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Residential Property Price Index in Japan: Discussion in Methodology and Data Sources

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Abstract

Fluctuations in housing prices have substantial economic impacts. Thus, it is essential to develop housing price indexes that can adequately capture housing market trends. However, construction of such indexes is very difficult due to the fact that residential properties are heterogeneous and do not remain at constant quality over time due to renovations and depreciation of the structure. In order to improve the quality of housing price statistics Eurostat published the Residential Property Price Indices Handbook in 2012. In constructing a housing price index, one has to make several non-trivial choices. One of them is the choice among alternative estimation methods, such as repeat-sales regression, hedonic regression, etc. There are numerous papers on this issue, both theoretical and empirical. Shimizu et al. (2010), for example, conduct a statistical comparison of several alternative estimation methods using Japanese data. However, there is another important issue which has not been discussed much in the literature, but which has been regarded as critically important from a practical viewpoint: the choice among different data sources for housing prices. There are several types of datasets for housing prices: datasets collected by real estate agencies and associations; datasets provided by mortgage lenders; datasets provided by government departments or institutions; and datasets gathered and provided by newspapers, magazines, and websites. Needless to say, different datasets contain different types of prices, including sellers' asking prices, transaction prices, valuation prices, etc. With multiple datasets available, one may ask several questions. Are these prices different? If so, how do they differ from one another? Given the specific purpose of the housing price index one seeks to construct, which dataset is the most suitable? Alternatively, with only one dataset available in a particular country, one may ask whether this is suitable for the purpose of the index one seeks to construct. The paper discusses alternative methods for obtaining constant quality housing price statistics and alternative data sources in the Japanese context.

Key Words : House price indexes; hedonic price indexes; repeat sales price indexes; aggregation bias; housing depreciation; land and structure components; flexible functional forms; Fisher ideal indexes.

JEL Classification : C2, C23, C43, D12, E31, R21.

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1 Introduction

Fluctuations in real estate prices have substantial impacts on economic activities. In Japan, a sharp rise in real estate prices during the latter half of the 1980s and its decline in the early 1990s led to a decade-long stagnation of the Japanese economy. More recently, a rapid rise in housing prices and its reversal in the United States triggered a global financial crisis. In such circumstances, the development of appropriate indexes that allow one to capture changes in real estate prices with precision is extremely important, not only for policy makers but also for market participants who are looking for the time when housing prices hit bottom. Recent research has focussed on methods of compiling appropriate residential property price indexes. The location, maintenance and the facilities of each house are different from each other in varying degrees, so there are no two houses that are identical in terms of quality. Even if the location and basic structure are the same at two periods of time, the building ages over time and the houses are not identical across time. In other words, it is very difficult to apply the usual *matching methodology* (where the prices of exactly the same item are compared over time) to housing.

As a result, one may say that the construction of constant quality real estate price indexes is one of the most difficult tasks for national statistical agencies. In order to address these measurement problems, Eurostat published the *Residential Property Price Indices Handbook* in 2012. Chapters 4 through 7 of this Handbook are devoted to methods for constructing constant quality price indexes.¹ Chapter 8 deals with the problems associated with decomposing an overall property price index into land and structure components,² Chapter 9 discusses data sources and Chapter 10 reviews methods currently used by private and government index providers.

In the wake of the release of this *Handbook*, how should different countries construct residential property price indexes? With the start of the Residential Property Price Indices Handbook project, the government of Japan set up an Advisory Board through the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT) and is proceeding with the development of a new Japanese official residential property price index. This paper outlines the results of the advisory board's ongoing review with regard to the development of a residential property price index for Japan.³

Sections 2 and 3 below summarize the results of deliberations by the Advisory Board regarding residential property price indexes estimation methods. The material in these sections is based on the paper by Shimizu, Nishimura and Watanabe (2010). Section 4 summarizes the results of deliberations regarding selection of data sources. Section 5 then

¹Chapters 4-7 deal with the following methods: stratification or mix adjustment methods, hedonic regression methods, repeat sales methods, and appraisal based methods.

²This decomposition is required in order to construct the national accounts for a country.

³The Advisory Board was set up by the Ministry of Land, Infrastructure, Transport and Tourism, with the participation of the Bank of Japan, Financial Services Agency, Ministry of Justice (which is the department responsible for the land registry), Statistics Japan (the department responsible for the consumer price index), the Cabinet Office (the department responsible for SNA), the Japan Association of Real Estate Appraisers and various realtor associations. As of 2013, the Advisory Board also began developing a official Commercial Property Price Index in addition to developing the Residential Property Price Index.

outlines the results of analysis of an outstanding issue: methods for separating housing prices into land and building component prices. Finally, section 6 summarizes what kind of index the government of Japan intends to publish as an official Residential Property Price Index.⁴

2 Alternative Methods for Constructing Residential Property Price Indexes

2.1 Introduction: The Two Main Methods for Making Quality Adjustments

A key starting point in estimating a housing price index is to recognize that each property at each point in time is a unique item. Even if the location and basic structure of the housing unit are the same at two points in time, depreciation, alternative maintenance policies and renovations alter the quality of the structure so that like cannot be precisely compared with like. Given this special feature of houses and hence housing services, an important task for researchers is to make adjustments for differences in quality. There are two methods widely used by practitioners and researchers: the *hedonic method* and the *repeat sales method*. A primary purpose of the paper by Shimizu, Nishimura and Watanabe (2010) was to compare these two methods using a unique dataset that we they compiled from individual listings in a widely circulated real estate advertisement magazine.

Previous studies on house price indexes have identified several problems for each of the two main methods for quality adjustment. The real estate literature has identified the following problems with the repeat sales method:

- The repeat sales method may suffer from *sample selection bias* because houses that are traded multiple times have different characteristics than a typical house.⁵
- The repeat sales method basically assumes that *property characteristics remain unchanged over time*. In particular, the repeat sales method neglects depreciation and possible renovations to the structure.⁶

On the other hand, the hedonic method suffers from the following problems:

- The *failure to include relevant variables* in hedonic regression may result in estimation bias.⁷

⁴Sections 2 and 3 draw heavily on the paper by Shimizu, Nishimura and Watanabe (2010).

⁵See Clapp and Giacotto (1992). Repeat sales that occur in very short time periods are often not regarded as “typical” sales. In particular, the initial sale may take place at a below market price and the subsequent rapid resale takes place at the market price, and this phenomenon may lead to an upward bias in the resulting repeat sales price index. Of course, this source of upward bias is partially offset by the downward bias in the repeat sales method due to its neglect to make a quality adjustment for the depreciation of the structure.

⁶See Case and Shiller (1987) (1989), Clapp and Giacotto (1992) (1998), Goodman and Thibodeau (1998), Case, Pollakowski, and Wachter (1991) and Diewert (2010).

⁷See Case and Quigley (1991) and Ekeland, Heckman, and Nesheim (2004).

- An *incorrect functional form* may be assumed for the hedonic regression model.⁸
- The assumption of *no structural change* (i.e., no changes in parameters over time) over the entire sample period may be too restrictive.⁹

Given that true quality adjusted price changes are not observable, it is difficult to say which of the two measures performs better. However, at least from a practical perspective, it is often said that the repeat sales method represents a better choice because it is less costly to implement.¹⁰ However, as far as the Japanese housing market is concerned, there are some additional concerns about the repeat sales method:

- The Japanese housing market is less liquid than those in the United States and European countries, so that a house is less likely to be traded multiple times.¹¹
- The quality of a house declines more rapidly over time in Japan because of the short lifespan of houses and the fact that — for various reasons — renovations to restore the quality of a house play a relatively unimportant role. This implies that depreciation plays a more important role in the determination of house prices, which is not taken into account in the repeat sales method.

Given these features of the Japanese housing market, Shimizu, Nishimura and Watanabe (2010) argued that, at least in Japan, the hedonic method is a better choice. Another important advantage of the hedonic method over the repeat sales method is that the former method can lead to a decomposition of the sales price of a property into land and structure components. This decomposition cannot be obtained using the repeat sales method.

In the remainder of this section, we will discuss the various variants of the hedonic regression and repeat sales models that are used in practice.

2.2 The Standard Hedonic Regression Model

We begin with a description of the standard hedonic regression model. Suppose that we have data for house prices and property characteristics for periods $t = 1, 2, \dots, T$. It is assumed that the price of house i in period t , P_{it} , is given by a *Cobb-Douglas function* of the lot size of the house, L_i , and the amount of structures capital in constant quality units, K_{it} :

$$P_{it} = P_t L_i^\alpha K_{it}^\beta \tag{1}$$

⁸See Diewert (2003a) (2003b).

⁹See Case, Pollakowski, and Wachter (1991); Clapp and Giaccotto (1992) (1998), Shimizu and Nishimura (2006) (2007) and Shimizu, Nishimura and Watanabe (2010).

¹⁰See Bourassa, Hoesli and Sun (2006). The hedonic method requires information on property characteristics whereas the repeat sales method does not require any characteristics information. However, this informational advantage of the repeat sales method is offset by its *informational sparseness disadvantage*; i.e., repeat sales information may be so infrequent so as to make the construction of accurate price indexes impossible. Moreover, unless the sample selection bias exactly offsets the depreciation bias, we can say that the repeat sales method is definitely biased whereas we cannot definitely assert that the hedonic method is biased.

¹¹This may be partly due to the presence of legal restrictions in Japan on reselling a house within a short period of time.

where P_t is the logarithm of the *quality adjusted house price index for period t* and α and β are positive parameters.¹² It is assumed that housing capital, K_{it} , is subject to *generalized exponential depreciation* so that the housing capital in period t is given by

$$K_{it} = B_i \exp[-\delta A_{it}^\lambda] \quad (2)$$

where B_i is the floor space of the structure, A_{it} is the age of the structure in period t , δ is a parameter between 0 and 1, and λ is a positive parameter. Note that if $\lambda = 1$, equation (2) reduces to the usual exponential model of depreciation with a constant rate of depreciation over time; if $\lambda > 1$, the depreciation rate increases with time; if $\lambda < 1$, the depreciation rate decreases with time.

By substituting (2) into (1), and taking the logarithm of both sides of the resulting equation, we obtain the following equation:

$$\ln P_{it} = \ln P_t + \alpha \ln L_i + \beta \ln B_i - \beta \delta A_{it}^\lambda. \quad (3)$$

Adding a vector of attributes of house i in period t other than A_{it} , L_i and K_{it} , denoted by \mathbf{x}_i ¹³ and an error term v_{it} leads to an estimating equation of the form:

$$\ln P_{it} = d_t + \alpha \ln L_i + \beta \ln B_i - \beta \delta A_{it}^\lambda + \boldsymbol{\gamma} \cdot \mathbf{x}_i + v_{it} \quad (4)$$

where $d_t \equiv \ln P_t$ is the logarithm of the constant quality population price index for period t , P_t , $\boldsymbol{\gamma}$ is a vector of parameters associated with the vector of house i characteristics \mathbf{x}_i , $\boldsymbol{\gamma} \cdot \mathbf{x}_i$ is the inner product of the vectors $\boldsymbol{\gamma}$ and \mathbf{x}_i and v_{it} is an iid normal disturbance.¹⁴

Running an OLS regression of equation (4) yields estimates for the coefficients on the time dummy variables, d_t for $t = 1, \dots, T$ as well as for the parameters $\alpha, \beta, \boldsymbol{\gamma}$, and δ . After making the normalization $d_1 = 0$, the series of estimated coefficients for the time dummy variables, d_t^* for $t = 1, \dots, T$, can be exponentiated to yield the time series of constant quality price indexes, $P_t \equiv \exp[d_t^*]$ for $t = 1, \dots, T$. Note that the coefficients $\alpha, \beta, \boldsymbol{\gamma}$, and δ are all identified in this regression model.

2.3 The Standard Repeat Sales Model

The standard repeat sales method¹⁵ starts with the assumption that property characteristics do not change over time and that the parameters associated with these characteristics

¹²McMillen (2003) adopted the same Cobb-Douglas production function for housing services. Thorsnes (1997) described housing output as a constant elasticity substitution production function of the lot size and housing capital, and provided some empirical evidence that the elasticity of substitution is close to unity, which implies that the Cobb-Douglas production function is a good approximation of the technology used in the production of housing services. In contrast, Diewert (2010) (2011) suggested some possible hedonic regression models that might lead to additive decompositions of an overall property price into land and structures components. Additive decomposition models have been estimated by Diewert, de Haan and Hendriks (2011a) (2011b) and Eurostat (2011) using Dutch data and by Diewert and Shimizu (2013) using data for Tokyo. We will discuss these additive models in Section 5 below.

¹³Note that we are assuming that the vector of house i attributes \mathbf{x}_i does not depend on the time of sale, t .

¹⁴Time dummy hedonic regression models date back to Court (1939).

¹⁵The repeat sales method is due to Bailey, Muth and Nourse (1963).

do not change either. The underlying price determination model is basically the same as in equation (4). However, the repeat sales method focuses on houses that appear multiple times in the dataset. Suppose that house i is transacted twice, and that the transactions occur in periods s and t with $s < t$. Using equations (4), the change in the logarithms of the house prices between the two time periods is given by

$$\ln(P_{it}/P_{is}) = d_t - d_s - \beta\delta(A_{it}^\lambda - A_{is}^\lambda) + v_{it} - v_{is}. \quad (5)$$

Note that the terms that do not include time subscripts in equation (4), namely $\alpha \ln L_i$, $\beta \ln B_i$ and $\gamma \cdot \mathbf{x}_i$, all disappear by taking differences with respect to time, so that the resulting equation is simpler than the original one.¹⁶ Furthermore, assuming no renovation expenditures between the two time periods and no depreciation of housing capital so that $\delta = 0$, equation (5) reduces to:

$$\ln(P_{it}/P_{is}) = d_t - d_s + v_{it} - v_{is}. \quad (6)$$

The above equation can be rewritten as the following linear regression model:

$$\ln(P_{it}/P_{is}) = \sum_{j=1}^T D_j^{its} d_j + v_{its} \quad (7)$$

where $v_{its} \equiv v_{it} - v_{is}$ is a consolidated error term and D_j^{its} is a dummy variable that takes on the value 1 when $j = t$ (where t is the period when house i is resold), the value -1 when $j = s$ (where s is the period when house i is first sold) and D_j^{its} takes on the value 0 for j not equal to s or t . In order to identify all of the parameters d_j , a normalization is required such as $d_1 \equiv 0$. This normalization will make the house price index equal to unity in the first period. The *standard repeat sales house price indexes* are then defined by $P_t \equiv \exp[d_t^*]$ for $t = 1, 2, \dots, T$, where the d_t^* are the least squares estimators for the d_t .

2.4 Heteroskedasticity and Age Adjustments to the Repeat Sales Index

As pointed out by previous studies, the standard repeat sales index defined above may be biased for two reasons:

- The disturbance term in equation (7) may be heteroskedastic in the sense that the variance of the disturbance term may be larger when the two transaction dates are further apart.¹⁷
- The assumption of no depreciation is too restrictive.

Case and Shiller (1987) (1989) address the heteroskedasticity problem in the disturbance term by assuming that the variance of the residual v_{its} in (7) increases as t and s are

¹⁶Thus the regression model defined by (5) does not require characteristics information on the house (except that information on the age of the house at the time of each transaction is required).

¹⁷However, if s and t are very close, the variance could also increase due to the “flipping phenomenon”; i.e., a house that is sold twice in a short time period may have a rate of price change between the two time periods that is unusually large on an annualized basis, causing the error variance to increase.

further apart; i.e., they assume that $E(v_{its}) = 0$ and $E(v_{its})^2 = \xi_0 + \xi_1(t - s)$ where ξ_0 and ξ_1 are positive parameters. The Case-Shiller repeat sales index is estimated as follows. First, equation (7) is estimated, and the resulting squared disturbance term is regressed on $\xi_0 + \xi_1(t - s)$ in order to obtain estimates for ξ_0 and ξ_1 . Denote these estimates by ξ_0^* and ξ_1^* . Then equation (7) is reestimated by Generalized Least Squares (GLS) where observation i , $\ln(P_{it}/P_{is})$, is adjusted by the weight $[\xi_0^* + \xi_1^*(t - s)]^{1/2}$. Denote the resulting GLS estimates for the coefficients d_t on the time dummy variables by d_t^* . The Case-Shiller *heteroskedasticity adjusted repeat sales indexes* are then defined by $P_t \equiv \exp[d_t^*]$ for $t = 1, 2, \dots, T$.¹⁸

We turn now to the lack of an age adjustment problem with the repeat sales method. Previous studies on the repeat sales method, including Bailey, Muth and Nourse (1963) and Case and Shiller (1987) (1989), do not pay much attention to the possibility that property characteristics change over time. However, there are no houses that do not depreciate, implying that the quality of a house at the time of selling depends on its age. Also, the quality of a house may change over time because of maintenance and renovation. Finally, its quality may change over time due to changes in the environment surrounding the house, such as the availability of public transportation, the quality of neighbourhood schools and so on.¹⁹ As far as the Japanese housing market is concerned, the structure of a house typically depreciates more quickly than in the United States and Europe, which is likely to cause a larger bias in price indexes if house price depreciation is ignored.

To take account of the depreciation effect, we go back to equation (5) and rewrite it as follows:²⁰

$$\ln(P_{it}/P_{is}) = d_t - d_s - \beta\delta[(A_{is} + t - s)^\lambda - A_{is}^\lambda] + v_{its}. \quad (8)$$

Note that repeat sales indexes that do not include an age term (such as the term involving A_{is} on the right hand side of the above equation) will suffer from a downward bias.²¹

McMillen (2003) considered a simpler version of this model with $\lambda = 1$, so that the depreciation rate is constant over time. When $\lambda = 1$, (8) reduces to (9):

$$\ln(P_{it}/P_{is}) = d_t - d_s - \beta\delta(t - s) + v_{its}. \quad (9)$$

Note that there is exact collinearity between $d_t - d_s$ and $t - s$, so that it is impossible to obtain estimates for the coefficients on the time dummies. McMillen (2003) measured the age difference between two consecutive sales in days while using quarterly time dummy variables, thereby eliminating the exact collinearity between the time dummies and the age difference.²²

¹⁸As usual, set $d_1^* \equiv d_1 \equiv 1$ so that $P_1 \equiv 1$.

¹⁹Note that the depreciation model defined by (2) can be regarded as a *net depreciation model*; i.e., it is depreciation less “normal” renovation and maintenance expenditures. See Diewert (2011) for more on the topic of constructing a house price index taking depreciation and renovation into consideration.

²⁰The analysis which follows is due to Shimizu, Nishimura and Watanabe (2010).

²¹It should be noted that the official S&P/Case-Shiller home price index is adjusted in the following way to take the age effect into account. Standard & Poor’s (2008: 7) states that “sales pairs are also weighted based on the time interval between the first and second sales. If a sales pair interval is longer, then it is more likely that a house may have experienced physical changes. Sales pairs with longer intervals are, therefore, given less weight than sales pairs with shorter intervals.”

²²However, one would expect approximate multicollinearity to hold in McMillen’s model so that the estimated dummy variable parameters may not be too reliable.

Shimizu, Nishimura and Watanabe (2010) eliminated exact multicollinearity by estimating the nonlinear model defined by (8).²³ Once the d_t parameters have been estimated by maximum likelihood or nonlinear least squares (denote the estimates by d_t^* with d_1^* set equal to 0), then the *Shimizu, Nishimura and Watanabe repeat sales indexes* P_t are defined as $P_t \equiv \exp[d_t^*]$ for $t = 1, 2, \dots, T$.

Note that the parameters β and δ are not identified in the nonlinear regression (8) because they appear only in the form of $\beta\delta$. This is in sharp contrast with the hedonic regression model defined by (4), in which β appears not only as a coefficient of the age term but also as a coefficient on $\ln B_i$, so that β and δ are identified.²⁴

2.5 Rolling Window Hedonic Regressions: Structural Change Adjustments to the Hedonic Index

Shimizu, Takatsuji, Ono and Nishimura (2010) and Shimizu, Nishimura and Watanabe (2010) modified the standard hedonic model given by equation (4) so that the parameters associated with the attributes of a house are allowed to change over time. Structural changes in the Japanese housing market have two important features. First, they usually occur only gradually, triggered, with a few exceptions, by changes in regulations by the central and local governments. Such gradual changes are quite different from “regime changes” discussed by econometricians such as Bai and Perron (1998) in which structural parameters exhibit a discontinuous shift at multiple times. Second, changes in parameters reflect structural changes at various time frequencies. Specifically, as found by Shimizu, Nishimura and Watanabe (2010), some changes in parameters are associated with seasonal changes in housing market activity. For example, the number of transactions is high at the end of a fiscal year, namely, between January and March, when people move from one place to another due to seasonal reasons such as job transfers, while the number is low during the summer. One way to allow for gradual shifts in parameters is to employ an *adjacent period regression*,²⁵ in which equation (4) is estimated using only two periods that are adjacent to each other so that the parameter vector γ in (4) is only held constant for two consecutive periods (as are the other parameters, α, β, δ and λ). The estimated second period price level, $P_2 \equiv \exp[d_2^*]$, is regarded as a chain type index which is used to update the previously determined index level for the first period, P_1 . This method of index construction allows for gradual taste changes thereby minimizing the rigidity disadvantage of the pooled regression model defined by (4). Triplett (2004), based on the presumption that coefficients usually change less between two adjacent periods than over more extended intervals, argued that the adjacent-period esti-

²³See Chau, Wong and Yui (2005) for another example where a nonlinear specification of the age effect was introduced into the hedonic regression in order to eliminate multicollinearity between the age variable and the time dummy variables.

²⁴If the estimated λ parameter for the model defined by (8) turns out to be close to one, then as is the case for McMillen’s model, there may be an approximate multicollinearity problem with the Shimizu, Nishimura and Watanabe repeat sales model.

²⁵The two period time dummy variable hedonic regression was considered explicitly by Court (1939; 109-111) as his hedonic suggestion number two. Griliches (1971; 7) coined the term “adjacent year regression” to describe the two period dummy variable hedonic regression model.

mator is “a more benign constraint on the hedonic coefficients.” However, as far as seasonal changes in parameters are concerned, this presumption may not necessarily be satisfied, so that an adjacent period regression may not work very well. To cope with this problem, Shimizu, Takatsuji, Ono and Nishimura (2010) and Shimizu, Nishimura and Watanabe (2010) proposed a regression method using multiple “neighborhood periods,” typically 12 or 24 months, rather than two adjacent periods. Specifically, they estimated parameters by taking a certain length as the estimation window and shifting this period as in rolling regressions. This method should be able to handle seasonal changes in parameters better than adjacent period regressions, although it may suffer more from the rigidity disadvantage associated with pooling.

To apply this method, estimate the model defined by equations (4) for periods $t = 1, \dots, \tau$, where $\tau < T$ represents the *window width*. As usual, set $d_1 = d_1^* \equiv 1$ and denote the remaining estimated time parameters for this first regression by d_2^*, \dots, d_τ^* . These parameters are exponentiated to define the sequence of house price indexes P_t for the first τ periods; i.e., $P_t \equiv \exp[d_t^*]$ for $t = 1, 2, \dots, \tau$. Then this τ period regression model using the data for the periods $2, 3, \dots, \tau + 1$ can be repeated and a new set of estimated time parameters, $d_2^{2*} \equiv 1, d_3^{2*}, \dots, d_{\tau+1}^{2*}$ can be obtained. The new *price levels* P_t^2 for periods 2 to $\tau + 1$ can be defined as $P_t^2 \equiv \exp[d_t^{2*}]$ for $t = 2, 3, \dots, \tau + 1$. Obviously, this process of adding the data of the next period to the rolling window regression while dropping the data pertaining to the oldest period in the previous regression can be continued. The focus in the Shimizu, Takatsuji, Ono and Nishimura (2010) paper was on determining how the structural parameters in (8) changed as the window of observations changed.²⁶ They did not address the problem of obtaining a coherent time series of price levels from the multiple estimates of price levels that result from these overlapping hedonic regressions.

A coherent strategy for forming a single set of price level estimates from the sequence of Rolling Window regressions works as follows. As indicated in the previous paragraph, the sequence of final price levels P_t for the first τ periods is obtained by exponentiating the estimated time dummy parameters taken from the first Rolling Window regression; i.e., $P_t \equiv \exp[d_t^*]$ for $t = 1, 2, \dots, \tau$. The next Rolling window regression the data for periods $2, 3, \dots, \tau + 1$ generates the new set of estimated time parameters, $d_2^{2*} \equiv 1, d_3^{2*}, \dots, d_{\tau+1}^{2*}$ and the new set of price levels P_t^2 for periods 2 to $\tau + 1$, defined as $P_t^2 \equiv \exp[d_t^{2*}]$ for $t = 2, 3, \dots, \tau + 1$. Now use only the last two price levels generated by the new regression to define the *final price level* for period $\tau + 1$, $P_{\tau+1}$, as the period τ price level generated by the first regression, P_τ , times (one plus) the rate of change in the price level over the last two periods using the results of the second regression model; i.e., define $P_{\tau+1} \equiv P_\tau(P_{\tau+1}^2/P_\tau^2)$. The next step is to repeat the τ period regression model using the data for the periods $3, 4, \dots, \tau + 2$ and obtain a new set of estimated time parameters, $d_3^{3*} \equiv 1, d_4^{3*}, \dots, d_{\tau+2}^{3*}$. Define new preliminary price levels $P_t^3 \equiv \exp[d_t^{3*}]$ for $t = 3, 4, \dots, \tau + 2$ and update $P_{\tau+1}$ by multiplying it by $(P_{\tau+2}^3/P_{\tau+1}^3)$ so that the final price level for period $\tau + 2$ is defined as $P_{\tau+2} \equiv P_{\tau+1}(P_{\tau+2}^3/P_{\tau+1}^3)$. Carry on with the same process until P_T has been defined. This model

²⁶They called their method the *Overlapping Period Hedonic Housing Model* (OPHM).

can be called the *Rolling Window Hedonic Regression model*.²⁷ A major advantage of this method over the repeat sales model is that as new data become available each period, previous period index levels are not revised. Note that the Rolling Window Hedonic Regression method reduces to an adjacent period hedonic regression model if τ equals 2.

In the following section, the various models defined in this section will be illustrated and compared using data for Tokyo on both houses and condominiums.

3 A Comparison of Alternative Housing Models for Tokyo

3.1 Data Description

Section 3 of this paper summarizes the results in Shimizu, Nishimura and Watanabe (2010), (henceforth referred to as SNW). The data for the SNW paper were collected from a weekly magazine, *Shukan Jutaku Joho* (Residential Information Weekly), published by Recruit Co., Ltd., one of the largest vendors of residential property listings information in Japan. The Recruit dataset covered the 23 special wards of Tokyo for the period 1986 to 2008, which included the bubble period in the late 1980s and its collapse in the early 1990s. It contained 157,627 listings for condominiums and 315,791 listings for single family houses, for 473,418 listings in total.²⁸ *Shukan Jutaku Joho* provided time series for the price of an advertised for sale unit from the week it is first posted until the week it is removed.²⁹ SNW used only the price in the final week of listing because that price was close to the final contract price.³⁰

²⁷This is the approach used by Shimizu, Nishimura and Watanabe (2010) to form an overall price index. Ivancic, Diewert and Fox (2009) recommended a variant of the rolling window model where their basic hedonic regression model was the Time Product Dummy model which is the application of Summer's (1973) Country Product Dummy model to the time series context (from the original application to multi-lateral comparisons of prices across countries). IDF recommended a (weighted) Rolling Year Time Product Dummy method where the window length was chosen to be 13 months. For extensions of the IDF model to more general hedonic regression models, see de Haan and Krsinich (2014). Diewert and Shimizu (2013) implemented a Rolling Window hedonic regression model for Tokyo houses which will be described later in section 5. The Rolling Window Hedonic Regression approach to the construction of house price indexes has also been applied by Eurostat (2011; Chapter 8) and by Diewert, de Haan and Hendriks (2011b).

²⁸Shimizu Nishimura and Asami (2004) reported that the Recruit data cover more than 95 percent of all transactions in the 23 special wards of Tokyo but the coverage for suburban areas is very limited. Therefore the study by Shimizu, Nishimura and Watanabe used only information for the units located in the special wards of Tokyo.

²⁹There are two reasons for removal of the listing of a unit from the magazine: a successful deal or a withdrawal; i.e., in the second case, the seller gives up looking for a buyer and thus withdraws the listing. SNW were allowed to access information regarding which of the two reasons applied for individual cases and they discarded prices where the seller withdrew the listing.

³⁰Recruit Co. Ltd. provided SNW with information on contract prices for about 24 percent of the population of listings. Using this information, SNW were able to confirm that prices in the final week were almost always identical to the contract prices; i.e., they differed at less than a 0.1 percent probability.

Table 1. List of variables

Abbreviation	Variable	Description	Unit
<i>GA</i>	Ground area	Ground area.	m ²
<i>FS</i>	Floor space	Floor space of building.	m ²
<i>RW</i>	Front road width	Front road width.	10cm
<i>AGE</i>	Age of a building at the time of transaction	Age of a building at the time of transaction.	Quarters
<i>TS</i>	Time to the nearest station	Time distance to the nearest station (walking time or time by bus or car).	Minutes
<i>TT</i>	Travel time to central business district	Minimum railway riding time in daytime to one of the seven major business district stations.	Minutes
<i>UV</i>	Unit volume	Unit volume/The total number of units of the condominium.	Unit
<i>RT</i>	Market reservation time	Period between the date when the data appear in the magazine for the first time and the date of being deleted.	Weeks
<i>BD</i>	Bus dummy	Time distance to the nearest station includes taking the bus = 1.; Does not include taking the bus = 0.	(0, 1)
<i>CD</i>	Car dummy	Time distance to the nearest station includes taking the car = 1.; Does not include taking the car = 0.	(0, 1)
<i>FD</i>	First floor dummy	The property is on the ground floor = 1. The property is not on the ground floor = 0.	(0, 1)
<i>BBD</i>	Before new building standard law dummy	Construction year is before 1980(when New Building Standard Law enacted)* = 1.; Construction year is after 1981 = 0.	(0, 1)
<i>SRC</i>	Steel reinforced concrete dummy	"Steel" reinforced concrete frame structure = 1.; Other structure(Reinforced concrete frame structure) = 0.	(0, 1)
<i>SD</i>	South-facing dummy	Main windows facing south = 1. Main windows facing no facing south = 0.	(0, 1)
<i>PD</i>	Private road dummy	Site includes a part of private road** = 1. Site does not include any part of private road = 0.	(0, 1)
<i>LD</i>	Land only dummy	The transaction includes "land" only (no building is on the site) = 1.; The transaction includes land and building = 0.	(0, 1)
<i>OD</i>	Old house dummy***	The transaction includes existing buliding which can not be used = 1.; The transaction doesn't include exsiting building which can be used = 0.	(0, 1)
<i>BA</i>	Balcony area	Balcony area.	m ²
<i>BLR</i>	Building-to-land ratio	Building-to-land ratio regulated by City Planning Law	%
<i>FAR</i>	Floor area ratio	Floor area ratio regulated by City Planning Law	%

Abbreviation	Variable	Description	Unit
WD_k	Ward dummies	Located in ward $k = 1$; Located in other ward = 0. ($k = 0, \dots, K$)	(0, 1)
RD_l	Railway line dummies	Located on railway line $l = 1$; Located on other railway line = 0. ($l = 0, \dots, L$)	(0, 1)
TD_m	Time dummies (monthly)	Month $m = 1$; Other month = 0. ($m = 0, \dots, M$)	(0, 1)

* The new building standard law established earthquake-resistance standards.

** The building standard law prohibits the construction of a building if the site faces a road which is narrower than 2 meters. If the site does not face a road which is wider than 2 meters, the site must provide a part of its own site as a part of the road.

*** If there is an existing building which cannot be used, the buyer has to pay the demolition costs.

Table 1 shows a list of the attributes of a house. Key attributes include the *ground area* of the land plot (GA), the *floor space area* of the structure (FS), and the front *road width* of the land plot (RW). The land plot area was available in the original dataset for single family houses but not for condominiums, so SNW estimated the land area that could be attributed to a condominium unit by dividing the land area of the property by the number of units in the structure.³¹ The age of a detached house was defined as the number of quarters between the date of the construction of the house and the transaction. SNW constructed a dummy (south-facing dummy, SD) to indicate whether the windows of a house are south-facing or not.³² The private road dummy, PD , indicated whether a house had an adjacent private road or not. The land only dummy, LD , indicated whether a transaction was only for land without a building or not. The convenience of public transportation from a house was represented by the travel time to the central business district (CBD),³³ which was denoted by TT , and the time to the nearest station,³⁴ which was denoted by TS . SNW used a ward dummy, WD , to indicate differences in the quality of public services available in each district, and a railway line dummy, RD , to indicate along which railway or subway line a house is located.

SNW used their Tokyo data sets on detached houses and condominiums to construct housing price indexes that used the hedonic regression and repeat sales models that were described in section 2 above. Table 2 compares the sample SNW used in their hedonic re-

³¹More specifically, the imputed land area attributed to a condo unit was calculated by dividing the sum of the floor space for each unit in the structure by $FAR \times BLR$, where FAR and BLR stand for the floor area ratio and the building to land ratio, respectively. The sum of the floor space of each unit in a structure was available in the original dataset. The maximum values for FAR and BLR are subject to regulation under city planning law. It was assumed that this regulation was binding.

³²Japanese people are particularly fond of sunshine!

³³Travel time to the CBD was measured as follows. The metropolitan area of Tokyo is composed of wards and contains a dense railway network. Within this area, SNW chose seven railway or subway stations as central business district stations: Tokyo, Shinagawa, Shibuya, Shinjuku, Ikebukuro, Ueno, and Otemachi. SNW then defined travel time to the CBD as the minutes needed to commute to the nearest of the seven stations in the daytime.

³⁴The time to the nearest station, TS , was defined as the walking time to the nearest station if a house was located within walking distance from a station, and the sum of the walking time to a bus stop and the bus travel time from the bus stop to the nearest station if a house is located in a bus transportation area. SNW used a bus dummy, BD , to indicate whether a house was located in walking distance from a railway station or in a bus transportation area.

gressions and the sample used in their repeat sales regressions. Since repeat sales regressions use only observations from houses that are traded multiple times, the repeat sales sample is a subset of the hedonic sample. The ratio of the repeat sales sample to the hedonic sample is 42.7 percent for condominiums and 6.1 percent for single family houses, indicating that single family houses are less likely to appear multiple times on the market.

The average price for condominiums was 38 million yen in the hedonic sample, while it was 44 million yen in the repeat sales sample. On the other hand, the average price for single family houses was 79 million yen in the hedonic sample and 76 million yen in the repeat sales sample. Turning to the attributes or characteristics of houses and condos, houses in the repeat sales sample tended to be larger in terms of the floor space, and more conveniently located in terms of time to the nearest station and travel time to a central business district, although these differences are not statistically significant. An important and statistically significant difference between the two samples was the average age of units in the case of single family houses: namely, the repeat sales sample consisted of houses that were constructed relatively recently. Somewhat interestingly, single family houses in the repeat sales sample were larger in terms of floor space, more conveniently located, more recently constructed, but were less expensive.

Table 2. Hedonic vs. repeat sales samples

Variable	Condominiums		Single family houses	
	Hedonic sample	Repeat sales sample	Hedonic sample	Repeat sales sample
Average price (10,000 yen)	3,862.26 (3,190.83)	4,463.43 (4284.10)	7,950.65 (8275.04)	7,635.24 (7055.96)
<i>FS</i> : Floor space (m ²)	58.31 (21.47)	59.54 (24.09)	102.53 (43.47)	105.82 (45.60)
<i>GA</i> : Ground area (m ²)	23.39 (12.79)	20.53 (11.97)	108.20 (71.19)	101.41 (63.17)
<i>Age</i> : Age of building (quarters)	55.61 (33.96)	60.07 (34.05)	54.06 (32.28)	21.26 (30.88)
<i>TS</i> : Time to the nearest station (minutes)	7.96 (4.43)	7.77 (4.28)	9.85 (4.54)	9.60 (4.37)
<i>TT</i> : Travel time to central business district (minutes)	12.58 (7.09)	10.73 (6.88)	13.23 (6.34)	11.89 (6.18)
	<i>n</i> = 157,627	<i>n</i> = 67,436	<i>n</i> = 315,791	<i>n</i> = 19,428

3.2 Estimation Results

Table 3 presents the regression results obtained by Shimizu, Nishimura and Watanabe (2010) for the standard hedonic model given by equation (4). This model worked well, both for condominiums and single family houses: the adjusted R^2 was 0.882 for condominiums and 0.822 for single family houses. The coefficients of interest are the ones associated with the age effect. The estimates of δ and λ are 0.033 and 0.691 for condominiums, implying that the initial capital stock of structures declines to 0.457 after 100 quarters, and that the average annual geometric depreciation rate for 100 quarters is 0.031. On the other hand, the estimates of δ and λ for single family houses are 0.020 and 0.688, implying that the initial capital stock of structures declines to 0.619 after 100 quarters, and that the average annual depreciation rate for 100 quarters is 0.019. These estimated depreciation rates seem to be quite reasonable.

Table 4 presents the SNW regression results for the age adjusted repeat sales model given by equation (8). The estimates for $\beta\delta$ and λ were 0.0098 and 0.894 for condominiums, and 0.002 and 1.104 for single family houses. Note that the repeat sales regressions do not allow us to estimate β and δ separately. If estimates of β are borrowed from the hedonic regressions, the repeat sales regression value of δ turned out to be 0.019 for condominiums and 0.004 for single family houses. These estimates imply that the average annual rate of depreciation for 100 quarters is 0.045 for condominiums and 0.025 for single family houses. Figure 1 compares the hedonic and repeat sales regressions in terms of the estimated age effect. It can be seen that the estimates from the repeat sales regressions indicate slightly faster depreciation than the ones from the hedonic regressions both for condominiums and for single family houses, although the difference is not very large.

Next, turn to the bottom panel of Table 4, which looks at the regression performance of the three types of repeat sales measures: the standard repeat sales index defined by equations (6) or (7), the heteroskedasticity adjusted repeat sales index (i.e., the Case-Shiller index), and the age adjusted repeat sales index defined by (8).³⁵ It can be seen that the age adjusted repeat sales index performed better than the standard one for both condominiums and single family houses. On the other hand, SNW failed to find a significant difference between the age adjusted index and the Case-Shiller index.

³⁵Note that the estimated coefficient for λ in the age adjusted repeat sales model was 0.89 for condos and 1.10 for single family houses. Thus the exact multicollinearity problem does not arise for these regressions.

Table 3. Hedonic regressions

Variable	Condominiums		Single family houses	
	Coefficient	<i>t</i> -value	Coefficient	<i>t</i> -value
Constant	3.263	372.920	4.508	265.376
<i>GA</i> : Ground area (m ²)	0.593	21.499	0.548	48.189
<i>TS</i> : Time to the nearest station (minutes)	-0.083	-86.748	-0.118	-129.946
<i>Bus</i> : Bus dummy	-0.313	-11.461	-0.079	-2.862
<i>Car</i> : Car Dummy	-	-	-0.408	-6.497
<i>Bus</i> × <i>TS</i>	0.070	6.453	-0.026	-2.580
<i>Car</i> × <i>TS</i>	-	-	0.068	2.330
<i>TT</i> : Travel time to central business district (minutes)	-0.041	-30.952	-0.076	-83.494
<i>MC</i> : Management cost	0.045	16.135	-	-
<i>UV</i> : Unit volume	0.024	33.752	-	-
<i>BBD</i> : Before new building standard law dummy	-0.085	-126.640	-0.093	-48.965
<i>SRC</i> : Steel reinforced concrete dummy	0.018	33.620	-	-
<i>BA</i> : Balcony area (m ²)	0.029	69.850	-	-
<i>RW</i> : Road width (10cm)	-	-	0.190	142.685
<i>PD</i> : Private road dummy	-	-	-0.001	-2.973
<i>LD</i> : Land only dummy	-	-	0.227	45.634
<i>SD</i> : South facing dummy	0.003	2.203	0.004	1.940
<i>OD</i> : Old house dummy	-	-	-0.103	-56.412
<i>BLR</i> : Building-to-land ratio	0.075	56.572	0.065	18.677
<i>FAR</i> : Floor area ratio	0.039	6.807	0.029	16.347
<i>FS</i> : Floor space (m ²)				
β	0.528	20.171	0.487	45.103
<i>Age</i> : Age of building (quarters)				
δ	0.033	4.153	0.020	2.423
λ	0.691	98.590	0.688	45.850
		<i>n</i> = 714, 506		<i>n</i> = 1, 540, 659
Log likelihood		391552.980		-5138.987
Prob > χ^2 =		0.000		0.000
Adjusted <i>R</i> ² =		0.882		0.822

Note : The dependent variable in each case is the log of the price.

Table 4. Age-adjusted repeat sales regressions

	$\beta\delta$	λ
Condominiums		
Coef.	0.0098	0.8944
Std. err.	0.0004	0.0113
<i>p</i> -value	[.000]	[.000]
Single family houses		
Coef.	0.0019	1.1041
Std. err.	0.0002	0.0269
<i>p</i> -value	[.000]	[.000]

	Standard error of reg.	Adjusted R^2	S.B.I.C.
Condominiums			
Standard repeat sales	0.175	0.751	-20311.0
Case-Shiller repeat sales	0.191	0.760	-12925.4
Age-adjusted repeat sales	0.190	0.761	-13246.6
Single family houses			
Standard repeat sales	0.211	0.478	-2087.0
Case-Shiller repeat sales	0.218	0.511	-1136.1
Age-adjusted repeat sales	0.218	0.513	-1176.4

S.B.I.C.: Schwarz's Bayesian information criterion

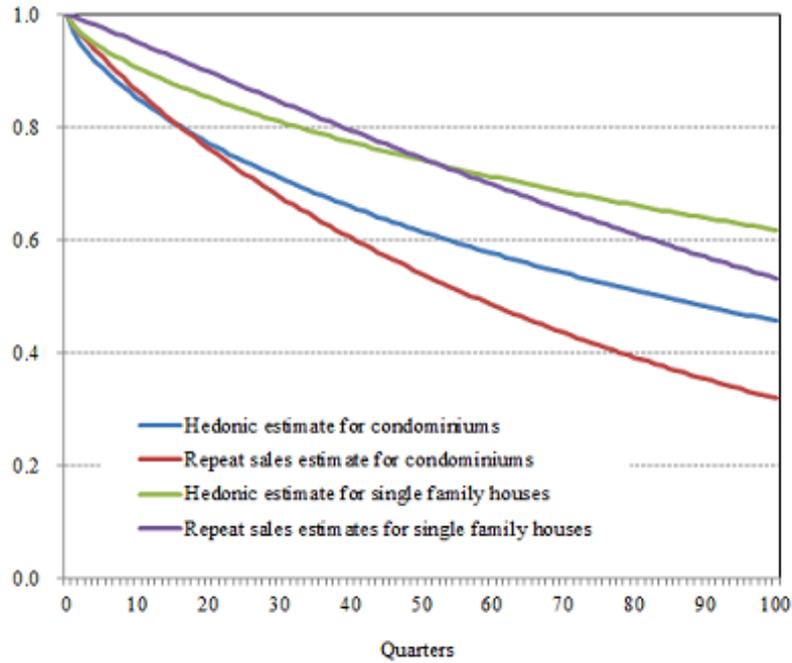


Figure 1. Estimated depreciation curves

Following the Rolling Year methodology introduced by Shimizu, Takatsuji, Ono and Nishimura (2010), Shimizu, Nishimura and Watanabe (2010) estimated the hedonic model defined by (4) using a window length of 12 months. Their results for the structural parameters (averaged over all regressions of window length 12) are presented in Table 5, which compares key parameters of the standard hedonic model and the corresponding rolling year hedonic models. For condominiums, it can be seen that the average value of each parameter estimated by the rolling hedonic regression was close to the estimate obtained by the standard hedonic regression. For example, the parameter associated with the floor space of a house was 0.528 using the standard time dummy hedonic regression model defined by (4) where the entire sample was used in the single regression, while the average value of the corresponding parameters estimated by the rolling window regression was 0.517. More importantly, SNW found that the estimated structural parameters fluctuated considerably during the sample period. For example, the parameter associated with the floor space of a house fluctuated between 0.508 and 0.539, indicating that non-negligible structural changes occurred during the sample period. Similar structural changes occurred for single family houses.

Table 5. Standard vs. rolling window regressions

	Const.	<i>FS</i>	<i>GA</i>	<i>Age</i> ($\beta\delta$)	(λ)	<i>TS</i>	<i>TT</i>
Condominium prices							
Standard hedonic model	3.263	0.528	0.593	0.017	0.691	-0.083	-0.041
12-month rolling regression							
Average	3.200	0.517	0.608	0.016	0.690	-0.082	-0.042
Standard deviation	0.086	0.079	0.040	0.001	0.035	0.015	0.013
Minimum	2.988	0.508	0.562	0.019	0.654	-0.097	-0.069
Maximum	3.429	0.539	0.613	0.011	0.710	-0.051	-0.025
Single family house prices							
Standard hedonic model	4.508	0.487	0.548	0.010	0.688	-0.118	-0.076
12-month rolling regression							
Average	4.691	0.485	0.532	0.006	0.681	-0.101	-0.079
Standard deviation	0.176	0.021	0.098	0.001	0.029	0.003	0.002
Minimum	4.496	0.480	0.512	0.007	0.670	-0.110	-0.079
Maximum	4.742	0.495	0.558	0.006	0.700	-0.041	-0.048

Number of models = 265

Note: *FS*: Floor space
GA: Ground area
Age: Age of building
TS: Time to the nearest station
TT: Travel time to central business district

3.3 Reconciling the Differences between the Five Models

Shimizu, Nishimura and Watanabe (2010) estimated the 5 models explained in section 2 above using their Tokyo data sets for both detached houses and condominiums.³⁶ Figure 2 shows the estimated five indexes for condominiums. The age adjusted repeat sales index starts in the fourth quarter of 1989, while the other four indexes start in the first quarter of 1986. To make the comparison easier, the indexes are normalized so that they are all equal to unity in the fourth quarter of 1989. The first thing that can be seen from this Figure is that there is almost no difference between the standard repeat sales index and the Case-Shiller repeat sales index. This suggests that heteroskedasticity due to heterogeneous transaction intervals may not be very important as far as the Japanese housing market is concerned. Second, the age adjusted repeat sales index behaves differently from the other two repeat sales indexes. Specifically, it exhibits a less rapid decline in the 1990s, i.e., the period when the bubble burst. This difference reflects the relative importance of the age effect, implying that the other two repeat sales indexes, which pay no attention to the age effect, tend to overestimate the magnitude of the burst of the bubble; i.e., the standard repeat sales indexes have the predictable downward bias due to their neglect of depreciation. Third, the two hedonic indexes exhibit a less rapid decline in the 1990s than the standard and the Case-Shiller repeat sales indexes, and the discrepancy between them tends to increase over time in the rest of the sample period.³⁷

Figure 3 shows the estimated indexes for single family houses. We see that the three repeat sales indexes and the standard hedonic index tend to move together, but the rolling hedonic index behaves differently from them. The spread between the rolling hedonic index and the other four indexes tends to expand gradually in the latter half of the 1990s, suggesting the presence of some gradual shifts in the structural parameters during this period.³⁸

³⁶Their Rolling Window results used a window length of 12 months and used the updating procedure explained at the end of section 2 above.

³⁷Note that the age adjusted repeat sales index is well above the other two repeat sales indexes which do not make an adjustment for depreciation of the structure. This result is to be expected. What is perhaps more surprising is that the age adjusted repeat sales index ends up well below the two hedonic indexes. This result may be due to sample selectivity bias in the repeat sales method or to an incorrect specification of the hedonic models.

³⁸The annual depreciation rate for houses appears to be much smaller than the corresponding rate for condos and thus the age bias in the repeat sales models will be much smaller for houses than for condos. The relatively large differences in the two hedonic indexes is a bit of a puzzle. Diewert and Shimizu (2013) also compared Rolling Window house price indexes with a corresponding index based on a single time dummy regression and did not find large differences (but the sample period was much shorter in the Diewert and Shimizu study).

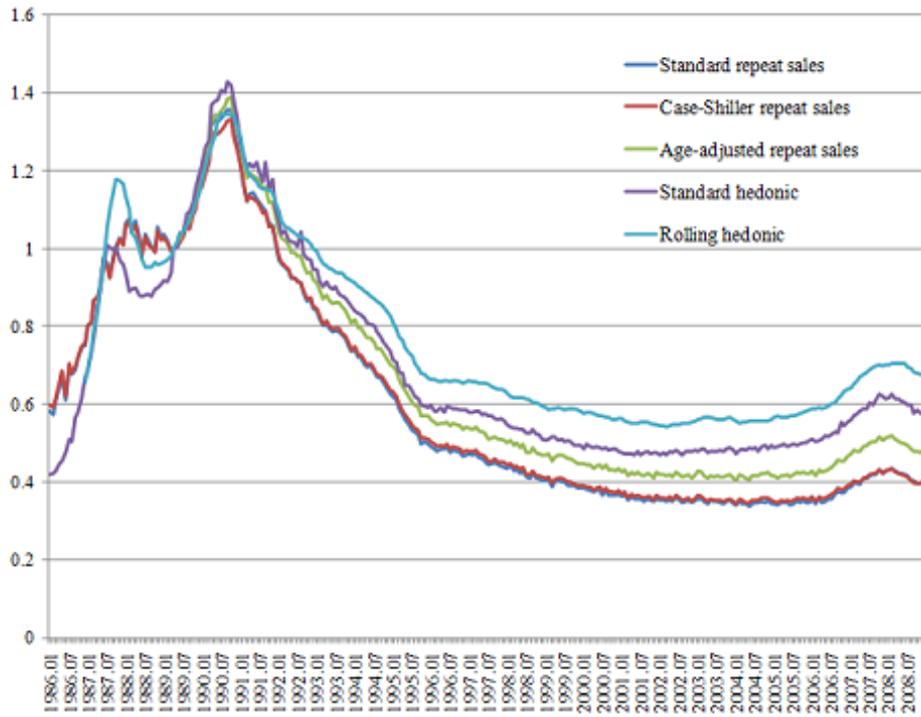


Figure 2. Estimated five indices for condominiums

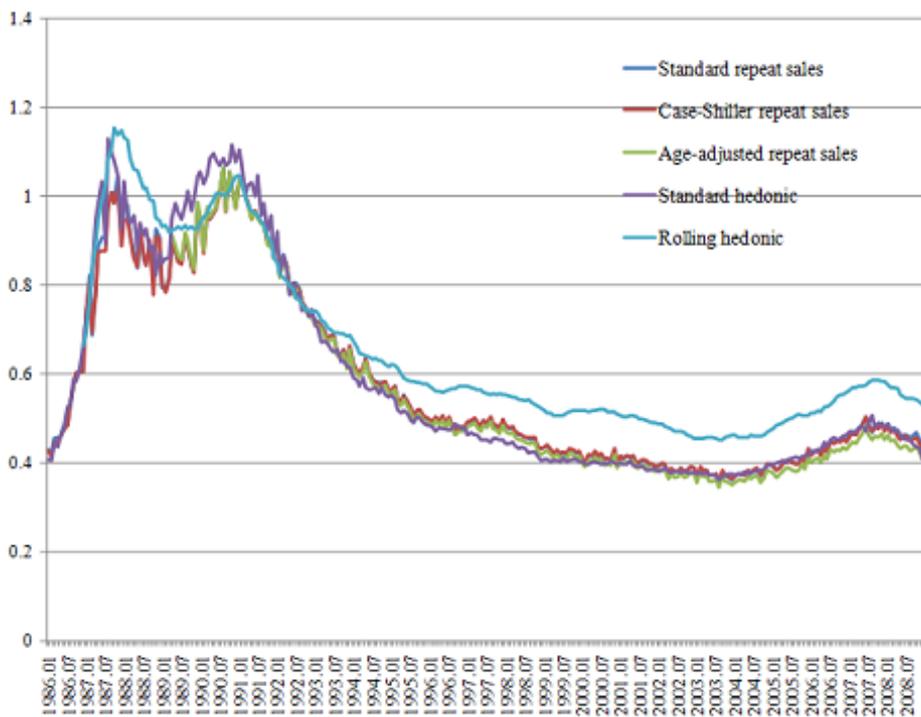


Figure 3. Estimated five indices for single family houses

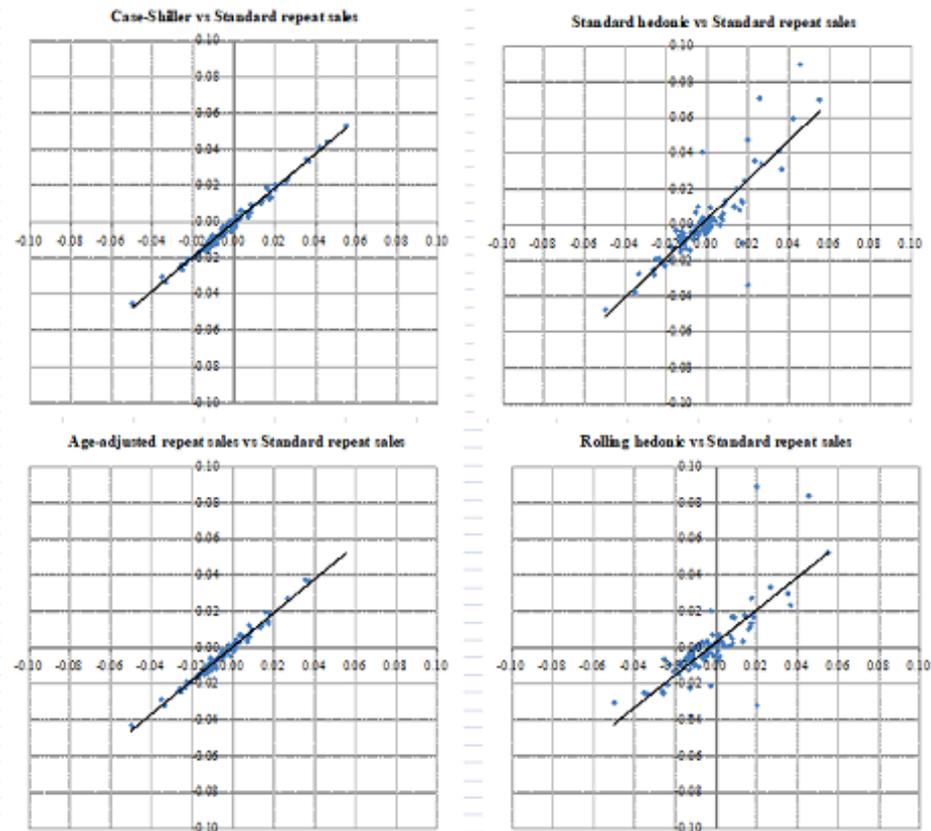


Figure 4. Comparison of the five indexes in terms of the quarterly growth rate

SNW compared the five indexes for condominiums in terms of their quarterly growth rates. The results are presented in Figure 4. The horizontal axis in the upper left panel represents the growth rate of the standard repeat sales index, while the vertical axis represents the growth rate of the Case-Shiller repeat sales index. One can clearly see that almost all dots in this panel are exactly on the 45 degree line, implying that these two indexes are closely correlated with each other. In fact, the coefficient of correlation is 0.995 at the quarterly frequency, and 0.974 at the monthly frequency. Regressing the quarterly growth rate of the Case-Shiller repeat sales index, denoted by y , on that of the standard repeat sales index, denoted by x , SNW obtained $y = 0.9439x - 0.0002$, indicating that the coefficient on x and the constant term are very close to unity and zero, respectively. Similarly, the lower left panel of Figure 4 compares the growth rate of the standard repeat sales index and the age-adjusted repeat sales index. Again, almost all dots are on the 45 degree line, indicating a high correlation between the two indexes (the coefficient of correlation is 0.991 at the quarterly frequency and 0.953 at the monthly frequency). However, the regression results show that the constant term is slightly above zero, indicating that the growth rates for the age adjusted repeat sales index are, on average, slightly higher than those for the standard repeat sales index. Turning to the upper right panel, which compares the standard hedonic index and the standard repeat sales index, the dots are again scattered along the

45 degree line but not exactly on it, indicating a lower correlation than before (0.845 at the quarterly frequency and 0.458 at the monthly frequency). More importantly, SNW obtained $y = 1.0948x + 0.0036$ by regressing the standard hedonic index on the standard repeat sales index, and the constant term turned out to be positive and significantly different from zero. In other words, the standard hedonic index tends to grow faster than the standard repeat sales index, which is consistent with what is seen in Figure 2.³⁹ Finally, the lower right panel compares the standard repeat sales index and the rolling hedonic index, showing that the two indexes are more weakly correlated (0.773 at the quarterly frequency and 0.444 at the monthly frequency), and that the rolling hedonic index tends to grow faster than the standard repeat sales index.

SNW also regressed the quarterly growth rate of one of the five indexes, say index A, on the quarterly growth rate of another index, say index B, to obtain a simple linear relationship $y = a + bx$. They then conducted an F -test against the null hypothesis that $a = 0$ and $b = 1$. The results of this exercise are presented in Table 6, where the number in each cell represents the p -value associated with the null hypothesis that $a = 0$ and $b = 1$ in a regression in which the index in the corresponding row is the dependent variable while the index in the corresponding column is the independent variable. For example, the number in the lower left corner of the upper panel, 0.0221, represents the p -value associated with the null hypothesis in the regression in which the growth rate of the rolling hedonic index is the dependent variable and the growth rate of the standard repeat sales index is the independent variable. The upper panel, which presents the results for condominiums, shows that in almost all cases the null hypothesis cannot be rejected. However, there are two cases in which the p -value exceeds 10 percent: when the standard hedonic index is regressed on the age adjusted repeat sales index (p -value = 0.2120), and when the rolling hedonic index is regressed on the standard hedonic index (p -value = 0.1208). Looking at the lower panel of Table 6, which presents the results for single family houses, we see that there are more cases in which the null hypothesis is rejected. For example, the p -value is very high at 0.7661 when the standard hedonic index is regressed on the standard repeat sales index, so that the null hypothesis that the hedonic and the repeat sales indexes are close to each other can easily be rejected.

³⁹It can be seen from the upper right panel of Figure 4 that several dots in the right upper quadrant are well above the 45 degree line, indicating that the growth rates of the standard hedonic index are substantially higher than those of the standard repeat sales index at least for these quarters. These dots correspond to the quarters between 1986 and 1987, during which the standard hedonic index exhibited much more rapid growth than the standard repeat sales index, as was seen in Figure 2.

Table 6. Contemporaneous relationship between the five measures

Condominiums					
	Standard repeat sales	Case-Shiller repeat sales	Age-adjusted repeat sales	Standard hedonic	Rolling hedonic
Standard repeat sales	–	0.0015	0.0001	0.0001	0.0001
Case-Shiller RS	0.0001	–	0.0001	0.0001	0.0001
Age-adjusted RS	0.0001	0.0001	–	0.0216	0.0058
Standard hedonic	0.0121	0.0028	0.2120	–	0.0057
Rolling hedonic	0.0221	0.0408	0.0001	0.1208	–
Single family houses					
	Standard repeat sales	Case-Shiller repeat sales	Age-adjusted repeat sales	Standard hedonic	Rolling hedonic
Standard repeat sales	–	0.8740	0.0104	0.0001	0.1029
Case-Shiller RS	0.6461	–	0.0001	0.0002	0.1122
Age-adjusted RS	0.0369	0.0001	–	0.0070	0.2819
Standard hedonic	0.7661	0.8889	0.0008	–	0.6547
Rolling hedonic	0.0001	0.0001	0.0001	0.0001	–

Note: We regress the quarterly growth rate of index A, y , on the quarterly growth rate of index B, x , to obtain the simple linear relationship $y = a + bx$. The number in each cell represents the p -value associated with the null hypothesis that $a = 0$ and $b = 1$ in the regression in which the index in the row is the dependent variable and the index in the column is the independent variable.

The presence of a close contemporaneous correlation in terms of quarterly growth rates between the five indexes does not immediately imply that the five indexes perfectly move together. It is still possible that there exist some lead-lag relationships between the five indexes. For example, one index may tend to precede the other four indexes. To investigate such dynamic relationships between the five indexes, SNW conducted pairwise Granger causality tests. The results for condominiums and single family houses are presented, respectively, in the upper and lower panels of Table 7. The number in each cell represents the p -value associated with the null hypothesis that the index in a particular row does not Granger-cause the index in the column. For example, the number in the cell in the third row and second column, 0.2018, represents the p -value associated with the null hypothesis that the Case-Shiller type repeat sales index does not cause the standard repeat sales index. The panel for condominiums shows that one can easily reject the null that the standard hedonic index does not cause the other four indexes. On the other hand, one cannot reject the null that each of the other four indexes does not cause the standard hedonic index. These two results indicate that fluctuations in the standard hedonic index tend to precede those in the other four indexes. The same property was observed for single family houses. To illustrate such lead-lag relationships between the five indexes, SNW compared them in terms of the timing in which each index bottomed out after the bursting of the housing bubble in the early 1990s. The result for condominiums is presented in Figure 5. It can be seen that all of the three repeat sales indexes bottom out simultaneously in the first quarter of 2004. In

contrast, the two hedonic indexes bottom out in the first quarter of 2002, indicating that the turn in the hedonic indexes preceded the one in the repeat sales indexes by two years.

Table 7. Pairwise Granger-causality tests

Condominiums					
	Standard repeat sales	Case-Shiller repeat sales	Age-adjusted repeat sales	Standard hedonic	Rolling hedonic
Standard repeat sales	–	0.0120	0.0019	0.0039	0.0000
Case-Shiller RS	0.2018	–	n.a.	0.0398	0.0000
Age-adjusted RS	0.0568	n.a.	–	0.1258	0.0000
Standard hedonic	0.0004	0.0001	0.0000	–	0.0000
Rolling hedonic	0.0053	0.0082	0.0022	0.1528	–

Single family houses					
	Standard repeat sales	Case-Shiller repeat sales	Age-adjusted repeat sales	Standard hedonic	Rolling hedonic
Standard repeat sales	–	0.2726	0.4345	0.1919	0.0048
Case-Shiller RS	0.2397	–	n.a.	0.1810	0.0088
Age-adjusted RS	0.3275	n.a.	–	0.1962	0.0078
Standard hedonic	0.0028	0.0028	0.0027	–	0.0048
Rolling hedonic	0.0812	0.0784	0.0781	0.1089	–

Note: The number in each cell represents the p -value associated with the null hypothesis that the variable in the row does not Granger-cause the variable in the column.

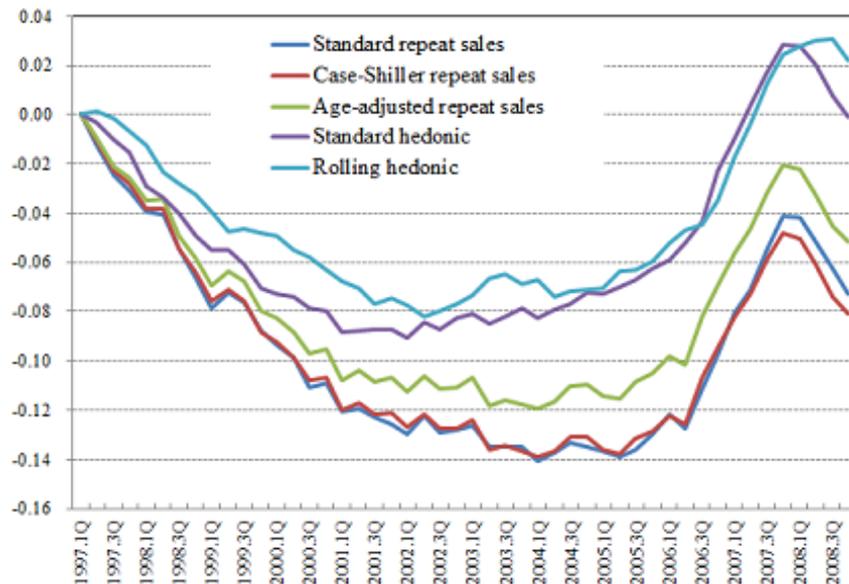


Figure 5. When did condominium prices hit bottom?

An important issue that needs to be addressed is where such lead-lag relationships between the hedonic and repeat sales indexes come from. There are at least two possibilities. First, the presence of the lead-lag relationships may be related to the omitted variable problem in hedonic regressions. It is possible that the variables omitted in hedonic regressions move only with some lags relative to the other variables, leading to an excessively quick response of the estimated hedonic indexes to various shocks. The second possibility is related to sample selection bias in the estimated repeat sales indexes.

As we saw in Table 2, the sample employed for producing the repeat sales index makes up only a very limited fraction of the total numbers of observations and, more importantly, might be biased in that it consists of houses whose prices exhibit a delayed response to various shocks.

How can we discriminate between these two possibilities? One way to identify the reason behind the relationships is to apply the hedonic regressions to the repeat sales sample (i.e., the sample consisting of houses that are traded multiple times).

The new hedonic index produced in this way and the standard hedonic index differ in terms of the sample employed but otherwise are identical in terms of the explanatory variables used, so that they suffer from the same omitted variables problem. Therefore, any remaining differences between the new and the standard hedonic index can be regarded as stemming from the difference in the sample employed. If a lead-lag relationship between the new and the standard hedonic index is still observed, this would imply that this lead-lag relationship is due to the sample selection bias in the repeat sales indexes.

Figure 6 presents the result of this exercise. SNW applied the hedonic regressions to four different samples: a sample of houses that were traded at least once (i.e., the entire sample); a sample of houses that were traded more than once (i.e., the original repeat sales sample); a sample of houses that were traded more than twice; and a sample of houses that were traded more than three times. SNW found that the indexes using the samples of houses that were traded more than once (“traded more than once,” “traded more than twice,” and “traded more than three times”) exhibited a later turn than the index estimated from the larger sample of houses that were “traded at least once,” suggesting that the lead-lag relationships between the hedonic and repeat sales indexes in Figure 5 mainly come from sample selection bias in the repeat sales indexes. Moreover, consistent with this interpretation, the delay in the turning point becomes even more pronounced when using the samples of houses “traded more than twice” and “traded more than three times.”

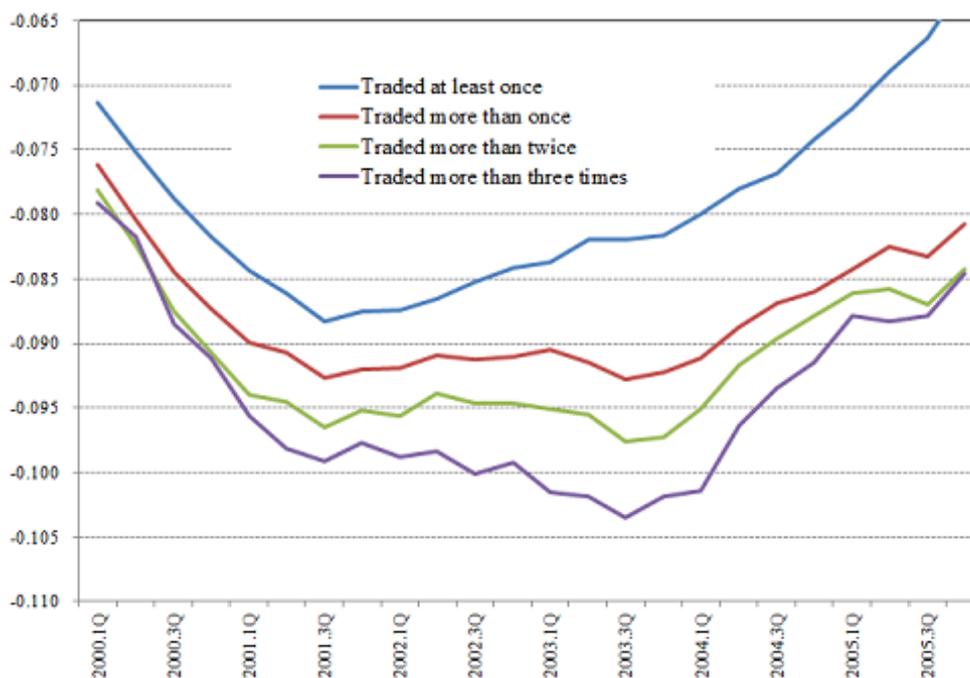


Figure 6. Hedonic indexes estimated using repeat-sales samples

4 The Selection of Data Sources for the Construction of Housing Price Indexes⁴⁰

4.1 Alternative Types of Real Estate Sales Prices

In constructing a housing price index, one has to make several nontrivial choices. One of them is the choice among alternative estimation methods, such as those discussed in section 2 above. There are numerous papers on this issue, both theoretical and empirical.⁴¹ However, there is another important issue which has not been discussed much in the literature, but has been regarded as critically important from a practical viewpoint: the *choice among different data sources for housing prices*. This is the topic to be discussed in this section.

There are several sources of data for housing prices:⁴²

⁴⁰The material in this section is drawn from Shimizu, Nishimura and Watanabe (2011) (2012). In this section, we will refer to these two papers as SNW.

⁴¹See for example Case, Pollakowski and Wachter (1991), Diewert (2010), Dorsey, Hua, Mayera and Wanga (2010), Eurostat (2011) and section 2 above. Recently, McMillen and Thorsnes (2006), McMillen (2012) and Deng, McMillen and Sing (2012) proposed a new index estimation method, the matching model method, which focused on the distribution of housing prices.

⁴²Eurostat (2011) provides a summary of the sources of price information in various countries. For example, in Bulgaria, Canada, the Czech Republic, Estonia, Ireland, Spain, France, Latvia, Luxembourg, Poland and the USA price data collected by statistical institutes or ministries is used. In Denmark, Lithuania, the Netherlands, Norway, Finland, Hong Kong, Slovenia, Sweden and the UK information gathered for registration or taxation purposes is used. In Belgium, Germany, Greece, France, Italy, Portugal and Slovakia data from real estate agents and associations, research institutes or property consultancies is used. Finally, in Malta, Hungary, Austria and Romania data from newspapers or websites is used.

- Data collected by real estate agencies and associations;
- Data collected by mortgage lenders;
- Data provided by government departments or institutions and
- Data gathered and provided by newspapers, magazines, and websites.

Needless to say, different data sets contain different types of prices, including *seller asking prices*, *transaction prices*, *assessor valuation prices*, and so on.

With multiple data sets available, one may ask several questions. Are these prices different? If so, how do they differ from each other? Given the specific purpose of the housing price index one seeks to construct, which data set is the most suitable? Alternatively, with only one data set available in a particular country, one may ask whether this is suitable for the purpose of the index one seeks to construct. Shimizu, Nishimura and Watanabe (2011) (2012) (abbreviated to SNW in this section) addressed these questions.⁴³ They conducted a statistical comparison of different house prices collected at different stages of the house buying and selling process. SNW collected four different types of prices:

- (1) Asking prices at which properties are initially listed in a realtor magazine;
- (2) Asking prices when an offer for a property is eventually made and the listing is removed from the magazine;
- (3) Contract prices reported by realtors after mortgage approval and
- (4) Land Registry prices.

SNW prepared data sets for these four types of price for condominiums traded in the Greater Tokyo Area from September 2005 to December 2009. The four prices are collected by different institutions and therefore recorded in different datasets: (1) and (2) are collected by a real estate advertisement magazine; (3) is collected by an association of real estate agents and (4) is collected jointly by the Land Registry and the Ministry of Land, Infrastructure, Transport and Tourism.

An important advantage of prices at earlier stages of the house buying/selling process, such as initial asking prices in a magazine, is that they are likely to be available earlier, so that house price indexes based on these prices become available in a timely manner. The issue of timeliness is important given that it takes more than 30 weeks before registry prices in Japan become available. On the other hand, it is often said that prices at different stages of the buying/selling process behave quite differently. For example, it is sometimes asserted that when the housing market is, say, in a downturn, prices at earlier stages of the buying/selling process, such as initial asking prices, will tend to be higher than prices at

⁴³There are several papers that focused on data sources for housing price indexes; see Gatzlaff and Haurin (1998), Genesove and Mayer (2001), Goetzmann and Peng (2006). However, these papers did not compare multiple data sources.

later stages. It is also asserted that, for various reasons, prices at earlier stages contain non-negligible amounts of “noise.”⁴⁴ For instance, prices can be renegotiated extensively before a deal is finalized, and not all of the prices appearing at earlier stages end in transactions because a potential buyer’s mortgage application is not always approved.⁴⁵

Do the four types of price for the same dwelling unit differ from each other, and if so, by how much? SNW focussed on the entire cross-sectional distribution for each of the four prices in order to determine whether the four prices are different or not.⁴⁶

Note that the cross sectional distributions for the four types of price may differ from each other simply because the datasets in which they are recorded contain houses with different characteristics. For example, the dataset from a realty magazine may contain more houses with a small floor space than the registry data set, which may give rise to different price distributions. Therefore, SNW tried to make adjustments to the various data sets so that like can be compared to like before comparing price distributions. They called this the *quality adjustment problem*.

SNW conducted quality adjustments in two different ways. The first was to only use the intersection of two different datasets, that is, observations that appeared in two data sets. For example, when testing whether initial asking prices in the magazine had a similar distribution as registry prices, they first identified houses that appear in both the magazine and registry data sets and then they compared the resulting two price distributions for those houses. In this way, they ensured that the two price distributions were not affected by differences in house attributes between the two data sets. This idea is quite similar to the one adopted in the repeat sales method, which is extensively used in constructing quality adjusted house price indexes. As is often pointed out, however, repeat sales samples may not necessarily be representative because houses that are traded multiple times may have certain characteristics that make them different from other houses.⁴⁷ A similar type of sample selection bias may arise even in the intersection approach. Houses in the intersection of the magazine dataset and the registry dataset are cases which successfully ended in a transaction. Put differently, houses whose initial asking prices were listed in the magazine but which failed to get an offer from buyers, or where potential buyers failed to get approval for a mortgage, are not included in the intersection.

The second method of quality adjustment used by SNW was based on hedonic regressions. This method is also widely used in constructing quality adjusted house price indexes. The

⁴⁴See Allen and Dare (2004), Haurin, Haurin, Nadauld and Sanders (2010), Knight, Sirmans and Turnbull (1998).

⁴⁵See Genesove and Mayer (1997) (2001) and Engelhardt (2003).

⁴⁶An alternative approach would be to compare the four prices in terms of their average prices or in terms of their median prices. However, these summary statistics capture only one aspect of cross-sectional price distributions.

⁴⁷As was noted in the previous section, Shimizu, Nishimura and Watanabe (2010) constructed five different house price indexes, including hedonic and repeat sales indexes, using Japanese data for 1986 to 2008. They found that there were substantial differences in terms of turning points between hedonic and repeat sales indexes. In particular, the repeat sales measure signaled turning points later than the hedonic measure. For example, the hedonic measure of condominium prices bottomed out at the beginning of 2002, while the corresponding repeat sales measure exhibited a reversal only in the spring of 2004.

hedonic regression that SNW employed differed from those used in previous studies, which are based on the assumption that the hedonic coefficient on, say, the size of a house is identical for high-priced and low-priced houses. This restriction on hedonic coefficients may not be problematic as long as one is interested in the mean or the median of a price distribution, but it is a serious problem when one is interested in the shape of the entire price distribution. In their papers, SNW used quantile hedonic regression techniques in which the hedonic coefficients were allowed to differ for high-priced and low-priced houses.

4.2 Condominium Prices in the Greater Tokyo Area from Alternative Sources

SNW collected the prices of condominiums traded in the Greater Tokyo Area from September 2005 to December 2009.⁴⁸ According to the register information published by the Japanese Legal Affairs Bureau, the total number of transactions for condominiums carried out in the Greater Tokyo Area during this period was 360,243. Ideally, SNW would have liked to collect price information for this entire “universe,” but they were only able to collect three subsets of this universe data set.

The first data set was collected by a weekly magazine, *Shukan Jutaku Joho* (Residential Information Weekly) published by Recruit Co., Ltd. This data set contains initial asking prices (i.e., the asking prices initially set by sellers), denoted by P_1 , and final magazine asking prices (i.e., asking prices immediately before they were removed from the magazine because potential buyers had made an offer), denoted by P_2 . The number of observations for P_1 and P_2 is 155,347, meaning that this dataset covers 43 percent of the universe. There may exist differences between P_1 and P_2 for various reasons. For example, if the housing market is in a downturn, a seller may have to lower the price to attract buyers. Then P_2 will be lower than P_1 . If the market is very weak, it is even possible that a seller may give up trying to sell the house and thus withdraws it from the market. If this is the case, P_1 is recorded but P_2 is not.

The second data set is a data set collected by an association of real estate agents. This dataset is compiled and updated through the Real Estate Information Network System, or REINS, a data network that was developed using multiple listing services in the United States and Canada as a model. This dataset contains transaction prices at the time when the actual sales contract are made, after the approval of any mortgages. They are denoted by P_3 . Each price in the dataset is reported by the real estate agent who is involved in the transaction as a broker. The number of observations is 122,547, for a coverage of 34 percent. Note that P_3 may be different from P_2 because a seller and a buyer may renegotiate the price even after the listing is removed from the magazine. It is possible that P_3 for a particular house is not recorded in the realtor data set although P_2 for that house is recorded in the magazine data set. Specifically, there are more than a few cases where the sale was

⁴⁸See Chapter 11 of Eurostat (2011) for detailed information on house price datasets currently available in Japan.

not successfully concluded because a mortgage application was turned down after the listing had been removed from the magazine.

The third data set was compiled by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). We refer to this data set as P_4 . In Japan, each transaction must be *registered* with the Legal Affairs Bureau, but the registered information does not contain transaction prices. To find out transaction prices, the MLIT sends a questionnaire to buyers to collect price information. The number of observations contained in this registry dataset is 58,949, for a coverage ratio of 16 percent. Since P_3 and P_4 are both transaction prices, there is no clear institutional reason for any discrepancy between the two prices for the sale of the same unit; however, it is still possible that these two prices differ, partly because they are reported by different parties: a real estate agent for P_3 and the buyer for P_4 . There may be reporting mistakes, intentional and unintentional, on the side of real estate agents, or on the side of buyers, or on both sides. Summary statistics for the three data sets are presented in Table 8.

Some housing units appear only in one of the three data sets, but others appear in two or three data sets. Using address information, SNW identified those housing units which appeared in two or all three of the data sets. For example, the number of dwelling units that appear both in the magazine data set and in the registry data set is 15,015; the number of housing units that are in the magazine data set but not in the registry data set is 140,332; and the number of housing units that are in the registry data set but not in the magazine data set is 43,934.⁴⁹ This clearly indicates that these two data sets contain a large number of different housing units, implying that the statistical properties of the two data sets may be substantially different. This suggests that it may be possible that the three data sets produce three different house price indexes, which behave quite differently, even if the identical estimation method is applied to each of the data sets.

⁴⁹The number of housing units that appear both in the realtor data set and in the registry data set is 22,613; the number of housing units that are in the realtor data set but not in the registry data set is 99,934; and the number of housing units that are in the registry data set but not in the realtor data set is 36,336.

Table 8. Summary of the three datasets

Magazine data (P_1, P_2) : completed				
	Mean	Std. Dev.	Min.	Max.
Magazine data: completed (155,347 observations)				
P_1 : First asking price (10,000 Yen)	2,958.51	1,875.16	200	33,000
P_2 : Final asking price (10,000 Yen)	2,889.27	1,831.34	200	29,800
log P_1 : Log of P_1	7.84	0.54	5.77	10.40
log P_2 : Log of P_2	7.82	0.54	5.77	10.30
FS : Floor space (m ²)	66.77	18.97	10.39	243.90
P_1/FS (10,000 Yen)	43.59	21.65	10.87	195.68
P_2/FS (10,000 Yen)	42.58	21.16	10.00	189.08
AGE : Age of building (years)	16.59	10.26	1.50	58.93
DS : Distance to the nearest station (m)	850.42	729.86	80	9,900
TT : Travel time to terminal station (minutes)	20.97	12.61	2	89
Magazine data (P_{1w}) : not completed				
	Mean	Std. Dev.	Min.	Max.
Magazine data: not completed (58,300 observations)				
P_{1w} : First asking price (10,000 Yen)	3,156.06	2,385.91	198	34,800
log P_{1w} : Log of P_{1w}	7.86	0.61	5.29	10.46
FS : Floor space (m ²)	66.99	20.91	10.60	250.00
P_{1w}/FS (10,000 Yen)	46.90	26.01	4.44	561.17
AGE : Age of building (years)	17.08	10.63	1.00	51.42
DS : Distance to the nearest station (m)	717.27	408.95	50	9,120
TT : Travel time to terminal station (minutes)	21.05	13.05	2	89
Realtor data (P_3)				
	Mean	Std. Dev.	Min.	Max.
Realtor data (122,547 observations)				
P_3 : Sales price (10,000 Yen)	2,431.81	1,632.88	160	29,074
log P_3 : Log of P_3	7.60	0.64	5.08	10.28
FS : Floor space (m ²)	64.87	20.27	10.10	238.81
P_3/FS (10,000 Yen)	37.44	19.65	10.00	187.96
AGE : Age of building (years)	16.79	10.38	1.50	57.14
DS : Distance to the nearest station (m)	881.37	804.67	80	9,900
TT : Travel time to terminal station (minutes)	23.21	13.65	2	89
Registry data (P_4)				
	Mean	Std. Dev.	Min.	Max.
Registry data (58,949 observations)				
P_4 : Sales price (10,000 Yen)	2,316.32	1,633.34	130	28,000
log P_4 : Log of P_4	7.53	0.68	4.87	10.24
FS : Floor space (m ²)	57.52	23.58	10.09	196.46
P_4/FS (10,000 Yen)	41.38	21.53	10.00	189.83
AGE : Age of building (years)	16.21	9.83	1.50	59.40
DS : Distance to the nearest station (m)	842.77	719.73	50	9,910
TT : Travel time to terminal station (minutes)	21.23	13.51	2	89

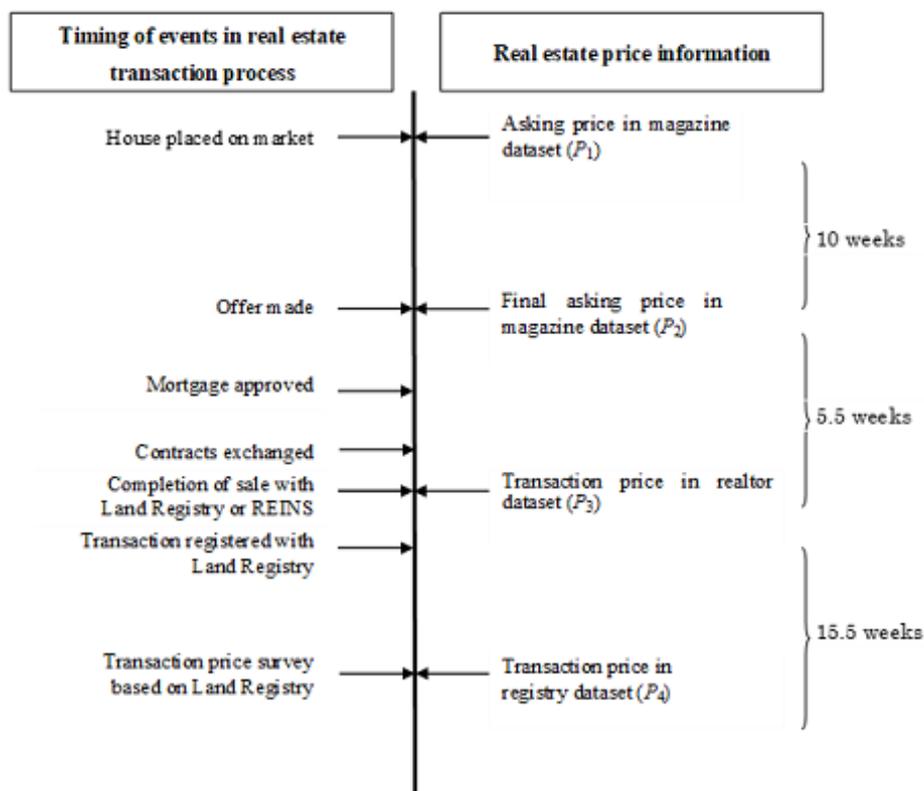


Figure 7. House purchase timeline

Figure 7 shows the timing at which each of the four prices, P_1 , P_2 , P_3 and P_4 , was observed in the house buying/selling process in Japan. There was a time lag of 70 days, on average, between the time when P_1 is observed (i.e., the time at which a seller posts an initial asking price in the magazine) and the time when P_2 was observed (i.e., the time when an offer was made by a buyer and the listing was removed from the magazine). Similarly, there was a lag of 38 days between the time at which P_3 was observed (i.e., the time at which a mortgage was approved and a contract was made) and the time at which P_2 was observed. Finally, there was a lag of 108 days between the time at which P_4 was observed (i.e., the time at which the MLIT received price information from a buyer) and the time at which P_3 was observed. In total, the time lag between P_1 and P_4 is, on average, 216 days, implying that a house price index can be available to the public much earlier by using P_1 instead of P_4 . At the same time, it may be the case that prices at the earlier stages of the house buying/selling process, such as P_1 , are not reliable since they are frequently updated up or down until a final contract has been reached. In addition, it is often pointed out that not all of the prices observed at the earlier stage of the house buying/selling process end in transactions.⁵⁰

⁵⁰Eurostat (2011: 147) sums up the situation as follows: “Each source of prices information has its advantages and disadvantages. For example a disadvantage of advertised prices and prices on mortgage applications and approvals is that not all of the prices included end in transactions, and the price may differ from the final negotiated transaction price. But these prices are likely to be available sometime before the

According to the land registry information, the day on which P_3 was observed and the day on which registration was made at the land registry were identical for 93 percent of all transactions. This means that the time lag between P_3 and P_4 mainly reflected the number of days it took for the MLIT to collect price information from buyers. Note that this type of time lag does not occur in most other industrialized countries, including the U.S. and the U.K., where the land registry requires sellers and/or buyers to report transaction prices as part of the registration information. However, according to Eurostat (2011), even in the U.K., there exists a long time lag between completion of the contract and the registration of property ownership transfers; that is, registration is typically completed only 4-6 weeks after the completion of transactions. This lack of timeliness means that price information gathered from the land registry is of limited usefulness in constructing *timely* house price indexes.

Figure 8 shows how time lags are distributed for the four prices. For example, the solid line represents the distribution of the time lag between the day P_1 and the day P_2 are observed for a particular property. It can be seen that more than fifty percent of all observations are concentrated at a time lag of 50 days, but there is a non-negligible probability that the time lag exceeds 150 days. Similarly, the time lag between P_1 and P_4 is most likely to be 200 days, but it is possible, although with a low probability, that it may be more than 300 days.

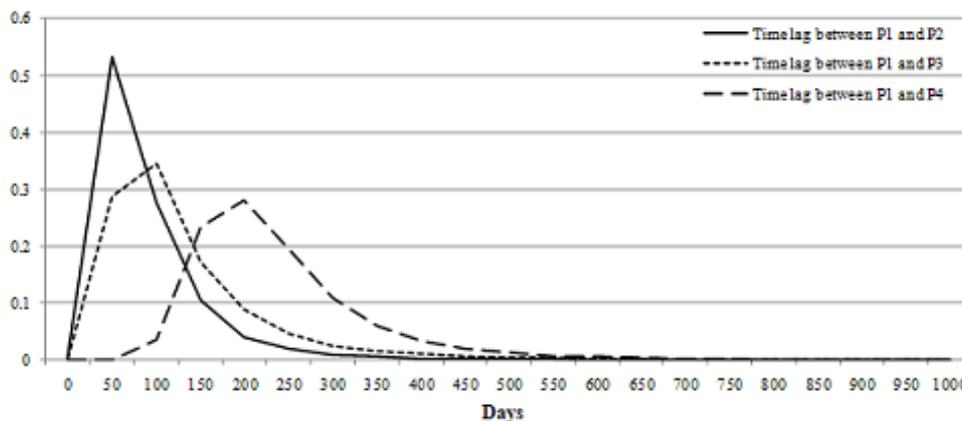


Figure 8. Intervals between events in the house buying/selling process

Figure 9 shows the cross-sectional distributions for the log of the four prices that SNW obtained in their empirical study of condo prices in Tokyo. The horizontal axis represents the log price while the vertical axis represents the corresponding density. It can be seen that the distributions of P_1 and P_2 are quite similar to each other. On the other hand, the distribution of P_3 differs substantially from the distribution of P_2 ; namely, the distribution of P_2 is almost symmetric, while the distribution of P_3 has a thicker lower tail, implying that the sample of P_3 contains more low-priced houses than the sample of P_2 . This difference in the

final transaction price. Indices that measure the price earlier in the purchase process are able to detect price changes first, but will measure final prices with error because prices can be renegotiated extensively before the deal is finalized.”

two distributions may be a reflection of differences in prices at different stages of the house buying/selling process, but it is also possible that the difference in the price distributions may come from differences in the characteristics of the houses in the two datasets.

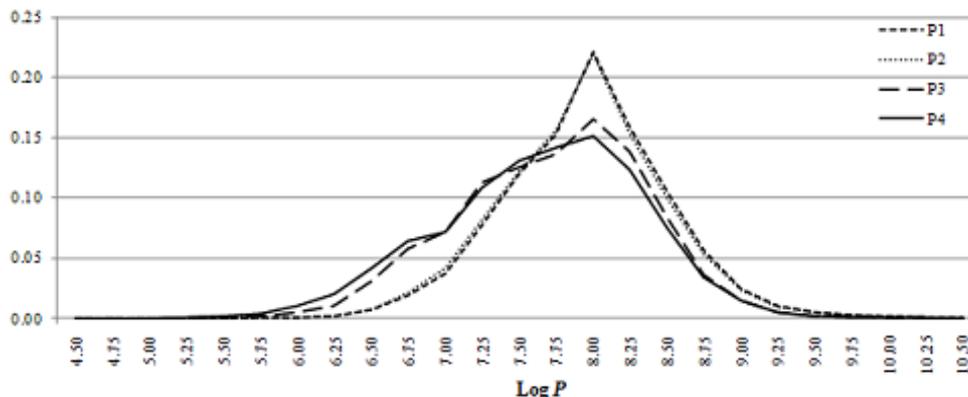
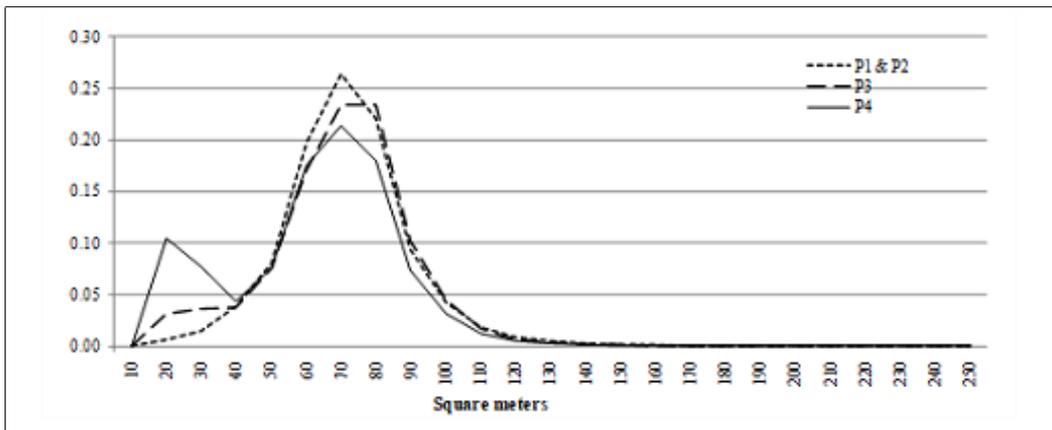


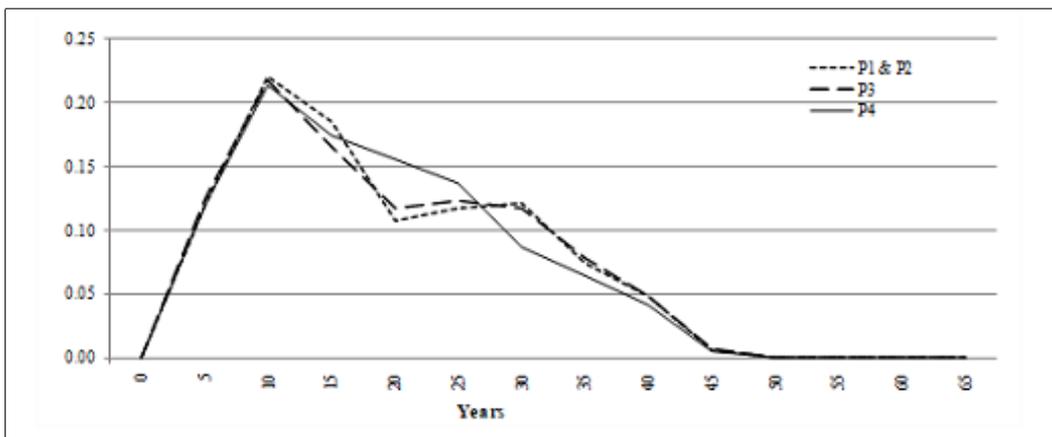
Figure 9. Price densities for P_1, P_2, P_3 and P_4

To investigate differences in the data sets in more detail, SNW compared the distributions of house attributes for each of the three data sets. The top panel of Figure 10 shows the distributions of floor space, measured in square meters, for the three data sets. The distribution labeled “ P_1 and P_2 ,” which was compiled from the magazine data set, is almost symmetric, while the distribution labeled “ P_3 ,” which is from the realtor data set, has a thicker lower tail, indicating that the realtor data set contains more small-sized condos whose floor space is 30 square meters or less. This pattern is even more pronounced in the land registry data set, i.e., in the distribution labelled “ P_4 .”

Turning to the middle and bottom panels of Figure 10, it can be seen that there are substantial differences between the three datasets in terms of the age of buildings and the distance to the nearest station. These differences in the distributions of house attributes may be related to the differences in the distributions of house prices. More specifically, the different price distributions exhibited in Figure 9 may be mainly due to differences in the composition of houses in terms of their size, age, location, etc. Put differently, it could be that the price distributions are identical once quality differences are controlled for in an appropriate manner.



FS: Floor space



AGE: Age of building



DS: Distance to the nearest station

Figure 10. Density functions for house attributes

4.3 The Quality Adjustment Problem

Shimizu, Nishimura and Watanabe (2011) (2012) (SNW) go on to consider two methods for making the distribution of condominium prices in their 3 Tokyo samples of prices more comparable with each other. They considered two methods.

Their first method for achieving greater comparability was to use prices only for condos that are present in two of the data sets. They refer to this approach as the *intersection approach*. They used address information to identify these houses. We will discuss their results for this approach in more detail below.

Their second method was based on running quantile hedonic regressions and SNW called this method the *quantile hedonic approach*. This method is based on the work by Machado and Mata (2005) and McMillen (2008). Since the method is rather complex, the reader is referred to the work of Shimizu, Nishimura and Watanabe (2011) (2012) for the results of this method.

We now describe the intersection method results obtained by SNW. Their magazine data set, which contained P_1 and P_2 , and the registry dataset, which contained P_4 , had 15,015 observations in common. On the other hand, there were 22,613 observations in the intersection of the realtor data set, which contained P_3 , and the land registry data set, which contained P_4 . SNW used these intersection samples to estimate the distance between the distributions of prices at different stages of the house buying/selling process.

SNW started by looking at the distribution of relative prices between P_1 and P_4 in the intersection of the magazine and land registry datasets. Figure 11 shows that the distribution of P_1/P_4 has the largest density at the range of 1.05 to 1.10, with more than thirty percent of the total observations being concentrated in this range, and that the densities above 1.10 are not negligible. In contrast, the number of houses for which P_4 exceeds P_1 is very limited, indicating that initial asking prices tend to be higher than registry prices. This may reflect the weak housing demand in the period from 2005 to 2009 when the price data was collected.

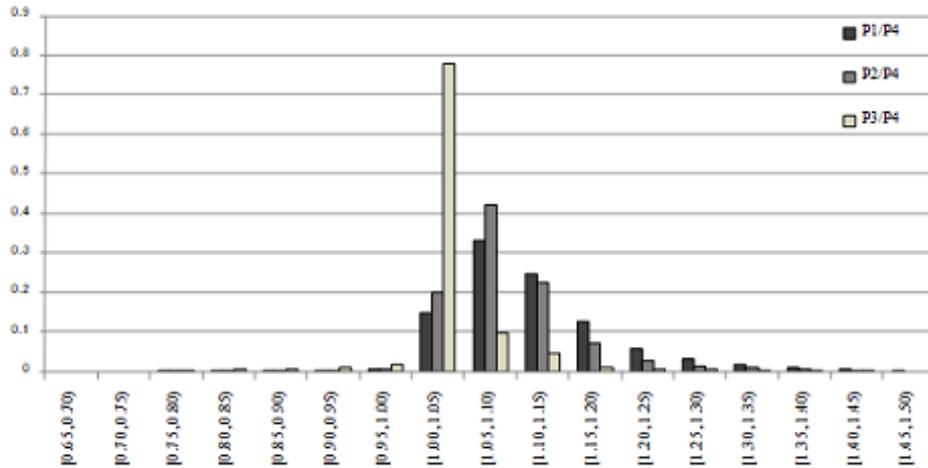
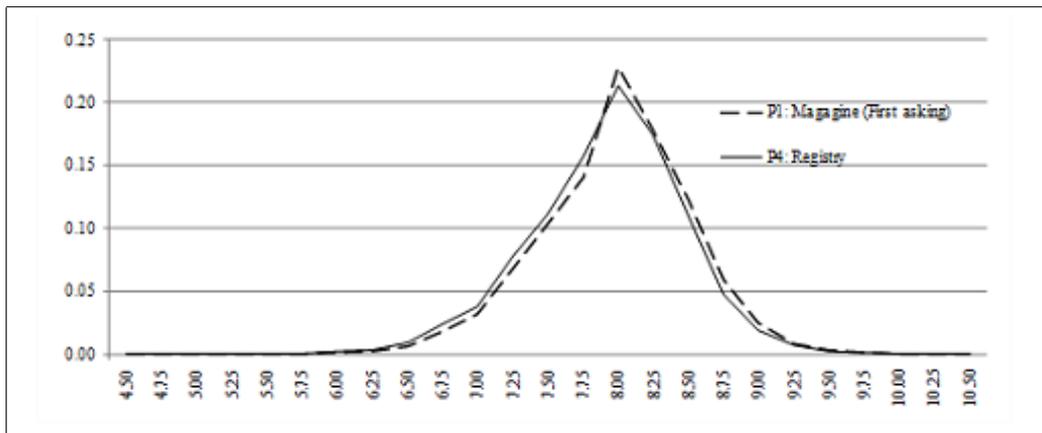


Figure 11. Densities for relative prices

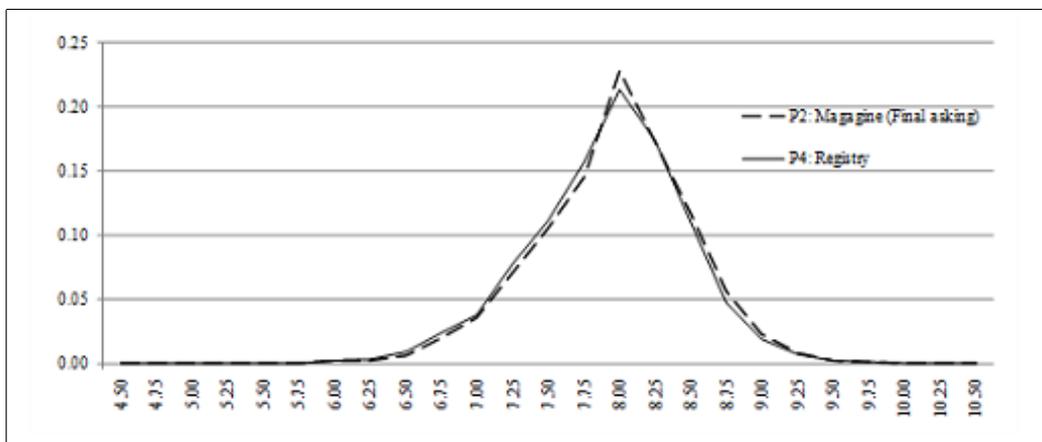
Turning to the distribution of the relative prices in the intersection of the P_2 and P_4 samples, SNW found that the densities in the range of 1.00 and 1.05, and in the range of 1.05 and 1.10, are slightly higher than those for the relative prices in the P_1/P_4 intersection sample, indicating that final asking prices listed in the magazine tended to be closer to registry prices than initial asking prices. This tendency is more clearly seen for the relative prices in the intersection sample P_3/P_4 between realtor prices and land registry prices: more than 70 percent of observations are concentrated in the range of 1.00 to 1.05 for P_3/P_4 . These results are of course in line with our intuition.

Next, Figure 12 shows the distribution of prices using the intersection samples. The top panel compares the distributions of the prices in samples P_1 and P_4 using the intersection sample of the magazine and the land registry data sets. In Figure 9, we saw that the distributions of P_1 and P_4 were quite different. However, now it can be seen that the difference between the two distributions (restricted to their common observations) is much smaller than before, clearly showing the importance of adjusting for quality. However, the two distributions are not exactly identical even after the quality adjustment. Specifically, the distribution of P_4 has a thicker lower tail than the distribution of P_1 . This may be interpreted as reflecting the fact that asking prices initially listed in the magazine were revised downward during the house selling/purchase process.

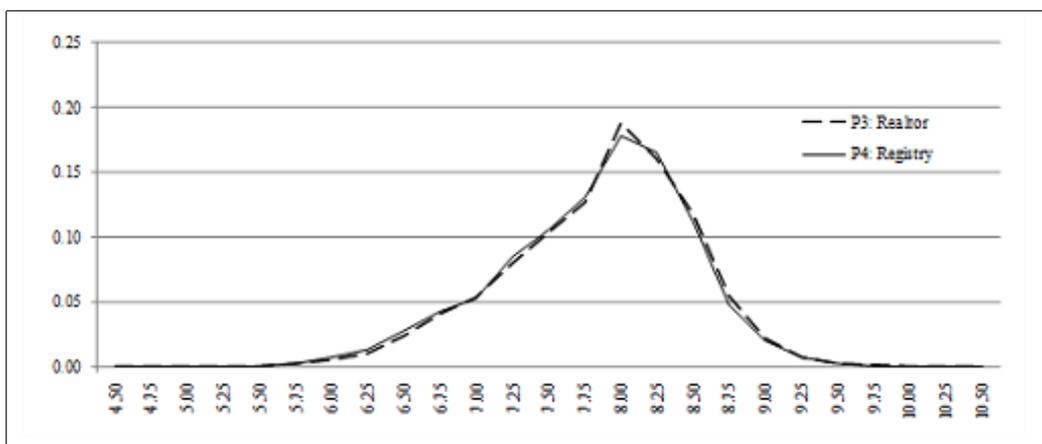
The middle panel in Figure 12 compares the distributions of the prices in the samples P_2 and P_4 using the intersection sample of the magazine and registry datasets, while the bottom panel compares the distributions of P_3 and P_4 using the intersection sample of the realtor and registry datasets. Both panels show that the differences between the distributions are much smaller than we saw in Figure 9, but there still remain some differences.



Densities for P_1 and P_4



Densities for P_2 and P_4



Densities for P_3 and P_4

Figure 12. Price densities for housing units observed in two datasets

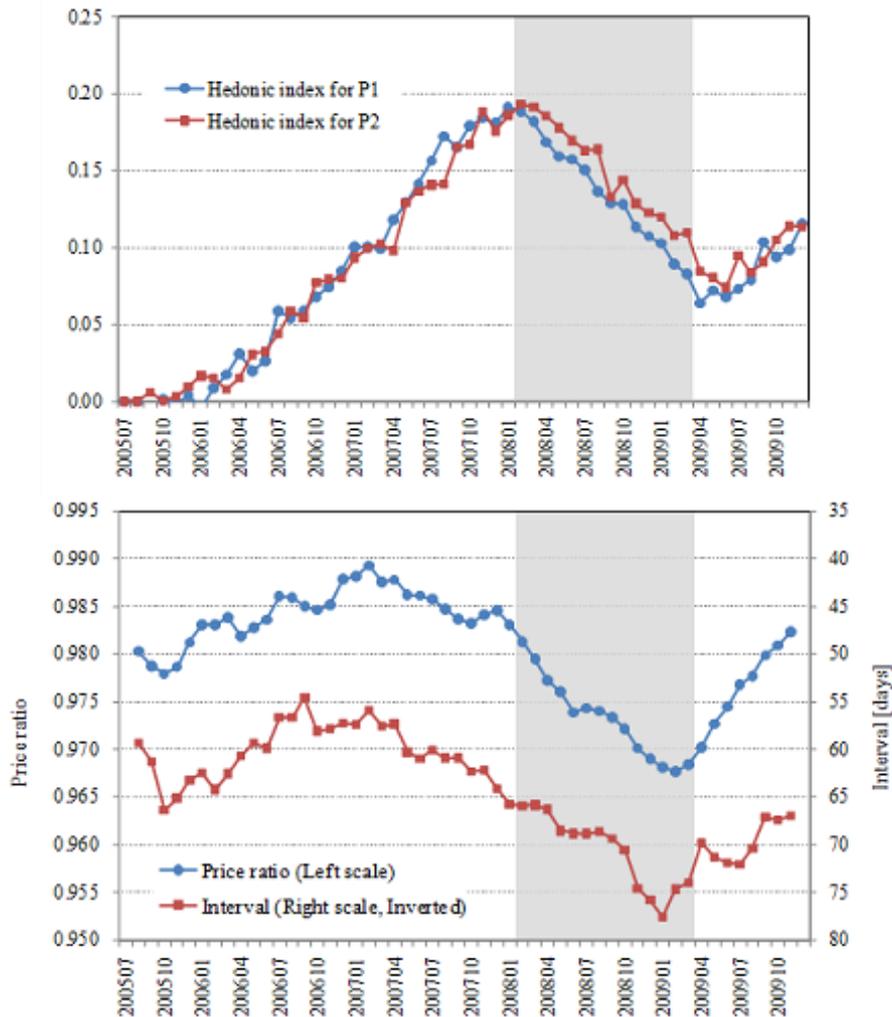


Figure 13. Fluctuations in the price ratio and the interval for P_1 and P_2

One may wonder how the deviations between the standard hedonic indexes generated by (4) using the four samples of prices compare over time. In particular, an important question to be asked is whether these indexes differ substantially depending on whether the housing market is in a downturn or in an upturn. To address this, SNW presented in Figure 13 a time series for the hedonic indexes generated by the P_1 and P_2 samples; see the top panel in Figure 13. In the bottom panel of Figure 13, the price ratio between the P_1 and P_2 prices is plotted, as well as a time series for the interval between the time when P_1 is observed (i.e., the time at which a seller posts an initial asking price in the magazine) and the time when P_2 is observed (i.e., the time when an offer is made by a buyer and the listing is removed from the magazine). The price ratio for a particular month is defined and calculated as the average of the ratios between P_2 and P_1 for housing units for which an offer is made in that month and for which an initial asking price P_1 was listed in the magazine some time prior to that month. As shown in the lower panel of Figure 11, the price ratio fluctuates

between 0.97 and 0.99, indicating that P_2 tends to be lower than P_1 by one to three percent. More importantly, it can be seen that fluctuations in the price ratio are closely correlated with the overall price movement in the housing market, which is represented by the hedonic indexes for P_1 and P_2 shown in the upper panel of Figure 11. Specifically, the hedonic index for P_1 declined by more than ten percent during the period between March 2008 and April 2009 indicated by the shaded area. During this downturn period, the price ratio exhibited a substantial decline, and more interestingly, changes in the price ratio preceded changes in the hedonic indexes.

Specifically, the price ratio started to decline in December 2007, three months earlier than the hedonic index for P_1 , and bottomed out in February 2009, two months earlier than the hedonic index for P_1 . As noted above, the interval for a particular month is calculated as the average of the time lags between the time P_2 is observed and the time P_1 is observed for those housing units for which an offer is made in that month. The interval fluctuates between 55 and 78 days, and more importantly, it is closely correlated with the hedonic indexes for P_1 and P_2 . Focusing on the downturn period, which is indicated by the shaded area, it can be seen that the interval increased from 65 days to 78 days, suggesting that, due to weak demand, sellers had to wait longer until an offer is made by a buyer. As in the case of the price ratio, changes in the listing interval tended to precede changes in the hedonic indexes; specifically, the interval peaked in December 2008, four months before than the hedonic index for P_1 hit bottom.

In the following section, we will outline a hedonic regression model that will allow one to obtain a decomposition of the sale price of a house into land and structure components.

5 The Decomposition of an RPPI into Land and Structure Components

5.1 Introduction

The usual application of a time dummy hedonic regression model to sales of houses does not lead to a decomposition of the sale price into a structure component and a land component. But such a decomposition is required for many purposes. This section of the paper will describe the results of Diewert and Shimizu (2013) (abbreviated to DS) to address this problem.

Section 5.2 below explains the data that DS used in their study. In sections 5.3 and 5.4 below, their hedonic regression model will be explained, which requires information on the selling price of the property V along with the following *basic characteristics* of the property:

- The land area of the property (L);
- The floor space area of the structure (S);
- The age of the structure (A) and

- The location of the property.

Using only information on these 4 characteristics plus the use of an exogenous residential house construction price index for Tokyo, DS were able to explain 81.68 percent of the variation in the sales data for Tokyo. Their basic nonlinear regression model is a generalization of the *builder's hedonic regression model* introduced by Diewert, de Haan and Hendriks (2011a) (2011b).

Section 5.5 contains a discussion of how DS aggregated up their separate land and structure indexes to form an overall house price index for Tokyo.

5.2 The Tokyo Housing Data

The basic data set used by DS included information on V, L, S, A , the location of the property and some additional characteristics to be explained below. The data were obtained from a weekly magazine, *Shukan Jutaku Joho* (Residential Information Weekly) published by Recruit Co., Ltd. The Recruit data set covered the 23 special wards of Tokyo for the period 2000 to 2010, including the mini-bubble period in the middle of 2000s and its later collapse caused by the Great Recession. As was explained in section 4 above, *Shukan Jutaku Joho* provides time series of housing prices from the week when it is first posted until the week it is removed due to its sale. DS used the price in the final week of listing. There were a total of 5578 observations (after range deletions) in the sample of sales of single family houses in the Tokyo area over the 44 quarters covering 2000-2010.⁵¹ The definitions for the above variables and their units are as follows:

- V = The value of the sale of the house in 10,000,000 Yen;
- S = Structure area (floor space area) in units of 100 meters squared;
- L = Lot area in units of 100 meters squared;
- A = Approximate age of the structure in years;
- NB = Number of bedrooms;
- WI = Width of the lot in meters;
- TW = Walking time in minutes to the nearest subway station;
- TT = Subway running time in minutes to the Tokyo station from the nearest station during the day (not early morning or night).

Over the sample period, the sample average sale price was approximately 62.3 million Yen, the average structure space was 110 m², the average lot size was 103 m², the average age of the structure was 14.7 years, the average number of bedrooms in the houses that were sold was 3.95, the average lot width was 4.7 meters, the average walking time to the nearest subway station was 9.9 minutes and the average subway travelling time from the nearest station to the Tokyo Central station was 31.7 minutes.

⁵¹DS deleted 9.2 per cent of the observations because they fell outside their range limits for the variables V, L, S, A, NB and W . DS noted that it is risky to estimate hedonic regression models over wide ranges when observations are sparse at the beginning and end of the range of each variable. The a priori range limits for these variables were as follows: $2 \leq V \leq 20$; $0.5 \leq S \leq 2.5$; $1 \leq A \leq 50$; $2 \leq NB \leq 8$; $2.5 \leq W \leq 9$.

There were fairly high correlations between the V, S and L variables. The correlations of the selling price V with structure and lot area S and L were 0.689 and 0.660 respectively and the correlation between S and L was 0.668. Given the large amount of variability in the data and the relatively high correlations between V, S and L , one can expect multicollinearity problems in a simple linear regression of V on S and L .⁵²

DS used the address information on each transaction in order to allocate each sale into one of 21 Wards for the Tokyo area. They constructed Ward dummy variables and made use of these variables in most of their regressions as locational explanatory variables.

5.3 The Basic Builder's Model

A basic model for valuing a residential property postulates that the value of a residential property is the sum of two components: the value of the land which the structure sits on plus the value of the residential structure.

In order to justify the model, consider a property developer who builds a structure on a particular property. The total cost of the property after the structure is completed will be equal to the floor space area of the structure, say S square meters, times the building cost per square meter, β say, plus the cost of the land, which will be equal to the cost per square meter, α say, times the area of the land site, L . Now think of a sample of properties of the same general type, which have prices or values V_{tn} in period t ⁵³ and structure areas S_{tn} and land areas L_{tn} for $n = 1, \dots, N(t)$ where $N(t)$ is the number of observations in period t . Assume that these prices are equal to the sum of the land and structure costs plus error terms ε_{tn} which we assume are independently normally distributed with zero means and constant variances. This leads to the following *hedonic regression model* for period t where the α_t and β_t are the parameters to be estimated in the regression:⁵⁴

$$V_{tn} = \alpha_t L_{tn} + \beta_t S_{tn} + \varepsilon_{tn}; \quad t = 1, \dots, 44; n = 1, \dots, N(t). \quad (10)$$

Note that the two characteristics in this simple model are the quantities of land L_{tn} and the quantities of structure floor space S_{tn} associated with property n in period t and the two *constant quality prices* in period t are the price of a square meter of land α_t and the price of a square meter of structure floor space β_t . Finally, note that separate linear regressions can be run of the form (10) for each period t in the sample.

The hedonic regression model defined by (10) applies to new structures. But it is likely that a model that is similar to (10) applies to older structures as well. Older structures

⁵²See Diewert, de Haan and Hendriks (2011a) (2011b) for evidence on this multicollinearity problem using Dutch data.

⁵³The period index t runs from 1 to 44 where period 1 corresponds to Q1 of 2000 and period 44 corresponds to Q4 of 2010.

⁵⁴Other papers that have suggested hedonic regression models that lead to additive decompositions of property values into land and structure components include Clapp (1980), Francke and Vos (2004), Gyourko and Saiz (2004), Bostic, Longhofer and Redfearn (2007), Davis and Heathcote (2007), Francke (2008), Koev and Santos Silva (2008), Statistics Portugal (2009), Diewert (2010) (2011), Rambaldi, McAllister, Collins and Fletcher (2010) and Diewert, Haan and Hendriks (2011a) (2011b).

will be worth less than newer structures due to the depreciation of the structure. Assuming that we have information on the age of the structure n at time t , say A_{tn} , and assuming a straight line depreciation model, a more realistic hedonic regression model than that defined by (10) above is the following *basic builder's model*:⁵⁵

$$V_{tn} = \alpha_t L_{tn} + \beta_t (1 - \delta_t A_{tn}) S_{tn} + \varepsilon_{tn}; \quad t = 1, \dots, 44; n = 1, \dots, N(t) \quad (11)$$

where the parameter δ_t reflects the *net depreciation rate* as the structure ages one additional period. Thus if the age of the structure is measured in years, we would expect an annual *net* depreciation rate to be between 0.25 and 2.5%.⁵⁶ Note that (11) is now a nonlinear regression model whereas (10) was a simple linear regression model. Both models (10) and (11) can be run period by period; it is not necessary to run one big regression covering all time periods in the data sample. The period t price of land will be the estimated coefficient for the parameter α_t and the price of a unit of a newly built structure for period t will be the estimate for β_t . The period t quantity of land for property n is L_{tn} and the period t quantity of structure for property n , expressed in constant quality units of a new structure, is $(1 - \delta_t A_{tn}) S_{tn}$ where S_{tn} is the floor space area of property n in period t .

Note that the above model is a *supply side model* as opposed to the *demand side models* of Muth (1971) and McMillen (2003). Basically, the builder's model assumes that housing is supplied competitively so that we are in Rosen's (1974; 44) Case (a), where the hedonic surface identifies the structure of supply. This assumption is justified for the case of newly built houses but it is less well justified for sales of existing homes.

DS used 5578 observations on sales of houses in Tokyo over the 44 quarters in years 2000-2010. Thus equations (11) above could be combined into one big regression and a single depreciation rate $\delta = \delta_t$ could be estimated along with 44 land prices α_t and 44 new structure prices β_t so that 89 parameters would have to be estimated. However, experience has shown that it is usually not possible to estimate sensible land and structure prices in a hedonic regression like that defined by (11) due to the *multicollinearity* between lot size and structure size.⁵⁷ Thus in order to deal with the multicollinearity problem, DS drew on *exogenous information* on new house building costs from the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT) and they assumed that the price of new structures is proportional to this index of residential building costs. Thus the new builder's model that uses exogenous information on structure prices was the following one:

$$V_{tn} = \alpha_t L_{tn} + \beta p_{Ct} (1 - \delta A_{tn}) S_{tn} + \varepsilon_{tn}; \quad t = 1, \dots, 44; n = 1, \dots, N(t) \quad (12)$$

⁵⁵This formulation follows that of Diewert (2010) (2011) and Diewert, Haan and Hendriks (2011a) (2011b). It is a special case of Clapp's (1980; 258) hedonic regression model.

⁵⁶This estimate of depreciation is regarded as a *net depreciation rate* because it is equal to a "true" gross structure depreciation rate less an average renovations appreciation rate. Since we do not have information on renovations and additions to a structure, our age variable will only pick up average gross depreciation less average real renovation expenditures. Note that we excluded sales of houses from our sample if the age of the structure exceeded 50 years when sold. Very old houses tend to have larger than normal renovation expenditures and thus their inclusion can bias the estimates of the net depreciation rate for younger structures.

⁵⁷See Schwann (1998), Diewert, de Haan and Hendriks (2011a) and (2011b) and Eurostat (2011) on the multicollinearity problem.

where all variables have been defined above except that p_{Ct} is the MLIT house construction cost index for Tokyo for quarter t . Thus DS had 5578 degrees of freedom to estimate 44 land price parameters α_t , one structure price parameter β that determines the level of prices over the sample period and one annual straight line depreciation rate parameter δ , a total of 46 parameters.

The R^2 for the resulting nonlinear regression model was only 0.5704,⁵⁸ which was not very satisfactory. Thus the simple Builder's Model defined by (12) applied to Tokyo house prices was not as satisfactory as was the corresponding Builder's Model for the small town of "A" in the Netherlands where the R^2 was 0.8703 using the same information on characteristics of the house and lot.⁵⁹ However, in the case of the town of "A", the structures were all much the same and all houses in the town had access to basically the same amenities. The situation in the huge city of Tokyo is very different: different neighbourhoods have access to very different amenities and Tokyo is not situated on a flat, featureless plain and so we would expect substantial variations in the price of land across the various neighbourhoods.

5.4 The Builder's Model with Locational Dummy Variables

In order to take into account possible neighbourhood effects on the price of land, DS introduced *ward dummy variables*, $D_{W,tn,j}$, into the hedonic regression (12). These 21 dummy variables are defined as follows: for $t = 1, \dots, 44; n = 1, \dots, N(t); j = 1, \dots, 21$.⁶⁰

$$D_{W,tn,j} \equiv \begin{cases} 1 & \text{if observation } n \text{ in period } t \text{ is in Ward } j \text{ of Tokyo;} \\ 0 & \text{if observation } n \text{ in period } t \text{ is not in Ward } j \text{ of Tokyo.} \end{cases} \quad (13)$$

DS modified the model defined by (12) to allow the *level* of land prices to differ across the 21 Wards of Tokyo. Their new nonlinear regression model was the following one:

$$V_{tn} = \alpha_t \left(\sum_{j=1}^{21} \omega_j D_{W,tn,j} \right) L_{tn} + \beta p_{Ct} (1 - \delta A_{tn}) S_{tn} + \varepsilon_{tn}; \quad t = 1, \dots, 44; n = 1, \dots, N(t). \quad (14)$$

Comparing the models defined by equations (12) and (14), it can be seen that DS added an additional 21 *ward relative land value parameters*, $\omega_1, \dots, \omega_{21}$, to the model defined by (12). However, looking at (14), it can be seen that the 44 land time parameters (the α_t) and the 21 ward parameters (the ω_j) cannot all be identified. Thus it is necessary to impose at least one identifying normalization on these parameters. DS chose the following normalization:

$$\omega_{10} \equiv 1. \quad (15)$$

⁵⁸All of the R^2 reported in this section are equal to the square of the correlation coefficient between the dependent variable in the regression and the corresponding predicted variable. The estimated net annual straight line depreciation rate was $\delta = 1.25\%$, with a T statistic of 17.3.

⁵⁹See Eurostat (2011).

⁶⁰The 21 Wards of Tokyo that had at least one transaction during the DS sample period (with the total number of transactions for that Ward in brackets) are as follows: 1: Minato (69); 2: Shinjuku (136); 3: Bunkyo (82); 4: Taito (15); 5: Sumida (32); 6: Koto (38); 7: Shinagawa (144); 8: Meguro (349); 9: Ota (409); 10: Setagaya (1158); 11: Shibuya (107); 12: Nakano (305); 13: Suginami (773); 14: Toshima (124); 15: Kita (53); 16: Arakawa (34); 17: Itabashi (214); 18: Nerima (925); 19: Adachi (271); 20: Katsushika (143); 21: Edogawa (197). Note that for each observation tn , $\sum_{j=1}^{21} D_{W,tn,j} = 1$; i.e., for each observation tn , the 21 ward dummy variables sum to one.

The tenth ward, Setagaya, had the most transactions in the sample (1158 transactions over the sample period) and thus the level of land prices in this Ward should be fairly accurately determined. Hence the remaining ω_j represent the level of land prices in Ward j relative to the level in Ward 10 so if say $\omega_1 > 1$, this means that on average, the price of land in Ward 1 was higher than the average price of land in Ward 10. Taking into account the normalization (15), it can be seen that the DS *builder's model with locational dummy variables* had 44 unknown land price parameters α_t , 20 ward relative land price parameters ω_j , one structure price level parameter β and one annual net depreciation parameter δ that needed to be estimated. DS estimated these parameters using the nonlinear regression option in Shazam; see White (2004). The detailed parameter estimates are listed in Table 9.⁶¹ The R^2 for this model turned out to be 0.8168 and the log likelihood (LL) was -9233.0 , a huge increase of 2270.6 over the LL of the model defined by (12). Thus the Ward variables are very significant determinants of Tokyo house prices.

Table 9. Estimated Coefficients for Model 1

Name	Est Coef	T Stat	Name	Est Coef	T Stat	Name	Est Coef	T Stat
ω_1	2.1348	41.112	α_3	3.7863	28.383	α_{25}	4.4053	35.093
ω_2	1.0020	30.511	α_4	3.9980	32.103	α_{26}	4.3998	35.979
ω_3	1.1553	30.269	α_5	3.7944	32.603	α_{27}	4.7558	31.124
ω_4	1.0552	11.541	α_6	3.7475	27.506	α_{28}	5.1506	40.423
ω_5	0.38569	5.621	α_7	3.3218	26.688	α_{29}	5.1939	37.356
ω_6	0.62467	9.992	α_8	3.4285	30.338	α_{30}	5.4013	37.140
ω_7	1.0214	27.35	α_9	3.7525	27.488	α_{31}	5.2080	33.905
ω_8	1.2304	58.353	α_{10}	3.3802	28.813	α_{32}	5.6581	39.967
ω_9	0.88449	46.691	α_{11}	3.0205	23.868	α_{33}	5.1146	31.804
ω_{11}	1.6639	41.882	α_{12}	3.3602	31.929	α_{34}	5.0592	31.877
ω_{12}	0.67269	34.870	α_{13}	3.8478	29.689	α_{35}	5.3721	32.813
ω_{13}	0.79505	64.468	α_{14}	3.7603	32.321	α_{36}	4.0782	23.219
ω_{14}	0.89487	26.294	α_{15}	3.5570	28.634	α_{37}	4.0863	22.016
ω_{15}	0.54123	8.8738	α_{16}	3.7025	22.845	α_{38}	3.9651	24.827
ω_{16}	0.44453	6.0919	α_{17}	3.8440	34.010	α_{39}	3.9528	24.771
ω_{17}	0.45904	16.009	α_{18}	3.8632	29.935	α_{40}	3.8021	23.690
ω_{18}	0.49218	39.188	α_{19}	3.4764	28.183	α_{41}	4.2077	27.508
ω_{19}	0.21120	8.9117	α_{20}	4.0631	30.474	α_{42}	4.4752	28.542
ω_{20}	0.28298	7.9508	α_{21}	4.1170	31.375	α_{43}	3.9829	25.538
ω_{21}	0.33419	12.273	α_{22}	4.1321	31.351	α_{44}	4.1515	29.487
α_1	3.7342	32.491	α_{23}	4.1994	28.264	β	3.4071	59.780
α_2	3.9089	33.202	α_{24}	4.2315	35.553	δ	0.01394	26.830

Diewert and Shimizu regarded this model as a minimally satisfactory model. Note that they used only four characteristics for each house sale: the land area L , the structure area S , the age of the structure A and its Ward location.⁶²

⁶¹The annual net depreciation rate for this model was estimated as $\delta = 1.39\%$ with a T statistic of 26.8.

⁶²Diewert and Shimizu (2013) estimated several additional models that were generalizations of the model defined by (14). These models made use of the NB, WI, TW and TT variables defined above in section 5.2. Their final most general Model 5 had an R^2 equal to 0.8476 and the corresponding log likelihood was -8709.9 .

5.5 The Construction of Land, Structure and Overall House Price Indexes

DS addressed the problem of how exactly should the land, structure and overall Tokyo house price index be constructed? The DS nonlinear regression model defined by (14) decomposes into two terms: one which involves the land area L_{tn} of the house, $\alpha_t(\sum_{j=1}^{21} \omega_j D_{W,tn,j})L_{tn}$, and another which involves the structure area S_{tn} of the house, $\beta p_{Ct}(1 - \delta A_{tn})S_{tn}$. The first term can be regarded as an estimate of the land value of house n that was sold in quarter t while the second term is an estimate of the structure value of the house. The problem now is how exactly should these two value terms be decomposed into constant quality price and quantity components? The view expressed by DS is that a suitable constant quality land price index for all houses sold in period t should be α_t and for house n sold in period t , the corresponding constant quality quantity should be $(\sum_{j=1}^{21} \omega_j D_{W,tn,j})L_{tn}$ which in turn is equal to $\omega_j L_{tn}$ if house n sold in period t is in Ward j .⁶³ The basic idea here is that DS regarded the term $\alpha_t(\sum_{j=1}^{21} \omega_j D_{W,tn,j})L_{tn}$ as a time dummy hedonic model for the land component of the house with α_t acting as the time dummy coefficient. Thus if we priced out house n that sold in period t in period s , our hedonic imputation for the land value component of this “model” would be $\alpha_s(\sum_{j=1}^{21} \omega_j D_{W,tn,j})L_{tn}$. Thus the quarterly time coefficients α_t act as *proportional time shifters of the hedonic surface for the land component* of the value of each house in our sample and the relative period t to period s land price for each constant quality house is α_t/α_s .

Similarly, a suitable *constant quality structure price index* for all houses sold in period t is βp_{Ct} and for house n sold in period t , the corresponding *constant quality quantity* should be approximately equal to the depreciated structure quantity $(1 - \delta A_{tn})S_{tn}$. Thus DS regarded the term $\beta p_{Ct}(1 - \delta A_{tn})S_{tn}$ as a time dummy hedonic model for the structure component of the house with βp_{Ct} acting as the time dummy coefficient. The quarterly time coefficients βp_{Ct} (or just the p_{Ct}) act as *proportional time shifters of the hedonic surface for the structure component of each house in our sample* and the period t to period s land price for each house in our sample turns out to be p_{Ct}/p_{Cs} .⁶⁴

Thus the *constant quality residential land price index* for Tokyo for quarter t was defined to be $P_{L,t} \equiv \alpha_t/\alpha_1$ and the corresponding *constant quality residential structures price index* for Tokyo for quarter t was defined to be $P_{S,t} \equiv p_{Ct}/p_{C1}$.⁶⁵ These price indexes were regarded by

⁶³An alternative way of viewing the land model is that land in each Ward can be regarded as a distinct commodity with its own price and quantity. But since all Ward land prices move proportionally over time, virtually all index number formulae will generate an overall land price series that is proportional to the α_t .

⁶⁴Our method for aggregating over different house “models” that have varying amounts of constant quality land and structures can be viewed as a hedonic imputation method but it can also be viewed as an application of Hicks’ Aggregation Theorem; i.e., if the prices in a group of commodities vary in strict proportion over time, then the factor of proportionality can be taken as the price of the group and the deflated group expenditures will obey the usual properties of a microeconomic commodity. “Thus we have demonstrated mathematically the very important principle, used extensively in the text, that if the prices of a group of goods change in the same proportion, that group of goods behaves just as if it were a single commodity.” J.R. Hicks (1946; 312-313).

⁶⁵DS normalized the price indexes $P_{L,t}$ and $P_{S,t}$ to equal 1 in quarter 1, which is quarter 1 of the year 2000.

DS as quarter t price levels for land and structures respectively and the corresponding Model 1 quarter t constant quality quantity levels, $Q_{L,t}$ and $Q_{S,t}$, were defined as the total quarter t values of land and structures divided by the corresponding price levels for $t = 1, \dots, 44$:

$$Q_{L,t} \equiv \sum_{n=1}^{N(t)} \left(\sum_{j=1}^{21} \omega_j D_{W,tn,j} \right) \alpha_t L_{tn} / P_{L,t} = \alpha_1 \sum_{n=1}^{N(t)} \left(\sum_{j=1}^{21} \omega_j D_{W,tn,j} \right) L_{tn}; \quad (16)$$

$$Q_{S,t} \equiv \sum_{n=1}^{N(t)} \beta p_{Ct} (1 - \delta A_{tn}) S_{tn} / P_{S,t} = \beta \sum_{n=1}^{N(t)} (1 - \delta A_{tn}) S_{tn}. \quad (17)$$

The price and quantity series for land and structures need to be aggregated into an overall Tokyo house price index. DS used the Fisher (1922) ideal index to perform this aggregation. Thus they defined the *overall house price level for quarter t* , P_t , as the chained Fisher price index applied to the land and structure series $\{P_{L,t}, P_{S,t}, Q_{L,t}, Q_{S,t}\}$.⁶⁶

The overall DS house price index for Tokyo, P_t , as well as the land and structure price indexes, $P_{L,t}$ and $P_{S,t}$, for Tokyo over the 44 quarters in the years 2000-2010 are graphed in Figure 14. DS also computed the quarterly mean and median house prices transacted in each quarter and then normalized these averages to start at 1 in Quarter 1 of 2000. These overall average price index series, $P_{\text{Mean},t}$ and $P_{\text{Median},t}$ are also graphed in Figure 14.

The land price series $P_{L,t}$ is the top line in Figure 14, followed by the overall hedonic house price index P_t , followed by the structure price index $P_{S,t}$ (at the end of the sample period). The mean and median price series track each other and the overall hedonic index price series P_t reasonably well until 2004 but in the following years, the mean and median series fall well below the overall quality adjusted house price series P_t .⁶⁷ Thus quality adjusting the sales of residential housing in Tokyo made a big difference to the resulting index.

⁶⁶The Fisher chained index P_t is defined as follows. For $t = 1$, define $P_t \equiv 1$. For $t > 1$, define P_t in terms of P_{t-1} and $P_{F,t}$ as $P_t \equiv P_{t-1} P_{F,t}$ where $P_{F,t}$ is the quarter t Fisher chain link index. The chain link Fisher index for $t \geq 2$ is defined as $P_{F,t} \equiv [P_{L,t} P_{P_a,t}]^{1/2}$ where the Laspeyres and Paasche chain link indexes are defined as $P_{L,t} \equiv [P_{L,t} Q_{L,t-1} + P_{S,t} Q_{S,t-1}] / [P_{L,t-1} Q_{L,t-1} + P_{S,t-1} Q_{S,t-1}]$ and $P_{P_a,t} \equiv [P_{L,t} Q_{L,t} + P_{S,t} Q_{S,t}] / [P_{L,t-1} Q_{L,t} + P_{S,t-1} Q_{S,t}]$. Diewert (1976) (1992) showed that the Fisher formula had good justifications from both the perspectives of the economic and axiomatic approaches to index number theory.

⁶⁷The mean and median series cannot adjust properly for changes in the relative prices of land and structures or for changes in the average age of the houses sold. Also our mean and median series are for all sales of houses in Tokyo and thus these series were not adjusted for changes in the number of properties sold in expensive wards and less expensive wards. We cannot expect the mean and median series to be very accurate constant quality indexes of house prices; see Eurostat (2011).

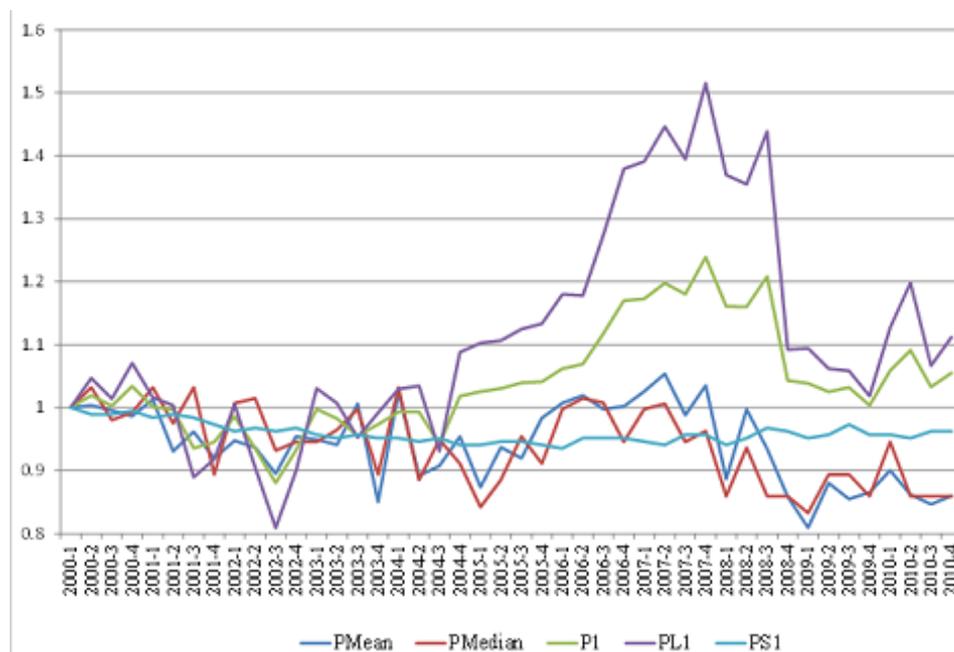


Figure 14. Mean Median and overall prices, land prices and structure price indexes

6 Conclusion

In the wake of the release of the *Residential Property Price Indices Handbook*, the following questions arise:

- Do the different methods suggested in the Eurostat Handbook (and in section 2 above) lead to different estimates of housing price changes?
- If the methods do generate different results, which method should be chosen.
- Which data source should be used for housing information?

Section 2 of this paper reviewed the 5 methods used by Shimizu, Nishimura and Watanabe (2010) to construct housing price indexes and Section 3 presented their empirical results. SNW found no significant differences between the five indexes in terms of contemporaneous correlation. They found that the five indexes are almost identical in terms of quarterly growth rates. However, they found significant differences between the five indexes in terms of dynamic relationships. Specifically, they found that there exists a substantial discrepancy in terms of turning points between the hedonic and repeat sales indexes, even though the hedonic index is adjusted for structural change and the repeat sales index is adjusted in the way that Case and Shiller suggested. The repeat sales measure tends to exhibit a delayed turn compared with the hedonic measure; for example, the hedonic measure of condominium prices hit the sample low point at the beginning of 2002, while the corresponding repeat-sales measure exhibits reversal only in the spring of 2004. Such a discrepancy cannot be

fully removed even if the repeat sales index is adjusted for depreciation (age effects). SNW presented empirical evidence suggesting that such differences between the hedonic and repeat sales indexes mainly come from non-randomness in the repeat sales samples. Although the 5 types of house index exhibited similar quarterly growth rates (with the exception of the Rolling Year Hedonic index which ended up well above the other 4 house price indexes), looking at Figure 2 that plots these 5 indexes for condominiums, it can be seen that 4 of the methods generate index levels at the end of the sample period that are quite different.⁶⁸ Thus it appears that the method of calculation does matter.

Given that the method matters, the question of which method is “best” remains open but the depreciation bias in the standard repeat sales method tends to lead us to prefer hedonic methods.⁶⁹

Given these results, the government of Japan decided to prepare an official residential property price index based on the hedonic method. In particular, it has been determined that it will be estimated with the rolling window hedonic method proposed by Shimizu, Takatsuji, Ono and Nishimura (2010) and Shimizu, Nishimura and Watanabe (2010) and system development is underway.

The next issue is the question of what data sources should be used. The choice of the data set has been regarded as critically important from the practical viewpoint, but has not been discussed much in the literature. Section 4 of this paper sought to fill this gap by comparing the distribution of prices collected at different stages of the house buying/selling process, including (1) asking prices at which properties are initially listed in a magazine, (2) asking prices when an offer is eventually made, (3) contract prices reported by realtors, and (4) land registry prices. These four prices, denoted by P_1, P_2, P_3 and P_4 are collected by different parties and recorded in different data sets.

Our findings in Section 4 have some practical implications for the construction of property price indexes. The first implication is that we may be able to rely on online data to construct a flash or preliminary estimate. Specifically, we may be able to use online asking price data recorded at the time when an offer is eventually made (i.e., using the P_2 prices) although we still have to cope with various practical issues, including how to identify the timing of a sale and how to find out if the disappearance of the listing price is due to a withdrawal or a sale. Second, the resulting preliminary price indexes could be revised as additional transaction information (i.e., P_3 and P_4 prices) become available. However, it should be noted that P_3 and P_4 information becomes available only gradually. As the P_3 and P_4 information comes in, we could gradually build up actual sales information for the past 4 quarters or so and at the end of each quarter, it would be possible to rerun the preliminary hedonic regressions or repeat sales regressions for the past 4 quarters using the newest relevant data set. Thus the preliminary index would be revised for at least 4 quarters until it becomes

⁶⁸The end of sample period price levels range from approximately 0.4 to 0.7. These differences were generated over a period of approximately 30 years so that the small differences in quarterly growth rates eventually cumulate into fairly substantial differences between the indexes.

⁶⁹We note that in order to implement the age adjusted repeat sales model, a form of hedonic regression is required.

“final”. Importantly, the quality of the flash estimate as a predictor of the final one depends not only on how prices evolve over time in the buying/selling process, which we empirically examined in Section 4, but also on the extent of sample selection in the sense that properties listed online do not necessarily proceed to the contract and finally to the registration. Since the government of Japan has a responsibility with regard to data source quality, it was decided to use the transaction price information collected by MLIT as the basis for the construction of the final price index. There was another reason for deciding to use MLIT data. Online information and information collected by realtors is concentrated on urban areas. But since the official housing price index is required to cover the entire country, it is preferable to use land registry data.

However, there are two major problems associated with the use of the land registry data base:

- The only information that can be obtained from the registry are the following variables: (i) the address of the property; (ii) the building floor space; (iii) the land area of the plot; (iv) the time of the transaction and (v) the transaction price. The quality of a hedonic regression model can be improved considerably if additional information on the characteristics of the property can be collected.⁷⁰ That being the case, when attempting to perform quality adjustment using the hedonic method, there may be insufficient information on housing-related characteristics in the MLIT data base.
- As was indicated in Section 4 of this paper, the MLIT information is not particularly timely. The Eurostat Handbook calls for a lag between data collection and publication of less than 3 months, which is problematic.

In order to address the second problem, the Japanese government decided to publish preliminary figures and final figures. Thus alternative data sources that are more timely will be used in order to form preliminary property price indexes.

As part of the above deliberations, MLIT began a full-scale implementation from the Fall 2014. Even once full-scale implementation of the official residential property price index has begun in Japan, issues will remain. One of these is the decomposition of property value into land and structure components. Section 5 of this paper summarized the results of research on this issue. For purposes of constructing the national accounts, it will be necessary to consider separating the residential property price index into a land index and structure index.

The present paper has indicated that constructing practical residential property price indexes will not be an easy task. Many difficult problems remain but a good start on the required methodology has been made.

⁷⁰In particular, the MLIT data base does not include the age of the structure, which is a key variable. MLIT has therefore constructed a system that collects location related information using Geographic Information Systems or GIS. In addition, a system was established for real estate appraisers to survey detailed characteristics.

References

- [1] Allen, M.T and W.H. Dare (2004), “The Effects of Charm Listing Prices on House Transaction Prices”, *Real Estate Economics* 32, 696-713.
- [2] Bai, J., and P. Perron (1998), “Estimating and testing linear models with multiple structural changes”, *Econometrica* 66, 47-78.
- [3] Bailey, M.J., R.F. Muth, and H.O. Nourse (1963), “A Regression Model for Real Estate Price Index Construction”, *Journal of the American Statistical Association* 58, 933-942.
- [4] Bostic, R.W., S.D. Longhofer and C.L. Readfearn (2007), “Land Leverage: Decomposing Home Price Dynamics”, *Real Estate Economics* 35:2, 183-208.
- [5] Bourassa, S.T, M. Hoesli and J. Sun (2006), “A Simple Alternative House Price Index Method”, *Journal of Housing Economics* 15, 80-97.
- [6] Case, B., H.O. Pollakowski, and S.M. Wachter (1991), “On Choosing among House Price Index Methodologies”, *AREUEA Journal* 19, 286-307.
- [7] Case, B. and J. M. Quigley, (1991), “The Dynamics of Real Estate Prices”, *Review of Economics and Statistics*, 22, pp.50-58.
- [8] Case, K.E., and R.J. Shiller (1987), “Prices of Single Family Homes since 1970: New Indexes for Four Cities”, *New England Economic Review* Sept./Oct., 45-56.
- [9] Case, K.E., and R.J. Shiller (1989), “The Efficiency of the Market for Single Family Homes”, *The American Economic Review* 79, 125-137.
- [10] Chau, K.W., S.K. Wong, C.Y. Yiu (2005), “Adjusting for Non-Linear Age Effects in the Repeat Sales Index”, *Journal of Real Estate Finance and Economics* 31, 137–153.
- [11] Clapp, J.M. (1980), “The Elasticity of Substitution for Land: The Effects of Measurement Errors”, *Journal of Urban Economics* 8, 255-263.
- [12] Clapp, J.M., and C. Giaccotto (1992), “Estimating Price Trends for Residential Property: A Comparison of Repeat Sales and Assessed Value Methods”, *Journal of Real Estate Finance and Economics* 5, 357-374.
- [13] Clapp, J.M., and C. Giaccotto (1998), “Price indexes Based on the Hedonic Repeat-Sales Method: Application to the Housing Market”, *Journal of Real Estate Finance and Economics* 16, 5-26.
- [14] Court, A. T. (1939), “Hedonic Price Indexes with Automotive Examples”, pp. 98-117 in *The Dynamics of Automobile Demand*, New York: General Motors Corporation.
- [15] Davis, M.A. and J. Heathcote (2007), “The Price and Quantity of Residential Land in the United States”, *Journal of Monetary Economics* 54, 2595-2620.

- [16] de Haan, J. and F. Krsinich (2014), "Scanner Data and the Treatment of Quality Change in Rolling Year GEKS Price Indexes", *Journal of Business and Economic Statistics*, forthcoming.
- [17] Deng, Y. D. McMillen and T.F. Sing (2012), "Private Residential Price Indices in Singapore: A Matching Approach", *Regional Science and Urban Economics* 42, 485-494.
- [18] Diewert, W.E. (1976), "Exact and Superlative Index Numbers", *Journal of Econometrics* 4, 114-145.
- [19] Diewert, W.E. (1992), "Fisher Ideal Output, Input and Productivity Indexes Revisited", *Journal of Productivity Analysis* 3, 211-248.
- [20] Diewert, W.E. (2003a), "Hedonic Regressions: A Consumer Theory Approach", pp. 317-348 in *Scanner Data and Price Indexes*, R.C. Feenstra and M.D. Shapiro (eds.), Studies in Income and Wealth 64, Chicago: University of Chicago.
- [21] Diewert, W.E. (2003b), "Hedonic Regressions: A Review of Some Unresolved Issues", paper presented at the 7th Meeting of the Ottawa Group, Paris, May 27-29.
- [22] Diewert, W.E. (2010), "Alternative Approaches to Measuring House Price Inflation", Discussion Paper 10-10, Department of Economics, The University of British Columbia, Vancouver, Canada, V6T 1Z1.
- [23] Diewert, W.E. (2011), "The Paris OECD-IMF Workshop on Real Estate Price Indexes: Conclusions and Future Directions", pp. 87-116 in *Price and Productivity Measurement, Volume 1: Housing*, W.E. Diewert, B.M. Balk, D. Fixler, K.J. Fox and A.O. Nakamura (eds.), Trafford Press.
- [24] Diewert, W. E. and C. Shimizu (2015), "Residential Property Price Indexes for Tokyo," *Macroeconomic Dynamics*, 19(8),1659-1714.
- [25] Diewert, W. E. and C. Shimizu (2016), "Hedonic Regression Models for Tokyo Condominium Sales," *Regional Science and Urban Economics*, 60, 300-315.
- [26] Diewert, W. E. and C. Shimizu. (2017), "Alternative Approaches to Commercial Property Price Indexes for Tokyo", *Review of Income and Wealth*, 63(3), 492-519.
- [27] Diewert, W.E., J. de Haan and R. Hendriks (2011a), "The Decomposition of a House Price Index into Land and Structures Components: A Hedonic Regression Approach", *The Valuation Journal* 6, (2011), 58-106.
- [28] Diewert, W.E., J. de Haan and R. Hendriks (2011b), "Hedonic Regressions and the Decomposition of a House Price index into Land and Structure Components" Discussion Paper 11-01, Department of Economics, University of British Columbia, Vancouver, Canada, V6T1Z1. Forthcoming in *Econometric Reviews*.

- [29] Dorsey, R.E, H. Hua, W.J. Mayera and H. Wanga (2010), “Hedonic versus Repeat-Sales Housing Price Indexes for Measuring the Recent Boom-Bust Cycle”, *Journal of Housing Economics* 19, 75–93.
- [30] Ekeland, I., J.J. Heckman, and L. Nesheim (2004), “Identification and Estimation of Hedonic Models”, *Journal of Political Economy* 112, 60-109.
- [31] Engelhardt, G.V. (2003), “Nominal Loss Aversion, Housing Equity Constraints and Household Mobility: Evidence from the United States”, *Journal of Urban Economics*, 53, 171-195.
- [32] Eurostat (2011), *Handbook on Residential Property Price Indices*, Luxembourg: Eurostat.
- [33] Fisher, I. (1922), *The Making of Index Numbers*, Boston: Houghton-Mifflin.
- [34] Francke, M.K. (2008), “The Hierarchical Trend Model”, pp. 164-180 in *Mass Appraisal Methods: An International Perspective for Property Valuers*, T. Kauko and M. Damato (eds.), Oxford: Wiley-Blackwell.
- [35] Francke, M.K. and G.A. Vos (2004), “The Hierarchical Trend Model for Property Valuation and Local Price Indices”, *Journal of Real Estate Finance and Economics* 28:2/3, 179-208.
- [36] Gatzlaff, D.H and D.R. Haurin (1998), “Sample Selection and Biases in Local House Value Indices”, *Journal of Urban Economics* 43, 199-222.
- [37] Genesove, D. and C. Mayer (1997), “Equity and Time to Sale in the Real Estate Market”, *American Economic Review*, 87, 255-269.
- [38] Genesove, D. and C. Mayer (2001), “Loss Aversion and Seller Behavior: Evidence from the Housing Market”, *Quarterly Journal of Economics* 116,1233-1260.
- [39] Goetzmann, W. and L. Peng (2006), “Estimating House Price Indexes in the Preference of Seller Reservation Prices”, *Review of Economics and Statistics* 88,100-112.
- [40] Goodman, A.C. and T.G. Thibodeau (1998), “Dwelling Age Heteroskedasticity in Repeat Sales House Price Equations”, *Real Estate Economics* 26, 151-171.
- [41] Griliches, Z. (1971), “Introduction: Hedonic Price Indexes Revisited”, pp. 3-15 in *Price Indexes and Quality Change*, Z. Griliches (ed.), Cambridge MA: Harvard University Press.
- [42] Gyourko, J. and A. Saiz (2004), “Reinvestment in the Housing Stock: The Role of Construction Costs and the Supply Side”, *Journal of Urban Economics* 55, 238-256.
- [43] Haurin, D.R, J.L. Haurin, T. Nadauld and A. Sanders (2010), “List Prices, Sale Prices and Marketing Time: An Application to U.S. Housing Markets”, *Real Estate Economics* 38, 659-685.

- [44] Hicks, J.R. (1946), *Value and Capital*, Second Edition, Oxford: Clarendon Press.
- [45] Hill, R, M. Scholz, C. Shimizu and M.Steurer (2018) “An Evaluation of the Methods Used by European Countries to Compute their Official House Price Indices,” *Economie et Statistique* n 500-501-502, 221–238.
- [46] Ivancic, L., W.E. Diewert and K.J. Fox (2009), “Scanner Data, Time Aggregation and the Construction of Price Indexes”, Discussion Paper 09-09, Department of Economics, The University of British Columbia, Vancouver, Canada.
- [47] Ivancic, L., W.E. Diewert and K.J. Fox (2011), “Scanner Data, Time Aggregation and the Construction of Price Indexes”, *Journal of Econometrics* 161, 24-35.
- [48] Knight, J.R., C.F. Sirmans and G.K. Turnbull (1998), “List Price Information in Residential Appraisal and Underwriting”, *Journal of Real Estate Research* 15, 59-76.
- [49] Koev, E. and J.M.C. Santos Silva (2008), “Hedonic Methods for Decomposing House Price Indices into Land and Structure Components”, unpublished paper, Department of Economics, University of Essex, England, October.
- [50] Machado, J. A. F. and J. Mata (2005), “Counterfactual Decomposition of Changes in Wage Distributions using Quantile Regression”, *Journal of Applied Econometrics* 20, 445-465.
- [51] McMillen, D.P. (2003), “The Return of Centralization to Chicago: Using Repeat Sales to Identify Changes in House Price Distance Gradients”, *Regional Science and Urban Economics* 33, 287-304.
- [52] McMillen, D.P. (2008), “Changes in the Distribution of House Prices over Time: Structural Characteristics, Neighborhood or Coefficients?”, *Journal of Urban Economics* 64, 573-589.
- [53] McMillen, D.P (2012), “Repeat Sales as a Matching Estimator”, *Real Estate Economics*, 40, 745–773.
- [54] McMillen, D.P and P. Thorsnes (2006), “Housing Renovations and the Quantile Repeat Sales Price Index”, *Real Estate Economics* 34, 567–587.
- [55] Muth, R.F. (1971), “The Derived Demand for Urban Residential Land”, *Urban Studies* 8, 243-254.
- [56] Pollakowski, H. O. (1995), “Data Sources for Measuring House Price Changes”, *Journal of Housing Research* 6(3), 377-387.
- [57] Rambaldi, A.N., R.R.J. McAllister, K. Collins and C.S. Fletcher (2010), “Separating Land from Structure in Property Prices: A Case Study from Brisbane Australia”, School of Economics, The University of Queensland, St. Lucia, Queensland 4072, Australia.

- [58] Rosen, S. (1974), “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition”, *Journal of Political Economy* 82, 34-55.
- [59] Schwann, G.M. (1998), “A Real Estate Price Index for Thin Markets”, *Journal of Real Estate Finance and Economics* 16:3, 269-287.
- [60] Shimizu, C., and K.G. Nishimura (2006), “Biases in Appraisal Land Price Information: The Case of Japan”, *Journal of Property Investment and Finance* 26, 150-175.
- [61] Shimizu, C., and K.G. Nishimura (2007), “Pricing Structure in Tokyo Metropolitan Land Markets and Its Structural Changes: Pre-Bubble, Bubble, and Post-Bubble Periods”, *Journal of Real Estate Finance and Economics* 35, 475-496.
- [62] Shimizu, C., K. G. Nishimura, and Y. Asami (2004), “Search and Vacancy Costs in the Tokyo Housing Market: An Attempt to Measure Social Costs of Imperfect Information”, *Review of Urban and Regional Development Studies* 16, 210-230.
- [63] Shimizu, C., K.G. Nishimura and T. Watanabe (2010), “Housing Prices in Tokyo: A Comparison of Hedonic and Repeat Sales Measures”, *Journal of Economics and Statistics* 230/6, 792-813.
- [64] Shimizu, C., K.G. Nishimura and T. Watanabe (2011), “House Prices at Different Stages in Buying/Selling Process”, Hitotsubashi University Research Center for Price Dynamics Working Paper Working Paper, No.69.
- [65] Shimizu, C., K.G. Nishimura and T. Watanabe (2012), “House Prices from Magazines, Realtors, and the Land Registry”, *Property Market and Financial Stability*, BIS Papers No.64, Bank of International Settlements, March 2012, 29-38.
- [66] Shimizu, C., H. Takatsuji, H. Ono, and K.G. Nishimura (2010), “Structural and Temporal Changes in the Housing Market and Hedonic Housing Price Indices”, *International Journal of Housing Markets and Analysis* 3:4, 351-368.
- [67] Standard & Poor’s (2008), *S&P/Case-Shiller Home Price indexes: Index Methodology*, March 2008.
- [68] Statistics Portugal (Instituto Nacional de Estatística) (2009), “Owner-Occupied Housing: Econometric Study and Model to Estimate Land Prices, Final Report”, paper presented to the Eurostat Working Group on the Harmonization of Consumer Price Indices”, March 26-27, Luxembourg: Eurostat.
- [69] Summers, R. (1973), “International Comparisons with Incomplete Data”, *Review of Income and Wealth* 29:1, 1-16.
- [70] Triplett, Jack (2004), *Handbook on Hedonic Indexes and Quality Adjustments in Price Indexes*, OECD Science, Technology and Industry Working Papers 2004/9.

- [71] Thorsnes, P. (1997), “Consistent Estimates of the Elasticity of Substitution between Land and Non-Land Inputs in the Production of Housing”, *Journal of Urban Economics* 42, 98-108.
- [72] White, K.J. (2004), *Shazam: User’s Reference Manual, Version 10*, Vancouver, Canada: Northwest Econometrics Ltd.
- [73] Wong.,SK, KW Chau, K. Karato, C.Shimizu (2017), “Separating the Age Effect from a Repeat Sales Index:Land and structure decomposition,” *Journal of Real Estate Finance and Economics*, published online.(<https://doi.org/10.1007/s11146-017-9631-2>)