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

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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

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

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

$$\sum_{i} S_i P\left(h| i, B_{hi}, P(h|i)\right) = H_h \quad \forall h$$

Supply (households)  Demand (households)
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

$$r^t_i = \ln \left( \sum_g \exp(B^t_{gi}) \right)$$
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:

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

\[
\sum_{i \in S^t} q^t(h|i) = \sum_{i \in S^t} \exp \left( b^t_h + b_{hi}(z^t_i, \beta) - r^t_{i-1} \right) = 1
\]

\[
\Rightarrow b^t_h = -\ln \left( \sum_{i \in S^t} \exp \left( b_{hi}(z^t_i, \beta) - r^t_{i-1} \right) \right)
\]
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* 

Exogenous Demand 

New agents \( (h) \) 

Adjustment of bids \((b_h) \ \forall h\) 

Adjusted bids 

Simulation of auctions and calculation of prices \( \forall i \) 

Best bidder for each auctioned unit 

Clearing (matching of \( h \) and \( i \)) 

STOP 

Prices \((p_i')\) 

Matched agents and locations \((h, i)\) 

Unlocated agents 

Empty units 

* 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

<table>
<thead>
<tr>
<th>Attribute</th>
<th>levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income level of the household ($inc_h$)</td>
<td>1 (0-1859 Euros)</td>
</tr>
<tr>
<td></td>
<td>2 (745-1859 Euros)</td>
</tr>
<tr>
<td></td>
<td>2 (1860-3099 Euros)</td>
</tr>
<tr>
<td></td>
<td>4 (3100-4958 Euros)</td>
</tr>
<tr>
<td></td>
<td>5 (&gt;4959 Euros)</td>
</tr>
<tr>
<td>Household size ($hh_size_h$)</td>
<td>1,2,3,4,5+</td>
</tr>
<tr>
<td>Number of children ($children_h$)</td>
<td>0,1,2+</td>
</tr>
<tr>
<td>Number of workers ($workers_h$)</td>
<td>0,1,2+</td>
</tr>
<tr>
<td>Number of cars ($cars_h$)</td>
<td>0,1,2,3+</td>
</tr>
<tr>
<td>Number of people with university degree ($univ_h$)</td>
<td>0,1,2+</td>
</tr>
</tbody>
</table>
## Case study – estimation results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std error</th>
<th>t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC2</td>
<td>-0.171</td>
<td>0.083</td>
<td>-2.07</td>
</tr>
<tr>
<td>ASC3</td>
<td>-0.461</td>
<td>0.113</td>
<td>-4.1</td>
</tr>
<tr>
<td>ASC4</td>
<td>2.05</td>
<td>0.374</td>
<td>5.47</td>
</tr>
<tr>
<td>ASC5</td>
<td>2.19</td>
<td>0.385</td>
<td>5.68</td>
</tr>
<tr>
<td>β_{house}</td>
<td>-0.128</td>
<td>0.0472</td>
<td>-2.7</td>
</tr>
<tr>
<td>β_{apartment}</td>
<td>-0.702</td>
<td>0.181</td>
<td>-3.88</td>
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<tr>
<td>β_{surface}</td>
<td>0.002</td>
<td>0.001</td>
<td>2.6</td>
</tr>
<tr>
<td>β_{high-inc}</td>
<td>3.97</td>
<td>1.24</td>
<td>3.21</td>
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<tr>
<td>β_{low-inc}</td>
<td>-3.94</td>
<td>0.701</td>
<td>-5.62</td>
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<tr>
<td>β_{education}</td>
<td>0.356</td>
<td>0.127</td>
<td>2.8</td>
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<tr>
<td>β_{industry}</td>
<td>-0.562</td>
<td>0.25</td>
<td>-2.25</td>
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<tr>
<td>β_{service}</td>
<td>0.046</td>
<td>0.020</td>
<td>2.31</td>
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<td>β_{shopping}</td>
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<td>0.018</td>
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<td>β_{pubtrans}</td>
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<td>β_{pubtrans2}</td>
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<td>0.101</td>
<td>-2.46</td>
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<tr>
<td>β_{car-access}</td>
<td>0.007</td>
<td>0.004</td>
<td>1.9*</td>
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<tr>
<td>γ</td>
<td>1.46</td>
<td>0.421</td>
<td>3.46</td>
</tr>
<tr>
<td>σ</td>
<td>-1.93</td>
<td>0.022</td>
<td>-89.42</td>
</tr>
</tbody>
</table>

Case study – Simulation results

Observed and predicted population in 2008
Case study – Simulation results

Increase of high income
-0.038 to -0.009
-0.009 to -0.003
-0.003 to 0.002
0.002 to 0.007
0.007 to 0.023
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

![Graph for 2001 showing observed versus predicted average prices.]

2008

![Graph for 2008 showing observed versus predicted average prices.]

[Logo: EPFL]
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

- Explanatory variables ($x_h, z_i$)
- Bid function ($B_{hi}$)
- Observed locations (choices)
- (latent) auction prices ($r_i$)
- Observed prices ($R_i$)

Auction price measurement model

* 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:

\[ R_i = a + \gamma \cdot r_i \]

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

- Likelihood:

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