Covid-19 and urban exodus: did urban dwellers contaminate rural dwellers?*

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October 31, 2021

Abstract

On March 14, 2020, the French government announced that all non-essential public spaces will be closed from March 17. As a results, millions of French urban dwellers anticipated the lockdown, and decided to flee the major cities for the duration of the lockdown (urban exodus). In this article, I am interested in the impact of this phenomenon on the spread of Covid-19. I more precisely examine whether this urban exodus led to an increase in Covid-19 cases. In a second phase, I also estimate the local determinants of the spread of Covid-19, and the effect of different types of mobilities on reducing the spread of the epidemic in France, i.e. the effectiveness of the lockdown. Using a quasi-natural experiment, I estimate that this urban exodus led to an increase in the number of hospitalizations between 1,850 (lowest estimates) and 13,500 (highest estimates). Secondarily, I find that local determinants of Covid-19 spread are population density and share of social housing, which confirmed that people living in poor and densely populated area are more likely to be contaminated. Finally, I compute the elasticity of the growth rate of Covid-19 cases in France to different mobility indices. Results suggest that a 10% reduction in retail and recreation mobility led to a relative decrease in the average daily deaths growth rate of 17%, of 35.4% for workplaces mobility and of 12.2% for parks mobility.

Keywords: Covid-19, Local government, Difference-in-differences, Natural experiment

JEL Classification: C31, H75, I10, R12

*I thank Renaud Bourlès, Laurent Gobillon, Thierry Magnac, Sonia Paty, Alain Trannoy, Etienne Wasmer and participants of the LAGV 2021 for their helpful comments. I also warmly thank Anna Zaytseva for her helpful suggestions of data. All remaining errors are my own. This work was supported by French National Research Agency Grants ANR-17-EURE-0020.

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1 Introduction

The first lockdown in France, which took place from noon on March 17 to May 11, 2020, has been accompanied by large population movements. Following the initial announcements of Edouard Philippe–the French Prime Minister–on March 14 that all non-essential public spaces will be closed, millions of French people anticipated the lockdown and decided to escape from major cities. We can therefore speak of an urban exodus: there were substantial movements of urban dwellers, who left their departments–an intermediate administrative unit[1]–of residence, for rural areas.

The main purpose of this paper is to use this natural experiment to answer the question whether this urban exodus led to an increase in Covid-19 cases. Indeed, since the big cities were the first and most affected by the epidemics, these "Covid-19 immigrants" could have spread it to rural areas. Using a difference-in-differences approach and new data on users' mobile phone location from the French mobile operators, to retrieve the movements of population before and during the lockdown, I estimate the causal impact of the movement of people leaving their main residences, on the national number of deaths and hospitalizations due to the epidemic.

To the best of my knowledge, this paper is the first to investigate the impact of such urban exodus preceding a lockdown on the spread of the epidemic. Many papers have already examined the relationship between population density and Covid-19 incidence, as discussed below in the related literature section, but none have specifically examined the impact of a large population shift from cities to suburbs. Thus, this article contribute to the long literature on urban and regional economics, as well as the recent economic and health literature on Covid-19.

According to official reports, there are two types of persons who left their department of residence for another department: (i) persons owning a secondary residence and (ii) students/young workers living in a densely populated municipality who moved back to their family residences. Most of these immigrants belong to the first category. Indeed, about 3.4

[1]In order: municipality $<$ department $<$ region $<$ State. Hereafter, I use the English term of department to refer to the French *départements*.

millions of French people owned a secondary residence in a department other than their main residence. Most of them come from major cities and densely populated department: 307,000 from Paris, 191,000 from the Hauts-de-Seine, 135,000 from the Bouches-du-Rhône (Marseille) and 134,000 from the Rhône (Lyon)[2].

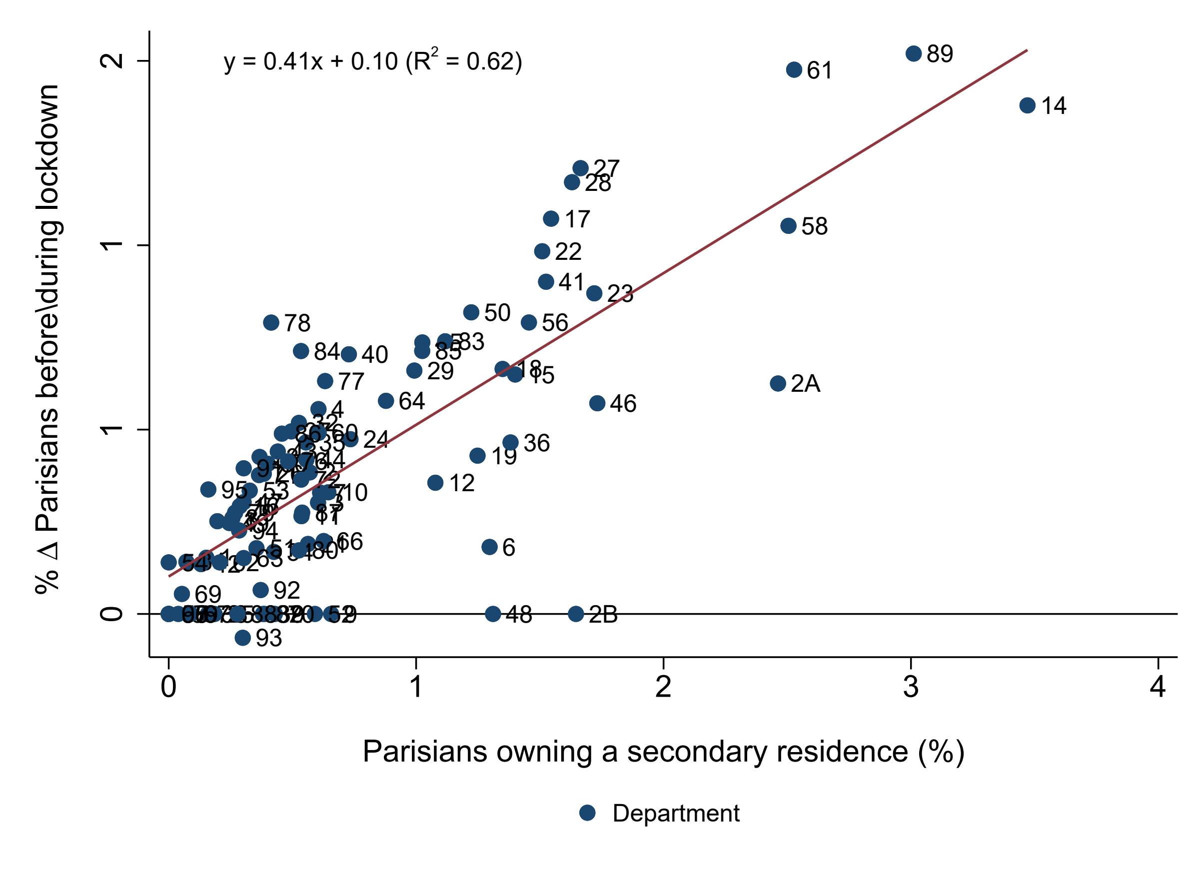
The case of Paris is a particularly interesting and useful example. Just before the lockdown, at least 218,000 inhabitants of Paris left the French capital to go to another department. It represents 10% of Paris' population and 71% of Parisians owning a secondary residences in another department. This displacement of Parisians toward their secondary residences is particularly visible in Figure 1, which shows a strong positive correlation between the percentage of variation of the Parisians in another department during the lockdown and the percentage of Parisians owning a secondary residence in that department.

This migration of people leaving their main residences–mainly located in large cities– to a quiet rural area is economically and politically interesting. Economically, it provides a starting point for a natural experiment on the possible spread of Covid-19 from urban to rural population: I use the fact that most of these "Covid-19 immigrants" went to the departments where they had a secondary residence, as a random distribution of these immigrants among the departments during the lockdown. Indeed, some departments have a very large share of secondary residences among the total of housing, while others have almost no secondary residences (see Figure B.2). As a result, the treatment intensity is very different across departments: there may have been a positive variation of non-residents during the lockdown, a negative variation (departments that most people fled), or zero variation (no "Covid-19 immigrants"). Politically, it is a good study case of the well-known regional divide[3]–the widespread feeling of wealthy, government-pampered urban dwellers against declining rural and suburban dwellers and abandoned areas excluded from the globalization–culminating in the yellow vests protest movement launched in 2018. Indeed, it was well commented in the local and national press that rural dwellers were frightened and reluctant about the arrival of these "Covid-19 immigrants". For ex-

[2] Source INSEE-Fideli 2017.

[3] *Fracture territoriale* in French.

Figure 1: Urban exodus of the Parisians according to the share of Parisians owning a secondary residence by departments



Notes: panel without outliers. The X-axis represents the share of Parisians owning a secondary residence in the department's total population.
Sources: INSEE, Population présente sur le territoire avant et après le début du confinement 2020 and Recensement de la population 2016-2017 (Fideli); author's graph.

ample, many television channels and newspapers reported that "just before the lockdown, Paris train stations was overcrowded with people wanting to leave the capital", or more objectionable "that the newcomers were subject to reprisals by the degradation of their vehicles, or verbal and physical threats" (see Table A.1 for some examples of newspapers headlines and articles on the urban exodus).

My identification strategy (1) uses the Covid-19 incubation period as a pivot for a pre- and post-period, (2) takes advantage of the differences in treatment intensity of the urban exodus–variation of population before and after the beginning of the lockdown–between departments (negative, positive or zero), and (3) captures heterogeneous effects in the departments with advanced epidemic stages before lockdown. As the mean days between hospitalizations and deaths are different, I also used two different periods of treatment (based on clinical studies) to disentangle the impact on deaths from the impact on hospitalizations. I estimate that urban exodus led to an increase in the number of hospitalizations. The lowest estimates set an excess number of around 1,850 hospitalizations and the highest estimates of about 13,500. I also show additional evidence that most if this excess Covid-19 cases come from the Parisians "immigrants".

In a second phase, I examine the local determinants of the Covid-19 propagation with a linear model and using an instrumental variable method to avoid a possible endogeneity issue. I also estimate the effect of mobility–thus of the effectiveness of the lockdown–on growth rate of regional cases with a log-log panel specification using users' mobile phone location from Google. I find that the local determinants of Covid-19 spread are population density and the share of social housing of the departments, confirming that people living in poor and densely populated areas are more likely to be contaminated (see also Brandily et al., 2020). Estimations of the elasticity of Covid-19 cases growth rate with respect to different mobility indices, suggest that a 10% reduction in retail and recreation mobility led to a relative decrease in the average daily deaths growth rate of 17%, of 35.4% for workplaces mobility and of 12.2% for parks mobility.

Finally, I perform a series of robustness checks such as a placebo test, different period, or using a standard errors correction for spatial correlation and a spatial econometric model to solve the possible endogeneity issue from the spatially heterogeneous social interactions–one of the main vectors of Covid-19 spread–between people, confirming that my results are unbiased and robust.

The remainder of this paper is organized as follows. Section 2 presents the current state of the knowledge on epidemics and their causes related to this study. Section 3 provides the sources and details of the data. Section 4 shows some graphical evidences regarding the common trend assumption and the spatial correlation between departments. Section 5 develops the empirical strategy, the econometric models and discusses the possible threat to identification. Section 6 presents the results and section 7 the robustness checks. Section 8 provides a discussion and analysis the results. Section 9 concludes the paper.

2 Related literature

Before Covid-19 epidemic, there were numerous economic and health studies on previous pandemics, especially on the 1918 influenza pandemic, aiming to estimate the causes of the spread. While it may seem intuitive that the influenza pandemic was positively associated with population density as the virus spread via human contact, previous studies show mixed results. For instance, Garrett (2007) finds a positive relationship between mortality rates and population density in the US. In contrast, some other studies show that population density is not necessarily linked with the spread and severity of the disease (Mills et al., 2004; Chowell et al., 2008).

Previous studies on respiratory infectious and pandemics show that the spread is mainly driven by social contacts. They show that the spread of the disease varies according to the duration of contact, age, region, and date for instance, and can be modeled using a matrix of contacts (see Mossong et al., 2008 and Prem et al., 2017). About Covid-19, Platteau and Verardi (2020) show that its spread is correlated a lot with local culture: there are differences in the infection rate and deaths toll between and within countries. They also explained that they observed significant variations between northern and southern France for example, and that there is no one explanation for all the geographical differences observed. My study can provide one explanation to this difference. Indeed, the urban exodus is mainly driven by the share of secondary residences in a department, and we know that there are significantly more secondary residences in the Southern and Western France for instance (see Figure B.2).

On the spatial dimension of the Covid-19 epidemic, some studies have examined the link between density and Covid-19 incidence. Wheaton and Kinsella Thompson (2020) used data on cities and towns in Massachusetts to provide a cross-section analysis of the per capita infection rate. They find that population density has a significant positive effect on the incidence of the disease, and that higher income areas have much larger cases per capita. Almagro and Orane-Hutchinson (2020) also examine this link but use data on the number of tests and positives across New York City zip codes, to provide descriptive evidence on the correlation between density and the spread of the pandemic.

They also find a significant positive relationship between population density and the share of positive tests, but their results also suggest that crowded spaces play a more important role than population density in the spread of Covid-19. Carozzi et al. (2020), using data from Google, Facebook, and the US Census, and an instrumental variables strategy, find convincing evidence that density has affected the time of the outbreak in each US county, with dense locations more likely to have an early outbreak. However, they find that once Covid-19 has arrived, spread of the epidemic is not faster than in rural areas, i.e. cities get hit first, but do not necessarily get hit harder. In France, using several administrative data sources by municipalities, Brandily et al. (2020) show that poor housing conditions and higher occupational exposure play a key role in the contamination, and that the impact of the epidemic is twice as large in the poorest municipalities.

Previous applied literature on Covid-19 (excluding specific clinical studies) has focused on the effect of social distancing measures on the spread of the epidemic, or to the compliance to such measures. For example, Soucy et al. (2020) find that a 10% decrease in mobility is associated with a 14.6% decrease in the average daily cases growth rate, and Yilmazkuday (2020) reaches similar conclusion using a difference-in-differences design over 130 countries. Using natural experiments, Bargain and Aminjonov (2020a) estimate the effect of poverty on human mobility after lockdown in poor countries, and conclude that the degree of work mobility reduction is driven by the intensity of poverty. In a second paper, Bargain and Aminjonov (2020b) estimate the relation between trust in government and compliance to lockdown measures in Europe, and found that compliance is significantly higher in high-trust regions.

On France, there are papers which attempt to estimate the effect of the French municipal election–which took place on March 15, 2020–on the Covid-19 spread, due to possible contamination in the polling places. These papers reach contradictory results. On the one hand, using observational data and sigmoidal model, Zeitoun et al. (2020) report no impact of the municipal elections on the spread of the epidemic. Bach et al. (2020)–using a regression discontinuity design–also estimate no higher mortality rate on the candidates at the elections, yet who where exposed the most by monitoring the voting process. On the other hand, Cassan and Sangnier (2020) using logistic epidemic model to construct a counterfactual of the epidemic spread for each department, estimate an excess of 15% hospitalizations by the end of March due to the elections. Finally, exploiting heterogeneity among municipalities and using instrument variables methods on the same dataset as Bach et al. (2020), Bertoli et al. (2020) conclude that a higher turnout is associated with a higher death counts in the elderly population.

This paper departs from these studies by estimating the impact of the large movements of population prior to the first lockdown in France, and providing a comprehensive estimate of the possible causes of the spread of the Covid-19, from the urban exodus, the local determinants such as poverty and density, to the lockdown measures to reduce some specific mobilities.

3 Data

All the data used in this paper are open access data. I use several datasets to perform this study: (1) official data from Public Health France (*Santé Publique France*) on the volume of deaths and hospitalizations due to Covid-19, (2) INSEE[4] (National Institute of Statistics and Economic Studies) data on the variation of population before and after the beginning of the lockdown, (3) Google data on population mobility, and (4) local data from various sources. This study is carried out at the spatial levels of departments and regions, two administrative levels (see Figures B.1 for maps of the French departments and regions). Of course, the ideal level to study the effect of mobility, and to disentangle the possible density effects on the spread of the epidemics, would be the municipality level. It would make it possible to distinguish between urban areas, which concentrate the commuting of population. Unfortunately, probably for confidentiality issues, neither the INSEE nor Google provide data at the municipality level. We hope that in the near future, they will allow researchers to access to their detailed databases.

[4] *Institut National de la Statistique et des Etudes Economiques.*

3.1 Deaths and hospitalizations

Data on deaths and hospitalizations due to Covid-19 come from Public Health France[5], and report the daily number declared by the French hospitals by department. These data are composed solely of the cases occurring in hospitals, thus excluding possible deaths occurring in retirement and nursing homes ([6]), as well as deaths at home. These data are available from March 19, 2020, onward[7] and these are the most complete and reliable data available at the department level. To better interpret the results, I convert these data to cases per 100,000 inhabitants[8]. Figures 2 show maps of the cumulated departmental deaths and hospitalizations per 100,000 inhabitants by March 16 and by May 31, 2020, i.e. before and after the lockdown.

3.2 Variation of population during the lockdown

Among the people who left the major cities to rural areas, we can distinguish those returning to their main residences–the permanent inhabitants or residents–and those leaving their main residences. According to INSEE, 1.5 million inhabitants went back to their department of residence when the lockdown was implemented, compared to the usual movements of people. Most of these people are workers on business trips or domestic tourists. The most attractive information is the movement of people leaving their main residences, i.e. the non-residents of the immigration department. According to official reports, there are two types of persons who left their department of residence for another department: (i) persons owning a secondary residence and (ii) students/young workers living in a densely populated municipality who moved back to their family residences.

These data correspond to the variation of population–splits in residents of the de-

[5]https://www.data.gouv.fr/fr/datasets/donnees-hospitalieres-relatives-a-lepidemie-de-covid-19/#_.

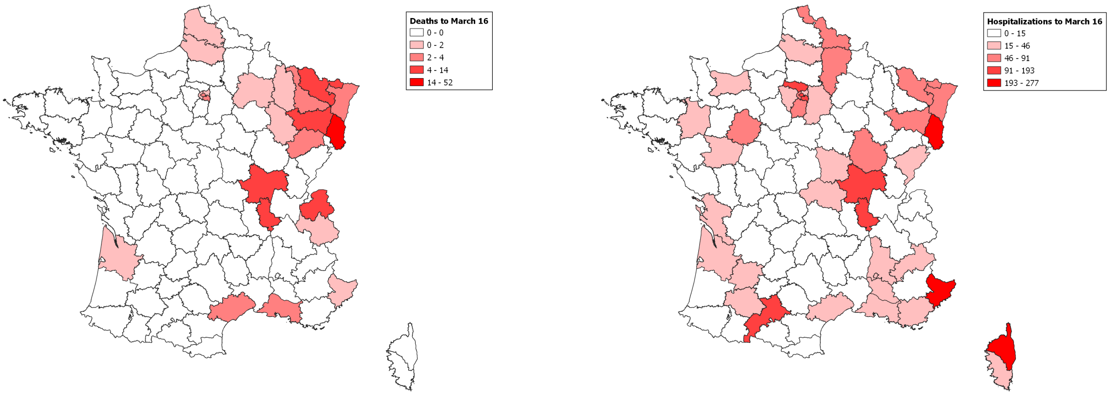
[6]EHPAD

[7]In order to recover the deaths and hospitalizations before March 19, I used secondary official datasets. Those datasets come from the Electronic Death Certification Data Associated with Covid-19 (*CEPIDC*). I do not use this dataset for the whole period of time, because it shows differences in the number of deaths compared to the official reports as time increase. For hospitalizations, I used the dataset from hospital emergency and SOS Médecins' reports. Again, I do not use this dataset for the whole period of time for the same reason as the previous dataset.

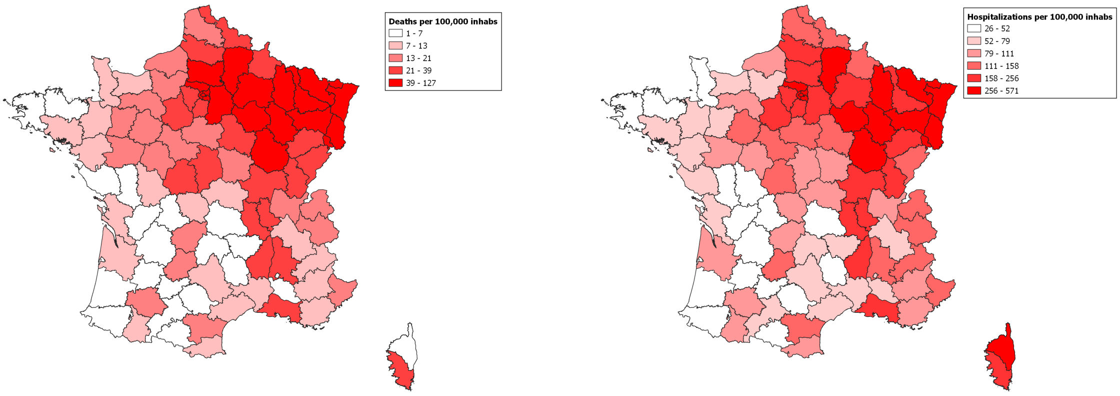
[8]This is done by dividing the number of deaths or hospitalizations by the population of the department, then multiplying by 100,000.

Figure 2: Covid-19's cases

(a) Cumulated at the beginning of the lockdown



(b) Cumulated at the end of the regressed period



Notes: cumulated number by March 16 for maps 2a and by May 31 for maps 2b. In the maps 2a, the cumulated number of deaths and hospitalizations are expressed in absolute value (and not per 100,000 inhabitants).
Source: Santé publique France, Covid-19 2020; author's maps.

partment, non-residents of the department, foreigners, and Parisians–before and after the beginning of the lockdown for each department. They are based on user's mobile phone location aggregated by French mobile operators[9] and compiled by the INSEE[10]. More specifically, the population counts come from mobile phones activation present on their networks. The analysis focuses on activation during the night only[11]. A mobile phone is considered to be overnight when it appears to be geographically stable over a significant period of time between midnight and 6 a.m.[12]. Operators have previously re-calibrated

[9] Orange, Bouygues Telecom and/or SFR.

[10] https://www.insee.fr/fr/information/4493611 and https://insee.fr/fr/statistiques/4635407#consulter.

[11] Mobile phones that are switched off or in airplane mode at night do not connect to the network and are not included in the raw counts.

[12] The length of this period may vary depending on the operator.

these overnight aggregates to make them representative of the entire population of the department, and not just to their customers. Next, the variation of population is estimated by comparing the distribution of the population present at night at the departmental level in metropolitan France between two average weeks before and during lockdown[13]. The percentage of variation is obtain by dividing the difference of population before/after the beginning of the lockdown, by the departmental average overnight stays over one week before lockdown. For example, a value of 2 means that, in this department, the population at night increased on average by 2% during the lockdown compared to the reference level (i.e. before lockdown). Figure 3 shows maps of the variation of population before/after the beginning of the lockdown. I refer sometimes to this variable as "urban exodus". From this dataset, I constructed 3 main variables: (1) the urban exodus, which represents the total variation of population[14], (2) the urban exodus of non-residents, which represents the variation of non-residents in a department (excluding the Parisians), and (3) the urban exodus of Parisians, which represents the variation of Parisians in a department. For a matter of convenience and interpretation, in the estimations I use a transformation of the percent of variation, into an index on a 0-100 scale, where the reference urban exodus variation takes the value of 100, i.e. no variation of population after lockdown.

3.3 Mobility

I use daily mobility data from Google Covid-19 mobility reports[15], which aggregate data from users' mobile phone location. These data presents daily percentage of variation of visits and lengths of stays at places compared to a reference (daily median of the weeks from January 3 to February 6, 2020) using information from Google maps. There are six location categories: (i) retail and recreation (restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters), (ii) grocery and pharmacy (grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and

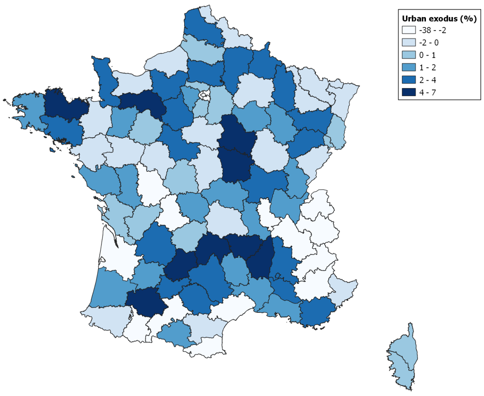
[13]The information provided by Bouygues Telecom runs from the night of March 2 to June 2, 2020, that of Orange from January 16 to May 31, 2020 and that of SFR covers the weeks of January 27, March 16, March 23, May 4, May 11 and May 18, 2020.

[14]Residents + non-residents + foreigners + Parisians.

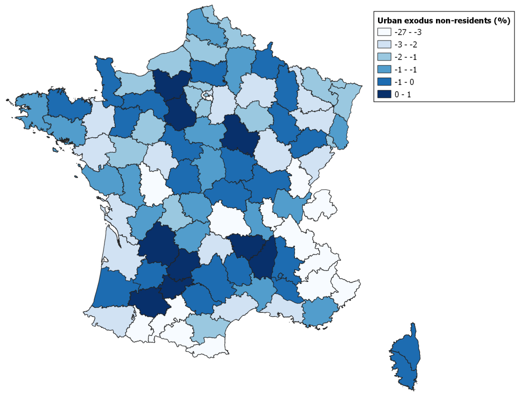
[15]https://www.google.com/covid19/mobility/.

Figure 3: Population before/after the beginning of the lockdown (%)

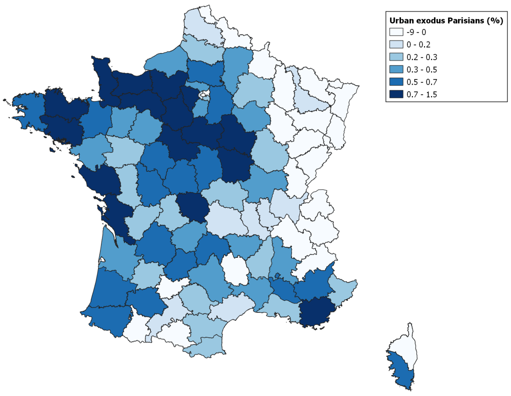
(a) Urban exodus



(b) Urban exodus non-residents



(c) Urban exodus Parisians



Notes: non-residents are non-inhabitants of the department (excluding the Parisians).
Sources: Population présente sur le territoire avant et après le début du confinement 2020; author's maps.

pharmacies), (iii) parks (national parks, public beaches, marinas, dog parks, plazas, and public gardens), (iv) transit stations (public transport hubs such as subway, bus, and train stations), (v) workplaces, and (vi) residential areas (places of residence). Information is provided at sub-national level, more precisely the regional administrative level.

For a matter of convenience and interpretation, I transform the percent of variation into an index on a 0-100 scale, where the reference mobility intensity takes the value of 100. For example, a retail and recreation mobility value of 70 in a region r in day d corresponds to a 30 percent decrease in mobility for this type of activity and this region compared to the reference level. Figure 4a plots a local polynomial fit of the "outside" mobilities from February 15 to May 31, 2020, and Figure 4b residential mobility for the same period. In graph of the "outside" mobility we can see large decreases–between March

17 to May 11, 2020, (lockdown period)–from around 50% for grocery and pharmacy, to 15% for retail and recreation, while residential mobility increases by around 30% compared to the baseline.

3.4 Socio-demographic data

Finally, I also use multiple socio-demographic data–at the department level–as covariates or to compare the departments. Not all the variables are used in the regressions, due to obvious multicollinearities. These data are composed of variables suspected of having an impact on Covid-19 propagation. These variables are, for instance, the population aged above 60, the population density, the number of passengers from airports traffic, the number of beds in intensive care unit, etc. Table A.2 provides summary statistics for all the variables.

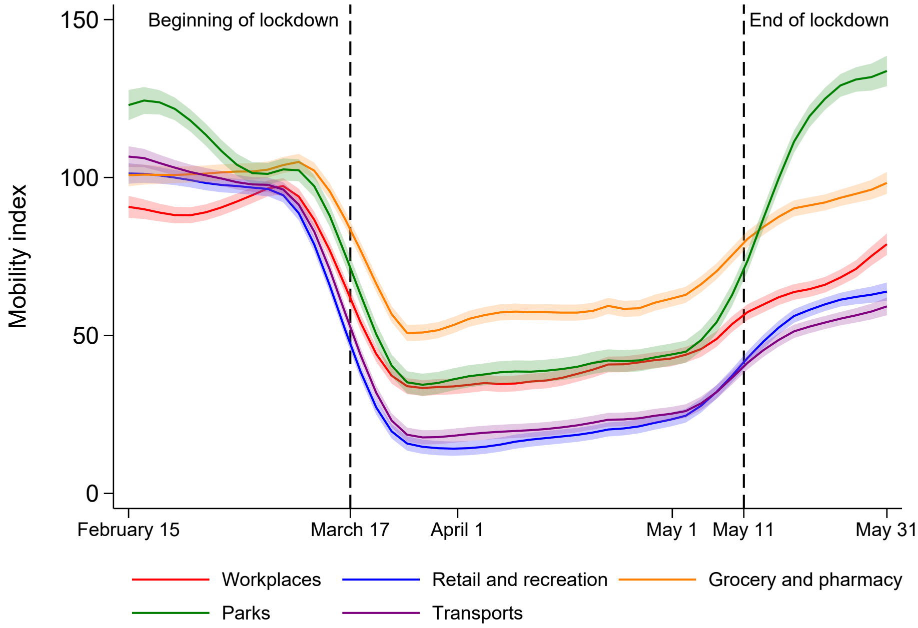
4 Graphical evidences

In the following sections, I use the term of urban exodus to refer to the variation of population during the lockdown. I also use the term of departments with positive or zero urban exodus group, because in my causal analysis of urban exodus I have not define actual treated and controlled groups. Indeed, as explained below, I use a treatment intensity variable (percentage change of variation of population) and not a dummy variable. The departments with urban exodus represents a positive variation of population during the lockdown (urban exodus > 0), and the departments with no urban exodus represents no variation of population during the lockdown (urban exodus $= 0$).

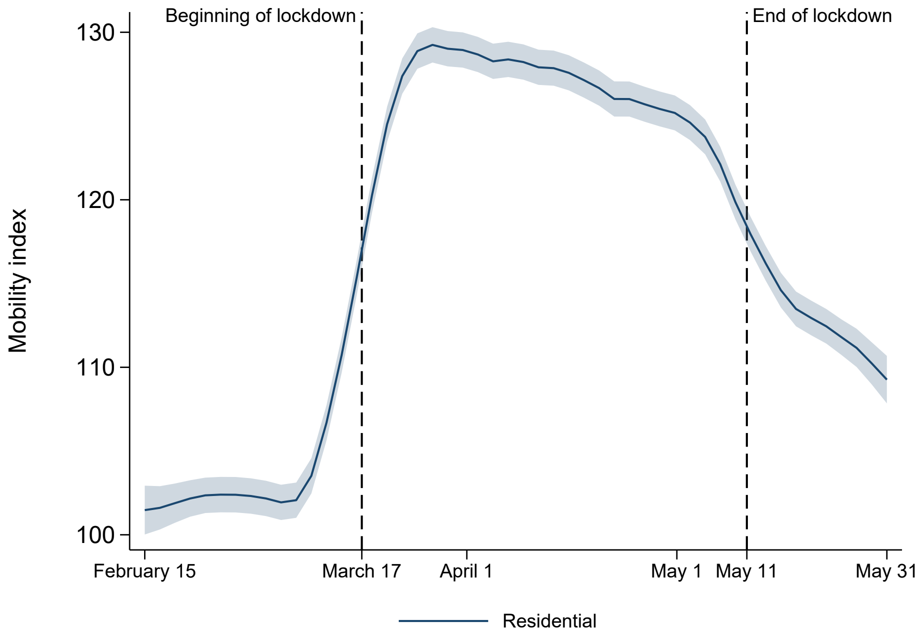
Common trend assumption. I begin with a visual examination of the departments with positive or zero urban exodus groups patterns, using a local polynomial fit with its 95% confidence interval of deaths and hospitalizations per 100,000 inhabitants. Figure 5 allows us to informally examine the common trend assumption for the DiD design, which is mostly verified for both groups. It shows that a few weeks after the beginning of the lockdown, the trends of the positive urban exodus group slightly increase for both

Figure 4: Mobility outside and inside residential location

(a) Outside mobility



(b) Residential mobility

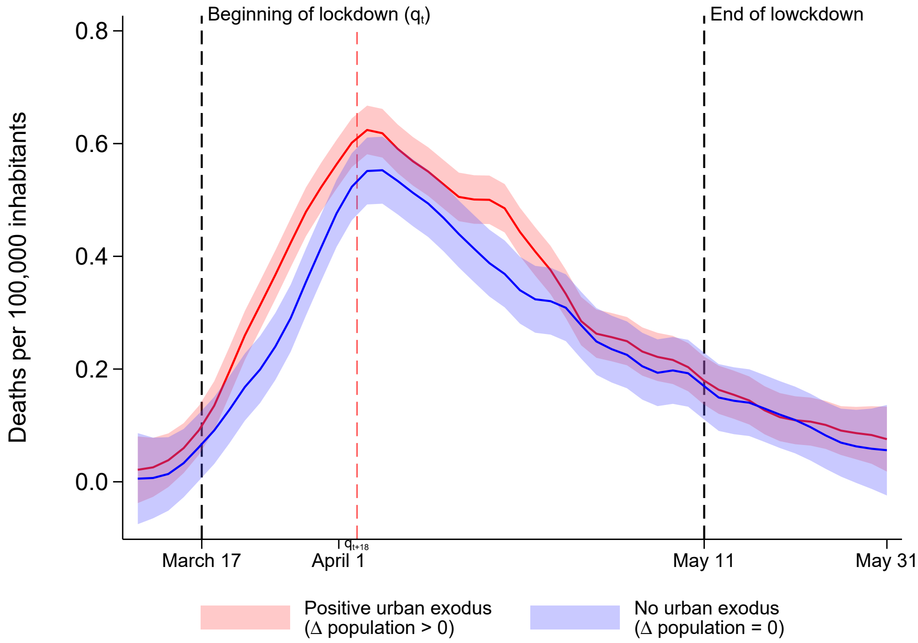


Notes: local polynomial fit using Epanechnikov kernel with a bandwidth of 4. Confidence intervals are 95% CI. Mobility is computed by regions (NUTS 2).
Source: Google mobility data 2020; author's computation.

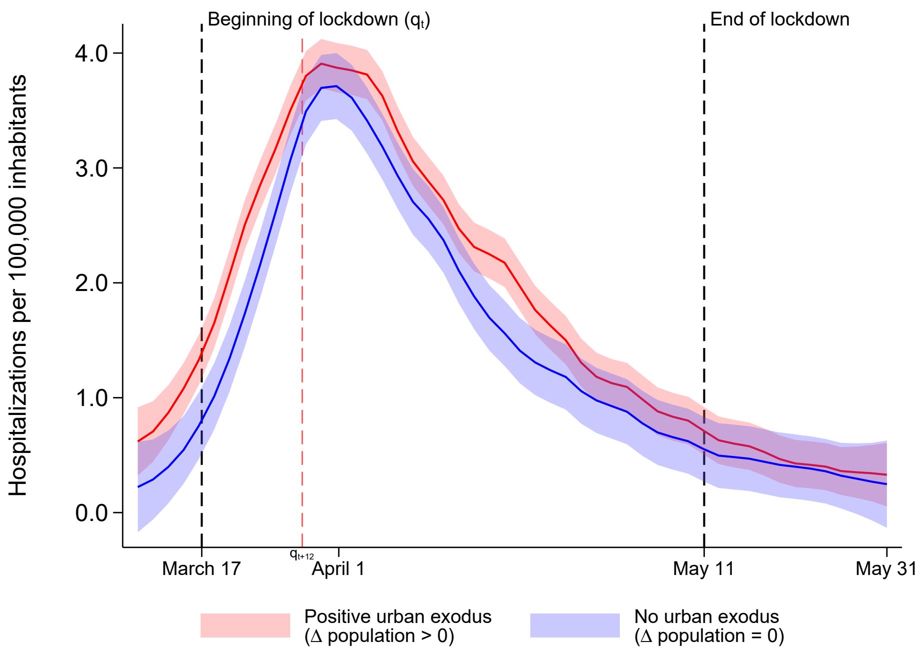
daily deaths and hospitalizations. Of course this is not a proof of any causal difference between departments of different treatment intensity (i.e. urban exodus), which requires a difference statistically different from zero to be confirmed.

Figure 5: Common trend between departments with positive or zero urban exodus

(a) Deaths



(b) Hospitalizations



Notes: local polynomial fit using Epanechnikov kernel with a bandwidth of 3. Confidence intervals are 95% CI.
Source: Santé publique France, Covid-19 2020; author's graph.

Spatial correlation. Looking at Figure 2, we can see a clear spatial correlation of the Covid-19 cases, for both deaths and hospitalizations. Indeed, the south-western departments are quite spared by the Covid-19, while he north-eastern departments are more affected than the rest of France. This correlation is confirmed by computing and plotting Moran's I. Moran's I is a measure of spatial autocorrelation. Negative (restively positive) values of the index indicate negative (respectively positive) spatial autocorrelation. Its values range from -1 (indicating perfect dispersion) to +1 (perfect correlation)[16]. Figure 6 shows the Moran's I plots where the X-axis represents the cumulated deaths or hospitalizations per 100,000 inhabitants[17] by May 31, 2020, and the Y-axis the spatially lagged variable using a row-standardized contiguity spatial weighting matrix. We can clearly see that departments with a high (low) level of deaths or hospitalizations are surrounded by departments with a high (low) level of deaths or hospitalizations. This is confirmed by both the Moran's I of 0.68 (p-value = 0.000) for the cumulated deaths or hospitalizations per 100,000 inhabitants, and by the Moran test for spatial dependence (see bottom part of Table 2), confirming that the error terms of the regressions are not spatially independents. In order to test for possible bias from this spatial correlation of the data, I perform both ordinary least squares (OLS) with a standard errors correction for spatial (across nearby units) autocorrelation, and spatial model regressions in the robustness checks section.

5 Empirical strategy

In this section I describe the identification strategy and the methodology of the study. As developed in detail in the following subsections, I use different econometric specifications to estimate (1) the causal impact of urban exodus using a difference-in-differences design, (2) the local determinants of the Covid-19 propagation using a standard linear model, and (3) the effect of population's mobility on Covid-19 propagation using a log-log model.

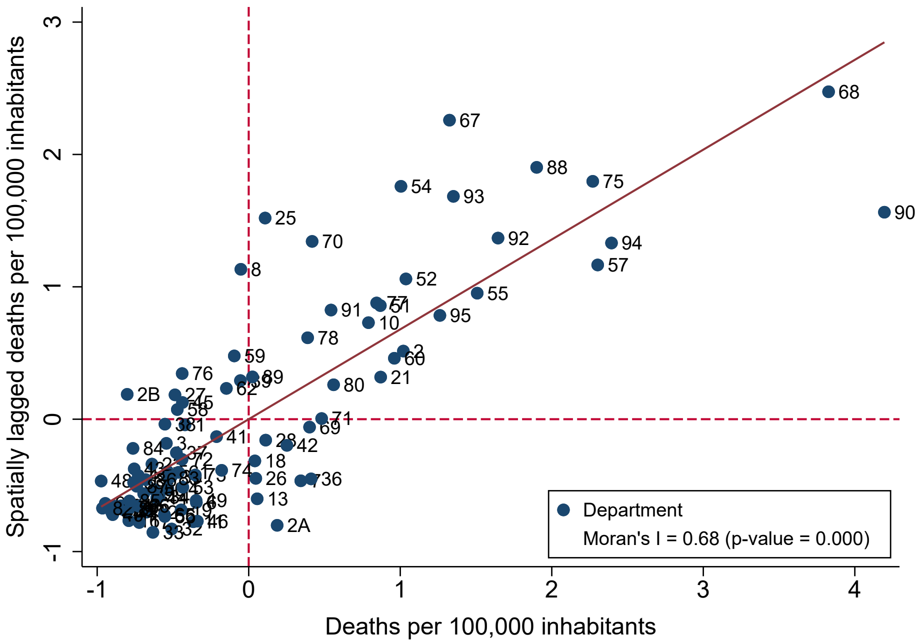
Period of treatment. I selected two different period of treatment (Post period): one for the hospitalizations per 100,000 inhabitants and one for the deaths per 100,000 in-

[16]0 is no autocorrelation (perfect randomness.)

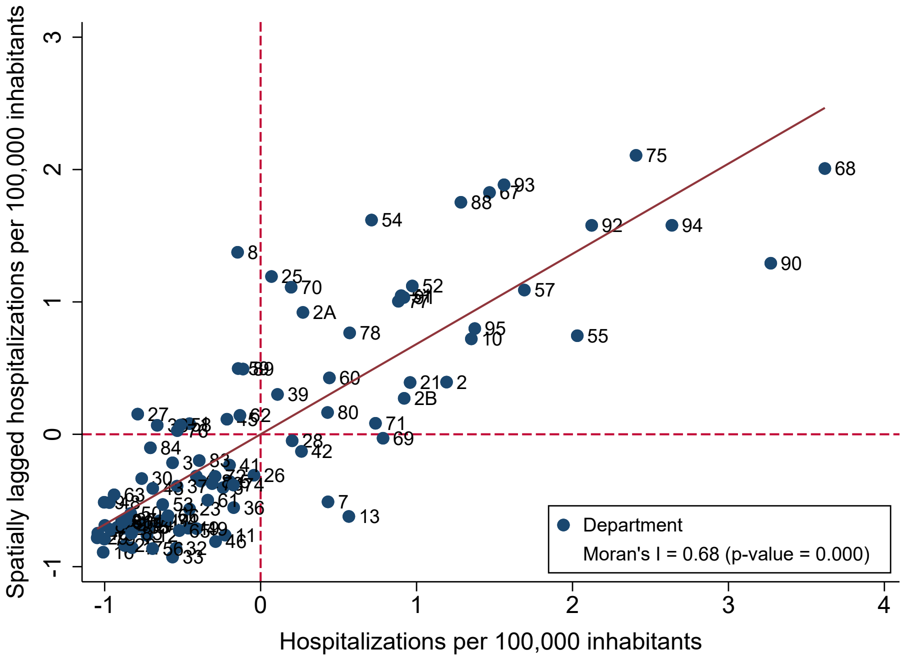
[17]Variables are standardized before to be plotted (i.e. with a mean of 0 and a variance of 1).

Figure 6: Moran's I plots

(a) Deaths



(b) Hospitalizations



Notes: the Y-axis represents Wy_{dt} (i.e. the row-standardized contiguity spatial weighting matrix W multiplied by the vector of deaths or hospitalizations per 100,000 inhabitants y_{dt} in department d at time t). Moran's I are plotted for all departments (i.e whole panel). Variables are standardized before to be plotted (i.e. with a mean of 0 and a variance of 1).
Source: Santé publique France, Covid-19 2020; author's graphs.

habitants. For hospitalizations as dependent variable, this post treatment period takes place 12 days after the first day of lockdown (i.e. March 28), and 18 days (i.e. April 03) for deaths as dependent variable. This 12 and 18 days periods come from the mean days estimated by clinical studies literature between infection and hospitalization then death. International studies using mainly Chinese data (such as Wang et al., 2020; Guan et al., 2020; Zhou et al., 2020 and Nie et al., 2020) and the French Institut Pasteur[18] announced an incubation period of 5 days, followed by a of 7 days elapsed between the onset of the first symptoms and admission to the hospital on average. Thus, a period of 12 days between infection and hospitalization. Zhou et al. (2020) also reported a median time to death of 18.5 days, while Verity et al. (2020) reported a mean time from onset to death of 18.8 days.

Placebo test. In a difference-in-differences framework, the most important assumption is that of common trend, which assumes that the evolution of the variables of interest would have been the same for the all sample groups, in the absence of the treatment (i.e. urban exodus). The placebo test is used to empirically test the validity of the common trend assumption, by regressing our variables of interests in a pre-treatment period, and prior the period used in the main regressions. Note that it is difficult to perform a correct placebo test, because before the beginning of the lockdown, the cases of Covid-19 are almost zero in all departments (especially the number of deaths) and start to increase a few days before the lockdown. Nonetheless, performing an event study model of equation 1 for the period March 10 - April 03, 2020 (i.e. 18 days after the beginning of the lockdown) for the deaths and March 10 - March 28, 2020 (i.e. 12 days after the beginning of the lockdown) for the hospitalizations, shows no effects of urban exodus on Covid-19's cases statistically different from zero for departments with no advanced epidemics cases. We only see some positive differences after the beginning of the lockdown, not all statistically different from zero, for departments with advanced epidemics cases (see Figure C.1). Consequently, the common trend assumption seems to be valid and the

[18] https://www.pasteur.fr/en/medical-center/disease-sheets/covid-19-disease-novel-coronavirus.

difference-in-differences design can be implemented.

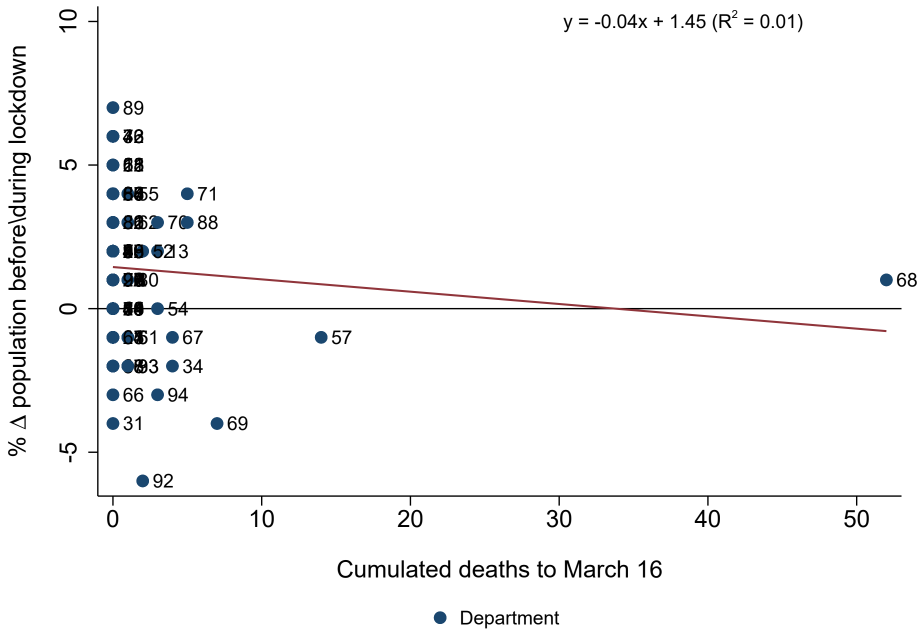
Threat to identification. This study faces a possible threat to identification, specifically an endogeneity issue. Indeed, one could argue that when urban dwellers left for rural areas, they went to the departments not or less affected by Covid-19. Such behavior would lead to a simultaneity bias. The main claim against this possible bias, is that according to official reports, urban dwellers who left their main residence for another department are two types of people: (i) people owning a secondary residence and (ii) students/young workers living in a densely populated municipality. Therefore, those "Covid-19 immigrants" did not take into account the previous Covid-19's cases when choosing their place of departure. They left depending on the location of their secondary or family residence (which obviously does not depend on Covid-19's cases).

Nonetheless, one could still argue that people who moved were people with secondary or family residences not in departments with advantaged epidemics stage. I find no evidence of such a correlation between the level of variation of population (i.e. urban exodus) and the level of deaths and hospitalizations before lockdown. Figure 7 illustrates this by plotting the variation of population before/after the beginning of the lockdown relative to the cumulated deaths and hospitalizations by March 16, 2020 (i.e. one day before the lockdown). We can observe a negative correlation close to zero (-0.04 with R^2 = 0.01 and -0.01 with R^2 = 0.10 respectively), and even a positive variation of population in the departments most impacted by Covid-19 before lockdown (in contradiction with the possible endogeneity bias). This is also confirmed by Table A.3, which shows no difference in the declared number of deaths and hospitalizations before lockdown between the departments, depending on their variation of population after lockdown. Note that Cassan and Sangnier (2020) faced exactly the same issue in their study, and using similar graphical evidence they also concluded that there is no correlation between the level of turnout at the French municipal elections and the previous cumulated number of Covid-19 cases in that department. This suggests that French people react similarly–at least at the department level–to information about the spread of the epidemic.

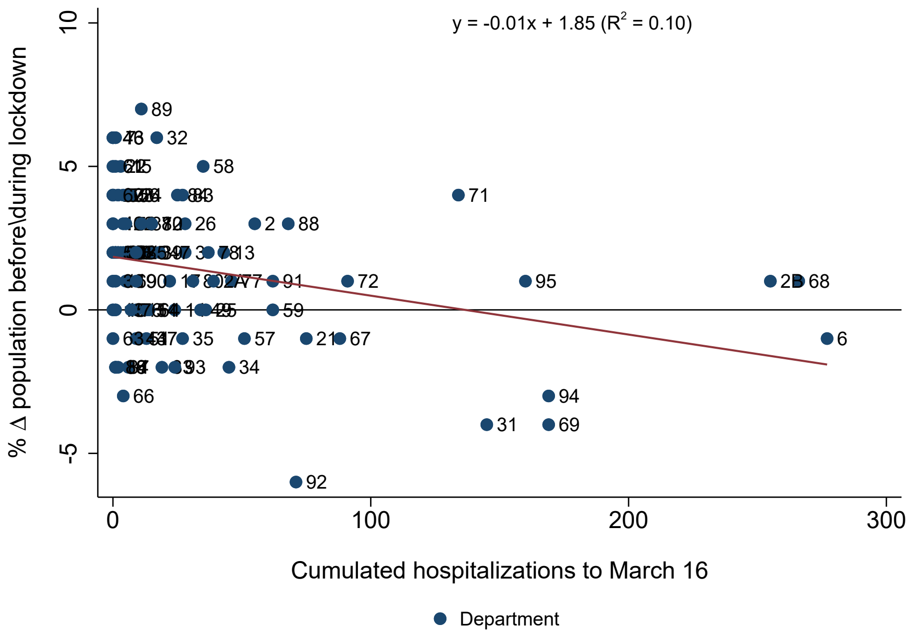
Additional evidence of the absence of problematic differences between the departments

Figure 7: Urban exodus according to the Covid-19's cases before lockdown

(a) △ population before\during lockdown (%) according to the cumulated deaths before lockdown



(b) △ population before\during lockdown (%) according to the cumulated hospitalizations before lockdown



Notes: plots for the panel without outliers.
Source: Santé publique France, Covid-19 2020; author's graphs.

with and without urban exodus, is provided by Table A.3, which reports a t-test–among multiple variables suspected of having an impact on Covid-19's cases–between the two groups. This test can be seen as a means of testing the treatment exogeneity (i.e. urban exodus), also known as conditional independence assumption (CIA) or selection on observables. It shows that there are no differences statistically different from zero between the groups for almost all variables. It appears that the share of social housing, the share of population living in a municipality densely populated, the share of small residences ($< 40\ m^2$), the number of beds in intensive care unit or nursing homes and population are slightly higher only for the departments with no urban exodus. These results are not surprising, as the urban exodus led urban dwellers to leave mainly for secondary or family residences, located mainly in rural areas. Therefore, the fact that departments with urban exodus are more rural than departments with no urban exodus should not be considered as a selection effect. Thus, I could argue that there is no selection bias: difference in the spread of Covid-19's cases by March 16, 2020 did not translate into a difference in variation of population during the lockdown between departments.

5.1 The causal impact of urban exodus: difference-in-differences

Identification source. To estimate the causal impact of urban exodus on the spread of Covid-19, I use a difference-in-differences specification, over the period from March 10 to May 31, 2020. My identification strategy relies on (1) the Covid-19 incubation period as a pivot for a pre- and post-period, (2) takes advantage of the differences in treatment intensity of the urban exodus–variation of population before and after the beginning of the lockdown–between departments (negative, positive or zero), and (3) captures heterogeneous effects of urban exodus in the departments with advanced epidemics stages before lockdown.

Two concerns about the causal impact of the urban exodus could be raised. First, the effect of urban exodus on the spread of the epidemic depends on density of population. But obviously, urban exodus leads to modifications of the local densities: decreasing in the urban areas, and increasing in the rural (treated) areas, especially them with a high share of secondary residences. Secondly, it could be considered that two treatments took place at the same time. Not only the urban exodus as an impact of the Covid-cases, but also the triggering factor of the urban exodus: the lockdown. Indeed, the lockdown as an impact on the spread of the epidemic, by reducing the social interactions and mobility of the population. This is why, when estimating the causal impact of the urban exodus, we do not estimate solely the average treatment effect (ATT) of the urban exodus, but the ATT of the urban exodus in period of lockdown. The ATT of the lockdown on the spread of the epidemic is therefore also part of the ATT of the urban exodus. Thus, the ATT of the urban exodus alone is different from the ATT of the urban exodus in period of lockdown.

Econometric model. The estimated model is:

$$\begin{aligned} \text{Covid-19 cases}_{dt} = \beta_0 + (\delta + \gamma \times \text{Advanced epidemics}_d) \times \text{Post} \times \text{Urban exodus}_d \\ + \alpha_d + \alpha_t + \varepsilon_{dt} \end{aligned} \tag{1}$$

$Covid-19\, cases_{dt}$ is either the daily number of deaths or hospitalizations per 100,000 inhabitants due to Covid-19, in department d at day t. $Urban\, exodus_d$ is a continuous treatment which corresponds to the variation of population before and after the beginning of the lockdown in department d. $Post$ is a dummy variable defining the treatment period. The treatment period is defined as $Post = 1$ for the number of hospitalizations 12 days after the beginning of the lockdown ($date > March\ 28$), and $Post = 1$ for the number of deaths 18 days after the beginning of the lockdown ($date > April\ 03$). $Advanced\, epidemics_d$ is a dummy variable defining whether a department had advanced Covid-19 epidemics cases before lockdown (i.e. by March 16). Specifically, departments at advanced epidemics stages (see Figure B.3a) are departments above the last quartiles of deaths and hospitalizations by March 16 (i.e. if cumulated number of Covid-19 cases by March 16 > 75^{th} percentile). In addition, the model includes also α_d which controls for department time-invariant characteristics (department fixed effects), and α_t which controls for differences across days shared by the sample groups (day fixed effects). Finally, ε_{dt}

the error term clustered at departmental level, and captures the $department \times day$ shocks to the dependent variable (assumed independent and identically distributed across panels and time).

$\widehat{\delta}$ estimates the mean effect of $Urban\,exodus$ in $Post$ period between departments (double-difference estimator), while $\widehat{\gamma}$ is equal to the additional effect of $Urban\,exodus$ in $Post$ period between departments at no advanced epidemics stages before lockdown, and departments at advanced stages of the epidemic before lockdown. Therefore, $\widehat{\gamma}$ studies how the double-difference varies according to the intensity of the epidemic before lockdown (heterogeneous effects of the spread of the epidemic).

I estimate this model on three different panels. (i) Panel A: the whole sample composed of the 96 departments. (ii) Panel B: the sample with no outliers, which excludes the departments with very high variation of population ($> 10\%$). These departments are Paris (75) and the four main winter tourism departments: Hautes-Alpes (5), Hautes-Pyrénnées (65), Savoie (73) and Haute-Savoie (74), see Figure B.3b for a map of these departments. (iii) Panel C: the sample composed of the departments with positive or zero urban exodus only (see Figure B.3c), i.e. departments were population decreased are excluded from the sample. I also distinguish between the different types of urban exodus: (1) the urban exodus, which represents the total variation of population[19], (2) the urban exodus of non-residents, which represents the variation of non-residents in a department (excluding the Parisians), and (3) the urban exodus of Parisians, which represents the variation of Parisians in a department.

5.2 The local determinants of the spread of Covid-19

This model is made in order to identify local characteristics that favor the spread of Covid-19. To do this, I use several local data suspected of having an impact on the intensity of the epidemic. To facilitate comparison of the coefficients, all the data are standardized (i.e. with a mean of 0 and a variance of 1). As discussed earlier, there is no reason nor evidence to suspect that urban exodus variable (variation of population

[19] Residents + non-residents + foreigners + Parisians.

before/during lockdown) is endogenous. Nevertheless, I also regress the following model using an instrumental variable, i.e. two-stage least squares (2SLS). I instrument the urban exodus variable with the share of secondary residences by department (see Figure B.2). Indeed, the share of secondary residences is correlated with the urban exodus variable, as most of the persons who left their main residences for another department went to their secondary residences. However, the share of secondary residences should not be directly correlated with Covid-19 cases, except through the non-residents of the department who went to their secondary residences (exclusion restriction). The estimated equation is:

$$\text{Covid-19 cases}_d = \beta_0 + X'\beta_1 + \varepsilon_d \tag{2}$$

In this model, $Covid - 19\, cases_d$ is either the cumulated number of deaths or hospitalizations per 100,000 inhabitants by May 31, 2020, due to Covid-19 in department d. X is a vector of variables suspected to be correlated with the Covid-19 propagation, and u_{dt} the error term.

5.3 Population's mobility

Another important aspect, which is interesting to estimate, is the effect of the lockdown on the Covid-19 propagation. To perform such estimations, I used Google daily mobility data (see subsection 3.3) to estimate the effect of reducing mobility on future Covid-19 deaths and hospitalizations. Contrary to the previous models which are performed at the French department level, the following model is regressed using the French regions level[20] (see Figure B.1b for a map of the French regions). Indeed, the Google mobility data are only available at the regional level. Regions–composed of around 7 departments each–are larger nuts in terms of surface area. Data on deaths and hospitalizations must be aggregated.

In the following model, I use the growth rate of Covid-19's cases, because as explained in Bargain and Aminjonov (2020b): "it is not possible to find a relationship between cur-

[20] However, this administrative division does not necessarily correspond to the reality of the relationship between people, and therefore, of the possible Covid-19 spatial propagation. This problem is well-known in the spatial econometrics literature and referred as the MAUP (Modifiable Areal Unit Problem).

rent mobility and future deaths, as both are highly correlated with the current mortality level. However, it is possible to establish how the upcoming deaths or hospitalizations growth rate responds to the instantaneous mobility index, reflecting the efficiency of lockdown policies". The following model is based on the method used in this paper, and that developed in Soucy et al. (2020). The log-log estimation model, carried out over the period from March 10 to May 31, 2020, is:

$$\log(\text{Growth rate}_{rt}) = \beta_0 + \varepsilon \cdot \log(\text{Mobility}_{rt}) + \alpha_r + \alpha_t + \epsilon_{rt} \tag{3}$$

where ε is equal to,

$$\varepsilon_{GR}^{Mob} = \frac{\partial \log(\text{Growth rate})}{\partial \log(\text{Mobility})} \cong \frac{\Delta\text{Growth rate}/\text{Growth rate}}{\Delta\text{Mobility}/\text{Mobility}} \tag{4}$$

the elasticity of future Covid-19's cases (deaths or hospitalizations growth rate) with respect to mobility.

$Growth\, rate_{rt}$ corresponds to the daily upcoming growth rate of deaths or hospitalizations per 100,000 inhabitants in region r at day t. To compute it, for each day I compare the current cumulated hospitalizations and deaths toll attributed to Covid-19 to that of 12 days and 18 days ahead respectively, and divide the corresponding growth rate by 12 or 18 to obtain a daily upcoming deaths growth rate. $Mobility_{rt}$ corresponds to the daily percentage of variation in mobility index (either retail and recreation, grocery and pharmacy, parks, transit stations or workplaces) in region r at day t. In addition, the model includes also α_r which controls for region time-invariant characteristics (region fixed effects), and α_t which controls for differences across days shared by the sample groups (day fixed effects). Finally, the error term ϵ_{rt}, clustered by region, and captures the *region* $\times$ *day* shocks to the dependent variable.

6 Results

6.1 The causal effect of urban exodus: DiD results

These results are surely the most interesting of this paper, as they present the causal impact of the urban exodus on the spread of the epidemic. Table 1 presents the results for the three panel and the three types (see previous subsection 5.1), and for the three types of urban exodus, i.e. the urban exodus, the urban exodus of non-residents, and the urban exodus of Parisians. The use of these alternative treatment variables is done in order to disentangle the causal effect of urban exodus between the total population, non-residents of the department, and Parisians, on the spread of the epidemic. First, we can see that for almost all panels, it shows negative coefficients for the advanced epidemics departments, while these coefficients are smaller in terms of magnitude than the coefficients for the departments with no advanced epidemics before lockdown.

Table 1: Difference-in-differences

Dependent variable:	Urban exodus		Non-residents urban exodus		Parisians urban exodus	
	(1) Deaths per 100,000 inhabitants **OLS**	(2) Hospitalizations per 100,000 inhabitants **OLS**	(3) Deaths per 100,000 inhabitants **OLS**	(4) Hospitalizations per 100,000 inhabitants **OLS**	(5) Deaths per 100,000 inhabitants **OLS**	(6) Hospitalizations per 100,000 inhabitants **OLS**
Panel A: Whole panel						
Post × Urban exodus	-0.0023	0.0057	-0.0019	0.0031	-0.012	0.043
	(0.0023)	(0.014)	(0.0022)	(0.024)	(0.017)	(0.10)
Post × Urban exodus × Advanced epidemics	-0.0019	-0.011**	-0.0017	-0.010**	-0.0018	-0.0098*
	(0.0017)	(0.0051)	(0.0016)	(0.0050)	(0.0017)	(0.0053)
Adjusted R-squared	0.21	0.32	0.21	0.32	0.21	0.32
Observations	7,968	7,968	7,968	7,968	7,968	7,968
Panel B: None outliers						
Post × Urban exodus	-0.0038	0.038	-0.010	-0.051	0.071	0.84**
	(0.0095)	(0.042)	(0.020)	(0.10)	(0.064)	(0.42)
Post × Urban exodus × Advanced epidemics	-0.0020	-0.010*	-0.0020	-0.012**	-0.0016	-0.0080
	(0.0018)	(0.0057)	(0.0019)	(0.0055)	(0.0017)	(0.0055)
Adjusted R-squared	0.20	0.31	0.20	0.31	0.20	0.31
Observations	7,553	7,553	7,553	7,553	7,553	7,553
Panel C: None $\triangle$ ***pop*** < 0						
Post × Urban exodus	0.026*	0.18**	0.11	2.01*	0.082	0.95**
	(0.014)	(0.081)	(0.089)	(1.14)	(0.066)	(0.42)
Post × Urban exodus × Advanced epidemics	-0.0052	-0.020*	0	0	-0.0016	-0.0074
	(0.0037)	(0.010)	(.)	(.)	(0.0017)	(0.0055)
Adjusted R-squared	0.18	0.27	0.15	0.16	0.20	0.31
Observations	5,810	5,810	1,494	1,494	7,470	7,470
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table reports estimates of equation 1, using OLS. Standard errors, given in parentheses, are clustered by department. Stars indicate significance level: * p<0.1, ** p<0.05 and *** p<0.01.

Urban exodus. Estimates for the total urban exodus (columns (1) and (2)) show no coefficient statistically different from zero for panel A and B for the departments with no advanced epidemics. These estimates mean that there was an effect of urban exodus on the departments at advanced stages of the epidemics, but that this effect is smaller than for the departments with no advanced stages of the epidemics (heterogeneous effects depending on the spread of the epidemic before lockdown). Performing the estimations on panel C (panel restricted to the purest urban exodus groups), we see positive and significant coefficients for both deaths and hospitalizations. Furthermore, the effect of urban exodus seems to be greater in terms of magnitude and significance on the number of hospitalizations per 100,000 inhabitants than on deaths (around 7 times higher). Thus, we have more evidence of a causal effect on the number of hospitalizations than on the number of deaths.

Non-residents urban exodus. In columns (3) and (4), I replace urban exodus variable by urban exodus among non-residents (excluding Parisians) only.Estimates of the difference-in-differences design show no difference from the previous results on the total urban exodus, for panel A and B. Estimates for panel C show larger coefficients in terms of magnitude, and no coefficients for the departments with advanced stage of epidemics before lockdown, due to a lack of observations for this sub-sample.

Parisians urban exodus. Now, I examine the urban exodus of the Parisians alone, who undoubtedly represent the largest share of non-residents who left their main residence for another department (mainly a secondary residence, see Figure 1). Estimates of the difference-in-differences design show no coefficients significantly different from zero for deaths, whereas the results for the total urban exodus show a positive and significant effect on deaths for panel C. Results of the double differences for hospitalizations present positive and significant effects for the departments with no advanced epidemics panel B and C, and coefficients for departments with advanced epidemics are not significantly different from zero for panel B and C (see columns (5) and (6)). Magnitude of the coefficients are larger for hospitalizations than for deaths. These results suggest a strong effect of the Parisians' urban exodus on the hospitalizations rate, confirming the conclusion of the main results.

Additional hospitalizations due to urban exodus. Estimates of table 1 columns (2), (4), and (6) panel C, from equation 1 allow to compute the excess Covid-19 cases (additional hospitalizations) due to the urban exodus, following the method from Cassan and Sangnier (2020). I only estimate the additional number of hospitalizations and not deaths, because as said previously, there are more evidences of an effect of urban exodus on hospitalizations than on deaths (see section 8 for an explanation of such a result). The following computation is performed only for the departments with a positive variation of population (i.e. urban exodus > 0) and omitting the outlier departments. Additional hospitalizations due to urban exodus are computed as follows:

$$\text{Additional hosp.}_d = (\widehat{\delta} + \widehat{\gamma} \times \text{Advanced epidemics}_d) \times \text{Post} \times \text{Urban exodus}_d \qquad (5)$$

In order to obtain the absolute value of excess Covid-19 case, I then multiply the results by the department d's population and the number of days in Post period[21], all divided by 100,000. Finally, I added up the additional hospitalizations of each department to obtain the total number of additional hospitalizations in France, for the period from March 28 to May 31, 2020. Since I use a continuous treatment variable, to really compare the differences in magnitude of the coefficients between the different population urban exodus, we need compare the additional hospitalizations. These results are surely an upper-bound, as they are computed on the mean daily effects, whereas these effects are expected to decrease over time.

My estimates on the total urban exodus suggest an increase in the number of hospitalizations of 9,379, which represents 8.37% of the cumulated hospitalizations for the period. For the non-residents urban exodus, estimates suggest an increase in the number of hospitalizations–due to the urban exodus of the non-residents of the department (excluding the Parisians)–of 1,855, which represents around 1.65% of the cumulated hos-

[21] i.e. 65 for hospitalizations' Post.

pitalizations for the period. These results are significantly lower, but confirm a causal effect of the urban exodus on the Covid-19 spread. Finally, estimates for Parisians urban exodus show an increase in the number of hospitalizations of 13,476, which represents 12.02% of the cumulated hospitalizations for the period. These results are larger than the estimates for the other population urban exodus on excess Covid-19 cases. I can conclude that most of the excess Covid-19 cases are due to the Parisians' urban exodus.

6.2 The local determinants of Covid-19 propagation: results

Table 2 shows that the main local characteristics that spread the Covid-19 are the population density (inhabitants/km^2) and the share of social housing. All these variables have a positive and significantly different from zero effect on the spread of the epidemic, for both the number of deaths and hospitalizations per 100,000 inhabitants.

Columns (3) and (4) show the results when instrumenting the urban exodus variable with the share of secondary residences. OLS and 2SLS estimations provide similar results in terms of magnitude and significance, except for the urban exodus variable, which now has a positive and significantly different from zero coefficient for deaths as dependent variable. Using Durbin and Wu-Hausman test of endogeneity, I can reject the null hypothesis of exogeneity of the variable for deaths per 100,000 inhabitants but curiously not for hospitalizations. This would suggest that urban exodus is not endogenous, but that the share of secondary residences is in fact indirectly correlated with the Covid-19 cases though urban exodus (as assumed previously).

6.3 The impact of population's mobility

In this subsection, I present the effects of human mobility on the spread of the epidemic during the lockdown. Thus, it could be interpreted as an estimation of the efficiency of the lockdown's measures. Results of equation 3 using a log-log model allow me to estimate the elasticity of future Covid-19's cases with respect to different mobility indices. Table 3 shows positive and significant effects on deaths growth rate for the retail and recreation, workplaces (at the 5% and 1% level respectively) and parks mobility indexes (at the 10%

Table 2: The local determinants of Covid-19 propagation

Dependent variable:	OLS		IV	
	(1) Deaths per 100,000 inhabitants **OLS**	(2) Hospitalizations per 100,000 inhabitants **OLS**	(3) Deaths per 100,000 inhabitants **2SLS**	(4) Hospitalizations per 100,000 inhabitants **2SLS**
Urban exodus (%)	0.090	0.067	0.35**	0.16
	(0.096)	(0.093)	(0.16)	(0.15)
Population > 60 years (%)	-0.099	-0.12	-0.15	-0.14
	(0.14)	(0.14)	(0.15)	(0.14)
Unemployment rate	0.015	0.045	-0.0058	0.037
	(0.088)	(0.086)	(0.089)	(0.083)
Population density (inhabs/km2)	0.30**	0.33***	0.39***	0.36***
	(0.13)	(0.12)	(0.13)	(0.12)
Airports traffic (nb of passengers)	0.079	0.11	0.066	0.10
	(0.092)	(0.089)	(0.092)	(0.086)
Social housing (%)	0.41***	0.37***	0.39***	0.37***
	(0.13)	(0.13)	(0.13)	(0.12)
Nb of beds in intensive care unit	-0.12	-0.10	-0.11	-0.097
	(0.14)	(0.13)	(0.14)	(0.13)
Adjusted R-squared	0.30	0.34	0.24	0.33
Observations	96	96	96	96
Moran test for spatial dependence				
H0: error is i.i.d				
Prob > χ^2	0.0000	0.0000		
Test of endogeneity				
H0: variables are exogenous				
Durbin Prob > χ^2			0.0288	0.4062
Wu-Hausman Prob > F			0.0356	0.4296

Notes: this table reports estimates of equation 2, using OLS and 2SLS. All the variables are standardized. The variable *Urban exodus* is instrumented with the *share of secondary residences* and the other variables. Standard errors are given in parentheses. Stars indicate significance level: * p<0.1, ** p<0.05 and *** p<0.01.

level). We see no coefficients statistically different from zero for the grocery and pharmacy index, as well as the transports index. For the hospitalizations growth rate, it shows a positive and significant coefficient (at the 10% level) for the retail and recreation index only.

What do those results mean in terms of impact on the spread of the epidemics. Interpreting the results, I can conclude that reducing retail and recreation mobility by 10% led to a relative decrease in the average daily deaths growth rate of 17%, of 35.4% for workplaces mobility and of 12.2% for parks mobility (i.e. elasticities of 1.7, 3.54 and 1.22 respectively.) For hospitalizations, reducing retail and recreation activities by 10%, yields to a decrease of 2.4% in the average hospitalizations growth rate (i.e. an elasticity of 0.24). Those estimates are quite similar to those obtained by Soucy et al. (2020) and Bargain and Aminjonov (2020b) from international samples.

7 Robustness checks

In this section, I perform a series of robustness checks. I perform different specifications, using different period, OLS with a standard errors adjustment for spatial autocorrelation, and spatial model, in order to test the reliability of the main estimates.

It is clear that with every infectious disease, especially in the event of a pandemic, transmission of the virus spreads spatially around clusters. As discussed above, the deaths and hospitalizations due to Covid-19 are positively spatially correlated between departments in France. To empirically account this spatial expansion of the Covid-19 over time–i.e. to have the best fitted data generating process–I use below an OLS model with standard error adjustment for spatial correlation, and a spatial econometric model (SEM).

7.1 Different period

I check the validity of the results to the choice of the period. To perform this test, I reduce the estimation period to the period of lockdown (i.e. from March 17 to May 11, 2020). Table D.1 shows mainly unaffected significativity of the coefficients, but slightly

Table 3: The impact of population's mobility

Dependent variable (log of):	(1) Deaths per 100,000 inhabitants (Growth rate) **OLS**	(2) Hospitalizations per 100,000 inhabitants (Growth rate) **OLS**
Mobility index: retail and recreation		
log(*Mobility*)	1.70**	0.24*
	(0.72)	(0.12)
Adjusted R-squared	0.77	0.98
Observations	1,079	1,079
Mobility index: workplaces		
log(*Mobility*)	3.54***	0.25
	(1.04)	(0.20)
Adjusted R-squared	0.77	0.98
Observations	1,079	1,079
Mobility index: grocery and pharmacy		
log(*Mobility*)	0.19	0.16
	(0.58)	(0.10)
Adjusted R-squared	0.76	0.98
Observations	1,079	1,079
Mobility index: parks		
log(*Mobility*)	1.22*	0.083
	(0.59)	(0.17)
Adjusted R-squared	0.77	0.98
Observations	1,079	1,079
Mobility index: transports		
log(*Mobility*)	-0.067	0.29
	(1.01)	(0.30)
Adjusted R-squared	0.76	0.98
Observations	1,079	1,079
Day FE	Yes	Yes
Region FE	Yes	Yes

Notes: this table reports estimates of equation 3, using OLS. Standard errors, given in parentheses, are clustered by region. Stars indicate significance level: * $p<0.1$, ** $p<0.05$ and *** $p<0.01$.

larger coefficients for all panels and urban exodus, compared to the main results. This is not surprising, considering that the statistical power increases mathematically when decreasing the regressed period. Thus, I can conclude that the estimates are robust to the choice of the estimation period.

7.2 Standard errors adjusted for spatial correlation

I perform an ordinary least squares (OLS) with a standard errors adjustment for spatial (across nearby units) autocorrelation. To do so, I use the estimation method pioneered by Conley (1999, 2008), and further developed by Hsiang (2010), to deal with the potential spatial correlation in the error term. I set the distance cutoff (the distance at which spatial correlation is assumed to vanish) to 150 km.

Results of Table D.2 show small changes in significativity. Standard errors appear to be mostly similar to those of the main results. It increases the significativity level of the coefficients already significantly different from zero compared to the main results, or some coefficients that were not significant are now significantly different from zero. No coefficients that were significant become insignificant. Therefore, our standard errors and results appear to be valid.

7.3 Spatial error model (SEM)

I choose a spatial error model (SEM) because it the best model in this case, from both empirical and theoretical point of view. Theoretically, as developed in Loonis et al. (2018), three parts of the econometric model could be spatially dependent: the dependent variable[22], the independent variables[23] and the error term[24].

Clearly, in this study, there is no reason to assume a spatial dependence of the independent variables on Covid-19 cases. For instance, population density is an aggravating factor, but the density of a department does not directly transmit Covid-19 to surrounding departments. The spread of the disease comes from infected individuals. Therefore,

[22] Endogenous interaction effects.

[23] Exogenous interaction effects.

[24] Interaction effect among the error terms.

we are interested in what determines the intensity of transmission of the Covid-19. As discussed in the related literature section, previous studies on respiratory infectious and pandemics show that it depends a lot on social contacts, and that its spread is correlated with local culture. They also explained that they observed significant variations between northern and southern France for example, and that there is no one explanation for all the geographical differences observed. What we learn from all these studies is that it is very difficult–and beyond the scope of this study–to compute a matrix of social contacts between and within all French departments. Such matrices rely on to much elements that must vary over time, which in turn depend on different cultures, habits and geographical characteristics of the departments.

It can be deduced that the transmission of Covid-19 between departments depends not only on the degree of contagion from surrounding departments, but also on the intensity of contacts between them. Since this matrix is unknown, such heterogeneous correlation will be part of the error term. Therefore, the error terms should be spatially dependent and heteroskedastic. Therefore, empirically, the best spatial econometric model we should consider is the spatial error model (only spatially lagged error terms). The spatial error model (SEM) is:

$$\begin{aligned}\text{Covid-19 cases}_{dt} = \beta_0 + (\delta + \gamma \times \text{Advanced epidemics}_d) \times \text{Post} \times \text{Urban exodus}_d \\ + \alpha_d + \alpha_t + u_{dt}, \quad u_{dt} = \lambda W u_{dt} + \varepsilon_{dt}\end{aligned} \tag{6}$$

u_{dt} is the spatially lagged error term composed of Wu_{dt}, the row-standardized contiguity spatial weighting matrix W times u_{dt}–which account for the spatial autocorrelation among the errors–, and ε_{dt} the error term. W is a row-standardized contiguity spatial weighting matrix which gives a weight of 1 if two departments are neighbors (i.e. have a common frontier), 0 otherwise. I choose a contiguity matrix first–rather than an inverse-distance matrix–because most of the usual commuting or displacements for leisure/shopping reasons are done between neighboring departments. The model is estimated using a quasi-maximum likelihood estimators (QMLE) for panel data (see Lee, 2004 and Lee and Yu, 2010 for more details). Results are presented in Table D.3.

Urban exodus. Estimations using the SEM model show positive and significant effects of urban exodus on both deaths and hospitalizations, with higher significant level than OLS estimates. These effects appear on panel B for hospitalizations and on both deaths and hospitalizations on panel C (see columns (1) and (2)).

My estimates suggest an increase in the number of hospitalizations of 6,821, which represents 6.08% of the cumulated hospitalizations for the period. These results are lower than the main estimates.

Non-residents urban exodus. Estimations show effects significantly different from zero only for the departments with advanced epidemics in panel A and B, and significant effects for the departments with no advanced epidemics for panel C, with magnitude similar to the main results (see columns (3) and (4)). My estimates suggest an increase in the number of hospitalizations–due to the urban exodus of the non-residents of the department (excluding the Parisians)–of 1,846, which represents around 1.65% of the cumulated hospitalizations for the period. Almost the same value than the main estimates.

Parisians urban exodus. SEM model shows no coefficients significantly different from zero for deaths, except for the departments with advanced epidemics before lockdown (again, the coefficients are negative). Finally, SEM double difference estimates on hospitalizations show positive and significant coefficients (at the 5% and 1% level) for the three panel, and of the same magnitude than the main results (see column (5) and (6)).

To compare the magnitude of the gap between these results and the main results, I estimate the resulting excess hospitalizations. Estimates show an increase in the number of hospitalizations–due to the urban exodus of Parisians–of 12,818, which represents respectively 11,43% of the cumulated hospitalizations for the period. These results are slightly lower than the main results on excess Covid-19 cases.

8 Discussion

In this section I will discuss and interpret some of the results, especially the significant negative effect of the advanced epidemics departments, and the larger evidence of a causal effect of urban exodus on the number of hospitalizations rather than on the number of deaths. At first glance, these results might seem strange or abnormal. However, we will see that it is not the case when we think about the logical interpretation of these estimates.

First of all, the negative coefficients of the departments with advanced stages of the epidemics ($\widehat{\gamma}$) should be interpreted as an additional or heterogeneous effects of urban exodus for departments with larger spread of the epidemic before lockdown. Since the double difference coefficients ($\widehat{\delta}$) are always larger in terms of magnitude–around 6 times larger–this means that there was indeed a positive effect of urban exodus on the Covid-19 cases in these departments ($\widehat{\delta} + \widehat{\gamma} > 0$). Nevertheless, this effect was less significant in the departments with a higher Covid-19 cases prior the lockdown. These results appear realistic if one considers that in these departments, social distancing measures were taken before the lockdown, and that people who immigrated to these departments were probably more vigilant. Thus, urban exodus could also had an impact in these departments, but with less intensity than in less affected departments before lockdown.

Second, the evidence in favor of a higher or single causal impact of urban exodus on hospitalizations rather than on deaths could be interpreted in the same way. Indeed, a few days before the lockdown, Edouard Philippe–the French Prime Minister–announced that from March 14, 2020, all non-essential public spaces will be closed, and that person-at-risk (elderly, long-term illnesses, etc) will have to stay-at-home. Thus, it can be assumed that on the days around the beginning of the lockdown, when the non-residents of the departments settled, the only inhabitants they met (for instance at the grocery store) were non-at-risk person. Therefore, even if there was a spread of the epidemic from non-residents to inhabitants, those contaminated and hospitalized were less likely to die from Covid-19; resulting in an increase in the number of hospitalizations but not necessarily in the number of deaths.

It should be noted that, at this stage, it is impossible to disentangle whether this excess number of hospitalizations is the result of contamination by the "Covid-19 immigrants" who contaminated the residents, or whether it comes from these non-residents solely. Indeed, if the urban dwellers who migrated to another departments were contaminated, they also went to the hospitals of the departments of migration. Thus, they further increased the number of Covid-19 cases in these departments. Theoretically and logically, the excess Covid-19 hospitalizations should be due to both effects combined. We could also assume that there are composition effects for deaths, such that non-residents arriving in the department are young and healthy (especially the young workers joining their family), and even if sick, they do not die. Such assumption would strengthen our previous statement in favor of more hospitalizations than deaths.

It is also important to remind that this study is specific to the first French lockdown, and thus that its external validity is limited by people' behaviors during this lockdown, and the measures taken by the French government to prevent the spread of the Covid-19 epidemic.

Finally, it is difficult to assert that the urban exodus effect was negative, even if it increased the number of Covid-19 cases. Indeed, it could be argued that, for example, contaminated Parisians who migrated to rural areas, unconsciously helped the most overcrowded hospitals of the capital, by being sick and hospitalized in a hospital of a less affected department. In such a case, we could assume that the urban exodus led to decrease the aggregated number of Covid-19 cases in the whole France, by auto-allocating the patients between departments, thus releasing patients congestion from the most impacted hospitals.

9 Conclusion

In conclusion, the contribution of this paper is threefold. (i) First, to estimate the causal impact of the urban exodus–which occurred around the beginning of the lockdown–and answer the question whether this urban exodus led to an increase in Covid-19 cases. (ii) Secondly, to examine the local determinants of the Covid-19 propagation. (iii) Finally, to estimate the effect of mobility on reducing the spread of the epidemic in France, i.e. the effectiveness of the lockdown.

Using a quasi-natural experiment, I estimate that urban exodus led to a significant increase in the number of hospitalizations. Non-residents of the departments–most of whom came to their secondary residences for the duration of the lockdown–actually increased the number of Covid-19 cases in these departments. Nevertheless, at this stage, it is not possible to disentangle the part of this excess Covid-19 cases that originated from contamination of the non-residents to the residents, from the hospitalizations of the non-residents contaminated before their migration solely. Lower-bound estimates show an excess number of around 1,850 hospitalizations, and upper-bound of around 13,500. Those numbers correspond respectively to around 1.65% and 12% of the cumulated hospitalizations for the period. Those approximations are consistent with previous studies, such as Cassan and Sangnier (2020) or Bertoli et al. (2020), which investigate the effect of the French municipal elections of March 15, 2020, on the Covid-19 epidemics. I also show additional evidence that most if this excess Covid-19 cases come from the Parisians "immigrants". This is not surprising, given that they represent an important share of the people who left their main residences to join another department (around 218,000), and that Paris region was one the most impacted place by the epidemic before the lockdown. Nonetheless, it is hard to say that the impact of the urban exodus was only negative. Indeed, it could have led to decrease the aggregated number of Covid-19 cases in the whole France, by auto-allocating the patients between departments, thus releasing patients congestion from the most impacted hospitals.

I also estimate that local determinants of Covid-19 spread are population density and the share of social housing. Those results confirmed that people living in poor and densely populated areas are more likely to be contaminated.

Finally, I assess the elasticity of Covid-19 cases growth rate in France with respect to different mobility indices, using regional data from Google mobility reports. Results suggest that a 10% reduction in retail and recreation mobility led to a relative decrease in the average daily deaths growth rate of 17%, of 35.4% for workplaces mobility and of 12.2% for parks mobility. It can therefore be concluded that the lockdown and stay-at-home measures implemented by the French government were truly effective in reducing the spread of the epidemic.

To conclude, these results can be used by decision- and policy-makers to adapt future social distancing or lockdown measures, in case the epidemic breaks out again. For instance, we can conclude that social distancing measures should take into account the displacements and commuting flows–between and within departments–to be most effective. In the event of a new lockdown, the French government should take into account the anticipatory behaviors of the population, and their possible exodus to more quiet places. This study could also be enriched in further research, provided that datasets based on users' mobile phone location are made available at the municipality level, or with health data from social security at the individual level, which could allow me to examine the geographical origin of hospitalized patients, and their exact pathology. Thus, to confirm the impact of urban exodus on the spread of the epidemics at the local level, and to disentangle the part of the excess hospitalizations between residents and non-residents.

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Appendices

A Tables

Table A.1: Examples of newspapers' title about urban exodus

Newspaper	Publication	Language	Title	URL
Le Parisien	16/03/2020	French	*Coronavirus : par crainte du confinement, ils fuient Paris*	https://www.leparisien.fr/
		English	Coronavirus: for fear of containment, they flee Paris	
France Bleu	19/03/2020	French	*Des voitures immatriculées "75" vandalisées sur l'Île de Noirmoutier*	https://www.francebleu.fr/
		English	Cars with license plate "75" vandalized on Île de Noirmoutier	
BFM TV	22/03/2020	French	*Confinement: l'exode des Parisiens vers le littoral, source de vives tensions avec les locaux*	https://www.bfmtv.com/
		English	Confinement: the exodus of Parisians to the coast, a source of great tension with the locals	
France info	22/03/2020	French	*"C'était comme les retrouvailles du 15 août" : l'exode massif des citadins à l'heure du confinement ne passe pas inaperçu*	https://www.francetvinfo.fr/
		English	It was like the reunion of August 15: the mass exodus of city dwellers at the time of confinement did not go unnoticed.	
Cnews	23/03/2020	French	*En Bretagne et en Vendée, des voitures immatriculées à Paris vandalisées*	https://www.cnews.fr/
		English	In Brittany and Vendée, cars registered in Paris were vandalized.	
La Depêche	23/03/2020	French	*Coronavirus : des voitures immatriculées en région parisienne vandalisées en Bretagne*	https://www.ladepeche.fr/
		English	Coronavirus: cars registered in the Paris region vandalized in Brittany	
Le Parisien	23/03/2020	French	*Coronavirus : des voitures immatriculées hors de Bretagne vandalisées*	https://www.leparisien.fr/
		English	Coronavirus: cars registered outside Brittany vandalized	
Ouest France	24/03/2020	French	*"C'est un confinement, pas des vacances" : l'afflux de Parisiens dans l'Ouest agace et inquiète*	https://www.ouest-france.fr/
		English	It's a confinement, not a holiday: the influx of Parisians in the West is annoying and worrisome	
Le Point	27/03/2020	French	*Face au confinement, les Parisiens ont bien pris la fuite*	https://www.lepoint.fr/
		English	Faced with the confinement, the Parisians have fled...	
Le Monde	15/05/2020	French	*"Certains ont confondu vacances et confinement" : le quotidien pas si doré des "Parisiens" réfugiés à l'île de Ré*	https://www.lemonde.fr/
		English	"Some people have confused holidays with confinement": the not so golden daily life of the "Parisians" who took refuge on the Ile de Ré.	

Sources: author's table.

Table A.2: Summary statistics

Variable	N	Mean	SD	Max	Min
Total # of deaths per 100,000 inhabs	91	25	24	127	1
Total # of hospitalizations per 100,000 inhabs	91	147	116	571	26
Urban exodus (%)	91	1	3	7	-6
Urban exodus non-residents (%)	91	-1	1	1	-6
Urban exodus Parisians (%)	91	0	0	2	0
Secondary residences (%)	91	11	9	40	1
Secondary residences non-residents (%)	91	7	7	34	0
Secondary residences Parisians (%)	91	1	1	3	0
Population > 60 years (%)	91	30	5	39	17
Population	91	671,65	505,034	2,588,988	76,286
Unemployment rate	91	8	2	13	5
Health and social expenses (*per capita*)	91	66	7	96	49
Surface area (km2)	91	5,752	1,875	9,976	176
Population density (inhabs/km2)	91	359	1,29	9,098	15
Nb of nursing homes (EHPAD)	91	75	43	225	6
Airports traffic (nb of passengers)	91	2,118,206	8,563,316	72,229,720	0
Pop living in a municipality densely populated (%)	91	20	25	100	0
Nb of tourist accommodations	91	277	182	856	27
Train station traffic (# of passengers)	91	20,402,164	49,253,065	286,662,112	0
Social housing (%)	91	13	5	32	5
Main residences < 40 m2 (%)	91	8	3	22	4
Nb of beds in intensive care unit	91	52	59	309	3
Pop living in an over-occupied accommodation (%)	91	5	5	31	2
Deaths to March 16	91	1	6	52	0
Hospitalizations to March 16	91	34	58	277	0

Notes: table reports descriptive statistics for the panel without outliers.

Table A.3: T-test of the variables mean difference between departments with positive and zero urban exodus

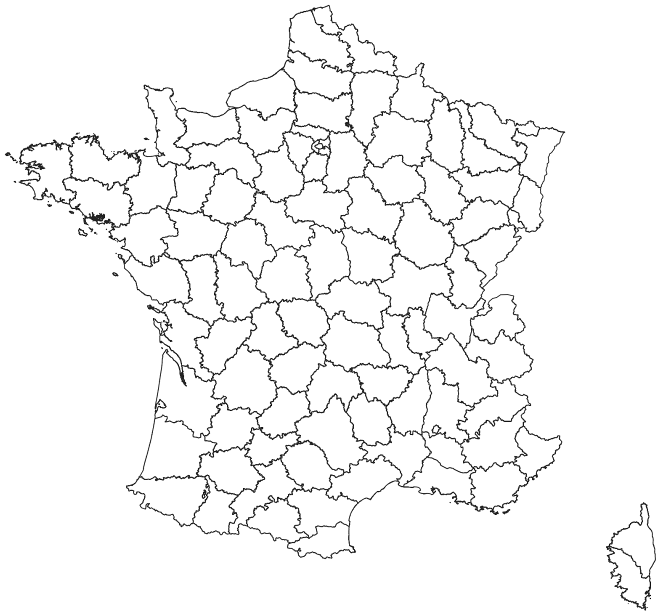
Variable	**Mean departments urban exodus > 0**	**Mean departments urban exodus = 0**	**Diff.**
Total # of deaths per 100,000 inhabs	24	20	4 (8.07)
Total # of hospitalizations per 100,000 inhabs	145	117	28 (37.67)
Urban exodus (%)	3	0	3*** (0.50)
Urban exodus non-residents (%)	-1	-2	1*** (0.29)
Urban exodus Parisians (%)	0	0	0 (0.13)
Secondary residences (%)	11	8	3 (2.92)
Secondary residences non-residents (%)	8	5	2 (2.34)
Secondary residences Parisians (%)	1	1	0 (0.26)
Population > 60 years (%)	31	28	3* (1.50)
Population	514,196	864,513	-350,317** (151,725.25)
Unemployment rate	8	8	-1 (0.50)
Health and social expenses (*per capita*)	65	70	-5** (1.91)
Surface area (km2)	5,721	6,301	-581 (529.13)
Population density (inhabs/km2)	118	142	-24 (55.15)
Nb of nursing homes (EHPAD)	64	93	-29** (12.97)
Airports traffic (nb of passengers)	1,682,342	467,155	1,215,187 (2,998,411.48)
Pop living in a municipality densely populated (%)	11	27	-16** (6.28)
Nb of tourist accommodations	250	274	-24 (60.16)
Train station traffic (# of passengers)	14,904,148	10,607,067	4,297,081 (13688709.40)
Social housing (%)	11	15	-4** (1.56)
Main residences < 40 m2 (%)	6	8	-2*** (0.67)
Nb of beds in intensive care unit	30	76	-46*** (16.15)
Pop living in an over-occupied accommodation (%)	5	4	0 (1.04)
Deaths to March 16	1	0	1 (2.15)
Hospitalizations to March 16	27	20	7 (17.16)

Notes: tables reports t-test for the panel limited to departments with positive or zero urban exodus (i.e. variation of population before\after the beginning of the lockdown greater than or equal to 0). Standard errors are in parentheses. Stars indicate significance level: * p<0.1, ** p<0.05 and *** p<0.01.

B Figures

Figure B.1: Maps of the French departments and regions

(a) French departments (NUTS 3)

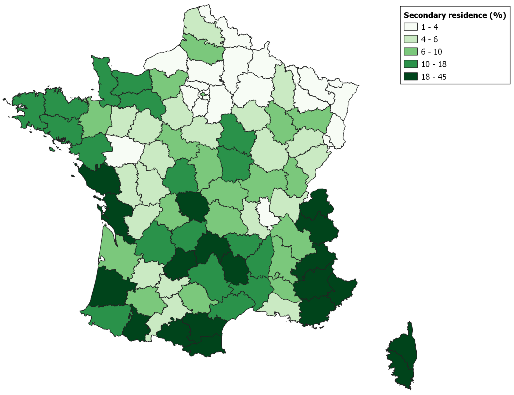


(b) French regions (NUTS 2)

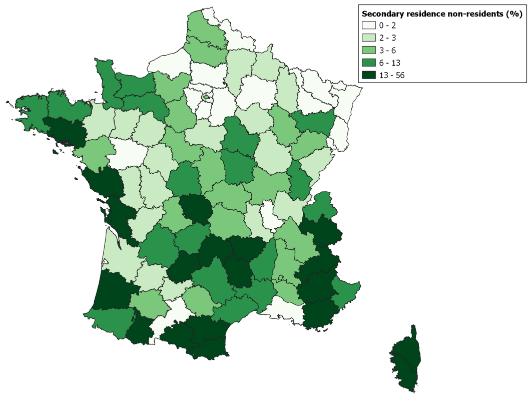
Source: author's maps.

Figure B.2: Secondary residences

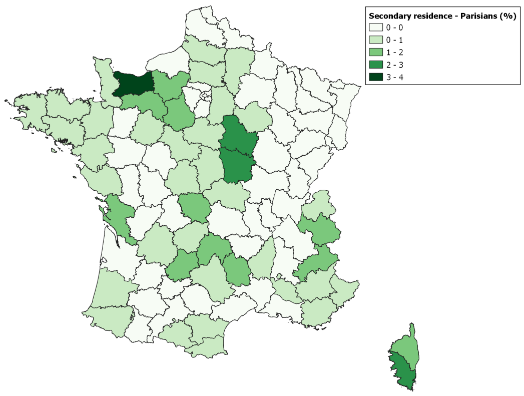
(a) Share of secondary residences



(b) Percentage of non-residents owning a secondary residences in the department (excluding Parisians)



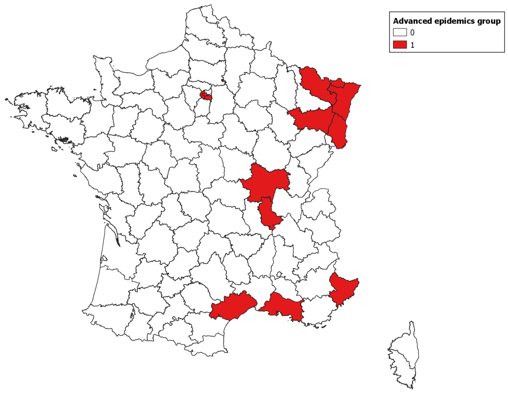
(c) Percentage of Parisians owning a secondary residences in the department



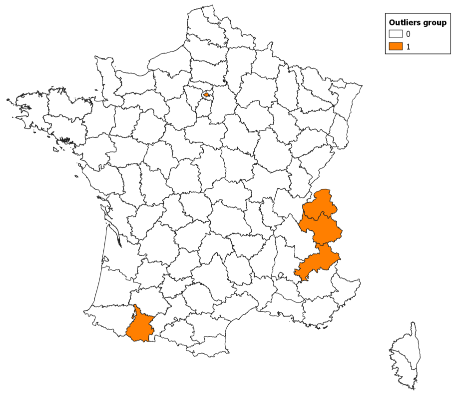
Notes: map B.2a represents the share of secondary residences among the total of housing, map B.2b represents the share of non-residents (excluding inhabitants of Paris) of the department owning a secondary residences among the total population of the department, and map B.2c represents the share of Parisians owning a secondary residences among the total population of the department.
Sources: INSEE, Recensement de la population 2016-2017 (Fideli); author's maps.

Figure B.3: Sample groups

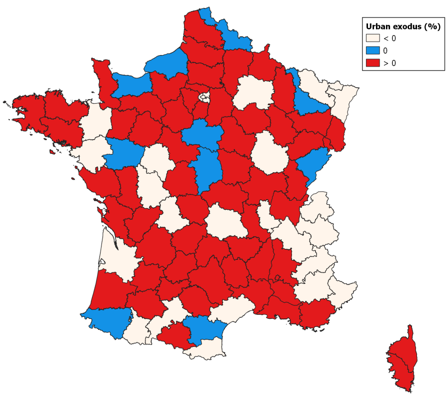
(a) Advanced epidemics departments



(b) Outliers departments



(c) Departments with positive or zero urban exodus

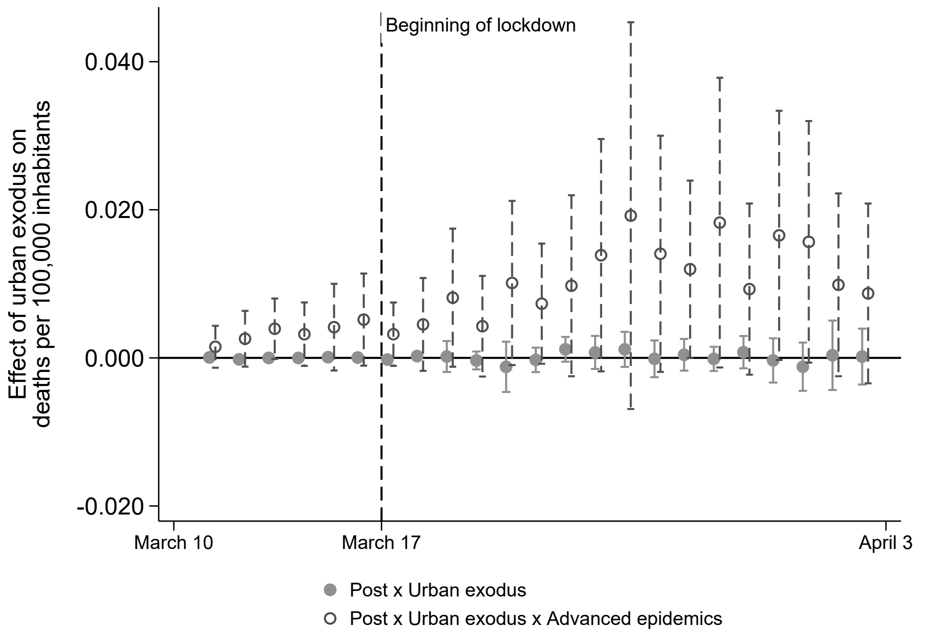


Source: author's maps.

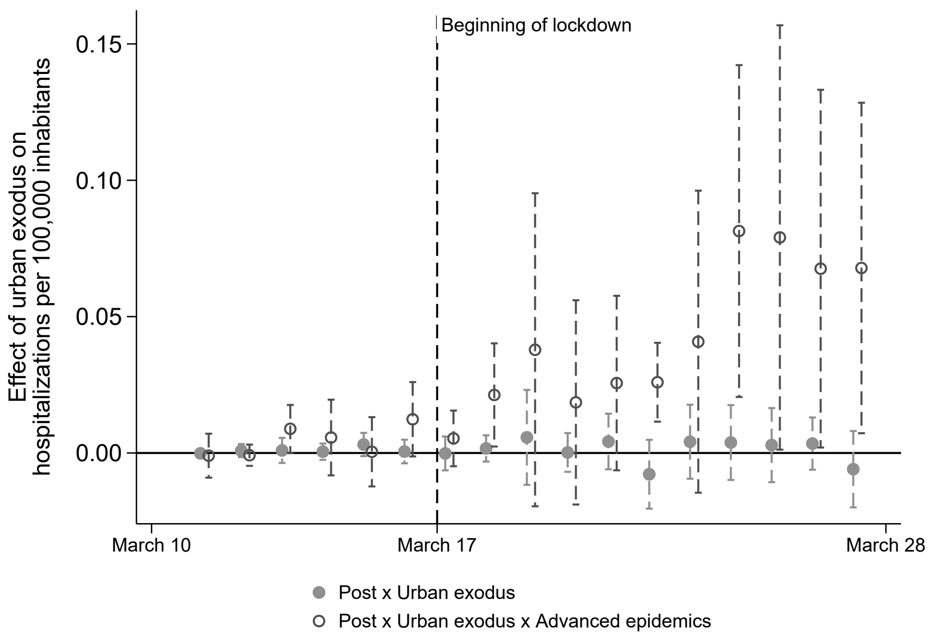
C Placebo test

Figure C.1: Placebo test

(a) Deaths



(b) Hospitalizations



Notes: period of regression from March 10 to April 03 for deaths variable, and from March 10 to March 28 for hospitalizations variable.
Source: author's computation.

D Robustness checks results

Table D.1: Difference-in-differences: different period

Dependent variable:	Urban exodus		Non-residents urban exodus		Parisians urban exodus	
	(1) Deaths per 100,000 inhabitants **OLS**	(2) Hospitalizations per 100,000 inhabitants **OLS**	(3) Deaths per 100,000 inhabitants **OLS**	(4) Hospitalizations per 100,000 inhabitants **OLS**	(5) Deaths per 100,000 inhabitants **OLS**	(6) Hospitalizations per 100,000 inhabitants **OLS**
Panel A: Whole panel						
Post × Urban exodus	-0.0025	0.015	-0.0023	0.0099	-0.013	0.12
	(0.0030)	(0.018)	(0.0028)	(0.028)	(0.023)	(0.14)
Post × Urban exodus × Advanced epidemics	-0.0026	-0.019**	-0.0024	-0.020**	-0.0025	-0.018**
	(0.0022)	(0.0080)	(0.0021)	(0.0077)	(0.0022)	(0.0082)
Adjusted R-squared	0.14	0.27	0.14	0.27	0.14	0.27
Observations	5,184	5,184	5,184	5,184	5,184	5,184
Panel B: None outliers						
Post × Urban exodus	-0.0037	0.065	-0.013	-0.011	0.11	1.23***
	(0.013)	(0.056)	(0.026)	(0.12)	(0.094)	(0.46)
Post × Urban exodus × Advanced epidemics	-0.0027	-0.018**	-0.0028	-0.020**	-0.0022	-0.016*
	(0.0024)	(0.0088)	(0.0025)	(0.0089)	(0.0022)	(0.0081)
Adjusted R-squared	0.14	0.25	0.14	0.25	0.14	0.26
Observations	4,914	4,914	4,914	4,914	4,914	4,914
Panel C: None $\triangle$ pop < 0						
Post × Urban exodus	0.039*	0.25**	0.15	2.01**	0.12	1.34***
	(0.020)	(0.10)	(0.12)	(0.86)	(0.096)	(0.46)
Post × Urban exodus × Advanced epidemics	-0.0067	-0.033*	0	0	-0.0021	-0.015*
	(0.0048)	(0.017)	(.)	(.)	(0.0022)	(0.0080)
Adjusted R-squared	0.13	0.22	0.10	0.14	0.13	0.25
Observations	3,780	3,780	972	972	4,860	4,860
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table reports estimates of equation 1, using OLS. Standard errors, given in parentheses, are clustered by department. Stars indicate significance level: * p<0.1, ** p<0.05 and *** p<0.01.

Table D.2: Difference-in-differences: with standard errors adjusted for spatial correlation (150 km cutoff)

Dependent variable:	Urban exodus		Non-residents urban exodus		Parisians urban exodus	
	(1) Deaths per 100,000 inhabitants **OLS**	(2) Hospitalizations per 100,000 inhabitants **OLS**	(3) Deaths per 100,000 inhabitants **OLS**	(4) Hospitalizations per 100,000 inhabitants **OLS**	(5) Deaths per 100,000 inhabitants **OLS**	(6) Hospitalizations per 100,000 inhabitants **OLS**
Panel A: Whole panel						
Post × Urban exodus	-0.0023	0.0057	-0.0019	0.0031	-0.012	0.043
	(0.0018)	(0.0086)	(0.0021)	(0.0090)	(0.015)	(0.076)
Post × Urban exodus × Advanced epidemics	-0.0019***	-0.011***	-0.0017**	-0.010***	-0.0018***	-0.0098***
	(0.00070)	(0.0037)	(0.00070)	(0.0037)	(0.00067)	(0.0035)
Adjusted R-squared	0.54	0.62	0.54	0.62	0.54	0.62
Observations	7,968	7,968	7,968	7,968	7,968	7,968
Panel B: None outliers						
Post × Urban exodus	-0.0038	0.038	-0.010	-0.051	0.071**	0.84***
	(0.0044)	(0.025)	(0.0080)	(0.051)	(0.036)	(0.21)
Post × Urban exodus × Advanced epidemics	-0.0020***	-0.010***	-0.0020***	-0.012***	-0.0016**	-0.0080**
	(0.00073)	(0.0037)	(0.00073)	(0.0038)	(0.00064)	(0.0034)
Adjusted R-squared	0.54	0.61	0.54	0.61	0.54	0.61
Observations	7,553	7,553	7,553	7,553	7,553	7,553
Post × Urban exodus	0.026***	0.18***	0.11*	2.01***	0.082**	0.95***
	(0.0071)	(0.040)	(0.061)	(0.43)	(0.037)	(0.22)
Post × Urban exodus × Advanced epidemics	-0.0052***	-0.020***			-0.0016**	-0.0074**
	(0.0012)	(0.0057)			(0.00065)	(0.0034)
Adjusted R-squared	0.51	0.57	0.41	0.46	0.54	0.61
Observations	5,810	5,810	1,494	1,494	7,470	7,470
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table reports estimates of equation 1, using OLS. Standard errors, given in parentheses, are adjusted for spatial (across nearby units) autocorrelation, with a distance cutoff of 150 km. Stars indicate significance level: * p<0.1, ** p<0.05 and *** p<0.01.

Table D.3: Difference-in-differences: SEM with contiguity matrix

Dependent variable:	Urban exodus		Non-residents urban exodus		Parisians urban exodus	
	(1) Deaths per 100,000 inhabitants **QMLE**	(2) Hospitalizations per 100,000 inhabitants **QMLE**	(3) Deaths per 100,000 inhabitants **QMLE**	(4) Hospitalizations per 100,000 inhabitants **QMLE**	(5) Deaths per 100,000 inhabitants **QMLE**	(6) Hospitalizations per 100,000 inhabitants **QMLE**
Panel A: Whole panel						
Post × Urban exodus	-0.00085	0.014	-0.0032	0.0029	0.0043	0.11**
	(0.0018)	(0.0097)	(0.0028)	(0.015)	(0.010)	(0.053)
Post × Urban exodus × Advanced epidemics	-0.0012***	-0.0092***	-0.0012***	-0.0097***	-0.0011***	-0.0086***
	(0.00034)	(0.0018)	(0.00033)	(0.0018)	(0.00034)	(0.0018)
λ						
e.Deaths per 100,000 inhabs	0.36***		0.36***		0.36***	
	(0.013)		(0.013)		(0.013)	
e.Hospitalizations per 100,000 inhabs		0.38***		0.38***		0.38***
		(0.012)		(0.012)		(0.012)
Pseudo R-squared	0.13	0.20	0.13	0.20	0.13	0.20
Observations	7,968	7,968	7,968	7,968	7,968	7,968
Panel B: None outliers						
Post × Urban exodus	-0.00018	0.044*	-0.0076	-0.021	0.035	0.79***
	(0.0043)	(0.023)	(0.0084)	(0.044)	(0.035)	(0.19)
Post × Urban exodus × Advanced epidemics	-0.0012***	-0.0086***	-0.0012***	-0.0098***	-0.0010***	-0.0075***
	(0.00035)	(0.0018)	(0.00035)	(0.0019)	(0.00034)	(0.0018)
λ						
e.Deaths per 100,000 inhabs	0.34***		0.34***		0.34***	
	(0.014)		(0.014)		(0.014)	
e.Hospitalizations per 100,000 inhabs		0.36***		0.36***		0.36***
		(0.013)		(0.013)		(0.013)
Pseudo R-squared	0.13	0.20	0.13	0.20	0.13	0.18
Observations	7,553	7,553	7,553	7,553	7,553	7,553
Panel C: None △ pop < 0						
Post × Urban exodus	0.021***	0.13***	0.12*	2.00***	0.039	0.90***
	(0.0071)	(0.037)	(0.066)	(0.38)	(0.037)	(0.19)
Post × Urban exodus × Advanced epidemics	-0.0041***	-0.017***	0	0	-0.0010***	-0.0065***
	(0.00053)	(0.0028)	(.)	(.)	(0.00035)	(0.0018)
λ						
e.Deaths per 100,000 inhabs	0.22***		0.24		0.32***	
	(0.015)		(0.024)		(0.014)	
e.Hospitalizations per 100,000 inhabs		0.23***		-0.0093		0.34***
		(0.014)		(0.026)		(0.013)
Pseudo R-squared	0.08	0.16	0.16	0.12	0.12	0.18
Observations	5,810	5,810	1,494	1,494	7,470	7,470
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table reports estimates of equation 6, using quasi-maximum likelihood estimators. Standard errors are given in parentheses. Stars indicate significance level: * p<0.1, ** p<0.05 and *** p<0.01.