affordability, homelessness, segregation, and exclusion (Heston, 2023; Brasington et al., 2014; Akbar et al., 2019; Spicker, 1998). These insights support inclusive, equitable housing policies that address systemic challenges and promote fair housing for all.

8. Conclusions

Accurate and reliable RPPIs are essential for capturing price dynamics in the housing market. Researchers must therefore adopt appropriate methodologies to ensure the robustness of these indices. This study pursues two main objectives. First, the study investigates the issue of model misspecification in traditional hedonic pricing models, particularly those that fail to separate the land component from the structural component in property valuation. Conventional time dummy hedonic price models treat property age as a predictor by implicitly assuming that both land and building structures depreciate over time, an assumption that can distort price estimates.

Second, this research seeks to produce more efficient and unbiased estimators by adopting a constant quality time dummy hedonic model. The recent literature suggests that excluding the land component from the depreciation effect leads to more accurate price indices, as failure to do so results in upward or downward biases depending on the magnitude of price fluctuations.

Inaccurate property price indices hinder market transparency and limit participation by buyers, sellers, developers, and investors. Mispricing can lead to inefficient land use, where land is either under– or over–utilized. If land values are underestimated, developers may underinvest, so that they miss opportunities for optimal development. Conversely, overestimated prices may lead to overbuilding and reduced investment returns. Furthermore, misaligned price signals can disrupt coordination among market participants, thus delaying development and leading to inefficient resource allocation. For example, landowners who are unaware of rising demand may hold out for unrealistic prices, which causes bottlenecks in the development pipeline.

This study applies a modified time dummy hedonic model to a dataset of 451,894 observations from selected popular residential developments in Hong Kong. The study first compares the RPPIs generated from both the traditional and modified models. The results show that the conventional model yields biased indices which understate price changes during periods of moderate variation and overstate them during periods of volatility. The modified model, in contrast, eliminates these biases by isolating the depreciation of the structure from the land component.

Subsequently, the RPPIs generated by the modified model are compared with those published by the RVD of the Hong Kong government. The findings show that, for all three regions of Hong Kong (Hong Kong Island, Kowloon, and the New Territories), the turning points, booms, and busts of the two sets of indices align closely.

This research offers both theoretical and empirical contributions to the construction of RPPIs in Hong Kong. Its insights are not only valuable to academics, but also to a wide range of stakeholders, including policymakers, developers, investors, and households, whose financial decisions and well–being are heavily influenced by property price movements.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

This research is supported by the General Research Fund of the Research Grants Council of the Hong Kong Special Administrative Region Government (Project Number 17620020)

References

Akbar, P. A., Li, S. J., Shertzer, A. and Walsh, R. P. (2019). *Racial Segregation in Housing Markets and the Erosion of Black Wealth*. NBER Working Paper Series, No. 25805. Available at: http://www.nber.org/papers/w25805.

Bailey, M., Muth, R. F. and Nourse, H. O. (1963). A Regression Method for Real Estate Price Index Construction. *Journal of the American Statistical Association*, 58(304): 933–942. https://doi.org/10.1080/01621459.1963.10480679

Biljanovska, N. (2023). ‘How Falling Home Prices could Strain Financial Markets as Interest Rates Rise, International Monetary Fund’, *IMF Blog*, 31 May. Available at: https://www.imf.org/en/Blogs/Articles/2023/05/31/how-falling-home-prices-could-strain-financial-markets-as-interest-rates-rise

Brasington, D. M., Hite, D. and Jauregui, A. (2014). House Price Impacts of Racial, Income, Education, and Age Neighborhood Segregation. *Journal of Regional Science*, 55(3): 442–467. https://doi.org/10.1111/jors.12173

Cannaday, R. E., Munneke, H. J. Yang, T. T. (2005). A Multivariate Repeat-sales Model for Estimating House Price Indices. *Journal of Urban Economics*, 57(2), 320–342. https://doi.org/10.1016/j.jue.2004.12.001

Case, B., Pollakowski, H. O. and Wachter, S. M. (1991). On Choosing among House Price Index Methodologies. *AREUEA Journal,* 19(3): 286–307. https://doi.org/10.1111/1540-6229.00554

Case, B. and Quigley, J. M. (1991). The Dynamics of Real Estate prices. *The Review of Economics and Statistics,* 73(1): 50–58.

Case, R. and Shiller, R. J. (1987). Prices of Single–family Homes since 1970: New Indexes for Four Cities. *New England Economic Review*, September/October, 45–56.

Chau, K. W., Wong, S. K. and Yiu, C. Y. (2005a). Adjusting for Non–linear Age Effects in the Repeat Sales Index. *The Journal of Real Estate Finance and Economics,* 3, 137–153. https://doi.org/10.1007/s11146-005-1369-6

Chau, K. W., Wong, S., Yiu, C. and Leung, H. (2005b). Real Estate Price Indices in Hong Kong. *Journal of Real Estate Literature,* 13(3), 337–356. https://doi.org/10.1080/10835547.2005.12090166

Clapp, J. M. and Giaccotto, C. (1992). Estimating Price Trends for Residential Property: A Comparison of Repeat Sales and Assessed Value Methods. *Journal of Real Estate Finance and Economics,* 5(4), 357–374.

Clapp, J. M. and Giaccotto, C. (1998). Price Indices Based on the Hedonic Repeat–Sales Method: Application to the Housing Market. *The Journal of Real Estate Finance and Economics,* 16, 5–26.

De Haan, J. and Diewert, E. (2013). Hedonic Regression Methods, in Eurostat et al., *Handbook on Residential Property Price Indices (RPPIs),* Eurostat, Luxembourg. Available at: https://ec.europa.eu/eurostat/documents/3859598/5925925/KS-RA-12-022-EN.PDF.pdf/df645fcf-7d99-4926-ad20-3263980954da?t=1414782579000

De Haan, J. and Krsinich, F. (2018). Time Dummy Hedonic and Quality–adjusted Unit Value Indexes: Do They Really Differ? *Review of Income and Wealth*, 64(4), 757–776. https://doi.org/10.1111/roiw.12304

Diewert, W. E (2003). *Hedonic Regressions: A Review of Some Unresolved Issues.* Proceedings of the 7th Meeting of the Ottawa Group, Paris, May 27–29, pp. 71–109.

Diewert, W. E., De Haan, J. and Hendriks, R. (2015). Hedonic Regressions and the Decomposition of a House Price Index into Land and Structure Components. *Journal of Econometric Reviews,* 34(1–2), 106–126. https://doi.org/10.1080/07474938.2014.944791

Diewert, W. E., Heravi, S. and Silver, M. (2009). 'Hedonic Imputation versus Time Dummy Hedonic Indexes', in Diewert, W. E., Greenless, J. S., and Hulten. C.R. (eds.) *Price Index Concepts and Measurement.* Chicago: University of Chicago Press, pp. 161–196.

Diewert, W. E., Heravi, S. and Silver, M. (2010). 'Hedonic Imputation Indexes versus Time Dummy Hedonic Indexes', in Diewert, W.E., Greenlees, J. and Hulten, C.R. (eds.). *Price Index Concepts and Measurement.* Chicago: University of Chicago Press, pp. 278–337.

Ellul, R., Darmanin, J. and Borg, I. (2019). Hedonic House Price Indices for Malta: A Mortgage–based Approach. Central Bank of Malta Working Paper, 1–46. Available at: https://www.centralbankmalta.org/site/excel/working-papers/WP-02-2019.pdf?revcount=3934

Furuta, S., Hatayama, Y., Kawakami, A. and Oh, Y. (2021). *New Hedonic Quality Adjustment Method Using Sparse Estimation*. Bank of Japan Working Paper series, No. 21–E–8, 1–46. Available at: https://www.boj.or.jp/en/research/wps_rev/wps_2021/wp21e08.htm

Gatzlaff, D. H. and Haurin, D. R. (1997). Sample Selection Biases and Repeat–Sales Index Estimates. *Journal of Real Estate Finance and Economics,* 14, 33–50.

Glaeser, E. L. and Gyourko, J. (2018). The Economic Implications of Housing Supply. *Journal of Economic Perspectives,* 32(1), 3–30.

Glaeser, E. L., Gyourko, J. and Saks, R. E. (2005). Urban Growth and Housing Supply. *Journal of Economic Geography,* 6(1), 71–89. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=917712

Halifax. (2022). *Halifax House Price Index.* Available at: https://www.halifax.co.uk/media-centre/house-price-index.html

Heston, T. F. (2023). The Cost of Living Index as a Primary Driver of Homelessness in the United States: A Cross–state Analysis. *Cureus,* 15(10). https://doi.org/10.7759/cureus.46975

HM Land Registry (2022). *UK House Price Index.* Available at: https://landregistry.data.gov.uk/app/ukhpi/

Holmgaard, J. (2016). *Hedonic House Price Index. Prices and Consumption, Statistics Denmark*. Available at: https://www.dst.dk/Site/Dst/SingleFiles/GetArchiveFile.aspx?fi=7570965344&fo=0&ext=kvaldel

Hulten, C. R. and Wykoff, F. C. (1980). 'The Measurement of Economic Depreciation', in Hulton, C.R. (ed.) *Inflation & the Taxation of Income from Capital*, Urban Institute, pp. 81–125.
Available at:
http://econweb.umd.edu/~hulten/webpagefiles/original%20hulten-wykoff%20economic%20depreciation%20study.pdf

Knight, J. R., Dombrow, J. and Sirmans, C. F. (1995). A Varying Parameters Approach to Constructing House Price Indexes. *Real Estate Economics,* 23(2), 187–205. https://doi.org/10.1111/1540-6229.00663

Johnson, R. W. (2015). *Housing Costs and Financial Challenges for Low–income Older Adults.* Available at: https://www.urban.org/research/publication/housing-costs-and-financial-challenges-low-income-older-adults

Langrin, R. B. and Moulton, A. (2016). Constructing Residential Real Estate Price Indices for Jamaica. *Bank of Jamaica*, 1–24.

Leung, C. K. Y. and Tang, E. C. H. (2015). Availability, Affordability and Volatility: The Case of the Hong Kong Housing Market. *International Real Estate Review,* 18(3), 383–428.

Maclennan, D., Leishman, C. and Goel, S. (2023). *How does the Housing Market affect Financial and Economic Stability?* Available at: https://www.economicsobservatory.com/how-does-the-housing-market-affect-financial-and-economic-stability

Molinsky, J. and Airgood–Obrycki, W. (2018). 'Older Adults Increasingly Face Housing Affordability Challenge, Joint Center for Housing Studies', 21 September. Available at: https://www.jchs.harvard.edu/blog/older-adults-increasingly-face-housing-affordability-challenges

Nagaraja, C. H., Brown, L. D. and Zhao, L. H. (2011). An Autoregressive Approach to House Price Modeling. *The Annals of Applied Statistics,* 5(1), 124–149. https://www.jstor.org/stable/23024823

OECD (2022). Housing Taxation in OECD Countries. *OECD Tax Policy Studies*, 29. https://doi.org/10.1787/03dfe007-en

Rambaldi, A. N., McAllister, R. R. and Fletcher, C. S. (2016). 'Decoupling Land Values in Residential Property Prices: Smoothing Methods for Hedonic Imputed Price Indices', *34th IARIW General Conference*, Dresden, Germany, 21-27 August. Available at: http://old.iariw.org/dresden/rambaldi.pdf

Rating and Valuation Department (2025). *Hong Kong Property Review Monthly Supplement. April, Government of Hong Kong Special Administrative Region.* Available at: https://www.rvd.gov.hk/doc/en/statistics/full.pdf

S&P Dow Jones Indices LLC (2022). S&P/Case–Shiller U.S. National Home Price Index [CSUSHPINSA], Retrieved from FRED, Federal Reserve Bank of St. Louis. Available at: https://fred.stlouisfed.org/series/CSUSHPINSA

Shiller, R. J. (1991). Arithmetic Repeat Sales Price Estimators. *Journal of Housing Economics,* 1, 110–126. https://doi.org/10.1016/S1051-1377(05)80028-2

Shimizu, C., Nishimura, K. G. and Watanabe, T. (2010). House Prices in Tokyo: A Comparison of Repeat–sales and Hedonic Measures. *Jahrbücher für Nationalökonomie und Statistik*, 230(6), 792-813. https://doi.org/10.1515/jbnst-2010-0612

Sia, S. X. R. (2022). Lease Decay and the Prices of Private Residential Properties in Singapore. *International Real Estate Review*, 25(3), 401–421.

Silver, M. (2014). The Degree and Impact of Differences in House Price Index Measurement. *Journal of Economic and Social Measurement,* 39(4), 305–328. https://doi.org/10.3233/JEM-150406

Silver, M. and Heravi, S. (2007). The Difference between Hedonic Imputation Indexes and Time Dummy Hedonic Indexes, Journal of Business & Economic Statistics, 25(2), 239–246.

Spicker, P. (1998). *Housing and Social Exclusion.* Shelter Scottish Campaign for Homeless People.

Statistics Netherlands (2013). *Method Description, New Dwellings, Output Price Indices Building Costs.* Available at: https://www.cbs.nl/-/media/imported/onze-diensten/methoden/dataverzameling/korte-onderzoeksbeschrijvingen/documents/2013/28/2013-outputnewdwellings-method.pdf?sc_lang=en-gb

Steele, M. and Goy, R. (1997). Short Holds, the Distribution of First and Second Sales, and Bias in the Repeat–sales Price Index. *Journal of Real Estate Finance and Economics,* 14(1–2), 133–154. https://doi.org/10.1023/A:1007780219924

Tang, B. S. and Ho, W. K. O**.** (2014). Cross–sectoral Influence, Planning Policy and Industrial Property Market in a High–density City: A Hong Kong Study 1978 – 2012. *Environment and Planning A: Economy and Space*, 46(12), 2915–31. https://doi.org/10.1068/a130195

Tang, B. S. and Ho, W. K. O. (2015). Land–use Planning and Property Market Adjustment: Restructuring of Industrial Space in Hong Kong, Land Use Policy, 43(1), 28–36.

Wallace, N. E. and Meese, R. A. (1997). The Construction of Residential Housing Price Indices: A Comparison of Repeat–sales, Hedonic–regression, and Hybrid Approaches. *Journal of Real Estate Finance and Economics,* 14(1), 51–73. https://doi.org/10.1023/A:1007715917198

Waters, T. and Wernham, T. (2023). *Housing Quality and Affordability for Lower-income Households.* Available at: https://ifs.org.uk/publications/housing-quality-and-affordability-lower-income-households

Wong, G. W. C. and Ho, L.S. (2017). Policy–driven Housing Cycle: The Hong Kong Case of Supply Intervention. *International Real Estate Review,* 20(3), 375–396.

Wong, S. K., Yiu, C. Y. and Chau, K. W. Chau. (2012). Liquidity and Information Asymmetry in the Real Estate Market. *Journal of Real Estate Finance and Economics*, 45, 49–62. https://doi.org/10.1007/s11146-011-9326-z

Wong, S. K., Chau, K.W., Karato, K. and Shimizu, C. (2018). Separating the Age Effect from A Repeat Sales index: Land and Structure Decomposition. *Journal of Real Estate Finance and Economics,* 57, 351–366. https://doi.org/10.1007/s11146-017-9631-2

Xu, Y. F., Zhang,G. H., Zheng, S. Q. and Zhu, G. Z. (2018). House Age, Price, and Rent: Implications from Land–structure Decomposition. *Journal of Real Estate Finance and Economics,* 56, 303–324. https://doi.org/10.1007/s11146-016-9596-6

Zhu, M. (2014). *Housing Markets, Financial Stability and the Economy, Internation Monetary Fund.* Available at: https://www.imf.org/en/News/Articles/2015/09/28/04/53/sp060514