Bid-auction framework for microsimulation of location choice with endogenous real estate prices

Ricardo Hurtubia
Francisco Martínez
Michel Bierlaire

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Motivation

- Land use models
  - Travel demand forecast
  - Policy and project evaluation
- Location choice
  - Preferences of decision makers (willingness to pay)
  - Friction between agents (location conflicts) not always considered
- How are conflicts solved? ➔ market
  - How to introduce this in a location choice model?

(residential) Real estate market

- Relatively scarce goods, almost inelastic demand
- Normally: A household can live in only one dwelling and a dwelling can't be used by more than one household
- Competition for goods implies conflict
- Conflict is solved through price adjustment
  - Changes in bid behavior of agents (bid-auction)
  - Changes in asking price of seller (choice)

interaction/transactions ➔ market clearing (prices)

Motivation - Market clearing

Modeling approaches to solve market clearing:

- Equilibrium (TRANUS, MEPLAN, MUSSA):
  - everyone is located or everything is sold
  - Aggregated
  - Cross sectional (no temporal dimension)
  - Fixed point problem
- Dynamic disequilibrium (DELTA, IRPUD, ILUTE, UrbanSim):
  - Aggregated or disaggregated (partial-eq. or individual transactions)
  - Period-wise models
  - Great variety of approaches (simplified vs expensive)

Market clearing

Re-visiting equilibrium:

- For each good (location) i find asking prices r_i such that

$$\sum_h H_h P\left(i|h, r_i, P(i|\overline{h})\right) = S_i \quad \forall i$$

- For each household h, find bids B_{hi} such that

$$\sum_i \underbrace{S_i}_{\text{Supply (households)}} P\left(h|i, B_{hi}, P(\overline{h}|i)\right) = \underbrace{H_h}_{\text{Demand (households)}} \quad \forall h$$

Idea

- Adjustment of price depends on the interaction between demand and supply → change in expected utility and bidding behavior given the "state of the market"

- Adjustment of expectation of agents before they enter the market can be based on the equilibrium approach to the problem.

Proposal: Quasi-equilibrium approach

- Auction market. Probability of agent *h* being best bidder for location *i* (at period *t*):

$$P^t(h \mid i) = \frac{\exp(B^t_{hi})}{\sum_g \exp(B^t_{gi})}$$

- Price of location is the expected maximum bid

$$r_i^t = \ln\left(\sum_g \exp(B^t_{gi})\right)$$

Quasi-equilibrium approach

- Agents bid according to their preferences and their expected utility levels

$$B_{hi}^t = b_h^t + b_{hi}(z_i^t, \beta)$$

- Agents perceive their probability of winning an auction as:

$$q^t(h \mid i) = \frac{\exp(b_h^t + b_{hi}^t)}{\sum_g \exp(B_g^t)} \approx \exp(b_h^t + b_{hi}^t - r_i^{t-1})$$

Quasi-equilibrium approach

- Agents will bid according to their perception of the market conditions: they want to make sure they get a location but they also don't want to over-bid

$$\sum_{i \in S^t} q^t(h|i) = \sum_{i \in S^t} \exp\left(b_h^t + b_{hi}(z_i^t, \beta) - r_i^{t-1}\right) = 1$$

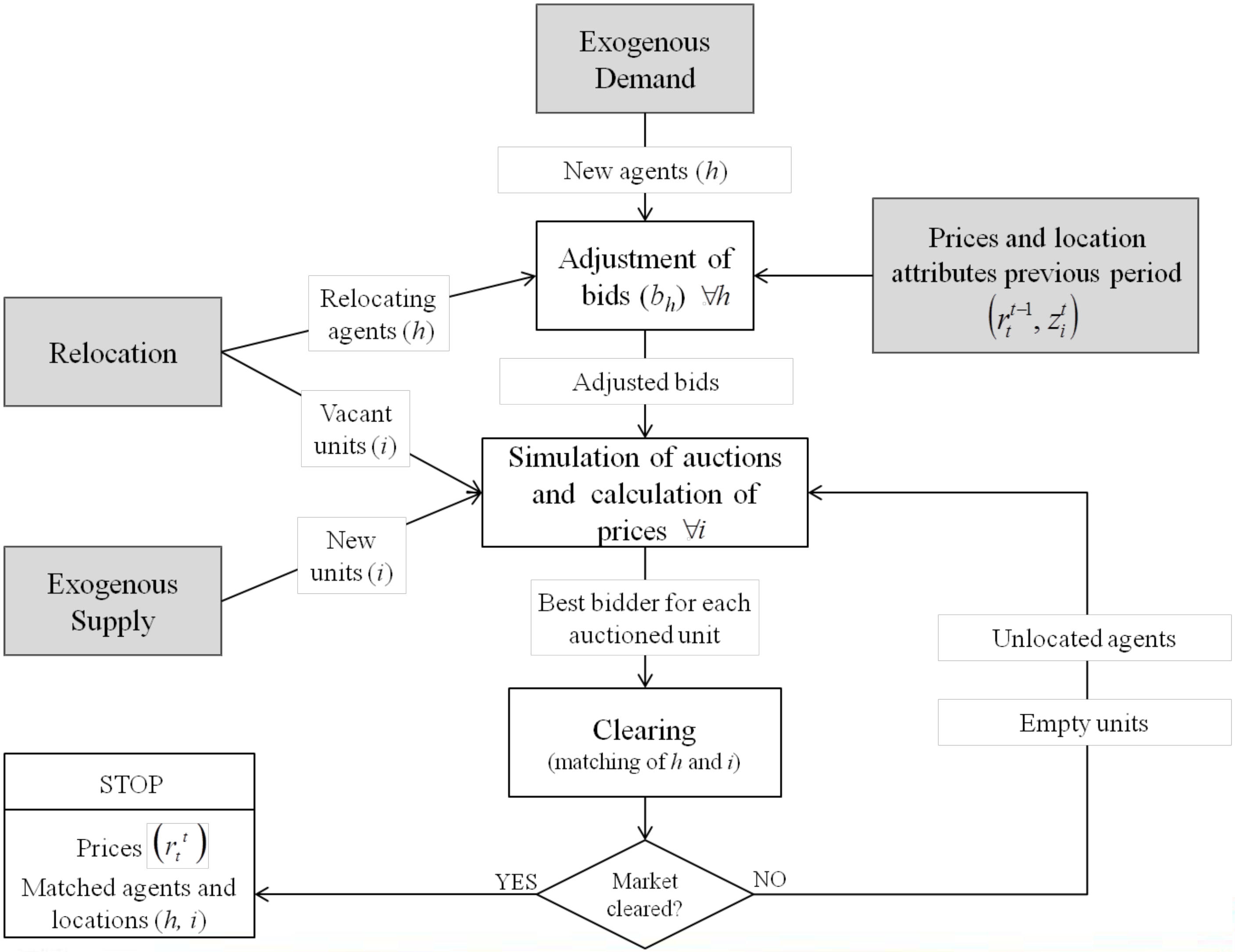
$$\Rightarrow \quad b_h^t = -\ln\left(\sum_{i \in S^t} \exp\left(b_{hi}(z_i^t, \beta) - r_i^{t-1}\right)\right)$$

Quasi-equilibrium approach

Market clearing mechanism:

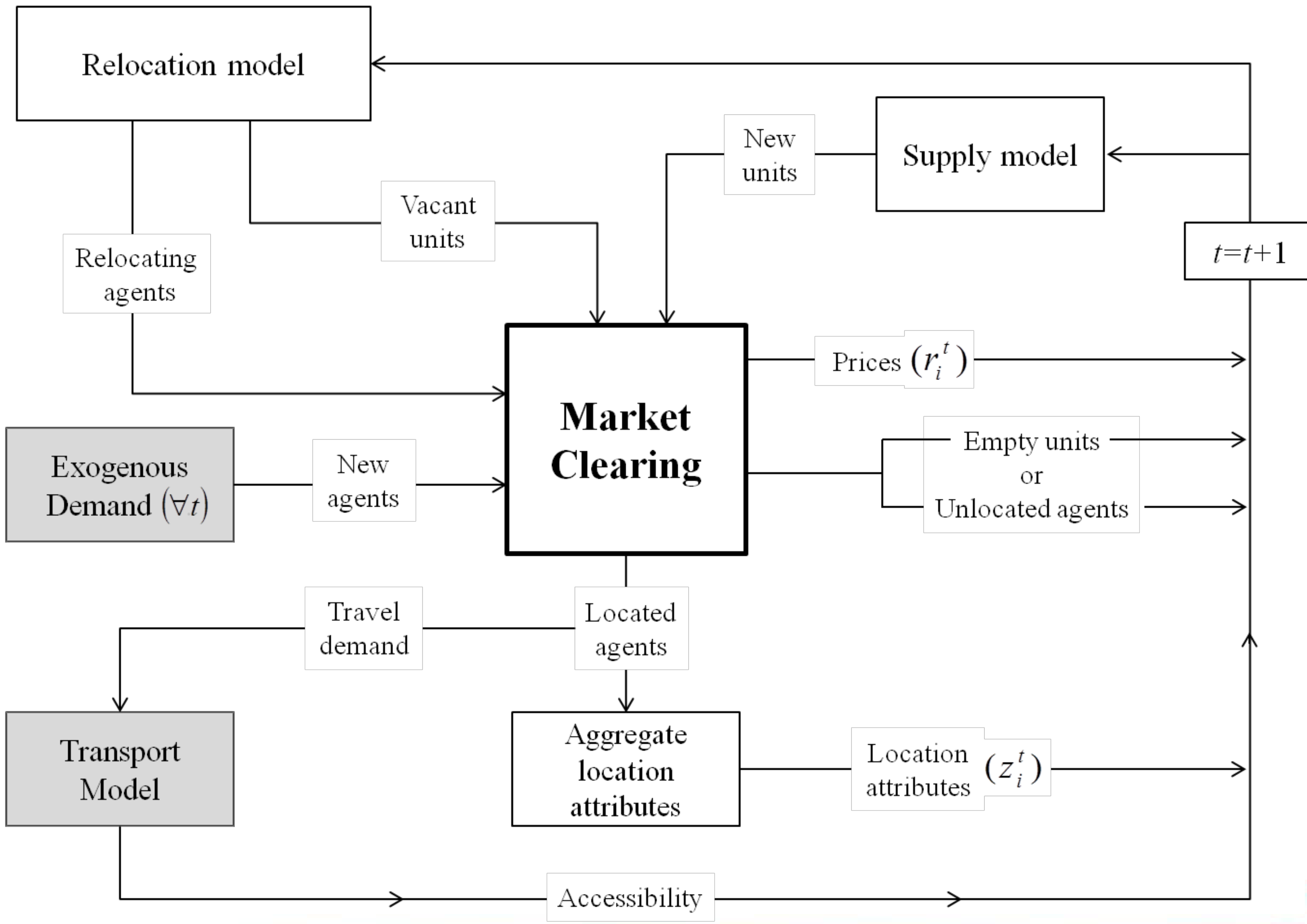
- After adjusting their perceptions, all active households bid simultaneously for all locations available in the market in a period
- If a household is the best bidder for more than one location, the maximum surplus location is chosen (given r_i)
- Empty locations and unlocated households interact in a new simultaneous auctions
- Repeat until all households are located or all locations are occupied
- move to next period.

Market clearing algorithm*



* Implemented in Python

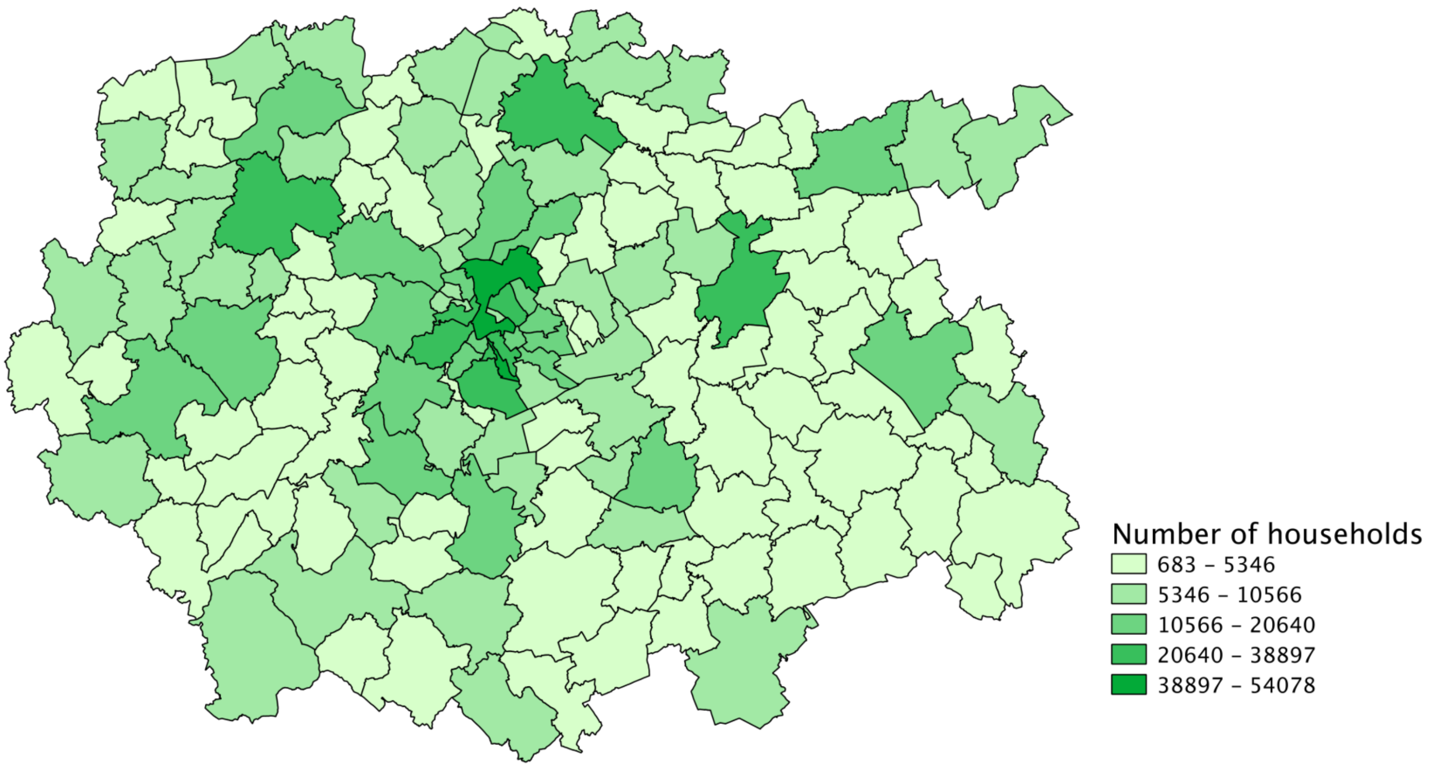
General framework algorithm*



* Implemented in Python

Case study – Area of study

- 151 communes and 4945 zones around Brussels (approx 1.2 million households)



Case study – Data

- Buildings: 4 types, average attributes at zone level (prices at commune level)
- Households: Data from Census (2001, zone level) and a travel survey (2002, ~1300 observations)
  ➔ Synthetic population

Attribute	levels
Income level of the household (inc_h)	1 (0-1859 Euros)
	2 (745-1859 Euros)
	2 (1860-3099 Euros)
	4 (3100-4958 Euros)
	5 (>4959 Euros)
Household size (hh_size_h)	1,2,3,4,5+
Number of children ($children_h$)	0,1,2+
Number of workers ($workers_h$)	0,1,2+
Number of cars ($cars_h$)	0,1,2,3+
Number of people with university degree ($univ_h$)	0,1,2+

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Case study – estimation results

Parameter	spatial attribute	×	household (hh) attribute
ASC_2	-		income level 2 constant (745-1859 Euros)
ASC_3	-		income level 3 constant (1860-3099 Euros)
ASC_4	-		income level 4constant (3100-4958 Euros)
ASC_5	-		income level 5 constant (>4959 Euros)
β_{house}	dummy for houses (types 1,2 or 3)	×	dummy for $\text{hh\_size}_h > 2$ and $\text{inc}_h > 2$
$\beta_{\text{apartment}}$	dummy for apartment (type 4)	×	dummy for $\text{hh\_size}_h > 2$ and $\text{inc}_h > 2$
β_{surface}	surface of dwelling v in zone i (m^2)	×	logarithm of hh_size_h
$\beta_{\text{high-inc}}$	% of hh's of income level 4 and 5 in commune c	×	dummy for income $\text{inc}_h > 2$
$\beta_{\text{low-inc}}$	% of hh's of income level 1 and 2 in commune c	×	dummy for income $\text{inc}_h > 3$
$\beta_{\text{education}}$	density of education jobs in commune c	×	dummy for $\text{univ}_h > 0$
β_{industry}	% of industry jobs in commune c	×	dummy for $\text{inc}_h > 3$
β_{service}	% of service (office and hotel) jobs in zone i	×	dummy for $\text{workers}_h > 0$
β_{shopping}	density of retail jobs in zone i	×	dummy for income $\text{inc}_h > 2$
β_{pubtrans}	public transport acces_i (facilities/km^2)	×	dummy for $\text{cars}_h = 0$
$\beta_{\text{pubtrans2}}$	public transport acces_i (facilities/km^2)	×	dummy for $\text{cars}_h > 1$
$\beta_{\text{car-access}}$	car accessibility in zone i (MATSim)	×	dummy for $\text{cars}_h > 0$

Parameter	Value	Std error	t-test
ASC_2	-0.171	0.083	-2.07
ASC_3	-0.461	0.113	-4.1
ASC_4	2.05	0.374	5.47
ASC_5	2.19	0.385	5.68
β_{house}	-0.128	0.0472	-2.7
$\beta_{\text{apartment}}$	-0.702	0.181	-3.88
β_{surface}	0.002	0.001	2.6
$\beta_{\text{high-inc}}$	3.97	1.24	3.21
$\beta_{\text{low-inc}}$	-3.94	0.701	-5.62
$\beta_{\text{education}}$	0.356	0.127	2.8
β_{industry}	-0.562	0.25	-2.25
β_{service}	0.046	0.020	2.31
β_{shopping}	0.040	0.018	2.24
β_{pubtrans}	0.257	0.094	2.72
$\beta_{\text{pubtrans2}}$	-0.249	0.101	-2.46
$\beta_{\text{car-access}}$	0.007	0.004	1.9*
α	-8.98	5.82	-1.54*
γ	1.46	0.421	3.46
σ	-1.93	0.022	-89.42

Hurtubia R. and Bierlaire M. (2012). Estimation of bid functions for location choice and price modeling with a latent variable approach. TRANSP-OR technical report.

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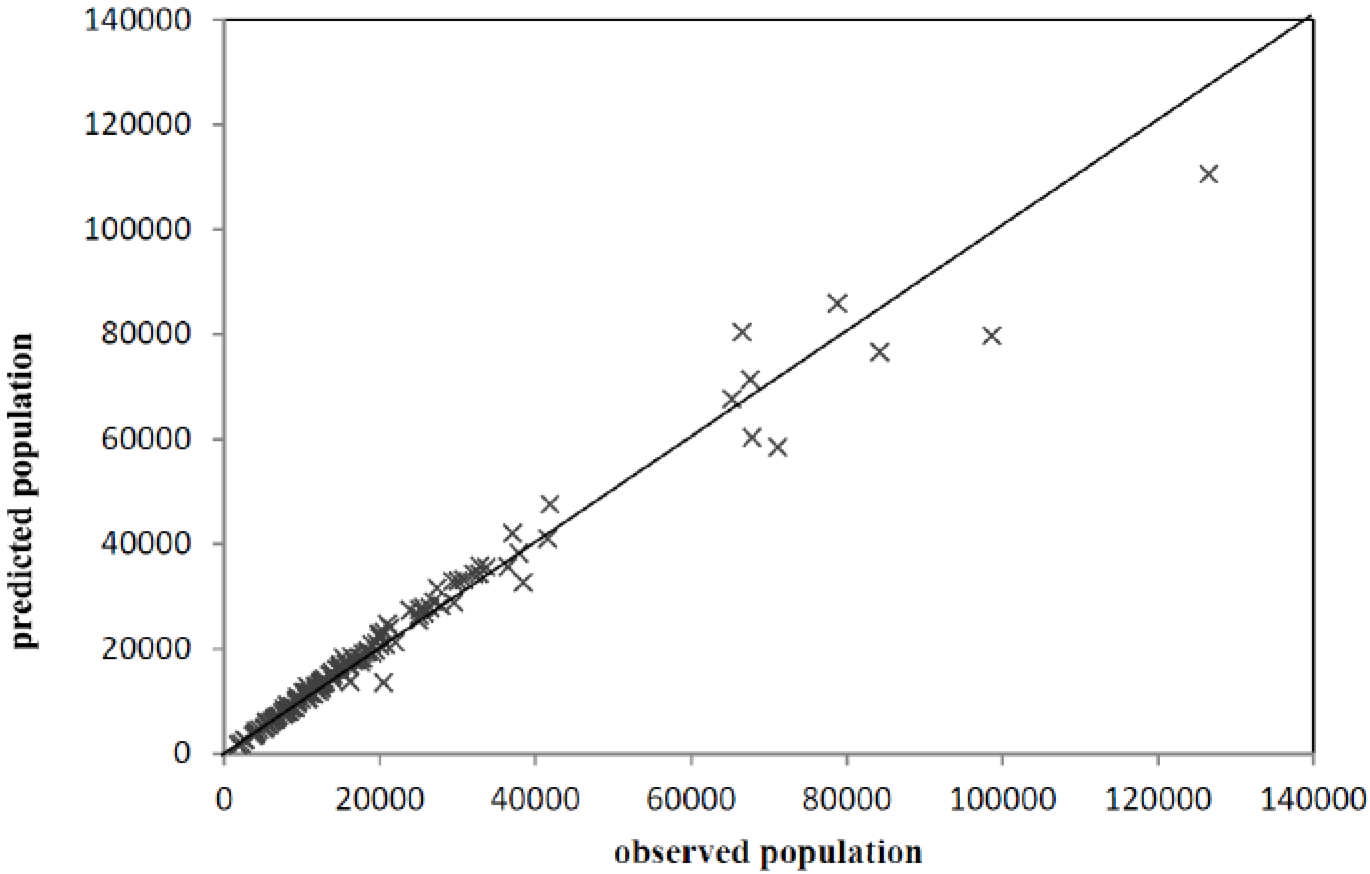
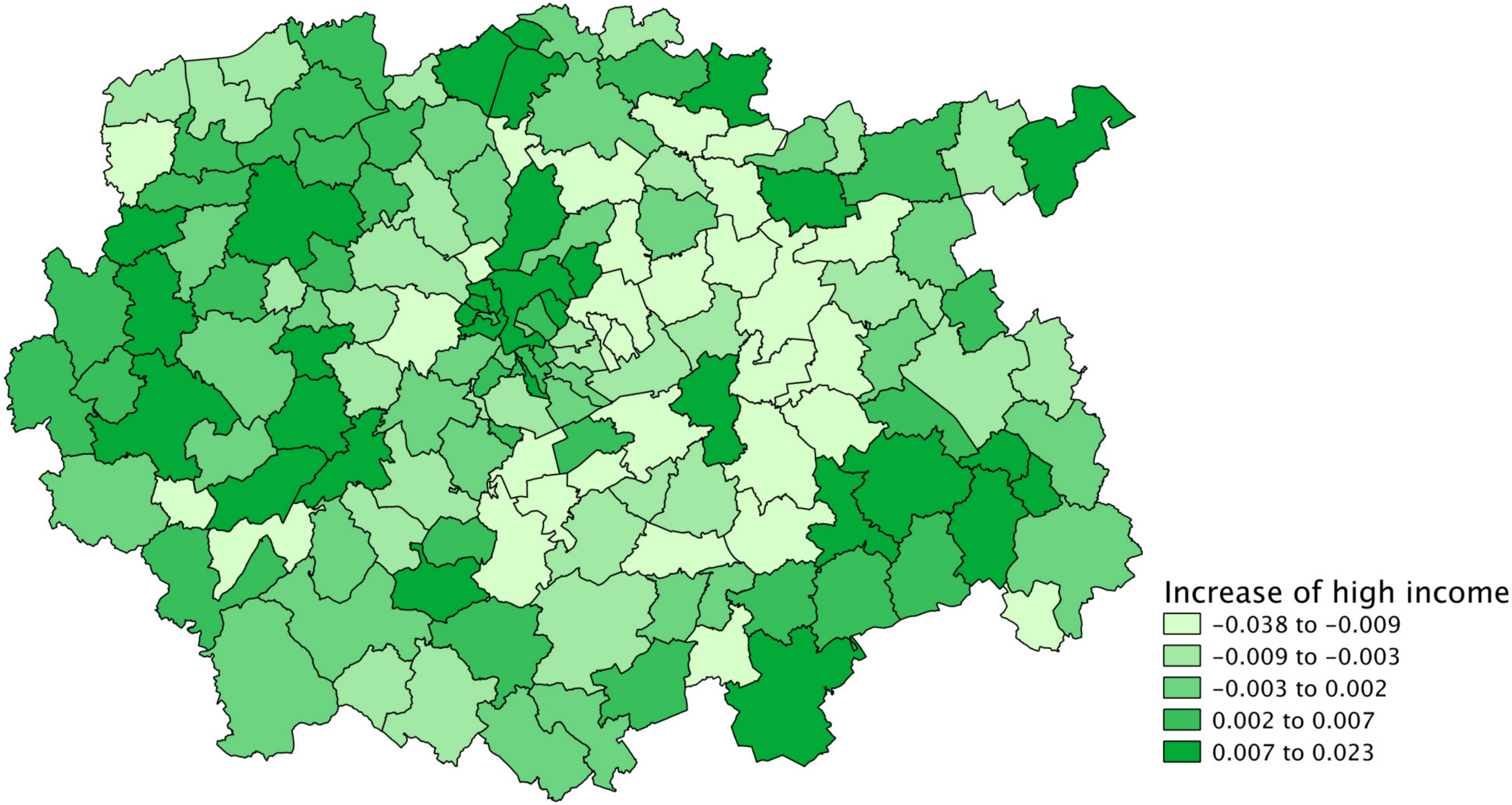
model

Case study – Simulation results

Observed and predicted population in 2008

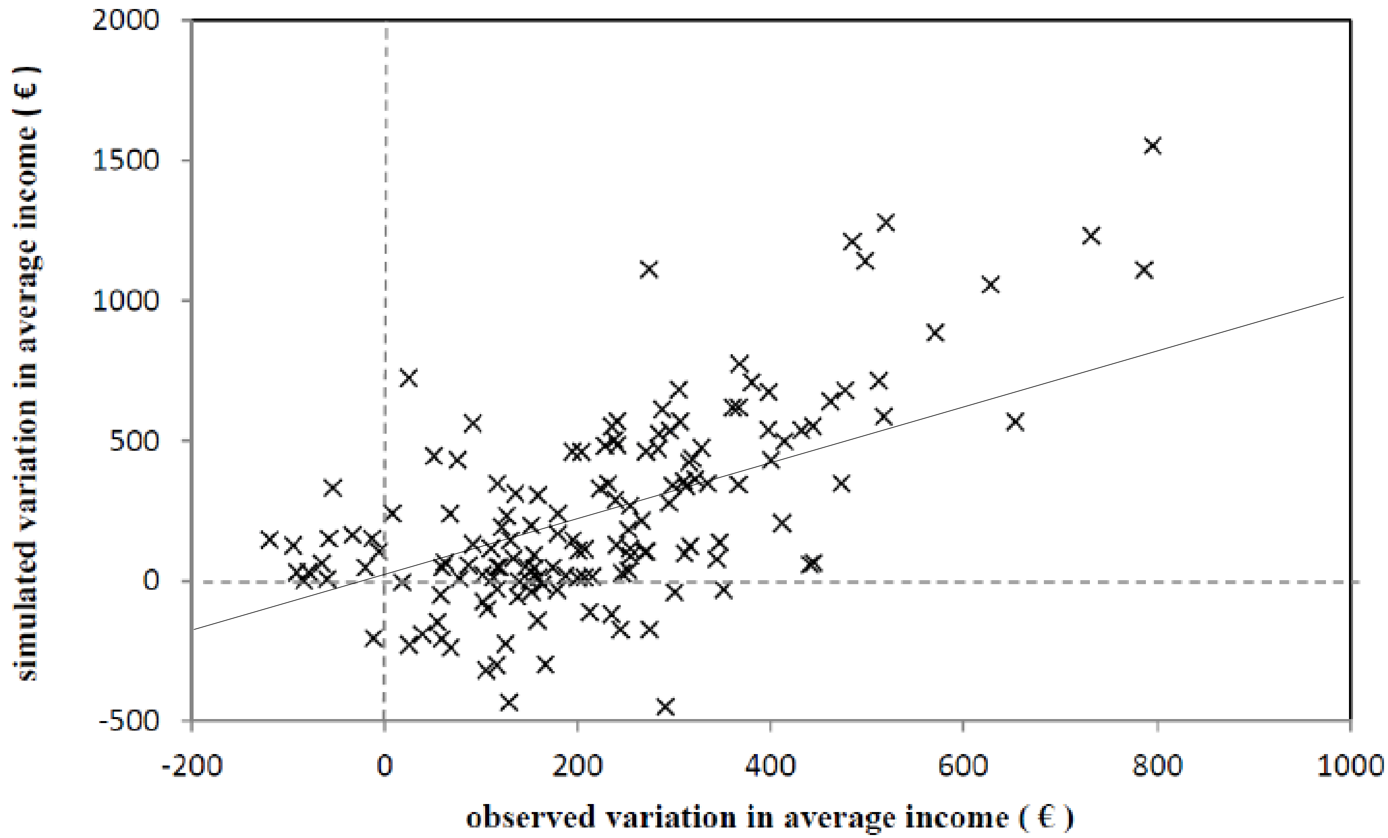


Case study – Simulation results

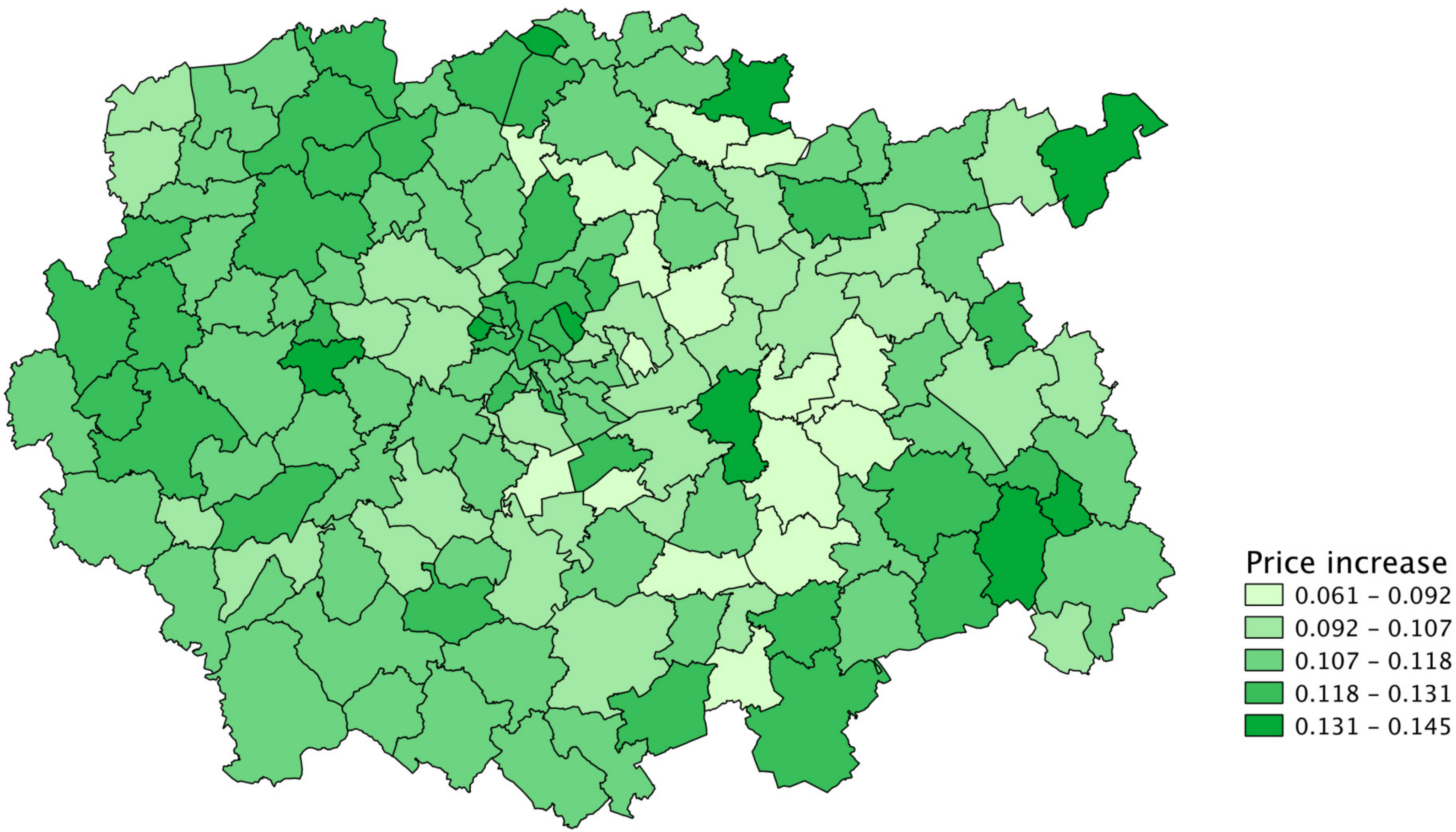


Case study – Simulation results

Variation in average income by commune 2001-2008

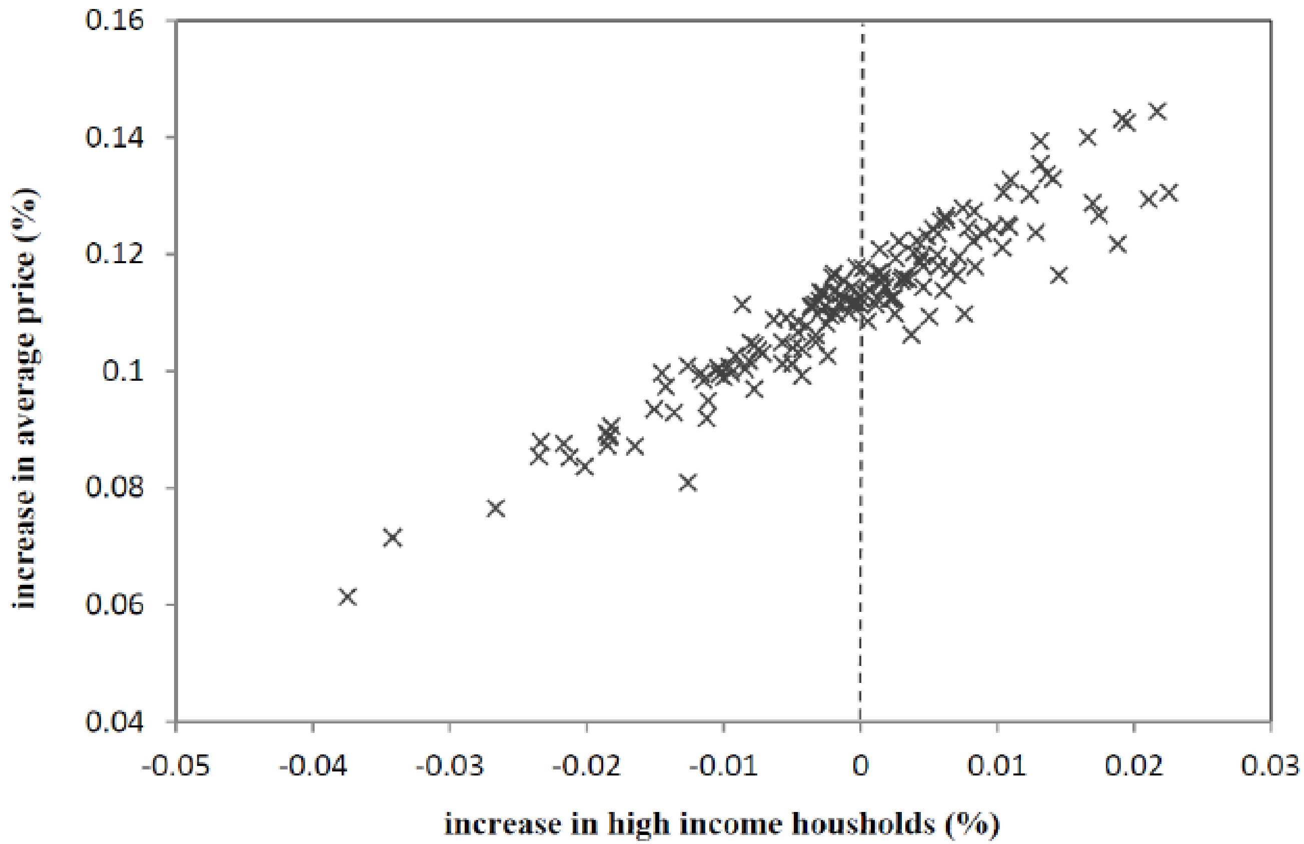


Case study – Simulation results



Case study – Simulation results

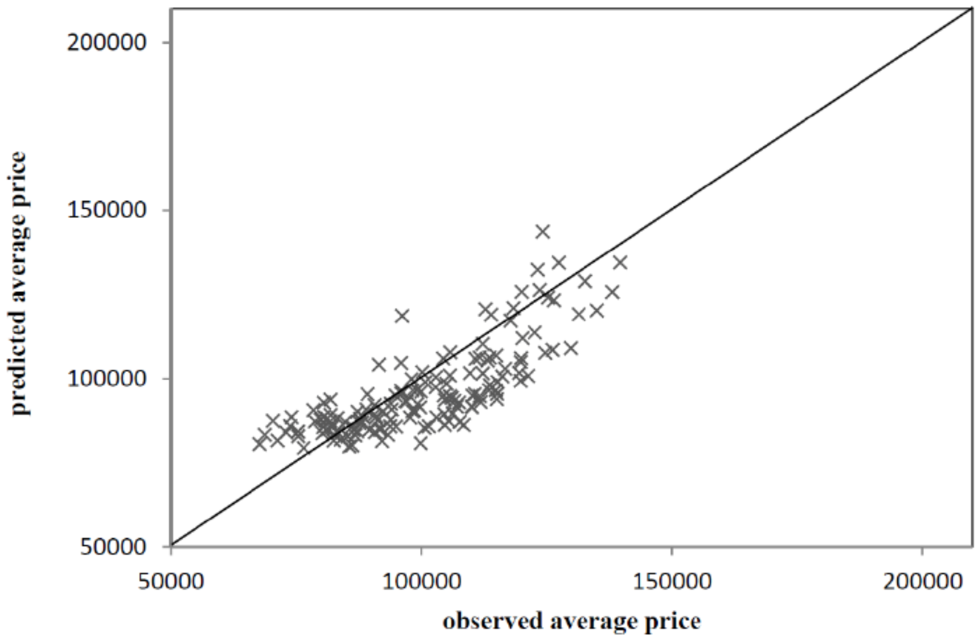
- Increase in price vs increase in income



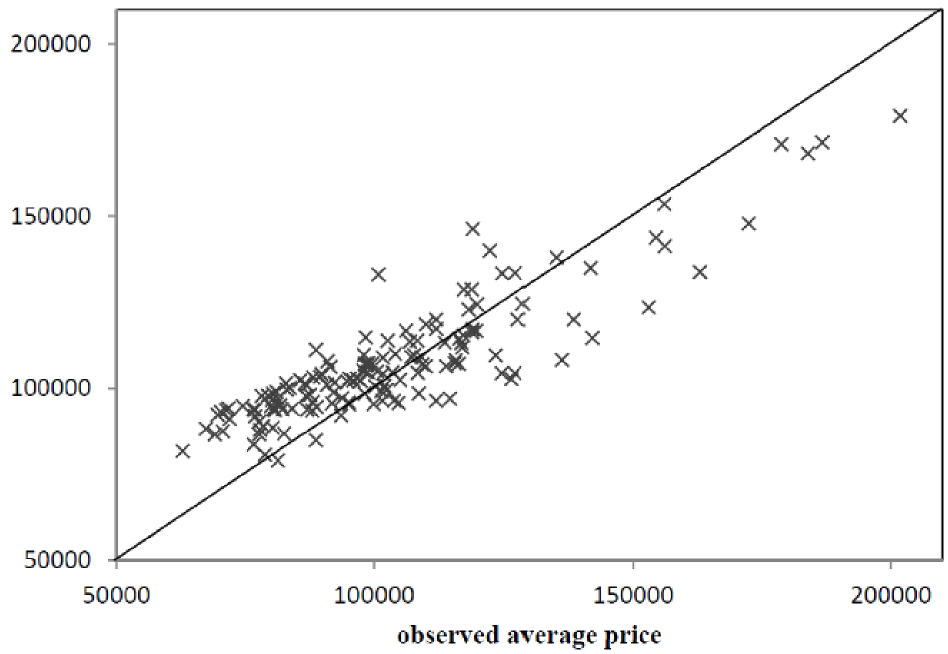
Case study – Simulation results

Average real estate price by commune 2001 - 2008

2001



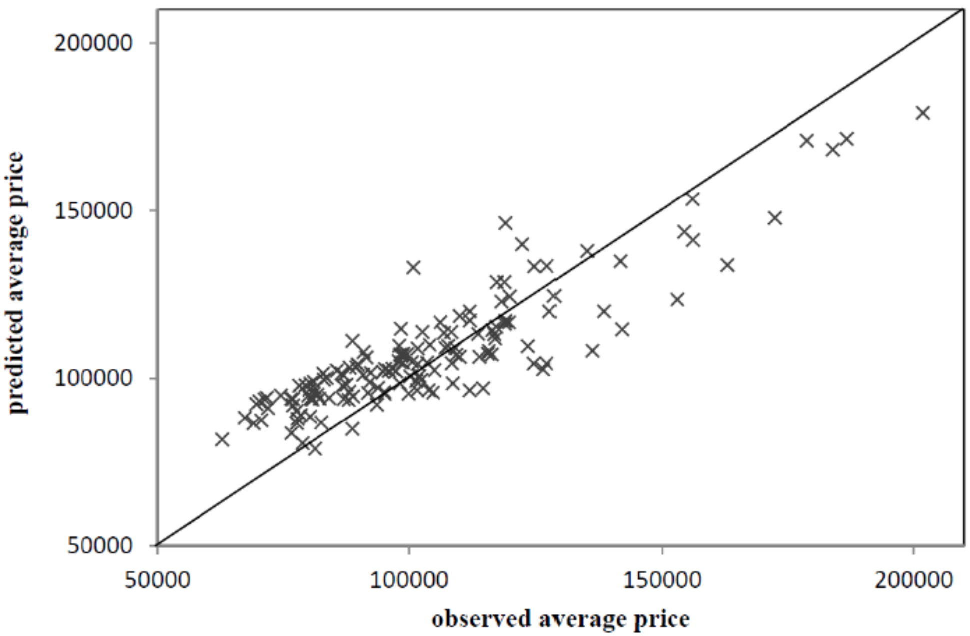
2008



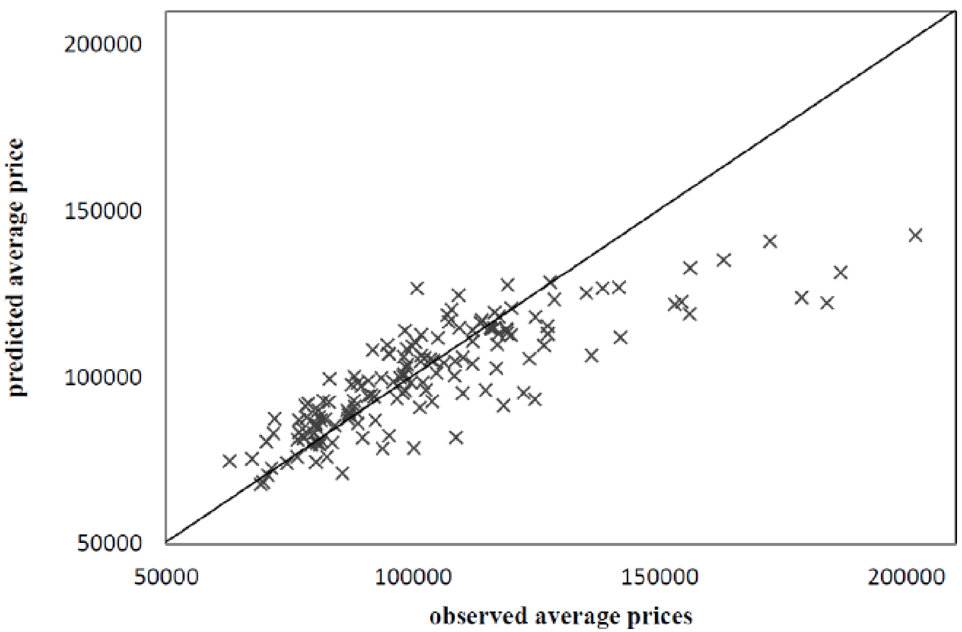
Case study – Simulation results

Average real estate price by commune in 2008

Proposed approach



No market clearing

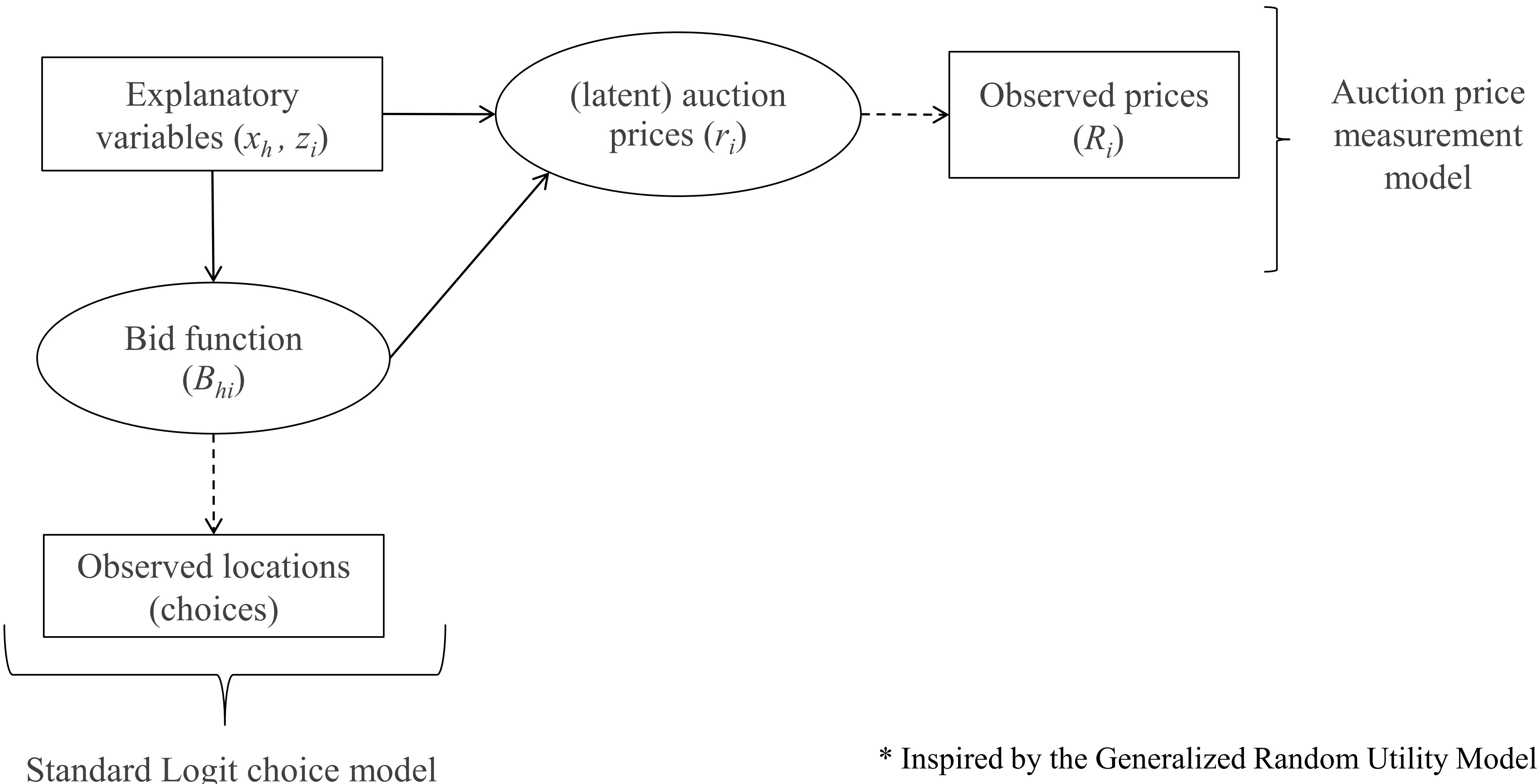


Conclusions

- Proposed approach accounts for adjustment of expectations of decision makers
- Individual adjustments allow to implement an agent based model (no need to solve fixed point problem)
- Results follow observed trends in spatial distribution of agents and evolution of prices
- Not considering market clearing produces an underestimation of prices

Thank you

Model with price indicator



* Inspired by the Generalized Random Utility Model (Walker and Ben-Akiva, 2002)

Model with price indicator

- Structural equation for prices:

$$r_i = \frac{1}{\mu} \ln\left(\sum_{g \in H} \exp(\mu B_{gi})\right)$$

- Measurement equation for prices:

$$R_i = a + \gamma \cdot r_i$$

$$\sim N(0,\sigma) \Rightarrow \quad f(R_i \mid r_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{R_i - a - \gamma \cdot r_i}{2\sigma^2}\right)$$

- Likelihood:

$$L = \prod_i \left(\prod_h \left(P_{h/i} \cdot f(R_i \mid r_i)\right)^{y_{hi}}\right)$$