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

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高齢化が地価に与える影響のプロセスの分解

~高解像度の空間パネルデータを用いて~

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背景（現状）

- 世界的な高齢化の進展
  - 経済水準の上昇 → 高齢化の加速
    (WPP; https://population.un.org/wpp/)
  - ➢途上国も含め、高齢化は全世界の問題

- 高齢化の経済活動に与える負の影響
  - 経済成長の鈍化 (Jiandong, 2016 *(J. Rural Studies)*, Acemoglu & Restrepo, 2017 *(AEJ)*, Aksoy et al., 2019 *(Behavioral Brain Scie.)*)
  - 生産性の低下 (Feyrer, 2007 (*Rev. Econ. Stat.*), Feyrer, 2008 (*Pop. Dev. Rev.*), Feyrer, 2011 (*JPE*))
  - 需要の減少 (Vargha et al., 2017 *(Demg. Res.)*)
  - 税収の減少 (Razin et al., 2002 *(JPE)*)
  - 年金システムの逼迫 (Flaherty et al., 2007 *(J. Am. Geriatrics Society)*)
  - 医療費の増大 (Zeng & Hesketh, 2016 *(Lancet)*)

背景（高齢化と不動産）

- 不動産の重要性
  1. Wealth effect:
     不動産は、個人の**担保**となるため、
     不動産の保有は、**消費行動**を促進する。
     (Kiyotaki and Moore, 1997 (*JPE*); Aladangady, 2017 (*AER*); Chen et al., 2020 *(Real Estate Econ.)*)
  2. 家計の最大資産:
     不動産は、**家計の最大資産**であるため、
     不動産価格の変動は、家計に大きな影響を及ぼす。
     (Flavin & Yamashita, 2002 (*AER*); Rosenthal & Strange, 2004 *(book)*; Chetty et al., 2017 *(J. Fin.)*)
  3. (企業への影響)
     (家計同様、不動産価格の変動は
     企業にも大きな影響を及ぼす)

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研究の目的と貢献

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- 高齢化効果の分解
  1. Age composition effect
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  3. Inheritance effect
- 用途地域 (zoning) による差異の検証

2. 空間パネルデータ: 高解像度×公示地価

- 既存研究の5つのバイアスへの対処
  1. Aggregation bias
  2. Omitted variable bias
  3. Representativeness bias of spatio-temporal distribution
  4. Sample selection bias
  5. Market friction

貢献(1)：高齢化効果の分解

1. 高齢化と地価の一般的な関係

1-1. age composition effect
(Takáts, 2012 (*J. Housing Econ.*); Hiller and Lerbs, 2016 (*Regi. Sci. Urban Econ.*))
・高齢化と地価には**負の相関関係**がある.

2. 高齢化と地価の関係のプロセス

2-1. income effect
(Mankiw & Weil, 1989 (*Regi. Sci. Urban Econ.*); DiPasquale & Wheaton, 1994 (*J. Urban Econ.*))
・高齢化 → 所得⇓ → 予算制約 → 需要⇓ → 地価⇓

2-2. preference effect (先行研究なし)
・高齢化 → 選好の変化 → 利便性の必要性⇓ → 地価の高い地域に住む必要性⇓

3. 遺産としての不動産

3-1. inheritance effect (先行研究なし)
・遺産動機があると、重複世代モデル (OLG) の過程が崩れる.
→ 高齢化の影響が緩和される.

貢献(1)：高齢化効果の分解

Effect	Describe	This paper	Previous studies
1-1. Age composition effect	Aging has a negative impact on price growth in real estate.	○ in residential × in commercial	○ at country [1], city [2], and province level [3]
2-1. Income effect	Budget constraint causes a negative impact of aging.	×	○ [4.5], △ [6], × [7,8,9]
2-2. Preference effect	Change in preference causes a negative impact of aging.	○	—
3-1. Inheritance effect	Bequest motives can mitigate the negative impact of aging.	○	—

過大評価

賛否両論

高解像度のみ

[1] (Takáts, 2012), [2] (Hiller & Lerbs, 2016) , [3] (Simo-Kengne, 2019), [4] (Mankiw & Weil, 1989), [5] (DiPasquale & Wheaton, 1994), [6] (Eichholtz & Lindenthal, 2014), [7] (Engelhardt & Poterba, 1991), [8] (R. Green & Hendershott, 1996), [9] (R. K. Green & Lee, 2016).

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2. 空間パネルデータ: 高解像度 × 公示地価

- 既存研究の5つのバイアスへの対処
  1. Aggregation bias
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  3. Representativeness bias of spatio-temporal distribution
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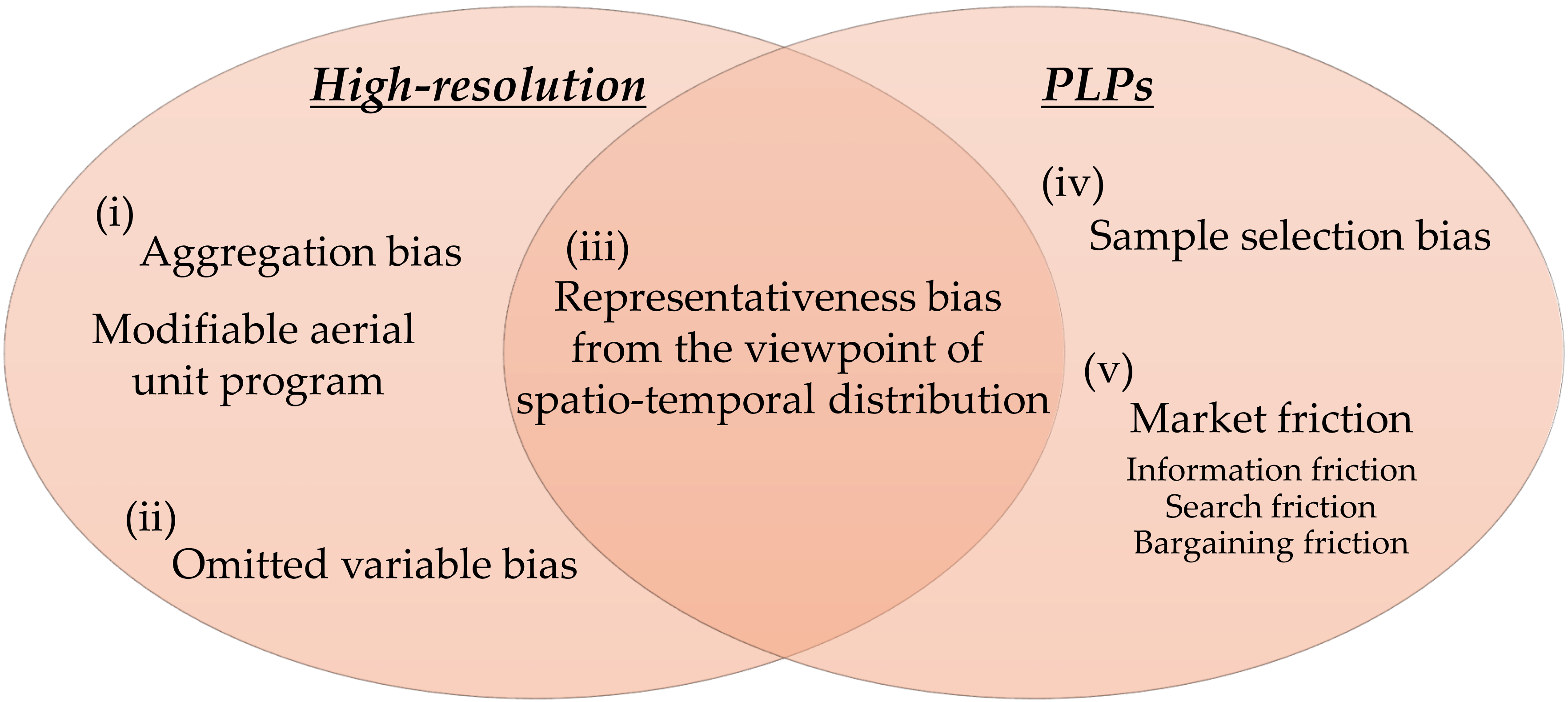
  5. Market friction

貢献(2)：バイアスへの対処 (高解像度×公示地価)

Overcoming biases using high-resolution panel data based on PLP



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貢献(2)：バイアスへの対処 (**高解像度**×公示地価)

(i) **Aggregate bias** への対処 (Gehlke & Biehl, 1934 *(J. Am. Stat. Asooci.)*)

◆**Aggregate panel** (既存研究)

- country level (Takats, 2012 *(Housing Econ.)*)
- city level (Hiller & Lerbs, 2016 *(Regi. Sci. Urban Econ.)*)
- province level (Simo-Kengne, 2019 *(Housing Buit. Envi.)*) のみ

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

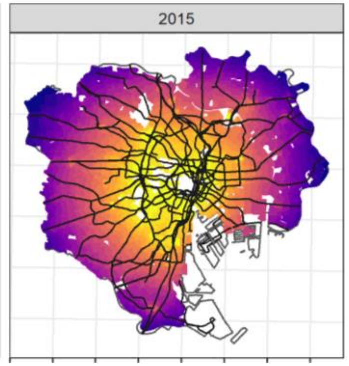
- 町丁目レベル ≒ 430×430m grid level

➢ fixed effects の向上 (Cornwell & Trumbull, 1994 *(Rev. Econ. Stat.)*):

a. Accessibility (Glumac et al., 2019; Yuan et al., 2020)
b. Land-use zoning (Glaeser et al., 2005; Huang & Tang, 2012; Nichols et al., 2013; Tan et al., 2020)
c. Urban green space (Morancho, 2003; Panduro & Veie, 2013; Schlapfer et al., 2015)
d. Geographical constraints (Albert, 2013; Hilber & Vermeulen, 2016)
e. Brand value (Lakshman, 1991)

貢献(2)：バイアスへの対処 (**高解像度**×公示地価)

(ii) **Omitted variable bias** への対処
(高解像度にすることによって浮かび上がる変数)



◆**Aggregate panel** (既存研究)

- country level, province level, city level では、
  中心地までの距離 (CBD) を変数に加えられない。
  cf. bid rent theory (Alonso 1964; Fujita 1989)

◆**<u>High-resolution panel</u>** (this paper)

- 町丁目レベル ≒ 430×430m grid level

➢ Omitted variable bias の解消

  - CBD score: 都市空間の時空間ダイナミックを構造化

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

s: 駅
S: 総駅数
$dist_{si}$: 駅sと町丁目iの重心の距離
$passenger_{st}$: 時間tにおける駅sの乗客数

貢献(2)：バイアスへの対処 (**高解像度×公示地価**)

(iii) **時空間分布の代表性**バイアス への対処

◆**取引価格 (既存研究)**：
実際の取引があった場合にのみ観測される.
➢解像度が高くなるほど、欠損値が増える.
➢その欠損値の**時空間分布**は一様ではない.

◆**鑑定価格 (this paper)**：
実際の取引に関係なく定められた周期で鑑定される.
➢解像度が高くなっても、欠損値の数を抑えられる.
(krigingを用いれば、欠損値をゼロにできる)
➢たとえ欠損値があっても、
欠損値の**時空間分布の代表性**は担保される.

貢献(2)：バイアスへの対処 (高解像度×**公示地価**)

(iv) **サンプル選択**によるバイアス への対処
(J.Heckman, 1979; Berk, 1983; Certo et al., 2016; Munafò et al., 2018)

◆**取引価格 (既存研究)**：
実際の取引があった物件のみ観測される.
- 不動産市場で取引される物件は、
  母集団に対して、**物件の特徴の偏り**を持つ可能性がある.
  e.g., 持家率が低い, 駅から近い
- サンプル選択にバイアスがある.
- 高齢化効果の分解という研究目的を脅かす.

◆**鑑定価格 (this paper)**：
実際の取引に関係なく定められた物件が鑑定される.
- 地域の物件の特徴を代表するように鑑定地点が選定される.
- サンプル物件の**代表性**は担保される.

貢献(2)：バイアスへの対処 (高解像度×**公示地価**)

(v) **Market friction** によるバイアス への対処

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

◆**取引価格 (既存研究)**：

i. **Information friction**：
不動産市場は情報の非対称性が多きい.

ii. **Search friction**：
不動産物件は1つしか存在しないため、
ある物件をキープし、他の物件を探すことが困難.

iii. **Bargaining friction**：
売り手と買い手の交渉力が価格に反映される.

➢取引価格は、高齢化による **fundamental** の影響よりも **market friction** の影響を、強くとらえる可能性がある.

◆**鑑定価格 (this paper)**：

➢取引価格と比べ、**market friction** の影響が少ない.

Contents

空間計量分析の必要性

- 地価, 所得, 人口などのデータは、
  観測値の大小が**空間的に偏り**を持っている.
- 換言すれば、ある地点の観測地は、
  距離が近い地点の観測地とより高い相関を持ち、
  距離が遠い地点の観測地とより低い相関を持つ.
  これを、**空間的相関** (spatial correlation) という.
- 空間的相関が存在する場合、OLSの前提条件が崩れる.
  そのため、空間的相関をコントロールする必要がある.
  その手法の1つが、**空間計量分析**である.

空間計量分析の必要性

空間計量経済学の一般モデル (SACモデル*)

*このモデルには複数の呼び方が存在する。
例えば、**General Spatial Model** (Anselin, 1988),
spatial autoregressive model with autoregressive disturbances, **SARAR** (Kelejian & Prucha, 1998),
spatial autocorrelation combined, **SAC** (LeSage & Pace, 2009).

$$y = \lambda \boldsymbol{W} y + X'\beta + u$$
$$u = \rho \boldsymbol{W} u + \varepsilon$$

where
- $\boldsymbol{W}$: spatial weight matrix
- λ : spatial autoregression term
- ρ : spatial error term

- 空間計量経済学では、 誤差項ε が $\varepsilon \sim i.i.d.(0, \sigma_i^2)$ となるように、空間重みづけ行列 ($\boldsymbol{W}$) を用いて空間的相関をコントロールする。

空間計量分析の必要性

Spatial weight matrix

$$W = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix}$$

i. Boundary base

$$w_{ij} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ are contigous} \\ 0 & \text{if } i \text{ and } j \text{ are not contigous} \end{cases}$$

ii. Distance base

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$

→ this paper

- Row standardization

$$w_{ij}^{s} = \frac{w_{ij}}{\sum_j w_{ij}}$$

空間パネル分析 (SACモデル)

- generic model

$$\Delta p_{it} = \lambda \boldsymbol{W} \Delta p_{it} + \beta_1 \Delta ODR_{it} + \beta_2 (\Delta ODR_{it} \times \Delta y_{it}) + \beta_3 (\Delta ODR_{it} \times \Delta CBD_{it})$$

$$+ \boldsymbol{x}'_{it} \boldsymbol{\gamma}_k + \mu_i + \varphi_t + u_{it}$$

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

where

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

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)]
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)]
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)]
HOR	Home ownership ratio	Logarithmic ration of residentials who live in the owing houses to residential who do not [%]	e-Stat [(2)]
CBD	Central business district	Logarithmic central business district score [person/distance]	Authors' calculation based on MLITT [(1)] and TMG [(4)]
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/)

(Authors)

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.

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Correlation between variables

Correlation between variables.

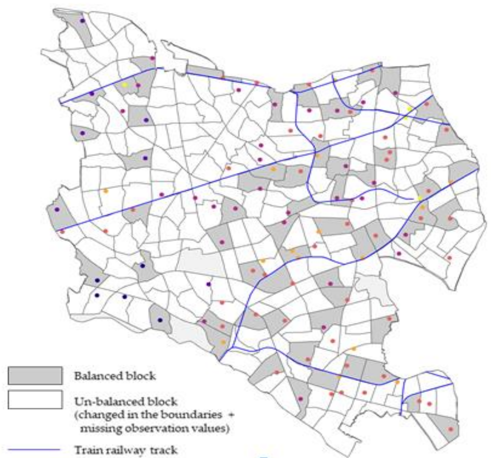
	Δp	Δpop	ΔCDR	ΔODR	Δy	ΔHOR	ΔCBD	$F5–9$	$F10–14$	$F15$
Δp	–	–	–	–	–	–	–	–	–	–
Δpop	0.009	–	–	–	–	–	–	–	–	–
ΔCDR	0.048	0.298	–	–	–	–	–	–	–	–
ΔODR	-0.052	-0.384	0.037	–	–	–	–	–	–	–
Δy	0.377	-0.016	0.003	-0.007	–	–	–	–	–	–
ΔHOR	-0.046	0.093	0.204	0.185	0.061	–	–	–	–	–
ΔCBD	0.545	0.034	0.045	-0.027	0.265	-0.022	–	–	–	–
$F5–9$	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	–

(Authors)

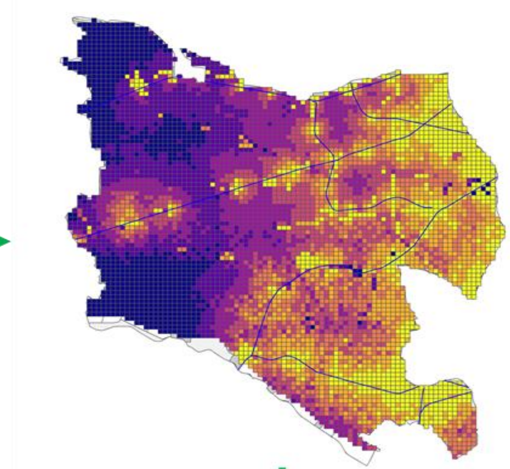
Development processes of panel data

例）世田谷区

(a) Observation points (point)

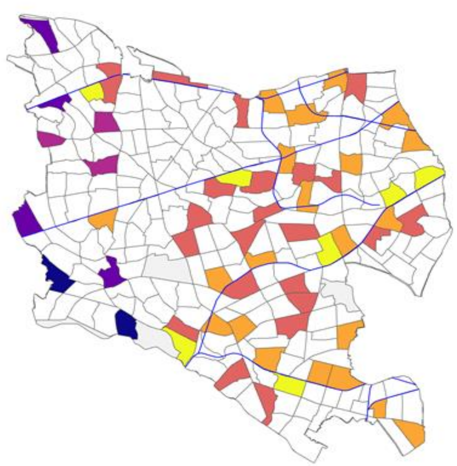


(c) Universal spatio-temporal kriging (100 × 100 m)

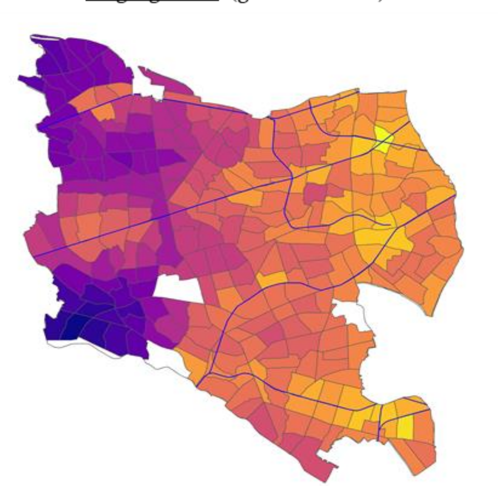


(b) Conventional average PLPs (*block*)
Non-kriging model

611 blocks in Tokyo



(d) Area-weighted average PLPs based on kriging (*block*)
Kriging model (generic model)



2,845 blocks in Tokyo

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Hypothesis 1-1. age composition effect

Hypothesis 1-1. age composition effect の理論背景

・重複世代モデル (overlapping-generations model: OLG)
(Samuelson, 1958 (*JPE*); P. A. Diamond, 1956 (*AER*); Takáts, 2012 (*J. Housing Econ.*))

→ 高齢化は地価に負の影響を及ぼす.

Hypothesis 1-1. age composition effect の検証方法

・空間パネル分析の高齢化率 ($\boldsymbol{ODR}$) の係数が**マイナス**となる。

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***

(Authors)

→ **居住エリア**のみ***ODR***の係数が**マイナス***

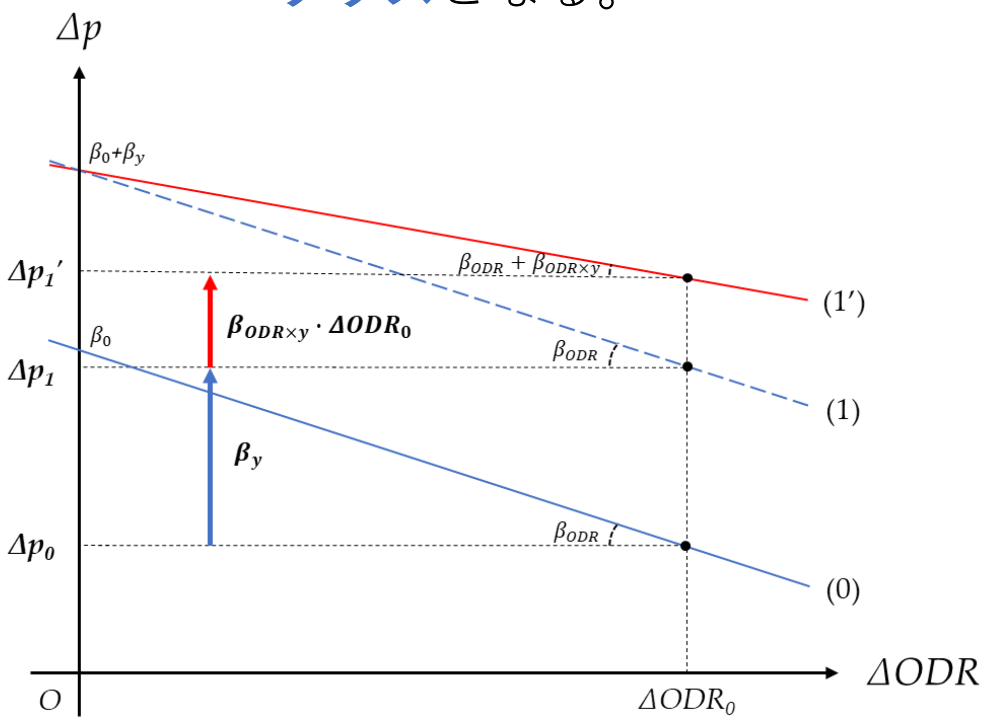
∴ **居住エリア**では、高齢化と地価の成長率に**負の相関関係**がある。

*商業地域では、異なる理論が働くと考えられる (*Ref.*)

Hypothesis 2-1. income effect

仮　　説：高齢化 → 所得⇓ → 需要⇓ → 地価⇓

検証方法：高齢化率と所得の交差項 ($\boldsymbol{ODR \times y}$) の係数が
プラスとなる。



<u>直線(0)</u>： 傾き(β_{ODR})がマイナス

<u>直線(1)</u>： 直線(0)からβ_yだけ
上方に平行移動

<u>直線(1′)</u>： 直線(1)に対して、
傾きが$\beta_{ODR\times y}$だけ**改善**

→ 所得があれば、本来の地価よりも
高い地域に住むことができる。
∴ 高齢者が<u>**予算制約**</u>に直面している。

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

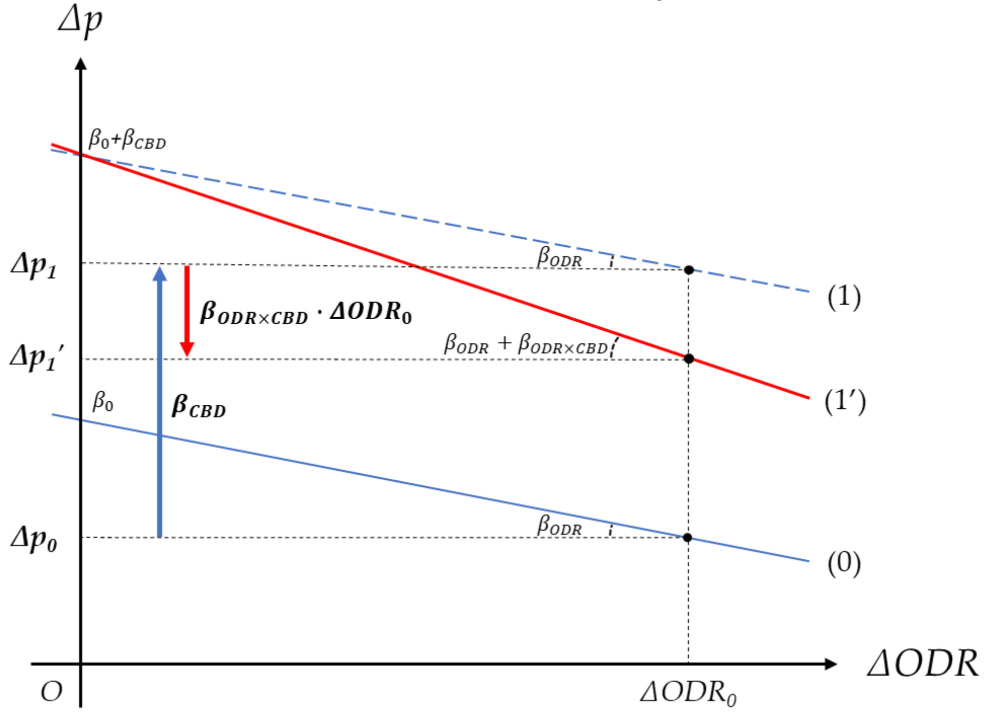
(+)　(−)　(+)　(+)

(Authors)

Hypothesis 2-2. preference effect

仮　　説：高齢化 → 選好の変化 → 地価の低い地域に住む必要性⇓

検証方法：高齢化率とCBDスコアの交差項 $(\boldsymbol{ODR} \times \boldsymbol{CBD})$ の係数が
マイナスとなる。



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

(+)　(−)　(+)　(−)

直線(0)：傾き(β_{ODR})がマイナス

直線(1)：直線(0)からβ_{CDB}だけ
上方に平行移動

直線(1′)：直線(1)に対して、
傾きが$\beta_{ODR\times CBD}$だけ**悪化**

→ 高齢化に伴い、CBDスコアや
最寄駅まで距離などの
地価に有意に作用する
効用の選好が変化する。
∴ 結果として、高齢者は
地価の低い地域を選択する。

(Authors)

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
  - $\beta_{ODR \times y}$は、マイナスが**少ない**。
  - $\beta_{ODR \times y}$がマイナスになる地域の特徴は、
    最寄り駅から遠い and/or **所得が低い** ことである。

- Result 2-2. preference effect
  - $\beta_{ODR \times CBD}$は、プラスが**多い**。
  - 特に、**所得が低い**地域で顕著である。

∴ 高齢化と地価の負の相関関係の原因は、
予算制約による需要の減少よりも、
むしろ**選好の変化**によって、結果的に
地価の低い地域を選択している可能性が高い。

KYUSHU UNIVERSITY

Hypothesis 3-1. inheritance effect

仮説：遺産動機があると高齢化が地価に与える影響が小さくなる。

重複世代モデル(OLG)では、個人が存在する期間のうちに
すべての所得を使い切ることが仮定されている。

しかし、土地を遺産として相続する場合、OLGの過程が崩れ、
代表的個人モデル(representative agent)に近くなるため、
高齢化の影響が小さくなると予測される。

検証方法：

持ち家率($\boldsymbol{HOR}$)によって場合分けをし、
空間パネル分析の高齢化率($\boldsymbol{ODR}$)の係数の大小を比較する。

$\beta_{ODR\_highHOR} > \beta_{ODR\_lowHOR}$ のとき、仮説3-1が支持される。

	higher MHR	*lower MHR*
ΔODR	β_{high} >	β_{low}

Result 3-1. inheritance effect

	all income level						high income level						low income level					
	high MHR			low MHR			high MHR			low MHR			high MHR			low MHR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Total effects																		
Δpop	-0.0588	-0.0640	-0.0584	-0.0651**	-0.0561*	-0.0659**	-0.1739***	-0.1769***	-0.1760***	-0.1720***	-0.1662***	-0.1738***	0.3137***	0.3194***	0.3211***	0.1022***	0.1099***	0.1006***
	(0.0410)	(0.0425)	(0.0439)	(0.0315)	(0.0327)	(0.0301)	(0.0520)	(0.0578)	(0.0542)	(0.0342)	(0.0346)	(0.0341)	(0.0553)	(0.0566)	(0.0498)	(0.0385)	(0.0404)	(0.0367)
ΔCDR	0.0235	0.0283	0.0240	0.0455*	0.0383	0.0402*	0.0741***	0.0770***	0.0761***	0.1268***	0.1220***	0.1244***	-0.1623***	-0.1682***	-0.1684***	-0.0754***	-0.0768***	-0.0767***
	(0.0232)	(0.0221)	(0.0215)	(0.0228)	(0.0241)	(0.0232)	(0.0246)	(0.0249)	(0.0240)	(0.0276)	(0.0242)	(0.0254)	(0.0360)	(0.0336)	(0.0319)	(0.0249)	(0.0270)	(0.0277)
ΔODR	-0.0624**	-0.0673*	-0.0690**	-0.1772***	-0.1757***	-0.1834***	-0.0846**	-0.0883**	-0.0897**	-0.1489***	-0.1464***	-0.1542***	0.0590	0.0566*	0.0640*	-0.1144***	-0.1185***	-0.1196***
	(0.0312)	(0.0349)	(0.0325)	(0.0224)	(0.0252)	(0.0251)	(0.0404)	(0.0447)	(0.0400)	(0.0271)	(0.0259)	(0.0247)	(0.0354)	(0.0354)	(0.0350)	(0.0316)	(0.0335)	(0.0296)
Δy	0.0974***	0.0972***	0.1008***	0.0584***	0.0707***	0.0634***	0.0803***	0.0813***	0.0820***	0.0637***	0.0760***	0.0676***	0.0496*	0.0554**	0.0515**	-0.0065	-0.0128	-0.0096
	(0.0148)	(0.0150)	(0.0153)	(0.0136)	(0.0144)	(0.0152)	(0.0172)	(0.0174)	(0.0193)	(0.0133)	(0.0144)	(0.0147)	(0.0257)	(0.0262)	(0.0254)	(0.0204)	(0.0210)	(0.0211)
ΔCBD	2.4579***	2.4925***	2.4814***	1.2541***	1.2293***	1.2389***	2.6214***	2.6130***	2.6140***	1.6006***	1.4804***	1.5049***	1.5578***	1.6686***	1.6552***	0.2860	0.5117**	0.4770*
	(0.2814)	(0.2737)	(0.2476)	(0.1877)	(0.1991)	(0.1971)	(0.4220)	(0.3805)	(0.3940)	(0.2326)	(0.2344)	(0.2449)	(0.2437)	(0.2628)	(0.2224)	(0.2436)	(0.2481)	(0.2426)
ΔODR × Δy	0.3321		0.7092*	-0.9166***		-0.5533**	-0.0131		0.1210	-0.6440***		-0.4516*	0.5138		1.0152**	-1.0953***		-0.6703
	(0.3540)		(0.3470)	(0.2489)		(0.2380)	(0.3847)		(0.3605)	(0.2288)		(0.2340)	(0.4703)		(0.4636)	(0.3692)		(0.4130)
ΔODR × ΔCBD		-5.0280***	-5.7305***		-5.9285***	-5.3082***		-2.4366	-2.5723		-3.5860***	-2.9313***		-4.4894***	-5.3007***		-4.9233***	-4.3497***
		(1.4557)	(1.3350)		(0.9855)	(1.0291)		(1.8488)	(1.9400)		(1.0216)	(1.1461)		(1.3503)	(1.3026)		(1.1681)	(1.2221)
control vari.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Regression diagnostics																		
Lambda	0.9204***	0.9198***	0.9197***	0.8934***	0.8923***	0.8924***	0.8979***	0.8979***	0.8979***	0.853***	0.8525***	0.8526***	0.8996***	0.8995***	0.8988***	0.8443***	0.843***	0.8429***
rho	-0.3841***	-0.3826***	-0.383***	-0.451***	-0.4503***	-0.4519***	-0.2622***	-0.2626***	-0.2625***	-0.4616***	-0.4621***	-0.464***	-0.5704***	-0.5688***	-0.5686***	-0.3128***	-0.3083***	-0.3076***
R^2	0.9814	0.9814	0.9814	0.9739	0.9739	0.9739	0.9811	0.9811	0.9811	0.9716	0.9716	0.9716	0.9794	0.9795	0.9795	0.9744	0.9744	0.9745
N	876	876	876	875	875	875	431	431	431	436	436	436	421	421	421	423	423	423
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	-0.886	-0.904	-0.905	1.195	1.241	1.147	0.336	0.337	0.337	-2.033**	-2.042**	-2.042**	-0.023	0.091	0.021	-1.238	-1.184	-1.179
IPS	-88.762***	-88.798***	-88.795***	-98.092***	-98.120***	-98.126***	-61.609***	-61.611***	-61.608***	-67.259***	-67.278***	-67.281***	-60.432***	-60.385***	-60.420***	-68.780***	-68.778***	-68.783***
CIPS	-2.502***	-2.507***	-2.507***	-2.712***	-2.710***	-2.711***	-2.447***	-2.448***	-2.447***	-2.322***	-2.662***	-2.737***	-2.790***	-2.786***	-2.787***	-2.566***	-2.564***	-2.563***

(Authors)

Result 3-1. inheritance effect

・所得水準に関わらず、
すべてのモデルにおいて、$\beta_{high} > \beta_{low}$ となる。

→ 持ち家率($\boldsymbol{MHR}$)が高いと、
高齢化率($\boldsymbol{ODR}$)の係数が大きくなる。

∴ 遺産相続などの**遺産動機**があると、
高齢化が地価に与える負の影響が**小さく**する。

Robustness check

1. Spatial weight matrix (Hiller and Lerbs 2016)
   i. Cutoff distance of 500 m
   ii. Cutoff distance of 1,500 m
   ➢ Generic: 1,000 m
2. Limited period (Takáts 2012)
   iii. 10 years from 2000–2010
   iv. 10 years from 2005–2015
   ➢ Generic: 15 years from 2000–2015
3. Lagged economic explanatory variables (Takáts 2012)
   v. one year lagged Δy and ΔCBD
4. Nonspatial panel analysis (Hiller and Lerbs 2016).
   vi. two-ways fixed effects

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	○	×	×
Inheritance 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)

Contents

Conclusion

1. 高齢化と地価の一般的な関係

1-1. age composition effect
(Takats, 2012 (*J. Housing Econ.*); Hiller and Lerbs, 2016 (*Regi. Sci. Urban Econ.*))
・高齢化と地価には**負の相関関係**がある.　※先行研究は過剰評価

2. 高齢化と地価の関係のプロセス

2-1. income effect
(Mankiw & Weil, 1989 (*Regi. Sci. Urban Econ.*); DiPasquale & Wheaton, 1994 (*J. Urban Econ.*))
・高齢化 → 所得⇓ → 予算制約 → 需要⇓ → 地価⇓

2-2. preference effect (先行研究なし)
・高齢化 → 選好の変化 → 利便性の必要性⇓ → 地価の高い地域に住む必要性⇓

3. 遺産としての不動産

3-1. inheritance effect (先行研究なし)
・遺産動機があると、重複世代モデル (OLG) の過程が崩れる.
→ 高齢化の影響が緩和される.

Summary of aging effects

Effect	Describe	This paper	Previous studies
1-1. Age composition effect	Aging has a negative impact on price growth in real estate.	○ in residential × in commercial	○ at country [1], city [2], and province level [3]
2-1. Income effect	Budget constraint causes a negative impact of aging.	×	○ [4.5], △ [6], × [7,8,9]
2-2. Preference effect	Change in preference causes a negative impact of aging.	○	—
3-1. Inheritance effect	Bequest motives can mitigate the negative impact of aging.	○	—

過大評価

賛否両論

高解像度のみ

[1] (Takáts, 2012), [2] (Hiller & Lerbs, 2016) , [3] (Simo-Kengne, 2019), [4] (Mankiw & Weil, 1989), [5] (DiPasquale & Wheaton, 1994), [6] (Eichholtz & Lindenthal, 2014), [7] (Engelhardt & Poterba, 1991), [8] (R. Green & Hendershott, 1996), [9] (R. K. Green & Lee, 2016).

(Authors)

Policy implication

- <u>income effect</u> (insignificant)
  - 高齢者の所得が増加しても、地価を押し上げる効果はない。
  - 高齢者への家賃補助や固定資産税優遇は意味が薄い。
- <u>preference effect</u>
  - 都市計画に際して、地価に対しては、
    若年層の効用が大事である。
- <u>inheritance effect</u>
  - 遺産動機が高齢化の負の影響を緩和する
  - 相続税の引き下げは、遺産動機を増加し、
    高齢化の負の影響を緩和できる可能性がある。

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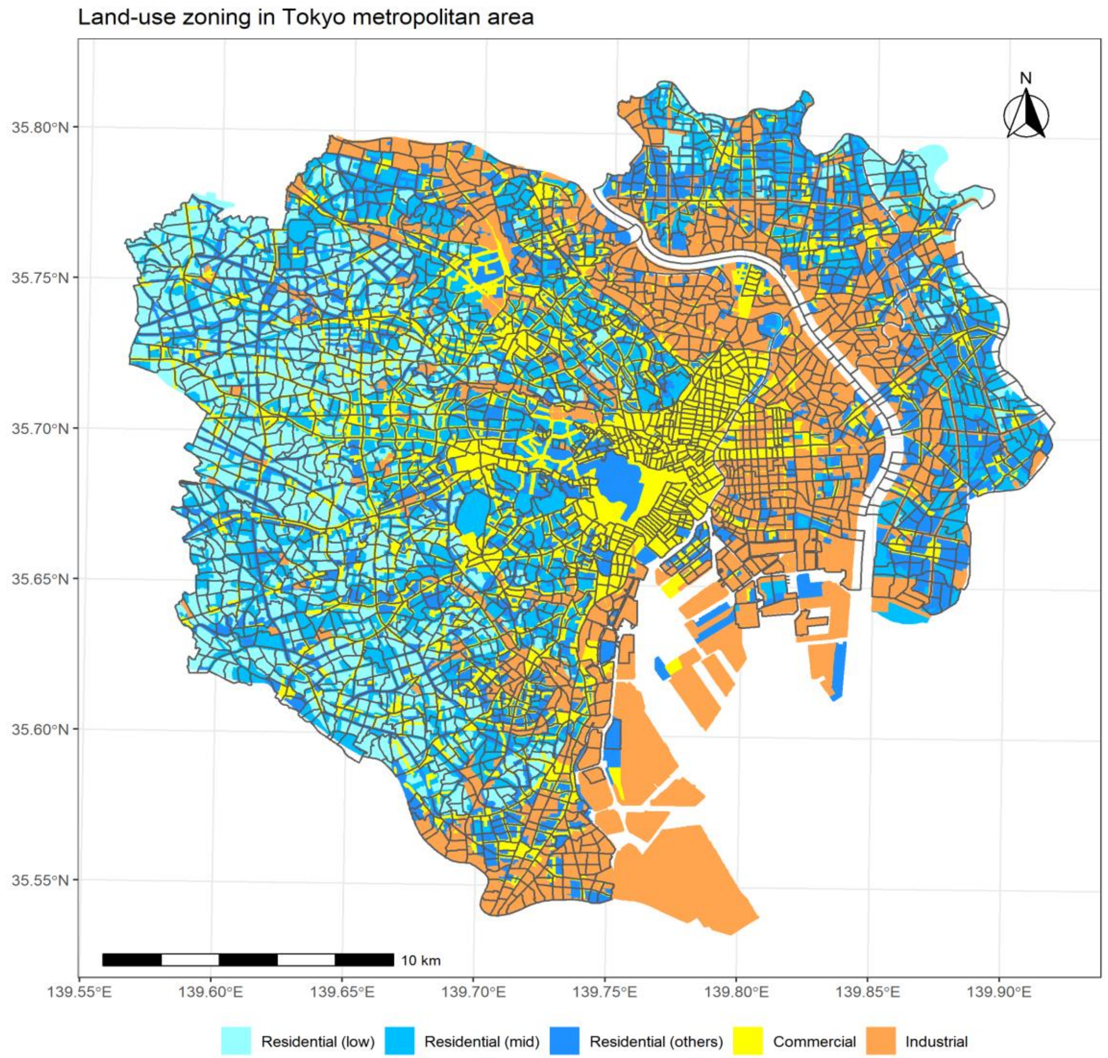
Thank you for your attention.

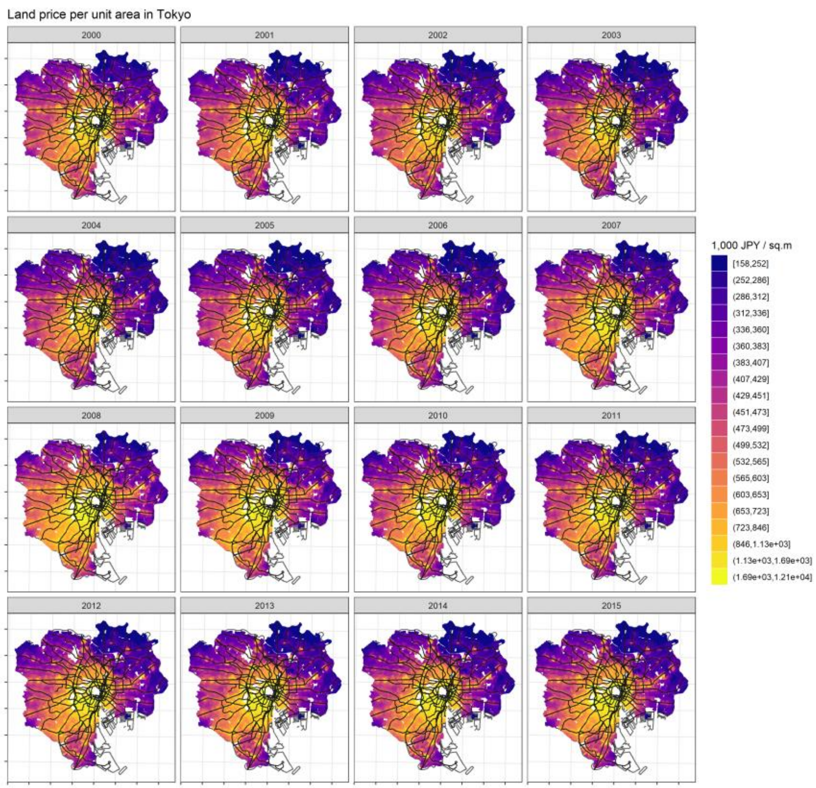
Map of study area and land-use zoning



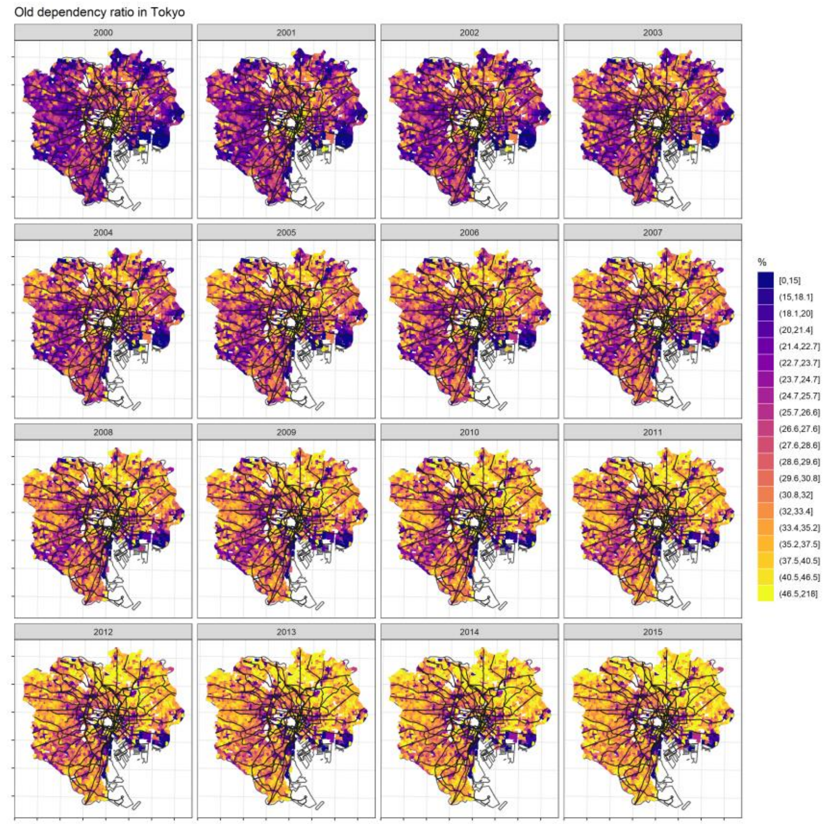
(Authors)

Mapping

Land price



Old dependency ratio



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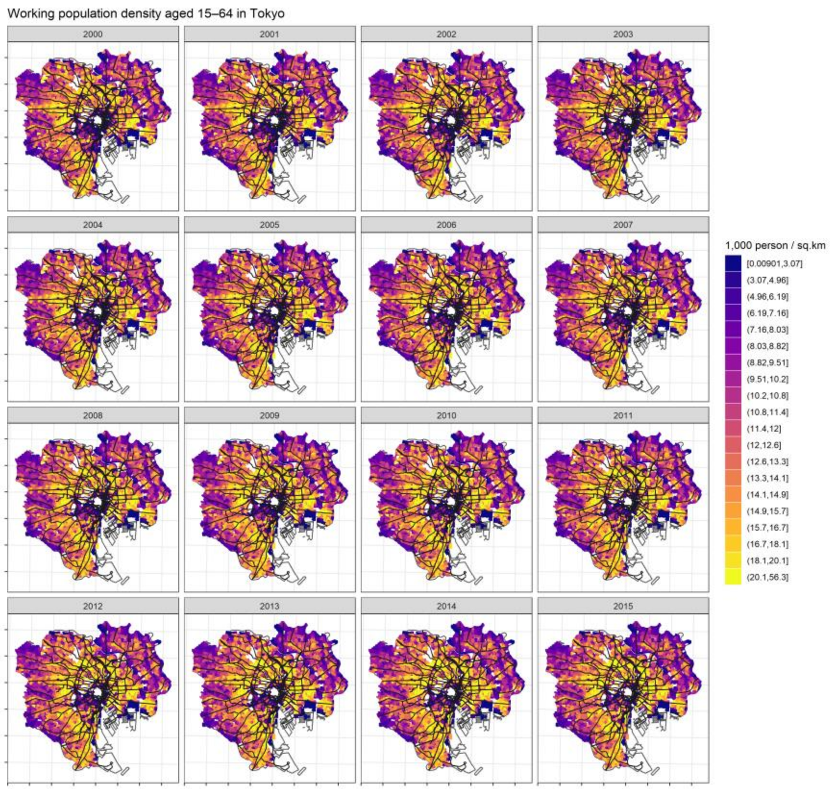
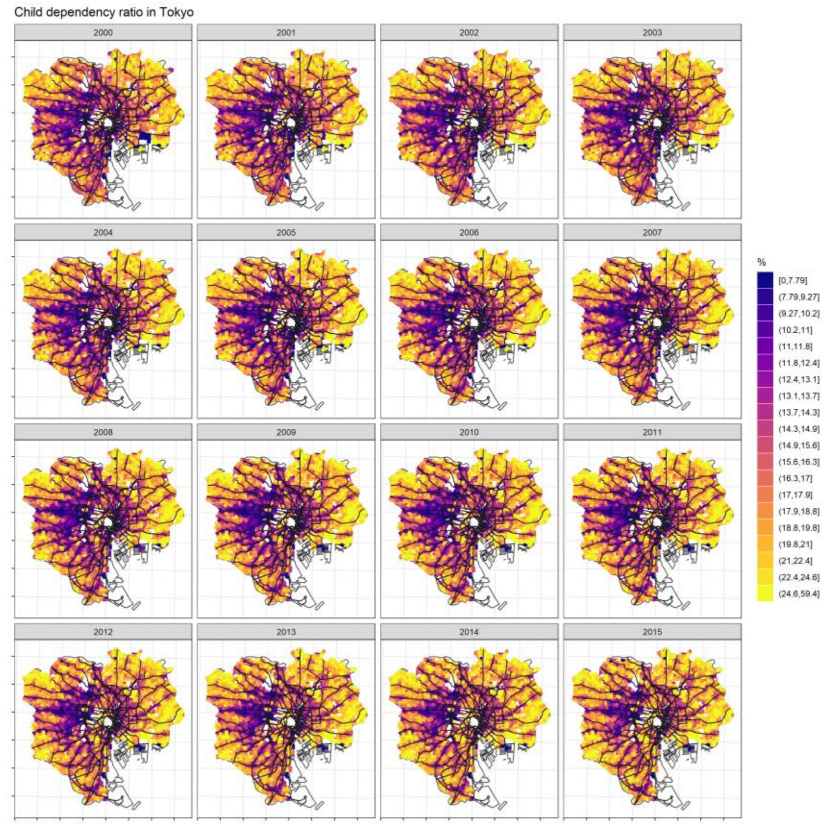
Mapping

Working Age population



Child dependency ratio



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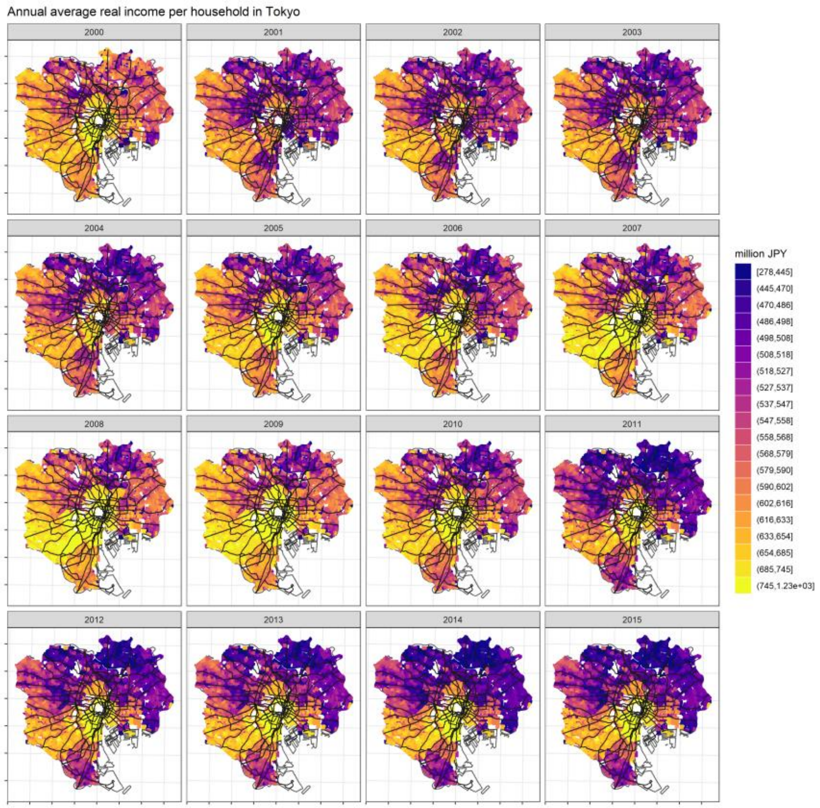
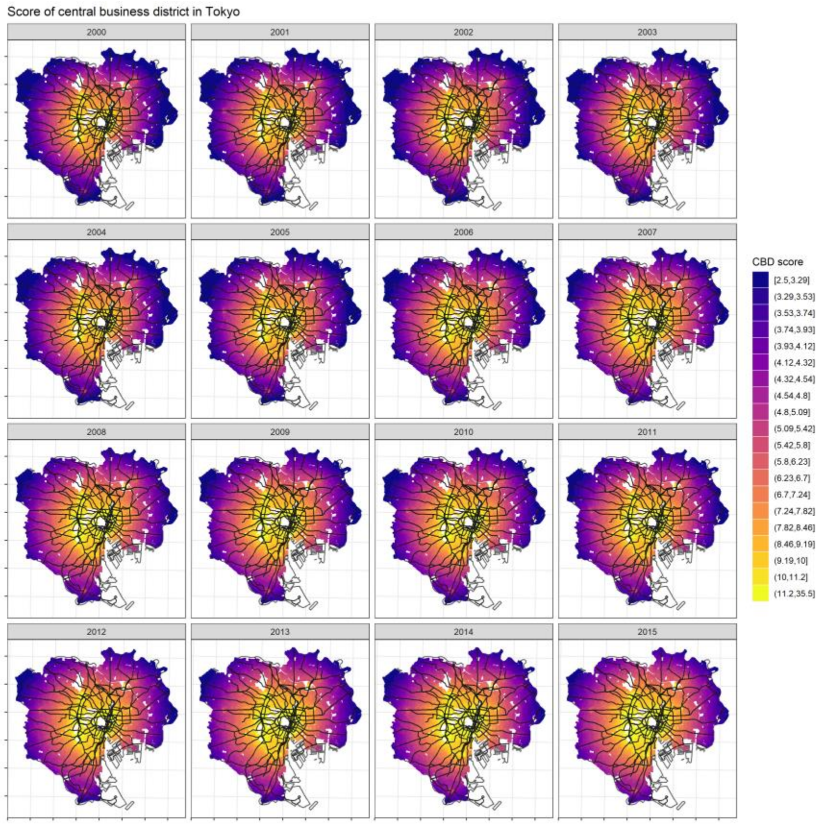
Mapping

Household income



CBD score



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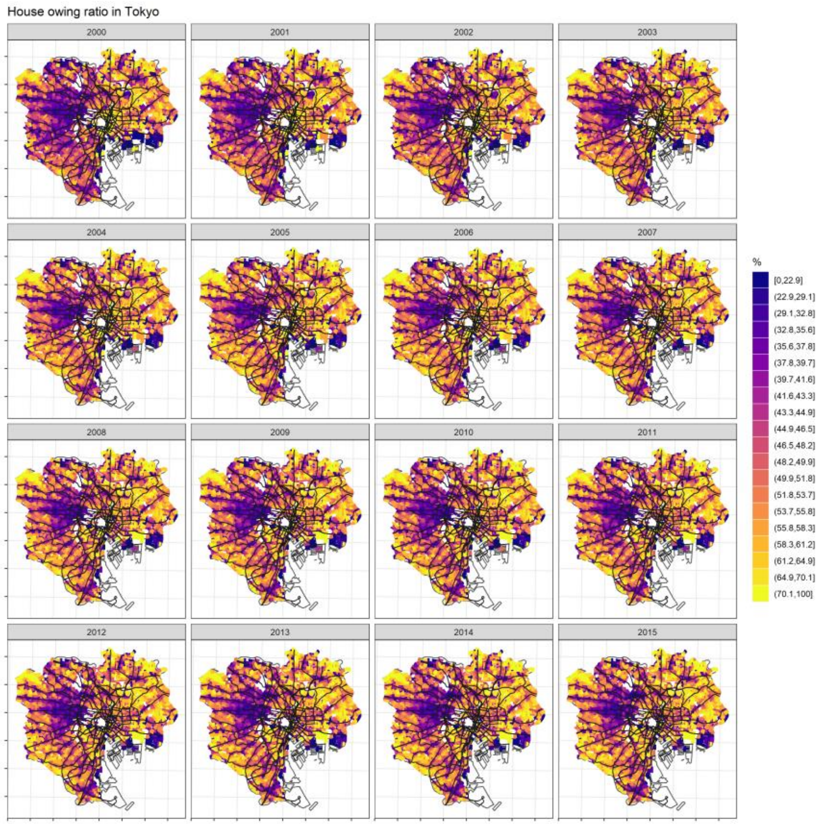
Mapping

Home ownership ratio



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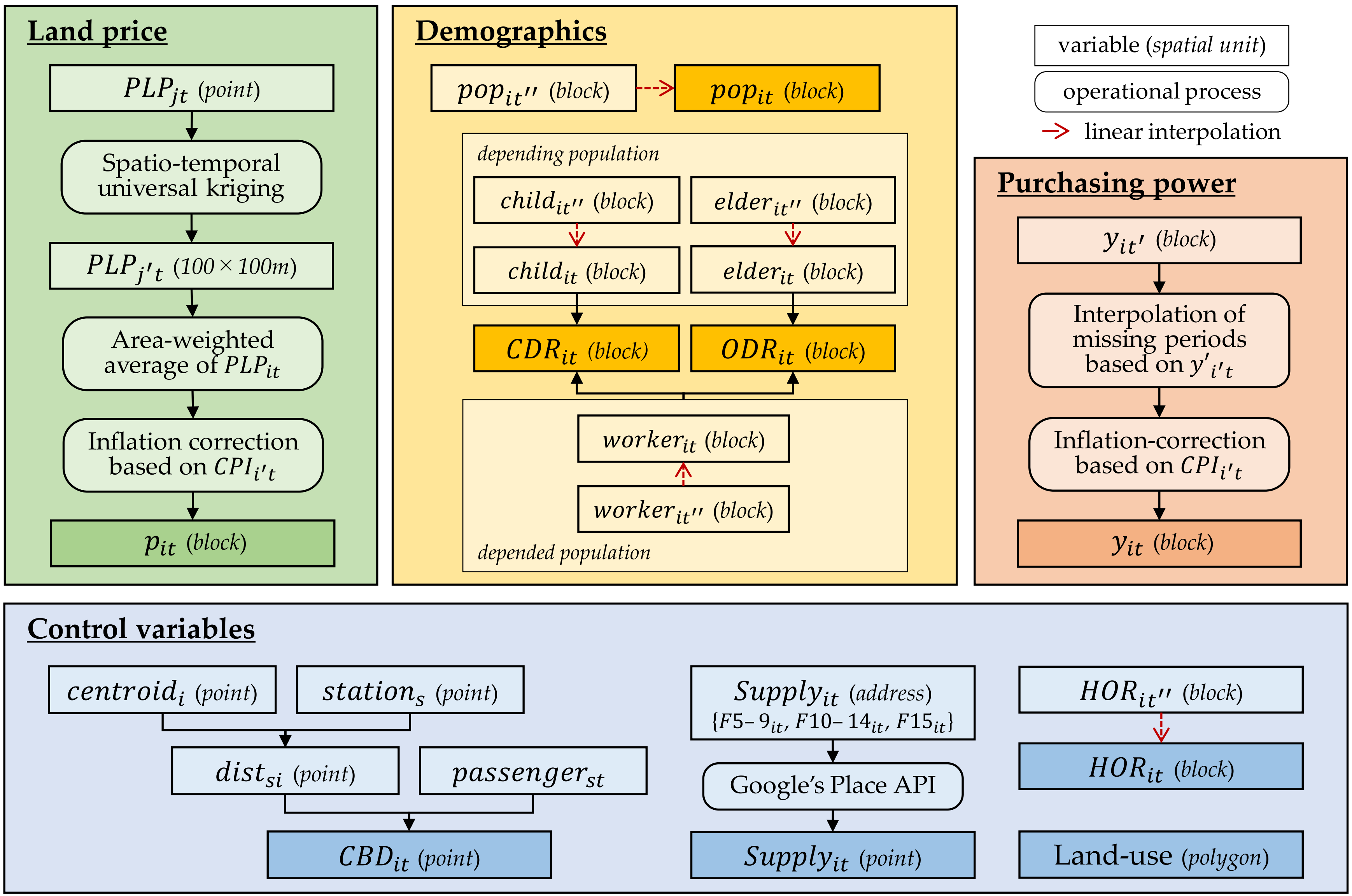
Development processes of panel data



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)

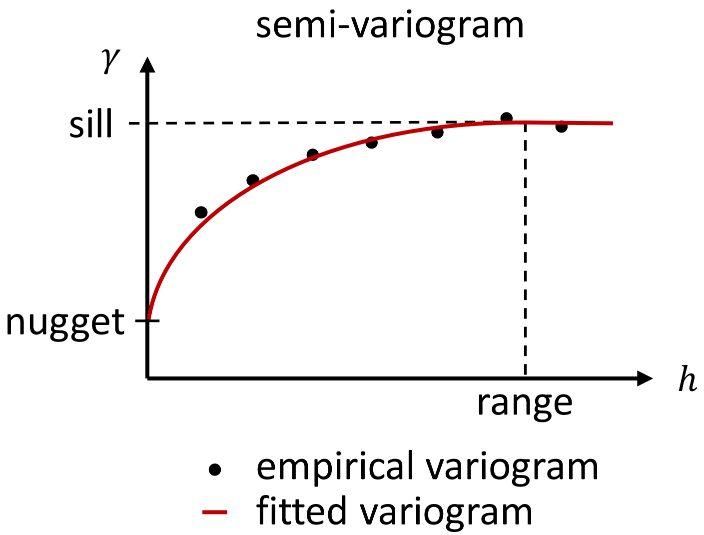
公示地価（時空間クリギング）

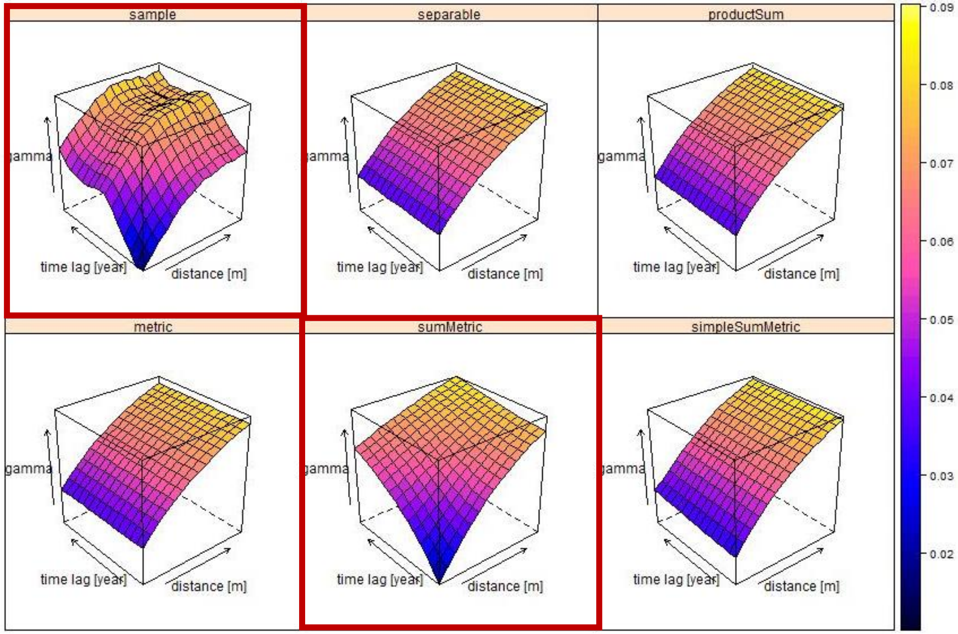
OLS回帰分析 → 残差の集計 → 標本バリオグラムの作成 → 適合バリオグラムの作成 → 誤差項の分散共分散行列の構造化 → GLS回帰分析 → 内挿

- OLS回帰分析: $y = \boldsymbol{X}'\beta + \varepsilon, \quad E(\varepsilon\varepsilon') \sim V$
- 残差の集計 ～ 誤差項の分散共分散行列の構造化: GLS回帰分析に必要な分散共分散行列を推定するために、バリオグラムを用いてOLS回帰分析の残差を時間と空間の距離の関数として構造化する。
- GLS回帰分析: $y_0 = \boldsymbol{X}_{\boldsymbol{0}}'\beta + \varepsilon_0, \quad E(\varepsilon\varepsilon') \sim \sigma_0^2$
- 内挿: 100×100mメッシュに内挿

公示地価（時空間クリギング）

時空間バリオグラム：分散共分散行列の構造化





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バリオグラムの推定モデル

exponential model (指数モデル)

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

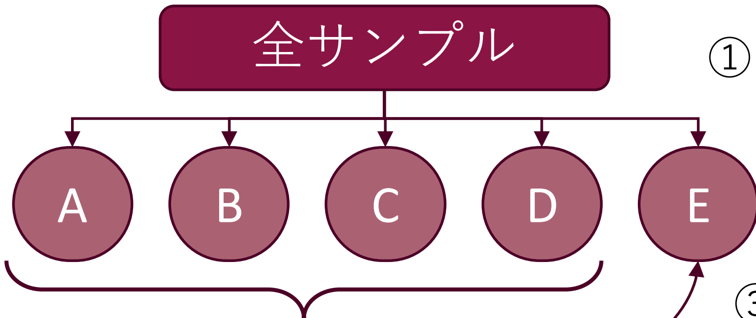
spherical model (球形モデル)

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

公示地価（時空間クリギング）

精度の検証

5分割交差検定法 (5-fold cross-validation)



① 属性に応じて
ランダム抽出

② 4グループをもとに
時空間クリギング

③ 残り1グループの
公示地価を内挿し
元データと比較

④ ①~③を5回繰り返し、平均二乗平方根誤差(RMSE)を算出

平均二乗平方根誤差 (RMSE: root mean square error)

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

y_i: 観測値, $\hat{y}_i$: 内挿値

RMSE = 1.0 のとき、誤差ゼロ
RMSE = 1.1 のとき、誤差10%

公示地価（時空間クリギング）

公示地価への応用

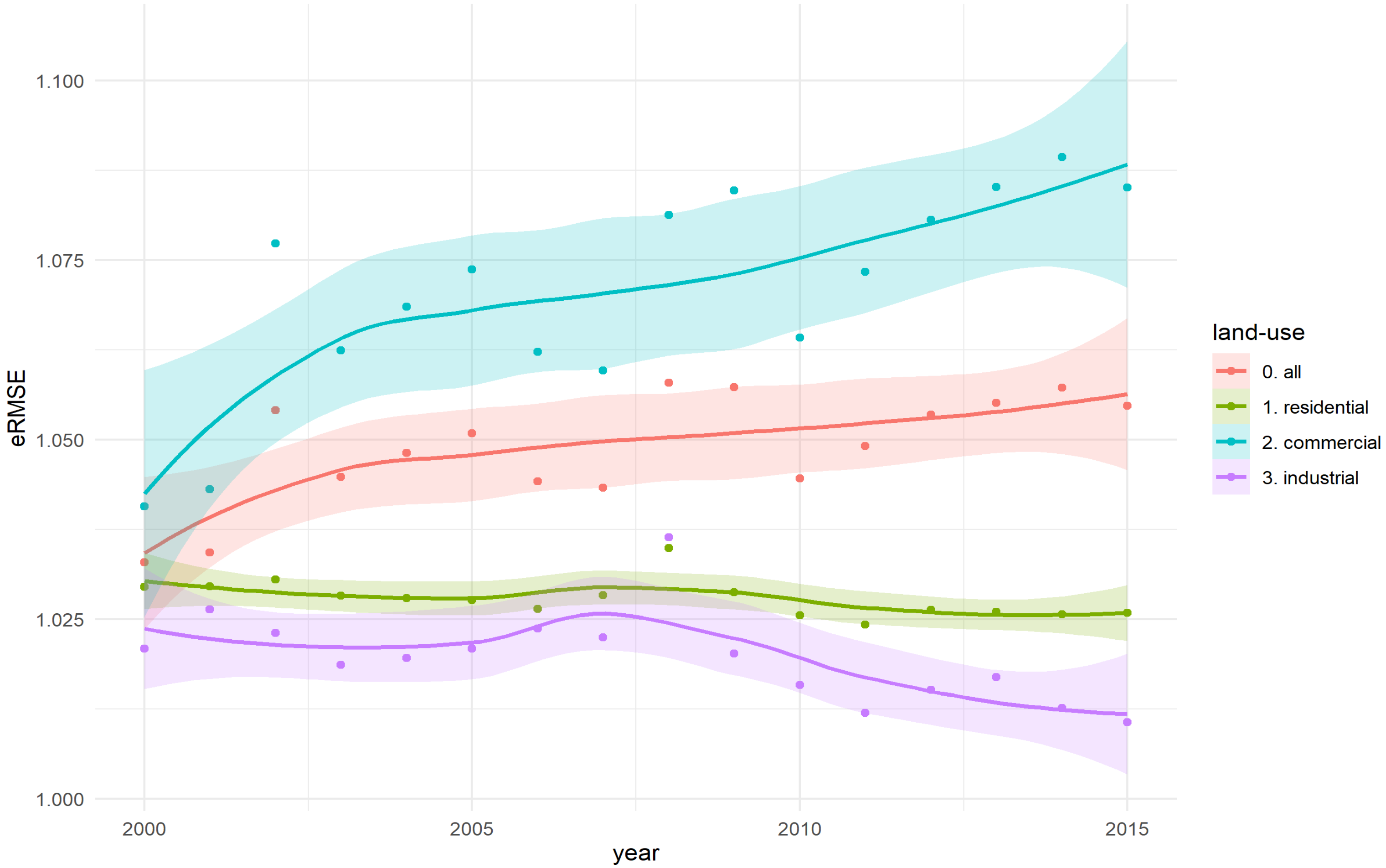
＜説明変数＞

- 最寄り駅から主要駅の距離 → GISを用いて算出
- 最寄り駅までの距離
- 地積
- 指定容積率
- 用途地域ダミー
- 前年度日経平均株価 → 経済に対するコントロール変数

（最寄り駅までの距離・地積・指定容積率・用途地域ダミー）→ 公示地価データの属性情報

公示地価（時空間クリギング）

公示地価への応用：eRMSE (東京23区における内挿精度)



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

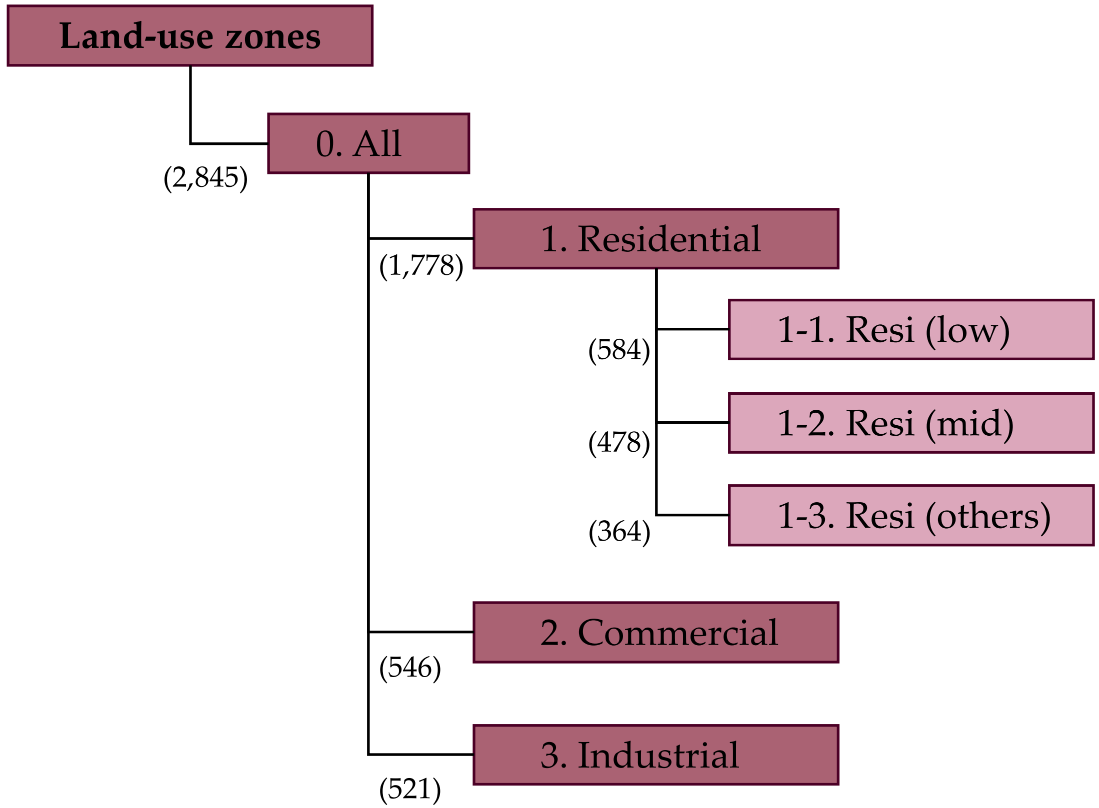
Land use zones

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



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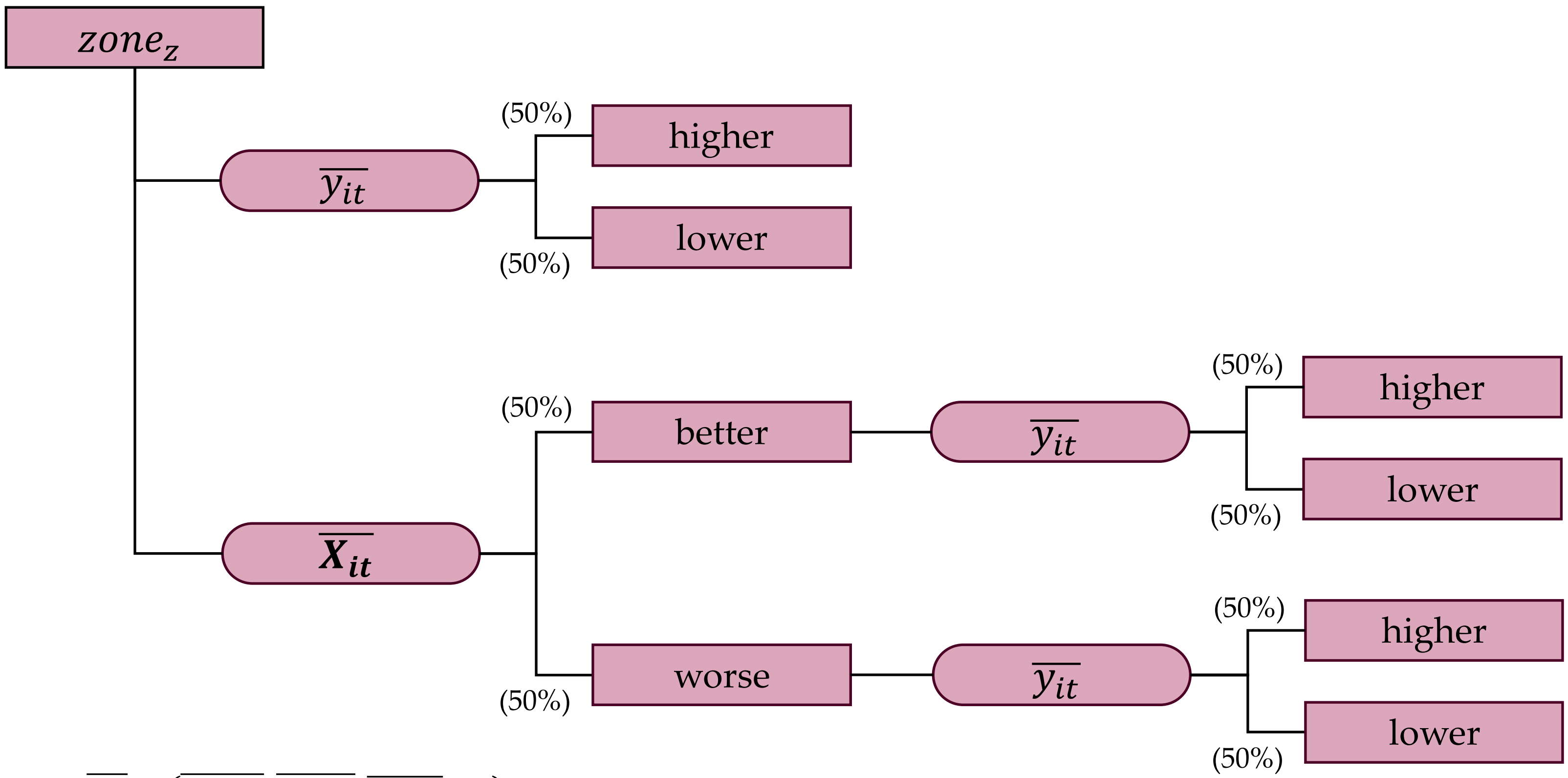
Dividing into cases



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

(Authors)

Hypothesis 1-1. age composition effect

重複世代モデル (overlapping-generations model: OLG) をもとに、
高齢化と資産価格の負の関係を導出する (Samuelson, 1958; P. A. Diamond, 1956 ; Takáts, 2012)。

・若年世代 (t期) ：所得(y_t)を得る。 y_tは、若年世代の消費(c_t^y)と貯蓄(s_t^y)に使われる
・高齢世代 (t+1期)：高齢世代の消費(c_{t+1}^o)は、t期の貯蓄(c_t^y)とその利子によって賄われる

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

・効用：個人は、若年期と高齢期の消費の合計が最大となるように経済活動をする

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

~~~ (略) ~~~

・資産価格の成長は、経済成長と人口成長によって説明される

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

Hypothesis 1-1. age composition effect

・高齢従属年齢率 (ODR_t) は、人口成長 ($1+d$) の逆数である

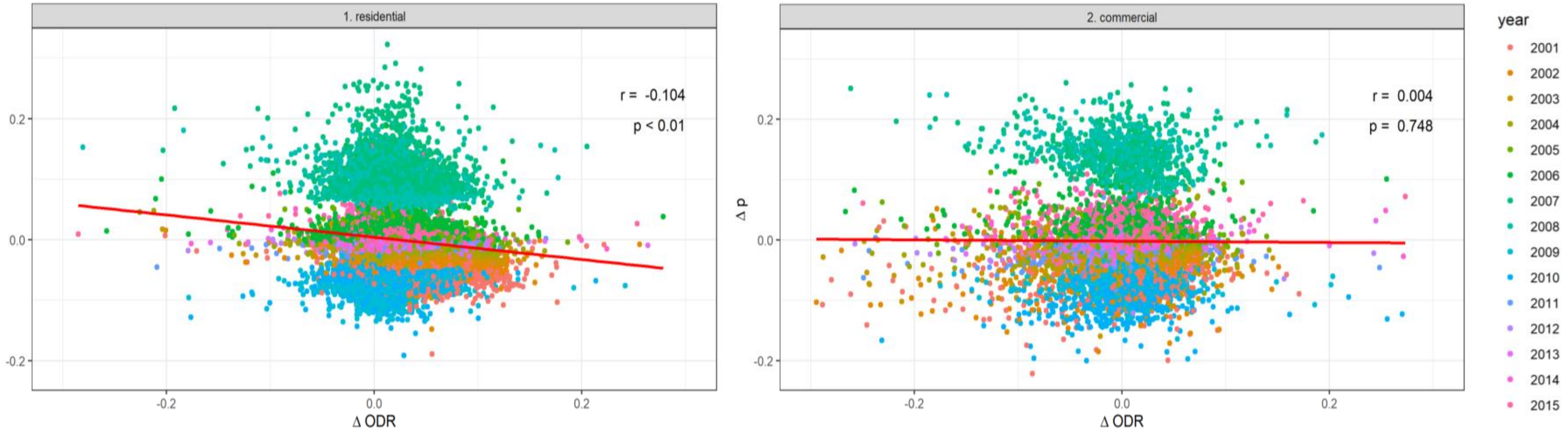
$$ODR_t = \frac{n_{t-1}^y}{n_t^y} = \frac{n_{t-1}^y}{n_{t-1}^y(1+d_{t-1}^y)} = \frac{1}{1+d_{t-1}^y}$$

∴ 高齢化(ΔODR)は、地価に負の影響を及ぼす。

Hypothesis 1-1. age composition effect の検証方法

・空間パネル分析の高齢化率 ($\boldsymbol{ODR}$) の係数が**マイナス**となる。

Result 1-1. age composition effect



*商業地域では、異なる理論が働くと考えられる