Short-term rentals and the economy in France: Insights from spatial statistics and causal inference

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June 14, 2023

Outline

Outline

Introduction

Sharing platforms really took off in the 2010s in most countries around the world (Adamiak, 2019).

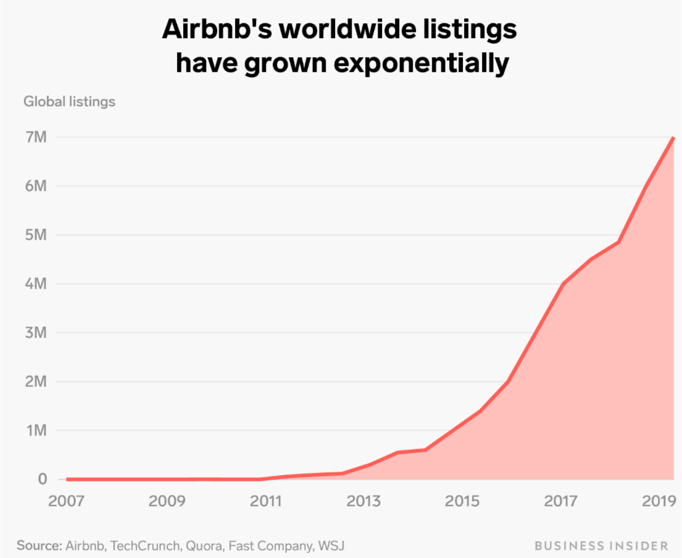
Airbnb is the best known and most used worldwide:

- More than 6 million houses, apartments and rooms for rent
- Active in nearly 220 countries

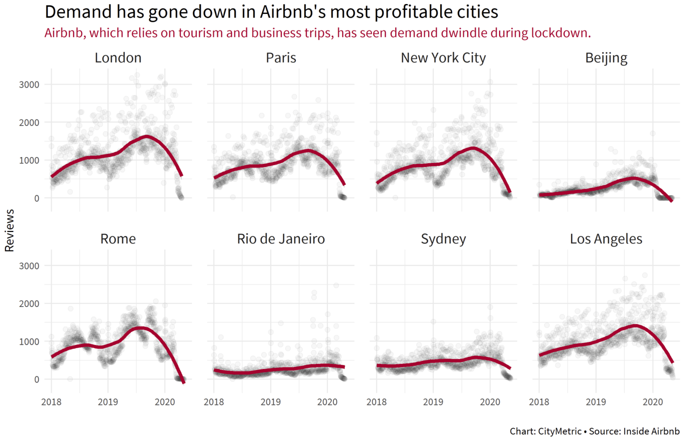
3 countries with the largest activity:

1. United States (2.25 million active listings in 2021)
2. France (1.2 million active listings in 2021)
3. China (1.15 million active listings in 2021)

Airbnb evolution (1)



Airbnb evolution (2)



Airbnb distribution (1)

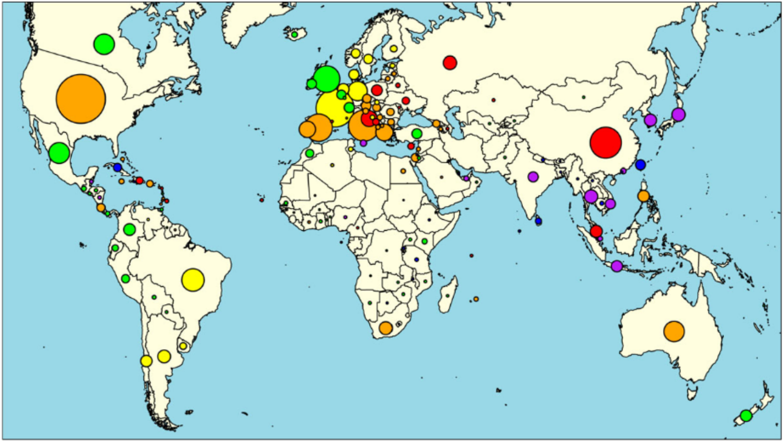


Figure 1. Distribution of active listings in 167 countries.

Source: Adamiak (2019)

Airbnb distribution (2)

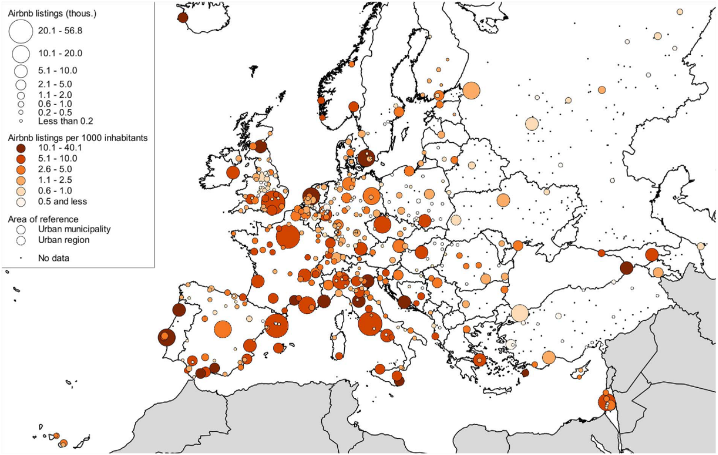
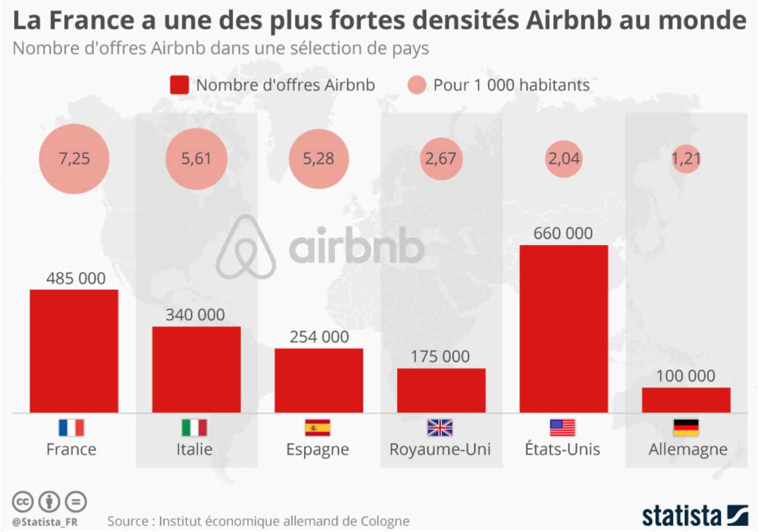


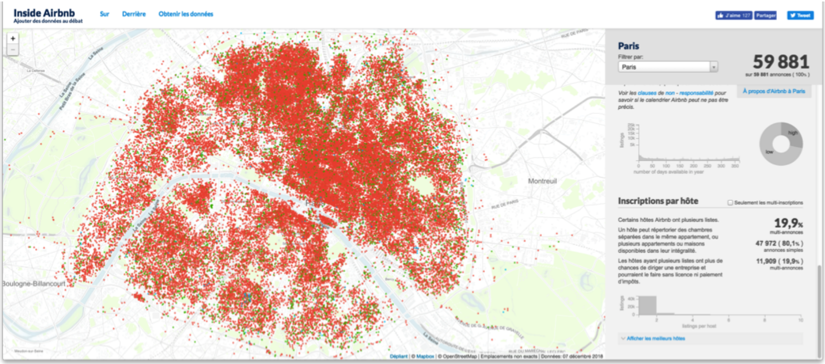
Fig. 1. Number of Airbnb listings and number of Airbnb listings per 1000 inhabitants in European cities.

Source: Adamiak (2018)

Airbnb in Europe



Airbnb in Paris

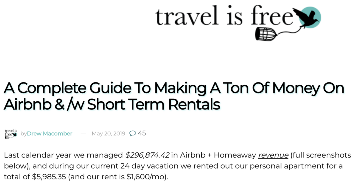


Source: Inside Airbnb

Introduction

The advocates (Lin, 2020):

- Additional income for homeowners
- Spread of tourism. The Association of Rural Mayors of France has joined forces with Airbnb to launch *les Campagnes d'Avenir* program in 2021, which aims to develop 15,000 tourist accommodations in rural France.
- Accommodations that fit tourists' budgets


travel is free

A Complete Guide To Making A Ton Of Money On Airbnb & /w Short Term Rentals

by Drew Macomber — May 20, 2019 45

Last calendar year we managed *$296,874.42* in Airbnb + Homeaway *revenue* (full screenshots below), and during our current 24 day vacation we rented out our personal apartment for a total of $5,985.35 (and our rent is $1,600/mo).


Les maires ruraux signent un accord avec Airbnb pour développer le potentiel touristique des campagnes

La plateforme de locations a annoncé un accord avec l'Association des maires ruraux de France (AMRF).

franceinfo avec AFP
France Télévisions

Publié le 18/02/2019 12:49 Mis à jour le 18/02/2019 13:03

Temps de lecture : 1 min.

Introduction

The opponents (Guttentag and Smith, 2017):

- Increased rents and housing prices
- Unfair competition with the hotel industry (Zervas et al., 2017)
- Socio-spatial problems such as commercial gentrification and displacement of residents in large metropolitan areas (Yrigoy, 2018)
- Negative externalities

REAL ESTATE

Airbnb is making rents in New York City spike as owners yank units off the market, study says

PUBLISHED WED, JAN 31 2018•8:44 PM EST | UPDATED THU, FEB 1 2018•7:27 AM EST

David Reid
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SHARE

Introduction

This opposition may be symptomatic of heterogeneous interests:

- STR activity is characterized by strong spatial heterogeneity
- Therefore it is also likely to have produced highly differentiated spatial effects depending on the territory

In France, the legislator gave municipalities the possibility of regulating the activity of STR according to their own interest:

- In France, municipalities can set obligations for STR owners, which can be light (registration number) or very heavy (rental against compensation)

Introduction

Various research projects for the Ministère de la Cohésion des Territoires et des Relations avec les Collectivités Territoriales

Participants:
- **Marie Breuillé** (CESAER, Researcher INRAE)
- **Julie Le Gallo** (CESAER, Prof Institut Agro Dijon)
- **Yacine Allam** (PhD student)
- **Kassoum Ayouba** (Researcher INRAE)
- **Camille Grivault** (INRAE, Research engineer)
- **Yuheng Ling** (post-doc)

Outline

Airbnb des villes et des champs à l'épreuve de la Covid-19

Airbnb in cities and rural areas in face of Covid-19

Y. Ling, Y. Allam, M. Breuillé, C. Grivault, J. Le Gallo

Introduction

Objectives is to understand:

- The determinants of STR supply at the municipal level throughout metropolitan France
- The spatial differentiation according to the INSEE's zoning in attraction areas of cities
- The temporal differentiation through the different episodes of the Covid-19 crisis
- The interaction between these two dimensions
- First large-scale study

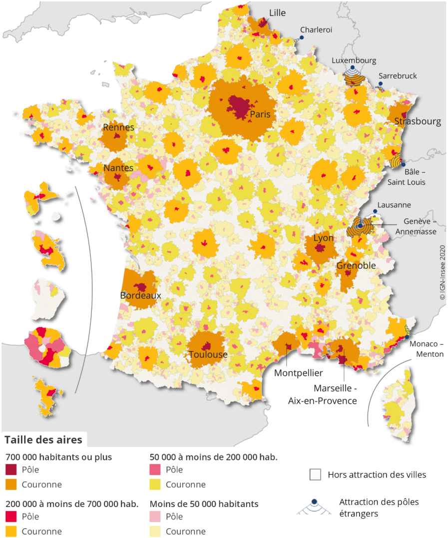
AirDNA: Data on STR

- Content: STR on Airbnb and HomeAway
- Period: January 2016 - December 2022
- Scope: Metropolitan France, 34873 municipalities
- Variables : Number of listings, Occupation Rate, Average Daily Rate
- For each variable, distinction single room/Entire apt, prof/non prof
- Comment: Data with a geolocation error of 150 meters

INSEE: Socio-economic data

- Content: key variables of the population census (population, jobs, surface area, position on the urban-rural gradient, individual/collective dwellings, share of owners/renters, vacant dwellings/second homes/main homes, low-income housing/private housing)
- Period: 2019
- Scope: Metropolitan France

Zonage en aires d'attraction des villes



INSEE / Tripadvisor: Touristic amenities

- Content: classification of the commune as a coastal or mountain area, ski resort, capacity of tourist reception, points of tourist interest and number of reviews on the Tripadvisor platform
- Period: 2019
- Scope: Metropolitan France

IGN: Accessibility

- Content: distance to the nearest train station, distance to the nearest high-speed train station, distance to Paris by road and high-speed train, distance to the nearest amenities
- Period: 2019
- Scope: Metropolitan France

Data and Descriptive Statistics

Data (3/3)

Santé Public France: Covid waves

- Content: monthly number of hospitalizations, admissions to intensive care and deaths by department
- Period: 2020-2022
- Scope: Metropolitan France

Covid waves

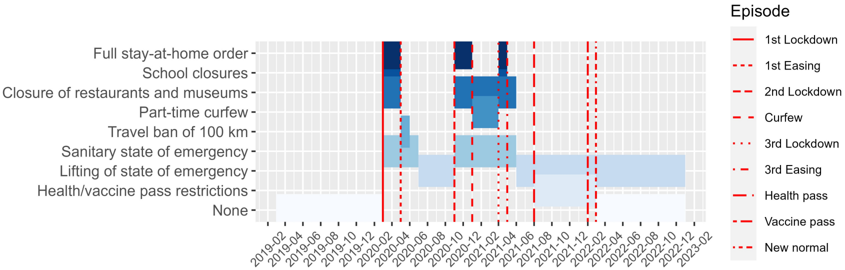


Figure: Evolution of the restriction measures introduced by the French government

Data and Descriptive Statistics

Descriptive Statistics (1/9)

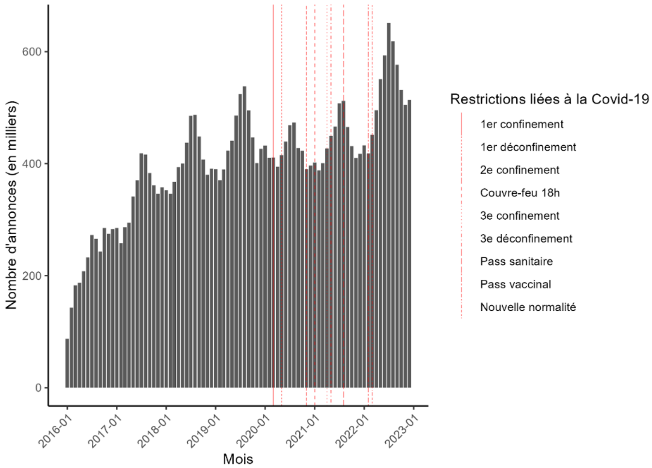
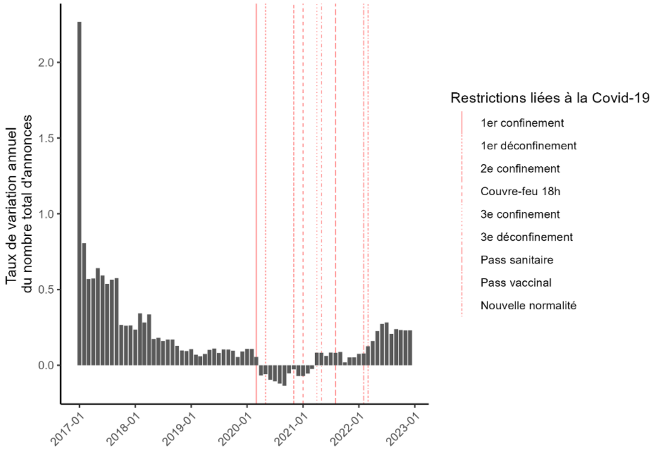


Figure: Evolution of the number of listings

The slowdown due to the Covid-19 crisis is much more marked when considering the evolution over a sliding year.



Data and Descriptive Statistics

Descriptive Statistics (3/9)

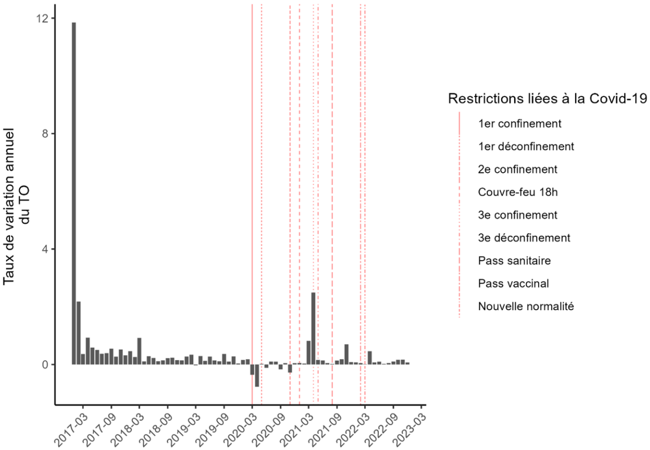


Figure: Evolution of the occupancy rate (1 sliding year)

Data and Descriptive Statistics

Descriptive Statistics (4/9)

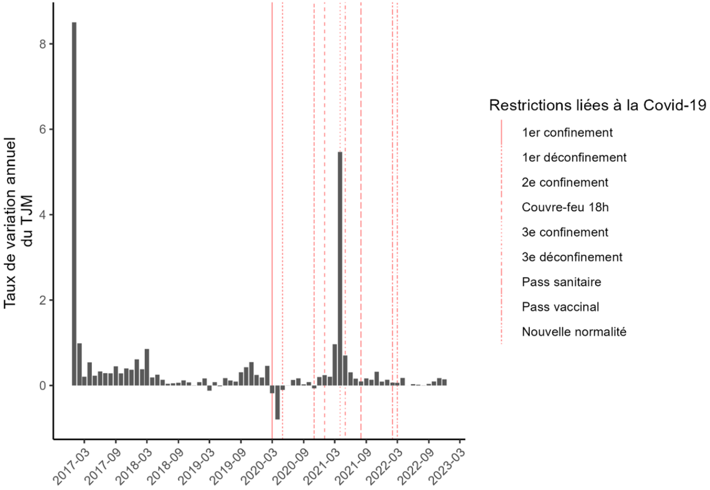


Figure: Evolution of the average daily rate (1 sliding year)

Data and Descriptive Statistics

Descriptive Statistics (5/9)

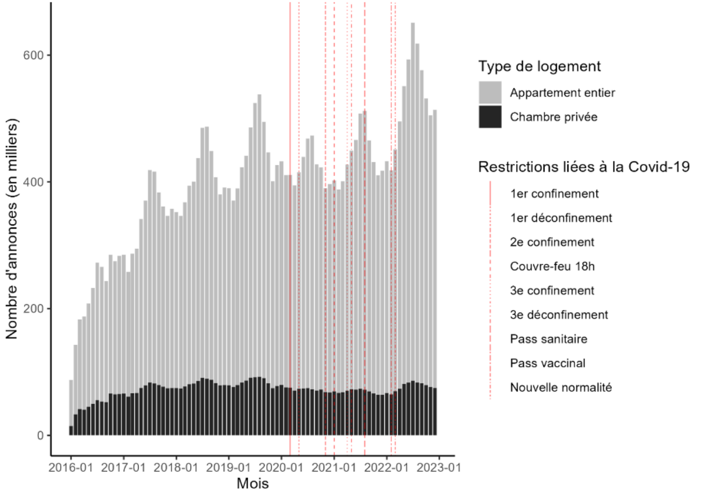


Figure: Evolution of the number of listings according to type of housing

Data and Descriptive Statistics

Descriptive Statistics (6/9)

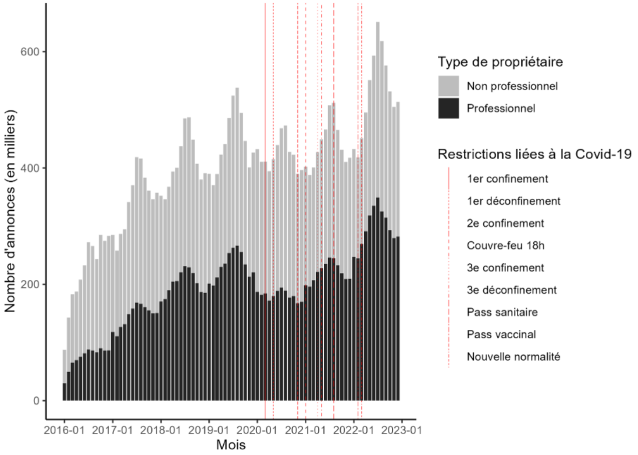


Figure: Evolution of the number of listings according to type of announcer

Data and Descriptive Statistics

Descriptive Statistics (7/9)

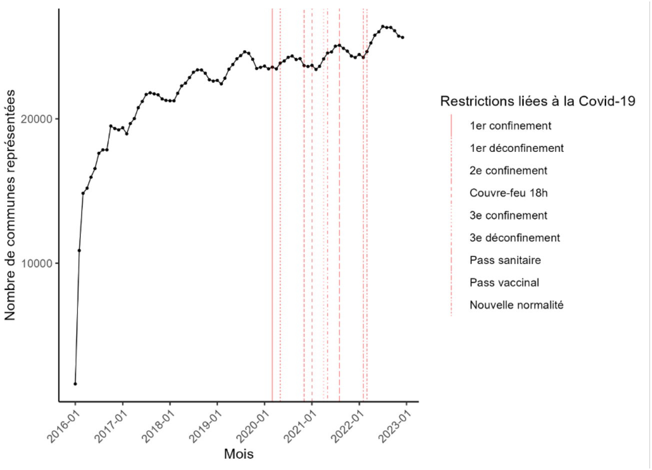
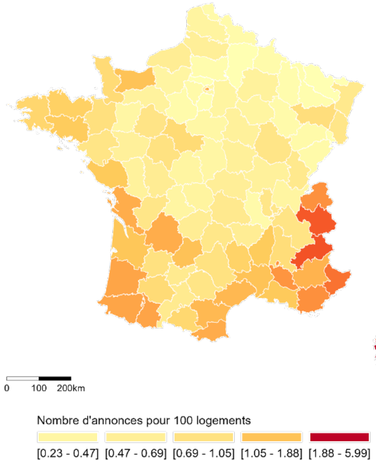


Figure: Number of municipalities with at least one listing per month over the 2016-2022 period

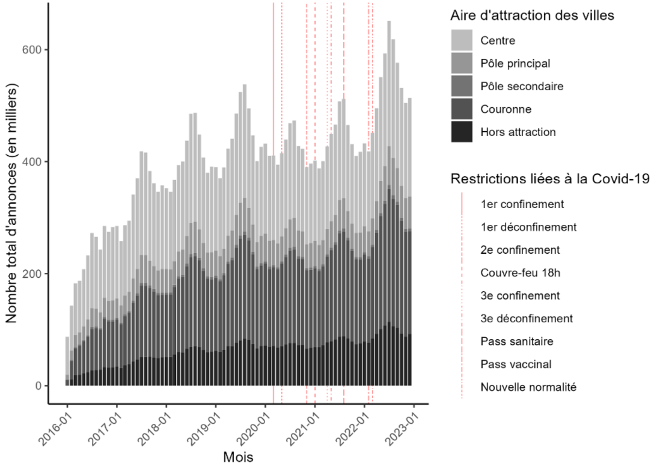
Data and Descriptive Statistics

Descriptive Statistics (8/9)

Although STR cover 70% of French municipalities, the phenomenon does not affect the territory with the same intensity.



Spatial heterogeneity also affects the typology of municipalities by city area of attraction.



Empirical Model

Semi-parametric models (1/2)

Specification, nested-model design:

$$\log\left(y_{it}\right) = \alpha + \beta_{\text{trend}}\, t + m_i' \beta_{\text{month}} + c_i' \beta_{\text{covid}} + ZAAV_i' \beta_{ZAAV} + x_{it}' \delta +$$
$$R \times t + \gamma_{ZAAV,c} + \mu_{it}$$
$$\mu_{it} = \rho \mu_{it-1} + \varepsilon_{it}$$

$i = 1, ...34878$ and $t = 1, ..., 84$ (Jan 2016 to Dec 2022)

Dependent Variables, Nb of listings:

	Mean	St.Dev	Min	Max	Nb Obs.
Nb total monthly listings	11	96,1	0	10 206	2 9297 332
Nb listings (Entire Apartment)	9	85,4	0	9 247	2 9297 332
Nb listings (Private Room)	2	13,4	0	1 635	2 9297 332
Nb professional listings	6	49,7	0	5 730	2 9297 332
Nb non-professional listings	6	48,7	0	5 010	2 9297 332

Empirical Model

Semi-parametric models (2/4)

Fixed effects:

- General temporal trends for all municipalities: $\beta_{\text{trend}}\, t$
- Monthly dummy (Reference group: January): $m_i' \beta_{\text{mois}}$
- Covid-episode dummy (Reference group: Pre-Covid period): $c_i' \beta_{\text{covid}}$
  1. 1st lockdown (17 March to 10 May 2020);
  2. 1st easing restrictions (11 May to 29 Oct. 2020);
  3. 2nd lockdown (30 Oct. to 14 Dec. 2020);
  4. Curfew 6pm (15th Dec. 2020 to 2nd April 2021)
  5. 3rd lockdown (3 April to 2 May 2021)
  6. 3rd easing restrictions (3 May to 8 August 2021)
  7. Sanitary pass (9 August 2021 to 23 January 2022)
  8. Vaccinal pass (24 January 2022 to 13 March 2023)
  9. New normal: no restrictions (from 14 March 2023)
- Municipality category dummy (Reference group: Center): $ZAAV_i' \beta_{ZAAV}$
  1. Main pole;
  2. Secondary pole;
  3. "Couronne";
  4. "Hors attraction des villes"

Empirical Model

Semi-parametric models (3/4)

Random effects:

- Specific trend for each region: $R \times t$, multivariate normal $(0,\sigma_R)$
- Category-period interaction $\gamma_{ZAAV,c}$, multivariate normal $(0,\sigma_{ZAAV,c})$
- AR1 process for each municipality over time: μ_{it}
- Idiosyncratic error: ε_{it}

Note:

- Random slope: $(\beta_{\text{trend}} + R) \times t$ (Bernardelli et al., 1995)
- Estimation: Restricted Maximum Likelihood (REML) (Wood, 2011)

Covariates $x'_{it}\delta$ (selected by post-lasso)

Dependent Variables	**Mean**	**St.Dev**	**Min**	**Max**
Surface (ha)	15.60	16.97	0.04	758.93
Nb ordinary dwellings	1 012.38	4 925.71	0	296 478
Nb second homes	99.38	622.53	0	33 526
Proportion vacant dwellings	8.69	4.71	0	100
Proportion apartments	8.90	13.50	0	98.75
Annual Temperature	10.98	1.39	0.13	16.30
Mean Temperature	12.81	6.01	- 1.19	26
Nb raining days in July	7.66	1.67	0.07	12.40
Coastal municipality	0.03	0.17	0	1
Municipality with ski stations	0.01	0.10	0	1
Tourism rate index	72.01	185.59	0	9 755.25
Nb TripAdvisor reviews (Radius 20km)	14 450.32	94 499.86	0	1 223 965
Nb school holidays	0.92	0.96	0	4
Nb public holidays	0.918	0.963	0	4
Distance to the nearest TGV station	57.42	54.71	1.04	587.77
Distance to Paris (TGV + road)	207.68	108.67	4.11	912.27
New Covid-19 cases in hospitals	1 836.54	3 04426	0	13 3034

Results

Table (1/4)

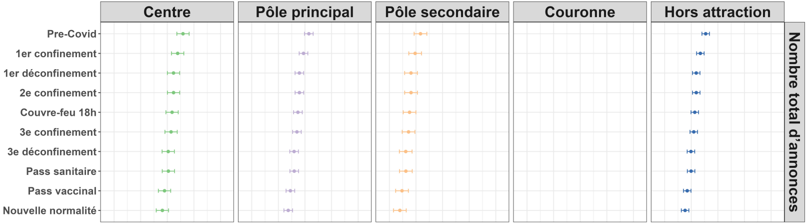
Tableau 4a. Résultats d'estimation ; nombre total de listings

Variable dépendante	**Nombre total de listings (en log)**	**Nombre d'annonces de professionnels (log)**	**Nombre d'annonces de particuliers (log)**
A. Coefficients paramétriques			
Episodes de la crise sanitaire			
Premier confinement	-0.1003 ***	-0.0752 ***	-0.0657 ***
Premier déconfinement	-0.1780 ***	-0.1241 ***	-0.1239 ***
Deuxième confinement	-0.1773 ***	-0.1372 ***	-0.1241 ***
Couvre-feu 18h	-0.2053 ***	-0.1100 ***	-0.1788 ***
Troisième confinement	-0.2239 ***	-0.1103 ***	-0.1953 ***
Troisième déconfinement	-0.2771 ***	-0.1415 ***	-0.2314 ***
Pass sanitaire	-0.2744 ***	-0.1429 ***	-0.2281 ***
Pass vaccinal	-0.3470 ***	-0.1796 ***	-0.2876 ***
Nouvelle normalité	-0.3872 ***	-0.1966 ***	-0.3159 ***
Zonage en aire d'attraction			
Pôle principal	-0.2215 ***	-0.3564 ***	-0.1890 ***
Pôle secondaire	-0.7102 ***	-0.7131 ***	-0.7053 ***
Couronne	-0.5086 ***	-0.6012 ***	-0.4248 ***
Hors attraction	-0.5236 ***	-0.6064 ***	-0.4349 ***

Results

Table (2/4) and Figure (1/1)

B. Termes aléatoires			
Episodes crise sanitaire*Centre	0.1450***	0.1870***	0.1102***
Episodes crise sanitaire *Pôle principal	0.0602***	0.0848***	0.0532***
Episodes crise sanitaire *Pôle secondaire	0.1089***	0.1765***	0.0027
Episodes crise sanitaire *Couronne	0.0016	0.0061***	0.0021
Episodes crise sanitaire *Hors attraction	0.0072***	0.0009	0.0095***
Variables de contrôle	OUI	OUI	OUI
Score fREML	-28,531 ***	-412,413***	-20,092***
Nombre d'observations	2,929,332	2,929,332	2,929,332



Results

Table (3/4)

Tableau 4b. Résultats d'estimation ; taux d'occupation

Variable dépendante	**TO moyen**	**TO pour les annonces de professionnels**	**TO pour les annonces de particuliers**
A. Coefficients paramétriques			
Episodes de la crise sanitaire			
Premier confinement	-1.0033 ***	-0.8424 ***	-1.0687 ***
Premier déconfinement	-0.1024 ***	-0.1207 ***	-0.0078
Deuxième confinement	-0.1699 ***	-0.2148 ***	-0.0815 ***
Couvre-feu 18h	0.0203	-0.0323	0.0319
Troisième confinement	-0.3717 ***	-0.4018 ***	-0.3561 ***
Troisième déconfinement	-0.2931 ***	-0.2847 ***	-0.2379 ***
Pass sanitaire	-0.1839 ***	-0.1924 ***	-0.1481 ***
Pass vaccinal	-0.2757 ***	-0.2661 ***	-0.2659 ***
Nouvelle normalité	-0.5326 ***	-0.5097 ***	-0.5008 ***
Zonage en aire d'attraction			
Pôle principal	0.0834	0.1516 **	0.0078
Pôle secondaire	-0.0461	-0.1610	-0.1706
Couronne	0.0111	0.0201	-0.0706
Hors attraction	-0.0674	-0.0504	-0.1190 *

Results
Table (4/4)

Tableau 4c. Résultats d'estimation ; taux journalier moyen

Variable dépendante	**TJM moyen**	**TJM pour les annonces de professionnels**	**TJM pour les annonces de particuliers**
A. Coefficients paramétriques			
Episodes de la crise sanitaire			
Premier confinement	-0.8257 ***	-0.7920 ***	-0.7456 ***
Premier déconfinement	-0.1690 ***	-0.4871 ***	-0.1277 ***
Deuxième confinement	-0.1347 ***	-0.4124 ***	-0.0997 ***
Couvre-feu 18h	-0.0540 ***	-0.2646 ***	-0.0904 ***
Troisième confinement	-0.1496 ***	-0.3020 ***	-0.2502 ***
Troisième déconfinement	-0.3799 ***	-0.4502 ***	-0.3514 ***
Pass sanitaire	-0.2633 ***	-0.3992 ***	-0.2442 ***
Pass vaccinal	-0.4134 ***	-0.4093 ***	-0.4126 ***
Nouvelle normalité	-0.6535 ***	-0.5473 ***	-0.5898 ***
Zonage en aire d'attraction			
Pôle principal	0.3560 ***	0.2546 ***	0.2494 ***
Pôle secondaire	-0.2016 *	-0.4589 ***	-0.3952 ***
Couronne	0.2393 ***	0.0336	-0.0107
Hors attraction	0.1799 ***	-0.0175	-0.0514

Conclusion

Temporally:

- STRs increased sharply across France between 2016 and 2018 before experiencing stagnation due to the Covid-19 pandemic.
- Stronger effects during the first lock-down
- Not all types of ST experienced the same stagnation in terms of the total number of STRs, OR and ADR.

Spatially:

- There was a strong heterogeneity in the magnitude of the Covid-19 pandemic on the total number of STRs.
- The central municipalities and principal poles were more affected by various restrictions to limit the spread of Covid-19.
- Municipalities located in the "Couronne" or non-attractive areas were less affected by the pandemic.

Conclusion

Determinants:

- The number of STRs was mainly determined by natural and tourist variables. Coastal municipalities, the presence of ski stations, and the average annual temperature were positively correlated with the total number of STRs (respectively $+112\%$, $+92\%$, and $+10\%$).
- The number of raining days in July (-51%) and the proportion of vacant dwellings (-92%) were negatively correlated with the total number of STRs.

From COVID-19 to "new normal" Revisiting Parisian STR markets and their dynamics

Where are Parisian Airbnb located? A multivariate log-Gaussian Cox process approach

Y. Ling, M. Breuillé, J. Le Gallo

Exploratory spatial lattice data analysis

- **Objective**: Space-time dynamics of STR listings and their booking and revenue performance before, during and after the COVID-19 pandemic in Paris
  - Evolution of the spatial clusters of STR in Paris? Differences between segments?
  - Has the STR market in Paris recovered from the pandemic?
- **Data**: 1,258,710 listings in Paris from 03.2019 to 12.2022 (AirDnA) with entire homes/private rooms and prof/non prof. Aggregation at the IRIS level
- **Method**: Global and local spatial autocorrelation statistics, Markov LISA

Evolution

Figure: Nb of listings, occupancy and ADR

Global Moran's I statistic

Global Moran's I statistic:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x}^2)}$$

where x_i is the observed value for area i, $\bar{x}$ is the observed value, w_{ij} is an element of spatial weight matrix (first-order contiguity).

Interpretation : Positive global spatial autocorrelation if $I > -1/(n-1)$, negative spatial autocorrelation if $I < -1/(n-1)$.
Inference by permutation.

Evolution of Moran's I statistic

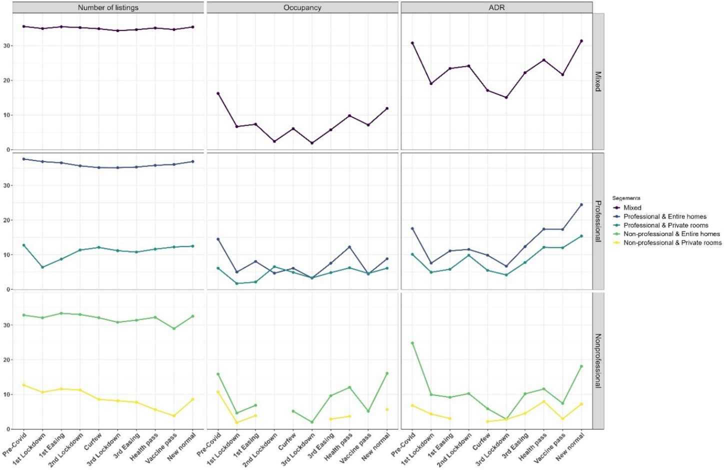


Figure: Evolution of Moran's I

Local spatial autocorrelation statistics

Moran scatterplot : decomposition of global spatial autocorrelation into four categories: High-High (HH, high values surrounded by high values), Low-Low (LL, low values surrounded by low values), High-Low (HL, high values surrounded by low values) and Low-High (LH, low values surrounded by high values).

LISA (for row-standardized matrix):

$$I = \frac{(x_i - \bar{x}) \sum_j w_{ij}(x_i - \bar{x})}{\sum_i (x_i - \bar{x}^2)}$$

Interpretation : Positive local spatial autocorrelation if $I_i > 0$, negative spatial local autocorrelation if $I_i < 0$.
Inference by conditional permutation with Bonferroni correction for multiple comparison, at most 7 comparisons.

Local Moran's I, nb of listings (1/2)

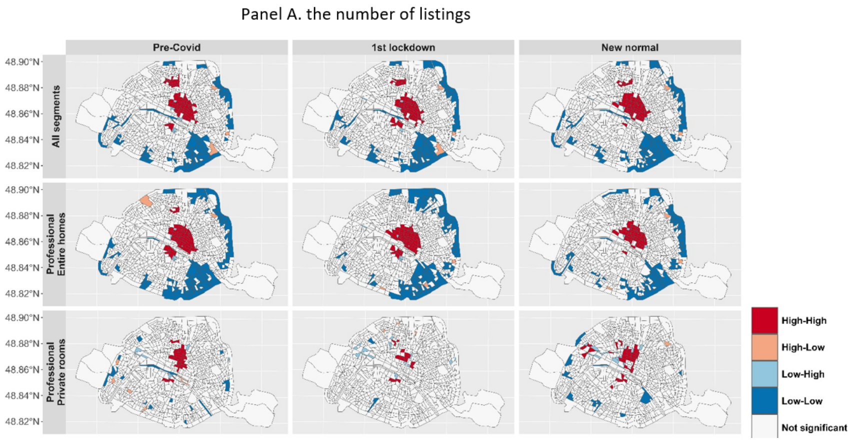


Figure: LISA, nb of listings

Local Moran's I, nb of listings (2/2)

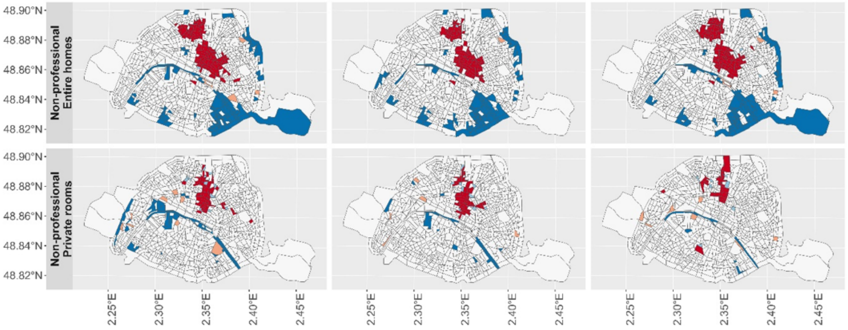


Figure: LISA, nb of listings

Local Moran's *I*, Occupancy and ADR

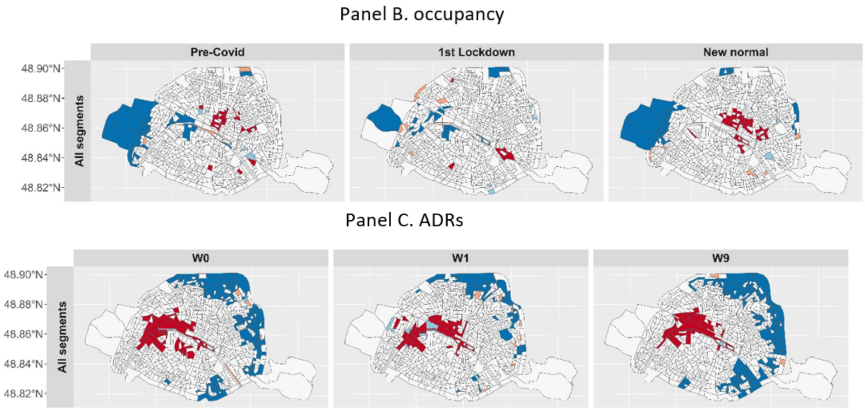


Figure: LISA, occupancy rate and ADR

Transition probabilities heatmap

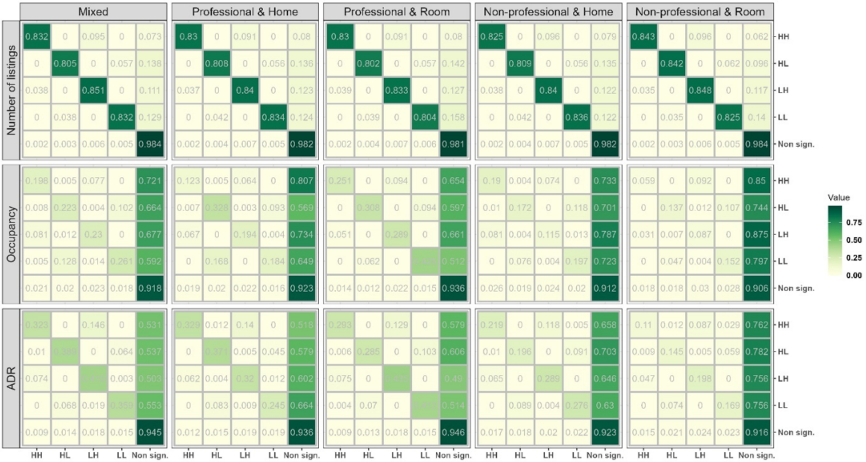


Figure: Transition probabilities heatmap

Where are Parisian Airbnb located? A log-Gaussian Cox process approach

The spatial location of Airbnb listings is generated by a two-dimensional point process.

Aims

- Identifying the determinants that explain Airbnb listings' location patterns.

Methods

- Exploratory spatial point pattern data analysis (ESDA): K function; L function, etc.
- Regression analysis: log-Gaussian Cox process models

Marks of points

- Houses including townhouses and houses
- Unique experience including barns, boat houses, dome houses, tree houses, castles, caves etc.
- Secondary residence including guest houses, guest suites and in-laws
- Flats by budget category (cheap, middle-end, high-end and luxury)

Table: Numbers of points per listing type

Type	Number of observations
House	902
Secondary residence	147
Unique experience	164
Cheap flats	15632
Middle-end flats	14124
High-end flats	10043
Luxury flats	7814

ESDA

Location (1/3)

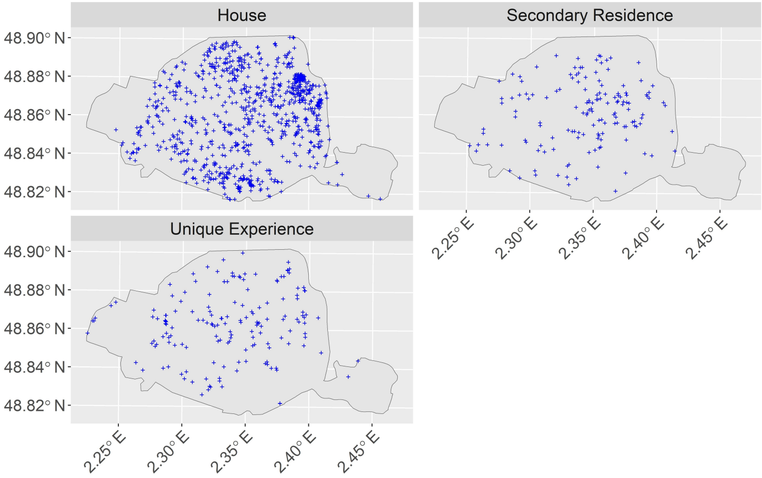


Figure: Locations of Airbnb listings (non-flat types)

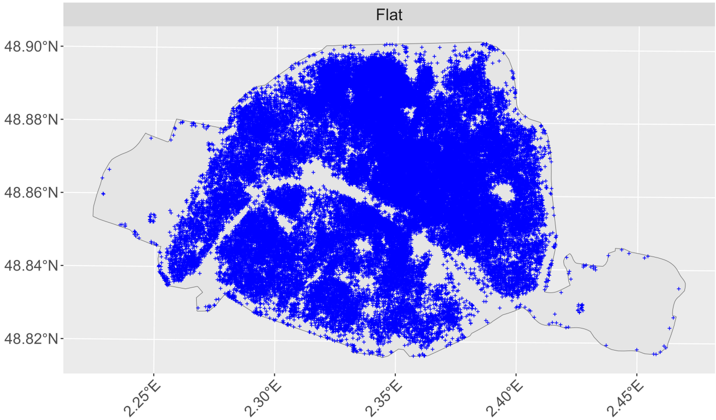


Figure: Locations of Airbnb listings (All flats mixed)

ESDA

Location (3/3)

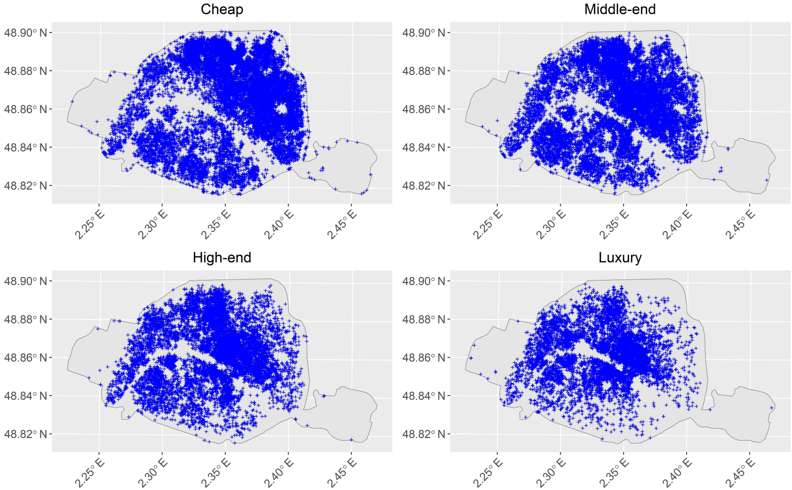


Figure: Locations of Airbnb listings per flat type

Quadrat counts

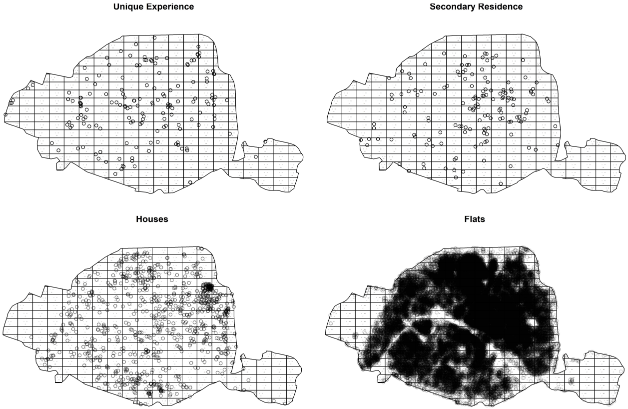


Figure: Quadrat counts Tests (Non-flat types)

ESDA

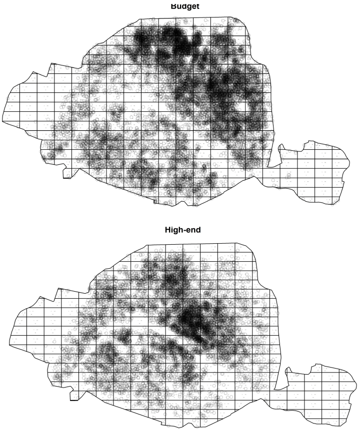


Figure: Quadrat counts Tests (Flat types)

ESDA

Monte Carlo test of complete spatial randomness (CRS) using quadrat counts

- Null Hypothesis (H0) = Airbnb listings are randomly distributed.
- Alternative Hypothesis (H1) = Airbnb listings are not randomly distributed.

	χ^2	**P-value**	**Pattern**
House	1765	0.002	$\chi^2 > 1$ Clustering
Secondary Residence	450.54	0.008	$\chi^2 > 1$ Clustering
Unique Experience	377.33	0.024	$\chi^2 > 1$ Clustering
Cheap Flats	19738	0.002	$\chi^2 > 1$ Clustering
Middle-end	18408	0.002	$\chi^2 > 1$ Clustering
High-end	17462	0.002	$\chi^2 > 1$ Clustering
Luxury	21312	0.002	$\chi^2 > 1$ Clustering

ESDA

Nearest Neighbour Analysis using Clark and Evans Test

- Null Hypothesis (H0) = Airbnb listings are randomly distributed.
- Alternative Hypothesis (H1) = Airbnb listings are not randomly distributed.

	Nearest Neighbour Index	P-value	Pattern
House	0.7558	0.002	Clustering
Secondary Residence	0.757	0.002	Clustering
Unique Experience	0.724	0.002	Clustering
Cheap Flats	0.768	0.02	Clustering
Middle-end	0.766	0.02	Clustering
High-end	0.735	0.02	Clustering
Luxury	0.681	0.02	Clustering

K function

$$K(r) = \lambda^{-1} E[\text{nb of extra events within distance r of a randomly chosen event}] \quad (1)$$

Hypothesis: point process exhibits CSR i.e. it follows a homogeneous Poisson process with $K(r) = r^2$
Estimator:

$$\hat{K}(r) = \hat{\lambda}^{-1} \sum_i \sum_{j \neq i} w(l_i, l_j)^{-1} \frac{I(d_{ij} < r)}{N} \quad (2)$$

where d_{ij} is the distance between the ith and jth points, and $I(x)$ is the indicator function with 1 if x is true and 0 otherwise. The edge correction is given by the weight function $w(l_i, l_j)$.
L function
Lest computes a transformation $L(r) = \sqrt{K(r)/\pi}$ which transforms the Poisson K function to the straight line $L_{Pois}(r) = r$

K function tests

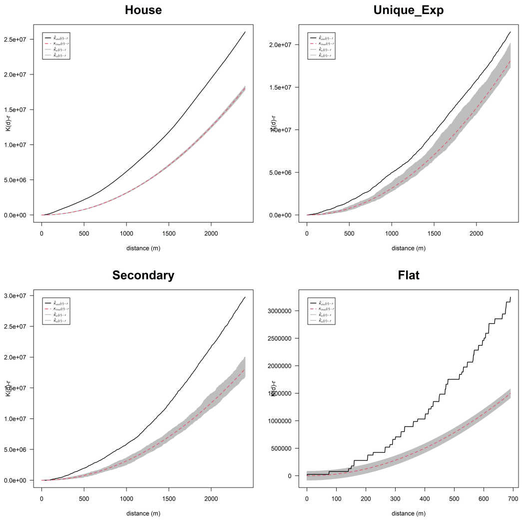


Figure: K function with envelope

K function tests

K functions for different flats

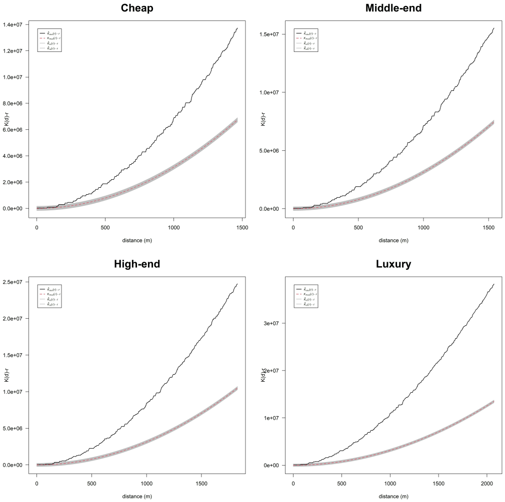


Figure: K function with envelope for different types of flats

L function tests

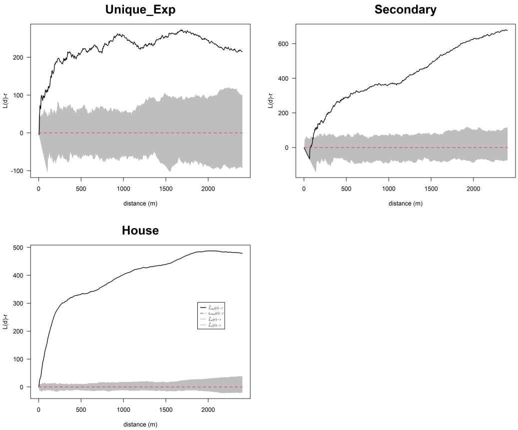


Figure: L function with envelope

Kernel Density Estimation

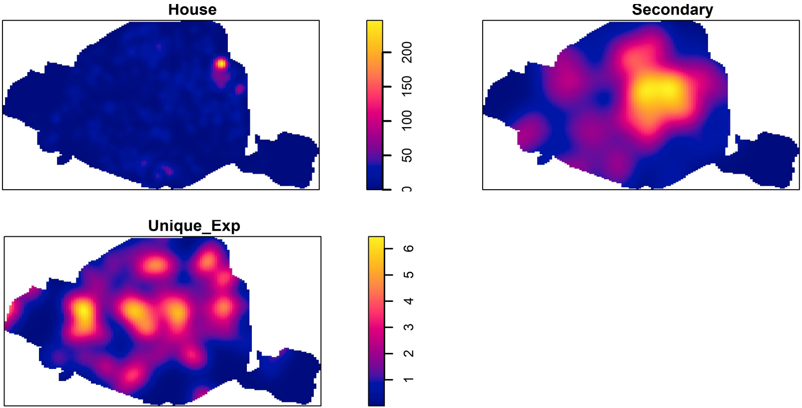


Figure: Kernel density estimation (1/2)

Kernel Density Estimation

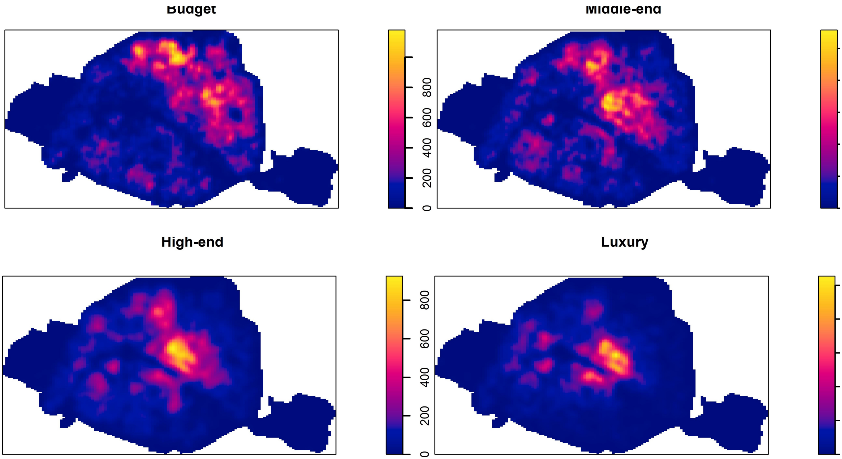


Figure: Kernel density estimation (2/2)

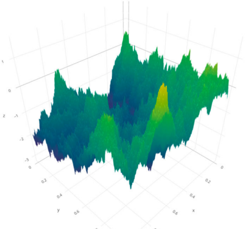
Log-Gaussian Cox process models

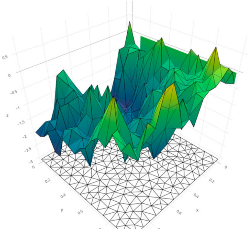
- Spatial point process (denoted $\boldsymbol{X}$): generates a random set of events (points) in space. The process is characterized by its intensity function $\lambda(u)$: local mean number of events per unit area at any point in space $\mathbb{R}^2$.
- *Poisson process*: Two properties: 1) The number of events in any region $\boldsymbol{D}$ follows a Poisson distribution with mean $\int_D \lambda(u)d(u)$; 2) Given the number of events in $\boldsymbol{D}$, those events are i.i.d. with probability density $\lambda(u)/\int_D \lambda(u)d(u)$.
- *Cox process*: generalization of the Poisson process with the intensity function as a realization of another stochastic process. In situations where the intensity function is less structured but exhibits spatial autocorrelation, the Cox process can incorporate a geostatistical process, i.e., log-Gaussian Cox process (LGCP), which uses a log-linear model for the intensity:

$$log\lambda(u) = X\beta + \omega(u), \text{with } \omega(u) \sim GP(0, \tau\Sigma) \tag{3}$$

The SPDE approach

- For GPs with a Matérn covariance function, a Gaussian Markov random field (GMRF) approximation can simplify computation, requiring only a sparse covariance structure.
- The GMRF approximation (Lindgren et al. 2011) is motivated by the fact that Gaussian fields with Matérn covariances are solutions to the stochastic partial differential equation (SPDE) below:
  $\tau \left(\kappa^2 - \Delta\right)^{\alpha/2} \omega(u) = \mathbf{W}(u), \quad u \in \mathbb{R}^d, \kappa > 0, \quad \alpha = v + d/2, \quad v > 0$
- The core of the SPDE approach is the finite-element GMRF representation of the GP.





Covariates of the local context, Iris level

- Tourism attraction density
- Urban green space density
- Shop density
- Supermarket density
- Convenient shop density
- Hotel density
- Restaurant density
- Mean income (in thousands)
- % of foreigners
- Dwelling density
- Density of existing houses
- Intensity of bus stops

Distance-based covariate

- Distance to the nearest metro station

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	**sd**	**0.025 quantile**	**0.975 quantile**
(Intercept)	-7,143	0,234	-7,602	-6,684
Tourism attraction density nb/surface	0,781	0,653	-0,5	2,061
Urban Green space density (nb/surface)	-0,134	0,689	-1,485	1,217
Shop density (nb/surface)	0,048	0,034	-0,019	0,114
Supermarket density (nb/surface)	-0,851	0,678	-2,18	0,478
Convenient shop density (nb/surface)	-0,111	0,18	-0,463	0,241
Hotel density (nb/surface)	-0,546	0,361	-1,252	0,161
Restaurant density (nb/surface)	-0,006	0,051	-0,105	0,093
Median Income in k	0,018	0,01	-0,002	0,039
Pct of foreigners	-3,944	1,407	-6,702	-1,185
Dwelling density (nb/surface)	0,004	0,001	0,002	0,006
Bus stop density	-0,054	0,358	-0,756	0,647
Distance to the nearest metro station	0,00007	0,00016	0,00003	0,00067
Range	1825	401	1197	2772
Stdev	0,956	0,136	0,721	1,26

Preliminary Results

Visualization of Gaussian random field

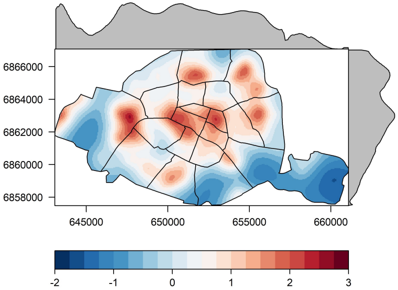


Figure: Summary (Posterior Mean) of the $\omega(u)$

Preliminary Results

Mark: Secondary residence

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	**sd**	**0.025 quantile**	**0.975 quantile**
(Intercept)	-6,944	0,265	-7,464	-6,424
Tourism attraction density nb/surface	0,813	0,596	-0,354	1,981
Urban Green space density (nb/surface)	-0,395	0,729	-1,823	1,033
Shop density (nb/surface)	0,03	0,028	-0,025	0,084
Supermarket density (nb/surface)	-0,177	0,537	-1,23	0,876
Convenient shop density (nb/surface)	-0,002	0,141	-0,278	0,274
Hotel density (nb/surface)	-0,013	0,264	-0,53	0,505
Restaurant density (nb/surface)	0,058	0,036	-0,012	0,129
Median Income in k	0,009	0,01	-0,011	0,03
Pct of foreigners	-1,997	1,603	-5,138	1,144
Dwelling density (nb/surface)	0,003	0,001	0,001	0,006
Bus stop density	-0,373	0,359	-1,077	0,331
Distance to the nearest metro station	-0,0015	0,0005	-0,0027	-0,0004
Range	2847	1729	931	7430
Stdev	0,479	0,134	0,261	0,786

Preliminary Results

Visualization of Gaussian random field

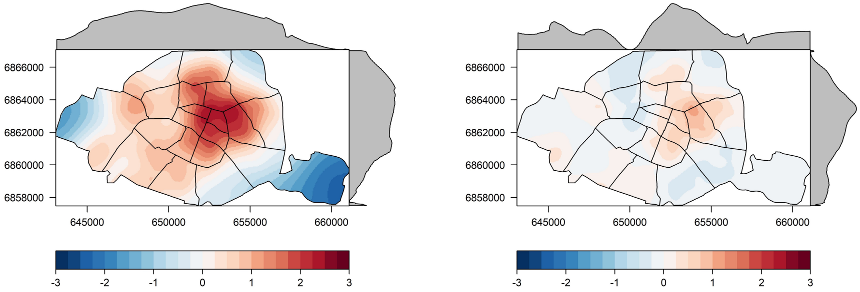


Figure: Summary (Posterior Mean) of $\omega(u)$

Preliminary Results

Mark: Houses

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	**sd**	**0.025 quantile**	**0.975 quantile**
(Intercept)	-6,71	0,157	-7,018	-6,403
Tourism attraction density nb/surface	-0,312	0,392	-1,081	0,457
Urban Green space density (nb/surface)	-0,156	0,307	-0,758	0,446
Shop density (nb/surface)	-0,061	0,02	-0,101	-0,021
Supermarket density (nb/surface)	0,464	0,251	-0,028	0,956
Convenient shop density (nb/surface)	-0,07	0,078	-0,223	0,082
Hotel density (nb/surface)	0,154	0,143	-0,127	0,435
Restaurant density (nb/surface)	0,047	0,024	0,0004	0,094
Median Income in k	0,03	0,006	0,018	0,041
Pct of foreigners	0,423	0,574	-0,701	1,547
Dwelling density (nb/surface)	0,005	0,001	0,003	0,006
Bus stop density	-0,5	0,168	-0,83	-0,17
Distance to the nearest metro station	-0,00067	0,0002	-0,001	-0,0003
Range	1904	312	1392	2619
Stdev	0,828	0,09	0,672	1,02

Preliminary Results

Visualization of Gaussian random field

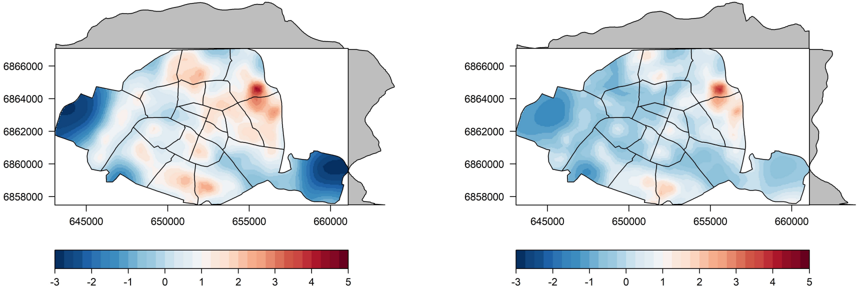


Figure: Summary (Posterior Mean) of $\omega(u)$

Preliminary Results

Mark: Flat, budget

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	sd	0.025 quantile	0.975 quantile
(Intercept)	-5,046	0,1	-5,241	-4,851
Tourism attraction density nb/surface	0,612	0,122	0,374	0,851
Urban Green space density (nb/surface)	0,051	0,097	-0,138	0,241
Shop density (nb/surface)	0,016	0,007	0,002	0,029
Supermarket density (nb/surface)	0,047	0,07	-0,09	0,184
Convenient shop density (nb/surface)	0,054	0,02	0,015	0,092
Hotel density (nb/surface)	0,228	0,048	0,134	0,322
Restaurant density (nb/surface)	-0,017	0,008	-0,032	-0,002
Median Income in k	0,005	0,002	0,001	0,01
Pct of foreigners	-0,846	0,242	-1,321	-0,371
Dwelling density (nb/surface)	0,005	0	0,004	0,005
Bus stop density	0,047	0,05	-0,051	0,146
Distance to the nearest metro station	-0,001	0,0001	-0,0011	-0,00072
Range	1790	207	1435	2253
Stdev	0,872	0,072	0,745	1,03

Preliminary Results

Visualization of Gaussian random field

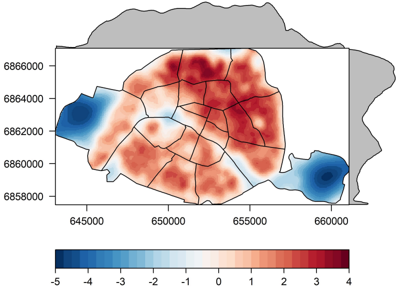


Figure: Summary (Posterior Mean) of $\omega(u)$

Preliminary Results

Mark: Flat, middle end

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	sd	0.025 quantile	0.975 quantile
(Intercept)	-5,451	0,172	-5,788	-5,114
Tourism attraction density nb/surface	0,249	0,103	0,046	0,451
Urban Green space density (nb/surface)	0,164	0,101	-0,033	0,362
Shop density (nb/surface)	0,032	0,006	0,021	0,044
Supermarket density (nb/surface)	-0,053	0,073	-0,195	0,089
Convenient shop density (nb/surface)	0,066	0,02	0,027	0,105
Hotel density (nb/surface)	0,355	0,043	0,27	0,44
Restaurant density (nb/surface)	-0,026	0,007	-0,04	-0,012
Median Income in k	0,01	0,002	0,006	0,014
Pct of foreigners	-1,388	0,264	-1,906	-0,871
Dwelling density (nb/surface)	0,004	000007	0,004	0,005
Bus stop density	-0,001	0,049	-0,097	0,095
Distance to the nearest metro station	-0,0006	0,0001	-0,0008	-0,0004
Range	2714	483	1910	3819
Stdev	1,18	0,164	0,894	1,54

Preliminary Results

Visualization of Gaussian random field

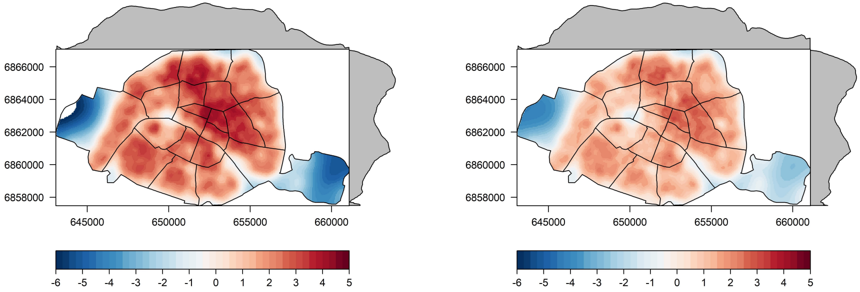


Figure: Summary (Posterior Mean) of $\omega(u)$

Preliminary Results

Mark: Flat, high end

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	**sd**	**0.025 quantile**	**0.975 quantile**
(Intercept)	-5,993	0,085	-6,159	-5,827
Tourism attraction density nb/surface)	-0,408	0,125	-0,654	-0,163
Urban Green space density (nb/surface)	-0,11	0,128	-0,361	0,14
Shop density (nb/surface)	0,037	0,007	0,024	0,05
Supermarket density (nb/surface)	0,467	0,105	0,262	0,672
Convenient shop density (nb/surface)	0,341	0,028	0,286	0,396
Hotel density (nb/surface)	0,403	0,051	0,303	0,503
Restaurant density (nb/surface)	0,012	0,008	-0,004	0,027
Median Income in k	0,016	0,003	0,011	0,021
Pct of foreigners	0,216	0,312	-0,397	0,828
Dwelling density (nb/surface)	0,31	0,031	0,25	0,371
Bus stop density	-0,045	0,062	-0,167	0,077
Distance to the nearest metro station	-0,00039	0,00014	-0,00068	-0,0001
Range	3140	625	2165	4625
Stdev	1,4	0,208	1,06	1,88

Preliminary Results

Visualization of Gaussian random field

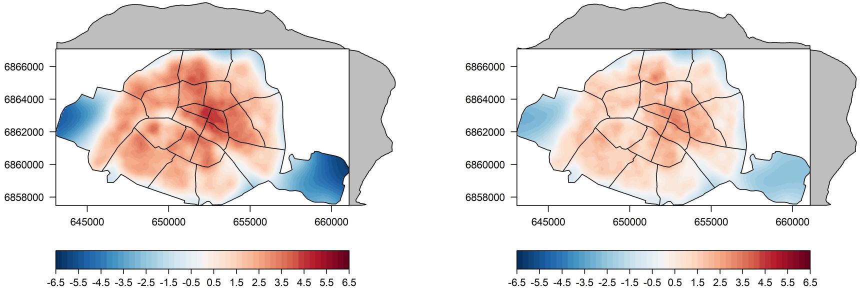


Figure: Summary (Posterior Mean) of $\omega(u)$

Preliminary Results

Mark: Luxury

Table: Posterior estimates (mean, standard deviation and quantiles) of the covariate coefficients β

	mean	**sd**	**0.025 quantile**	**0.975 quantile**
(Intercept)	-6,2	0,24	-6,67	-5,729
Tourism attraction density nb/surface	0,007	0,121	-0,23	0,244
Urban Green space density (nb/surface)	-0,3	0,151	-0,596	-0,005
Shop density (nb/surface)	0,066	0,007	0,053	0,079
Supermarket density (nb/surface)	0,422	0,115	0,197	0,648
Convenient shop density (nb/surface)	0,359	0,03	0,301	0,417
Hotel density (nb/surface)	0,244	0,055	0,136	0,352
Restaurant density (nb/surface)	-0,012	0,009	-0,029	0,004
Median Income in k	0,013	0,003	0,008	0,018
Pct of foreigners	-0,382	0,341	-1,051	0,287
Dwelling density (nb/surface)	0,279	0,036	0,209	0,349
Bus stop density	0,011	0,066	-0,119	0,14
Distance to the nearest metro station	-0,00028	0,00016	-0,00061	0,00005
Range	2949	470	2149	4006
Stdev	1,5	0,187	1,18	1,92

Preliminary Results

Visualization of Gaussian random field

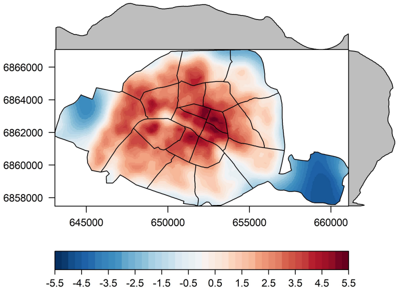


Figure: Summary (Posterior Mean) of $\omega(u)$

Outline

Airbnb and rents (1)

Article

International Regional Science Review
1-29

DOI: 10.1177/0160017618821428
journals.sagepub.com/home/irx
SAGE

Does Airbnb Disrupt the Private Rental Market? An Empirical Analysis for French Cities

Kassoum Ayouba[1], Marie-Laure Breuillé[1], Camille Grivault[1] and Julie Le Gallo[1,*]

Airbnb and rents (2)

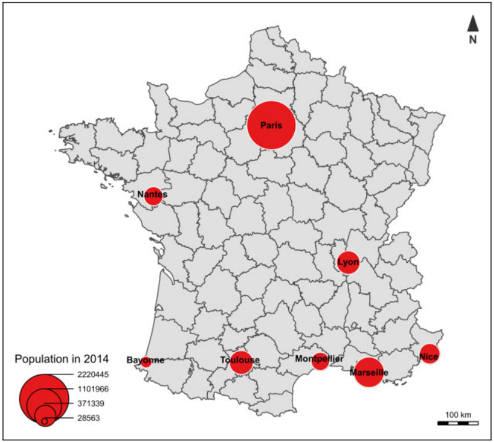


Figure 1. Geographical scope.

Airbnb and rents (3)

Table 3. Rent Data and Structural Variables.

Label	Description	Source
RENT	Monthly rent excluding charges at the survey date (euros)	OL
HOUSTYPE	Type of dwelling (1: individual; 2: collective)	OL
BUILDPER	Building period (1: before 1946; 2: 1946–1970; 3: 1971–1990; 4: 1991–2005; 5: after 2005)	OL
MANAGTYPE	Type of dwelling management (1: delegated; 2: direct)	OL
SURFACE	Total surface area (m^2)	OL
AVSUROOM	Average surface area per room (m^2)	OL
TIMESPENT	Tenant occupancy (years)	OL
FLOOR	Floor	OLAP
ELEVATOR	Presence of an elevator (1: yes; 2: no)	OLAP
BUILDMANAG	Presence of a concierge (1: yes; 2: no)	OLAP
PROPTYPE	Presence of common area maintenance charges (1: no; 2: yes)	OLAP
PARKING	A parking space is included in the rent (1: yes; 2: no)	OLAP
NBTOIL	Number of toilets	OLAP
NBBATH	Number of bathrooms	OLAP

Note: OL = "rental market observatory." OLAP = rental market observatory of Paris area.

+ large range of other control variables (accessibility, environmental quality, socioeco context

Airbnb and rents (4)

$$\ln(\text{RENT}_{it}) = \beta_1 + D_t\beta_2 + f(\text{STRUCT}_{it})\beta_3 + f(\text{SOC\_ECO}_{it})\beta_4 + f(\text{AME}_{it})\beta_5 + f(\text{ACCES}_{it})\beta_6 + f(\text{AIRBNB}_{it})\beta_7 + \varepsilon_{it},$$

Table 8. Quality of Adjustment by City for All Observations and for the Sample Restricted to the New Tenancy Agreements.

	All Observations		New Tenancy Agreements	
City	R^2	Adjusted R^2	R^2	Adjusted R^2
Bayonne	.6530	.6518	.7396	.7361
Lyon	.7977	.7972	.8299	.8289
Marseille	.6444	.6436	.7080	.7041
Montpellier	.7960	.7955	.8741	.8727
Nantes	.8269	.8263	.8103	.8074
Nice	.7817	.7813	.9209	.9197
Paris	.9092	.9090	.8062	.8053
Toulouse	.7674	.7671	.7080	.7041

+ Splines and spatial robust inference

Airbnb and rents (5)

Table 9. Effect of Airbnb Densities for the Whole Sample.

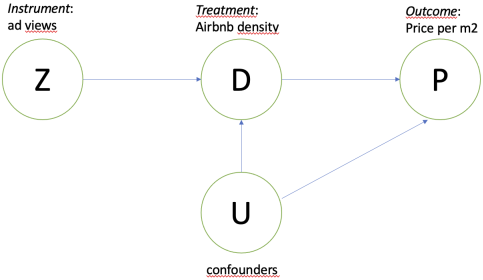
City	D_AIRBNB			D_AIRBNB_PRO		
	Estimate	Std. Error	*p* Value	Estimate	Std. Error	*p* Value
Bayonne	−.6249	.4236	.1381	−0.0888	1.0758	.9338
Lyon	.3851	.1885	.0413**	1.2380	0.7980	.12167
Marseille	.5600	.4150	.1775	1.7054	1.007	.0915*
Montpellier	.3982	.2412	.0990*	0.5484	0.8064	.4959
Nantes	.2966	.5432	.5846	0.6641	2.7717	.8087
Nice	.1997	.2559	.4352	0.1378	0.42459	.7451
Paris	.5242	.1182	.0001***	1.2372	0.2686	.0001***
Toulouse	.8771	.6472	.1758	3.1593	1.9358	.1047

Table 10. Effect of Airbnb Densities for the Restricted Sample of New Tenancy Agreements.

City	D_AIRBNB			D_AIRBNB_PRO		
	Estimate	Std. Error	*p* Value	Estimate	Std. Error	*p* Value
Bayonne	0.0936	0.8958	.9164	0.7140	3.3000	.8265
Lyon	0.2386	0.2637	.3654	1.2928	1.0465	.2173
Marseille	1.3040	0.9215	.1578	6.4641	3.5239	.0705*
Montpellier	2.9960	0.5895	.0001***	7.9153	1.7208	.0001***
Nantes	−2.3485	2.2767	.2911	−10.2137	7.2313	.1228
Nice	−1.1637	1.3628	.3872	−1.8658	1.9808	.3369
Paris	1.3537	0.3661	.0002***	1.7083	0.7106	.0167**
Toulouse	0.7402	0.5954	.2141	1.7713	1.9121	.3539

Introduction

- Multiplication and concentration of STR increases the tension in the private rental market with many studies showing a significant impact on housing prices (Barron et al 2021, Garcia-Lopez et al 2020...)
- No large-scale studies in Europe
- This work focuses on France and uses novel instruments: internal and external validity



Data (1)

STR data: AirDNA, January 2018-December 2019

Figure: Number of Listings and Number of Days Reserved

Figure: (a) Number of Listings

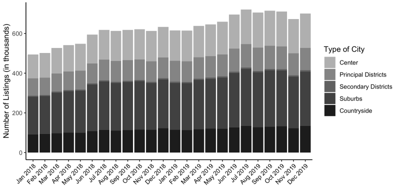
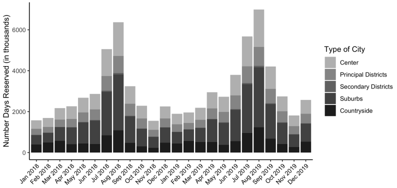


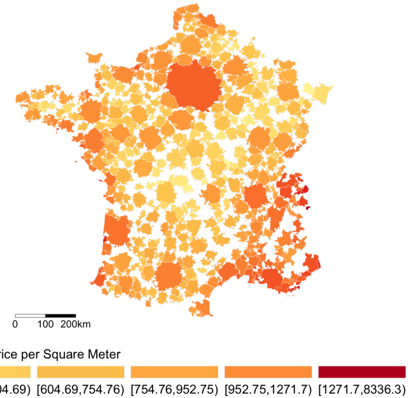
Figure: (b) Number of Days Reserved



Data (2)

Real estate data: CEREMA, all real estate transactions, geolocalized, structural characteristics

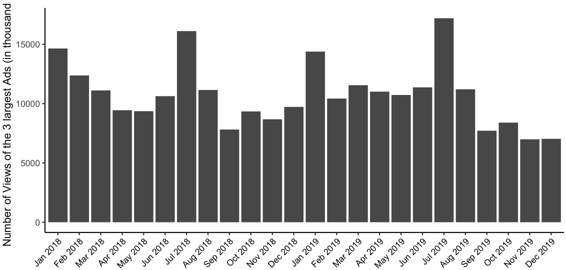
Figure: Median Price per Square Meter



Data (3)

Ad views data: leboncoin (45 million ads, 29 million monthly users). Aggregated data by municipalities and computation of the total number of views of the 3 most visited ads by municipality

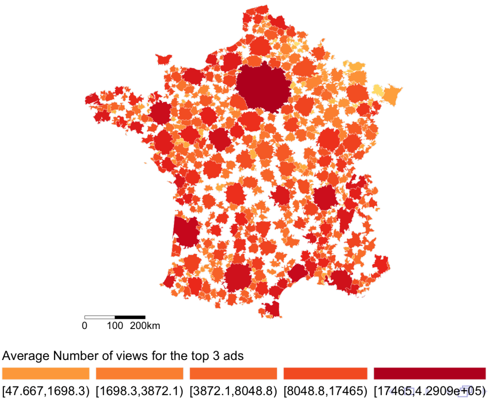
Figure: Number of Views of the Top 3 Ads - Evolution



Data (4)

Ad views data: leboncoin (45 million ads, 29 million monthly users). Aggregated data by municipalities and computation of the total number of views of the 3 most visited ads by municipality

Figure: Number of Views of the Top 3 ads - Zoning



Data (5)

Tripadvisor data: scraping the points of interest (POI) on the TripAdvisor platform. Aggregated at the municipality level.

Socio-economic characteristics: Large range of socio-economic characteristics at the municipality level (INSEE, Open Street Map, ...)

Empirical strategy (1)

$$P_{it} = \alpha \times Density_{it} + \beta \times X_i + \gamma \times Trans_{it} + MonthYear_t + Zone_i + C + \epsilon_{it} \quad (4)$$

where P_{it} is the real estate price per square meter in municipality i in month t, $Density_{it}$ is the density of STR listings in municipality i in month t, X_i is the vector of socio-economic characteristics of municipality i, $Trans_{it}$ is the number of real estate transactions of the commune i in month t, $MonthYear_t$ and $Zone_i$ are the time and space fixed effects, C is the constant and ϵ_{it} the error term.

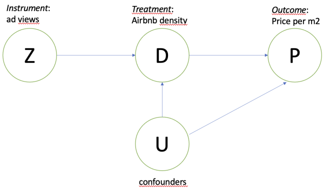
Aim: Consistent estimation of the average casaul effect of D on P

Issues: 1/ Unobserved confounders 2/ Reverse causality

Empirical strategy (2)

Instrumental variable Z (Hernan and Robins, 2020, chap 16):

- *Relevance*: Z must be correlated with P, $Z \perp\!\!\!\perp P$ does not hold
- *Exclusion restriction*: Z must causally affect P only through D
- *Marginal exchangeability*: Z must be independent from unobserved confounding factors U



Empirical strategy (3)

Instruments: 1/ Number of views of the 3 most viewed ads in the municipality, 2/ 2-month variation

Figure: Number of Listings and Number of Views

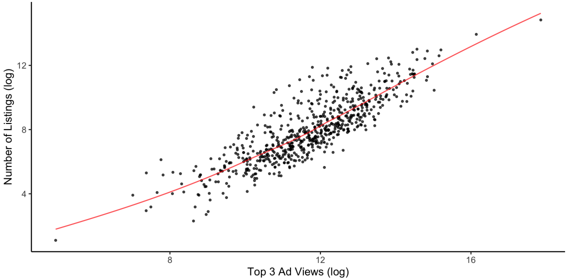


Figure: *Notes:* The number of listings and top ad views are aggregated at the attraction zoning level.

Empirical strategy (4)

Validity of instruments

Table: Instruments have no effects on Prices in Cities without Airbnb

	Price per square meter (log)
Top 3 Ad Views	0.008
	(0.006)
Top 3 Ad Views Variation	0.001
	(0.001)
Observations	6,891
Adjusted R^2	0.366
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results (1)

Table: First Stage Regression

	Density of Listings (log)				
	(1)	(2)	(3)	(4)	(5)
Nb of Views (log)	0.238***	0.133***	0.076***	0.088***	0.089***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Growth of Nb of Views	−0.003***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266
Adjusted R^2	0.466	0.606	0.684	0.686	0.692

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results (2)

Table: Main Results

	Price per square meter (log)				
	(1)	(2)	(3)	(4)	(5)
Density of Listings (log)	0.088***	0.055***	0.102***	0.108***	0.109***
	(0.004)	(0.008)	(0.014)	(0.012)	(0.012)
Sargan Test	0.867	0.816	0.071	0.121	0.146
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266
Adjusted R^2	0.444	0.472	0.543	0.543	0.542

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results (3)

Table: Main Results including Spatial Spillovers

	Price per square meter (log)				
	(1)	(2)	(3)	(4)	(5)
Density of Listings (log)	0.088***	0.080***	0.103***	0.108***	0.110***
	(0.004)	(0.008)	(0.014)	(0.012)	(0.012)
Sargan Test	0.869	0.146	0.165	0.246	0.282
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266
Adjusted R^2	0.444	0.477	0.543	0.542	0.542

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results (4)

Table: Municipality Profile Heterogeneity

	Price per square meter (log)				
	(1)	(2)	(3)	(4)	(5)
Center	0.116***	0.091***	0.088***	0.091***	0.092***
	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
Principal	0.092***	0.067***	0.062***	0.065***	0.066***
	(0.004)	(0.008)	(0.008)	(0.007)	(0.007)
Secondary	0.086***	0.068***	0.062***	0.065***	0.066***
	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)
Suburbs	0.090***	0.071***	0.066***	0.069***	0.070***
	(0.004)	(0.008)	(0.008)	(0.007)	(0.007)
Countryside (not touristic)	0.112***	0.087***	0.082***	0.085***	0.086***
	(0.005)	(0.008)	(0.008)	(0.008)	(0.007)
Countryside (touristic)	0.056***	0.041***	0.039***	0.042***	0.043***
	(0.006)	(0.009)	(0.009)	(0.008)	(0.008)
Sargan Test	1.000	1.000	1.000	1.000	1.000
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266
Adjusted R^2	0.446	0.472	0.473	0.473	0.473

Note: *p<0.1; **p<0.05; ***p<0.01

Results (5)

Table: Municipality Ranking Heterogeneity

	Price per square meter (log)				
	(1)	(2)	(3)	(4)	(5)
Zone A	0.037***	0.032***	0.101***	0.103***	0.104***
	(0.005)	(0.008)	(0.014)	(0.012)	(0.012)
Zone B1	0.081***	0.078***	0.116***	0.118***	0.119***
	(0.005)	(0.008)	(0.014)	(0.012)	(0.012)
Zone B2	0.126***	0.116***	0.127***	0.130***	0.131***
	(0.004)	(0.008)	(0.013)	(0.012)	(0.012)
Zone C	0.174***	0.157***	0.143***	0.146***	0.147***
	(0.004)	(0.008)	(0.013)	(0.012)	(0.012)
Sargan Test	0.535	0.230	0.090	0.110	0.120
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266

Results (6)

Table: Secondary Housing Heterogeneity

	Price per square meter (log)				
	(1)	(2)	(3)	(4)	(5)
Density of Listings (log)	0.038***	−0.028***	0.0001	0.010	0.011
	(0.004)	(0.009)	(0.015)	(0.014)	(0.013)
Density of Listings (log)	0.008***	0.008***	0.008***	0.007***	0.008***
× Secondary Housing	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Sargan Test	0.429	0.513	0.228	0.339	0.346
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266
Adjusted R^2	0.447	0.468	0.544	0.545	0.545

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results (7)

Table: Distance to Train Station Heterogeneity

	Price per square meter (log)				
	(1)	(2)	(3)	(4)	(5)
Density of Listings (log)	0.089^{***}	0.062^{***}	0.108^{***}	0.113^{***}	0.115^{***}
	(0.004)	(0.008)	(0.014)	(0.013)	(0.012)
Density of Listings (log)	-0.0001^{**}	-0.0004^{***}	-0.0004^{***}	-0.0004^{***}	-0.0004^{***}
× Distance to Train	(0.00003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sargan Test	0.383	0.803	0.319	0.454	0.515
Municipal Characteristics	✓	✓	✓	✓	✓
Touristic Amenities	×	✓	✓	✓	✓
Spatial Fixed Effects	×	×	✓	✓	✓
Monthly Fixed Effects	×	×	×	✓	×
Month × Year Fixed Effects	×	×	×	×	✓
Observations	221,266	221,266	221,266	221,266	221,266
Adjusted R^2	0.444	0.471	0.542	0.542	0.542

Outline

Conclusion

We have data on:

- Spatial point data for whole France: Airbnb listings ($>$ 2M points, 2016-2022) with characteristics, POIs, housing transactions, public transport stations, public infrastructures
- Spatial line data for whole France: road, railways
- Multiscale polygon panel data : Municipal / intermunicipal groups / Regional level data for socioeconomic characteristics, environmental, political variables

... and probably a lot more to be done with it!

- Spatial complementarity/substituability hotels/STR
- Impact of STR on other outcomes (vacancy, well-being, etc.)
- ...

Thank you for your attention