# THE SPREAD OF AIRBNB AND ITS IMPACT ON THE HOUSING MARKET: SOME EVIDENCE FROM THE ITALIAN CASE

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# Empirical Evidence

The rapid spread of short-term rentals through the Airbnb platform has produced significant impacts on urban contexts.

One of the central issues is the conflict with permanent residents, both in qualitative and quantitative terms.

International literature identifies a positive relationship between the presence of short-term rental facilities and the sale or rental prices of housing: is this also true for the Italian case?

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# The Multidimensionality of Spill-overs

The literature highlights various spillover effects regarding the spread of Airbnb and the impact it has had on multiple fronts.

**Airbnb Spread**

| | |
|---|---|
| Impact on Hotel Market | Mhlanga, 2020; Dogru et al., 2020; Nakamura et al., 2024 |
| Impact on the Labour Market | Basuroy et al., 2020 |
| Impact on neighborhoods | Petruzzi et al., 2020; Stergiou and Farmaki, 2020 |
| Impact on the Real Estate Market | Garcia-Lopez et al., 2020; Koster et al., 2021; Mozo Carollo et al., 2024 |

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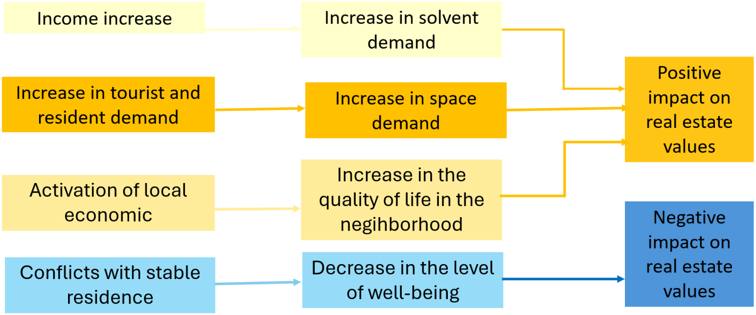
# The Multidimensionality of Spill-overs



# The Dataset

**Airbnb Data**: **INSIDE AIRBNB,** which provides geolocated scraping of the listings along with their corresponding geographic maps.

**Property prices per sqm**: **IDEALISTA.IT**, which offers historical data on property prices for sale in Italian cities. These data are also *georeferenced*.

Based on this information, a *panel* (2012-2022) was built at the **neighborhood level** for 10 Italian cities: **Bari, Bergamo, Bologna, Florence, Lecce, Milan, Rome, Naples, Palermo, Venice**.

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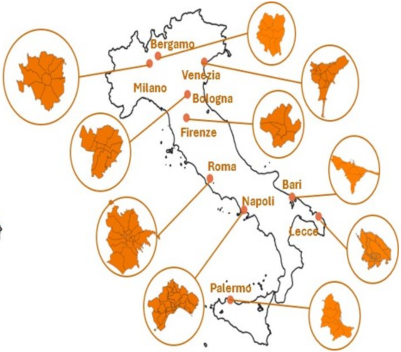
# The Territorial Level: Cities and Neighborhoods

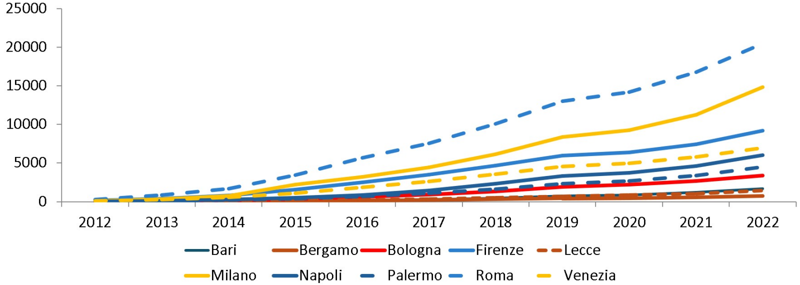




Panel Dataset (2012-2022): for 10 Italian cities at the neighborhood level, including information on property sale prices and the characteristics of Airbnb listings.

# The Distribution of Airbnb in Cities

## New Airbnb Listings per Year, Cumulative Distribution

Rome, Milan, Florence, and Venice are the cities with the highest absolute number of Airbnb listings.

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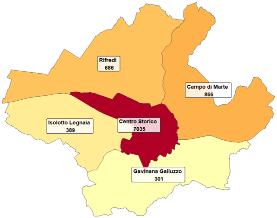
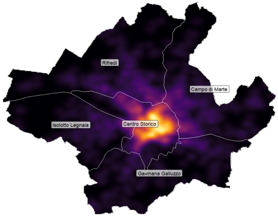
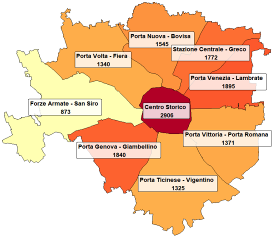
# The Distribution of Airbnb in Cities

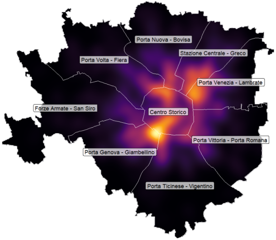
## Airbnb spread in the city of Florence




## Airbnb spread in the city of Milan



# The Dataset

## Explanatory Variables on AIRBNB

- **The year** is identified based on the first review. For each year, the existing listings in each neighborhood are considered;
- **Multi-host**: when the **host** ID is repeated, it means the **host** owns multiple apartments in the city. The number of apartments owned by each **host** within each neighborhood is counted;
- **Airbnb bed capacity** in each neighborhood;
- **Average Airbnb price** in each neighborhood.

## Other Explanatory Variables Related to Property Prices

- **Population** of each neighborhood;
- **Average Irpef income** per taxpayer in each city, as a *proxy* for the economic level;
- **University students** from outside the city enrolled in each city;
- **Capital stock** per taxpayer in each city;
- **Hotel bed capacity** in each city;
- **Tourist arrivals** in each city.

# The Dataset

### Variables Identifying Cities and Areas within a City

- **Zone**: a *dummy* variable that identifies central areas with 1 and peripheral areas with 0 in a city;
- **Type**: a *dummy* variable that identifies cities primarily focused on cultural tourism with 0, and those catering to multiple segments of demand, not limited to cultural tourism, with 1;
- **Geography**: a *dummy* variable that identifies southern cities with 0 and central-northern cities with 1.

### Dependent Variable

**Average price per sqm of properties in each neighborhood per year**

# Mixed Effects Model (Mixed Model)

## Why do we need a mixed regression model?

- **Data with hierarchical structure**: neighborhoods nested within cities.
- **In this case, the research question involves both levels**, aiming to measure the effects of the characteristics of individual cities (and individual neighborhoods) on property prices.

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# The Mixed Effects Model

### Mixed Effects Model Structure

$$\boxed{Y_{ijt} = \alpha + \beta_1 X_{ijt} + \beta_2 X_{jt} + \beta_3 X_j + \beta_4 X_i + u_i + u_j + \epsilon_{ijt}}$$

i = first level, neighborhood; j = second level, city; t = year

**Fixed Effects**

- $X_{ij}$: matrix of variables at the neighborhood and city level
- $X_j$: matrix of variables at the city level

**Random Effects**

- $u_i$: random effect at level 1 (neighborhood) with standard deviation $\sigma_{u_i}$
- $u_j$: random effect at level 2 (city) with standard deviation $\sigma_{u_j}$
- $\epsilon_{ijt}$: error term with standard deviation $\sigma_\epsilon$

# Overall Model: The Results

| Explanatory Variables | Estimate | P-value |
|---|---|---|
| Intercept | 3.559 | 0.003*** |
| **Time Effect** | | |
| t | -0.034 | 0.003*** |
| $t^2$ | 0.003 | 0.183 |
| $t^3$ | 0.000 | 0.071* |
| t:Geography | 0.084 | 0.002*** |
| $t^2$:Geography | 0.021 | 0.000*** |
| $t^3$:Geography | -0.001 | 0.000*** |
| **Neighborhood level** | | |
| Average Price Airbnb (Log) | 0.006 | 0.424 |
| Multi Host | 0.078 | 0.000*** |
| Airbnb Listings (*1000 dwellings) | 0.002 | 0.000*** |
| **City leve** | | |
| Pop (Log) | -0.185 | 0.000*** |
| Hotel per capita | 2.339 | 0.004*** |
| Students per capita | 2.632 | 0.000*** |
| Average Income | 0.055 | 0.000*** |
| Geography (Dummy north/suoth) | 0.068 | 0.670 |
| Zone (Dummy center/periphery) | 0.334 | 0.000*** |
| N neighborhoods | 94 | |
| N cities | 10 | |
| Observations | 1034 | |
| $R^2$ Marginal | 0.618 | |
| $R^2$ Conditional | 0.985 | |

1. The third-degree function, interacted with geography, accounts for the different price trends between northern and southern cities;
2. In general, property prices are higher when income is higher, in tourist cities with many students and in central neighborhoods;
3. Airbnb listings, weighted against residential properties, show a positive and significant correlation with property prices;
4. Prices also increase in the presence of multi-hosts.

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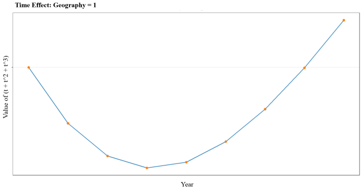
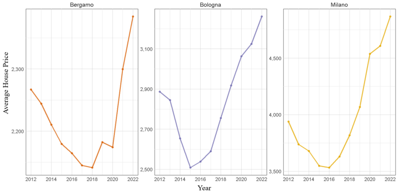
# Temporal Dynamics

### Estimated Annual Effect for Cities with Geography = 1



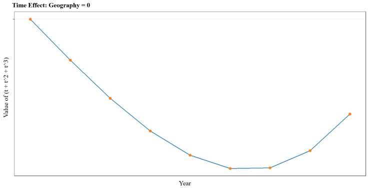

### Trend of Average Prices per Neighborhood in 3 Northern Cities



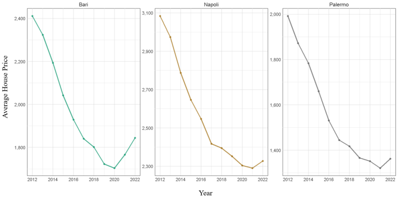

The model captures the upward trend over time compared to the year 2012 that characterized northern cities.

# Temporal Dynamics

### Estimated Annual Effect for Cities with Geography = 0




### Trend of Average Prices per Neighborhood in 3 Southern Cities




The model captures the upward trend over time compared to the year 2012 that characterized southern cities.

# Model with Interaction: Results

| Explanatory Variables | Estimate | P-value |
|---|---|---|
| Intercept | 3.322 | 0.000*** |
| **Time effect** | | |
| t | -0.029 | 0.009*** |
| $t^2$ | -0.004 | 0.083* |
| $t^3$ | 0.000 | 0.015* |
| t:Geography | -0.008 | 0.000** |
| $t^2$:Geography | 0.024 | 0.000*** |
| $t^3$:Geography | -0.001 | 0.000*** |
| **Neighborhood level** | | |
| Average Airbnb price (Log) | 0.003 | 0.673 |
| Multi Host | 0.069 | 0.000*** |
| Airbnb listings (*1000 dwellings) | 0.018 | 0.000*** |
| **City level** | | |
| Pop (log) | 0.222 | 0.006*** |
| Hotel per capita | 2.777 | 0.000*** |
| Students per capita | 2.925 | 0.000*** |
| City tipology | -0.255 | 0.064 |
| Average income | 0.043 | 0.000*** |
| Geography (Dummy north/south) | 0.198 | 0.192 |
| Zone (Dummy center/periphery) | 0.338 | 0.000*** |
| Airbnb listings: Tipology | 0.005 | 0.000*** |
| N neighborhoods | 94 | |
| N cities | 10 | |
| Observations | 1034 | |

Compared to the previous model, the interaction variable between Airbnb listings and city type is positive and significant. This means that one additional listing in a city with a non-exclusively cultural or artistic vocation (like Milan or Bologna) has a greater effect on prices than one additional listing in a city with a predominantly cultural/artistic tourism focus.

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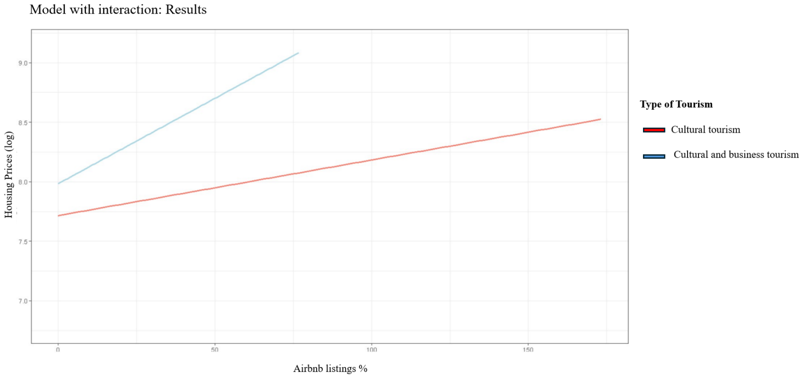
# Model with Interaction: Results




Multiplicative Effect of the impact of Airbnb on property prices when dealing with cities that have not exclusively cultural tourism. The presence of Airbnb in neighborhoods has a greater impact in cities also characterized by business tourism.

# Cronbach's Model: Within and Between Effects

In multilevel analyses, the hierarchical structure of groups (number of groups, how many members each group has) is predefined: the objective of the analysis is to understand the relationships BETWEEN groups and WITHIN groups.

$$\boxed{Y_{ijt} = \alpha + \beta_1(X_{ijt} - \overline{X}_{.jt}) + \beta_2(\overline{X}_{.jt} - \overline{X}_{..t}) + \beta_3\overline{X}_{..t} + \mu_i + \mu_j + \epsilon_{ijt}}$$

$(X_{ijt} - \overline{X}_{.jt})$: **WITHIN effect (neighborhood)**: deviation from the group (neighborhood) mean

$(\overline{X}_{.jt} - \overline{X}_{..t})$: **WITHIN effect (city)**: deviation from the group (city) mean

$\overline{X}_{..t}$: **BETWEEN effect**: deviation of the average neighborhood from the mean of all neighborhoods

# Model Structure

## Model with Within and Between Effects

$$
\begin{aligned}
\log(\text{PropertyPrices})_{ijt} = {} & \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 \text{Listings.within.neighborhood} \\
& + \beta_5 \text{Listings.within.city} + \beta_6 \text{Listings.between} \\
& + \beta_7 \text{MultiHost.within.neighborhood} + \beta_8 \text{MultiHost.within.city} \\
& + \beta_9 \text{MultiHost.between} + \ldots + u_i + u_j + \epsilon_{ijt}
\end{aligned}
$$

### Random Effects Structure

- **Random effects**: $u_i$ and $u_j$ are random effects at the neighborhood and city levels.
- **Residuals**: $\epsilon_{ijt} = a\epsilon_{t-1,ij} + v_{ij}$. A shock at time t can have consequences at time t+1. Therefore, an autoregressive structure is chosen for the residuals.

**The variables of interest are decomposed into three components: WITHIN neighborhood, WITHIN city, and BETWEEN.**

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# Within/Between Model: Results

| Explanatory Variables | Estimate | P-value |
|---|---|---|
| Intercept | 4.735 | 0.000*** |
| **Time effect** | | |
| t | -0.038 | 0.000*** |
| $t^2$ | -0.003 | 0.114 |
| $t^3$ | 0.000 | 0.000*** |
| t:Geography | -0.056 | 0.000*** |
| $t^2$:Geography | 0.017 | 0.000*** |
| $t^3$:Geography | -0.001 | 0.000*** |
| **Neighborhood level** | | |
| Multi Host Within Neighborhood | 0.014 | 0.253 |
| Multi Host Within city | 0.049 | 0.050** |
| Multi Host Within Between | -0.071 | 0.296 |
| Airbnb listings Within neighborhood | 0.001 | 0.056* |
| Airbnb listings Within city | 0.002 | 0.029** |
| Airbnb listings Between | 0.000 | 0.961 |
| **City level** | | |
| Pop (log) | 0.193 | 0.000*** |
| Students per capita | 0.649 | 0.137 |
| Hotel per capita | 0.872 | 0.112 |
| Average Income | 0.013 | 0.001*** |
| Geography (Dummy north/south) | 0.274 | 0.031** |
| Zone (Dummy center/periphery) | 0.343 | 0.000*** |

1. Regarding the number of Airbnb listings: neighborhoods with a higher-than-average number of Airbnb listings have higher property prices; the same applies to cities. Both coefficients for WITHIN effects are positive and significant;
2. Regarding the Multi-host variable: cities with a higher-than-average number of Airbnb listings have higher property prices.

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# Post Estimation: 2 Scenarios

## Scenario 1

A 10% increase in **Airbnb** listings in Neighborhood 1 (historic center) of Florence

↓

**Increase of 82 euros per sqm (1.6%)**

## Scenario 2

The central neighborhood of Bologna reaches the level of **Airbnb** penetration of Neighborhood 1 in Florence

↓

**Increase of 344 euros per sqm (8.2%)**

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# Conclusions

- Among the factors that contribute to determining housing prices is household income, which serves as a *proxy* for the city's economic system;
- Even in the Italian case, there is a positive and significant relationship between the presence of Airbnb and housing prices;
- This relationship is even more evident in historic centers compared to suburban areas and in cities with a broader tourist appeal (Milan and Bologna) compared to those more oriented toward cultural tourism;
- The impact on housing prices is greater in the presence of a more organized supply (hosts managing multiple properties);

$$\downarrow$$

Greater regulation (Barcelona, Florence) may be necessary, especially in contexts where the presence of these listings is more significant and thus a source of greater conflict with the local population.

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# Thank you

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