



Quantile Regression and the Decomposition of House Price Distribution

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Abstract

Following the global financial crisis, the importance of developing property price indexes as part of official statistics has been recognized, and in light of this, in 2014, the U.N., International Monetary Fund (IMF), BIS, OECD, and World Bank jointly published the *Handbook on Residential Property Price Indexes*. Since then, the development of housing price indexes has been progressing. In general, however, the purpose of these indexes is to observe changes in prices over time, which means that even when changes in price by country or region are observable, it is not possible to compare differences in price level. This paper proposes a new housing price index estimation method that enables temporal trends in housing prices by city/region and cross-sectional price levels to be compared at the same time. This paper estimated a housing price index focusing on major cities in Japan during the period of the 1980s real estate bubble and subsequent collapse. The real estate bubble that occurred in Japan in the 1980s has been called the greatest bubble of the twentieth century. It warrants the question thus, how did housing prices fluctuate during the bubble and the quarter-century following its collapse? In order to answer this question, this paper estimated housing price indexes by region and clarified the spatial housing price fluctuation process. When attempting to analyze fluctuations in housing prices by region, it is necessary to capture the price levels or price distribution at the same time as the price fluctuations. Therefore, using quantile regression, we first developed a method that enables the price distribution and price index to be estimated simultaneously. Second, using the method we developed and focusing on Tokyo, we identified what factors caused changes in housing prices. Third, we estimated the price indexes and price distributions for six leading Japanese cities and identified the price fluctuation structure that existed in each region during the bubble formation period, bubble collapse period, and subsequent quarter-century.

Key Words: quantile regressions; decomposition; price distribution; quality adjustment; asset bubble

JEL Classification: R21; R31; C10

1. Introduction

The formation and collapse of property bubbles has a profound impact on the economic administration of many leading nations. The property bubble that began around the mid-1980s in Japan has been called the greatest bubble of the twentieth century. In the aftermath of the bubble's collapse, the country faced a period of long-term economic stagnation dubbed the "lost decade." Many other countries have had similar experiences concerning this type of problem -- for example, Sweden's economic crisis in the 1990s and the global financial crisis and economic stagnation caused by the formation and collapse of the U.S.-centered property bubble in the early twenty-first century.

In light of this, it was indicated that the existing "information gap" at the time between policy-making authorities and the property (including housing) and financial markets was a problem. In 2009, the IMF proposed the creation of a housing price index to the G20 in order to fill this information gap, and the proposal was adopted. However how should these property price indexes be created?

Property standards and facilities vary to a greater or lesser extent for each building, so there is no such concept as identical properties. Even if one assumed that the standards and facilities were the same, the process by which property quality deteriorates would differ by building age, so the buildings would become non-homogeneous over time. In other words, property has the particularity of being a non-

homogeneous commodity. In addition to this problem, the development of building technology is relatively fast, so quality changes over time. That is, not only does a building's functionality decline over time, but it also becomes economically obsolete with the advance of technology. As well, in cases where the surrounding environment changes significantly through redevelopment and the like, location characteristics such as transport accessibility of the city center also change.

When attempting to capture temporal fluctuations in property prices while dealing with the problems caused by property being a heterogeneous good as well as changes in quality, it is necessary to perform quality adjustment.

In order to address these problems, there are quite a few points that can be adapted from existing index theory, as typified by consumer price statistics. For example, with regard to changes in quality accompanying technological development, the quality adjustment method known as the hedonic approach is used in private vehicle price statistics and the like. It would therefore be natural to consider also quality adjustment with the hedonic method for property price indexes, since this enables consistency with other types of economic statistics.

However, when it comes to methods of quality adjustment for property price indexes, if one looks at the Residential Property Price Indices Handbook published by Eurostat in 2014,¹ it presents a variety of methods along with their advantages and disadvantages: a) Stratification or Mix Adjustment Methods, b) Hedonic Regression

¹ The RPPI Handbook may be viewed via the following link:
http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/methodology/hps/rppi_handbook

Methods, c) Repeat Sales Methods, and d) Appraisal-Based Methods. This is because, in reality, multiple methods have been applied in the estimation of property price indexes. After comparing the advantages and disadvantages of the various methods, the Handbook recommends using the hedonic method.

This paper will attempt to estimate housing price indexes by region, starting off by estimating a housing price index that focuses on Japan's major cities during the period from the late 1980s to 2015, which includes Japan's bubble era, based on the hedonic method recommended in the RPPI Handbook.

When attempting to capture accurately housing market trends, price indexes by region are a necessity. This is because the housing market possesses a high degree of regionalization and it is possible that trends will vary by region, even within the same country. In addition, even within the same city, it is possible that there will be differing trends for upscale residential districts, average houses, housing selected by low-income families, and so forth. Moreover, when attempting to compare housing markets between regions, one naturally wants to observe not just housing price trends but also differences in "*price levels*."

In this paper, in order to address this issue, we will estimate a housing price index estimation method using quantile regression that makes it possible to capture temporal price changes at the same time as price levels/price distribution. Next, we will analyze in detail the structure of Tokyo's housing market dynamics before the bubble period, during the bubble, after the bubble's collapse, and during the subsequent period.

Furthermore, we will expand the analysis to include the key cities of Yokohama and Kawasaki in the Tokyo metropolitan area and Osaka, Kyoto, and Kobe in the Kansai area in order to clarify the spatial dynamics of housing markets in major Japanese cities over a period of 30 years.

2. Background

2.1 Price Indices

To capture the price movement at average level, the standard hedonic technique is commonly used for constructing a house price index (Rosen 1974, Palmquist 1980, Mark and Goldberg 1984). In the hedonic model, the house price log is expressed as a function of structural characteristics and location characteristics. The former include living space, date of construction and number of bedrooms etc, while the latter contain distance to subway, schools and parks, recreation facilities and green space, etc. Time dummy variables are also included in hedonic model, the coefficients of which reflect the price changes. The standard hedonic model is:

$$Y_{it} = \alpha + \beta Z_{it} + \sum_{t=1}^T \delta_t D_{t,i} + u_{it} \quad (1)$$

where Y_{it} is logarithm of house price i at time t , Z_{it} is hedonic feature of home i at time t , and $D_{t,i}$ is time dummy of time t (if home i sale at t , $D_{t,i} = 1$ and $D_{-t,i} = 0$). Rosen (1974) pointed out the correct functional form cannot be determined by theoretical grounds unless there is costless repackaging of the characteristics. Thus, the hedonic

model cannot avoid the “omitted variable” problem. In addition, the hedonic model assumes no structure change of the average market characteristics. However, the average characteristics of each market change and the sensitivity of characteristics to the price changes as well violate the assumption of structure change.

Besides the hedonic price index, the repeat sales price index is another commonly used method. The repeat sales price index was proposed by Bailey, Muth and Nourse (BMN 1963). Subsequently, Case and Shiller (1989) extended it as the most commonly used repeat sale index of the US market.² The repeat sales index requires the houses in the dataset to be transacted at least two times. The formation is:

$$Y_{i1} - Y_{i0} = \delta_1 - \delta_0 + u_{i1} - u_{i0} \quad (2)$$

where Y_{i1} and Y_{i0} are logarithm of price for house i at t_1 and t_0 . This function assumes that Z_i is not changing with time t . The repeat sales estimator is often presented as a potential solution to the omitted bias that occurs in hedonic estimation, since the omitted effect disappears if structural and neighborhood features are constant over time. However, the sample of repeat sales houses sold many times may

² It should be noted that an adjustment to cope with the age effect is conducted in constructing the official S&P/Case-Shiller home price index. Standard & Poor's (2008) 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." (page 7)

not represent all transactions in the property market. Moreover, the assumption of Z_i as constant might be violated due to the age problem and renovation. Case and Quigley (1991) constructed a hybrid model to solve the age problem.³

Besides traditional mean-based price indices, McMillen (2013) constructed a local quantile house price index focusing on the local weighted quantile regression approach. McMillen found appreciation rates were high for low-priced homes in the South Side and West Side neighborhoods of Chicago between 2000 and 2006. McMillen indicated distribution change is sensitive to location and quantile regression is more general to construct housing price indexes. While McMillen added the time dummy for quantile regression, which extends the mean-based hedonic index for entire distributions, the value of our approach lies in its utilization of the rolling window approach to capture the change of distribution, allowing the coefficients of structural and locational variables to change over time.

Given that a hedonic price index and repeat sales price index are both unable to solve the structure change problem and describe the change of distribution, we intend to use the method of decomposition to construct a housing price index and distribution change to compensate for their limitations.

³ Shimizu, Nishimura and Watanabe (2010) have analyzed the lead-lag structure of hedonic price indexes, BMN-type repeat sales indexes, Case and Shiller-type repeat sales indexes, and age-adjusted repeat sales indexes. The results they obtained clearly showed that even when adjusted for age, repeat sales indexes have a lag with respect to hedonic price indexes. This makes it evident that when it comes to the causes of this lag, sample selection bias is more significant than the lack of age adjustment.

2.2 Decomposition

The decomposition method was first proposed by Oaxaca (1973) and Blinder (1973), and is called the Oaxaca-Blinder decomposition. This Oaxaca-Blinder decomposition is widely used for labor studies to decompose average earnings. Different from the linear regression Oaxaca (1973) decomposition model, Machado and Mata (2005) constructed a decomposition approach based on quantile regressions. This quantile approach is more general than the conventional Oaxaca decomposition. The conditional quantiles approach was provided by Koenker and Bassett (1978). Let $Q_i^\theta(y | z)$ for $\theta \in (0,1)$ denote the θ -th quantile of the conditional distribution. In the housing market context, we model conditional quantiles by:

$$Q_\theta(y | z) = z'\beta(\theta) \quad (3)$$

where $\beta(\theta)$ is the vector of quantile coefficients, and z includes the hedonic feature of houses. Machado and Mata (2005) used conditional quantile regression estimators to decompose wages with coefficient change and covariance change.

McMillen (2008) was the first to introduce the MM (Machado and Mata 2005) method to the housing market. By comparing Chicago data from 1995 and 2005, McMillan found the entire distributional changes of Chicago houses price could be explained by the changes of coefficients rather than explanatory variables. Subsequently, Nicodem and Raya (2012) showed evidence from Spanish cities in

2004 and 2007. Then, Thomschke (2015) found the changes of distribution in Berlin during 2007 and 2012. In addition, Fesselmeier, Le and Seah (2013) provided evidence of differing housing prices for Caucasians and African Americans in the US market. Qin, Zhu and Zhu (forthcoming) use the decomposition method to analyze the land market of China. These studies have focused on comparing decomposition analyses of two separate one-year periods.

The contribution of our research has two forms. First, our research deviates from existing studies' employment of comparison of distribution between two separate one-year periods as it extends the distribution analysis along a continuous period for Tokyo from 1986 to 2015, which includes the whole period of the asset bubble around the 1990s and recovery period. Thus, it illustrates the dynamics of distribution for each year, particularly for those that occurred before and after the asset bubble. Second, our research compares the distributional changes of six large metropolitan areas in Japan, and determines how distribution differs between cities in reaction to the boom and burst that occurred during the bubble period. To the best of our knowledge, there is no existing continuous time study employing the decomposition method and distributional analysis of the 1990s Japanese asset bubble. The next section introduces our empirical methods.

3. Empirical Methodology

The main empirical method in this study is the decomposition approach, employed to capture the distributional changes of Tokyo and five other major cities of Japan. Different from the traditional Oaxaca-Blinder decomposition (Oaxaca 1973, Blinder 1973), the MM decomposition method is based on quantile regression, which allows for entire distribution analysis. In addition, Albrecht et al. (2009) prove the consistency and asymptotic normality of the Machado and Mata (2005) approach.

Based on the Japanese dataset from 1986 to 2015, the mean of logarithmic transacted price of house unit, y , can be described as a function of a set of structural characteristics, X , and neighborhood characteristics, L . Thus, $y = \alpha + X\beta + L\gamma + u = Z\lambda + u$, where u is an error term, $Z = (1 \ X \ L)$ is the matrix of explanatory variables, and $\lambda = (\alpha \ \beta \ \gamma)'$ is the coefficient vector. Considering the case of analysis of two separate periods, the Oaxaca-Blinder mean decomposition can be written as:

$$\bar{y}_1 - \bar{y}_0 = (\bar{Z}_1 - \bar{Z}_0)\widehat{\lambda}_1 + \bar{Z}_0(\widehat{\lambda}_1 - \widehat{\lambda}_0) \quad (4)$$

where $\bar{y}_1 - \bar{y}_0$ is the average total change of logarithmic property price from $t = 1$ to $t = 0$. The first part of the right hand side, $(\bar{Z}_1 - \bar{Z}_0)\widehat{\lambda}_1$, shows the effect of changes in the value of the explanatory variables, called attribute effect. It is also possible for separate change of structural and location features. The second part, $\bar{Z}_0(\widehat{\lambda}_1 - \widehat{\lambda}_0)$, shows the effect of coefficient change controlled attribute change, which denotes the

coefficient change of property controlled explanatory variables, called coefficient effect.

In this paper, in differentiating from the two-period studies mentioned before, we compare the total effect and coefficient effect of transaction in time t ($t \in [1, n]$) and time 0 for the continuous dataset.

The Oaxaca-Blinder decomposition in equation (4) is typically calculated at mean value Z . Although it can just as easily be evaluated at any given set of values like median or other value of Z , the result is based on the underlying conditional expectations $E(y|Z)$, a simple expected value of y . Different from the Oaxaca-Blinder decomposition, Machado and Mata (2005) proposed a decomposition framework with quantile regression. As the coefficients of quantile regressions of different quantile Q are different ($Q = 0.01, 0.02, \dots, 0.99$), the MM approach is a kind of bootstrap procedure to simulate the coefficient change and variable change of entire distribution.

The decomposition methodology for each of the two-period studies is:

1. Estimate quantile regressions (QR) with the same formula of hedonic model for Q values of $\theta \in (0, 1)$, for example $Q = 99$ from .01 to .99. The estimators are Q number of $\widehat{\lambda}_1$ for t_1 and Q number of $\widehat{\lambda}_0$ for t_0
2. Draw with replacement from quantile regression coefficient vectors. The individual draws are denoted $\widehat{\lambda}_{0m}$ and $\widehat{\lambda}_{1m}$, where $m = 1, \dots, M$. A uniform distribution is used, i.e., each θ is equally likely to be drawn.
3. Draw with replacement from z_{0i} and z_{1j} , where z_{0i} is the vector of explanatory variables for observation i ($i = 1, \dots, n_0$) in t_0 , and z_{1j} is

the vector of explanatory variables for observation j ($j = 1, \dots, n_1$) in t_0 .

The bootstrap sample are denoted as z_{0m} and z_{1m} , $m = 1, \dots, M$.

4. Estimate the density functions for M replacement of $z_0\widehat{\lambda}_0$, $z_1\widehat{\lambda}_1$ and $z_0\widehat{\lambda}_1$.

Total change is $z_1\widehat{\lambda}_1 - z_0\widehat{\lambda}_0$, coefficients (price) change is $z_0\widehat{\lambda}_1 - z_0\widehat{\lambda}_0$ and attributes (variables) change is $(z_1 - z_0)\widehat{\lambda}_0$.

The density functions estimated are then used to decompose the overall change in the distribution of predicated houses price. The decomposition is presented as follows:

$$z_1\widehat{\lambda}_1 - z_0\widehat{\lambda}_0 = (z_1\widehat{\lambda}_1 - z_0\widehat{\lambda}_1) + (z_0\widehat{\lambda}_1 - z_0\widehat{\lambda}_0) \quad (5)$$

where $z_1\widehat{\lambda}_1 - z_0\widehat{\lambda}_1$ is the portion due to changes in the distribution of the explanatory variables and $z_0\widehat{\lambda}_1 - z_0\widehat{\lambda}_0$ is the portion associated with changes in the estimated coefficients.

Different from McMillen (2008), Nicodemo and Raya (2012) and Thomschke (2015), we compare the distribution changes for continuous time instead of comparing two separate one-year periods. We use the rolling window approach to analyze quarterly data in the following procedure:⁴

⁴ The rolling window method was proposed by Shimizu et al. (2010), and was noted as one of the most recommended methods by Eurostat (2013). It is an estimation method that deals with structural changes over time.

1. Select the base year t_0 , which could be any year (e.g. 1986 or 2000) or full sample. Use rolling window approach to make each quarter q as one-year length $t_q = [q, q + 3]$ ($q = 2000Q1, 2000Q2, \dots, 2015Q4$). For example, the t for $q = 2010Q2$ is four quarters from 2010Q2 to 2011Q1.
2. Apply above four step decomposition approach for each t_q and t_0 , and get z_0 , z_q and $\widehat{\lambda}_q$ for each quarter q .
3. Estimate the distribution of $z_q \widehat{\lambda}_q$, $z_0 \widehat{\lambda}_q$.

The results of the above procedures are the simulated distributions of total effect and price effect for each quarter compared with base period. We are interested in the counterfactual exercises. On the one hand, $z_q \widehat{\lambda}_q$ is the density of total effect, which is the simulated price density function of t_q . On the other hand, the density of the coefficient effect, $z_0 \widehat{\lambda}_q$, is the house price density in t_q if only the attributes of houses are distributed as base period t_0 . For example, given the based year is 2000, the $z_q \widehat{\lambda}_q$ for $q = 2010Q2$ is the price density with attributes of houses from 2010Q2 to 2011Q1, while the $z_0 \widehat{\lambda}_q$ is the price density assuming attributes of houses from base year 2000.

Thus, the mean, median, quantile 10% and 90% of total effect and coefficient effect can be presented as quarterly indexes. Because the total effect and coefficient effect of t_0 , $z_0 \widehat{\lambda}_0$, are identical, the difference of total effect and coefficients effect of t_q , $z_q \widehat{\lambda}_q - z_0 \widehat{\lambda}_q$, is the change in the distribution of explanatory variables.

In addition, besides the decomposition of coefficient and attribute effect, we divide the attribute effect into two dimensions; structural attribute effect and location attribute effect.

4. Data and Descriptions

4.1. Data and Summary Statistics

The dataset used in this paper is a condominium data listing for six large cities in Japan over 30 years (120 quarters) starting from the first quarter of 1986 and ending with the fourth quarter of 2015. This dataset is provided by Suumo (Residential Information Website), owned by Recruit Co., Ltd., one of the largest vendors of residential lettings information in Japan.⁵ This dataset contains final week listing price before removal due to sale.⁶ It also contains the structural features, i.e. floor space, number of bedrooms, age of building and material structure (reinforced concrete or steel reinforce concrete) and the location features are walking time to the nearest station, time to nearest terminal station from the nearest station, city code,

⁵ Shimizu et al. (2004) report that the Recruit data cover more than 95 percent of the entire transactions in the 23 special wards of Tokyo. On the other hand, its coverage for suburban areas is very limited. We therefore use only information for the units located in the special wards of Tokyo.

⁶ There are two reasons for the listing of a unit being removed from the magazine: a successful deal or a withdrawal (i.e., the seller gives up looking for a buyer and thus withdraws the listing). We were allowed to access information regarding which of the two reasons applied for individual cases and discarded those where the seller withdrew the listing. Shimizu, Nishimura and Watanabe (2016) showed that the final week listing prices in this dataset were almost identical to contract price.

address, latitude and longitude. The observations of Tokyo are 241,702, and observations of six cities are 447,953.

In the first part of our empirical study, we apply our decomposition method for the Special Wards of Tokyo from 1986 to 2015. Table 1 reports the summary statistics of listing houses in Tokyo by year from 1986 to 2015.⁷ Key attributes include the floor space (FS), Age, Time to Nearest Station, Time to Tokyo station and structure dummy (SRC dummy). The age of a house is defined as the number of year between the date of the construction of the house and the transaction. The convenience of public transportation from a house is represented by the travel time to the central business district (CBD or Terminal station) denoted by TT, and the time to the nearest station, which is denoted by TS.

The average listing price in 1986 was 26 million yen, while in 1990, was 55 million yen. This reveals that house prices peaked in 1990, followed by the bursting period that lasted until 2000, where at that point the average price was 29 million yen. Properties before 1990 were newer and smaller when compared to those after 1995.

Table 2 presents summary statistics of six cities in 1990 and 2015. On the one hand, it implies that house structures of other large cities have similar trends as that of Tokyo, for example, properties in 1990 are newer and smaller than in 2015. On the other hand, the volumes of price movements are different, for example, Osaka had a

⁷ Time to the Tokyo station is measured in average in the daytime (9:00am-5:00pm).

similar high price level as that of Tokyo in 1990, but a much lower price level compared with Tokyo in 2015.

4.2. Raw Kernel Density of Housing prices

To provide a clear picture of distributional movement of house prices, we plot the raw kernel density of log price. Figure 1 shows the kernel densities of Tokyo house prices in eight different years. The density for 1990 has higher median price and smaller variance compared with other years. Although the density of 2005 and 2010 have similar median price, their variances are different. It suggests that price movement could not be fully presented though a mean-based price index.

In addition, Figure 2 shows the kernel density of floor space and age of Tokyo. The densities of floor space in 1986 and 1990 have large portions in small houses, which are different from the other six years. The median for age in 1986 are the smallest of the eight years, which implies that the developers constructed more properties before the bubble period. The peak of density for age moves to the right as time goes by, which represents that most of the market stock was built in the beginning of asset bubble build up. There were many new houses built after 2000, which is at the bottom of property price.

Figure 3 presents the kernel densities of six cities in 1990, 2000, 2010 and 2015. In 1990, the densities of Tokyo, Kawasaki and Osaka have similar shape, while the density of Osaka moves left more dramatically. Compared with other cities, movement

of median house price of Yokohama is the smallest. The variances of Yokohama are smallest in 1990 and 2015, but that in 2000 is large.

These kernel densities show that the distributional changes are not ignorable and different for cities. Compared with the mean-based housing price index, the distributional price index could express the price movement better.

5. Empirical Results

5.1 OLS and Quantile Regressions estimation results

We first conduct a standard hedonic regression for (the log of) the four prices using a similar specification as the one adopted by Shimizu et al. (2010, 2016) and others. The logarithmic house price is the dependent variable. Explanatory variables are structural features, such as floor space, age and structural material, as well as location features, such as commuting time to station and city center. The regression equation is as follows:

$$\begin{aligned} \ln(\text{Price}) = & \beta_0 + \beta_1 \text{area} + \beta_2 \text{age} + \beta_3 t_{\text{station}} + \beta_4 t_{\text{center}} \\ & + \beta_5 \text{SRC} + \beta_6 x + \beta_7 y \end{aligned} \quad (6)$$

The regression results are shown in the first two columns of Table 4. The results are standard: house prices increase with floor space and decline with age, distance to the nearest station, and commuting time to the central business district; in addition,

prices are higher for houses with main windows facing south, and for houses with a steel reinforced concrete frame structure. There are some differences across the four period (1990, 2000, 2010 and 2015) in the estimated coefficients, but they are not very large. Each of the four regressions explains more than 65 percent of the variation in the log of house price.

The results are standard: in every year, house prices increase with unit size, and prices decline with age, and time to station and city center. However, the coefficients of floor space, age and other factors are different between the boom and burst periods. For example, housing prices have less sensitivity for age depreciation in 1990. The housing prices in 1990 are 0.8% cheaper than those that had been constructed one year earlier (1989), while the housing price in 2015 are 1.5% cheaper than those that had been constructed one year earlier (2014). These results challenge the assumption of the hedonic price index that coefficients do not change over time.

We also run 97 quantile regressions for quantiles ranging from $\theta=0.02$ to 0.98 in increments of 0.01. Table 3 shows the estimates for representative (25 percent, 50 percent, and 75 percent) quantiles, while Figure 5 shows the regression coefficients by quantile. We see that several variables exhibit significant quantile effects. Specifically, the estimated coefficient on the age of a building is negative but tends to become closer to zero at higher quantiles (especially for bubble period, 1990), implying that age decreases house prices, but less so for high-priced houses.

Moreover, we present estimations with similar OLS regressions for six cities in 1990 and 2005. Table 4 shows the OLS regressions results. The signs of coefficients for different cities are the same as Tokyo. It shows that property depreciation denoted by the coefficients of age, changes with time and differs among cities. Property depreciation is smaller in 1990 compared with 2015 for each city, and the difference is larger in Tokyo, Kyoto, Osaka and Kobe than in Yokohama and Kawasaki.

5.2 Quantile Decomposition of Tokyo

First, we present the hedonic price index and sample mean in Figure 4. The first graph shows the dynamics of Tokyo property prices, including the bubble booming period before 1990, bursting period (1990-2000), and recovery period (2000-2008).⁸ The Tokyo property market was also affected by the globe financial crisis in 2008, and has witnessed a growth period since 2012. The hedonic price index has notable differences with the sample means around 1990. Moreover, the hedonic price indices of six cities are also shown in Figure 4, where we observe Osaka has the largest growth within the asset bubble period.

Sentence for Figure 5

Using our quantile decomposition method mentioned before, we present the decomposition results in Figure 6. The base year we select here is 2000, and we report

⁸ The Japanese bubble collapsed in 1990. Beginning in the latter half of the 1980s, a system for reporting housing transactions to the government was introduced, but no significant effect was seen. However, after the Bank of Japan implemented restrictions on the total amount of loans issued to the real estate industry in 1990, property prices plummeted.

the results based on 1986 and full sample later. The blue line is total effect, $z_q\widehat{\lambda}_q$, while green line is price effect, $z_0\widehat{\lambda}_q$. The difference between the two lines is the attribute effect. The first graph of Figure 6 shows that, on the median level, attribute effect contributes more during the bubble period, as well as the global financial crisis. However, the differences of the two lines are an indication of the contrast between these two periods. Price effect is greater than total effect around 1990, which implies that the housing bubble is more volatile than what we observed, which might be due to the structural change of characteristics of houses transacted around 1990, for example they were small and new on average. In the period of the global financial crisis, the total effect is greater than the price effect, representing that price growths before 2008 and drops later are overestimated. The characteristic change contributes to part of the volatility during this period.

The second and third graph of Figure 6 reports the 10th and 90th percentile of the decomposition density. These results show that the difference between price effect and total effect for the 10% quantile is not as significant as the median. On the contrary, the difference between price effect and total effect for the 90th percentile is more notable than the 10th and 50th percentiles, which implies that the expensive properties have more attribute change than normal and low price properties. In addition, we observe that the volatilities of high price properties are higher than that of low price properties. In 1987, there is a big temporary drop and return for 50% and 90% quantile houses, but 10% houses do not have such trend.

Figure 7 shows the violin plot composed of house price kernel densities by year. The three lines in each kernel density are 10%, 50% and 90%. We can see the variance is small in 1990 and large in 1987. The 90% have a temporary drop from 1987 to 1988, while there is no decline among the 10%.

Sentence for Figure 8

Figure 9 presents the partial decomposition of price density. We decompose house price in price change and two kinds of attribute change, structural and location. The total effect and price effect are same with above results. The yellow line represents the effect of price and location, which means that we control the structural attributes constant as base year and allow the location feature change over time. The pink line is the effect of price and structural, which means that we control the location constant as base year and allow the structural attribute change. The results show that location has a more significant contribution to attribute change.

~~Figure 8 and Figure 9 show the decomposition results with base year 1986 and full sample. The results are similar with the full sample based and provide robust evidence. The results with base year 1986 have small differences in total and price change. The 10% and 90% quantile results are interesting. From the results with base year 1986, the 90% quantile price changes are overestimated largely due to attribute change. The 10% quantile price changes on the contrary are underestimated. In the results of the full sample base, the attribute change contributes consistently within all periods.~~

5.3 Quantile Decomposition of Six Cities

In this section, we use the quantile decomposition approach to compare six large cities, of Japan: Tokyo, Yokohama, Kawasaki, Kyoto, Osaka, and Kobe. Figure 10 reports the median of the price effect density and total effect density. The attribute changes are significant for cities, especially for Kyoto and Kobe. The median of Kyoto and Kobe price effect density is larger than that of Yokohama but the median of total effect density is similar among the three cities. More interesting, we find the time of asset bubble booming is different for cities. The Tokyo metropolitan area (Tokyo, Yokohama and Kawasaki) had a temporary drop in 1988. Although Osaka has the highest median in the peak of bubble, the property price of the Kansai area (Kyoto, Osaka and Kobe) increases later and more fiercely than the Tokyo metropolitan area. The difference of price in the Osaka area and the Tokyo area is small in 1990 but quite significant in 1988.

Figure 11 reports the 10th percentile and 90th percentile of price effect density. The median and 10% houses of Osaka have the highest price of these cities, but the 90% houses of Osaka prices are lower than that of Tokyo. The 10% quantile housing prices of Tokyo are similar with Kawasaki and Yokohama, but 90% quantile housing price are much higher than Kawasaki and Yokohama and other cities. The time sequence of the asset bubble for different cities also exists, but the differences between the Osaka area and the Tokyo area is large for the 10th percentile but small

for the 90th percentile. However, the difference for the 90th percentile is large within the Tokyo area compared with the 10th percentile and the drop of the 90th percentile in Tokyo area is significant. The 90th percentile houses of Osaka area have growth earlier than the 10th percentile.

The first graph of Figure 11 is an index of the low price range, looking at changes in the 10% quantile, while the second is an index of the high price range, looking at changes in the 90% quantile. Comparing the two graphs shows that housing prices in the high price range in the Tokyo metropolitan area (Tokyo, Yokohama and Kawasaki) surged from 1986 to 1987. Subsequently, these indexes showed a temporary decline, but then rose again starting in 1988. At that time, one can see that housing prices in the Kansai area (Kyoto, Osaka and Kobe) and all housing prices in the low price range in all cities also rose simultaneously.

Turning our attention to the bubble collapse process, we can see that housing prices in the low price range in the Tokyo metropolitan area and the Kansai area and in the high price range in the Kansai area peaked in 1990 and then decreased abruptly. There was a one-year delay for the high price range market in the Tokyo metropolitan area, which began to decline in 1991.

Next, let us consider the price recovery period. After the bubble's collapse in 1990 and 1991, Japan's housing market experienced a long-term price decline lasting more than 10 years. This was followed by a recovery period, with the timing varying

by market: it began in 2000 for the Tokyo high price range market and in 2002 to 2003 in the other markets.

Specifically, it was 2001 in Tokyo's high price range market, 2003 in Yokohama, 2003 in Kawasaki, 2003 in Kyoto, 2005 in Osaka and 2005 in Kobe.

Here, it is important to note the extent of the decline. Focusing on the high price range market, if we compare the price level during the peak to the price level when it bottomed out at the point of recovery, the decline stopped at the 54% level for Tokyo, but prices dropped to 53% in Yokohama, 54% in Kawasaki, 66% in Kyoto, 68% in Osaka and 57% in Kobe.

Subsequently, prices continued to rise until the latter half of 2007, when the global financial crisis began. After the economic crisis, prices dropped once again, in tandem with housing markets in Western countries. The real estate market at that time has been dubbed both a "fund bubble" and "mini-bubble," but in terms of magnitude, the scope of this bubble remained relatively small compared to Western countries.

However, as the market was trending toward recovery after the drop in housing prices following the financial crisis, the Great East Japan Earthquake struck in March 2011. This situation led to temporary economic confusion, and due to problems arising from radioactive contamination accompanying the failure of the Fukushima Daiichi Nuclear Power Plant, one can see that housing prices once again trended downward in Tokyo, Yokohama and Kawasaki, which are located near Fukushima.

On the other hand, it is interesting to note that Kyoto, Osaka and Kobe were not affected by this, in part because they are geographically removed from Fukushima.

Starting in 2012, one can see that, with the exception of Kobe, prices began to rise regardless of the price range, thanks to monetary easing based on the Abenomics policies introduced with the advent of the Abe administration and increased demand for real estate development accompanying the decision to award the 2020 Olympics to Tokyo.

5.4 Time of Asset Bubble

In figure 12, we compare the price effect of Tokyo and Osaka, to find the difference of asset bubble time. It is notable that the boom of the Tokyo property market occurred almost two years earlier than that of the Osaka property market, regardless of the percentile. The largest price difference between the two cities is in 1987, when Tokyo obtained great growth but Osaka had not. After 1987, Osaka experienced significant growth and caught up to the price level of Tokyo, while the Tokyo housing price fluctuated. Price difference between two cities is more significant among the 90th percentile and is smaller among 10th percentile. In addition, properties of Osaka have bigger depreciation than Tokyo after 2000.

6. Conclusion

This paper proposed a price index estimation method that makes it possible to estimate simultaneously, temporal changes in housing prices and price distribution by applying quantile regression. Specifically, it developed an index that makes it possible to not only estimate the typical price level but also to capture temporal changes in different market segments (low price properties, high price properties) by generating a quality-adjusted price distribution for each period using quantile regression.

Consequently, compared to the standard hedonic price method, which is the most typical estimation method for price indexes, the following results were obtained:

For housing price indexes estimated for Tokyo's ward area:

- Looking at the formation period of the bubble that occurred in Japan during the 1980s, for all cities, including Tokyo, the price index for high price properties (90% percentile) increased ahead of the other indexes. In addition, the price increase was relatively small for low price properties (10th percentile).
- On the other hand, during the period of the bubble's collapse that began in 1990, the decline began with the price index for low price properties (10th percentile).

These kinds of differences in price level and distribution are estimated in terms of price distribution differences, using results that reflect spatial differences (upscale residential neighborhoods, standard residential neighborhoods, disadvantaged residential neighborhoods) as well as differences in grade (luxury housing, standard housing, low-quality housing). In other words, estimating the price distribution means it is possible to construct a price index without performing spatial segmentation or

quality segmentation. Moreover, the fact that certain price ranges were identified as preceding or lagging behind the market as a whole signifies price indexes using this method offer more information than price indexes based on the standard hedonic method or repeat sales method.

In addition, based on the indexes estimated for each city:

- The 1980s bubble occurred from 1986 to 1987 in the Tokyo area (Tokyo, Kawasaki, and Yokohama), and then, at the time when it almost came to an end, price increases occurred in the Kansai region (Osaka, Kyoto, and Kobe). This shows the bubble spread from Tokyo to the Kansai area in 1987. Subsequently, even though the original Tokyo housing bubble had almost come to an end, prices in Tokyo began to rise once again starting in 1988, influenced by the rising prices in the Kansai region, until the bubble collapsed in 1990.

- The indexes show the bubble collapsed abruptly in the Kansai region, after which prices began to decline gradually in the Tokyo area.

As mentioned previously, with conventional hedonic price indexes and repeat sales indexes, it was not possible to anticipate the formation and collapse of the above Japanese property bubble.

The method proposed here has a high potential for application.

In general, the purpose of a price index is to capture average fluctuation within a given market, but since the housing market possesses a high degree of heterogeneity in terms of space or grade, there are many cases where it is important to observe changes

by more segmented market units. Furthermore, when it comes to comparing housing purchasing power, it is necessary to observe not just price changes but also price levels—the importance of this can be seen, for example, in the government policy target set during the bubble era of controlling housing prices so they do not exceed annual income by more than 5 times.

Accordingly, it is possible to develop an affordability index by comparing the average income for each city and the quality-adjusted housing price distribution and index using quantile regression for each city proposed here.

Furthermore, the method proposed in this paper enables price fluctuations and price levels by city to be estimated simultaneously using data obtained online, which is another benefit.

Following the publication of the *International Handbook on Residential Property Prices*, statistical agencies in various countries have been trying to move forward with developing housing price indexes. However, there are various issues such as data limitations, and the progress being made in developing these indexes is dependent on the data sources and methods being used. If it were possible to obtain international housing price information via the Internet, it would be possible to estimate indexes with identical methods, using equivalent data sources; this would facilitate the development of housing price indexes and affordability indexes that enable truly meaningful international comparisons. Going forward, we intend to address this among remaining issues.

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Table 1: Summary Statistics of Tokyo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	1986	1990	1995	2000	2005	2010	2015
Listing Price (10,000 Yen)	3740.6 (1824.6)	2568.9 (1425.9)	5500.5 (1854.9)	3586.1 (1714.3)	2924.0 (1504.7)	3164.1 (1576.7)	3460.0 (1529.7)	3958.3 (1727.5)
Unitprice (Price/Area)	68.22 (31.67)	56.60 (28.78)	119.2 (40.22)	63.96 (18.02)	48.21 (14.30)	50.59 (16.21)	56.90 (18.16)	65.42 (22.05)
Floor Space (m^2)	56.82 (18.53)	47.93 (17.86)	48.89 (16.39)	55.92 (18.50)	59.67 (18.80)	62.01 (18.58)	61.13 (17.63)	61.39 (18.06)
Age (year)	14.74 (8.217)	7.995 (4.564)	10.60 (5.781)	14.46 (6.007)	16.24 (8.114)	15.69 (9.865)	16.67 (9.960)	17.80 (9.715)
Time to Nearest Station (minutes)	7.321 (4.191)	7.111 (4.155)	7.408 (4.206)	7.197 (4.134)	7.236 (4.126)	7.178 (4.089)	7.422 (4.289)	7.709 (4.266)
Time to Tokyo Station (minutes)	26.20 (8.414)	25.13 (8.339)	26.71 (8.023)	26.55 (8.480)	26.44 (8.517)	25.94 (8.380)	26.71 (8.577)	26.16 (8.601)
SRC (dummy)	0.489 (0.500)	0.579 (0.494)	0.540 (0.498)	0.531 (0.499)	0.508 (0.500)	0.443 (0.497)	0.387 (0.487)	0.310 (0.463)
Observations	241702	4942	8299	13859	4525	4721	3969	10918

Note: mean as coefficients; sd in parentheses

Table 2: Summary Statistics of Six Cities

	(1) Tokyo		(2) Yokohama		(3) Kawasaki		(4) Kyoto		(5) Osaka		(6) Kobe	
	1990	2015	1990	2015	1990	2015	1990	2015	1990	2015	1990	2015
Listing Price (10,000 Yen)	5500.5 (1854.9)	3958.3 (1727.5)	4721.1 (1484.2)	2951.6 (989.1)	5198.5 (1615.6)	3305.5 (1079.1)	4772.2 (1738.1)	2529.5 (1370.3)	5503.8 (1728.0)	2416.7 (907.6)	4705.8 (1682.6)	2322.1 (1072.8)
Unitprice (Price/Area)	119.2 (40.22)	65.42 (22.05)	83.05 (22.55)	42.33 (12.04)	90.28 (20.54)	47.52 (14.73)	84.46 (25.46)	39.28 (16.36)	97.62 (31.67)	35.68 (10.75)	75.29 (25.57)	31.33 (11.67)
Floor Space (m^2)	48.89 (16.39)	61.39 (18.06)	59.29 (17.90)	70.17 (14.78)	59.31 (17.10)	70.04 (13.03)	58.65 (17.05)	64.64 (18.83)	58.67 (15.24)	67.89 (14.50)	63.99 (14.11)	74.40 (16.16)
Age (year)	10.60 (5.781)	17.80 (9.715)	8.943 (5.832)	18.77 (8.289)	8.983 (5.604)	16.68 (8.526)	8.416 (5.073)	16.63 (9.096)	9.148 (4.764)	18.03 (9.750)	9.019 (5.702)	17.87 (8.056)
Time to Nearest Station (minutes)	7.408 (4.206)	7.709 (4.266)	10.38 (5.340)	10.01 (5.012)	9.701 (4.673)	9.977 (4.710)	8.552 (4.709)	8.074 (5.195)	6.752 (3.661)	6.150 (3.591)	9.040 (4.654)	7.359 (4.407)
Time to Terminal Station (minutes)	13.57 (6.352)	13.21 (6.506)	15.46 (7.918)	14.95 (8.174)	22.85 (7.447)	22.18 (7.617)	17.94 (8.855)	15.86 (8.965)	11.55 (6.428)	10.26 (6.108)	15.83 (6.909)	14.16 (7.901)
SRC (dummy)	0.540 (0.498)	0.310 (0.463)	0.227 (0.419)	0.150 (0.357)	0.308 (0.462)	0.156 (0.363)	0.394 (0.489)	0.178 (0.383)	0.797 (0.402)	0.513 (0.500)	0.334 (0.472)	0.308 (0.462)
Observations	8299	10918	4792	4069	1199	1377	558	815	3350	2692	1447	1430

Note: mean coefficients; sd in parentheses

Table 3: Quantile Regressions of Tokyo

	OLS		25%		50%		75%	
	Coef.	Std err.	Coef.	Std err.	Coef.	Std err.	Coef.	Std err.
Total(271,702 observations)								
Constant	344.325	1.035	308.403	1.090	336.142	1.014	362.250	1.127
Floor Space(m^2)	0.018	0.000	0.018	0.000	0.018	0.000	0.018	0.000
Age of Building (Year)	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
Time to Nearest Station (mins)	-0.013	0.000	-0.013	0.000	-0.013	0.000	-0.013	0.000
Time to Tokyo Station (mins)	-0.014	0.000	-0.011	0.000	-0.013	0.000	-0.015	0.000
Adjusted R-squared	0.796							
Year 1990(8,299 observations)								
Constant	323.388	5.239	266.206	5.282	308.836	4.689	348.871	6.929
Floor Space(m^2)	0.016	0.000	0.017	0.000	0.016	0.000	0.015	0.000
Age of Building (Year)	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
Time to Nearest Station (mins)	-0.011	0.001	-0.010	0.001	-0.010	0.001	-0.012	0.001
Time to Tokyo Station (mins)	-0.016	0.000	-0.011	0.000	-0.014	0.000	-0.019	0.001
Adjusted R-squared	0.656							
Year 2000(4,525 observations)								
Constant	340.527	6.882	312.216	6.542	341.751	6.237	361.837	8.018
Floor Space(m^2)	0.019	0.000	0.019	0.000	0.019	0.000	0.020	0.000
Age of Building (Year)	-0.002	0.000	-0.002	0.000	-0.002	0.000	-0.001	0.000
Time to Nearest Station (mins)	-0.011	0.001	-0.012	0.001	-0.012	0.001	-0.011	0.001
Time to Tokyo Station (mins)	-0.011	0.000	-0.009	0.001	-0.011	0.000	-0.012	0.001
Adjusted R-squared	0.827							
Year 2010 (3,969 observations)								
Constant	322.404	6.829	306.620	7.320	318.945	7.207	338.154	5.776
Floor Space(m^2)	0.017	0.000	0.017	0.000	0.017	0.000	0.017	0.000
Age of Building (Year)	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
Time to Nearest Station (mins)	-0.015	0.001	-0.015	0.001	-0.016	0.001	-0.015	0.001
Time to Tokyo Station (mins)	-0.012	0.000	-0.010	0.001	-0.011	0.001	-0.011	0.000
Adjusted R-squared	0.780							
Year 2015(10,918 observations)								
Constant	340.664	4.486	322.415	3.391	347.564	5.062	365.397	5.137
Floor Space(m^2)	0.016	0.000	0.016	0.000	0.016	0.000	0.016	0.000
Age of Building (Year)	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
Time to Nearest Station (mins)	-0.018	0.000	-0.018	0.000	-0.019	0.001	-0.018	0.001
Time to Tokyo Station (mins)	-0.015	0.000	-0.015	0.000	-0.015	0.000	-0.016	0.000
Adjusted R-squared	0.760							

Note: Dependent variables is log(price); latitude, longitude and quarterly dummy variables are controlled.

Table 4: Hedonic Regressions of Six Cities

	(1) Tokyo		(2) Yokohama		(3) Kawasaki		(4) Kyoto		(5) Osaka		(6) Kobe	
	1990	2015	1990	2015	1990	2015	1990	2015	1990	2015	1990	2015
Floor Space (m^2)	0.0160*** (111.00)	0.0160*** (109.38)	0.0150*** (98.32)	0.0129*** (49.48)	0.0166*** (54.50)	0.0114*** (20.44)	0.0172*** (33.30)	0.0191*** (35.59)	0.0146*** (54.19)	0.0149*** (46.53)	0.0168*** (41.19)	0.0136*** (27.28)
Age (year)	-0.00937*** (-20.19)	-0.0154*** (-67.99)	-0.0128*** (-31.76)	-0.0152*** (-38.70)	-0.0136*** (-18.13)	-0.0178*** (-26.68)	-0.0184*** (-11.62)	-0.0245*** (-24.00)	-0.0148*** (-18.65)	-0.0223*** (-51.35)	-0.0126*** (-12.45)	-0.0221*** (-27.93)
Time to Nearest Station (minutes)	-0.0109*** (-20.14)	-0.0178*** (-36.82)	-0.0111*** (-26.00)	-0.0162*** (-23.89)	-0.0142*** (-14.46)	-0.0208*** (-17.34)	-0.00874*** (-4.47)	-0.0254*** (-15.91)	-0.0211*** (-20.10)	-0.0169*** (-18.01)	-0.00795*** (-6.51)	-0.0204*** (-13.12)
Time to Terminal Station (minutes)	-0.0182*** (-49.27)	-0.0181*** (-47.47)	-0.00146*** (-4.74)	-0.00432*** (-9.50)	-0.00394*** (-4.40)	-0.0129*** (-12.58)	-0.00141 (-1.43)	-0.00840*** (-8.75)	-0.0173*** (-28.24)	-0.0185*** (-32.64)	-0.0135*** (-12.70)	-0.0182*** (-17.90)
SRC (dummy)	0.0155*** (3.13)	0.0234*** (4.71)	0.0409*** (7.23)	0.0658*** (7.03)	0.0196*** (2.09)	0.0465*** (2.97)	0.0394*** (2.21)	0.0565*** (2.08)	0.0669*** (7.52)	0.0483*** (6.09)	-0.00722 (-0.61)	-0.0887*** (-6.03)
x	-0.959*** (-35.18)	-0.906*** (-38.55)	0.497*** (10.44)	0.490*** (6.71)	-0.276* (-1.92)	0.465*** (2.86)	-0.0374 (-0.14)	0.188 (0.72)	0.891*** (8.74)	1.418*** (12.47)	2.248*** (19.55)	0.344*** (3.03)
y	-1.153*** (-30.00)	-1.853*** (-48.29)	0.932*** (27.98)	1.176*** (21.22)	0.722*** (2.94)	3.195*** (11.95)	3.814*** (15.63)	4.328*** (15.37)	-0.495*** (-5.23)	0.512*** (5.06)	-2.390*** (-8.36)	1.066*** (3.59)
Constant	183.3*** (47.54)	200.6*** (59.91)	-94.71*** (-14.22)	-102.6*** (-10.08)	20.75 (0.78)	-170.6*** (-5.67)	-120.7*** (-3.23)	-169.7*** (-4.53)	-95.42*** (-7.00)	-202.5*** (-13.22)	-213.2*** (-21.68)	-76.02*** (-6.62)
Observations	8299	10821	4792	4047	1199	1371	558	810	3350	2671	1447	1423
R ²	0.649	0.763	0.763	0.613	0.815	0.634	0.715	0.787	0.541	0.776	0.674	0.662

Note: Dependent variables is log(price); t statistics in parentheses; robust standard divination are used

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

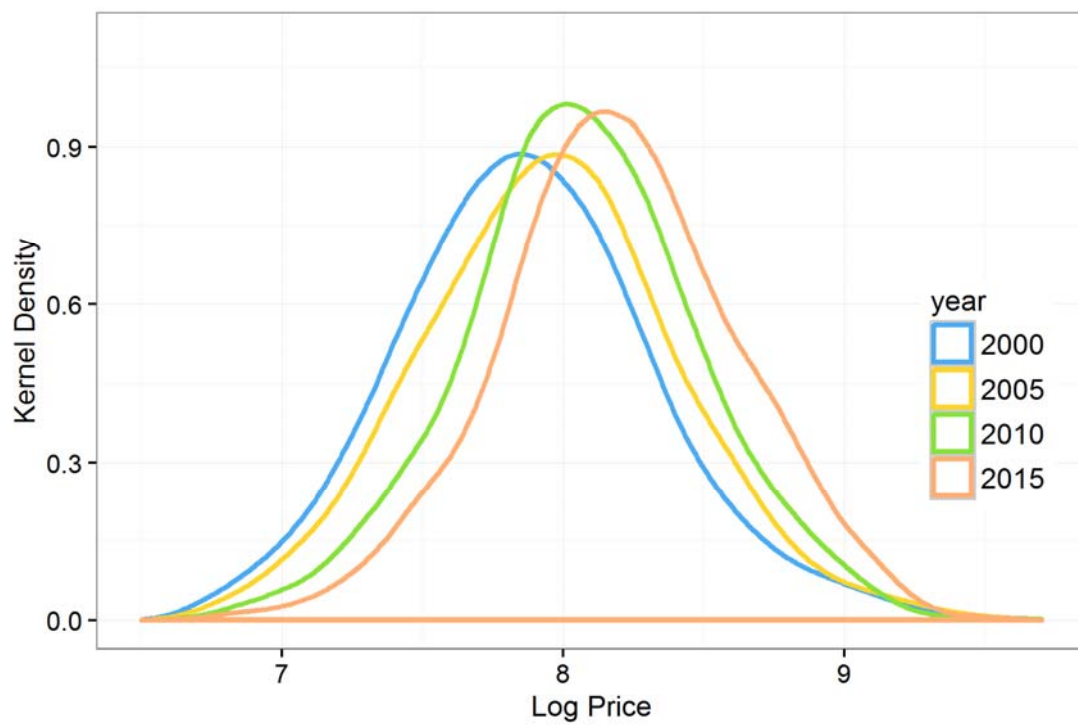
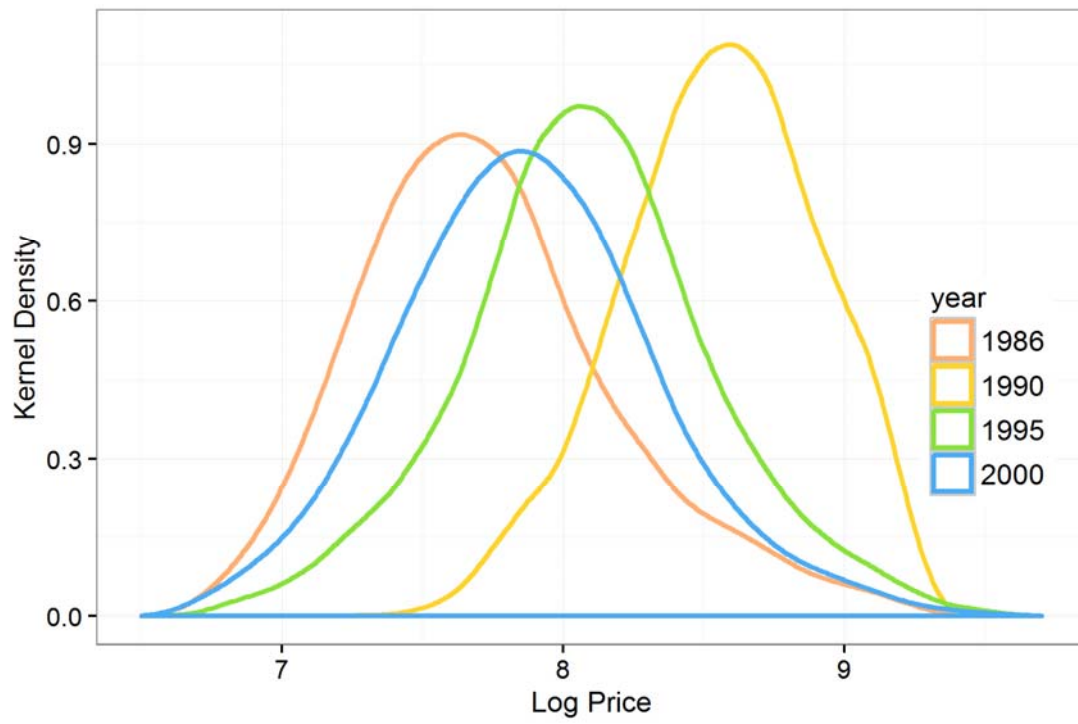


Figure 1: Price Kernel Density of Tokyo

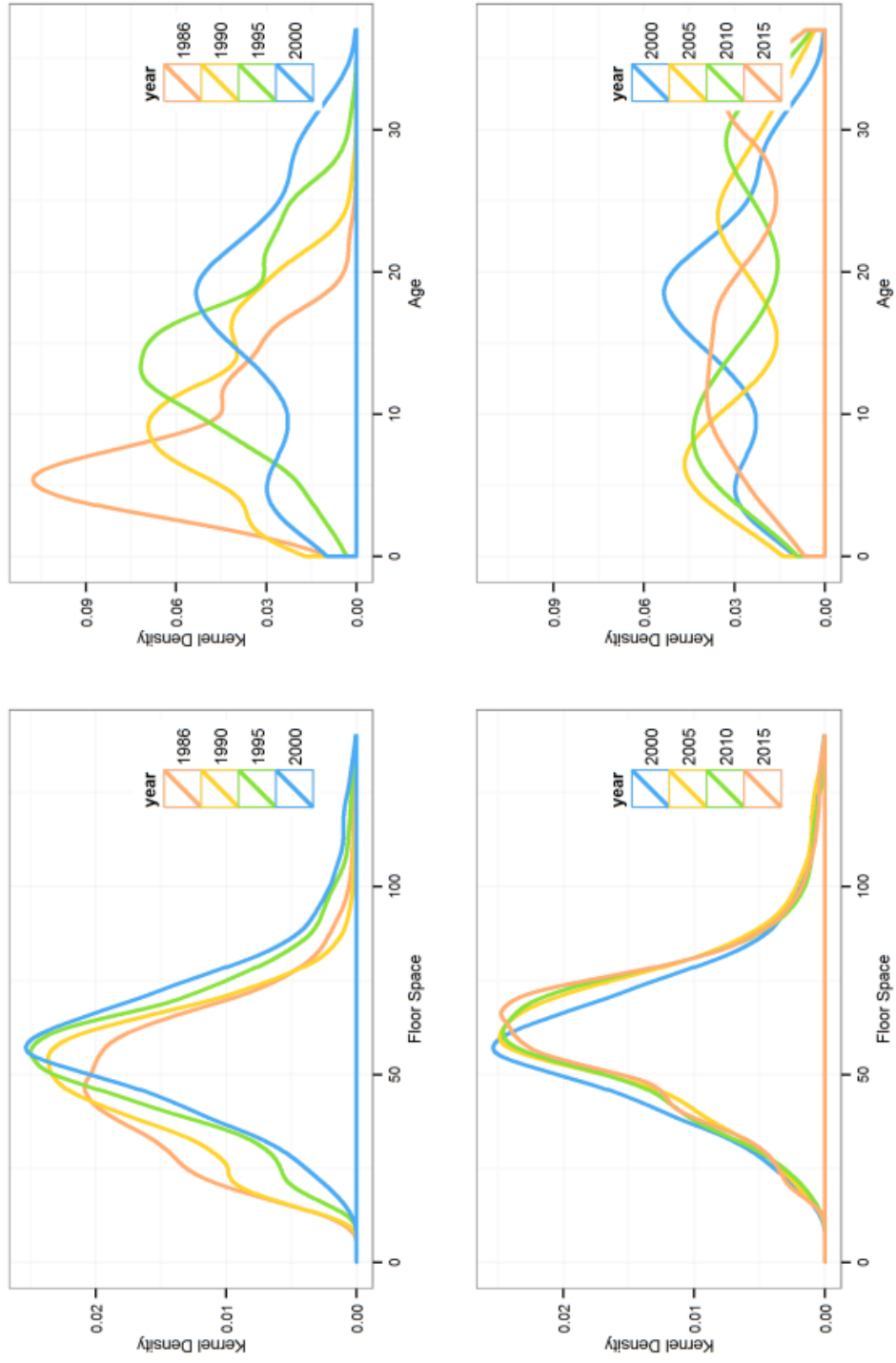


Figure 2: Space and Age Kernel Density of Tokyo

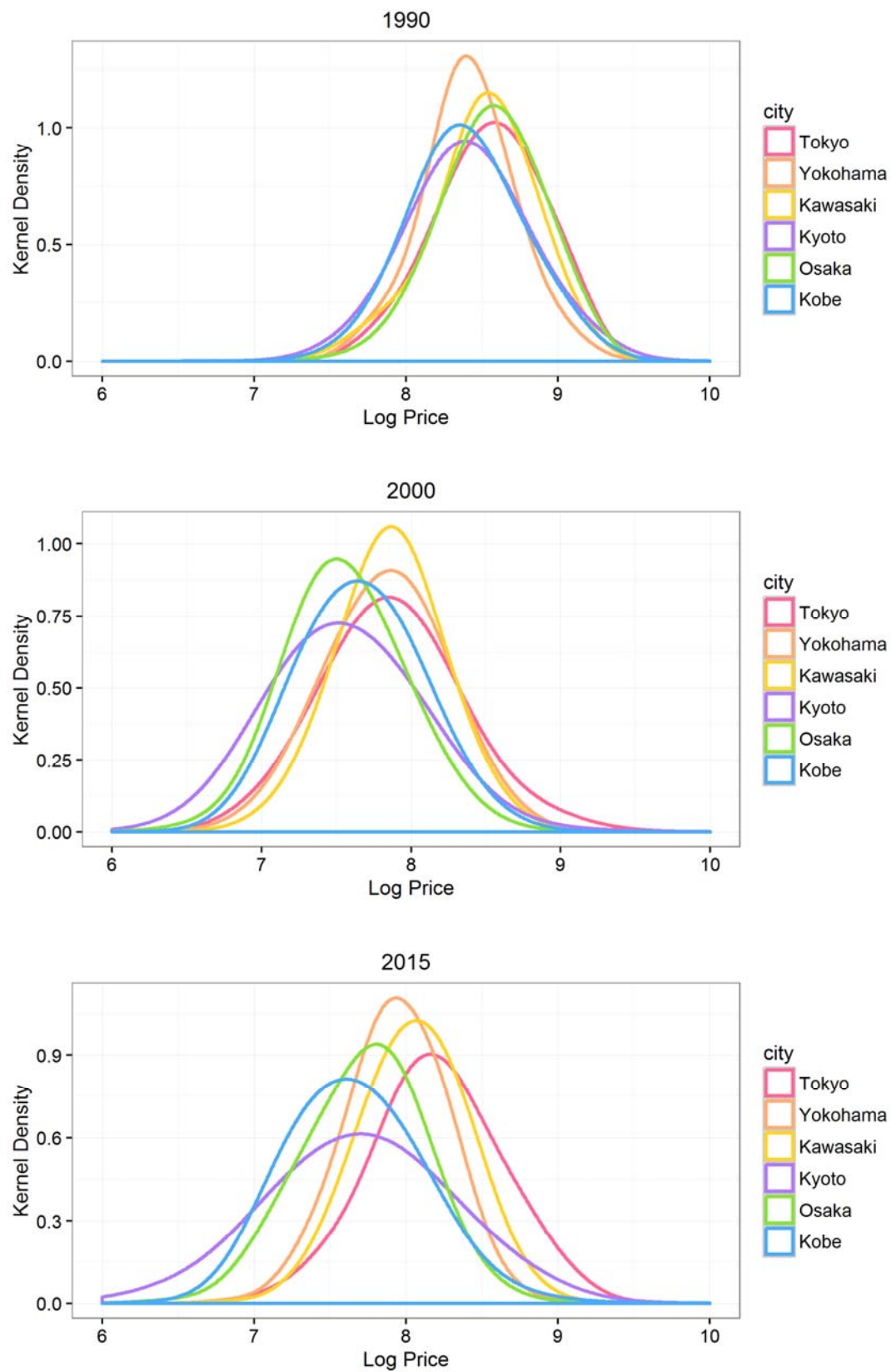


Figure 3: Kernel Density of Six Cities

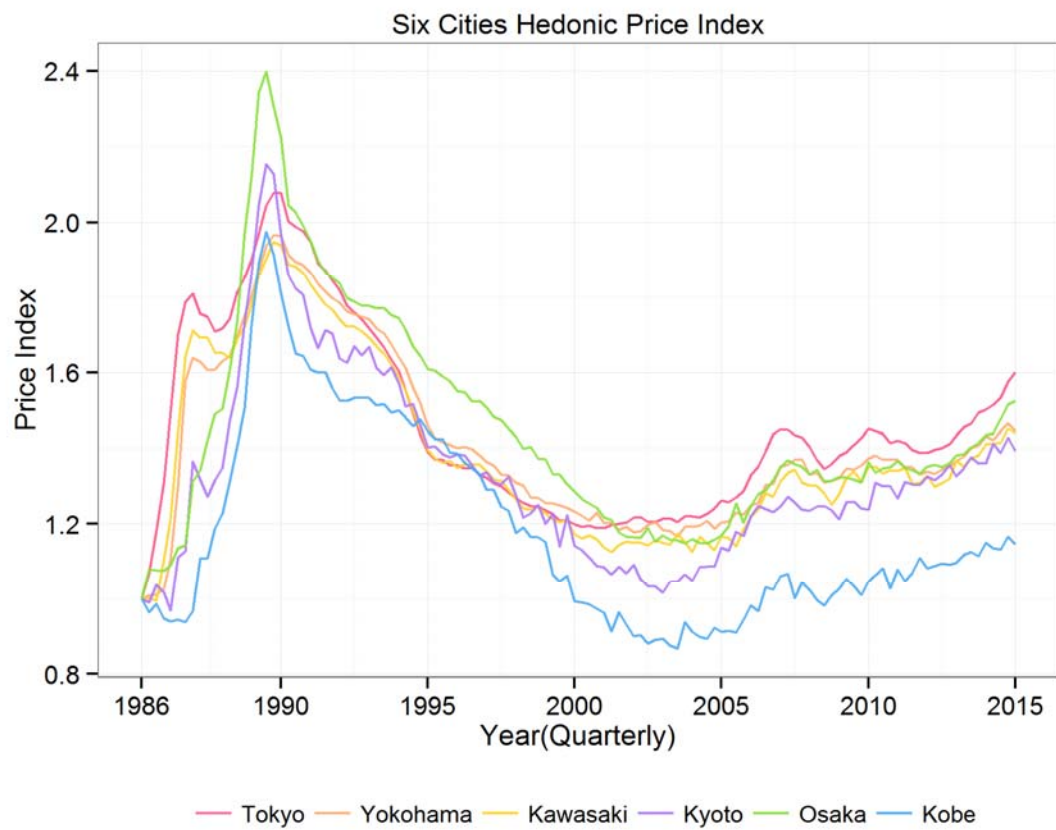
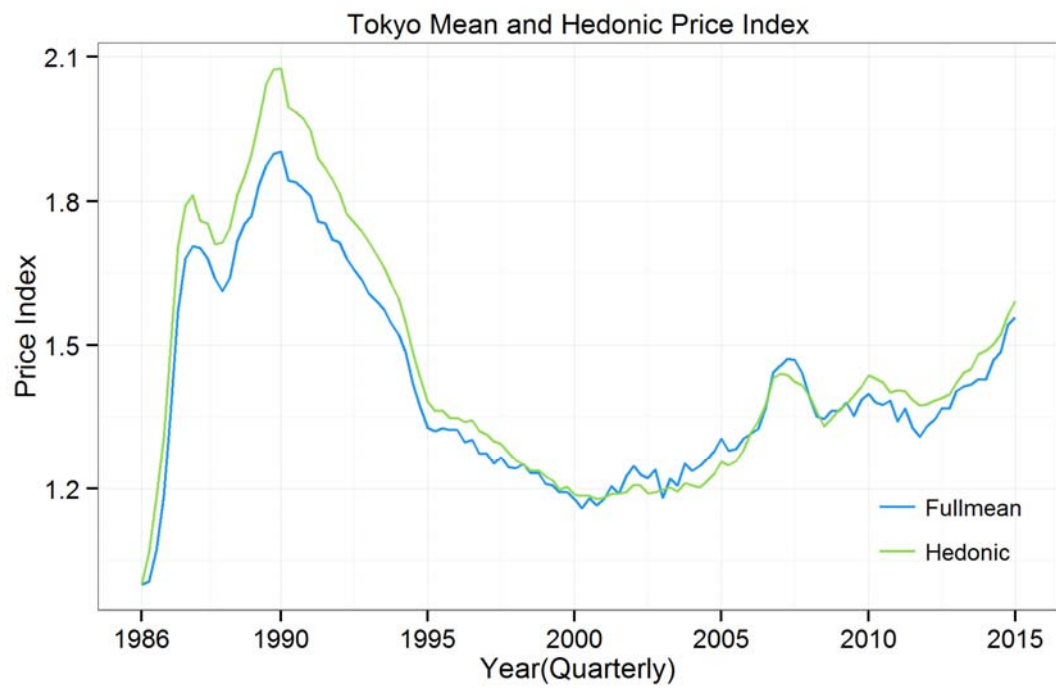


Figure 4: Hedonic Price Index

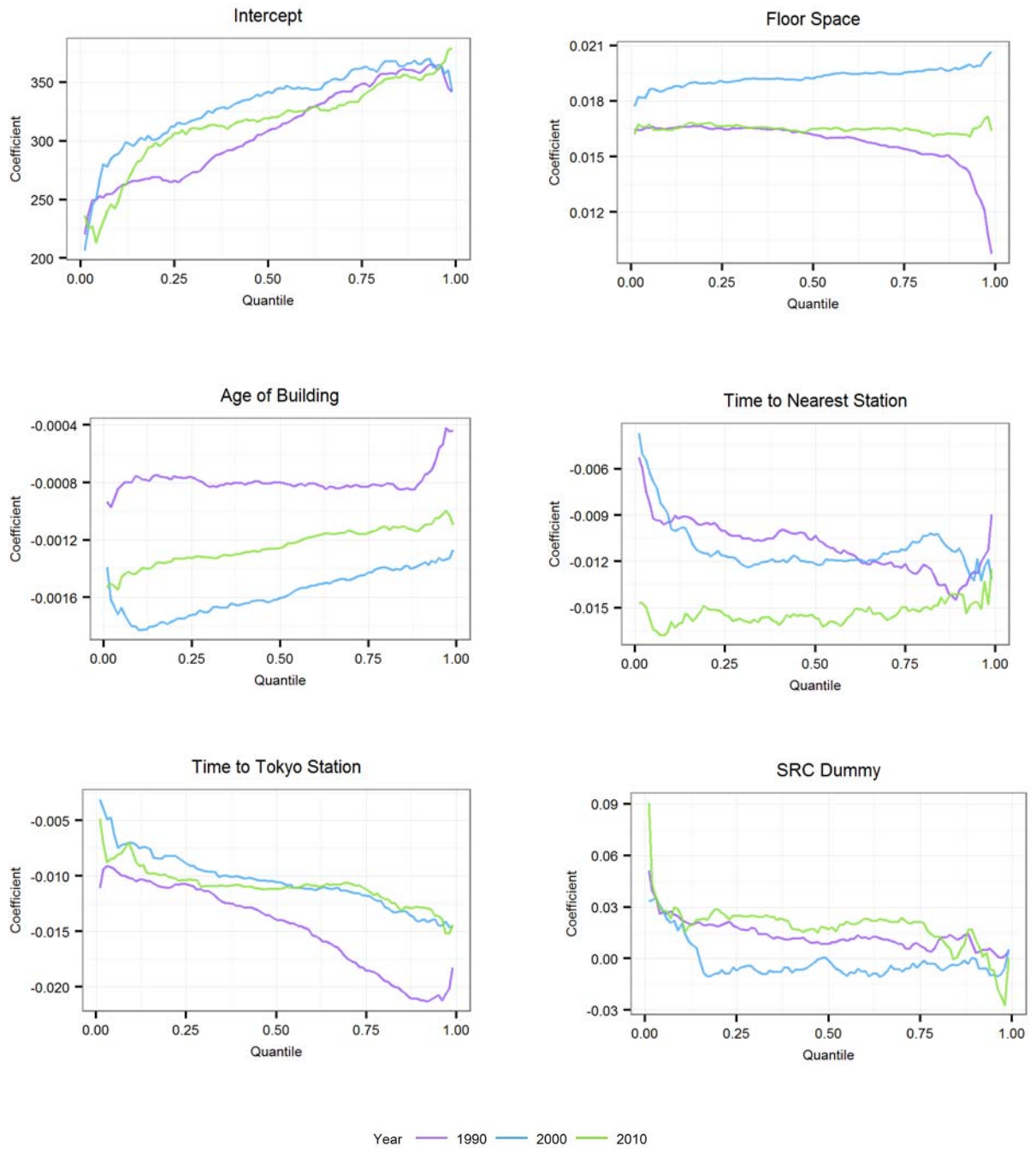


Figure 5: Quantile Regression Coefficients

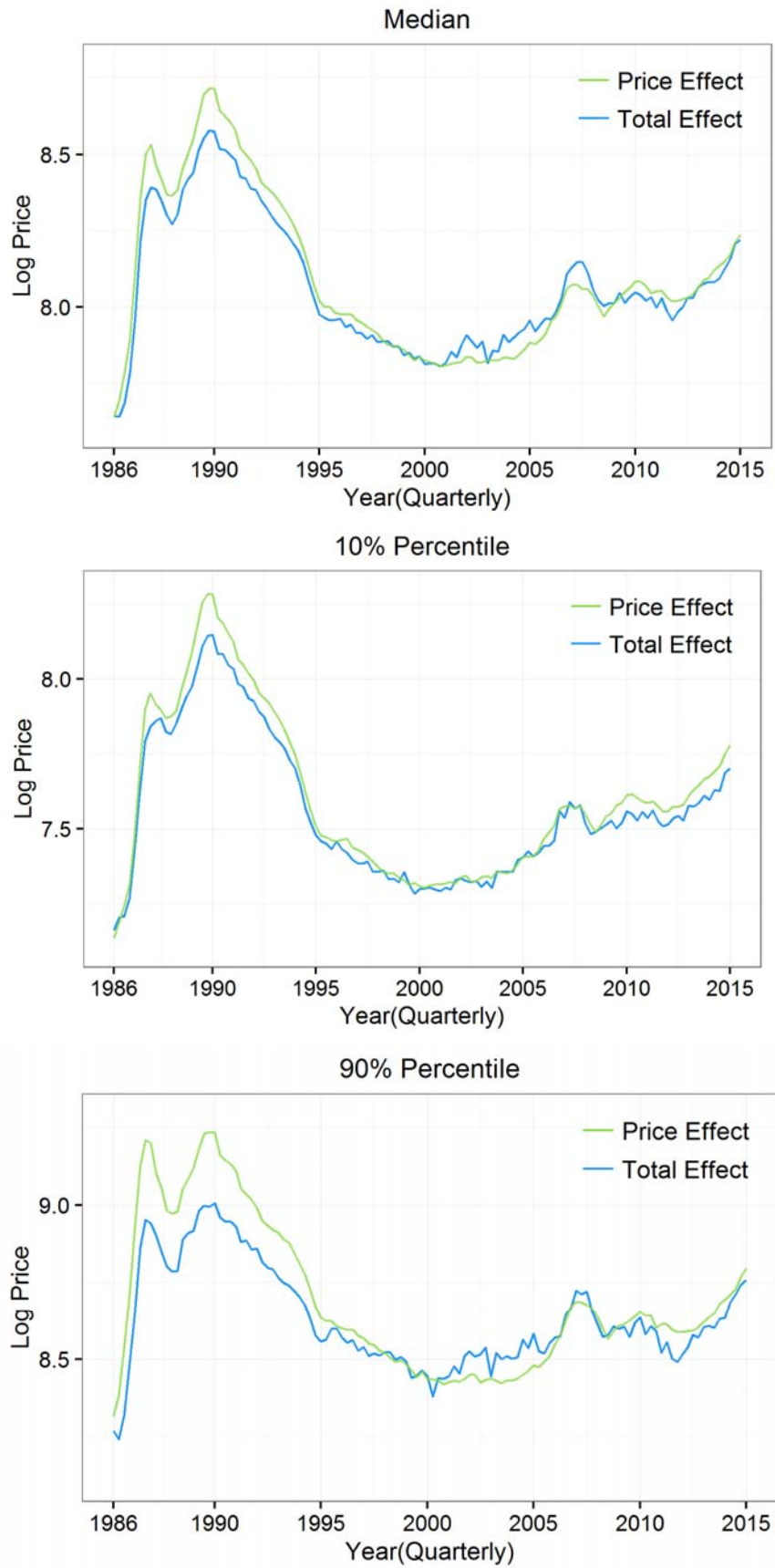


Figure 6: Decomposition of Tokyo House Price

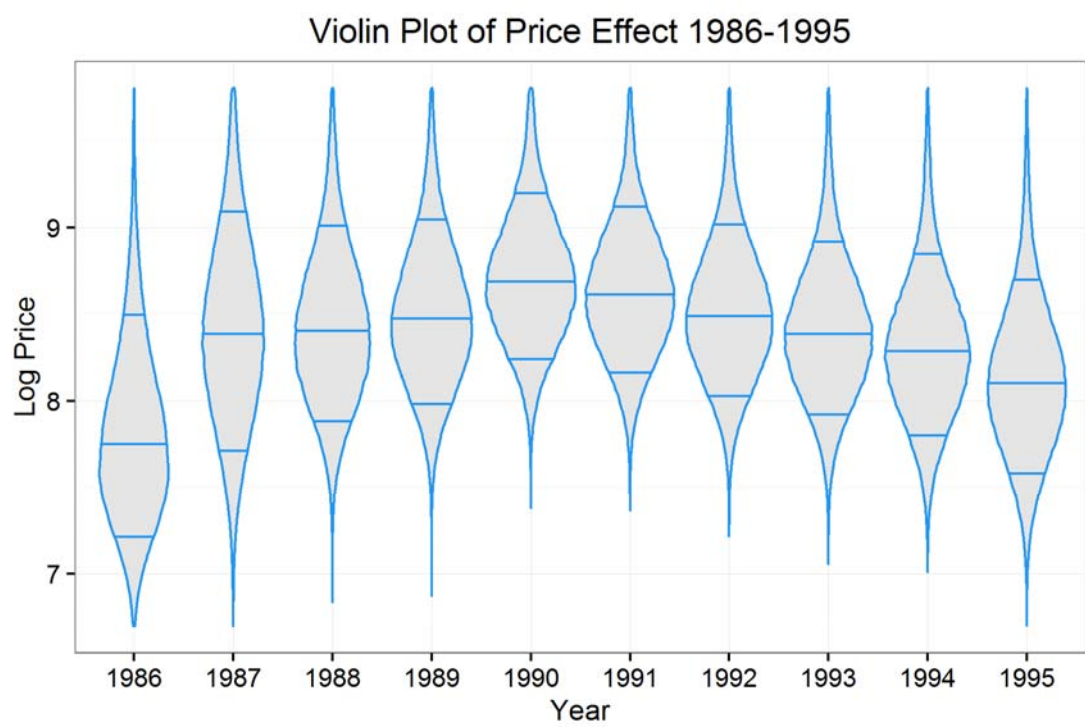
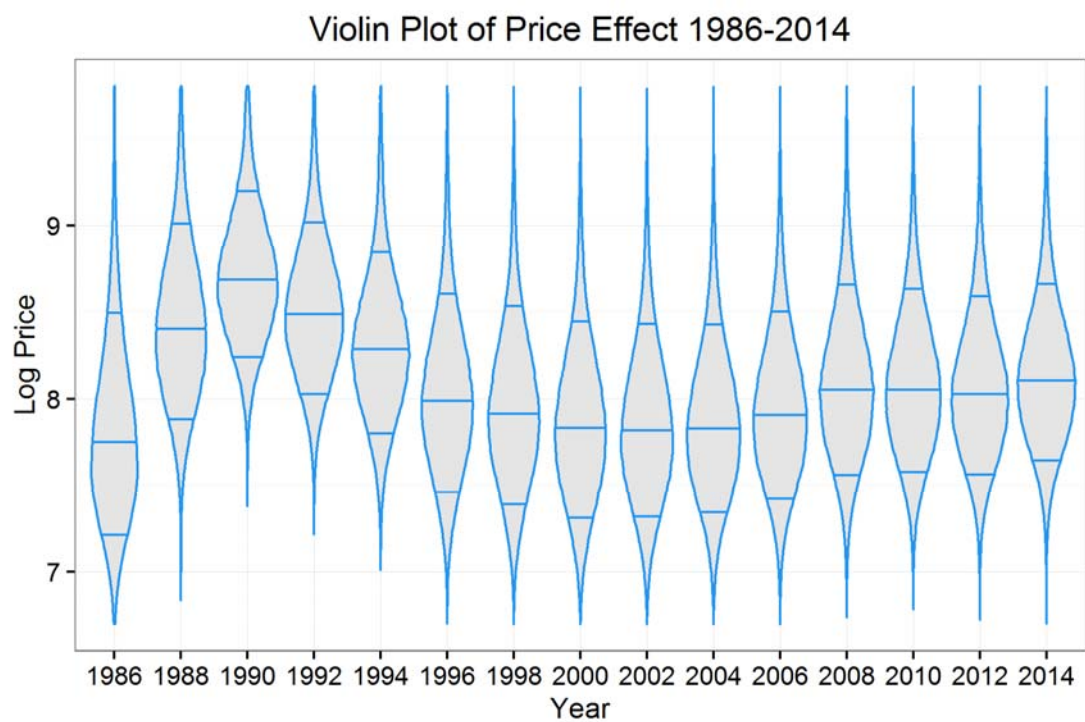


Figure 7: Violin Plot of Tokyo House Price

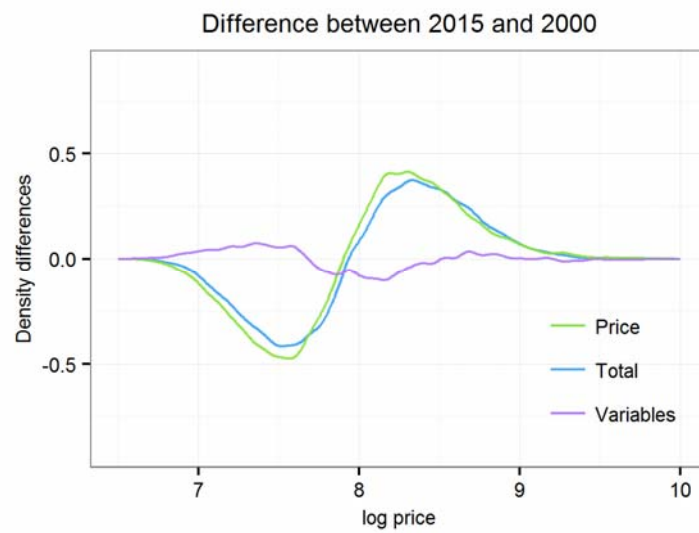
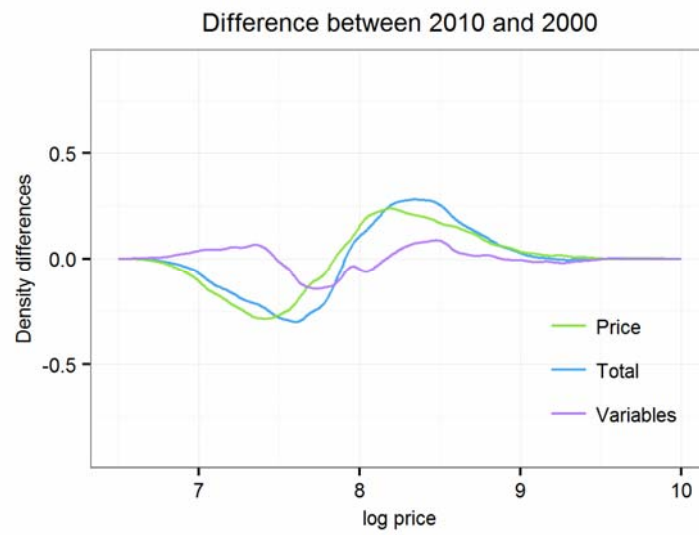
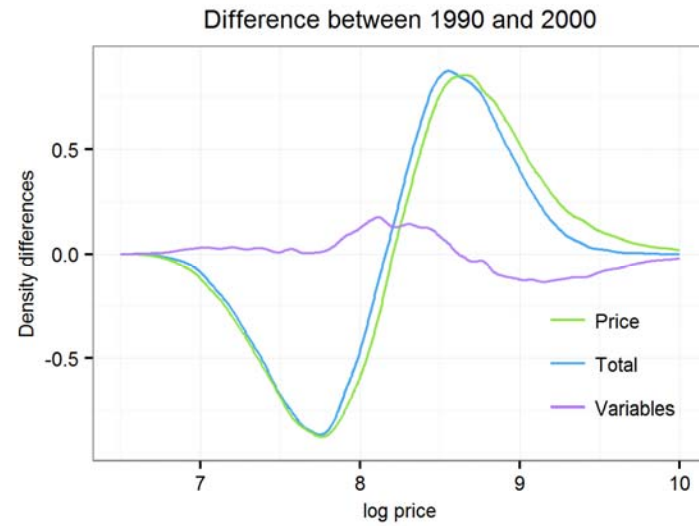


Figure 8: Decomposition of Density Difference

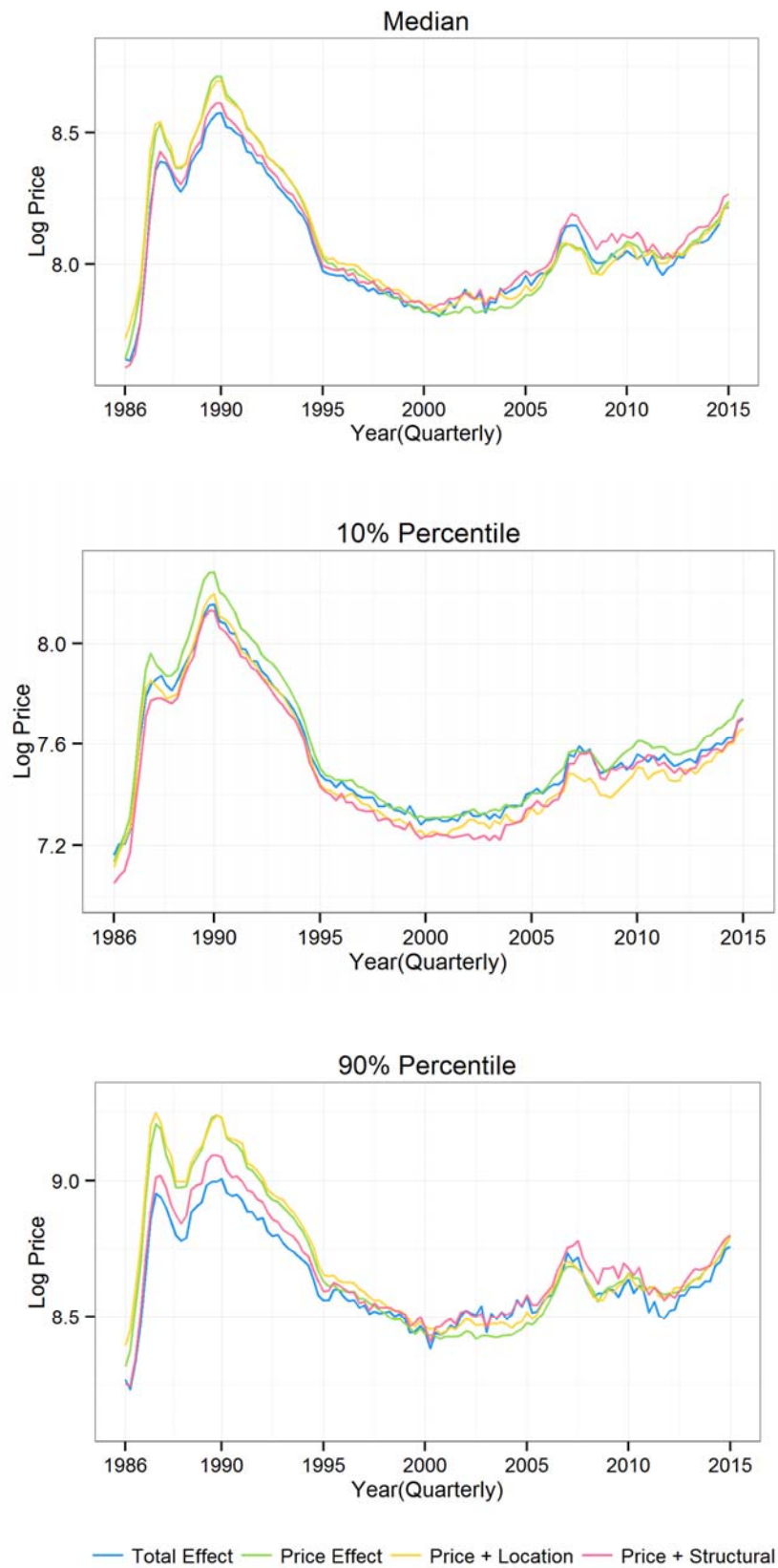


Figure 9: Structural and Location Decomposition of Tokyo House Price

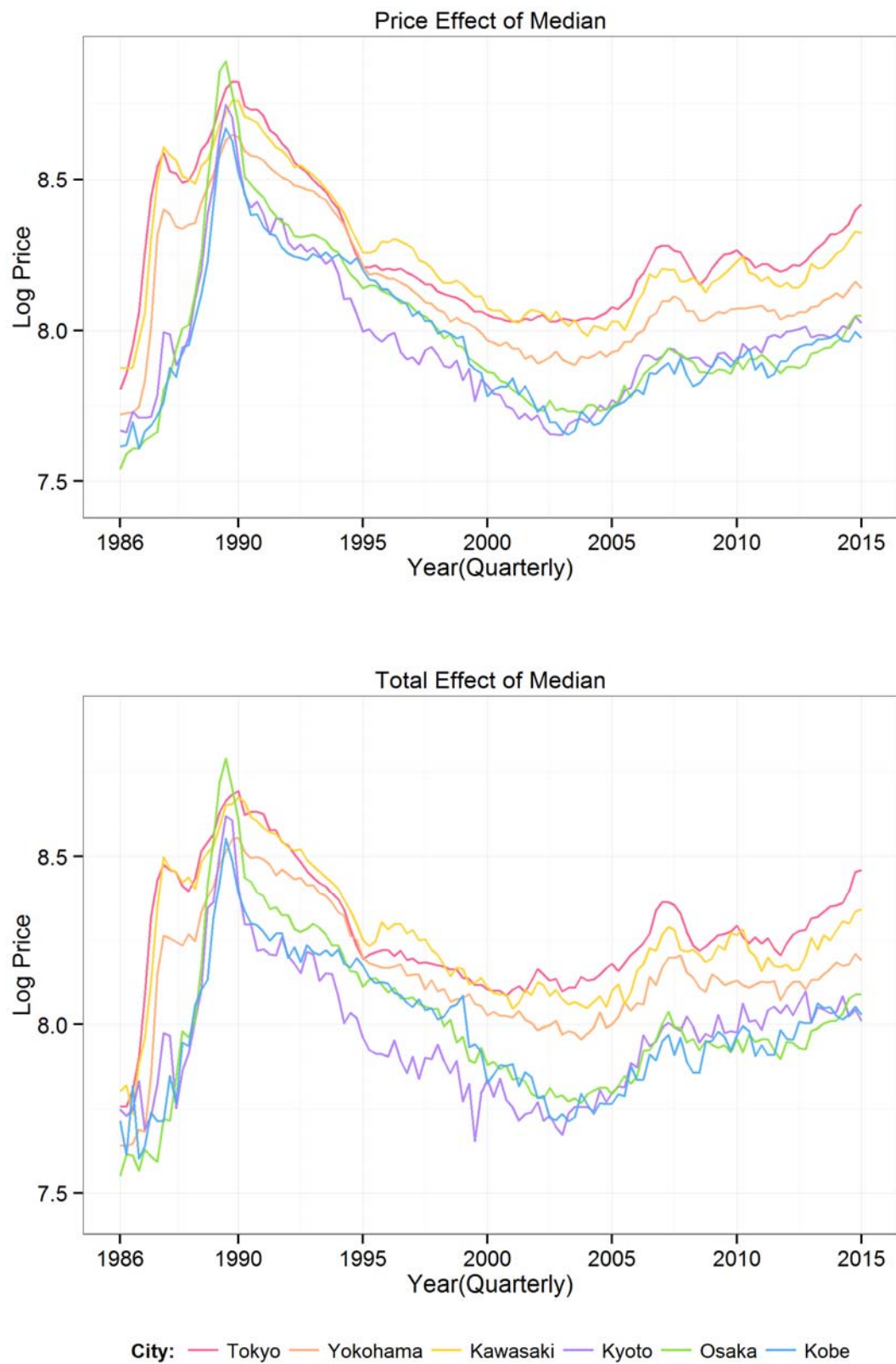


Figure 10: Decomposition of Six Cities House Price: Price and Total Effect

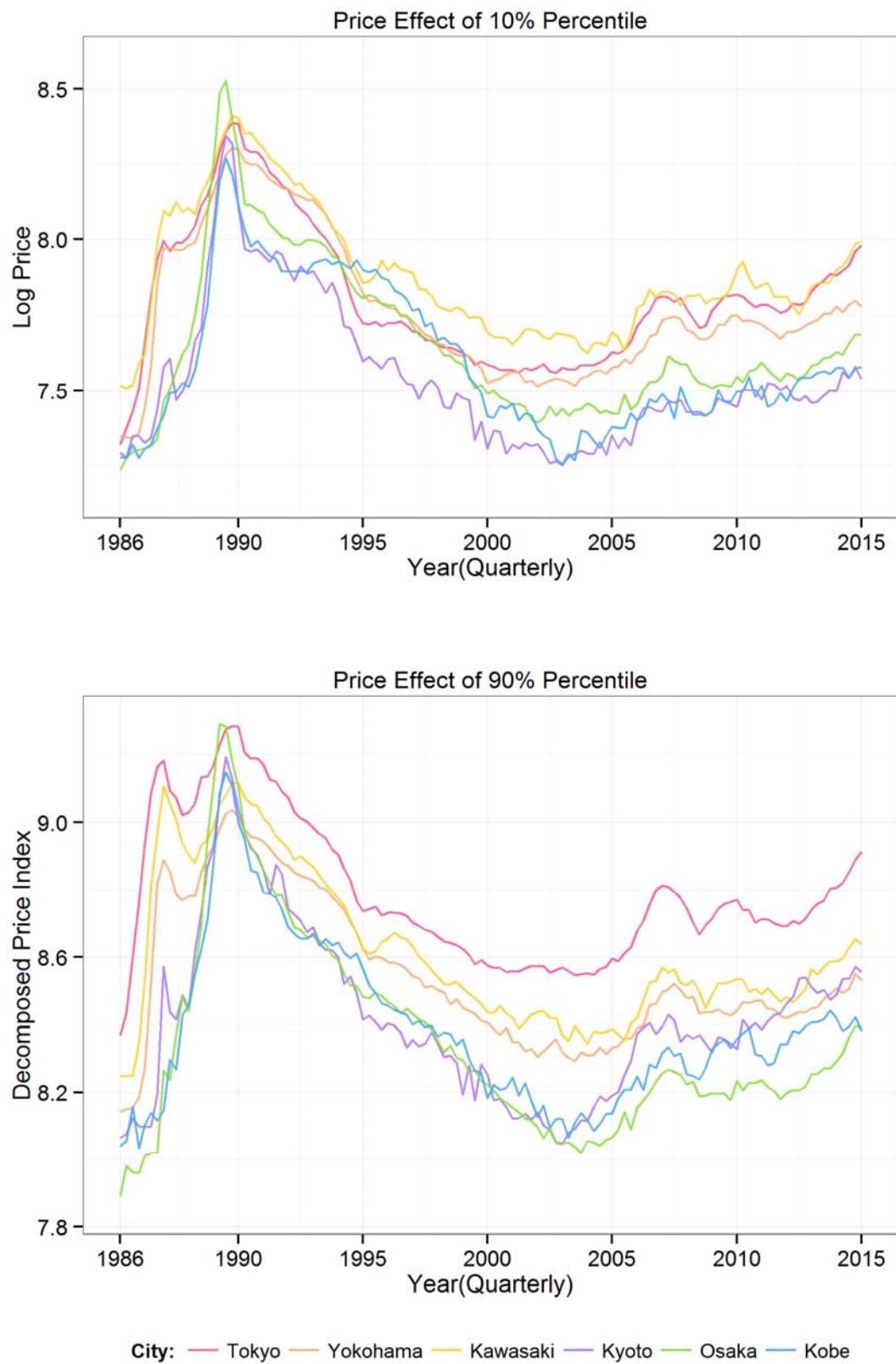


Figure 11: Decomposition of Six Cities House Price: 10% and 90% of Price Effect

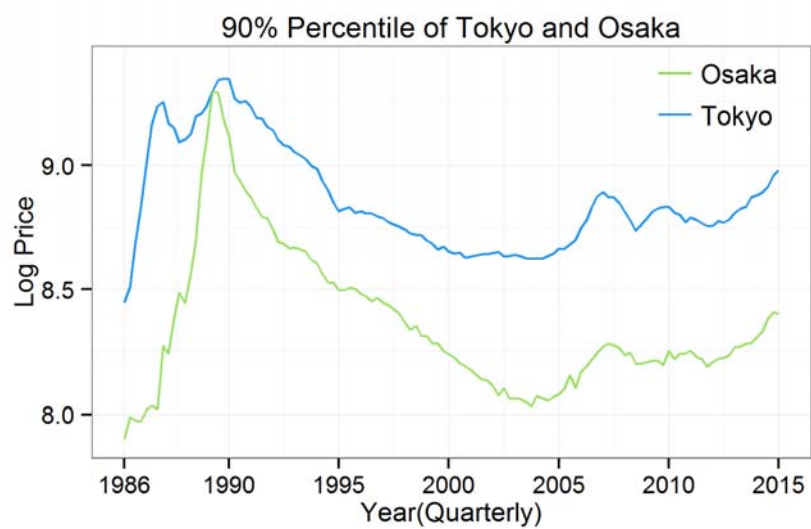
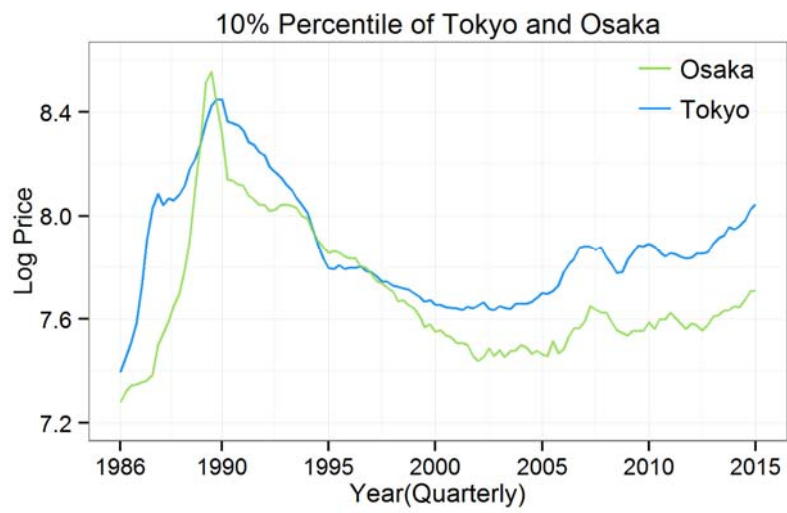
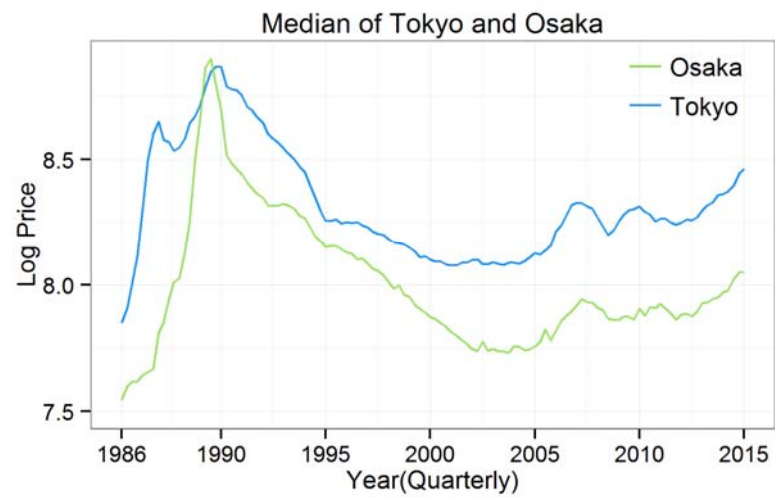


Figure 12: Comparison of Tokyo and Osaka Price Effect