ANALYZING THE SUBSIDIZED HONG KONG REAL ESTATE MARKET: A CASE FOR THE HEDONIC INDEX APPROACH

Yifan (Victor) Ye
Departments of Economics and Statistical Sciences
Duke University

Abstract

Using data from Hong Kong's government-subsidized real estate sector, we present evidence supporting the application of hedonic indices in housing policy research. We find that the hedonic approach has substantial benefits over an average-price index: the mean post-adjustment value change to individual transactions is approximately 13%. We also provide evidence of endogenous home quality heterogeneity in the Hong Kong market. This suggests that match-model housing indices are susceptible to significant reliability issues, as quality biases dependent on market trends are resilient to match-model adjustments. However, these biases can be controlled with hedonic models, strengthening the policy-side case for such methods.

JEL: R28, R31, R58

Keywords: Housing; Hedonic; Policy; Price Index

1. Introduction

In the past sixty years, the global percentage of urban residents has nearly doubled (World Bank, 2015). As of 2014, approximately 54% of the world's population live in cities. Along with numerous benefits of this process, urbanization also presents significant challenges. Rising property prices tie up larger portions of household holdings in real estate, with correspondingly greater wealth effects. Rapidly expanding real estate markets create serious issues for regulatory institutions that focus on the smoothing of housing price fluctuations and the guaranteeing of access to basic living conditions.

The circumstances require policy-makers to accurately assess the behavior of real estate systems and the effect of regulations, both of which crucially depend on the capacity of housing price indices to reflect market demand and supply. If inter-period quality variations in home transaction pools cannot be sufficiently adjusted for, the resulting index will be biased, leading to estimation errors and poorly informed policy decisions. However, given the asset heterogeneity and long resale cycles of residencies, the constructing of quality adjustment procedures can be a significant challenge.

Different price index construction methodologies vary in their ability of controlling for heterogeneity (Bollerslev, Patton, & Wang, 2014). Median-price indices, for example, enjoy construction simplicity but often do not sufficiently reduce quality noise. Match-model indices, which track repeated sales of the same house, and hedonic indices, which use quality vector panels to evaluate perceived price values of specific attributes of a residency, perform much better in this regard. The advantages and underlying assumptions of both methods have been extensively discussed in literature (Baltagi, Bresson, & Etienne, 2014; Cho, 1996, Rappaport, 2007).

This paper develops the discussion in an empirical context. Data from the semi-commercial sector of the Hong Kong real estate market is used to establish the benefits of the hedonic approach over a median-price index. We demonstrate that without hedonic adjustments, size estimations of policy-induced market shocks are highly inaccurate. For the Hong Kong subsidized market, we find that quality heterogeneity distorts monthly index level estimates by approximately 2.1% on average and up to 7.6% for individual indices.

These findings are particularly relevant from the perspective of modern, emerging economies. Careful housing price evaluations and quantitative policy investigations are common for historically advanced economies such as the US and parts of Europe, yet the use of advanced housing price index construction methods is not widespread even among wealthy emerging economies. As these economies urbanize and develop sophisticated, market-driven housing sectors, the importance of having robust aggregate housing price estimates becomes greater. The issues with current housing indices in Hong Kong highlighted in this paper are good examples of the kind of issues that may arise from the lack of quality-adjusted indices for other economies.

We further present evidence that intra-market substitution effects lead to systemic quality heterogeneity in housing markets with price distortions. For the Hong Kong market, we find a significant, negative correlation between the average quality of subsidized apartments transacted within a period and the price spread between subsidized and non-subsidized apartments. This suggests that apartments of different quality levels tend to, on average, be transacted at different phases of the housing market price cycle. We also find similar own-market effects: transactions of higher-quality apartment are associated with high subsidized market prices.

These observations suggest a key advantage of the hedonic approach compared to match-model indices that cannot control for specific quality factors. If high-quality homes are sold more frequently during periods of housing market expansion, the resulting match-model index will, by assuming similarly distributed house quality over different periods, systematically *over-estimate* the size of market fluctuations. Given the proliferation of market-distorting elements in modern housing markets, we conclude that hedonic indices are generally preferable to both match-model and median-price alternatives, and should be adapted if conditions allow.

Section two begins with a short overview of housing index construction methods and outlines the theoretical framework of the time dummy hedonic regression method. Section three offers a descriptive summary of the historical and current conditions of the subsidized Hong Kong housing market. Section four provides a brief review of existing literature on hedonic methods. Section five summarizes the model and analysis methods used to derive hedonic adjustment values and presents the index. Section six illustrates the advantages of the hedonic index approach by examining two policy-related events, the 1997 land supply cutoff and the 2013 deregulation legislations. Section seven concludes.

2. Housing price index construction

The challenges of constructing housing price indices reflect, in more ways than one, the challenges of investigating housing markets in an economic framework. Each residency, even those that are part of a larger building or block, are by definition a unique piece of asset. Compared to other consumer goods that often have a limited number of readily identifiable features which contribute to their worth, the price of a house can be influenced by an indefinite number of variables. The effect of some variables, such as that of local amenities, can be difficult to evaluate on a case-by-case basis. Other variables, such as hidden quality issues or minor living inconveniences, have price influences that are practically impossible to measure. Furthermore, as owners and neighborhoods change, the quality of a house also changes over time. Depreciation, renovations and neighborhood development all play a major part in the value of a home over time. The long sale-resale cycle of residences also contributes to the challenge, as two consecutive sales of the same house may be years or even decades apart.

A perfect housing price index design must be able to account for all of these factors. However, limited by data and statistical tools, three main methods have been devised with different strengths and weaknesses. The first and simplest method involves averaging transaction prices of all houses within a given period. Ideally, given a normal distribution of quality across homes and no long-term quality level shifts, averaging across a large number of transactions could sufficiently minimize heterogeneity - however, these conditions rarely if ever hold in reality. The mean-price index construction method is used by many developing economies; China's Real Estate Index System (CREIS) employs this method for city-level indices. Official commercial housing indices in Hong Kong also use the mean-price approach, with the aggregate index a weighted average of sub-indices classified by usable house size.

The second method involves tracking sales of the same piece of property through time. Conceptually, a house shares many quality factors with itself in another period, allowing for some level of heterogeneity control. Assuming that the quality of each house is largely constant for the duration of the index, this method is capable of significantly reducing quality bias across periods. The effectiveness of the match-model approach also depends on the assumption that the average home's quality level remains constant across time periods. In other words, individual period transaction pools must be similar to each other in order for the match-model to function; if houses sold in one period and those sold in another are mutually exclusive, the match-model index cannot accurately evaluate the price change between the two periods.

The third and most complicated approach is the hedonic index model. By using past data on transaction prices and a vector of quality variables available for each transaction, the effective perceived "value" of each quality is determined through regression analysis. The price of each house can therefore be adjusted to remove the price influence of its specific qualities. In an ideal situation, where all price-influencing quality factors are identified and controlled for, this approach derives a "perfect" index completely devoid of heterogeneity issues, which exclusively reflects demand-and-supply driven market trends. However, the practical challenge in constructing hedonic indices lies in the inaccessibility of housing quality data and the difficulty of computation. Ideally, quality variable weights for a hedonic index should be reassessed after each transaction period, an extremely time-consuming procedure. Quality variable data is also often not available or not complete, particularly for housing markets of emerging economies.

Specifically, for a standard hedonic housing price index approach, the linear-linear regression for a single time period t is represented by the equation:

$$P_{it} = \delta_0 + D_{it}\delta_v + \sum_{j=1}^{k} B_j X_{ijt} + \varepsilon_{it} \tag{1}$$

P_{it} is the transaction price of house i, and δ_0 is a constant intercept term for the base period time effect. The term D_{it} is the time dummy vector, which equals 0 or 1 depending on whether the observation is in time period t. δ_v is the time effect of being in period t, X_{ijt} a vector of quality variables in the regression input, and B_j the corresponding vector of home quality coefficients for observation i.

The regression therefore produces two results: a vector of coefficients that describes how different quality variables affect the price of the house in question and a constant term, which approximates the base-period time effect. To generate an adjusted price level for period *t*, the expected value of δ_v at *t* or expected time effect of period *t* is derived with the equation:

$$\exp(\hat{\delta}_v) = \frac{\prod_{i\in S_t} (P_{it})^{1/n_t}}{\prod_{i\in S_1} (P_{i1})^{1/n_1}} \exp\left[\sum_{j=1}^{k} \hat{B}_j (\bar{X}_{j1} - \bar{X}_{jt})\right] \qquad (2)$$

The left part of the right side of the equation $(\prod_{i\in S_t}(P_{it})^{1/n_t})/(\prod_{i\in S_1}(P_{i1})^{1/n_1})$ is simply a ratio of geometric mean sample prices between period *t* and period 1. This ratio is then adjusted with the right part, which compares the quality variables of the samples in period *t* with those in period 1 and removes the influence of the discrepancy in quality. Quality difference between houses is therefore adjusted to a standard, average level, and would not interfere with market-level price changes *if* the adjustments are perfect. By performing the regression over periods 1 to *t*, this equation produces a price index with *t* data points, with the first period price being normalized to 1. In terms of describing the overall housing market, the result can be considered as the price changes of a single, representative apartment over time.

Note that a linear regression may not be the best choice for this type of work. A more practical approach would be using a by-period log-log regression or regression that incorporates log-terms instead. Log-log regressions enable the direct comparison of the influence of different characteristic variables, which may not have the same unit or magnitude of size. More importantly, log-log regressions reduce the severity of heteroscedasticity problems in a regression model. In this paper, a variety of functional forms of the housing price variable, including exponential and different power models, are tested and selected according to overall explanatory power. Response variables denoted in distance are all log-transformed.

3. Housing Purchase Subsidies in Hong Kong

One of the common issues associated with island nations and city-states in general, housing shortage is in many ways a chronic problem for Hong Kong. The region rapidly developed as a manufacturing hub during the 1960s, seeing substantial growth in population, income levels, living standards and land use. Housing demand, particularly demand for housing suitable for middle-class families, rapidly increased as large segments of the Hong Kong population found new, stable sources of income. However, by 1960 the housing market in Hong Kong largely remained as it was in the early 1940s: a small number of high-end, private estates coupled with extensive rent subsidy programs, most of which focused on satiating the need for minimal shelter. (Smart, 2006) Apartments provided by these early programs, such as the Low Cost Housing Scheme (LCHS) and Hong Kong Model Housing Society (HKMHS) were typically small and cramped, often with limited access to water and electricity (Huang, 1999).[1]

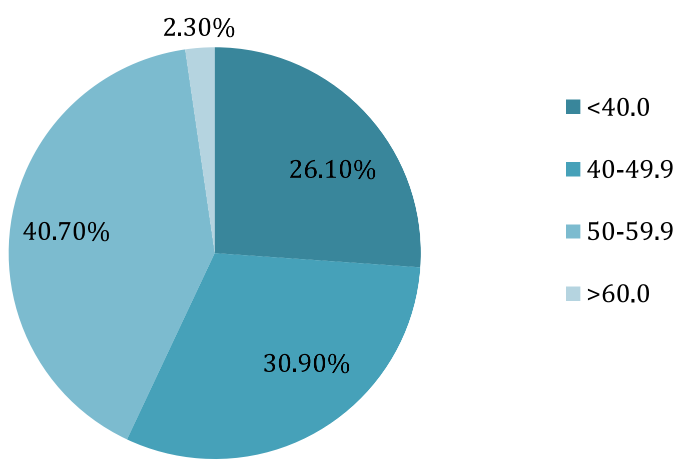
During the 1960s, government officials decided that circumstances called for greater state involvement in the housing market. A third, “semi-commercial” housing market would be created to bridge the gap between the high-end commercial market and rent subsidy programs designed for low-income families (Liu, 2001). The term for the market, “Home Ownership Scheme” (HOS) was coined in 1970. Specifically, HOS was designed to accommodate the so-called “sandwich class” – citizens who desired to own property yet could not afford commercial estates. Designers of HOS also argued at the time that encouraging higher-income rental unit tenants to move out and

[1] As of 2013, the average per person living area for public rent unit residents is 12.9 m^2. (Hong Kong Housing Authority, 2014) The averages for 1999 and 2004 are 10.4 m^2 and 11.5 m^2, respectively (Hong Kong Legislative Council, 2005). It can be assumed that the actual per person living area as of 1960 is most likely much smaller than that of 1999 and the conditions conceivably worse.

purchase apartments at lower-than-market rates could alleviate pressure on public rent units, which were generally in high demand (Er & Li, 2008).

Funded by a HK$1.39 billion pledge from the Hong Kong Legislative Council (LegCo), the first HOS apartment groups, or "courts," were completed between 1978 and 1982. True to the Hong Kong government's hands-off approach to markets, HOS was designed from the beginning to be highly privatized in nature – courts were built and, to this day, listed for sale by private real estate developers. Similar programs such as the Tenant Providence Scheme (TPS), Flat For-sale Scheme (FFS) and Sandwich Class Housing Scheme (SCHS) would appear in the following years, but HOS remains to be the largest housing subsidy program in Hong Kong. As of the program's initial cancellation in 2003, 219 courts, with a total of some 314,000 apartments, were built under the HOS program.[2,3]

Fig.1 Size distribution (m^2) of existing HOS apartments[4]



[2] A court is a group of apartment building sharing a name and street address.
[3] As of 2002 the total housing stock in Hong Kong is some 2,224,000 apartments, of which 14.1% are units built under the HOS title. Source: HKRVD
[4] Source: *25 Years of HOS: Changes and Developments*, Guoyu Liu, 2003

In 2003, the HOS program was "permanently" terminated in response to the housing market slump that followed the Asian financial crisis of 1997. Secondary market transactions continued after the termination, but no new land was allocated to HOS and other housing subsidy projects (Zhao, 2005). Policy-makers at the time argued that across-the-board deregulation of the housing market would create inflationary pressure on commercial estate prices, providing aid to homeowners struggling with loan payments amid low property values. This approach, along with other deregulatory initiatives with similar goals, appeared to be ineffective, as housing prices saw further decline after 2002. The program was eventually restarted in late 2013 in response to rapid housing price growth between 2009 and 2012. However, as of this writing all new HOS projects are still either in the planning phase or under construction; hence, at present there is no primary market for HOS apartments in Hong Kong.[5]

Only so-called "eligible citizens" are allowed to purchase apartments sold under HOS in the primary market. Requirements include family size, income and the absence of ownership of other property. These requirements have been revised multiple times and, as a general trend, gradually loosened. The process itself is seen as an integral element driving price fluctuations in both primary and secondary HOS markets (Liu, 2003), since the removal of rigid purchase criteria greatly increases potential demand for such estates.

Those who are eligible could, depending on the demand for property in the specific court in question, either directly enter into a purchase contract or submit their name to a lottery with a small pledge (Er & Li, 2008). A specific, prior-quoted discount would then be placed on the purchasing price of the apartment in question. In other words, primary market apartments are quoted at a "commercial" rate determined by the HKHA, from which the subsidized price is accordingly

[5] The first new HOS apartments will be completed in Q4 2015. Source: HKHA

discounted. Note that this does not mean that buyers of HOS are not eligible for housing subsidies of alternative forms. All individuals who are allowed to purchase HOS apartments are also automatically granted access to low-interest, long-term mortgage contracts provided by the HKHA.

True to its market-oriented nature, HOS apartments can, after a certain amount of time since the original purchase date, be freely traded either between eligible applicants or on an "open market" as commercial units. The HOS secondary market was opened in August 1997 following public demand for the ability to resell HOS apartments. Transactions between eligible individuals are appraised at a mutually accepted price and made with the original discount applied as a “continuation” of the subsidy. Transactions on the open market occur at market prices, but a percentage of the total transaction amount equal to the original subsidy is paid back to the HKHA as a “refund” of the original subsidized amount. This practice ensures that the initial subsidy can only be enjoyed by those who meet HOS criteria.

Since its inception, the HOS secondary market has been subjected to a wide range of criticism. The nature of the secondary market, especially the open-market transaction system that caters to individuals that would otherwise not be eligible to own HOS apartments, puts it in direct competition with the commercial market for small and medium sized apartments. Because of the low profit margins of HOS apartments, they are ofen listed on the secondary market at prices lower than similar property pieces listed by real estate dealers, causing deflationary pressure in the commercial housing sector. Despite often being used as an example of government overreach in Hong Kong, the secondary market has remained robust, with more than 2,200 transactions per year on average between 1998 and 2013 (Fig.2).

Fig.2 No. of transactions per month, HOS Secondary Market, Aug 1997-Jul 2004[6]

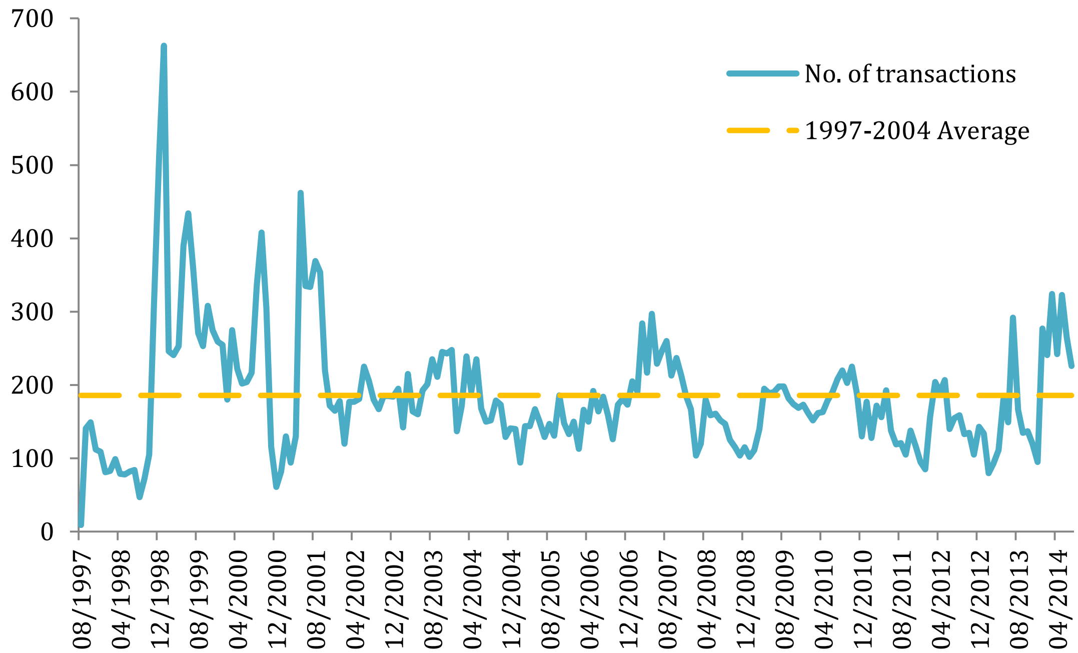
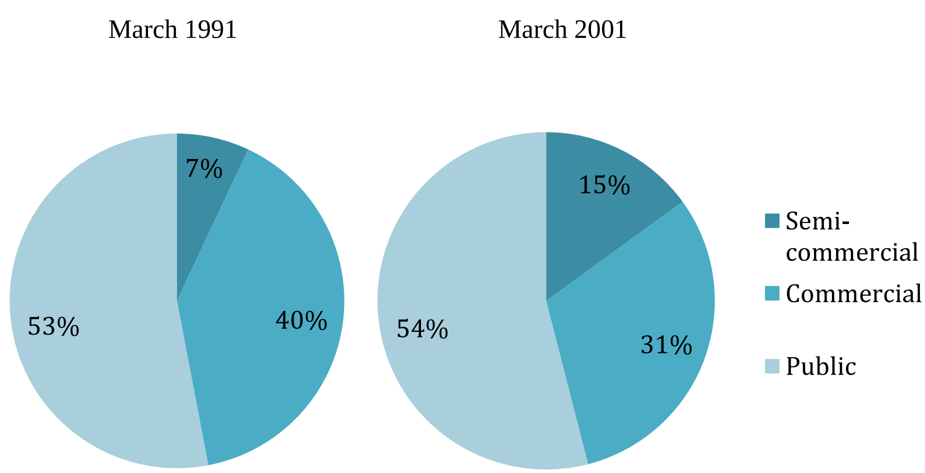


Fig.3 Hong Kong housing market composition, 1991 and 2001 compared[7]



Note that the impact and size of housing purchase subsidy programs such as HOS and TPS make them stand out among similar government initiatives. China's Economic and Comfortable

[6] 520 transactions occurred between August and December 1997, and 1898 transactions occurred in 2014 as of July. Source: HKHA

[7] Data Source: *Property Market Statistics: 1992*, Hong Kong Rating and Valuations Department. *HKHA Performance and Statistics: 2002*, HKHA

Housing Program (ECH), established in 1994, was heavily influenced by the success of these Hong Kong programs. As of 2010, however, only 3.8% of all housing starts by area in Mainland China come from subsidized purchasing programs such as ECH (Zou, 2013). In contrast, over 15% of all housing units in Hong Kong fall under some kind of purchase subsidy scheme (Fig.3) as of the cessation of new HOS court constructions in 2002 (Liu, 2003). Singapore's Housing and Development Board (HDB) projects may be vastly larger in scope, but their nature is so far removed from the closely market-oriented subsidy schemes of Hong Kong that it is difficult to establish any sort of comparison between housing policies of the two city-states.[8]

4. Literature Review

In support of the use of hedonic indices, Chen and Zhao (2004) note that for housing markets that are insufficiently large in size, the long purchase-resale cycle of houses makes it essentially impossible to carry out conventional match sample adjustment methods in constructing a price index.[9] Considering the inherent difficulty of controlling for all or most characteristics of a house that may influence its final sale price, they conclude that regression-based hedonic methods are a better option for typical housing markets.[10]

With regard to the choice of hedonic models for housing, Silver and Hervai (2006) demonstrate that the time dummy hedonics approach is an acceptable quality adjustment method for relatively stable parameters and characteristics sets with little variation over time. However, rapidly

[8] As of 2014, 81.9% of all residencies in Singapore fall under HDB public housing programs. Source: Singapore Department of Statistics, http://www.singstat.gov.sg/statistics/latest_data.html#20

[9] The match-model index approach involves pairing up an item's transaction in a certain period with transactions of the same item in other periods. Quality differences are controlled simply because the item is assumed to remain unchanged in terms of quality between the periods.

[10] Hedonic regressions can be used to derive the relative impact of each individual characteristic of a piece of property and adjust for the differences between property units. Each transaction essentially becomes adjusted to the price at which a "representative house" would be sold at the same time and circumstances. If the adjustment is perfect, then there should only be speculation or market-related price changes in the long run. However, hedonic model differ greatly in flexibility and complexity.

fluctuating parameters or numerous new characteristics can greatly decrease the ability of a model to analyze the influence of a single characteristic. The time dummy hedonic adjustment method is therefore sufficient for property market research as long as parameters contributing to a house's retail price remain relatively stable within the time frame of the regression model. Diewert (2003) develops the theoretic regression models built on Silver and Hervai's work. In particular, Diewert suggests that traditional match model techniques can in fact be as effective as a hedonic regression, but only in theory and with a sufficiently large number of matches.

There is also criticism of the general concept of using hedonic regression models to derive quality-adjusted price indices. Hill (2011) proposes four potential pitfalls of using hedonic regressions: omitted variable bias, functional form misspecification, lack of transparency, and sample selection bias. Since hedonic regressions are aimed at deriving an essentially "clean" adjustment of qualities, removing the impact of some variables and not that of others can bias the result. This issue is especially problematic when attempting to analyze variables that are not directly measurable, such as the impact of noise on housing. A larger dataset can potentially alleviate the omitted variable bias problem and significantly improve sample selection quality. However, the second and third pitfalls are not as easily addressed (Malpezzi, 2003).

It is also true that all hedonic regressions require active choices made by an “index provider” – two researchers given the same dataset will almost certainly come up with different hedonic models (Shiller, 2008). As a result, a hedonic index can never be as transparent or accessible as a direct-weight or matched price index, the creating of which does not need to involve any subjective decision. Omitted variable bias may also be especially problematic for housing market indices, since property prices are influenced by a larger group of variables than typical consumer goods.

There is extensive research involving the application of hedonic models to housing markets. As early as 1978, Goodman (1978) applies time dummy hedonics to data collected from the New Haven urban area and confirms that area-specific hedonic regression can be used to reveal nuanced price structure differences in sub-markets usually obscured by general assumptions about market size and composition. Quality-adjusted housing indices have also been used to determine demand for clean air by urban residents (Harrison & Rubinfeld, 1978), effects of location-specific characteristics such as commute time to the Central Business District area (Ottensmann, Payton, & Man, 2008), the influence of airport expansions on property values (McMillen, 2004), and the effect of school availability on homebuyers (Hayes & Taylor, 1996).

More closely related to the theme of this paper, Chow (2011) uses time-panel data from the Centaline Property Agency to construct a hedonic index model for the commercial Hong Kong housing sector. Chow concludes that there are a significant positive relationships between apartment price and factors including floor area, absolute height in stories and school network strength. Despite data limitations, Chow notes that short-term price fluctuations reflected in the unadjusted index are smoothed out when the price index is adjusted with a vector of quality factors. In other words, a significant amount of price movement in the currently employed Hong Kong price indices can be attributed to disparities of apartment qualities between transactions.

5. The Regression Model and Hedonic Index

To create quality-adjustment vectors for the hedonic index, a best-fit regression model using a 2/3rd power transformation and 88 variables, including dummies for month, year, district of transaction and a select number of indicators for outlier apartment groups is fitted over the dataset.[11,12] Interaction terms with the time period of transaction are used with a variety of geographical variables, and interaction terms with steepness of slope are applied to elementary school and metro proximity measurements for greater accuracy.[13] The model sufficiently explains most of the variance between transaction prices of apartments in the dataset, generating an R^2 of 0.930. After the inclusion of district and apartment group dummies, outlier elimination is limited to the removal of 4 observations with residuals greater than two standard deviations away from the predicted mean. Details about the data sources and empirical methods involved in the regression model can be found in the appendix.

The statistical strength of the model can be examined through a variety of methods. The model reports an RMSE value of 75.94, considerably smaller than the standard deviation of adjusted price (286.6). The adjusted R^2 of the model is 0.930, suggesting that over-fitting is not a significant issue. In comparison, a reduced model with only year and month dummies reports an R^2 of 0.647 and an RMSE value of 170.3.

Residuals of the regression are plotted against a variety of factors including price of apartments, time period of transaction, size, latitude and longitude. With the exception of a slight bias towards greater negative residuals for apartments with prices below 2,000,000 HKD, in all cases residuals seem to be fairly evenly distributed across the range of the variable in question.[14] There appears to be no particular latitude/longitude combinations or apartment sizes within the scope of the dataset with substantially greater residual sizes than the average. Therefore, it can be expected that the

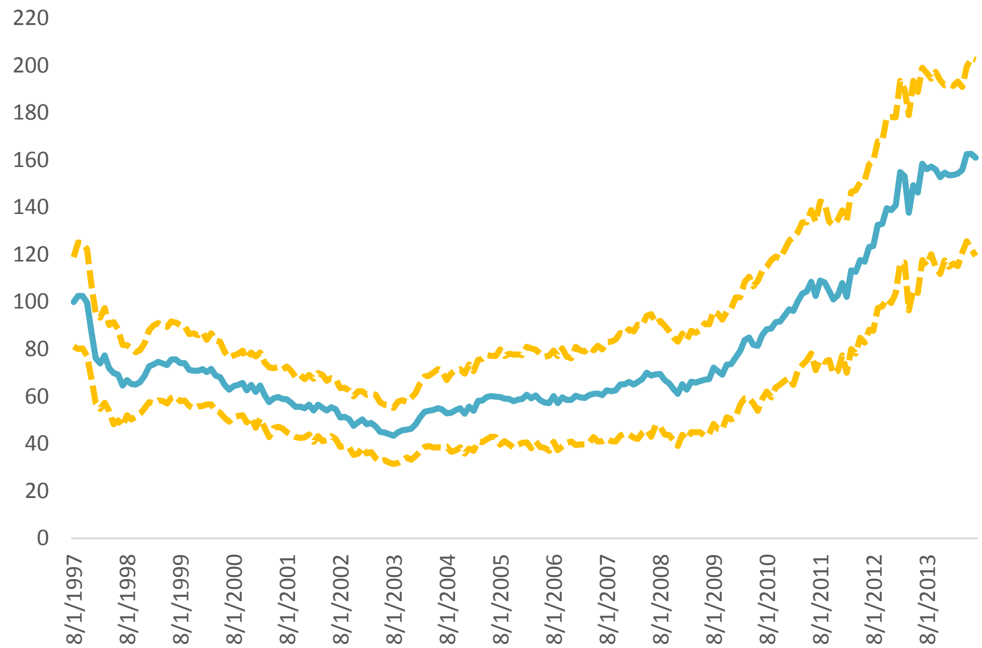
[11] The 2/3rd power transformation means that $P_{regression} = P_{actual}$^(2/3).
[12] Indicator terms for court no.94 "Kornhill," court no. 190 "Tung Yuk Court" and court no.33 "Yu Shing Court" are added in the regression. The first two courts can be explained as outliers for their geographical location, which are, respectively, extraordinarily favorable and unfavorable. The third court does not seem to display any characteristics that may negatively impact its price. It is assumed that there are certain local level effects not captured by the model.
[13] Time period terms are expressed as a series from 1 to 204, denoting the specific month that a transaction occurred.
[14] An intuitive explanation is that low-price apartments are not cheap without good reason. Quality effects unique to the single unit (interior damage, previous incidents, etc.) cannot be captured by normal methods of adjustment.

predictive power of the regression model remain consistent across geospatial variations as well as apartment heterogeneity. Residual plots for these factors are presented in the appendix.

In constructing the hedonic index, apartments in individual transactions are adjusted to the quality of a "representative apartment" with averaged characteristics. This is completed by removing the price influence of all transaction-level and geospatial quality terms, evaluated at the level of the respective terms for each transaction. The influence of these terms evaluated at the average level of all dataset transactions is then added back to the price. For indicator terms such as district fixed effects, coefficients are averaged to estimate the price effect of being in a single, representative district. The adjusted prices of observations within each month in the dataset are then averaged for an estimation of the monthly subsidized housing price levels.

The graphs below describe the hedonic subsidized housing index constructed using this approach. Fig.4 plots the hedonic index along with 95% confidence interval boundaries defined by upper and lower 1-standard-deviation bounds for each month's predicted average price value, with the estimated market price level on August 1997 set as a base level of 100.

Fig.4 Hedonic index for HOS secondary market, with 1-SD/2-SD boundaries, Aug 1997 – Jul 2014 (Aug 1997 = 100)[15]



Compared to the average-price index, the quality-adjusted index shows less variation across observations, with smaller local maximums and larger local minimums in general. From a quantitative perspective, the standard deviation of all indices of the hedonic index is 30.9 compared to 32.4 for the unadjusted index. The average post-quality-adjustment absolute change to the selling price of individual transactions in absolute terms is approximately 13.0%, and the average absolute change to monthly index figures 2.1%.

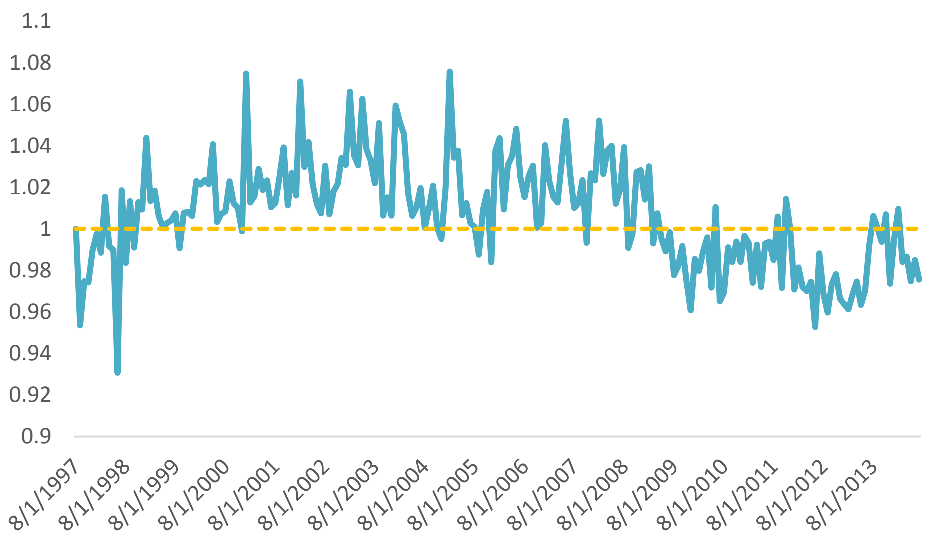
The difference between these two values can be considered as a rough approximation of the amount of apartment quality heterogeneity within each month addressable by averaging over transaction prices. If one considers the hedonic approach used in this paper robust enough to adjust to near-perfect "representative apartment" price levels, it would imply that around 91.5% of the

[15] Index levels since 2003 can be considered as reflecting trends of the entire subsidized market. Primary market transactions occurring between 1997 and 2002 are not accounted for. New, primary market flats that experienced delays in interior work or did not pass initial quality inspections might have been sold after 2002, though.

total quality variation-induced price variation in the dataset is already removed in the average-price index, with a further 8.5% gain from using the hedonic index.

Note that a 2% improvement to the market-trend describing ability of a price index cannot be considered trivial if the goal goes beyond general indication of demand-supply trends. Control of quality variation between price indices is crucial for specific tests of external shocks or leading/lagging behavior of the market. This is truer if quality-induced noise is not random in nature, but has distinct patterns related to own-market performance and the market's standing among competing markets.

Fig.5 Ratio of adjusted/unadjusted indices for HOS secondary market, Aug 1997 – Jul 2014 (Aug 1997 = 1)[16]



A closer look at the quality adjustments of the hedonic index reveals that this is indeed the case. As shown in Fig.5, the adjustments do not seem to be random over time. To the contrary, between late 1998 and early 2009 almost every single period had its index value adjusted upwards –

[16] Note that ratios greater than 1 indicate that the post-adjustment apartments prices are more expensive, and ratios smaller than 1 indicates that the post-adjustment prices are less expensive.

suggesting that the apartments sold during this period are on average of lower quality than the dataset average. The opposite trend can be observed for 2009-2014, when most periods have had their prices adjusted downwards.

Using the post-quality-adjustment change to the monthly index level as a proxy for the quality difference between apartments of a certain transaction period and the representative apartment, per-period transacted apartment quality is significantly correlated with the price index gap between the subsidized market and commercial market for small and medium apartments.[17,18] When the subsidized market is more expensive relative to the commercial market, subsidized apartments sold are on average of lower quality. However, when subsidized market prices grows *faster* than commercial market prices, measured as the between-period change in the spread between the two indices, higher-quality subsidized apartments tend to be sold.[19,20]

In other words, transaction activity of high-quality subsidized apartments increases when the subsidized market appears to be more appealing than the commercial market, and decreases when the subsidized market appears to be more expensive or experiencing a slowdown. This suggests that the subsidized and commercial markets are somewhat substitutional in nature, and that it is possible for policy-induced price distortions in the subsidized market to feed into the commercial housing sector.

---

[17] The post-adjustment change for a given month is evaluated as $100^*(p_{adj} - p_{unadj})/p_{unadj}$, where p_{adj} and p_{unadj} denote, respectively, the adjusted and unadjusted index level for the subsidized market. Note that an adjusted index level higher than the unadjusted index level implies that period apartments are on average of *lower* quality than the representative apartment. Conversely, a negative value for $100^*(p_{adj} - p_{unadj})/p_{unadj}$ implies that period apartments are of higher quality.

[18] $P \approx 0.011$, controlled for overall time trend of apartment prices, with a 6-period (6-month) lag applied to the post-adjustment change response variable.

[19] This is evaluated by measuring how the current period price index gap compares to the index gap of the previous period. If the current period index gap is numerically larger than that of the previous period, prices in the subsidized market are either rising faster or falling slower than prices in the commercial market.

[20] Evidence is somewhat suggestive at $P \approx 0.072$, after controlling for overall trend of apartment price levels. The 6-month lag on post-adjustment change is also used for this regression.

There is also evidence of similar, own-market effects. Overall subsidized market price levels are significantly correlated to the average quality of apartments being sold. When prices are higher in general, higher-quality apartments are sold.[21] Higher-quality apartments also tend to be transacted when the price trend of subsidized apartments is more positive.[22] This can be explained by considering the major sources of supply in the somewhat "inferior" market of subsidized apartments: when subsidized market price levels are high or rapidly rising, owners of subsidized apartments are likely to exchange apartments for commercial units of better quality. Owners of high-quality subsidized apartments enjoy the largest wealth effects, and are therefore most likely to upgrade. Conversely, when subsidized housing price levels are low or falling, transactions are likely from individuals in bad financial situations liquidating their apartments. Since owners of low-quality subsidized apartments often have correspondingly low income, they are also more likely to endure financial hardship. Hence, low-quality residencies tends to be sold when the market is in bad shape.

Note that these effects are specifically pro-cyclical or de-cyclical to housing trends. While the exact extend to which these quality-related distortions affect housing price level estimates is unclear, it is conceivable that quantitative estimates, particularly those related to long-term price trends, are much more heavily influenced by this kind of distortion compared to random noise. Quality noise from random transaction pool differences is unlikely to cause biases beyond individual price level estimates. Yet quality noise systematically associated with market behavior could skew the results of analyses in both the short-term and long-term time frame.

[21] $P<0.001$. The subsidized market price level is evaluated as standard deviations from the mean price index level between August 1997 and July 2014.

[22] $P \approx 0.01$. The short-term price trend is estimated as the difference between the current-period price level and the price level of the previous period. This trend is positive when the current month's prices are higher than that of last month's.

Also note that match-model indices such as Case-Shiller are not capable of adjusting for these biases. For match-model indices to deliver perfectly adjustment, the same house must have a more or less equal chance of being transacted in each time period – which is not true for the case in this paper. Consider the hypothetical case of a market with two perfectly distinct groups of houses of high and low quality. If only high-quality homes are sold during housing booms and only low-quality homes sold during housing busts, the match-model index will over-estimate the gap between peak and trough prices by *exactly* the quality difference between the two groups. The ideal hedonic index, on the other hand, has no difficulty in accurately describing market trends in this scenario. Taking these observations into account, the case for a hedonic, quality-adjusted index becomes much stronger.

We expect these results to have broader implications for housing indices beyond those of developing countries and emerging markets. Case-Shiller-type indices are widely adapted among advanced economies and are instrumental in the investigating of a variety of economic policies. The evidence presented here suggests that in addition to other, well-established pitfalls, match-model indices are also vulnerable to market trend effects when tiered housing sectors are involved. Given that the housing sectors of most advanced economies are not nearly as heavily regulated as that of Hong Kong, the extent to which this effect is present in other markets, particularly those in the Europe and US, could be an interesting issue for future research.

6. Applications of the Hedonic Index

This section offers two examples to illustrate the policy-side potential of a subsidized housing hedonic index for Hong Kong. The first example comes from the HOS program land supply cutoff of 1998. After a year of extreme contraction in the real estate sector, the HKHA abruptly halted land supply to the HOS program in July 1998 as part of a rescue package to increase consumer confidence and stabilize real estate prices. Their efforts did not seem to be effective, and housing price levels in Hong Kong continued to decline for almost five more years. It has been suggested that the policy worsened the housing price slump by pushing up prices and generating activity in the subsidized secondary market (Lok, 2000). Literature on the incident describes sellers taking full advantage of the unexpected boon to liquidate their properties and, as buyers rushed to the subsidized market, sales and prices of commercial units were further depressed.

Fig.6 plots both hedonic and quality-unadjusted indices for the subsidized market against the unadjusted, average-price indices of two sections of the commercial market.[23] All three markets were in a freefall state until Q2 1998, after which they briefly recovered before continuing the downward trend. However, it can be observed that the subsidized market not only experienced the greatest price surge between Q3 1998 and Q1 1999, but also stayed at a higher index level than the other two markets afterwards. Between December 1998 and June 1999 there was a price increase of 9.7% in the subsidized market, whereas the commercial market for small or medium apartments fell by 2.5% and the commercial market for large apartments grew by 1.5%. The size of the “recovery” of 1998-1999, estimated by the maximum price difference between June 1998 and June 1999, is 17.1% for the subsidized market, and only 12.9% and 11.4% for the commercial small or medium and large markets, respectively.

[23] Commercial market indices are obtained from HKRVD. The HKRVD indices are commercial-market, average-price indices using monthly transactions of apartment groups classified by size, collected during apartment registration. It does not include subsidized market secondary transactions. Source: http://www.rvd.gov.hk/en/property_market_statistics/

Fig.6 Commercial and subsidized housing market indices in Hong Kong, Aug 1997 – Dec 1999 (Aug 1997 = 100)[24]

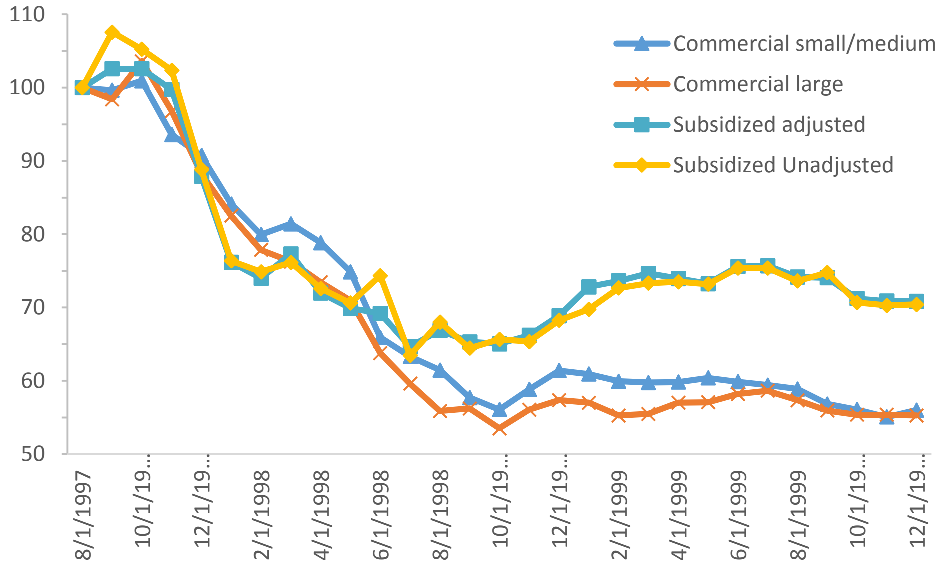


Fig.7 Comparison of housing market 6-month price level changes, Dec 1997 – Jun 2000

% Changes (12-1997)	Subsidized Adjusted	Subsidized Unadjusted	Small/ medium	Large
06-1998	-21.3	-16.3	-27.4	-27.7
12-1998	-0.4	-8.2	-6.8	-10.1
06-1999	9.7	10.4	-2.5	1.5
12-1999	-6.3	-6.6	-6.5	-5.0
06-2000	-8.4	-8.1	-10.5	-5.4

Although this analysis is far from quantitatively rigorous, a few interesting observations can be made. The first one is that sector-specific policy decisions have the potential to push prices in one sector of the market significantly above that of other sectors. In this case, since the long-term supply constraint only occurred in the subsidized market, its price levels were understandably pushed beyond those of the commercial sector. Normally, one would not expect such effects to be persistent, as consumers shift away from consumption in one sector of a market when its relative

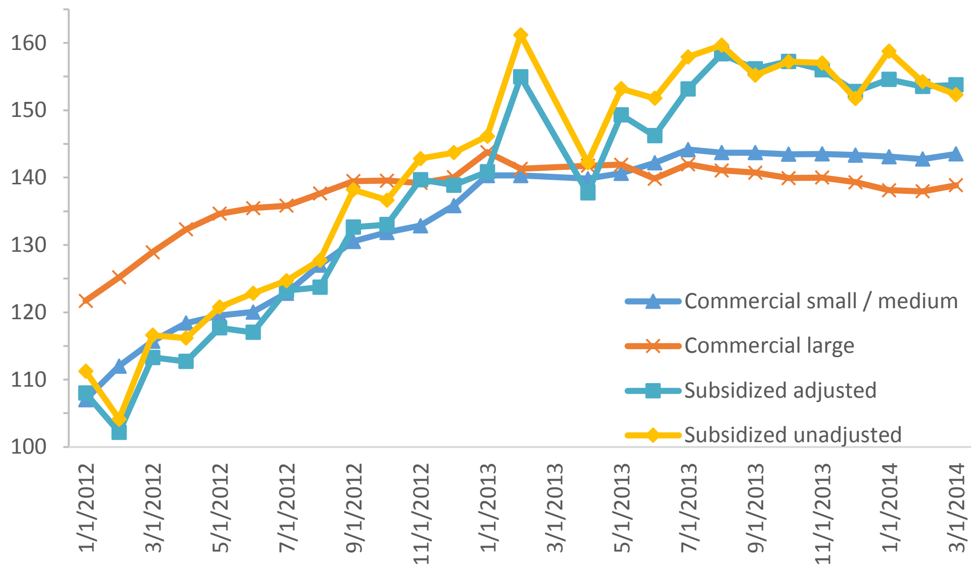
[24] "Small" apartments are those with a saleable area of $40m^2$ or less. "Medium" apartments are those with a saleable area of greater than $40m^2$ but less than $100m^2$. "Large" apartments are those with a saleable area of greater than $100m^2$. Note that this is not the same metric as the "gross floor area" variable used in the regression model, with the gross floor area typically being much larger for a given apartment. Source: http://www.rvd.gov.hk/doc/en/statistics/15_technotes.pdf

price increases. However, such mechanisms are likely not effective with regard to the subsidized housing market because of its internal price distortions and barriers to entry.

A second observation is that, given that the baseline effect of the other policy initiatives of the rescue package can be estimated by price level changes to the commercial sector, it is possible that with further, macro-level adjustments, the short-term price effect of an abrupt termination of land supply to the subsidized market can be evaluated. Even if there may be not insubstantial errors associated with a quantitative policy shock estimate, it would still provide a valuable perspective if Hong Kong policy-makers are once again under circumstances unfortunate enough to contemplate such an option.

The second example comes from the subsidized market deregulation of 2012-2013. A series of policies that relaxed the eligibility criteria of secondary market buyers were announced on November 2012 and enacted on January 2013, the most significant being an increase of the maximum family income ceiling to $40,000 HKD per month from the original, decade-old $30,000 HKD limit. The move has since been criticized as being excessive, allowing high-income individuals to access government subsidies and crowd out less-wealthy families.

Fig.8 Commercial and subsidized housing market indices in Hong Kong, Jan 2012 – Mar 2014 (Aug 1997 = 100)



As shown in Fig.8, the criticism seems to be well-founded. The subsidized market experienced an enormous price hike of 11.6% between December 2012 and February 2013. During the same period, prices increased by 3.3% in the small and medium apartment commercial market and 0.9% in the commercial market for large apartments. Clearly, relaxing purchase eligibility standards had resulted in a short-term demand surge of subsidized apartments. However, there is also evidence that HOS secondary market prices have been pushed to higher long-term levels because of the new eligibility requirements. After a period of price volatility in Q1 and Q2 of 2013, the subsidized index has stabilized to levels 5-10% higher than the commercial indices.

This contrasts sharply with figures for early and mid-2012. In the months prior to January 2013, there were virtually no price level disparities between the subsidized and commercial small and medium markets. For 2012, the average 12-month index level of the subsidized market is 121.8 and the average index level of the small and medium apartment commercial market is 122.8. For 2013, the respective index averages are 152.6 and 142.9 – a difference of 6.8%. These results suggest that there are fundamental distortions of demand-supply relationships caused by an over-relaxing of HOS eligibility requirements. Compared to short-term price shocks, such long-term effects are without doubt much more problematic and challenging.

Beyond own-market demand shock effects, it is also likely that commercial sector prices, particularly those of small and medium apartments, are actually suppressed by the relaxation of eligibility requirements. During periods of housing market expansion, the value of HOS apartments increases, yet the general purchasing power of potential HOS apartment buyers, capped by monthly income requirements, stays relatively low. This disparity dis-incentivizes HOS apartment holders from selling their apartments, since few buyers are able to afford them at prices acceptable to sellers. While it is possible to sell apartments on the open market and refund the original subsidy, there might not be much demand on the open, commercial market for apartments at HOS quality levels. Procedures to make refunds and transform subsidized apartments into commercial ones can also be quite complex and time-consuming.

The new policies expand the eligible buyer base into a segment of the population with monthly income levels between $30,000 and $40,000 HKD. When ineligible to participate in HOS, individuals at such income levels could only shop among small and medium commercial apartments. However, once eligible for HOS subsidies, many of them enter the subsidized market where they become unequivocally high-income buyers. Sellers, more than happy to see such buyers, take advantage of the demand surge and begin to list apartments. In the process demand falls for commercial apartments, and downwards price pressure ensues. With inflationary effects in the subsidized market and deflationary effects in the commercial market, an artificial wedge is driven between price levels of the two markets.

Note that this explanation is supported by the findings presented in section 5. The significant correlation between quality levels of subsidized apartments sold and relative price of the two housing markets can only occur if they are at some level substitutes for each other. In this case, the example suggests that regulatory actions in the subsidized market should be cautiously handled. Any substantial price fluctuations in the subsidized market will have unintended and, quite likely, averse influences on the commercial housing sector. Long-term policy-induced price distortions such as those suggested by Fig.8 can lead to region-wide, lasting wealth effects that are difficult to correct for.

Also note that for both examples, the adjustment effect of the hedonic index is clearly present and highly influential for numeric estimates based on subsidized market price levels. In the 6-month price change figures in Fig.7, estimates from the two indices differ significantly. The quality-adjusted subsidized index decreased by 0.4% between June and December 1998, while the unadjusted index decreased by 8.2% during the same period. With such inaccuracies being a real concern, the unadjusted subsidized index is not meaningful for any type of quantitative analysis. However, once quality-induced noise has been eliminated, market behavior can simply be read from changes in the index.

In a final note, while the by-category commercial housing index used in this section does not involve quality adjustments, one can expect the larger per-month observation set sizes of commercial market indices to generate price-level estimates that are more accurate than the unadjusted index for subsidized housing. Although hedonic housing indices such as the Centa-city index (CCI) and Centa-city leading index (CCL) are available in Hong Kong, their scope of adjustment is highly limited and do not involve the extensive geospatial modelling methods used in this paper.[25] These indices are therefore not presented in this section. However, the extent to which these options reflect market trends is unclear, and merits further investigation.

7. Conclusion

This paper presents empirical evidence in support of the use of hedonic indices in housing policy research. We demonstrate that for certain situations, mean-price indices fail to account for significant quality heterogeneity issues and are therefore unsuitable for quantitative policy-side investigations. The benefits of using a comprehensively designed hedonic index are found to be substantial in this regard.

We further present an example of between-period quality heterogeneity in housing markets. We find statistical links between market trends or market price levels and the average quality of period-transacted apartments: this type of bias cannot be accounted for with a match-model index approach but can be readily identified and controlled with hedonic methods. Comprehensive, the two findings suggest that despite their complexity, hedonic indices hold key advantages over alternative methods and should be seen as more reliable and generally preferable, especially when the housing market in question has subsidies or similar price distortions involved.

In achieving these two goals, this paper introduces a hedonic price index for the Hong Kong subsidized housing market covering a highly expansive range of quality factors. By explaining up to 93% of the total variance across transaction, the model shows great potential in terms of understanding the size, duration and external effects of policy-induced price level fluctuations. Two examples are selected from 1998 and 2013, respectively, to demonstrate the versatility of the index with regard to policy-side applications.

[25] The CCI and CCL indices are also whole-market indices that do not differentiate between small and large apartments, and therefore may be skewed by the high price and high geo-locational qualities of large, luxury apartments.

The aforementioned inquiry methods can be readily applied to other policy-induced changes in the subsidized market. It would be of great interest to local-policy makers to expand on the presented examples and explore other policy events related to the subsidized market. Future research is also needed to better understand the relationship between different housing sectors in Hong Kong, as well to improve on the hedonic adjustment process outlined in this paper.

References

Baltagi, B. H., Bresson, G., & Etienne, J.-M. (2014). Hedonic housing prices in Paris: An unbalanced spatial lag pseudo-panel model with nested random effects. *Journal of Applied Econometrics*.

Bollerslev, T., Patton, A. J., & Wang, W. (2014). *Daily House Price Indexes: Construction, Modeling, and Longer-Run Predictions.* Duke University.

Chen, L., Zhao, S., Romanis, P., & Lim, P. P. (2004). *Exploring Hedonic Methods for Constructing a House Price Index*. Canberra: Australian Bureau of Statistics.

Cho, M. (1996). House price dynamics: A survey of theoretical and empirical issues. *Journal of Housing Research, 7*, 27.

Chow, W. (2011). *Hedonic Price Index: An Illustration with Residential Property Prices*. HKMA: Economic Analysis and Business Facilitation Unit.

Diewert, E. (2003). Hedonic Regressions. A Consumer Theory Approach. In R. C. Feenstra & M. D. Shapiro (Eds.), *Scanner Data and Price Indexes* (pp. 317-348). Chicago: University of Chicago Press.

Er, D., & Li, J. (2008). *Home Ownership Courts of Hong Kong: An Exploration* Hong Kong: Ming Bao Publishing

Goodman, A. C. (1978). Hedonic Prices, Price Indices and Housing Markets. *Journal of Urban Economics, 5*(1), 14.

Harrison, D., & Rubinfeld, D. L. (1978). Hedonic Housing Prices and the Demand for Clean Air. *Journal of Environmental Economics and Management, 5*(1), 21.

Hayes, K. J., & Taylor, L. L. (1996). Neighborhood school characteristics: What signals quality to ho-mebuyers. *Federal Reserve Bank of Dallas Economic Review, 4th Quarter*, 7.

Hill, R. (2011). Hedonic Price Indexes for Housing. *OECD Statistics Working Papers*.

Hong Kong Housing Authority. (2014). *Housing Statistics 2014*. Hong Kong: Hong Kong Housing Authority.

Hong Kong Legislative Council. (2005). *Summary Statistics: Public Housing in Hong Kong*. Hong Kong Hong Kong Legislative Council.

Huang, H. (1999). *Scandels of Public Housing in Hong Kong: A Reporter's In-depth Investigation*. Hong Kong: Jin Yi Bu Publishing.

Liu, G. (2001). *Housing Statistics in Hong Kong: An Overview*. Hong Kong: Hong Kong City University.

Liu, G. (2003). *25 Years of HOS: Changes and Developments* Paper presented at the Housing Development Forum 2003, Shenzhen.

Lok, S. (2000). *A Case Study of Economic Ecology: The Hong Kong Economy's Plunge into a Deep Recession in 1998.* Lingnan University.

Malpezzi, S. (2003). Hedonic Pricing Models: A Selective and Applied Review. In A. OSullivan & K. Gibb (Eds.), *Housing Economics: Essays in Honor of Duncan Maclennan*. Malden, MA: Blackwell.

McMillen, D. (2004). Airport Expansions and Property Values: The Case of Chicago OHare Airport. *Journal of Urban Economics, 55*.

Ottensmann, J. R., Payton, S., & Man, J. (2008). Urban Location and Housing Prices within a Hedonic Model. *Journal of Regional Analysis and Policy, 38*(1), 16.

Rappaport, J. (2007). A guide to aggregate house price measurements. *Economic Review, Federal Reserve Bank of Kansas City*, 30.

Shiller, R. J. (2008). *Derivatives Markets for Home Prices*. Cowles Foundation Discussion Paper, (1630).

Sliver, M., & Heravi, S. (2006). The Difference Between Hedonic Imputation Indexes and Time Dummy Hedonic Indexes. *IMF Working Papers*.

Smart, A. (2006). *The Shek Kip Mei Myth: Squatters, Fires and Colonial Rule in Hong Kong, 1950-1963*. Hong Kong: Hong Kong University Press.

World Bank. (2015). World Development Indicators: Urbanization.

Zhao, L. (2005). *Where will Hong Kong's Housing Policy Go?* Hong Kong: Hong Kong University Department of Urban Planning and Environment Management.

Zou, Y. (2013). *Contradictions in China's affordable housing policy: Goals vs. structure.* Temple University, Philadelphia

Appendix

1. List of variables and variable names used in regression model

feb	Dummy for transaction being in February
mar	Dummy for transaction being in March
apr	Dummy for transaction being in April
may	Dummy for transaction being in May
jun	Dummy for transaction being in June
jul	Dummy for transaction being in July
aug	Dummy for transaction being in August
sep	Dummy for transaction being in September
oct	Dummy for transaction being in October
nov	Dummy for transaction being in November
dec	Dummy for transaction being in December
yd1998	Year Dummy 1998
yd1999	Year Dummy 1999
yd2000	Year Dummy 2000
yd2001	Year Dummy 2001
yd2002	Year Dummy 2002
yd2003	Year Dummy 2003
yd2004	Year Dummy 2004

yd2005	Year Dummy 2005
yd2006	Year Dummy 2006
yd2007	Year Dummy 2007
yd2008	Year Dummy 2008
yd2009	Year Dummy 2009
yd2010	Year Dummy 2010
yd2011	Year Dummy 2011
yd2012	Year Dummy 2012
yd2013	Year Dummy 2013
yd2014	Year Dummy 2014
age	Age of apartment in year (with higher order terms in regression)
lgsize	Size of apartment in m^2, with natural log transformation
floorM	14-26 floors in height
floorH	>27 floors in height
discountrate	Amount which apartment is subsidized
unluckynum	Apartment with number 4 or 13 in address
luckynum	Apartment with number 8 in address
lgdtonosec	Distance to nearest major road, defined as highways or four lanes and above, with natural log transformation
lgdtocentralcar	Logged driving distance to central Hong Kong by automobile
INTperioddtocentral	Time period of transaction in months interacted with Logged driving distance to central (with higher order terms)
lgttocentralcar	Logged driving time to central Hong Kong by automobile
INTperiodttocentcar	Time period of transaction in months interacted with Logged driving time to central (with higher order terms)
lgttocentralpublic	Logged public transit time to central Hong Kong
INTperiodttocentpub	Time period of transaction in months interacted with Logged time by public transit (with higher order terms)
lgincome	Logged income of district where apartment is located in
INTincomeborder[26]	Distance from apartment to district border interacted with logged income level of district where apartment is located in
lgelev	Logged elevation level of apartment, meters
lgcoast	Logged distance to coast, meters

[26] The inclusion of a district border distance-income interaction is meant to introduce some degree of nuance into district-level income figures. The link could be explained by the way modern Hong Kong districts are established: they do not serve many practical purposes but are often drawn with borders in places with least population or human activity. This means that in general, regions with greater amounts of commercial activity, and hence higher average income and living costs, will be located closer to the center of districts.

CountDSS	Number of DSS middle schools in a 3km radius of the apartment
INTperiodDSS	Time period of transaction interacted with number of DSS middle schools in a 3km radius of apartment (with higher order terms)
lgWalkElemt	Logged walking distance to nearest elementary school, meters
INTperiodelementary	Time period of transaction in months interacted with logged walking distance to nearest elementary school (with higher order terms)
SlopeElementary	Average slope between apartment and nearest elementary school, degrees
INTslopewalkelem	Average slope between apartment and nearest elementary school interacted with logged walking distance to nearest elementary school
lgMTRonehalf	Logged walking distance, in best fit equivalent estimation, to nearest metro station, meters
WalkMTRangle	Average slope between apartment and nearest metro station, degrees
INTMTRcompslope	Average slope between apartment and nearest metro station interacted with logged walking distance to nearest metro station
dtoairportkm	Distance to nearest airport, kilometers
courtsize	Size of apartment group, units
dcodeX	Dummy for being in district X, with 15 districts in total
ncode190	Dummy for being in court “Kornhill”
ncode94	Dummy for being in court “Tun Yuk Court”
ncode33	Dummy for being in court “Yu Shing Court”

2. Hedonic regression model output

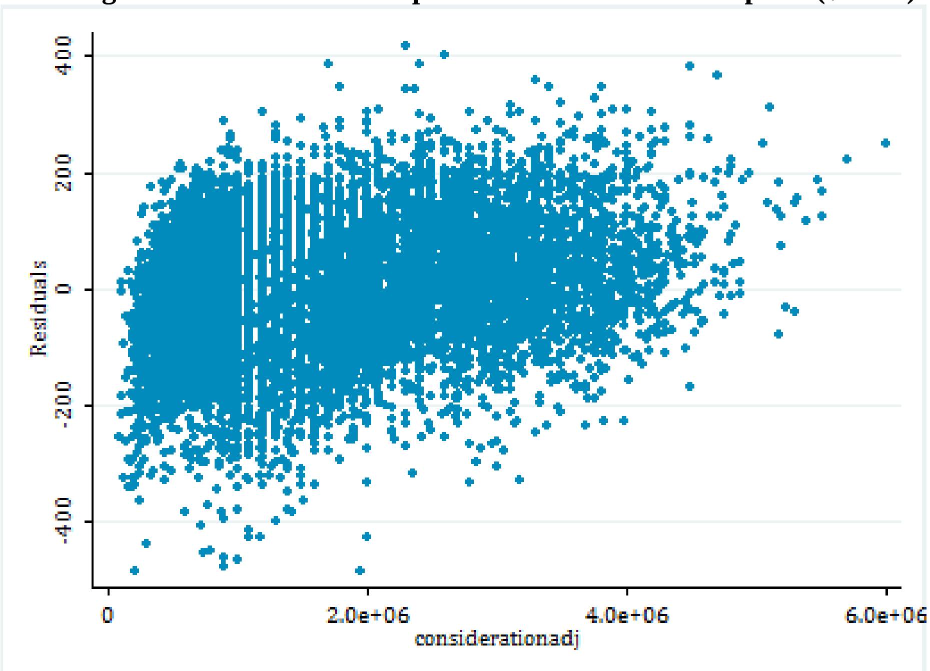
Source	SS	df	MS
Model	2.8845e+09	88	32778673
Residual	217163980	37656	5767.04855
Total	3.1017e+09	37744	82176.9607

Number of obs	= 37745
F(88, 37656)	= 5683.79
Prob > F	= 0.0000
R-squared	= 0.9300
Adj R-squared	= 0.9298
Root MSE	= 75.941

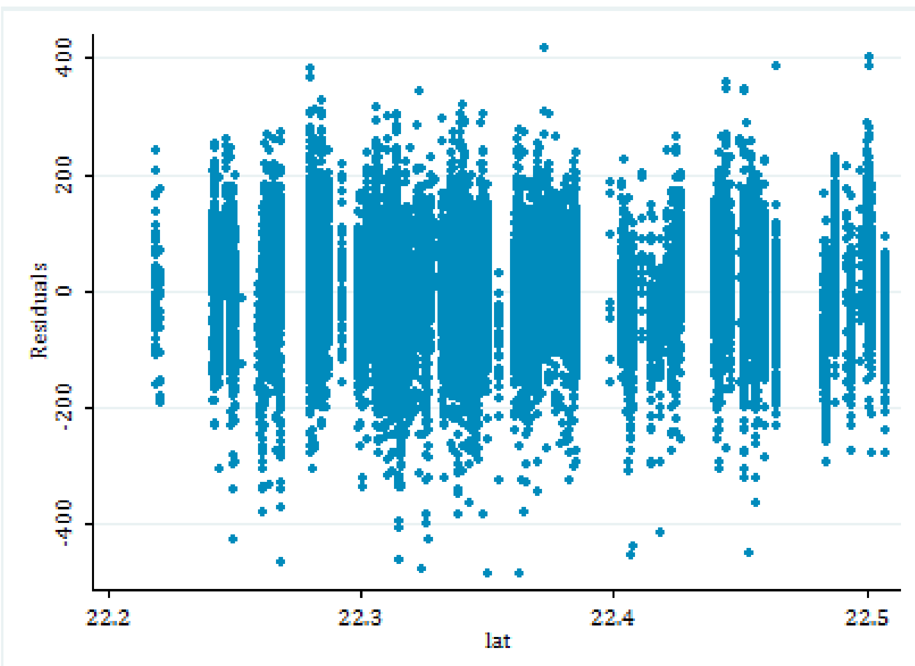
priceadjtwothird	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
feb	6.267646	2.064175	3.04	0.002	2.221808	10.31349
mar	18.60077	1.964897	9.47	0.000	14.74952	22.45202
apr	26.46751	2.035945	13.00	0.000	22.477	30.45802
may	33.90122	1.986659	17.06	0.000	30.00732	37.79513
jun	44.47692	2.09937	21.19	0.000	40.36209	48.59174
jul	52.17508	2.179748	23.94	0.000	47.90272	56.44745
aug	59.74368	2.293789	26.05	0.000	55.24779	64.23957
sep	66.81224	2.399469	27.84	0.000	62.10922	71.51526
oct	71.30201	2.496199	28.56	0.000	66.4094	76.19463
nov	74.33912	2.651315	28.04	0.000	69.14247	79.53577
dec	83.07476	2.796911	29.70	0.000	77.59274	88.55678
yd1998	-88.83367	5.583359	-15.91	0.000	-99.77721	-77.89014
yd1999	63.56388	8.138634	7.81	0.000	47.61194	79.51583
yd2000	156.5645	10.91939	14.34	0.000	135.1622	177.9668
yd2001	221.8377	13.25151	16.74	0.000	195.8644	247.811
yd2002	293.3	15.18029	19.32	0.000	263.5462	323.0538
yd2003	348.1088	16.85266	20.66	0.000	315.0771	381.1405
yd2004	508.5509	18.4371	27.58	0.000	472.4137	544.6882
yd2005	644.8428	19.93569	32.35	0.000	605.7683	683.9172
yd2006	733.6841	21.43503	34.23	0.000	691.6708	775.6973
yd2007	828.8928	22.88499	36.22	0.000	784.0376	873.748
yd2008	944.3168	24.39514	38.71	0.000	896.5017	992.1319
yd2009	992.4911	25.84873	38.40	0.000	941.8269	1043.155
yd2010	1149.702	27.36571	42.01	0.000	1096.065	1203.34
yd2011	1310.752	29.01756	45.17	0.000	1253.877	1367.627
yd2012	1419.257	30.78148	46.11	0.000	1358.924	1479.589
yd2013	1609.623	32.97017	48.82	0.000	1545	1674.245
yd2014	1629.452	35.46912	45.94	0.000	1559.932	1698.972
age	98.76466	11.9553	8.26	0.000	75.33195	122.1974
sqrage	-24.47612	2.402262	-10.19	0.000	-29.18462	-19.76763
age3	2.387324	.2366214	10.09	0.000	1.92354	2.851108
age4	-.1155994	.0121579	-9.51	0.000	-.1394292	-.0917696
age5	.0026948	.0003117	8.65	0.000	.0020839	.0033057
age6	-.000024	3.14e-06	-7.64	0.000	-.0000302	-.0000178
lgsize	142.9555	2.60638	54.85	0.000	137.8469	148.0641
floorm	36.77543	.9196493	39.99	0.000	34.97289	38.57796
floorh	50.67992	1.013061	50.03	0.000	48.69429	52.66555
discountrate	-3.788236	.0602543	-62.87	0.000	-3.906336	-3.670136
unluckynum	-16.95358	2.134466	-7.94	0.000	-21.13719	-12.76997
luckynum	8.629191	1.282952	6.73	0.000	6.11457	11.14381
lgdtoNoSec	-.3966299	.3860973	-1.03	0.304	-1.153391	.3601312
lgdtocentralcar	-179.4157	17.19418	-10.43	0.000	-213.1167	-145.7146
INTperioddtocentral	4.595493	.3403459	13.50	0.000	3.928406	5.26258
INTperioddtocentral2	-.0184446	.0015539	-11.87	0.000	-.0214903	-.0153988

lgttocentralcar	32.43666	22.95859	1.41	0.158	-12.56281	77.43612
INTperiodttocentral	-.3139625	.5898407	-0.53	0.595	-1.470066	.8421412
INTperiodttocentral2	-.0326846	.0048038	-6.80	0.000	-.0421003	-.023269
INTperiodttocentral3	.0001257	.0000136	9.24	0.000	.000099	.0001523
lgttocentralpublic	47.94877	10.36984	4.62	0.000	27.6236	68.27393
INTperiodcentralpublic	-5.703425	.3495382	-16.32	0.000	-6.38853	-5.018321
INTperiodcentralpublic2	.0401846	.0037658	10.67	0.000	.0328035	.0475657
INTperiodcentralpublic3	-.0000733	.0000118	-6.21	0.000	-.0000964	-.0000502
lgdtoborder	-127.0069	34.89896	-3.64	0.000	-195.4098	-58.60396
lgincome	127.6456	26.73498	4.77	0.000	75.24429	180.0468
INTincomeborder	12.38592	3.572977	3.47	0.001	5.382784	19.38905
lgelev	2.320344	.9005951	2.58	0.010	.555153	4.085534
lgcoast	-3.990305	1.119347	-3.56	0.000	-6.184254	-1.796356
countdss	-.3845319	.2288844	-1.68	0.093	-.8331515	.0640878
INTperiodDSS	-.0247872	.0083196	-2.98	0.003	-.0410937	-.0084806
INTperiodDSS2	.0002422	.0000892	2.71	0.007	.0000673	.000417
INTperiodDSS3	-8.52e-07	2.79e-07	-3.05	0.002	-1.40e-06	-3.05e-07
lgwalkelementary	24.91483	1.661573	14.99	0.000	21.6581	28.17156
INTperiodelementary	-.2513562	.0343377	-7.32	0.000	-.3186589	-.1840534
INTperiodelementary2	.0012663	.0001588	7.97	0.000	.0009551	.0015775
slopeelementary	39.1732	1.425423	27.48	0.000	36.37933	41.96707
INTslopewalkelem	-7.430824	.2551369	-29.12	0.000	-7.930899	-6.930749
lgmtronehalf	-14.18257	.9296417	-15.26	0.000	-16.00469	-12.36045
walkmtrangle	-14.43456	1.852028	-7.79	0.000	-18.06458	-10.80453
INTmtrcompslope	1.668664	.2786628	5.99	0.000	1.122477	2.21485
dtoairportadj	-.0003271	.0001273	-2.57	0.010	-.0005767	-.0000775
courtsize	-.0071154	.0004487	-15.86	0.000	-.0079947	-.006236
dcode2	-102.5085	9.600835	-10.68	0.000	-121.3264	-83.69063
dcode3	-5.366907	9.560381	-0.56	0.575	-24.10551	13.3717
dcode4	58.52261	6.272558	9.33	0.000	46.22823	70.817
dcode5	116.0198	5.950018	19.50	0.000	104.3576	127.682
dcode6	54.30747	7.987772	6.80	0.000	38.65122	69.96372
dcode7	-16.19138	3.247488	-4.99	0.000	-22.55654	-9.826212
dcode8	47.70415	4.026691	11.85	0.000	39.81173	55.59658
dcode9	142.2875	7.666229	18.56	0.000	127.2615	157.3135
dcode10	82.99183	3.720582	22.31	0.000	75.69939	90.28427
dcode11	89.78031	6.114951	14.68	0.000	77.79484	101.7658
dcode12	-10.49501	8.431582	-1.24	0.213	-27.02114	6.03112
dcode13	146.79	6.049083	24.27	0.000	134.9336	158.6464
dcode14	147.4052	4.913077	30.00	0.000	137.7755	157.035
dcode15	-81.69436	9.097531	-8.98	0.000	-99.52577	-63.86296
ncode190	-134.6933	6.440079	-20.91	0.000	-147.316	-122.0706
ncode94	192.3898	5.016556	38.35	0.000	182.5572	202.2224
ncode33	234.0675	5.750387	40.70	0.000	222.7966	245.3385
_cons	-484.1725	266.8052	-1.81	0.070	-1007.118	38.77291

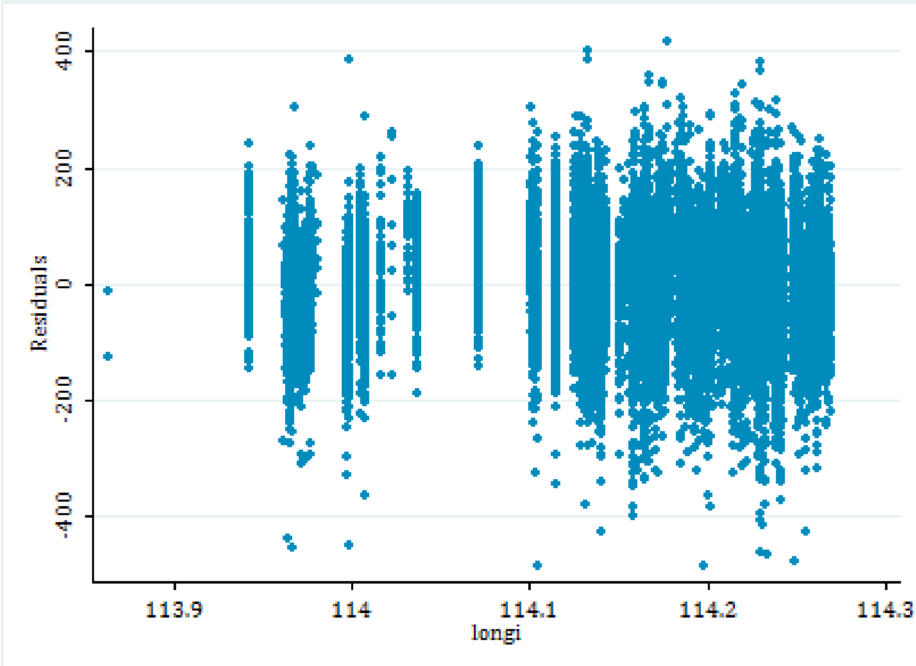
3. Regression residual scatter plot over total transaction price ($HKD)



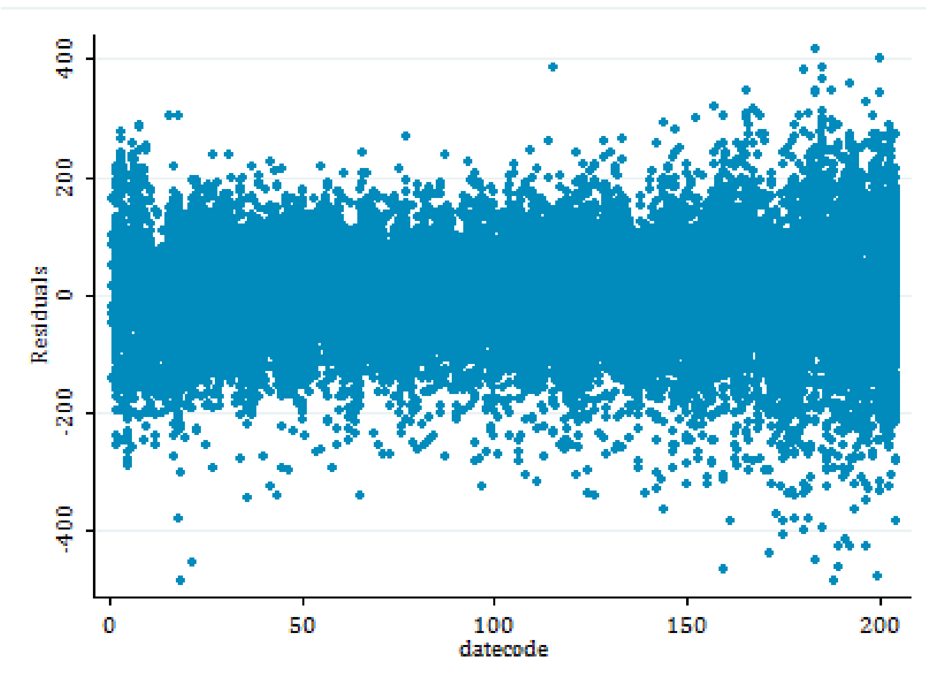
4. Regression residual scatter plot over latitude (decimal)



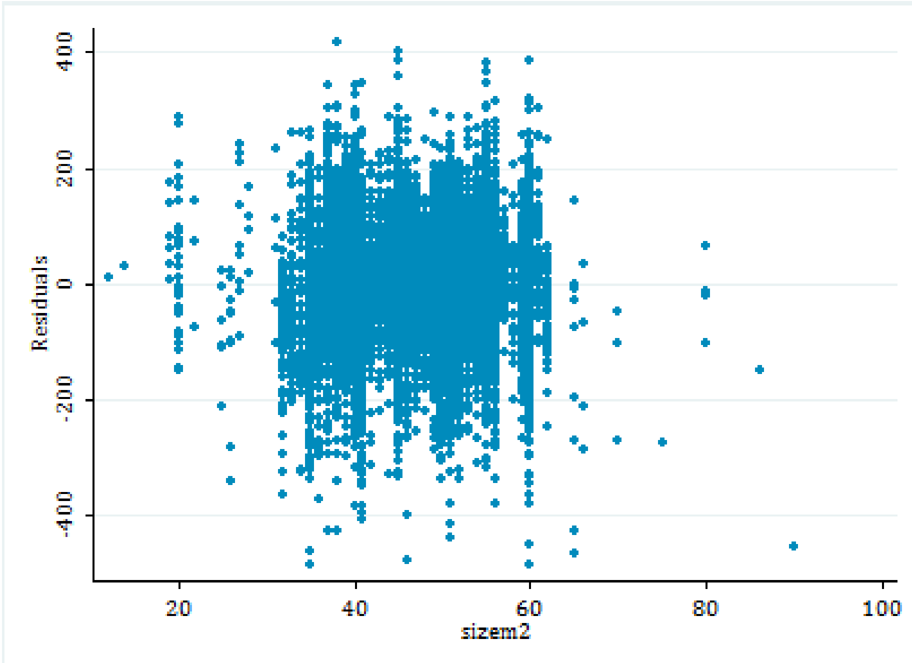
5. Regression residual scatter plot over longitude (decimal)



6. Regression residual scatter plot over transaction date (Aug 1997 = 1)



7. Regression residual scatter plot over size of apartment (m^2)



Yifan (Victor) Ye is a M.S Statistical and Economic Modeling (M.S.E.M) candidate at Duke University, where he completed his bachelor's degree in Economics (B.S) and Philosophy (A.B.II). His research primarily involves geospatial modelling and topics in urban economics, as well as computable general equilibrium projects. He is currently working as a research intern for the United Nations Economic and Social Commission for Asia and the Pacific (ESCAP).