QUANTIFICATION OF THE 'AIRBNB EFFECT' IN THE CITY OF MADRID

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1. Introduction (iii)

• Sharing economy has been growing rapidly in recent years.
• Positive effects: it facilitates the opportunities to individuals to generate extra income and, hence, affording better and more expensive houses.
• Negative effects: it produces unfair competition, legal problems, intrusiveness and even an increase of criminal cases.
• These conditions have affected the traditional business model, introducing new practices and a need for new policies to correct its management and growth.
• Previous literature = no clear conclusions...
2. Airbnb’s effects in Spain

- **Unravelling Airbnb: Urban perspectives from Barcelona**

- **The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona**

- **A policy approach to the impact of tourist dwellings in condominiums and neighbourhoods in Barcelona**

- **The irruption of Airbnb and its effects on hotel profitability: An analysis of Barcelona's hotel sector**

- **The irruption of Airbnb and its effects on hotel profitability: An analysis of Barcelona's hotel sector**
2. Airbnb’s effects in Spain (ii)

In Barcelona:

• Airbnb constitutes almost half of the formal hotel supply.
• Strong spatial concentration of Airbnb’s lodgings, which are not working as a de-centralizing force.
• Hence: tourist overcrowding of central areas, which may become a serious threat for the residents’ wellbeing.
• These abrupt growth of new tourist dwellings has negative effects on the livability and security in neighborhoods and also in condominiums.
• Alarm caused by the presence of significant listings by professional companies.
3. Main research questions and innovations

• **Main research questions:**

  a) Has the presence of Airbnb lodgings a positive or negative impact for the real estate?
  b) Are these effects varied depending on specific areas or submarkets inside the city?
  c) Has this global/local effect of Airbnb been stable over the last four years across the neighborhoods of Madrid?
3. Main research questions and innovations (ii)

• **Main research questions:**

  d) What is the value of an extra Airbnb host in the city of Madrid? Is it a cost or a benefit for its residents?

  e) Hence, are justified the future policy actions of the council of Madrid to regulate –and limit– this business? Should they be applied evenly across the entire city?
3. Main research questions and innovations (iii)

Innovations:

1. Firstly, we analyze the city of Madrid: one of the first studies for this city.

2. Secondly, we apply a hedonic house price equation to quantify the Airbnb ‘cost’.

3. Thirdly, we apply a conditionally parametric (CPAR) Locally Weighted Quantile regression to estimate different Airbnb costs, depending on:
   - sphere of influence
   - city areas
   - price levels.
4. Data description

• Property price and characteristics: idealista.com (Jan. 2018). **20,603 observations.**
• Airbnb lodging: Inside Airbnb (Jan. 2018): **16,313 observations.**
• Accessibility measures: **GIS self-elaboration** from databases provided by the regional statistics office of Madrid (Instituto de Estadística de la Comunidad de Madrid).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>lprice</td>
<td>Sale price</td>
<td>Idealista</td>
<td>Euros (logs)</td>
</tr>
<tr>
<td><strong>Structural variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>floor</td>
<td>Building floors</td>
<td>Idealista</td>
<td>number</td>
</tr>
<tr>
<td>lm2</td>
<td>Surface</td>
<td>Idealista</td>
<td>m² (logs)</td>
</tr>
<tr>
<td>bedr</td>
<td>Bedrooms</td>
<td>Idealista</td>
<td>number</td>
</tr>
<tr>
<td>bath</td>
<td>Bathrooms</td>
<td>Idealista</td>
<td>number</td>
</tr>
<tr>
<td>reform</td>
<td>Needs renovation</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>new</td>
<td>New dwelling</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>nolift</td>
<td>Building without elevator</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>interior</td>
<td>All the rooms are facing an inner courtyard</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>exterior</td>
<td>All the rooms are facing outdoor public areas</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>garage</td>
<td>Garage space</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>store</td>
<td>Storage room</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>builtw</td>
<td>Built-wardrobes</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
<tr>
<td>aircon</td>
<td>Air-conditioner unit</td>
<td>Idealista</td>
<td>0-1</td>
</tr>
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<td>terrace</td>
<td>Terrace</td>
<td>Idealista</td>
<td>0-1</td>
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<td><strong>Variables of accessibility</strong></td>
<td></td>
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<tr>
<td>discen</td>
<td>Distance to the business center (&quot;Nuevos Minist.&quot;)</td>
<td>Self-elaboration</td>
<td>Km</td>
</tr>
<tr>
<td>periph</td>
<td>Peripheral districts (outside Central Almond)</td>
<td>Self-elaboration</td>
<td>0-1</td>
</tr>
<tr>
<td>dm40</td>
<td>Distance to closest entrance to the M-40</td>
<td>Self-elaboration</td>
<td>Km</td>
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<tr>
<td>mincerca</td>
<td>Distance to the closest train station</td>
<td>Self elab./C.Madrid</td>
<td>Km</td>
</tr>
<tr>
<td>Minairp</td>
<td>Distance to the international airport</td>
<td>Self elab./C.Madrid</td>
<td>Km</td>
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<tr>
<td>minpark</td>
<td>Distance to the closest green area (over 1 Ha.)</td>
<td>Self elab./C.Madrid</td>
<td>Km</td>
</tr>
<tr>
<td>dishiper</td>
<td>Distance to closest hypermarket</td>
<td>Self elab./C.Madrid</td>
<td>Km</td>
</tr>
<tr>
<td>mincc</td>
<td>Distance to closest shopping center</td>
<td>Self elab./C.Madrid</td>
<td>Km</td>
</tr>
<tr>
<td>minsanit</td>
<td>Distance to closest hospital</td>
<td>Self elab./C.Madrid</td>
<td>Km</td>
</tr>
<tr>
<td><strong>Airbnb influence variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Airbuf25</td>
<td>Airbnb hosts in a sphere of 25 m. around each dwelling (‘local’ influence)</td>
<td>Inside Airbnb, Idealista &amp; GIS</td>
<td>number</td>
</tr>
</tbody>
</table>
Airbnb hosts (yellow)
On-sale houses (grey)
City of Madrid, January 2018
Four policy zones (‘zonas’) defined by the city Council.

- **Zone 1**: Hosts will be allowed to rent their houses:
  - If they are located in the main boroughfares: Gran Vía, Alcalá and Plaza Mayor.
  - No more than 3 months a year.
  - More than 3 months if they have a direct exit to the street.

- **Zone 2 & Zone 3**: Tourist apartments will only be allowed in 10% of the residential use of a building (1 per 10 homes in a condo).
Variable ‘Airbuf25’:
Local influence of Airbnb on house price.
Example: Centro district (Zone 1).

In red: Airbnb hosts
In green: Dwellings’ influence area, condo level (25 meters)
Variable ‘Airbuf25’: Local influence of Airbnb on house price. Example: Barajas district (Zone 4).

In red: Airbnb hosts
In green: Dwellings’ influence area, condo level (25 meters)
Houses with Airbnbs (at 25 m. radius)
- 1
- 2
- 3 to 5
- 5 to 8
- 8 to 22
5. Method
5.1. Quantile regression (QR)

• QR dates from the **late seventies** when it was first developed by Koenker and Basset (1978).
• Despite the fact that it is not a recent breakthrough, QR has **not been used as extensively as OLS** in spite of its advantages under certain circumstances.
• It provides good results when facing situations of **heteroskedasticity, non-normality** due to the presence of outliers, **structural change** and/or **spatial regimes**.
• In these cases, the **conditional mean** of the response variable provided by the **OLS estimation** is not always the most representative one.
5.1. Quantile regression (ii)

- In a **intuitive way**:
  - The mean is not always the most representative measure of a variable distribution, when **extreme values** or a **very large variability** occur in the sample.
  - In the same way, the OLS estimation line that produces the conditional mean $E(y \mid X)$ is not always the best expression of the relationship among those variables if any of the aforementioned problems arises.
  - QR offers the possibility to **create different regression lines for different quantiles** of “y”.
5.1. Quantile regression (iii)

- \( y_i = X_i \beta_\tau + u_i \); \( \beta_\tau \) is the parameter corresponding to quantile \( \tau \) to be estimated.

- OLS model: estimates a unique regression line:
  \[
  E(y_i|X_i) = X_i \hat{\beta}_{OLS} \rightarrow E(u_i|X_i) = 0
  \]

- QR model: there are as many lines -and hence vectors \( \beta_\tau \)- as quantiles considered:
  \[
  \text{Quant}_\tau(y_i|X_i) = X_i \hat{\beta}_\tau \rightarrow \text{Quant}_\tau(u_{\tau i}|X_i) = 0.
  \]

- **Main advantage** in presence of outliers in “y” (and “u”): minimization of \(|e|\) provide estimations almost **unaffected by the extreme values**, as errors are linearly penalized (OLS minimization of \(e^2\) attaches more importance to these values by penalizing them quadratically).
5.1. Quantile regression (iv)

\[ y_i = X_i \beta_\tau + u_i \]

- \( \text{Quant}_\tau (u_{\tau i}|X_i) = 0 \), the only assumption made on \( u_i \).
- No distribution is assumed for “\( u_i \)”
- \( \Lambda_\tau = \text{Cov}(\beta_\tau) \) not known.
- Design **matrix bootstrap**: the best estimator for \( \Lambda_\theta \).

\[
\hat{\beta}_\tau \in \mathbb{R} \left[ \sum_{y_i \geq X_i \hat{\beta}_\tau} \rho_\tau |y_i - X_i \hat{\beta}_\tau| + \sum_{y_i < X_i \hat{\beta}_\tau} (1 - \rho_\tau) |y_i - X_i \hat{\beta}_\tau| \right]
\]

- **Asymmetric weighted sum** of absolute deviations.
- For each “\( i \)” the \( \Sigma |e| \) is weighted in accordance to the \( \tau \) whose regression line is being estimated.
5.2. McMillen (2013)’s quantile CPAR LWR models

Basic log-linear hedonic regression \[ \log(p_i) = x_i'\beta + u_i \]

Quantile regression model \[ \text{Quant}_\tau(\log(p_i) \mid x_i) = x_i'\hat{\beta}_\tau, \]

Quantile CPAR model \[ \text{Quant}_\tau(\log(p_i) \mid x_i, lo, la) = x_i'\hat{\beta}_\tau(lo, la) \] geographic coordinates

- The coefficients are allowed to vary by observation as well as by quantile.
- **Summary** of the impacts (changes in prices with changes in the explanatory variables):
  1. Kernel distributions.
5.2. McMillen (2013)’s quantile CPAR LWR models (ii)

CPAR models **estimation:**

- Non-parametric framework.
- By specifying a **kernel weight function:** gives the weight to an observation $i$ with coordinates $(lo_i, la_i)$ to estimate the function at a target point $j$.
- It allows the coefficients to **vary smoothly over space.**
- Selection of **kernel function:** tri-cube, Epanechnikov, Gaussian...
- Selection of **distance:** Euclidean, Mahalanobis...
- Selection of **bandwidth** (# observations to be used for estimation each $i$).
- A total of **NM predictions**, $N =$ observations; $M =$ quantiles.
5.2. McMillen (2013)’s quantile CPAR LWR models (iii)

- This approach is important for this application because Airbnb effects are supposed (by public authorities) to be not uniform across the entire sample area. Some areas of the city could be valued at higher rates than others, in terms of Airbnb hosts’ concentration.
- Airbnb concentration is also variable in some areas than others.
- The locally weighted approach accounts for geographic differences in Airbnb effect levels than varies smoothly over space.
- Not necessary to impose a unique common structure for spatial variation (or specifying a spatial weight matrix).
- Useful for a first descriptive analysis of complex micro-data spatial structures.
6. Empirical model

- **Baseline OLS model:**

\[ lp_i = \alpha + \sum_{j=1}^{5} \beta_j S_{ji} + \sum_{l=1}^{4} \gamma_l A_{li} + \lambda_1 al_i + \lambda_2 ag_i + u_i \]

- **S:** structural characteristics (surface, bathrooms, storage, air-conditioner, built-wardrobes).
- **A:** accessibility variables (distances to city center, airport, shopping centers, hospitals).
- **al:** Airbnb local influence (condo level: 25 meters)
- **ag:** Airbnb global influence (quarter level: 500 meters)

- Problems of an OLS estimation: non-normality, heteroskedasticity, and spatial autocorrelation, which would produce inefficiency and bias.
6. Empirical model (ii)

- **Standard quantile model:** \( \tau \) is one of 99 percentiles

\[
lp_i = \alpha_\tau + \sum_{j=1}^{5} \beta_\tau j S_{ji} + \sum_{l=1}^{4} \gamma_{\tau l} A_{li} + \lambda_{\tau 1} a_{li} + \lambda_{\tau 2} ag_{i} + u_{i}
\]

- **Conditionally LWR quantile regression models:**

\[
\text{Quant}_\tau(\log(p_i) \mid x_i, lo, la) = x_i' \hat{\beta}_\tau(lo, la)
\]

\( p \): housing price (log)
Eliminated: all the **distance-based accessibility** explanatory variables.

Distance: **Euclidean**.
Kernel function: **tri-cube kernel** weight function
Bandwidth: **30%** (observations used to estimate LWQR for a target point \( i \)).
7. Some preliminary results

• Analysis of the coefficients for the Airbnb effect

Summary results:
• Scatter and linear plots
• Kernel distributions
• Maps
7. Some preliminary results (ii)

- Correlation between house price and # Airbnb hosts in the condo (25 m. radius) is non-linear (exponential).
- House price drops exponentially with Airbnb hosts.
- Log Price drops from 2 Airbnb’s hosts onwards.

\[ y = e^{\beta x} \rightarrow \text{lineal} \rightarrow \log(y) = \beta x \]
7. Some preliminary results (iii)

Residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.99743</td>
<td>-0.19218</td>
<td>-0.00925</td>
<td>0.18375</td>
<td>1.45670</td>
</tr>
</tbody>
</table>

Coefficients:

| Estimate  | Std. Error | t value | Pr(>|t|) |
|-----------|------------|---------|---------|
| (Intercept) | 8.772e+00 | 2.866e-02 | < 2e-16 *** |
| LM2B       | 8.793e-01 | 5.835e-03 | 150.685 < 2e-16 *** |
| HOUSE      | 1.208e-01 | 1.139e-02 | 10.605 < 2e-16 *** |
| FLAT       | -3.363e-02 | 6.006e-03 | -5.599 2.19e-08 *** |
| BATHR      | 6.253e-02 | 2.779e-03 | 22.502 < 2e-16 *** |
| REFORM     | -8.698e-02 | 6.014e-03 | -14.462 < 2e-16 *** |
| STORE      | 4.291e-02 | 5.136e-03 | 8.355  < 2e-16 *** |
| BUI LTW    | 1.859e-02 | 4.769e-03 | 3.899 9.69e-05 *** |
| AI RCON    | 6.092e-02 | 4.797e-03 | 12.699 < 2e-16 *** |
| GARAGE     | 1.304e-01 | 5.806e-03 | 22.468 < 2e-16 *** |
| POOL       | 2.892e-01 | 6.517e-03 | 44.379  < 2e-16 *** |
| DISCEN     | -1.205e-05 | 2.832e-06 | -4.253 2.12e-05 *** |
| M NAI RP   | -1.401e-05 | 6.793e-07 | -20.618 < 2e-16 *** |
| M NM40     | 8.088e-05 | 2.130e-06 | 37.972 < 2e-16 *** |
| M NCC      | -6.093e-05 | 4.044e-06 | -15.068 < 2e-16 *** |
| M NSANI T  | -3.736e-05 | 3.096e-06 | -12.067 < 2e-16 *** |
| M NHOT5    | -2.582e-05 | 2.492e-06 | -10.359 < 2e-16 *** |
| ZONA3      | -2.226e-01 | 6.513e-03 | -34.171 < 2e-16 *** |
| PERLPH     | -3.993e-01 | 8.370e-03 | -47.704 < 2e-16 *** |
| AI RBUF25  | -9.620e-03 | 1.821e-03 | -5.282 1.29e-07 *** |

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.304 on 20583 degrees of freedom
Multiple R-squared:  0.9088, Adjusted R-squared:  0.9087
F-statistic: 1.079e+04 on 19 and 20583 DF,  p-value: < 2.2e-16

Basic OLS estimation.
Hedonic Price model.

\[ E(y_i | X_i) = X_i \hat{\beta}_{OLS} \]
7. Some preliminary results (iv)

Quantile Regression. Hedonic Price model. \( \text{Quant}_\tau(y_i | X_i) = X_i\hat{\beta}_\tau \)

<table>
<thead>
<tr>
<th>( \tau )</th>
<th>Coefficients</th>
<th>Coefficients</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05</td>
<td>( \text{Intercept} )</td>
<td>8.68751, 0.05280</td>
<td>164.52081, 0.00000</td>
</tr>
<tr>
<td>0.5</td>
<td>( \text{Intercept} )</td>
<td>8.68751, 0.05280</td>
<td>164.52081, 0.00000</td>
</tr>
<tr>
<td>0.95</td>
<td>( \text{Intercept} )</td>
<td>8.68751, 0.05280</td>
<td>164.52081, 0.00000</td>
</tr>
</tbody>
</table>

| \( \text{Intercept} \) | 8.68751, 0.05280 | 164.52081, 0.00000 | 8.73596, 0.03383 | 262.40290, 0.00000 |
| \( \text{LM2B} \) | 0.81094, 0.01068 | 75.89496, 0.00000 | 0.85284, 0.00704 | 121.17238, 0.00000 |
| \( \text{HOUSE} \) | 0.08828, 0.02149 | 4.10715, 0.00004 | 0.15259, 0.01612 | 9.46747, 0.00000 |
| \( \text{FLAT} \) | 0.03126, 0.01418 | 2.20467, 0.02749 | -0.02890, 0.00747 | -3.87139, 0.00011 |
| \( \text{BATHR} \) | 0.05814, 0.00549 | 10.59438, 0.00000 | 0.07456, 0.00379 | 19.69713, 0.00000 |
| \( \text{REFORM} \) | 0.06607, 0.01130 | 5.84642, 0.00000 | 0.08138, 0.00670 | 12.14536, 0.00000 |
| \( \text{STORE} \) | 0.05215, 0.01048 | 4.97709, 0.00000 | 0.04039, 0.00583 | 6.93196, 0.00000 |
| \( \text{BUILTW} \) | 0.09471, 0.00977 | 3.95236, 0.00000 | 0.02517, 0.00571 | 4.40797, 0.00000 |
| \( \text{AI RCON} \) | 0.01861, 0.00882 | 4.97709, 0.00000 | 0.06437, 0.00537 | 11.99328, 0.00000 |
| \( \text{GARAGE} \) | 0.17956, 0.01137 | 15.78826, 0.00000 | 0.11657, 0.00646 | 18.04692, 0.00000 |
| \( \text{POOL} \) | 0.27444, 0.01299 | 21.12077, 0.00000 | 0.28908, 0.00786 | 36.77854, 0.00000 |
| \( \text{DI SCEN} \) | 0.00002, 0.00001 | 3.18990, 0.00143 | 0.00001, 0.00000 | -1.66978, 0.09498 |
| \( \text{M RAI RP} \) | 0.00002, 0.00000 | 12.43345, 0.00000 | 0.00002, 0.00000 | -24.66308, 0.00000 |
| \( \text{M NMAO} \) | 0.00007, 0.00000 | 15.37100, 0.00000 | 0.00009, 0.00000 | 33.12432, 0.00000 |
| \( \text{M NCC} \) | 0.00007, 0.00000 | 9.31823, 0.00000 | 0.00007, 0.00000 | -14.01331, 0.00000 |
| \( \text{M NSANI T} \) | 0.00004, 0.00001 | 7.21979, 0.00000 | 0.00003, 0.00000 | -9.75530, 0.00000 |
| \( \text{M NHTS} \) | 0.00003, 0.00000 | 5.47090, 0.00000 | 0.00003, 0.00000 | -10.22212, 0.00000 |
| \( \text{ZONA3} \) | 0.27332, 0.01379 | 19.82189, 0.00000 | 0.20712, 0.00764 | -27.12484, 0.00000 |
| \( \text{PERI PH} \) | 0.46186, 0.01700 | 26.24641, 0.00000 | 0.39045, 0.01028 | 37.97618, 0.00000 |
| \( \text{AI RBF25} \) | 0.00463, 0.00178 | -2.59254, 0.00953 | 0.01177, 0.00138 | -8.54577, 0.00000 |
7. Some preliminary results (v)

Results for a standard QR

- Either below or above the house price average (350,000 €), Airbnb impact on house price is negative and decreasing with house price.
Median house Price (350,000 €):

- Airbnb hosting has negative externalities in practically the entire city.
- However, it has positive externalities in the West (Aravaca) and some Southern districts (Latina, Carabanchel, Usera and Villaverde).
AIRBNB LOCAL INFLUENCE BY HOUSE PRICE QUARTILES

FOR THE MEDIAN OF HOUSE PRICE:

In most cases, Airbnb’s impact produces a devaluation on house price.

But...

One mode for Airbnb’s positive externality in house Price (‘Aravaca’)

N = 20603  Bandwidth = 0.001142
10<sup>th</sup> percentile (31,000-120,000 €): in the Barajas airport area poorest residents are willing to pay from 2-8% more for one less Airbnb host in their condo.

90<sup>th</sup> percentile (165,000-9,000,000 €): wealthiest residents are willing to pay from up to 5% for one extra Airbnb host!

For all house price percentiles: house price appreciates with Airbnb hosts in the West and Southern periphery.
AIRBNB LOCAL INFLUENCE BY HOUSE PRICE QUARTILES (CPAR model):

Most of the low-priced home-owners would pay an extra 2% for one less Airbnb's host in their condo.

In a 2nd group of low priced houses: 1 extra Airbnb host has no impact in house price.

High priced-houses, an additional Airbnb host in the condo would:
- have no impact in house price.
- have a 2% revaluation.

Negative impact of one extra host increases with house price.
AIRBNB LOCAL INFLUENCE BY HOUSE PRICE QUARTILES

Low-price houses (red):
Small cluster of Airbnb’s no impact.

High-price houses (cyan):
- A 2\textsuperscript{nd} mode of Airbnb no impact.
- A 3\textsuperscript{rd} mode of Airbnb positive impact.
Some preliminar interpretations... (ii)

In light of the results obtained, the city council should reconsider its position in the policy Zones.

- Residents of the Eastern quarters in Zones 2 and 3 (6 hosts) are more affected by Airbnb due to its vicinity to the motorway to the airport.

- In certain areas of **Zone 4** (NO ACTION, low concentration): residents for almost all the percentiles of house price are willing to pay from 2-5% for 1 less Airbnb host. They are located in the NW (‘El Pilar’ quarter) and the NE quarters nearby the Barajas Airport.
In a 15 km. radius, negative impact increases with vicinity to the airport up to -6%.

In a 3.5 km. radius, negative impact increases with vicinity to communication hubs.

In a 2 km. radius, negative impact increases with vicinity to the shopping centers up to -2%.

10th percentile (31,000-120,000 €): Negative impact of extra Airbnb hosts: Negative impact increases with Airbnbs’ density per census tracts, from 0-20 hosts up to -2%.
90th percentile (165,000-9,000,000 €), Negative impact of extra Airbnb hosts:

- Negative impact increases with Airbnb's density per census tracts, from 0-30 hosts up to -2%.
- Negative impact increases with distance from M40.
- Negative impact increases with vicinity to 5-star hotels up to -2%.
- In a 8 km. radius, negative impact increases with vicinity to the C.B.D up to -2%.
Some preliminar interpretations...

- Airbnb effects vary depending on house price and zones.
- House price rises from 1 to 2 Airbnb hosts, but drops from 2 onwards.
- Above the house price average, residents are willing to pay more than 1% extra for one less Airbnb host.
- In general, Airbnb hosting has negative externalities across the entire city and for all house price percentiles.
- However, for all house price percentiles, a group of residents are willing to pay more than 2% for having one extra Airbnb host in their condo, particularly in the main access highways (North, West and Southwest).
- Close to the Barajas Airport area: poorer residents would pay up to 8% more for one less Airbnb host but wealthier ones will experience an appreciation of their dwellings up to 5% with extra Airbnb hosts.