Decomposing the Effects of Aging on Real Estate Prices using High-resolution Spatial Panel

Takuya Shimamura
Graduate School of Engineering, Kyushu University

Supervisor: Prof. Shunsuke Managi
Director, Urban Institute, Kyushu University

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Contents

Contents

1. Background (broad view)

- Global issue
  - Economic standard $\uparrow$ $\Rightarrow$ aging speed $\uparrow$
    (World Population Prospects, https://population.un.org/wpp/)
- The negative impacts of aging on economics
  - Slowdown of economic activities
    (Feyrer 2007; Feyrer 2008; Feyrer 2011; Jiandong 2016;
    Acemoglu & Restrepo 2017; Vargha et al. 2017; Aksoy et al. 2019)
  - Damage on social welfare
    (Razin et al. 2002; Flaherty et al. 2007; Zeng & Hesketh 2016)

1. Background (aging and real estate)

- The importance of real estate

    1. Wealth effect:
       individuals' mortgage → **consumption**.
       (Aladangady 2017; Chen et al. 2020)

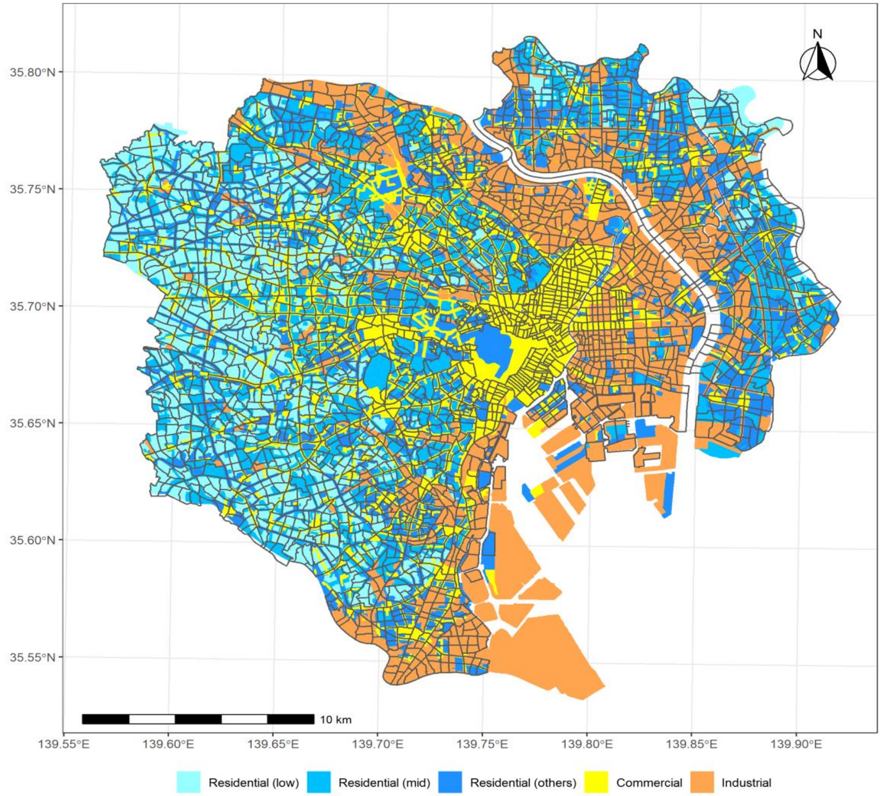
    2. Household portfolio:
       biggest asset for household
       (Flavin & Yamashita 2002; Rosenthal & Strange 2004; Chetty et al. 2017)

    3. (impacts on corporations)

1. Background (outline of this study)

- Outline
  - Area:
    - Tokyo 23 Special Districts
  - Resolution:
    - *block*-level
      (≒ 430 × 430m mesh)
    - N = 2,845
  - Period:
    - 2000–2015
    - T = 16 (annually)
  - Explained variable:
    - Published land prices
      (PLPs) = appraisal prices

Tokyo 23 Special Districts



(Authors)

Contents

2. Objective & contribution

1. **Spatial panel: high-resolution × PLPs**
   - Handling biases of previous studies:
     1. Aggregation bias
     2. Omitted variable bias
     3. Representativeness bias of spatio-temporal distribution
     4. Sample selection bias
     5. Market friction
2. **The detail analysis**
   - Decomposing:
     1. Age composition effect
     2. Income effect & preference effect
   - Zoning

2-1. high-resolution × PLPs

Biases

High-resolution

(i)
Aggregation bias

Modifiable aerial
unit program

(ii)
Omitted variable bias

PLPs

(iv)
Sample selection bias

(v)
Market friction

Information friction
Search friction
Bargaining friction

(Authors)

2-1 (i). **high-resolution** × PLPs

(i) **Aggregate bias** (Gehlke & Biehl 1934)

◆**Aggregate panel** (previous studies)

- country level (Takats 2012)
- city level (Hiller & Lerbs 2016)
- province level (Simo-Kengne 2019)

◆**High-resolution panel** (this paper)

- *Block*-level ≒ 430 × 430m grid level

➢ Improvement of fixed effects (Cornwell & Trumbull 1994):

a. Accessibility (Glumac et al., 2019; Yuan et al. 2020)
b. Land-use zoning (Glaeser et al. 2005; Nichols et al. 2013; Tan et al. 2020)
c. Green space (Morancho 2003; Panduro & Veie 2013; Schlapfer et al. 2015)
d. Geographical constraints (Albert 2013; Hilber & Vermeulen 2016)
e. Brand value (Lakshman 1991)

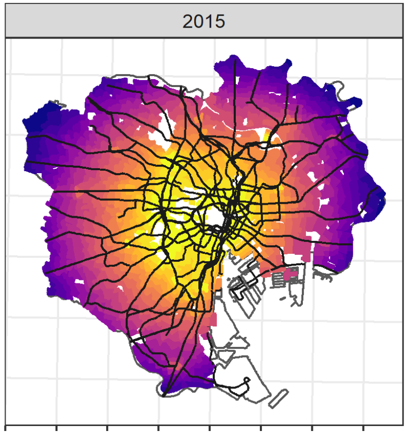
2-1 (ii). **high-resolution** × PLPs

(ii) **Omitted variable bias**

- **Aggregate panel** (previous studies)
  - City level does not allow to capture central business district (CBD).

    cf. bid rent theory (Alonso 1964; Fujita 1989)
- **<u>High-resolution panel</u>** (this paper)
  - *Block*-level ≒ 430 × 430m grid level
  - ➢ Dealing with omitted variable bias by structuralizing spatio-temporal CBD score.

$CBD\ score\ in$ 2015



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$$CBD_{it} = \ln\left(\sum_{s=1}^{S} \frac{passenger_{st}}{dist_{si}}\right)$$

s: station
S: the total number of stations
$dist_{si}$: the distance between station s and centroid of *block* i.
$passenger_{st}$: the average number of passengers at time t.

2-1 (iii). high-resolution × **PLPs**

(iii) **Sample selection bias**

(J.Heckman 1979; Berk 1983; Certo et al. 2016; Munafò et al. 2018)

◆**Market prices (previous studies)**：

Observed *only when transactions* occur

e.g., higher aging ratio will have

(a) higher house owing ratio and

(b) lower frequency of transactions.

➢Violates the objective to analyze the aging effect

◆**Appraised prices (this paper)**：

Independent to transactions → **represent the properties**

2-1 (iv). high-resolution × **PLPs**

(iv) **Market friction**

(Quan & Quigley 1991; Kling et al. 2012; Han & Strange 2015; Piazzesi et al. 2020)

◆**Market prices (previous studies)：**

i. **Information friction：information asymmetry**

ii. **Search friction：only one property**

iii. **Bargaining friction：bargaining powers**

➢Market prices: **market friction > fundamentals**

◆**Appraised prices (this paper)：**

➢ **less market friction**.

2. Objective & contribution

1. **Spatial panel: high-resolution × PLPs**
   - Handling biases of previous studies:
     1. Aggregation bias
     2. Omitted variable bias
     3. Representativeness bias of spatio-temporal distribution
     4. Sample selection bias
     5. Market friction
2. **The detail analysis**
   - Decomposing:
     1. Age composition effect
     2. Income effect & preference effect
   - Zoning

2-2. Decomposing the effect of aging

1. Aggregated demand in the entire market

   1-1. age composition effect (Takáts 2012; Hiller and Lerbs 2016)

   ・**Negative impact**

2. Changes in elderly individuals' behaviors

   2-1. income effect (Mankiw & Weil 1989; DiPasquale & Wheaton 1994)

   Controversial

   ・income ↓ ⇒ budget constraint ⇒ demand ↓ ⇒ land prices ↓

   2-2. preference effect (**no previous study**)

   ・change in preference ⇒ necessity of accessibility ↓ ⇒ land prices ↓

Contents

3. Data & methodology

1. High-resolution dataset

   a. Spatio-temporal kriging

   - To develop **high resolution spatial panel**, we apply spatio-temporal kriging.

2. Spatial panel (SAC) model

   - To cope with **spatial correlation**, we apply SAC (LeSage & Pace, 2009) model.

3-1. Variable description and data source

Variable description and data source

Variable		Definition	Data Source
p	Real land price	Logarithmic inflation-corrected average published land prices per unit area [JPY/area]	Authors' calculation based on MLITT (1)
ODR	Old dependency ratio	Logarithmic ratio of residentials aged 65+ to residential aged 15–64 [%]	e-Stat (2)
y	Real purchasing power	Logarithmic inflation corrected average income per household [JPY/household]	ESRI Japan Inc. (3), TMG (4)
CBD	Central business district	Logarithmic central business district score [person/distance]	Authors' calculation based on MLITT (1) and TMG (4)
pop	Working age population	Logarithmic the number of residentials population aged 15–64 [person]	e-Stat (2)
CDR	Child dependency ratio	Logarithmic ratio of residentials aged 0–14 to residential aged 15–64 [%]	e-Stat (2)
HOR	Home ownership ratio	Logarithmic ration of residentials who live in the owing houses to residential who do not [%]	e-Stat (2)
F5–9	Low building supply	Dummy variable whether there was any construction of buildings with floor 5–9 in time *t-1*	One of a kind Inc. (5)
F10–14	Midlle building supply	Dummy variable whether there was any construction of buildings with floor 10–14 in time *t-1*	One of a kind Inc. (5)
F15	High building supply	Dummy variable whether there was any construction of buildings with floor 15+ in time *t-1*	One of a kind Inc. (5)

(1) Ministry of Land, Infrastructure, Transport and Tourism (https://nlftp.mlit.go.jp/ksj/index.html)
(2) Protal Site of Official Statistics of Japan (https://www.e-stat.go.jp/gis)
(3) ESRI Japan Inc. (https://www.esrij.com/)
(4) Statistic Division, Bureau of General Aaffairs, Tokyo Metoropolitan Government (https://www.toukei.metro.tokyo.lg.jp/index.htm)
(5) Mansion Review, One of a kind Inc. (https://www.mansion-review.jp/)

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3-1. Descriptive statistics

Descriptive statistics.

	Mean	St. dev.	Min	Max	CD test	CIPS test	N×T
Δp	-0.0015	0.0553	-0.2215	0.3225	7171.66***	-1.90***	2,785×15
Δpop	0.0094	0.0385	-0.8635	2.7248	111.13***	-0.94	2,785×15
ΔCDR	0.0039	0.0535	-2.202	2.5576	274.71***	-1.10	2,785×15
ΔODR	0.0220	0.0407	-0.9045	1.0304	261.07***	-0.79	2,785×15
Δy	-0.0068	0.0591	-0.6318	0.5654	4986.77***	-2.47***	2,785×15
ΔHOR	0.0034	0.0584	-2.3979	4.6092	1165.82***	-0.98	2,785×15
ΔCBD	0.0132	0.0168	-0.0272	0.2215	7395.45***	-1.63**	2,785×15

CD is cross-sectional dependence test in panel time-series data (Pesaran 2021). The null hypothesis of CD test is no cross-sectional dependence. CIPS is cross-sectional dependence augmented IPS test (Pesaran, 2007). Since CIPS is based on cross-sectional augmented ADF (CADF), the null hypothesis is non-stationary. All CIPS test are performed without an intercept and a linear trend, and with a lag. The relevant lower 1%, 5%, and 10% level critical values are -1.62, -1.51, and -1.43, respectively, assuming $(N, T) = (200, 15)$. This is because Pesaran (2007) provides the table II(a) critical values on p.279, but maximum N is 200. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

(Authors)

3-1. Correlation between variables

Correlation between variables.

	Δp	Δpop	ΔCDR	ΔODR	Δy	ΔHOR	ΔCBD	$F5–9$	$F10–14$	$F15$
Δp	–	–	–	–	–	–	–	–	–	–
Δpop	0.009	–	–	–	–	–	–	–	–	–
ΔCDR	0.048	0.298	–	–	–	–	–	–	–	–
ΔODR	-0.052	-0.384	0.037	–	–	–	–	–	–	–
Δy	0.377	-0.016	0.003	-0.007	–	–	–	–	–	–
ΔHOR	-0.046	0.093	0.204	0.185	0.061	–	–	–	–	–
ΔCBD	0.545	0.034	0.045	-0.027	0.265	-0.022	–	–	–	–
$F5–9$	0.031	0.053	-0.004	-0.052	0.026	0.003	0.020	–	–	–
$F10–14$	0.024	0.133	-0.004	-0.134	0.035	-0.019	0.040	0.064	–	–
$F15$	0.043	0.132	0.032	-0.089	0.024	0.003	0.031	0.021	0.083	–

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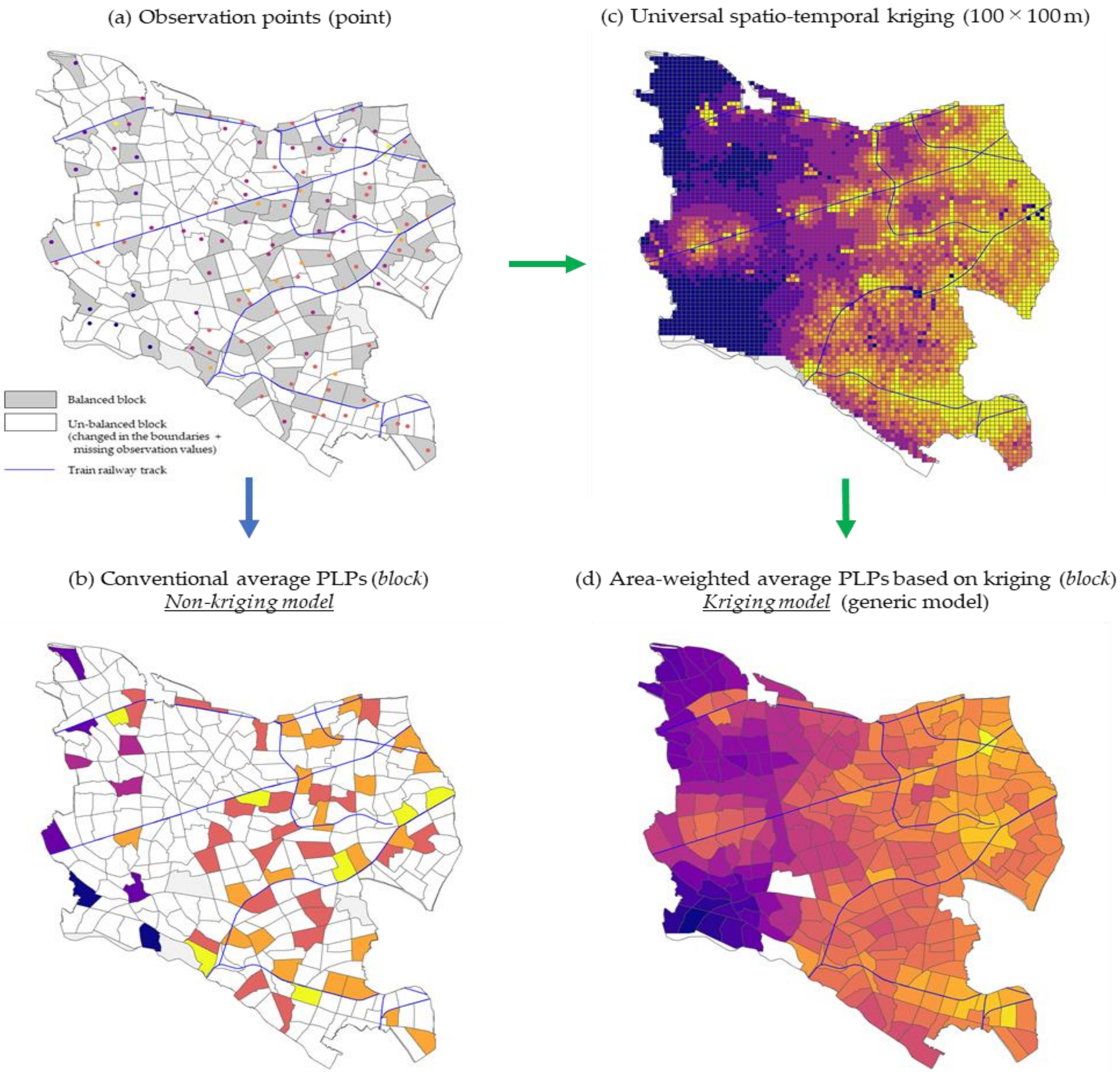
3-2. Spatio-temporal kriging

Example in Setagaya-ward (one of the 23 special districts)



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Validity of Kriging

Kriging model vs. non-kriging model

	M1: Kriging model (generic model)	M2: Non-kriging model	M3: Kriging model with limited blocks
Age composition effect	○	○	○
Income effect	×	○	○
Preference effect	○	×	×
Total number of blocks	2,845	611	611

"○" denotes the effect is significantly positive, "×" denotes the effect is rejected. Colored in red refers to the different result from the kriging model (M1).

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3-3. Spatial econometrics model

- Generic model: SAC, two-way fixed effect

$$\Delta p_{it} = \lambda \boldsymbol{W} \Delta p_{it} + \beta_1 \Delta ODR_{it}$$
$$+\beta_2 (\Delta ODR_{it} \times \Delta y_{it}) + \beta_3 (\Delta ODR_{it} \times \Delta CBD_{it})$$
$$+\boldsymbol{Z}'_{it} \boldsymbol{\gamma}_k + \mu_i + \varphi_t + u_{it}$$

$$with \;\; u_{it} = \rho \boldsymbol{W} u_{it} + \varepsilon_{it}, \qquad \varepsilon_{it} \sim N(0, \sigma_i^2)$$

where:

$\boldsymbol{Z}'_{it} = (\Delta pop_{it}, \Delta CDR_{it}, \Delta y_{it}, \Delta CBD_{it}, \Delta HOR_{it}, \Delta F5\text{–}9_{it}, \Delta F10\text{–}14_{it}, \Delta F15_{it})$

$\boldsymbol{W}$: row-standardized distance-based spatial weight matrix with buffer

cf. Takáts (2012): country level, non-spatial panel, pooled OLS (with controlling time trend).

Hiller and Lerbs (2016): city-level, SAC, two-ways fixed.

Contents

Hypothesis 1-1. age composition effect

Hypothesis 1-1. the theory

- Overlapping-generations model (OLG)
  (Samuelson 1958; P. A. Diamond 1956; Takáts 2012)

  Negative impact:
  aging ↑ ⇒ real estate price growth ↓

Hypothesis 1-1. the validation

- $\Delta \boldsymbol{ODR}$ ： **negative**.

Result 1-1. age composition effect

	all	resi	resi (low)	resi (mid)	resi (others)	com
Total effects						
Δpop	-0.0532***	-0.0507	0.0134	-0.0908***	-0.0514*	-0.0185
	(0.0148)	(0.0350)	(0.0540)	(0.0349)	(0.0274)	(0.0205)
ΔCDR	0.0209**	0.0639***	-0.0508	0.0826***	0.0058	0.0136*
	(0.0099)	(0.0207)	(0.0314)	(0.0232)	(0.0147)	(0.0082)
ΔODR	0.0085	-0.1486***	-0.0777***	-0.1534***	-0.0624**	-0.0084
	(0.0133)	(0.0275)	(0.0307)	(0.0277)	(0.0278)	(0.0186)
Δy	0.0740***	0.0662***	0.0911***	0.0504***	0.0556***	0.0502***
	(0.0125)	(0.0151)	(0.0175)	(0.0162)	(0.0153)	(0.0111)
ΔMHR	-0.0140	-0.0684***	-0.0578*	-0.0271	-0.0222	0.0077
	(0.0090)	(0.0211)	(0.0328)	(0.0179)	(0.0173)	(0.0129)
ΔCBD	0.5625***	1.5816***	2.7471***	1.9680***	1.2229***	0.3634***
	(0.1320)	(0.2330)	(0.3428)	(0.2969)	(0.1725)	(0.0965)
Δs (F 5-9)	-0.0004	0.0026	-0.0033	0.0022	0.0005	-0.0032
	(0.0014)	(0.0020)	(0.0020)	(0.0023)	(0.0020)	(0.0021)
Δs (F 10-14)	0.0051***	0.0053*	-0.0064	-0.0007	0.0036	0.0034*
	(0.0017)	(0.0031)	(0.0043)	(0.0032)	(0.0025)	(0.0018)
Δs (F 15+)	0.0033	0.0137**	0.0226	0.0126*	-0.0126***	0.0015
	(0.0032)	(0.0063)	(0.0162)	(0.0072)	(0.0050)	(0.0037)
Regression diagnostisc						
R-squared	0.9635	0.9800	0.9890	0.9839	0.9640	0.9474
N	2784	1773	577	460	338	515
T	15	15	15	15	15	15
lambda	0.8728***	0.9378***	0.9115***	0.8818***	0.7579***	0.7012***
rho	0.254***	-0.2544***	-0.2708***	-0.1711***	-0.2014***	-0.0058
cutoff	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m
PCD	-1.614	-1.802*	-0.167	-1.436	-0.769	-1.969**
IPS	-147.078***	-131.056***	-73.551***	-63.433***	-53.417***	-58.815***
CIPS	-2.354***	-2.510***	-2.687***	-2.552***	-2.593***	-2.514***

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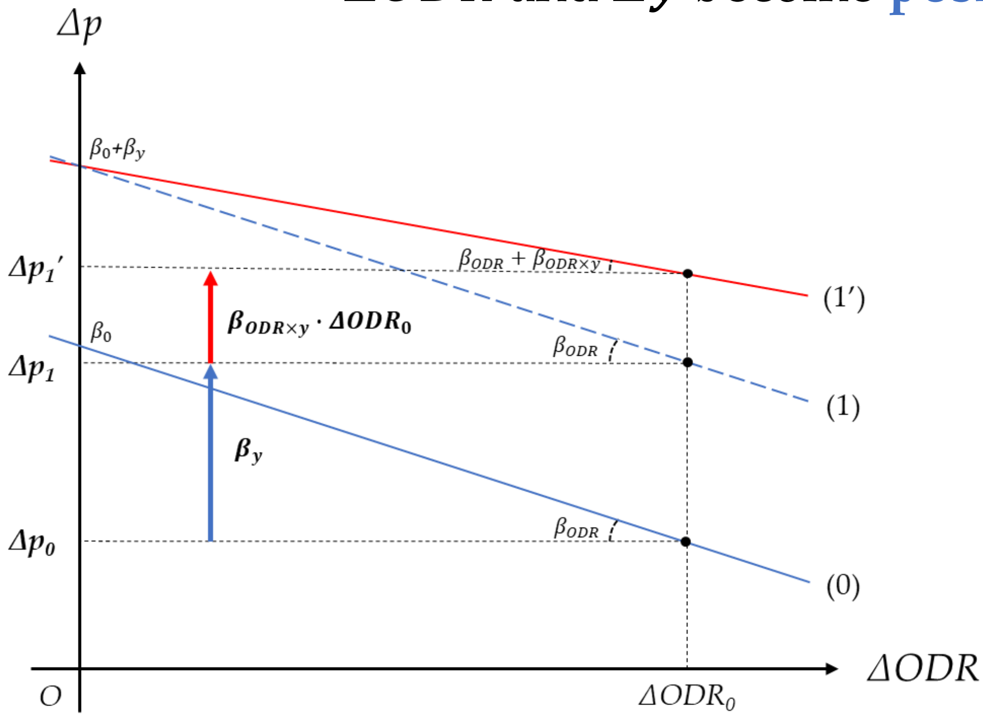
→ ***ODR*** is **negative** in **residential area.**

Hypothesis 2-1. income effect

<u>Hypothesis</u>：aging → income⇓ → demand⇓ → land price⇓

<u>Verification</u>：whether the coefficient of the interaction term of $\boldsymbol{\Delta ODR}$ and $\boldsymbol{\Delta y}$ become **positive**.



<u>Line(0)</u>： $\beta_{\Delta ODR}$ is negative

<u>Line(1)</u>： parallel translation from line(0) as the magnitude of $\beta_{\Delta y}$.

<u>Line(1′)</u>：**improvement** as the magnitude of $\beta_{\Delta ODR\times\Delta y}$

→ with higher income, elderly residents can live in higher land price area.

∴ they face <u>**budget constraint**</u>.

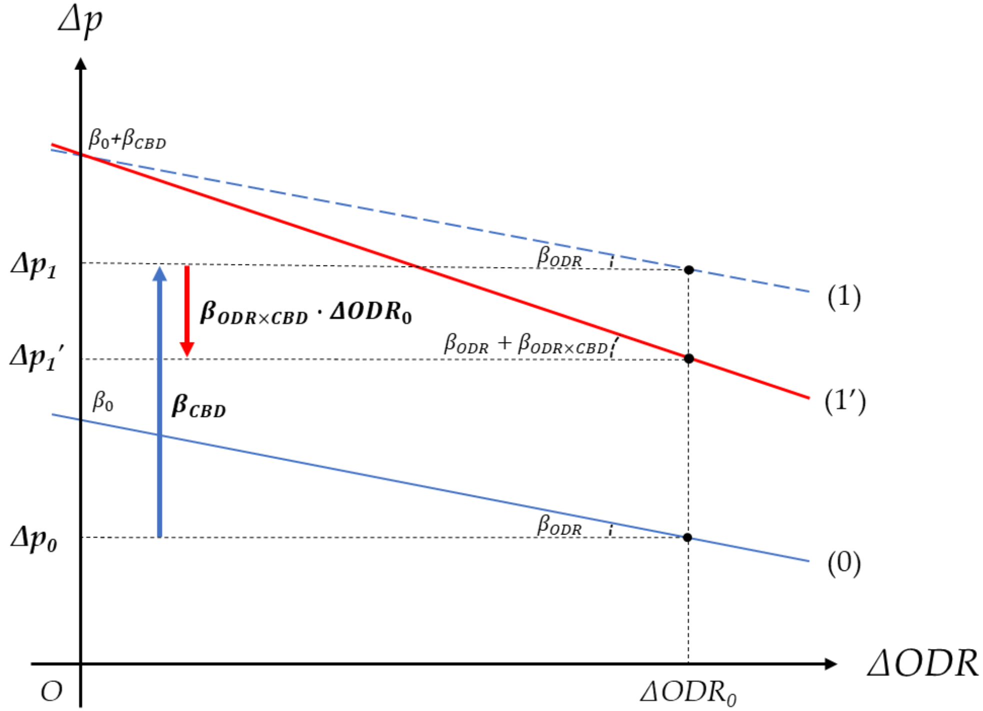
$$\Delta p = \beta_0 + \beta_{ODR}\Delta ODR + \beta_y \Delta y + \beta_{ODR\times y}(\Delta ODR \times \Delta y) + \boldsymbol{X}'\boldsymbol{\beta_x} + \varepsilon$$

(+) (–) (+) (+)

Hypothesis 2-2. preference effect

<u>Hypotheses</u>：aging→ change in preference → lection cheaper area⇓

<u>Verification</u>： whether the coefficient of the interaction term of $\boldsymbol{\Delta ODR}$ and $\boldsymbol{\Delta CBD}$ become **negative**.



<u>Line(0)</u>： $\beta_{\Delta ODR}$ is negative

<u>Line(1)</u>： parallel translation from line(0) as the magnitude of $\beta_{\Delta y}$.

<u>Line(1′)</u>： **decline** as the magnitude of $\beta_{\Delta ODR\times\Delta CBD}$

→ with aging, they decline the preference to better accessibility compared with when young.

∴ As a result, elderly residents select <u>**cheaper area**</u>.

$$\Delta p = \underset{(+)}{\beta_0} + \underset{(-)}{\beta_{ODR}}\Delta ODR + \underset{(+)}{\beta_{CBD}}\Delta CBD + \underset{(-)}{\beta_{ODR\times CBD}}(\Delta ODR \times \Delta CBD) + \boldsymbol{X}'\boldsymbol{\beta}_{\boldsymbol{x}} + \varepsilon$$

Result 2-1, 2-2. income & preference effect

	income						CBD						the nearest station					
	high			low			high			low			close			far		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Total effects																		
Δpop	-0.1467***	-0.1500***	-0.1475***	0.1563***	0.1585***	0.1563***	-0.0924**	-0.0961**	-0.0943**	0.1067**	0.1025**	0.1060**	-0.0821***	-0.0799***	-0.0825***	-0.0653*	-0.0727*	-0.0659*
	(0.0388)	(0.0377)	(0.0374)	(0.0361)	(0.0401)	(0.0360)	(0.0455)	(0.0412)	(0.0427)	(0.0431)	(0.0476)	(0.0453)	(0.0310)	(0.0307)	(0.0313)	(0.0390)	(0.0379)	(0.0383)
ΔCDR	0.0925***	0.0935***	0.0926***	-0.0658**	-0.0690**	-0.0688***	0.0747***	0.0756***	0.0752***	-0.0609*	-0.0633*	-0.0641*	0.0755***	0.0749***	0.0758***	0.0058	0.0031	0.0008
	(0.0217)	(0.0224)	(0.0216)	(0.0269)	(0.0270)	(0.0242)	(0.0238)	(0.0211)	(0.0241)	(0.0344)	(0.0334)	(0.0341)	(0.0198)	(0.0187)	(0.0194)	(0.0267)	(0.0272)	(0.0276)
ΔODR	-0.1061***	-0.1094***	-0.1084***	-0.0862***	-0.0852***	-0.0865***	-0.1806***	-0.1877***	-0.1870***	-0.0402	-0.0424	-0.0397	-0.1560***	-0.1601***	-0.1613***	-0.0937***	-0.1008***	-0.0951***
	(0.0306)	(0.0308)	(0.0282)	(0.0286)	(0.0286)	(0.0294)	(0.0366)	(0.0375)	(0.0342)	(0.0296)	(0.0271)	(0.0304)	(0.0251)	(0.0275)	(0.0258)	(0.0248)	(0.0247)	(0.0243)
Δy	0.0726***	0.0720***	0.0737***	0.0218	0.0172	0.0192	0.0603***	0.0612***	0.0621***	0.0629**	0.0614**	0.0591**	0.0586***	0.0622***	0.0608***	0.1023***	0.1017***	0.1012***
	(0.0164)	(0.0156)	(0.0166)	(0.0220)	(0.0198)	(0.0224)	(0.0159)	(0.0161)	(0.0171)	(0.0259)	(0.0272)	(0.0266)	(0.0128)	(0.0135)	(0.0132)	(0.0148)	(0.0157)	(0.0164)
ΔCBD	2.1580***	2.1406***	2.1375***	0.6034***	0.7557***	0.7448***	1.4773***	1.4529***	1.4504***	1.5974***	1.8307***	1.8513***	1.6299***	1.6064***	1.6102***	2.0068***	2.0839***	2.1351***
	(0.3129)	(0.2900)	(0.3228)	(0.2129)	(0.2121)	(0.2255)	(0.2693)	(0.2713)	(0.2646)	(0.3637)	(0.4091)	(0.3993)	(0.1927)	(0.1889)	(0.1963)	(0.2536)	(0.2722)	(0.2622)
ΔODR × Δy	0.0650		0.1303	-0.7429**		-0.3031	-0.0637		0.0953	-0.0266		0.4098	-0.2549		-0.1166	1.0421***		1.5495***
	(0.2654)		(0.2791)	(0.3889)		(0.3705)	(0.3014)		(0.2941)	(0.3504)		(0.3819)	(0.2149)		(0.2177)	(0.3335)		(0.3728)
ΔODR × ΔCBD		-0.9458	-1.1289		-4.4763***	-4.2090***		-2.7378**	-2.8530*		-4.3842***	-4.8142***		-2.7458**	-2.5976**		-3.0757***	-4.6006***
		(1.2293)	(1.4265)		(1.0791)	(1.0784)		(1.3292)	(1.4925)		(1.2581)	(1.2508)		(1.0971)	(1.0170)		(1.0612)	(1.0331)
control vari.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Regression diagnostics																		
lambda	0.9076***	0.9075***	0.9076***	0.907***	0.9064***	0.9065***	0.9076***	0.9074***	0.9074***	0.9372***	0.9372***	0.937***	0.8688***	0.8686***	0.8686***	0.9358***	0.9357***	0.9353***
rho	-0.1537***	-0.1539***	-0.154***	-0.441***	-0.4393***	-0.4392***	-0.1635***	-0.1647***	-0.1646***	-0.3447***	-0.3428***	-0.343***	-0.2591***	-0.2598***	-0.2599***	-0.4637***	-0.4624***	-0.4621***
R^2	0.9802	0.9802	0.9802	0.9777	0.9778	0.9778	0.9773	0.9773	0.9773	0.9837	0.9838	0.9838	0.9742	0.9742	0.9742	0.9872	0.9872	0.9872
N	868	868	868	873	873	873	883	883	883	889	889	889	881	881	881	872	872	872
T	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
cutoff	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m	1000 m
PCD	0.964	0.988	1.000	-2.179**	-2.188**	-2.185**	-1.147	-1.202	-1.177	-1.885*	-1.864*	-1.885*	0.663	0.626	0.640	1.029	1.165	1.089
IPS	-88.454***	-88.483***	-88.481***	-94.471***	-94.412***	-94.413***	-93.343***	-93.363***	-93.372***	-98.155***	-98.125***	-98.158***	-90.287***	-90.391***	-90.398***	-100.828***	-100.920***	-100.856***
CIPS	-2.408***	-2.409***	-2.411***	-2.880***	-2.915***	-2.904***	-2.420***	-2.416***	-2.423***	-2.629***	-2.622***	-2.625***	-2.422***	-2.417***	-2.418***	-2.795***	-2.780***	-2.793***

(Authors)

Result 2-1, 2-2. income & preference effect

- Result 2-1. income effect
  - $\beta_{\Delta ODR \times \Delta y}$: insignificant or **negative** (against to the hypothesis)
- Result 2-2. preference effect
  - $\beta_{\Delta ODR \times \Delta CBD}$: **positive** (consist with the hypothesis)

∴ The cause of negative impact of aging:

× budget constraints
◎ **prefer city outskirts**
where price growth is slower

Contents

Summary

1. Aggregated demand in the entire market

   1-1. <u>age composition effect</u> (Takáts 2012; Hiller and Lerbs 2016)

   ・**Negative impact**

2. Changes in elderly individuals' behaviors

   2-1. <u>income effect</u> (Mankiw & Weil 1989; DiPasquale & Wheaton 1994)

   ・income ↓ ⇒ budget constraint ⇒ demand ↓ ⇒ land prices ↓

   Controversial

   2-2. <u>preference effect</u> (**no previous study**)

   ・change in preference ⇒ necessity of accessibility ↓ ⇒ land prices ↓

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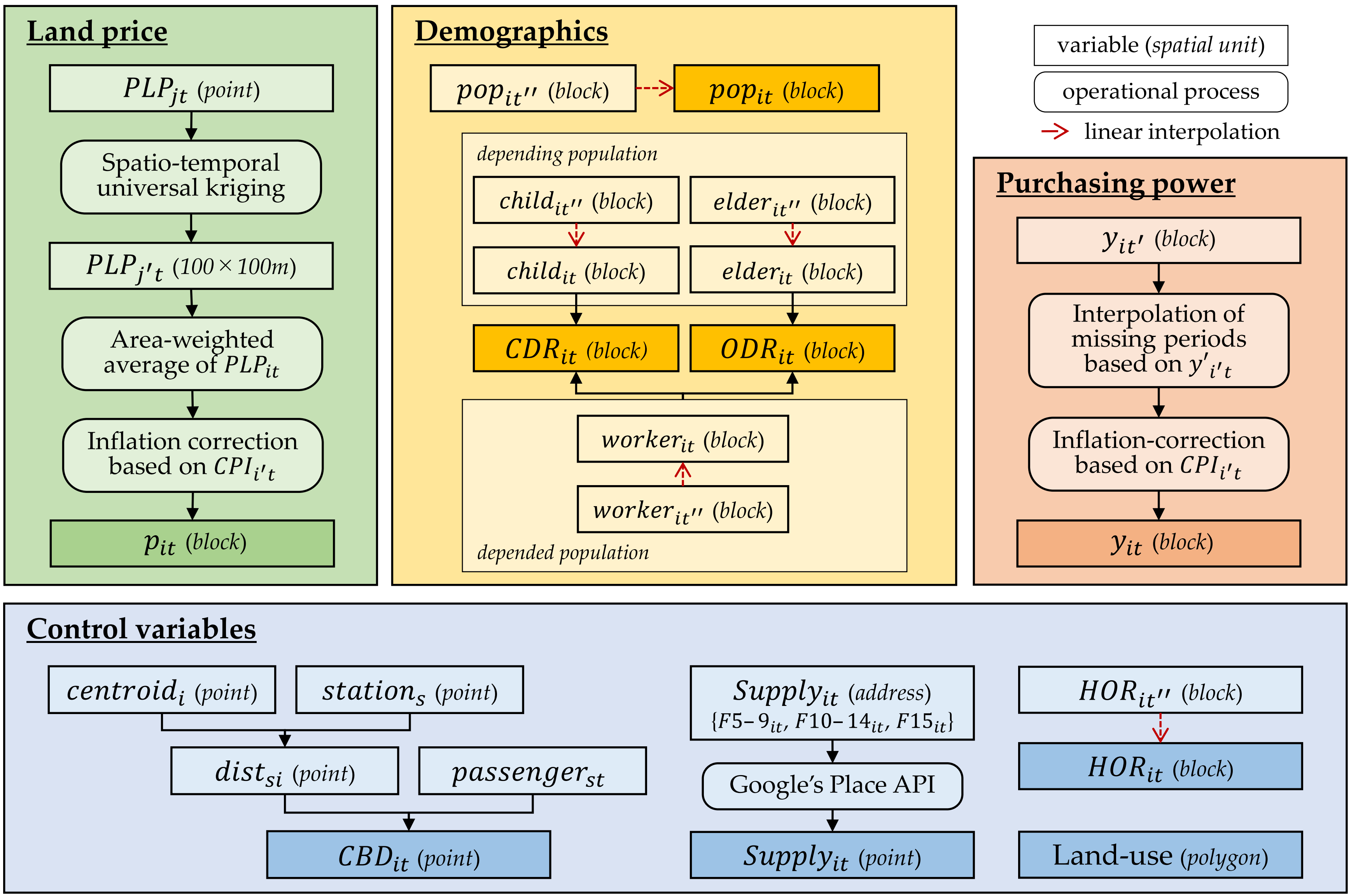
Thank you for your attention.

Development processes of panel data



i: *block-level*; i': ward level; j: PLP observation points; j': 100 × 100 m grids; s: stations in the study area;
t: 2000–2015; t': 2000, 2005, 2010, 2013, and 2015; t'': 2000, 2005, 2010, and 2015; *block*: block polygons

(Authors)

Validity of Kriging

Kriging model vs. non-kriging model

	M1: Kriging model (generic model)	M2: Non-kriging model	M3: Kriging model with limited blocks
Age composition effect	○	○	○
Income effect	×	○	○
Preference effect	○	×	×
Total number of blocks	2,845	611	611

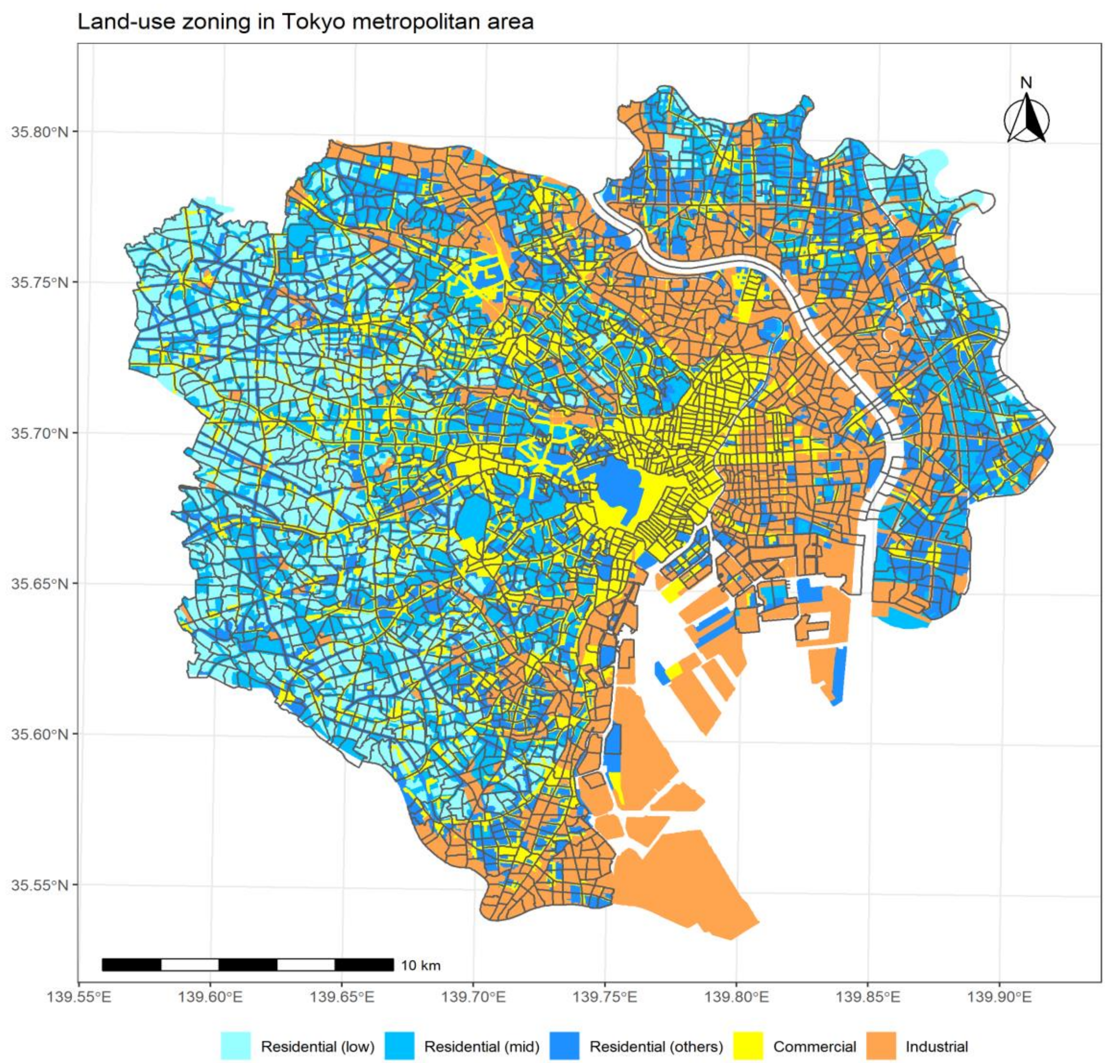
"○" denotes the effect is significantly positive, "×" denotes the effect is rejected. Colored in red refers to the different result from the kriging model (M1).

(Authors)

Policy implication

- income effect (nonsignificant)
  - Increased income dose not push up land price.
  - ***Aged-based*** **policies** (**rent subsidies**, **property tax exemption**) are less effective. *they work for all generation *equally*.
- preference effect
  - Elderly residents have less preference of **CBD**.
  - Under the aging society, improving accessibility is less effective. Other measurement like **greening** may work well.
- inheritance effect
  - Bequest motive can mitigate the negative effect of aging.
  - **Lower inheritance tax** reinforces bequest motive, then, may mitigate the negative effect of aging.

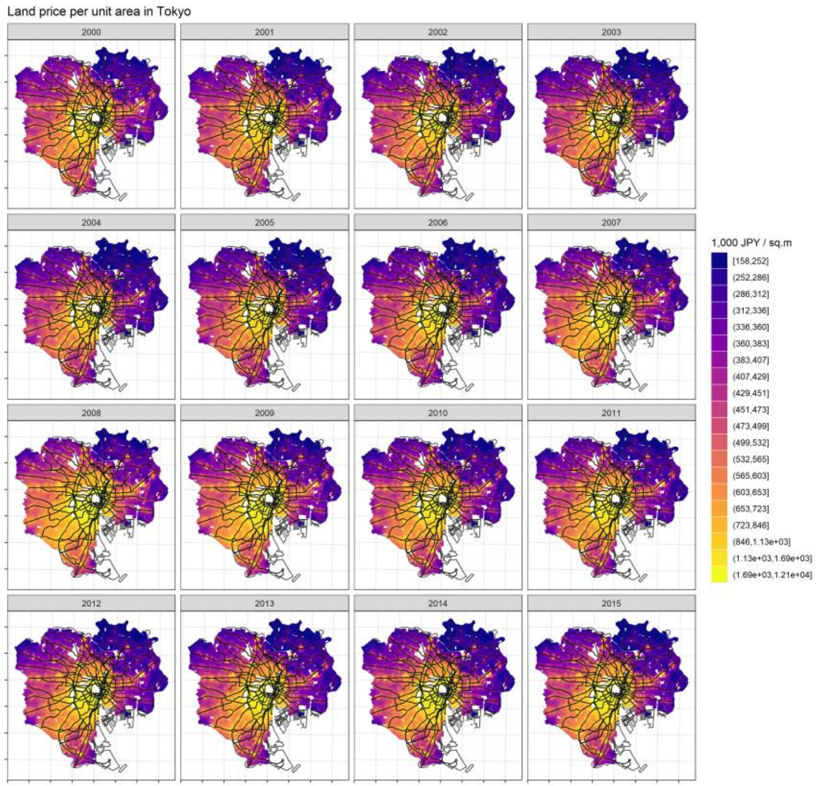
Map of study area and land-use zooning



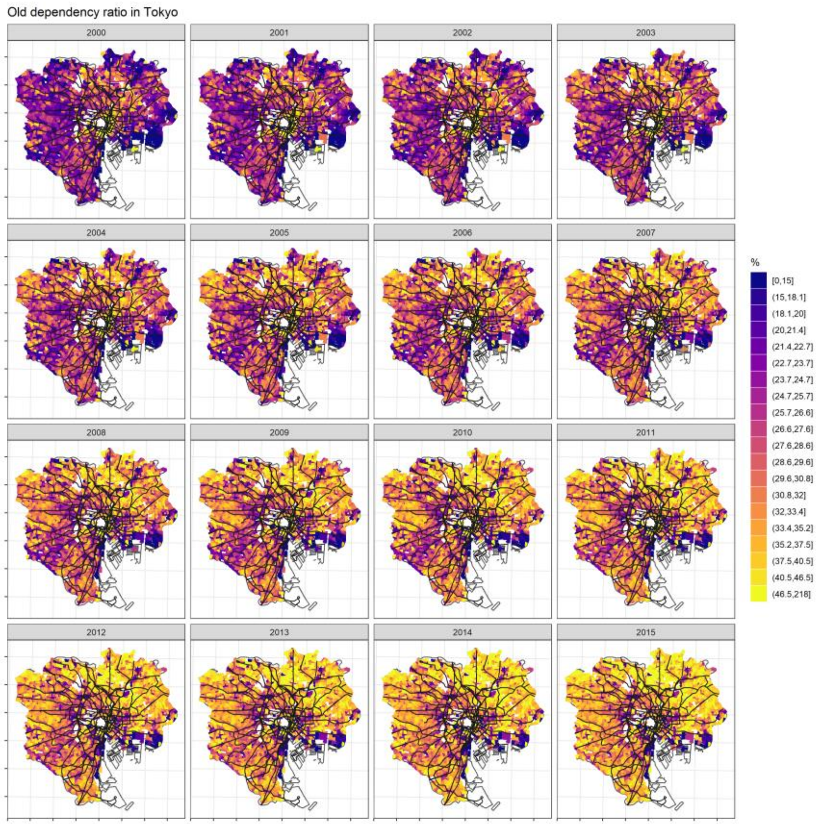
(Authors)

Maps

Land price



Old dependency ratio



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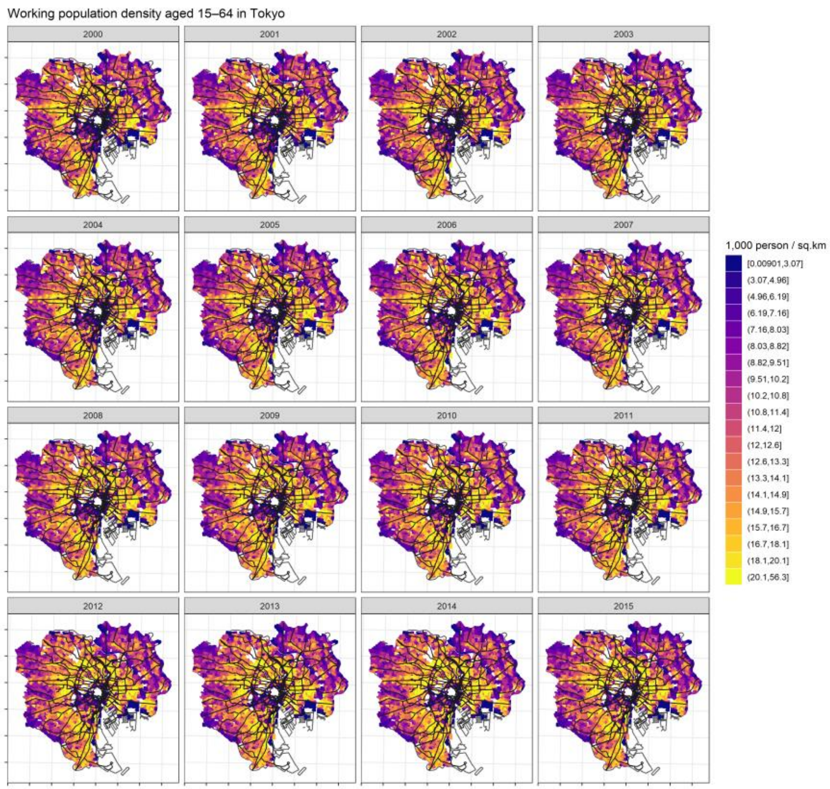
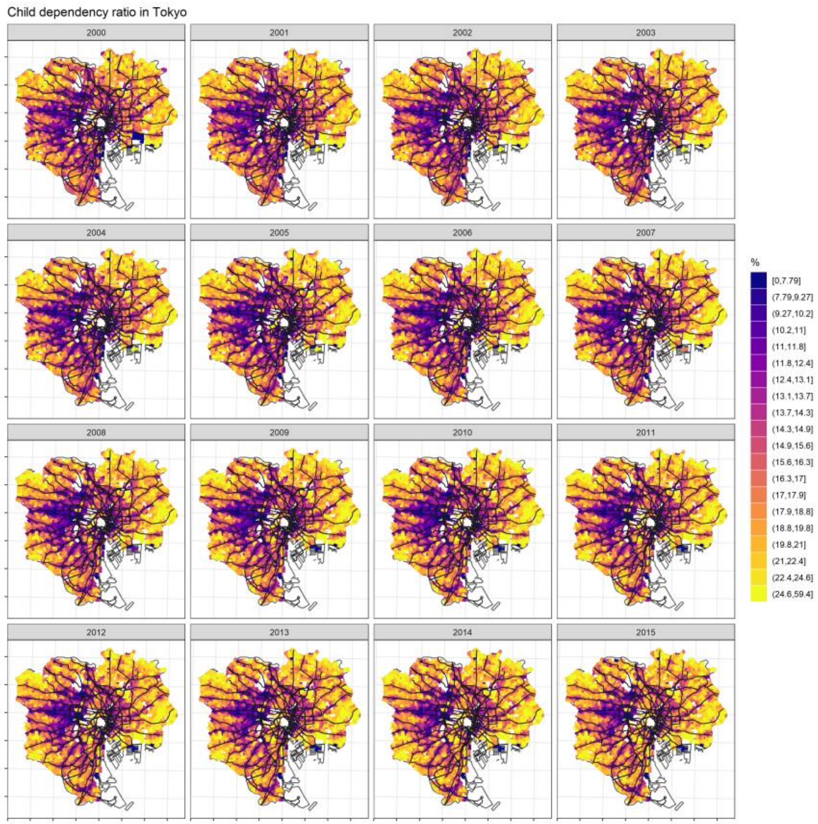
Maps

Working Age population



Child dependency ratio



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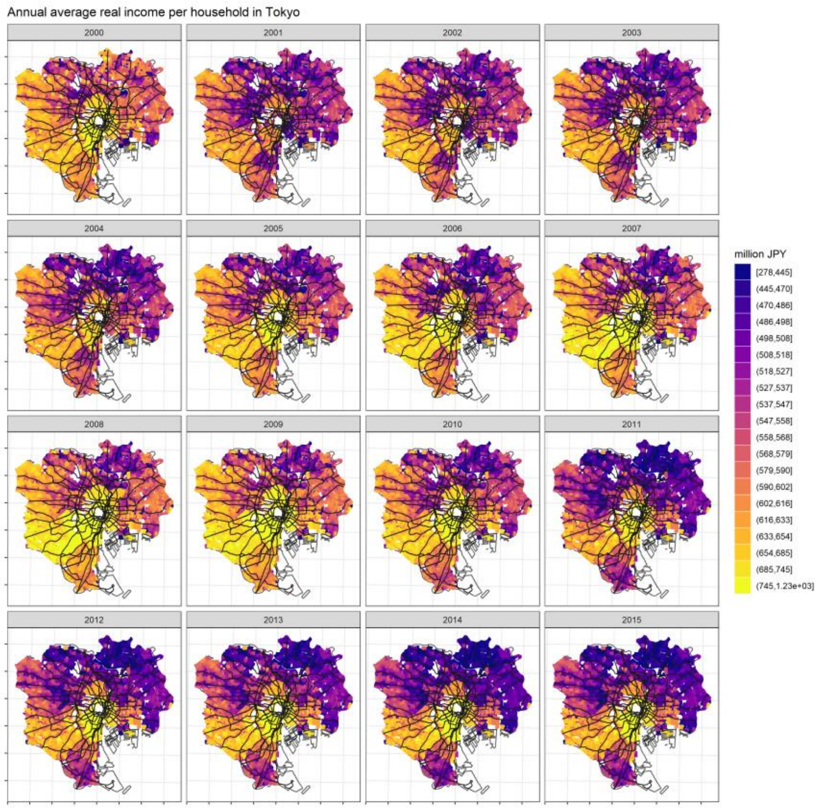
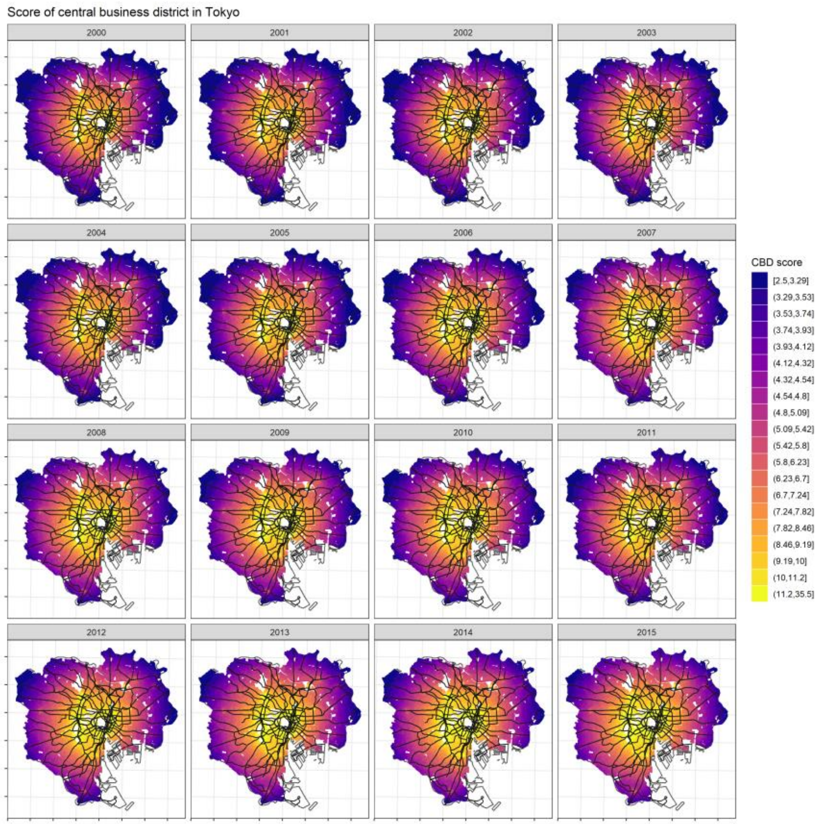
Maps

Household income



CBD score



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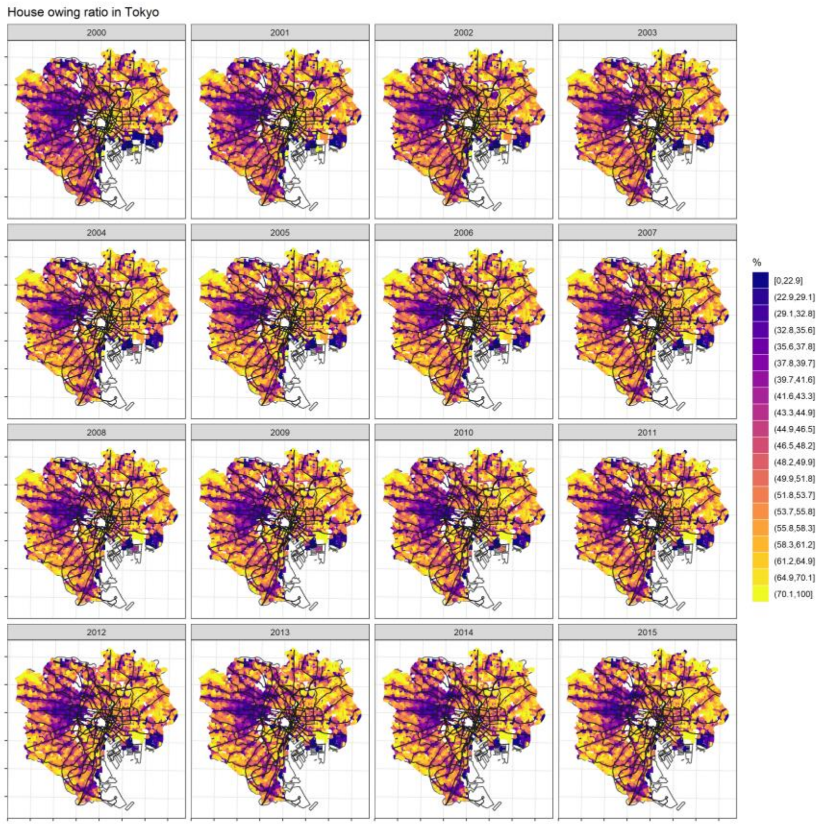
Maps

Home ownership ratio



(Authors)

Spatio-temporal Kriging（land prices）

Run OLS regression

↓

Calculate residuals of the OLS

↓

Compute empirical variogram

↓

Estimate fitted variogram

↓

Structuralize variance-covariance matrix

↓

Run GLS regression

↓

Interpolate

$$y = \boldsymbol{X}'\beta + \varepsilon, \quad E(\varepsilon\varepsilon') \sim V$$

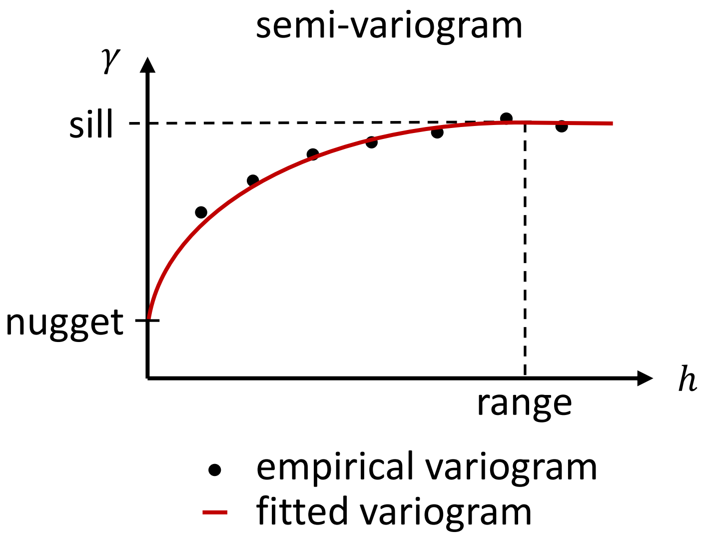
Estimate variance-covariance matrix for the GLS, using variogram structuralized from spatio-temporal distances of the residuals of OLS.

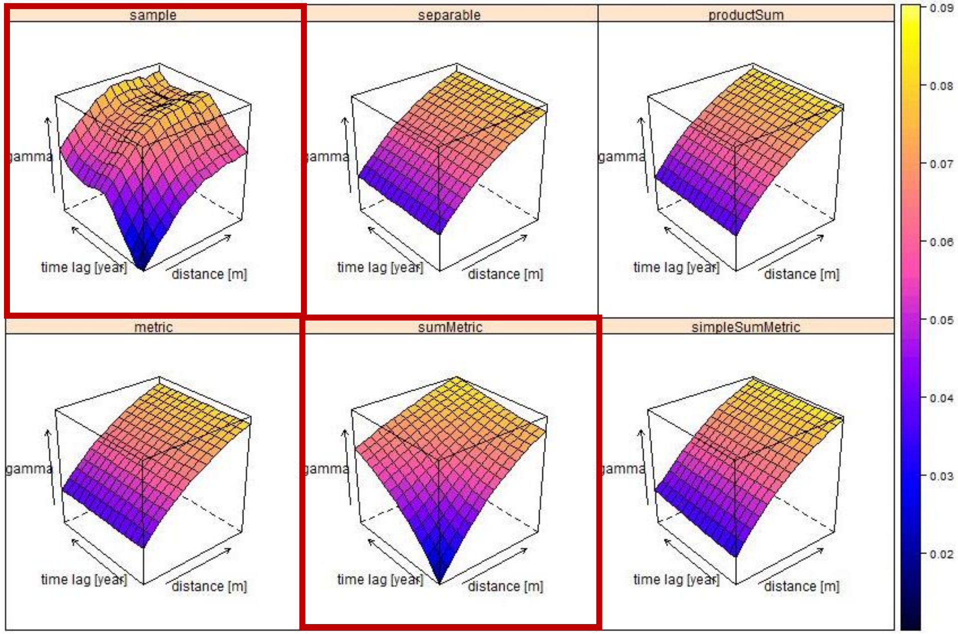
$$y_0 = \boldsymbol{X}_{\boldsymbol{0}}'\beta + \varepsilon_0, \quad E(\varepsilon\varepsilon') \sim \sigma_0^2$$

Interpolate into 100 × 100m mesh

Spatio-temporal Kriging（land prices）

Spatio-temporal variogram：structuralizing variance-covariance matrix





(Authors)

Estimation model of variogram

exponential model

$$\gamma(\boldsymbol{h}, t) = \begin{cases} t_0 + t_1\left(1 - e^{-\frac{\|\boldsymbol{h}\|}{t_2}}\right), & \|\boldsymbol{h}\| > 0 \\ 0, & \|\boldsymbol{h}\| = 0 \end{cases}$$

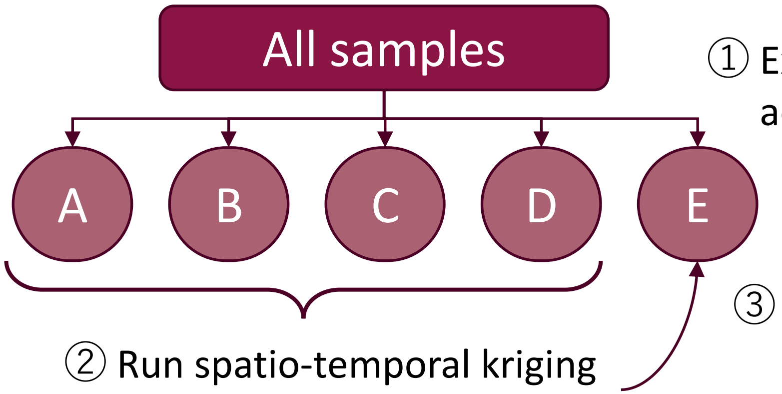
spherical model

$$\gamma(\boldsymbol{h}, t) = \begin{cases} t_0 + t_1, & \|\boldsymbol{h}\| > t_2 \\ t_0 + t_1\left[\frac{1}{2}\frac{\|\boldsymbol{h}\|}{t_2} - \frac{3}{2}\left(\frac{\|\boldsymbol{h}\|}{t_2}\right)^3\right], & 0 < \|\boldsymbol{h}\| \le t_2 \\ 0, & \|\boldsymbol{h}\| = 0 \end{cases}$$

Spatio-temporal Kriging（land prices）

Validation of accuracy

5-fold cross-validation



① Extract randomly according to attributes

② Run spatio-temporal kriging using the four groups

③ Compare the estimations of ② and the observations of the rest group

④ Repeat ①~③ for 5 times and calculate root mean square errors (RMSE).

Exponential RMSE (eRMSE)

$$eRMSE = \exp\left(\sqrt{\sum_{i=1}^{N} \frac{(\ln(\hat{y}_i) - \ln(y_i))^2}{N}}\right)$$

y_i: observation,
$\hat{y}_i$: interpolated value

When eRMSE = 1.0, there are no errors.
When eRMSE = 1.1, there is 10% of errors.

Spatio-temporal Kriging（land prices）

Apply for land prices

＜Explanatory variables＞

・the distance from main stat. → Calculate by GIS

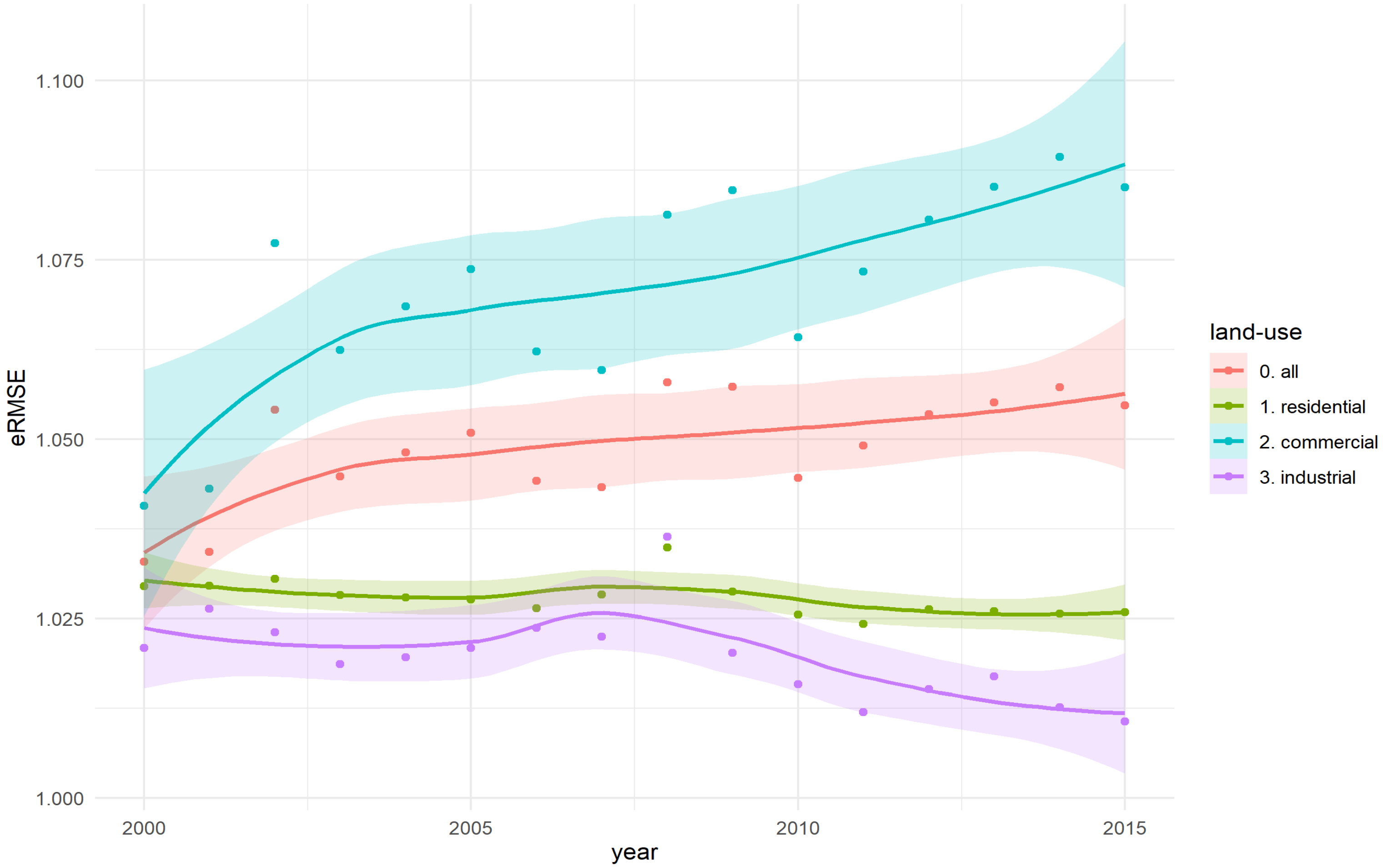
・the distance from the nearest stat.
・the area of land
・floor-area ratio
・land-use zooning

Attributions of PLPs

・the annual average Nikkei-stock → Control variable for economic condition

Spatio-temporal Kriging（land prices）

Apply for land prices：eRMSE (the accuracy in Tokyo)



Residential zone

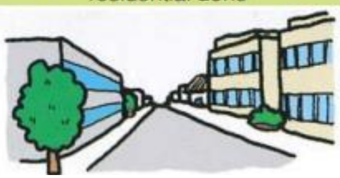
Residential (low) zone

Category I exclusively low-rise residential zone

Category II exclusively low-rise residential zone

Residential (mid) zone

Category I mid/high-rise oriented residential zone



Category II mid/high-rise oriented residential zone

Residential (others) zone

Category I residential zone

Category II residential zone

Quasi-residential zone

Commercial zone

Neighborhood commercial zone

Commercial zone

Industrial zone

Quasi-industrial zone

Industrial zone

Exclusively industrial zone

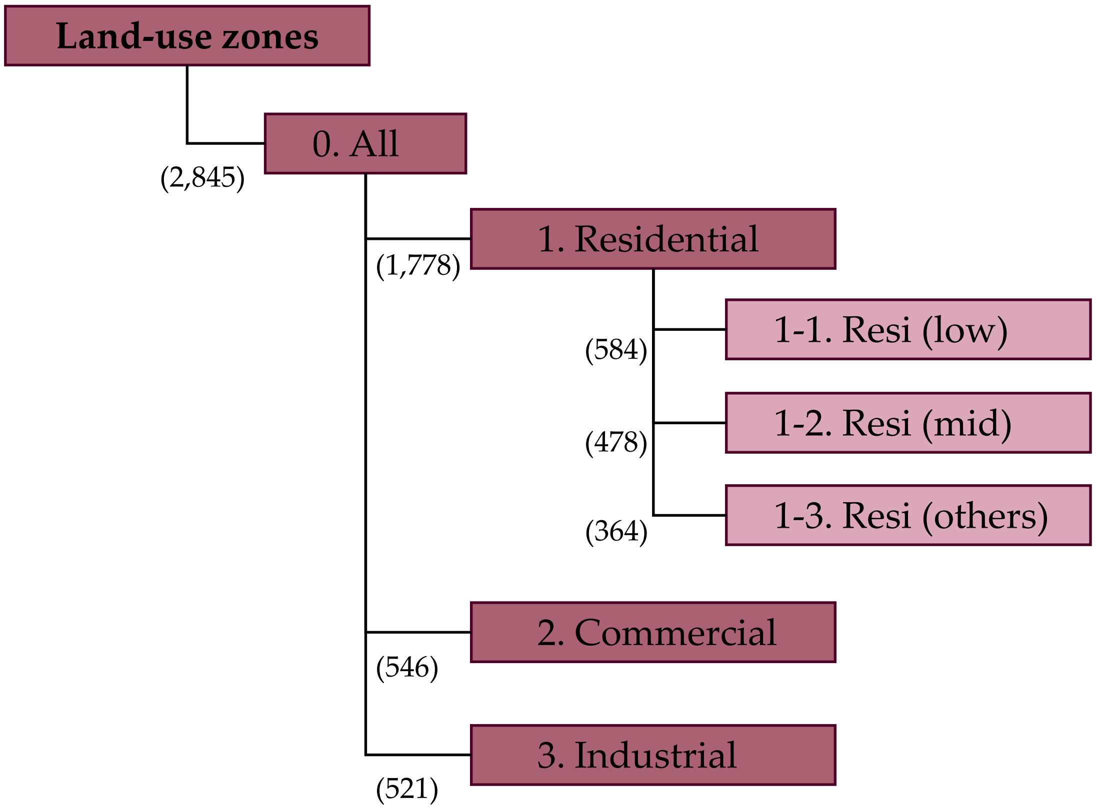
Land use zones

Examples of buildings	Category I exclusively low-rise residential zone	Category II exclusively low-rise residential zone	Category I mid/high-rise oriented residential zone	Category II mid/high-rise oriented residential zone	Category I residential zone	Category II residential zone	Quasi-residential zone	Neighborhood commercial zone	Commercial zone	Quasi-industrial zone	Industrial zone	Exclusively industrial zone	Areas with no land-use zone designation (Urbanization Control Areas are excluded)
Houses, Houses with other small scale function (store, office, etc.)													
Kindergartens, Schools (Elementary, Junior High, Senior High)													
Shrines, Temples, Churches, Clinics													
Hospitals, Universities													
Stores (mainly selling dairy commodities)/Restaurants with floor space of 150m² max. on the first or second floor (excluding※)												D	
Stores/Restaurants with floor space of 500m² max. on the first or second floor (excluding※)												D	
Stores/Restaurants not specified above (excluding※)				A	B								
Offices, etc. not specified above				A	B								
Hotels, Inns					B								
Karaoke boxes (excluding※)													
Theaters, Movie theaters (excluding※)							C						
※Theaters, Movie theaters, Stores, Restaurants, Amusement facilities and so on, with more than 10,000m² of floor area													
Bathhouses with private rooms													
Independent garage with floor space of 300m² max. on the first or second floor													
Warehouse of warehousing company, Independent garage of other types than specified above													
Auto repair shop					E	E	F	G	G				
Factory with some possibility of danger or environmental degradation													
Factory with strong possibility of danger or environmental degradation													

Note A : Must not be built on the third floor or higher. Must not exceed a floor area of 1,500m².
B : Must not exceed a floor area of 3,000m².
C : Audience seating floor area must not exceed 200m².
D : Stores and restaurants must not be built
E : Floor area must not exceed 50m².
F : Floor area must not exceed 150m².
G : Floor area must not exceed 300m².

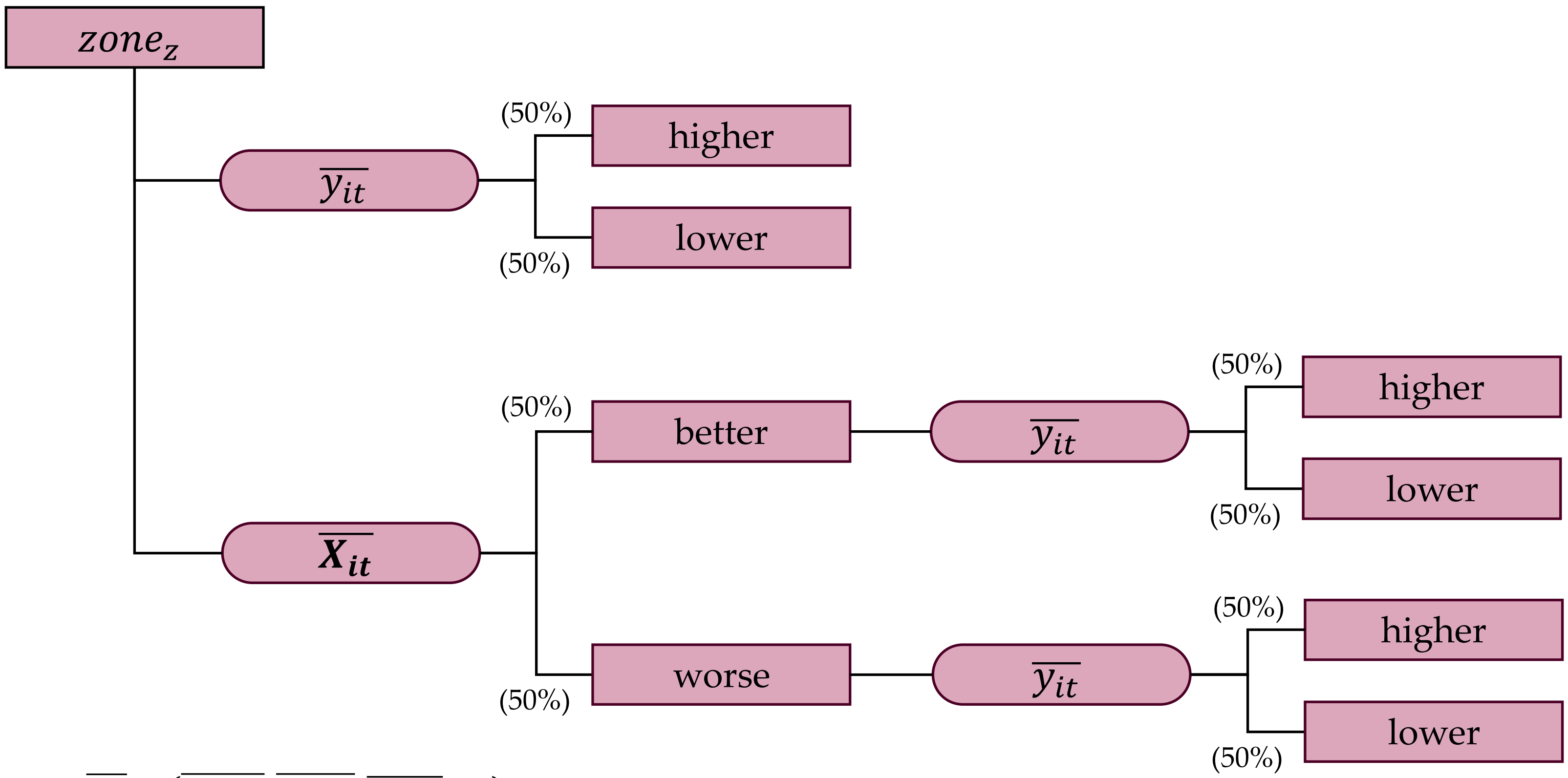
(City Planning Division, City and Regional Development Bureau, Ministry of Land, Infrastructure and Transport, 2003)

Dividing into cases



(Authors)

Dividing into cases



$\overline{\boldsymbol{X}_{it}} = (\overline{HOR_{it}}, \overline{CBD_{it}}, \overline{stat_{it}}, \overline{p_{it}})$

(Authors)

Hypothesis 1-1. age composition effect

Based on Overlapping-generations (OLG) model,
the negative effect of aging on real estate is proofed (Samuelson 1958; P. A. Diamond 1956; Takáts 2012)。

- Youth (t) ：earing income (y_t). y_t is used for consumption when young (c_t^y) and saving (s_t^y).
- Old (t+1) ：consumption in old (c_{t+1}^o) is payed from saving (c_t^y) and its interest

$$c_t^y + s_t = y_t$$
$$c_{t+1}^o = (1 + r_{t+1})s_t$$

- Utility (U) ：individuals maximize the utility through consumptions when young and old.

$$\max_{c_t^y, c_{t+1}^o} \quad U = ln(c_t^y) + \frac{1}{1+\delta} ln(c_{t+1}^o)$$
$$\text{s.t.} \quad y_t = c_t^y + \frac{c_{t+1}^o}{1 + r_{t+1}}$$

~~~ (omitted) ~~~

- The growth of asset prices is explained by economic and population growth.

$$1 + r_t = \frac{p_{t+1}}{p_t} = (1 + g_t)(1 + d_t^y)$$
~~~

Hypothesis 1-1. age composition effect

・Old dependency ratio (ODR_t) is equal to the inverse of population growth $(1+d)$.

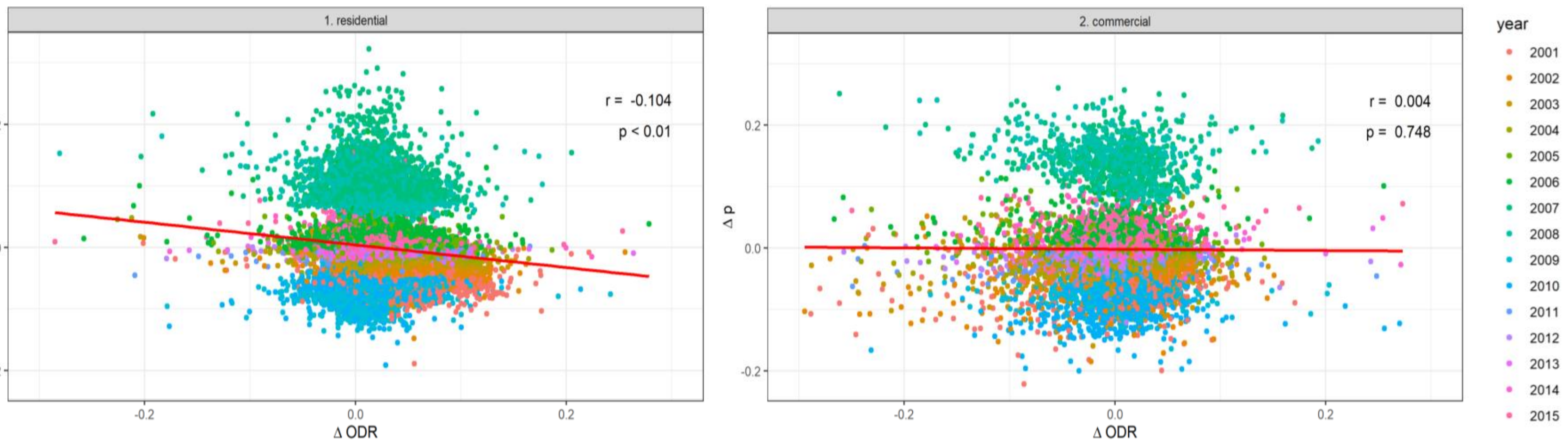
$$ODR_t = \frac{n_{t-1}^y}{n_t^y} = \frac{n_{t-1}^y}{n_{t-1}^y\left(1+d_{t-1}^y\right)} = \frac{1}{1+d_{t-1}^y}$$

$\therefore$ ΔODR negatively affects land price growth.

<u>Vilification method 1-1. age composition effect</u>

・whether the coefficient of $\boldsymbol{ODR}$ is **negative**.

Result 1-1. age composition effect



*OLG model does not work in commercial areas.