

Comments on

“Decompositions of Spatially Varying Quantile Distribution Estimates:

The Rise and Fall of Tokyo House Prices”

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1. Methods

1) Counterfactual Decompositions of Distributional Changes

Application of Machad and Mata (2005) Journal of Applied Econometrics

Decompositions of “distributional changes”: “Blinder/Oaxaca approach”

decomposing changes in the distribution of the dependent into

- the explanatory variables
- coefficients

by allowing for changes in the location of the observations

Generation of “counterfactual distribution”: “DiNardo, Fortin, and Lemieux (DFL)”

Counterfactual distribution of (y_i) : Real Estate Price

= y_i (real distribution)

$$\propto \frac{\textit{Probability of a point has a charactreristics of A}}{\textit{Probability of a point **does not** have a characteristics of A}}$$

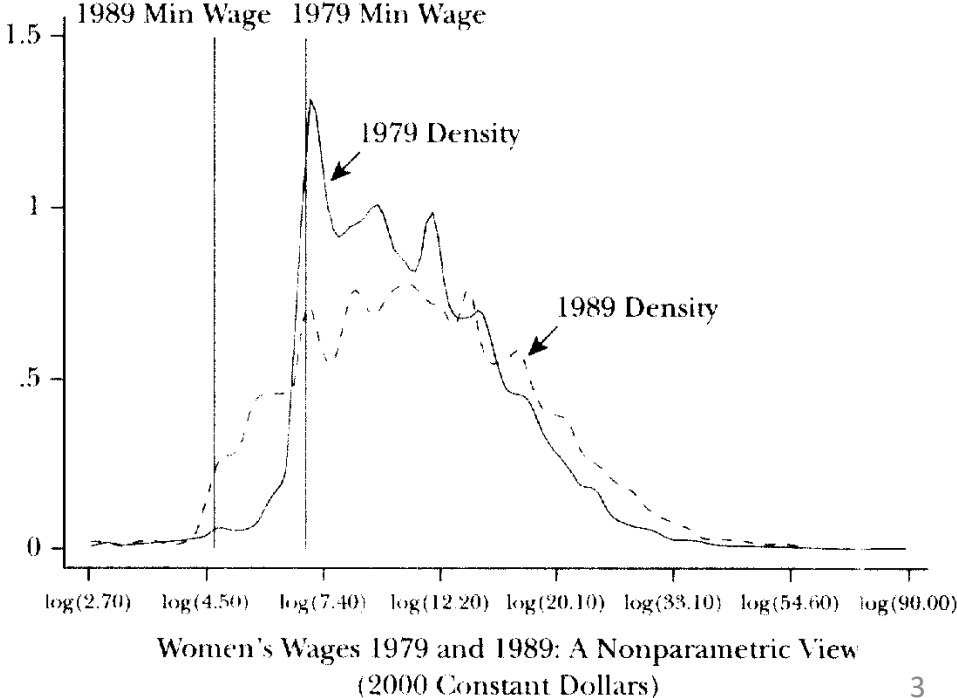
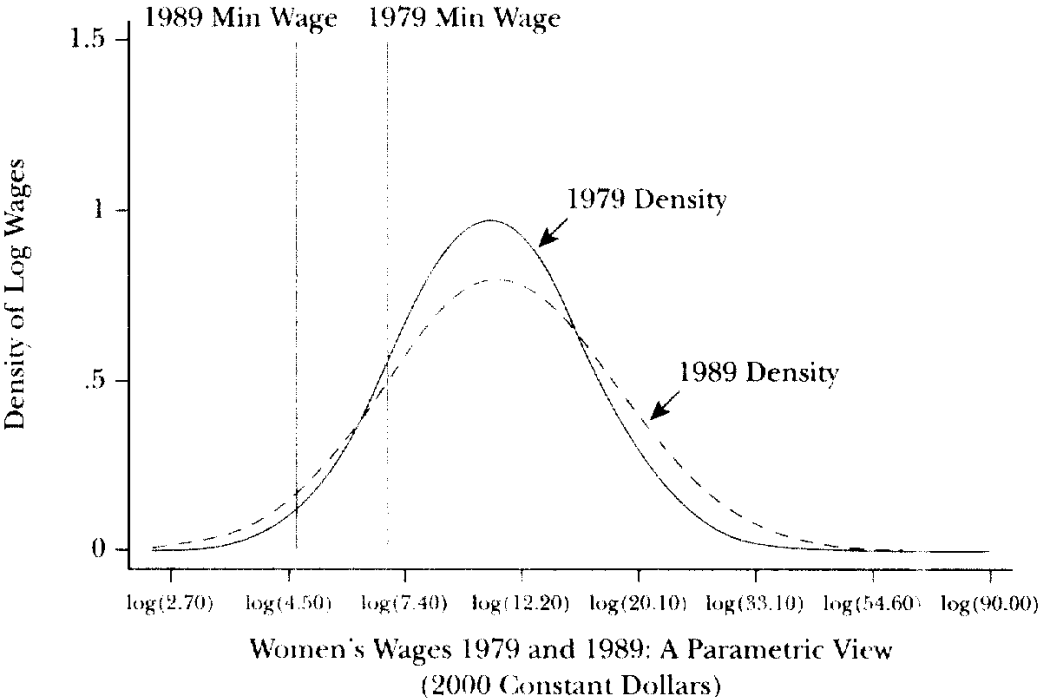
1. Methods

Why “distributional change” is important?

DiNardo and Tobias (2001) *Nonparametric Density and Regression Estimation*, JEP

<Fig. 1.>
Parametric estimation may undermine the understanding of the whole picture of wage distribution: the rise of inequality of women’s wage can be explained by the decreased 1989 min wage, not by the rise in inequality as a whole.

Minimum wage and wage inequality (US)



1. Methods

Decompositions of Spatially varying coefficients (Mcmillen-Shimizu)

$y_1(z_1, \tau) - y_2(z_2, \tau)$ *Change in Real Estate Price*

$$y_1(z_1, \tau) = x_1\beta_1(z_1, \tau) + \delta_1(z_1, \tau), \quad y_2(z_2, \tau) = x_2\beta_2(z_2, \tau) + \delta_2(z_2, \tau)$$

$$= \left(x_1\beta_1(z_1, \tau) - x_2\beta_1(z_1, \tau) \right) \quad \text{Variables}$$

$$+ \left(x_2\beta_1(z_1, \tau) - x_2\beta_2(z_1, \tau) \right) \quad \text{Coefficients}$$

$$+ \left(\delta_1(z_1, \tau) - \delta_2(z_1, \tau) \right) \quad \text{Time Coefficients}$$

$$+ \left(x_2\beta_2(z_1, \tau) - x_2\beta_2(z_2, \tau) \right) \quad \text{Locations (Based on coefficients2)}$$

$$+ \left(\delta_2(z_1, \tau) - \delta_2(z_2, \tau) \right) \quad \text{Locations (Based on time2)}$$

1. Methods

Computation for marginal densities

1. Estimate three locally weight models:

$$y_{1(1,1)}(z_1, \tau) = x_1 \beta_1(z_1, \tau) + \delta_1(z_1, \tau),$$

time 1 locations, time 1 data, B quantiles

$$y_{2(2,2)}(z_2, \tau) = x_2 \beta_2(z_2, \tau) + \delta_2(z_2, \tau),$$

time 2 locations, time 2 data, B quantiles

$$y_{2(1,2)}(z_1, \tau) = x_2 \beta_2(z_1, \tau) + \delta_2(z_1, \tau),$$

time 1 locations, time 2 data, B quantiles

2. Make M draws from both $\text{seq}(1, \dots, n_1)$ $\text{seq}(1, \dots, n_2)$ with replacement.

Results are denoted \mathbf{o}_1 and \mathbf{o}_2 .

3. Form the following matrices:

$$\hat{\beta}_1[\mathbf{o}_1, \cdot] \quad \hat{\delta}_1[\mathbf{o}_1, \cdot] \quad \hat{\beta}_2[\mathbf{o}_2, \cdot] \quad \hat{\delta}_2[\mathbf{o}_2, \cdot] \quad \hat{\beta}_{21}[\mathbf{o}_1, \cdot] \quad \hat{\delta}_{21}[\mathbf{o}_1, \cdot] \quad x_1[\mathbf{o}_1, \cdot] \quad x_2[\mathbf{o}_2, \cdot]$$

1. Methods

2) Extended Model for quantile price indices

The CPAR (conditionally parametric) estimates

Quantile is one of the conditionals

Quantile Price Indices

- The standard quantile regression estimating equation:

$$Q_{lnP}(q|X_{it}, D_{it}) = X_i\beta(q) + \sum_{t=2}^T D_{it}\delta_t(q)$$

- $q = .50$ is comparable to hedonic estimation.
- It is comparable to repeat sales estimator if the sample is restricted to properties that have sold at least twice.
- Can trace out the full distribution by estimating across many quantiles.

2. Findings

1) Cause of change in sales price

Large picture

The CPAR estimates reveal substantial portion of the change in sales prices

{ Rapid rise period (Bubble period: 1986 – 1990)

{ Sharp decline period (Post-bubble period: 1991 – 1995)

Decompositions of distributional changes:

Prices rose most rapidly and sharply declined near downtown Tokyo:

Attributable to change in explanatory variable

2. Findings

2) Shift in distribution of sales price

Changes in location of sales

Bubble period: 1986 – 1990
Post-bubble period: 1991 – 1995



Shift of distribution of sales price:
Further to the left

Sales in post-bubble period were more likely to be in locations farther from downtown Tokyo, where prices are lower

<Related papers>

Deng, McMillen and Sing (2012):

The rise in real estate price in Singapore happened for high price locations.

Landvit, Piazzesi and Sheneider (2015):

Cheaper credit for poor households was a major driver of prices of real estate boom near San Diego around 2000s.

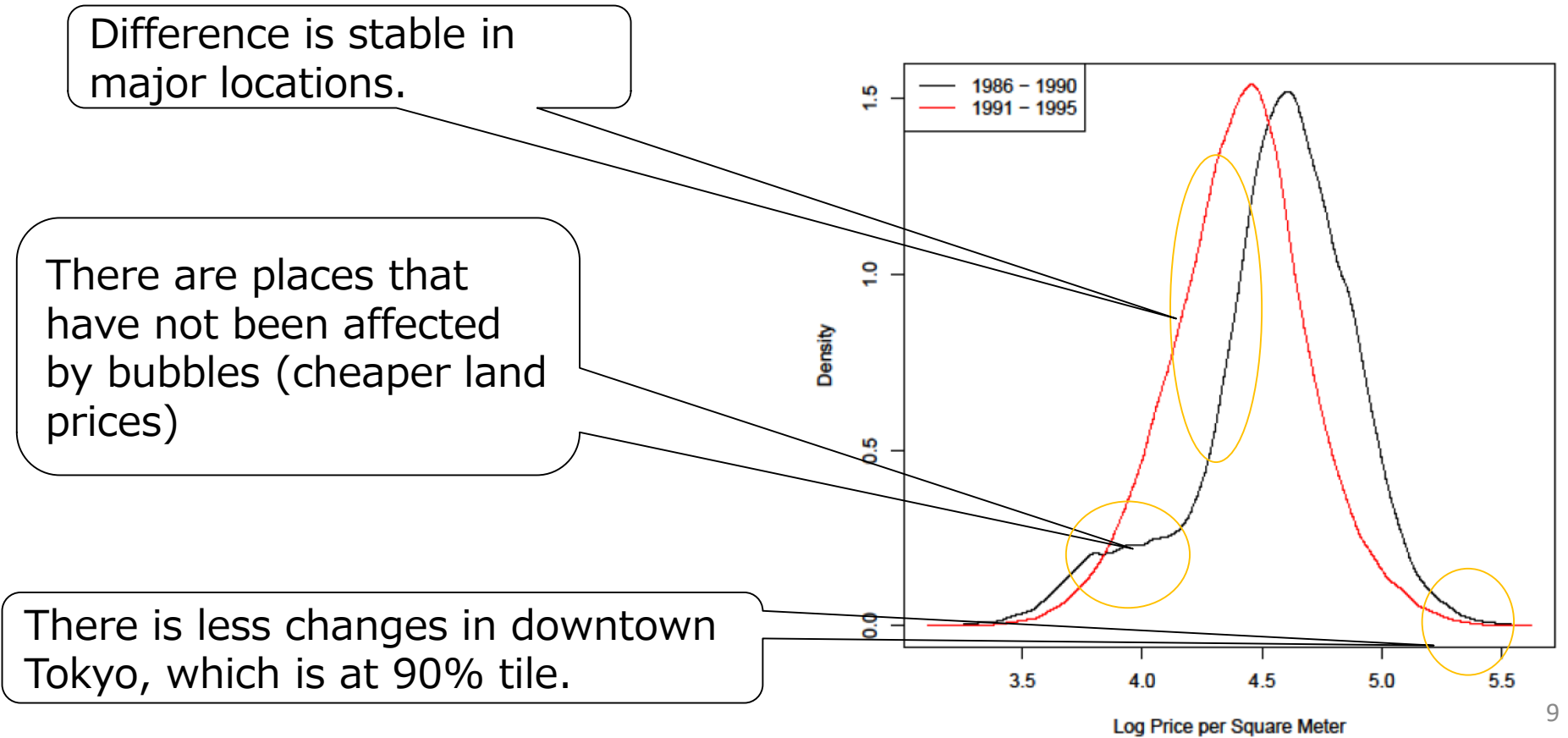
3. Questions and Discussions

1) Interpretation of shift in distribution

What is the nature of the “bubble”?

Is the gentrification happens in Tokyo?

Figure 5: Kernel Density Estimates for Log Price per Square Meter



3. Questions and Discussions

2) Questions regarding the “Decomposition”

<Fig 11>

Changing prices and locations toward left when the location change

x1b1 → (left) → **x2b1** : age effect

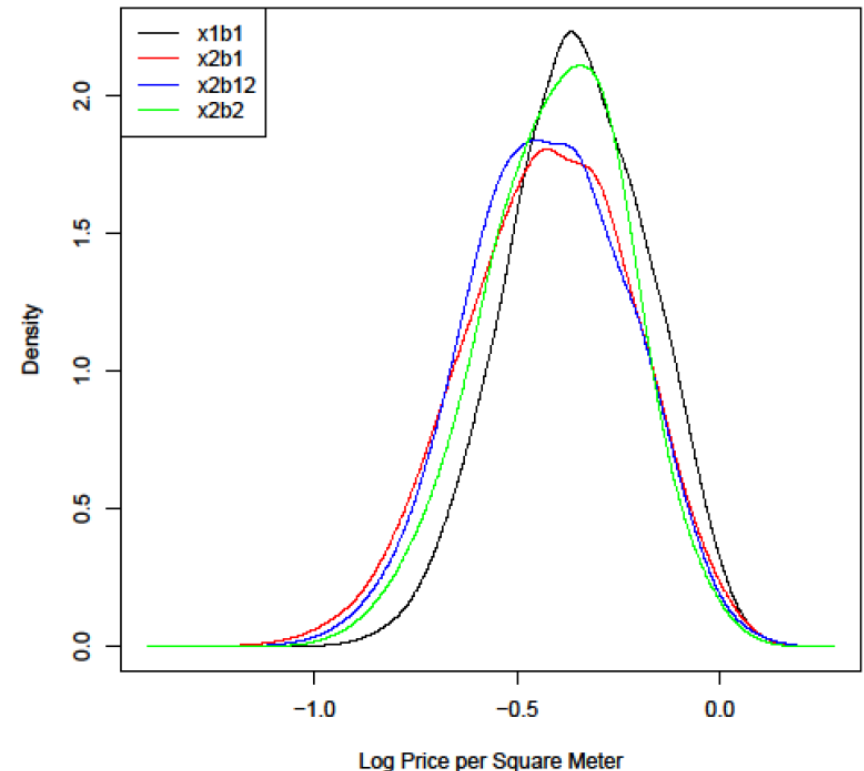
→ (left) → **x2b12** :
location change effect
except for very low price

→ (right) → **x2b2** :
change in coefficients to post bubble

Are the structure (=coefficients ?)of sales prices changes before/after the bubble?

What is the nature of the change?
Is the “rise” and “fall” are asymmetric?

Figure 11: Decomposition 1986 – 1990 to 1991 – 1995, X



3. Questions and Discussions

2) Questions regarding the “Decomposition”

<Fig 12>

Change in distribution according to the sales period.

$x2b2 + D11$

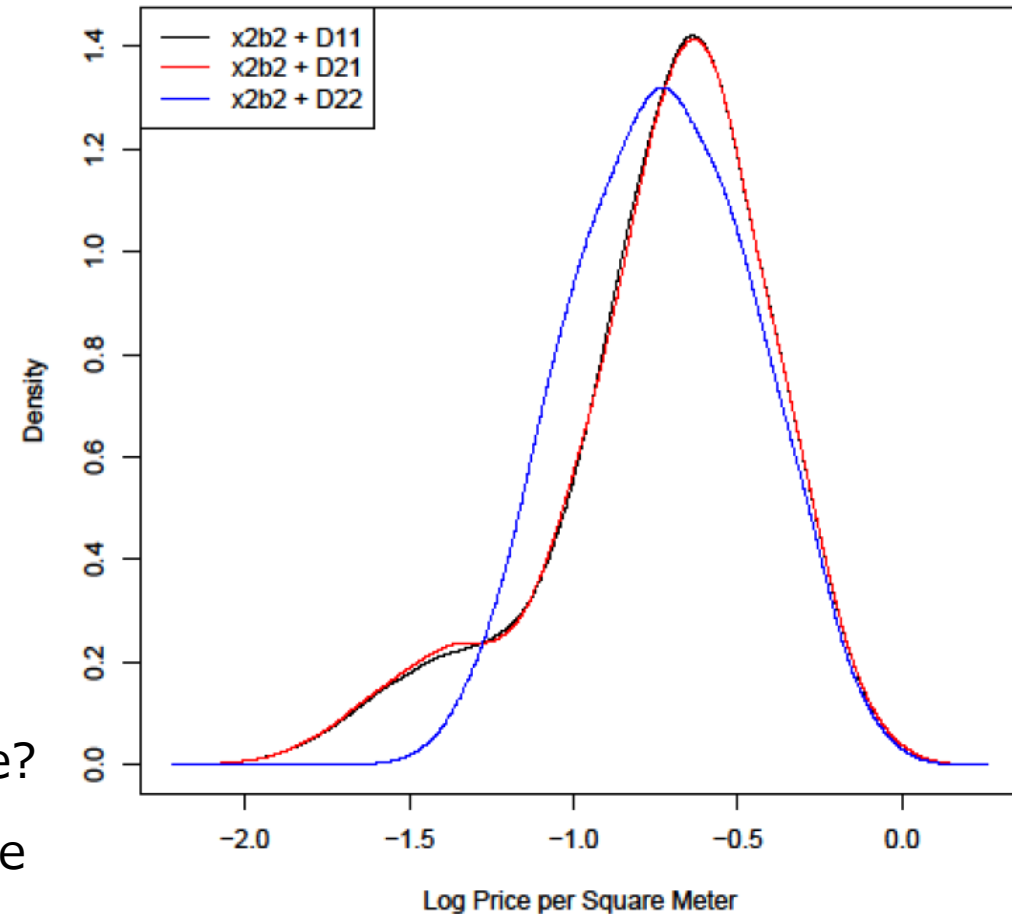
→ (little effect) → **$x2b2 + D21$** :
There is little change in distribution even if we change the sales period..

→ (skews to left) → **$x2b2 + D22$** :
When the time coefficients are changed, the distribution skews toward left and the tail disappears.

Time coefficients is the sing of the bubble?

What is the meaning of the disappearance of the tails?

Figure 12: Decomposition 1986 – 1990 to 1991 – 1995, Time of Sale



3. Questions and Discussions

3) Comparison with other models

Are we collect to interpret that...

Hedonic model

As a whole sample, it may incur the problem of effects by higher or lower prices example.

Repeated Sales

This method may incur selectivity biases for properties those tend to have "repeated sales"

Matching distribution

This method is flexible enough to imply both hedonic and repeated sales model data.

(What is the main shortcomings of the model other than computational complexities?)

3. Questions and Discussions

4) Other points

- Is the negative coefficient for “building area” is actually related to the regulated use of the land?

 - low built-area may be associated with the housing use and incurs building with lower height and premium for the real estate.

- What will be the implication of using condominium prices compared to all real estate

- Is there any characteristics of Tokyo compared to

 - other local cities in Japan: what is the nature of major cities?

 - foreign cities (US etc.): condition of credit market binds?