Decomposed Housing Price Index with Quantile Regression: Change of Distributions

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Introduction

Economic measurement is an important issue for housing market. The common approach for constructing house price indexes is hedonic regression estimators. However, hedonic approach faces the structure change problems.

In this work, we construct a decomposed housing price index, using quantile regressions and resampling procedure. This housing price index could separate the coefficient change and the attributes change in houses price density.

The data we use is condominium listing data of Tokyo from 2000 to 2015 with 87,000 observations. From our decomposed housing price index, the attributes change contributes more in boom and bust period compared with flat period. In addition to, we use this method and conditionally parametric quantile model to compare the housing market in different cities. It makes possible to compare different cities even countries housing market that using decomposition distribution method.

Method

Hedonic Price Index have structure change problems. Firstly, it assumes the house price sensitivity are not changed with time. To solve the first problems, we cut each estimators to different small rolling time period. It allows the influence of attributes on house price could change with time. Our house price index is based on discontinued quantile regressions for each periods.

Secondly, it assumes the attributes distribution of houses are constant. We use the decomposition approach to solve this problem. In the earliest literature, Oaxaca (1973) and Blinder (1973) propose a decomposition approach using OLS:

$$E(y_1 - y_0) = \underbrace{\boxed{(z_1 - z_0)\beta_1}}_{\text{Attributes Change}} + \underbrace{\boxed{z_0(\beta_1 - \beta_0)}}_{\text{Coefficient Change}}$$

Machado and Mata (2005) propose a decomposition approach based model using Quantile Regression (QR). It can separate distribution change for attributes change and coefficient change (price change). This approach are used by McMilllen (2008), Nicodemo and Raya(2012), Fesselmeyer et al.(2013) for housing market. Different with previous work, we use it to analyze long time periods data and construct a price index instead of comparing two periods.

Step 1. Estimate Quantile Regressions (QR) with the same formula of hedonic model for denoted set of $\theta \in (0,1)$, e.g. N=99 from 0.01 to 0.99 . The set of estimators are $\hat{\beta}_0(\theta)$ and $\hat{\beta}_1(\theta)$, i.e. $\hat{\beta}_t(\theta)$ t=0,1

Step 2. For QR coefficients set of $\hat{\beta}_t(\theta)$, yield m estimates from QR coefficients, e.g. m=50,000

Step 3. Generate a random sample of size m with replacement from transactions in each time period z_0 and z_1

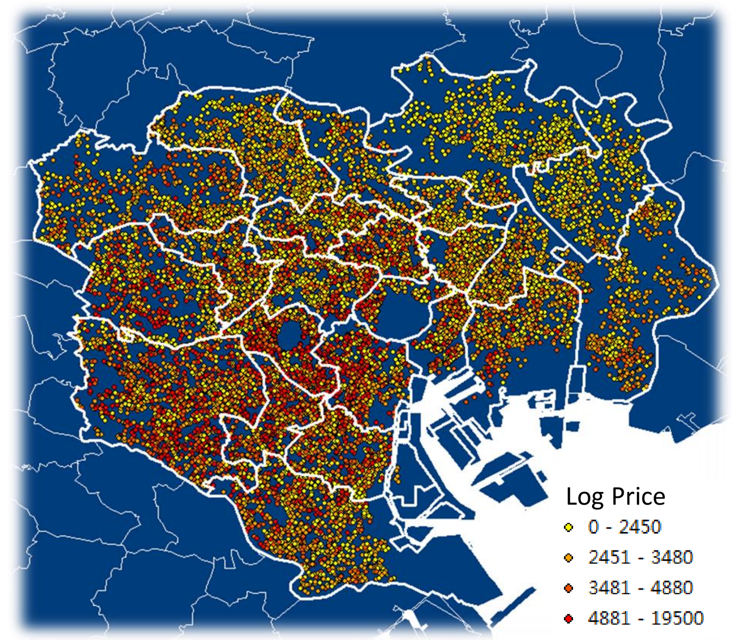
Step 4. Multiple set of $\hat{\beta}_t(\theta)$ with z_0 and z_1. We get estimated samples of house prices with size m. $z_0\hat{\beta}_0(\theta)$, $z_1\hat{\beta}_1(\theta)$ and $z_0\hat{\beta}_1(\theta)$.

Total Change(a):	$z_1\hat{\beta}_1(\theta) - z_0\hat{\beta}_0(\theta)$
Coefficient Change(b):	$z_0\hat{\beta}_1(\theta) - z_0\hat{\beta}_0(\theta)$
Attributes Change(a)-(b):	$(z_1 - z_0)\hat{\beta}_1(\theta)$

In this dataset, we set year 2000 as t_0. For each quarter q, we set $t_1 = [q-4, q]$. We get a Total Change index $Z_t\hat{\beta}_t(\theta)$ and Price (Coefficient) Change index $Z\hat{\beta}_t(\theta)$.

The hedonic formula is :

$$\ln(Price) = \beta_0 + \beta_1 Area + \beta_2 Age + \beta_3 t_{Tokyo} + \beta_4 t_{station} + \beta_5 D_{src} + \beta_6 D_{south} + \beta_7 x + \beta_8 y + \beta_9 D_{city} + \varepsilon$$



Tab.1 Summary Statistics

	(1) Total	(2) 2000	(3) 2005	(4) 2008	(5) 2012	(6) 2015
Transaction Price	3304.2	2835.1	3143.2	3674.0	3209.7	3893.2
(10,000 Yen)	(1696.3)	(1504.6)	(1691.6)	(1838.6)	(1506.2)	(2005.6)
Area of Structure	61.29	59.78	62.20	62.52	60.93	61.69
(m^2)	(18.07)	(18.94)	(18.79)	(17.20)	(16.68)	(18.96)
Age	203.5	194.7	187.5	178.9	215.3	213.1
(month)	(116.9)	(97.44)	(118.5)	(116.5)	(120.3)	(117.5)
Time to the Nearest	7.389	7.247	7.179	7.427	7.344	7.622
Station (minutes)	(4.228)	(4.128)	(4.087)	(4.229)	(4.238)	(4.242)
Time to Tokyo Station	25.94	26.45	25.92	25.79	25.79	26.03
(minutes)	(8.480)	(8.518)	(8.379)	(8.374)	(8.385)	(8.633)
Structure Dummy: SRC	0.410	0.507	0.442	0.414	0.377	0.307
	(0.492)	(0.500)	(0.497)	(0.493)	(0.485)	(0.461)
Face Dummy: South	0.343	0.406	0.369	0.342	0.318	0.311
	(0.475)	(0.491)	(0.483)	(0.474)	(0.466)	(0.463)
N	87872	4552	4766	4591	8850	5503

Results

This decomposition method could describe the distribution of total change and price change. The mean price level are similar at 2005&2012 and 2008&2015, but the distributions are quite different, such as variation. It could not be observed by hedonic estimators.

Fig.1 Hedonic Index

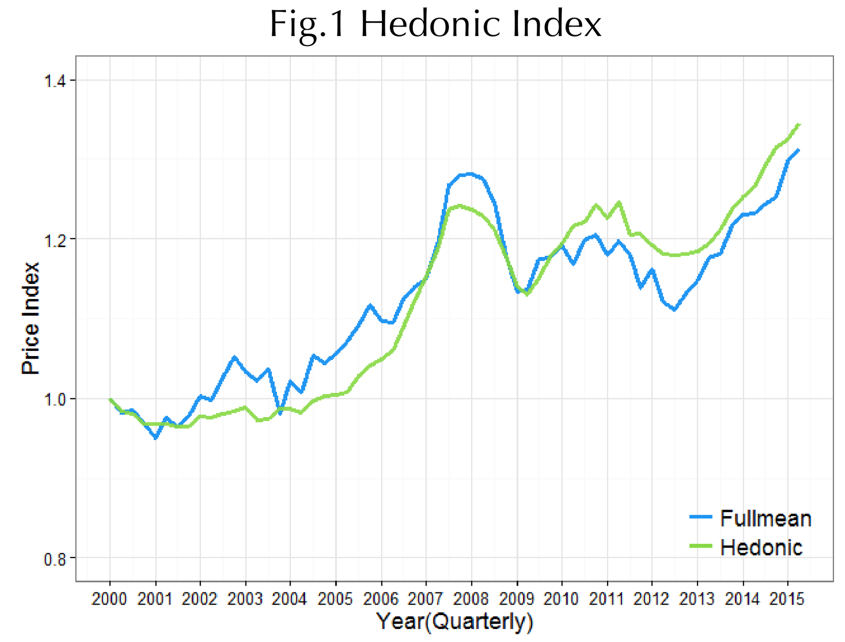
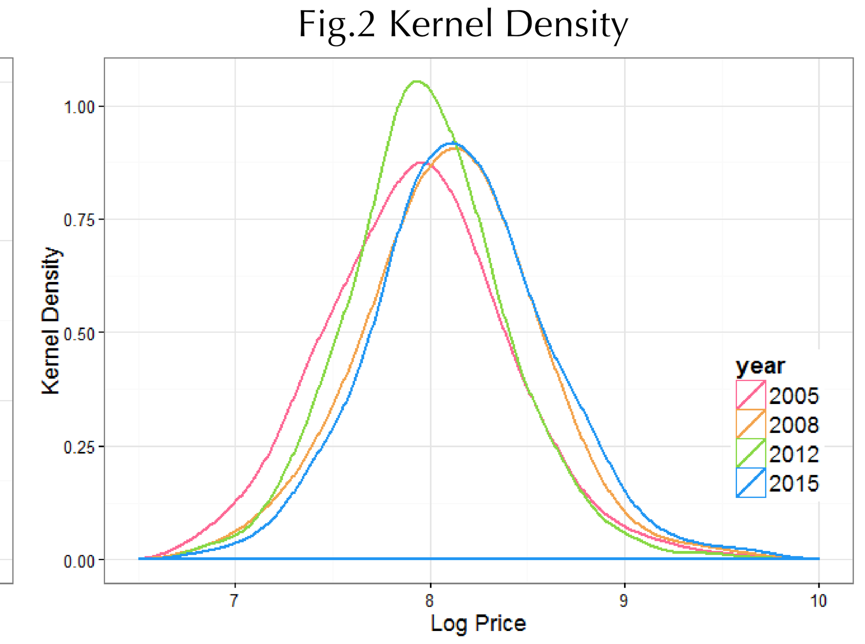


Fig.2 Kernel Density



Firstly we calculate decomposed price index of Tokyo. It denotes that the attributes change contributes more at boom and bust periods than flat periods. Decomposed price index with controlled attributes change could be used to describe distribution change.

Fig.3 Total and Price Change

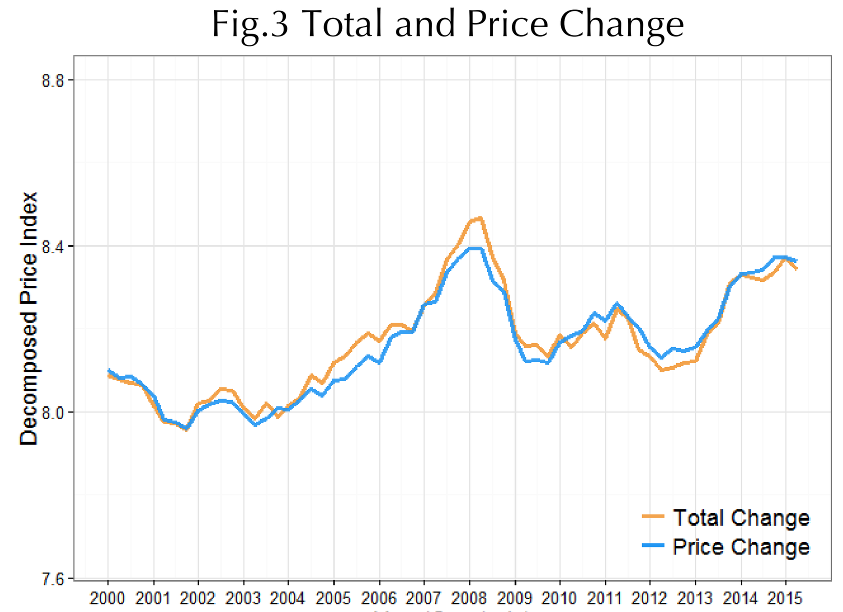
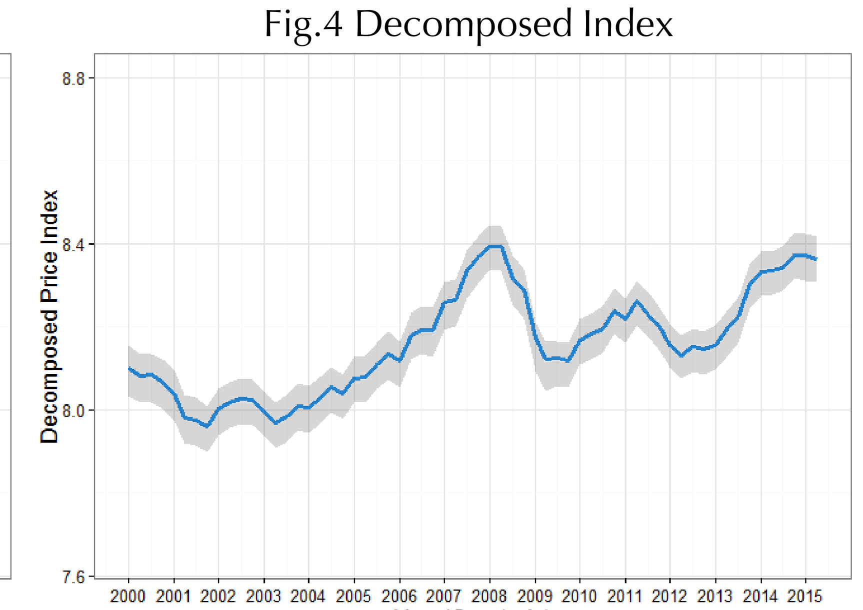


Fig.4 Decomposed Index



In addition, this decomposed price index could be used to compare different cities even countries housing price. We compare 6 cities in Japan, i.e. Tokyo, Yokohama, Kawasaki, Kyoto, Osaka and Kobe. Decomposed Index allows the start point of price index different and separate attributes change with price change.

Fig.5 Kernel Density

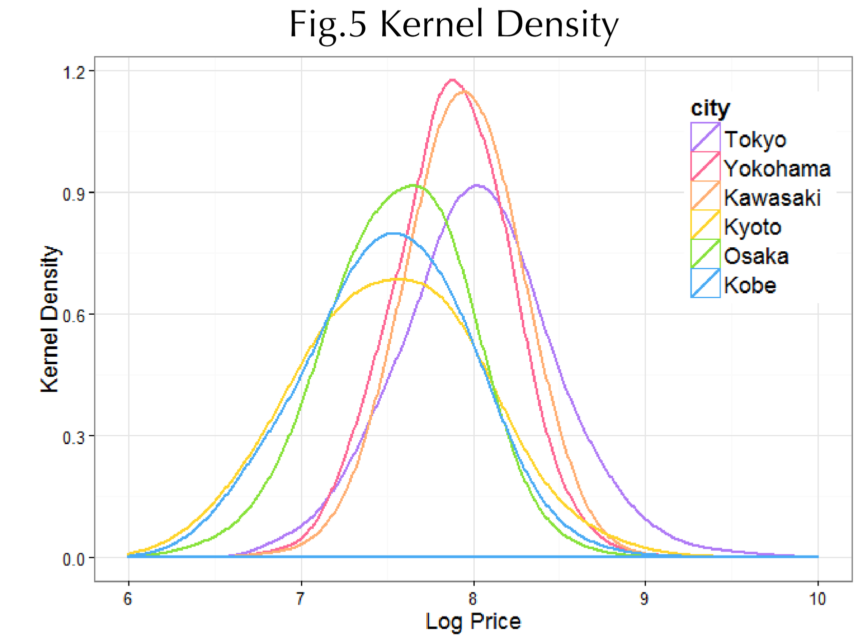


Fig.6 Hedonic Index

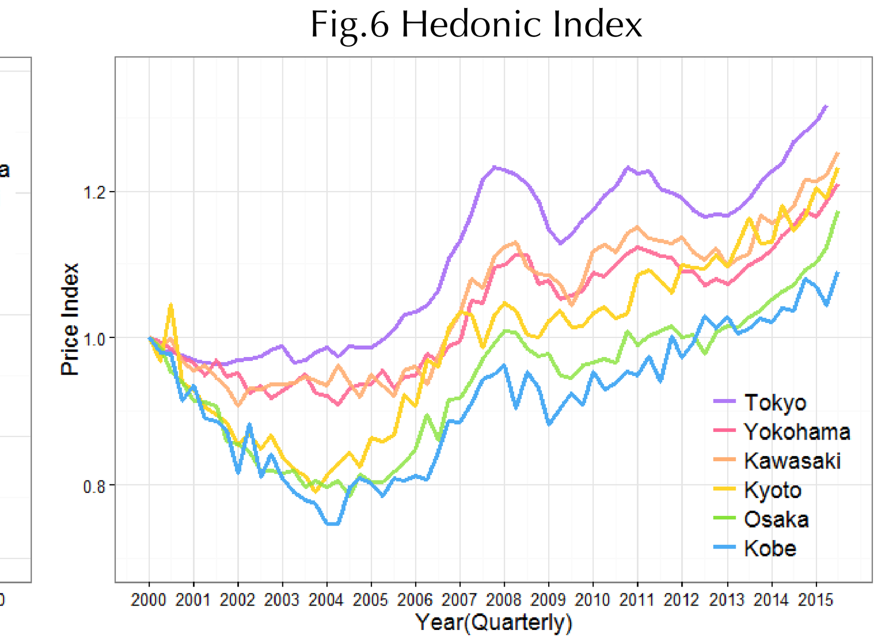


Fig.7 Decomposed Total Change

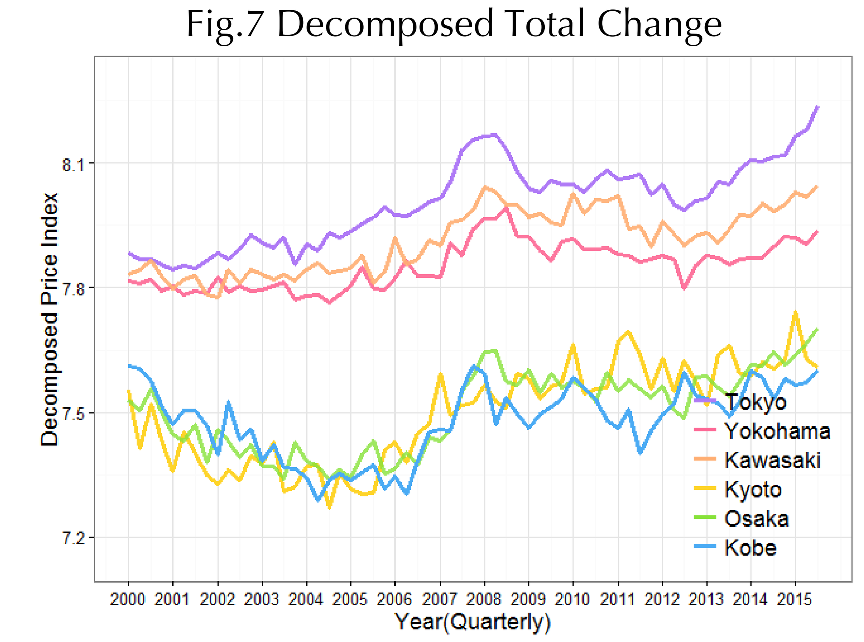
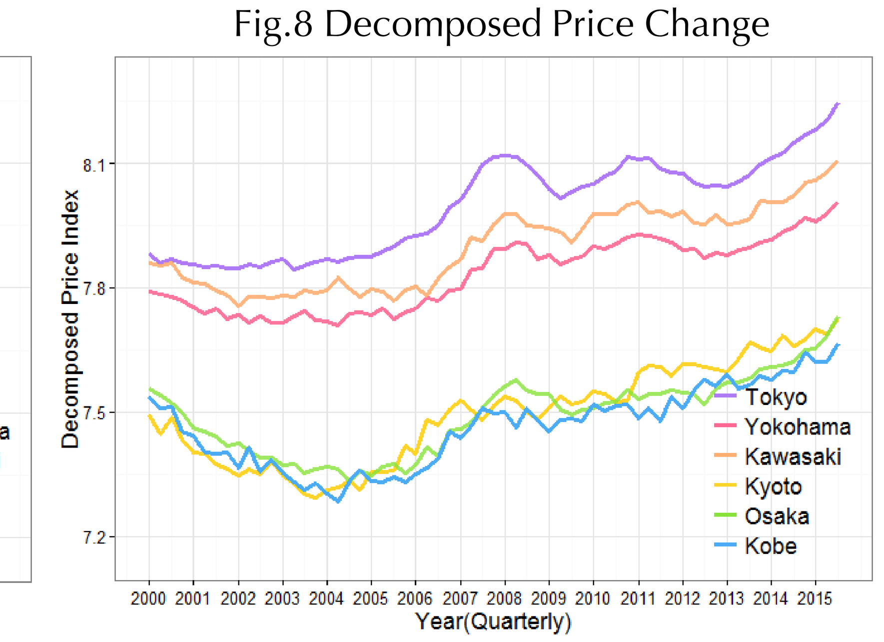
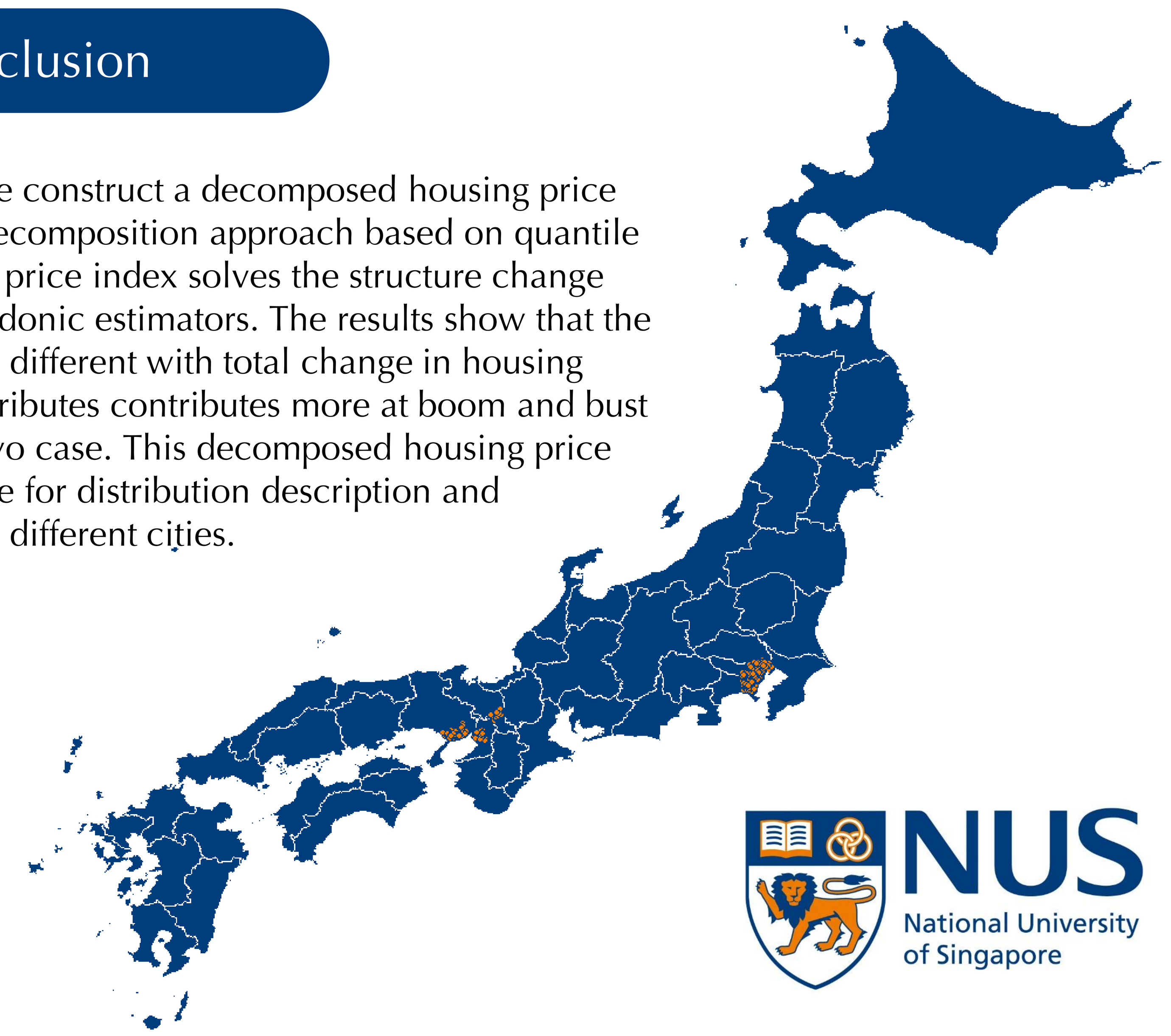


Fig.8 Decomposed Price Change



Conclusion

In this work, we construct a decomposed housing price index. Using decomposition approach based on quantile regression, this price index solves the structure change problems of hedonic estimators. The results show that the price change is different with total change in housing market. The attributes contributes more at boom and bust periods in Tokyo case. This decomposed housing price index is suitable for distribution description and comparison for different cities.



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