Residential Migration and the COVID-19 Crisis: Towards an Urban Exodus in France?

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Abstract – Much has been written about the potential effect of the COVID-19 crisis on residential mobility. To explore its effects in France, we reconstruct flows of mobility intentions based on owner and buyer estimates on the platform MeilleursAgents from January 2019 to September 2021, and we analyze, using logit and nested logit models, how the pandemic has changed the probability that individuals from both urban and rural intend to relocate. Our results show that, after a time of shock during the first lockdown in spring 2020, the desire to migrate, either to rural municipalities or to other catchment areas, increased as the pandemic and the restrictive measures continued, and was particularly pronounced after the end of the third and last lockdown.

JEL: C35, R23
Keywords: COVID-19, platform data, residential location choice, discrete choice models, real estate

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In France, since the first lockdown put in place in March 2020 to contain the COVID-19 pandemic, urban exodus has become a highly popular topic in the press. Households are described as eager to move to bigger homes, with large green spaces, in less dense areas. According to a survey by MeilleursAgents (an online real estate platform) in 2021,[1] among people who have changed their primary residence since July 2020 or planned to do so before January 2022, one half changed their search criteria to have a garden (39% of them), to be closer to nature (34%) or to live in a smaller city (19%).

Yet, attraction to rural areas is not a new phenomenon. Over the previous three decades, a report from the Observatoire des Territoires (2018) concludes that France has experienced a decrease in population concentration, with big centres losing attractiveness while the surrounding areas attract new inhabitants. According to D'Alessandro *et al.* (2021), between 2007 and 2017, the average annual population growth was 0.66% in rural areas, but only around half of that (0.38%) in urban areas. The attraction for rural areas seems to be mostly restricted to rural suburban cities. In 2017, 26.9% of people moving from an urban to a rural area moved to a city in the catchment area of a city centre (D'Alessandro *et al.*, 2021).

In addition, though yearly residential mobility is higher in France than in Europe on average (11% of the French population moving each year *vs* 9% in Europe), the Observatoire des Territoires (2018) notes that French people move less and less far since 1990. Three-quarters of movers choose a location close to their current residence (in the same *département*). This report also shows that the mobility rate decreases with age and increases with education level, and that managers, professionals and associate professionals tend to move further, between Paris and other big cities, than clerical or service and sales workers. Housing market constraints prevent all social classes from moving in the same direction or to the same places, which may reinforce social segregation.

In 2019, a survey from Ifop[2] revealed that 57% of people living in urban areas wanted to leave. Three main obstacles prevented them from taking the leap, specifically, the lack of services (for 60%), the lack of transport infrastructures (for 53%), and difficulties in accessing employment (for 46%). The use of telework since COVID-19 crisis, firstly widespread and mandatory during the first lockdown and then more balanced and negotiated between workers and employers, could remove this third obstacle to urban exodus, at least partially.[3] Since March 2020, MeilleursAgents has noted a 13% increase in transaction volume in rural areas.[4] This trend also seems to be reflected in the evolution of residential property prices:[5] in 2020, Paris experienced a decline in prices, while rural areas experienced a greater increase in prices than the largest cities. The price increase mainly concerns rural suburban areas[6] (+9.7% in 2020) and rural areas with a large proportion of secondary homes.

However, can we speak of an urban exodus since the COVID-19 crisis? The impact of the COVID-19 crisis on the determinants of residential mobility is obviously an emerging subject in the literature. Based on the New York Fed Consumer Credit Panel/Equifax microdata, Li & Su (2021) observe that, since the COVID-19 pandemic, Americans both moved from immediate dense surroundings of city centers to suburbs that are more distant with lower density, and from high-density population metropolitan statistical areas (MSAs) to low density MSAs, thus partially counterbalancing the spatial sorting. They then use a spatial equilibrium model to analyze the welfare effects of these migration changes. Ramani & Bloom (2021) use both data from address changes from the US Postal Service to estimate migration patterns and real estate rents, and price indices from the website Zillow to proxy for real estate demand. They find that CBDs (Central Business Districts) and dense areas experienced a relative price decrease compared with less dense areas. They interpret this as a "donut effect" for prices, which seems to be limited to highly populated, dense cities. Additionally, they find that migrations are less frequent between than within metropolitan areas. Introducing both part-time and full-time work-from-home in their equilibrium model allow them to explain this by the fact that telework will only concern part of the working time, and thus, a significant

1. *Toluna survey for MeilleursAgents, conducted from July 5 to 11, 2021 on 2,722 people representative of the French population, including 1,133 people who have moved or intend to move.*
2. *https://www.ifop.com/publication/le-retour-a-la-campagne/*
3. *In the Toluna survey, MeilleursAgents show that around 50% of workers consider pursuing work-from-home after the pandemic. However, 60% of them would like to work remotely only two days or less per week and only 19% would like to work remotely full-time.*
4. *2021 MeilleursAgents Press Conference:* "Quelles sont les nouvelles tendances pour le marché immobilier ?" *https://backyard-static.meilleursagents.com/press/6b615242cec200af47aec27515746e25a8174bf6.pdf*
5. *MeilleursAgents Real Estate Price Index of September 1, 2021.*
6. *Rural suburban areas are rural cities that are part of catchment areas of cities with more than 50,000 inhabitants.*

distance to employment location remains. In other words, households are prepared to move away but not too far. Also relying on Zillow data, in addition to productivity, amenity and industry indices, Brueckner *et al.* (2021) find no support for their model's prediction of falling prices and rents in low-amenity cities with high work-from-home potential. They also show that telework imposes capital losses on real estate owners in high-productivity cities and capital gains to renters. Furthermore, as remote work reduces commuting costs, they find that it increases disutility for places with high crime rates and high taxes. This phenomenon makes the suburbs more attractive.

In the case of France, the detailed and representative data that would allow analyzing whether the determinants of residential mobility have changed since the COVID-19 crisis are not yet available.[7] To provide some early answers to this question and contribute to the literature, we turn to an analysis of the change in households' intentions to move since the start of the COVID-19 crisis, based on users' searches on the real estate platform MeilleursAgents. The originality of our paper is to exploit, over a period of almost three years (from 2019 to 2021), the processing traces left by users on the platform. We reconstruct 100,193 rows of residential mobility intentions from users who log on to the platform first to estimate a property with an owner status, then to estimate another property with a buyer status, tracking them with their user ID. The data from these searches provide, almost in real time, the price estimate, the location and characteristics of the current and targeted properties.

Based on these data, we first estimate, using binary logit models separately for urban and rural residents, the probability of intentions to stay in the same catchment area[8] or to move to another one and the probability of choosing an urban destination. We then estimate nested logit models, again separately for urban and rural residents, to analyze users' intentions in a sequence where they choose first whether they intend to stay in the same catchment area or to move to another one and, in each options, if they target an urban or a rural city. We capture the effect of the COVID-19 through the timing of the search.

Our results show that the pandemic has influenced residential mobility intentions, both through the choice of the catchment area and the location on the urban-rural gradient. The COVID-19 effect varies over the course of the pandemic (and the lockdowns), the appeal for other catchment areas and rural cities being the strongest after the end of the last lockdown in early May 2021. Moreover, comparing the probability of intentions to move before or since the COVID crisis, the odds (i.e. the ratio of these probabilities) that an urban resident searches for a property in an urban rather than a rural city is 0.923 times lower, and even decreases to 0.644 for a resident from a city centre (*pôle urbain*) also searching for a residence in the city centre, whereas the crisis seems to have had no impact on the choice of rural residents.

The rest of the article is organized as follows. We present the data in Section 1 and the methodology in Section 2. In Section 3, we analyze the results from the discrete choice models. Finally, we conclude and highlight the challenges for further research.

1. Data, Sample and Descriptive Statistics

1.1. Platform Data Description

MeilleursAgents (hereafter MA) is the main real estate platform providing online property estimates in France. It attracts 2.4 million unique visitors per month, with 500,000 online estimates per month made by the users.[9] The use of such high frequency data in the academic literature is very recent and promising, since it makes it possible to explore users' behaviour by following each step of their home-buying project. MA traffic data has already been used by Vidal (2021) to analyze matching and pricing mechanisms on the real estate market. Van Dijk & Francke (2018), Rae & Sener (2016) and Piazzesi *et al.* (2020) also exploit platform traffic data to calculate market tightness indicators and to analyze market segmentation.

We can track users who log onto the MA platform with their user ID, which is required to obtain estimates (but not for consulting ads for instance). The estimation tool is based on a form in which users provide information on their status (owner, owner-seller or buyer), the characteristics of the dwelling estimated and its location. The tool returns a price range for the dwelling. For users who seek an estimate as buyers, the tool is used at an advanced stage of

7. The new data from the population census and from the Housing survey, required to compare residential mobility since the COVID-19 crisis to the pre-COVID situation, will only become available in the years to come.
*8. This zoning, which is consistent with the zonings used by Eurostat and the OECD, has been used as the zoning of reference since 2020 in France. It divides the territory in more than twice the number of "*zones d'emploi*" (employment areas), enabling a more detailed analysis; it also contains a category "*hors attraction des villes*" (i.e. excluding cities' attraction), which is of particular interest for our study.*
9. Figures for November 2021.

their project. Indeed, because users need specific information, they generally use it to estimate the price of a dwelling that they have visited or they are going to visit: they want to have an idea of the price to make an offer close to market price. Consequently, we use these estimations, that reveal a strong intention to buy (but not that the purchase was actually made), as an early information of a buying process.

In order to reconstruct an intended mobility path, we select in our database the users who make an estimate both as owner and as buyer. We thus have information on the initial location (from the owner estimate) and on the desired location (from the buyer estimate). Moreover, we have information on the characteristics of the current residence and of the searched one (detailed in Appendix).

The sample consists exclusively of homeowners. Beyond credit access conditions, income or anticipation of price changes, the choice of occupancy status is influenced by position in the life cycle (see Artle & Varaiya, 1978 for the first theoretical model that introduced life cycle in the determinants of home-ownership). The rate of home-ownership sharply increases with the stabilization of professional situations at the start of a professional career. The birth of children often leads homeowner couples to opt for a house with more space around, with a stable peak zone reached around at 60 years of age. The rate of home-ownership also varies over the territory, with larger shares of owners in the crowns of local hubs, periurban spaces and less densely populated hinterland than city centres (INSEE, 2017).

We cannot rule out potential selection bias linked to the use of remote matching tools, either in terms of users' education or distance between the current and the desired location.[10] Unfortunately, we have no information on the characteristics of the users (e.g. age or income) or their household (e.g. number of children living at home) though the literature has stressed their role in explaining residential mobility choices. However, the size of the dwelling and the number of rooms, likely to be correlated with family size, can capture part of this effect. Another data limitation is that the MA website is not used uniformly throughout France, the activity being mainly driven by Paris and other big cities areas. We also need to keep in mind that the increase in website traffic is simultaneous to our period of study.

1.2. Platform Data Processing

We process the data from our database in several ways. Firstly, we remove the outliers, i.e. estimates for dwellings with a very small (less than 9 square meters) or a very large (more than 250 square meters) surface. In addition, we ensure consistency between the surface and the number of rooms. We also remove estimates that return a very low or a very high price, i.e., for which the price is lower than half the first percentile and more than twice the 99th percentile of prices estimated. Finally, to avoid having estimates made by robots in our data set, we remove the percentile of users who made the highest number of estimates in the period.

Secondly, we account for multiple estimates by the same user. Regarding buyer estimates, if a user made several estimates of the same dwelling, we keep only the most recent one. Regarding owner estimates, if a user made several estimates for the same address in the same city (or for another address but in an identical area or with an identical number of rooms), we keep the oldest one because it represents the first intention to move. In the event of several searches in the same month by the same user, we keep only the last estimate because we infer that the user's visits for the previous properties were unsuccessful. Thirdly, among all possible types of property that are estimated (principal residence, secondary residence, dwelling owned for investment purposes), we only keep the estimates done for principal residences.[11]

Once this data processing is complete, we keep all owner estimates (i.e. those who have an intention to move and those who do not) and we merge them by user ID with buyer estimates. As a result, we have information concerning the owner estimate (location and characteristics of the principal residence) and the buyer estimate (location and characteristics of the principal residence, as well as those of the desired property).[12] In the database, each row then links an estimate made as an owner and an estimate made as a buyer by the same user.

10. The average distance calculated from the INSEE Fichiers détails "Migrations résidentielles des individus" *between previous and new housing is close to 80 km. At the same time, according to a CSA Research study for Codis France published in 2019, the average distance between previous and new housing (for both renters and home-owners) is 118 km, regardless of the channel through which they moved (platform, local real estate agency, etc.). In our dataset of home-owners, the average distance is in between, with 103 km.*

11. As it does not provide any information on the intention to move, we also removed links when owner and buyer estimates are done for the same dwelling, which could result from tests carried out by the same user. However, we have kept such users in the database in case they carry out estimates for other properties.

12. We postulate that the typical user first estimates the value of the property they own to have an approximate idea of their maximum budget before starting their search for a new home, and then make estimates for the dwellings they visit to ensure that they are not overpriced. We cannot, however, completely exclude the case of a user making first an estimate as a buyer and then as an owner.

At last, in order to avoid searches for investment purposes, we removed the observations for which the size of the current dwelling was too different from that of the desired dwelling. We also removed extreme outliers, i.e. the first percentile (surface difference lower than −157 square meters) and the last percentile (surface difference above 132 square meters).

Our final database contains owner estimates from February 22, 2012, to September 20, 2021, matched to buyer estimates from January 1, 2019, to September 20, 2021, covering periods of relatively similar length before and after the beginning of the COVID-19 crisis.

1.3. Characteristics of the Location

With regards to the location, a key factor to address our question is whether the dwelling is located in a rural or an urban area. For that purpose, we use the rural zoning from the Observatoire des Territoires,[13] which splits French cities between 4,193 urban cities and 30,772 rural cities based on the INSEE communal density grid. Figures S1-1 and S1-2 in the Online Appendix (link at the end of the article) map the territorial coverage of our owners and buyers estimates.

We also use the INSEE zoning of catchment areas[14] to characterize more precisely the intended mobility, accounting for the area of influence of major French cities. A catchment area is a set of municipalities, in a single block and without enclaves, which defines the extent of the influence of a population and employment pole on surrounding municipalities, this influence being measured by the intensity of commuting. A catchment area is composed of a "*pôle*" (cluster) and a "*couronne*" (periphery). The "*pôle*" is determined with respect to thresholds of population density and employment level. Among the cities that belong to the *pôle*, the city with the highest population is the "*commune centre*". Other municipalities where at least 15% of the workforce is employed in the "*pôle*" constitute the "*couronne*" of the area. Figure S2-1 in the Online Appendix maps this split in 699 catchment areas ("*aires d'attraction des villes*" as defined by INSEE and based on the intensity of commuting to the employment cluster). Additionally, catchment areas are ranked according to their population size (see Online Appendix, Figure S2-2).

Furthermore, we characterize municipalities using a large range of socioeconomic data from INSEE, specifically the median population income, services and equipment levels (cf. Hilal *et al.*, 2020), age distribution of the population and structure of the housing stock.[15] The list of all variables is provided in Appendix.

1.4. Descriptive Statistics

Our dataset contains 100,193 observations of intentions to move (i.e. estimations of a property to buy) from 01/01/2019 to 20/09/2021. These observations are split between 83,991 observations of users who originally live in an urban city and 16,202 observations of users who originally live in a rural city. The dataset contains 80,662 different users including 66,507 users with a unique link and 14,155 users with several links. Table 1 shows that 40.5% of our sample concern dwelling searches between January 2019 and the announcement of the first lockdown (12 March 2020) and 59.5% after. We decompose the time after the beginning of the crisis into six periods that are described in Appendix 1. Our sample splits into 2.6%, 4.5% and 4.4% respectively for each of the three lockdowns, 18.4% in the intermediate period between the first two lockdowns, 13.6% in the intermediate period between the last two lockdowns, and 16% afterwards. Interestingly, after dividing the number of estimates with respect to

13. *https://www.observatoire-des-territoires.gouv.fr/typologie-urbain-rural*
14. Aire d'attraction des villes *in French.*
15. *See Delance & Vignolles (2017), for an analysis of the key factors influencing residential mobility.*

Table 1 – **Evolution of buyers estimates with respect to the timing of the crisis**

	Number of days	Number of buyers estimates	% of buyers estimates	Average number of estimates per day
Before	436	40,557	40.5	93.0
Lockdown 1	60	2,572	2.6	42.9
Intermediate 1	170	18,468	18.4	108.6
Lockdown 2	49	4,519	4.5	92.2
Intermediate 2	105	13,641	13.6	123.7
Lockdown 3	33	4,400	4.4	133.3
After	141	16,036	16.0	113.7
Sum	994	100,193	100	

Source: Authors based on data from MeilleursAgents.

the number of days in the period considered, the first lockdown appears as a time of shock leading to a decrease by more than half of the number of buyer estimates on the platform. This number then sharply increased just after the first lockdown to such an extent that it exceeded the level before COVID-19, with an average of 108.6 estimates per day against 93. After a decrease during the second lockdown, this number continued to grow until the end of the last lockdown, reflecting an increasingly marked desire to migrate as the pandemic (and the restrictive measures) continue.

Regarding the place of origin of people with an intention to move, there is almost no difference before and after COVID-19. By contrast, we observe an effect on the choice of destination. Searches in rural areas represented 16.7% before the COVID-19 crisis and have increased to 20.4% since the beginning of the pandemic. Looking at the sub-periods within the crisis (Table 2), we observe that the rate of searches in rural areas is the highest during the first lockdown, with 22.6% of searches. It then slightly dropped between the end of the first lockdown and the end of second lockdown, yet remaining above the pre-COVID level. Since then, the attraction for rural areas has been persistent, showing moderate growth. The demand for houses follows a similar trend with respect to the timing of the crisis, showing an increasing desire to live in a house (see Table 3).

Table 2 – **Evolution of buyers estimates in rural versus urban areas with respect to the timing of the crisis**

	Start date	End date	Rural (%)	Urban (%)
Before	01/01/2019	11/03/2020	16.7	83.3
Lockdown 1	12/03/2020	10/05/2020	22.6	77.4
Intermediate 1	11/05/2020	27/10/2020	19.8	80.2
Lockdown 2	28/10/2020	15/12/2020	18.6	81.4
Intermediate 2	16/12/2020	30/03/2021	20.0	80.0
Lockdown 3	31/03/2021	02/05/2021	20.5	79.5
After	03/05/2021	20/09/2021	21.5	78.5

Source: Authors based on data from MeilleursAgents.

Table 3 – **Evolution of buyers estimates for flats versus houses with respect to the timing of the crisis (%)**

	Flats	Houses
Before	52.7	47.3
Lockdown 1	45.8	54.2
Intermediate 1	47.0	53.0
Lockdown 2	50.3	49.7
Intermediate 2	48.6	51.4
Lockdown 3	46.7	53.3
After	47.2	52.8

Source: Authors based on data from MeilleursAgents.

The analysis of migration intentions (Table 4) shows that urban-urban intentions to move were largely predominant before the crisis with three-quarters of intentions, followed by urban-rural (9.2%), rural-urban (8%) and rural-rural (7.5%) migration. During the first lockdown, intentions of urban-urban migration decreased to two-thirds, essentially due to the simultaneous rise of rural-rural and urban-rural migration intentions. The largest increase over the period concerns urban to rural migration intentions, from 9.2% to 12.2%.

Table 4 – **Analysis of migration intentions (%)**

	Rural to rural	Urban to urban	Rural to urban	Urban to rural
Before	7.5	75.3	8.0	9.2
Lockdown 1	10.4	67.3	10.1	12.2
Intermediate 1	8.3	72.7	7.5	11.5
Lockdown 2	8.1	73.6	7.8	10.5
Intermediate 2	8.5	71.8	8.1	11.6
Lockdown 3	9.2	71.4	8.1	11.3
After	8.7	70.1	8.3	12.9

Source: Authors based on data from MeilleursAgents.

Lastly, we combine the categorization of catchment areas with the intention to move to a rural *vs* an urban zone. Before the COVID-19 crisis, 61% of users had the intention to move to an urban city in the same catchment area, whereas this decreases to 55.5% from the beginning of the crisis, as shown by Table 5.

Table 5 – **Evolution of the intention to move to another catchment area combined with the destination choice "rural *versus* urban"**

	Different area		Same area	
	Rural	Urban	Rural	Urban
Search before COVID	9.1	22.3	7.6	61.0
Search after COVID	11.8	24.1	8.6	55.5

Source: Authors based on data from MeilleursAgents.

2. Empirical Strategy

To estimate the effect of the COVID-19 crisis on the residential migration intentions, we estimate logit models. Discrete choice models are used in most empirical studies to describe and understand household location choices. In addition to national factors (mortgage, inflation rates, demographic changes and economic context), the literature distinguishes among three categories of determinants. The first concerns the trade-off between prices (and thus dwelling size) and accessibility to employment (Waddell, 1993; Srour *et al.*, 2002; Rivera & Tiglao, 2005; Cornelis *et al.*, 2012). Additionally, the sensitivity to the distance to place of work may vary if remote working is available (Ettema, 2010, in the Netherlands). The second set of determinants groups spatial and social amenities, e.g. school quality (Pinjari *et al.*, 2009; Kim *et al.*, 2005; Bayoh *et al.*, 2006), service density (Zondag & Pieters, 2005), security (Filion *et al.*, 1999), presence of green spaces (Gueymard, 2006) or quality of the neighborhood (De Palma *et al.*, 2005, 2007; Goffette-Nagot & Schaeffer, 2013). The last set of determinants includes household characteristics, i.e., income and household size (Waddel, 1996) and life cycle (Walker & Li, 2007; Habib & Miller, 2007). Regarding all these determinants, Schirmer *et al.* (2014) notice that household preferences should be compared with the same level of choice. Indeed, in their literature review, Schirmer *et al.* (2014) point out that early studies used discrete choice models at an aggregated level (choice of zone) but that building- or unit-level data should be preferred (Habib & Miller, 2009; Lee *et al.*, 2010).

We estimate two binary logit models and then a nested logit model, both estimated on two distinct sub-samples, one of urban residents and the other of rural residents. The dependent variable is the location of the target property, and the effect of the COVID-19 crisis is captured *via* the date of the search. We use alternatively only a binary variable equal to 1 if the search occurred after March 12, 2020 (i.e. the announcement of the first lockdown) and 6 binary variables corresponding to the sub-periods defined by the lockdowns (see Appendix 1), the pre-COVID period going from January 2019 to the start of the first lockdown. All the specifications include a wide range of structural and socioeconomic variables describing the origin and the destination. The selection of control variables is done by elastic net (Zou & Hastie, 2005).

The choice of location is made among a set of mutually exclusive alternatives and decision makers choose the alternative that provides them the highest level of utility. Independent variables describe each alternative in terms of location characteristics (socioeconomic environment) and dwelling characteristics (area, number of rooms, etc.). As we cannot observe all the characteristics of the alternatives, an error term is introduced in the model (Train, 2003). The nested logit model has the advantage of overcoming the Independence of Irrelevant Alternatives (IIA) problem, which arises when, among a set of alternatives, odds of choosing A over B does not depend on whether some other alternative C is present or absent. Contrary to a multinomial logit model, the nested logit model groups together alternatives suspected of sharing unobserved effects into nests, which sets up the disturbance term correlation that violates the assumption. In other words, alternatives are gathered by groups in which the IIA assumption holds, but it does not hold across groups. These nested logit models can be estimated only if there is a limited number of alternatives. Moreover, a reference alternative needs to be set and all interpretations are relative to this alternative.

2.1. The Binary Logit Model

Consider N individuals indexed by i that are confronted with two mutually exclusive alternatives. Let y_i denote the response variable of individual i, with for instance:

$$y_i = \begin{cases} 0 & \text{if individual } i \text{ has the intention to move} \\ & \text{to a rural area} \\ 1 & \text{if individual } i \text{ has the intention to move} \\ & \text{to an urban area} \end{cases}$$

The discrete choice model is:

$$y_i = x_i^{'}\beta + \mu_i \qquad (1)$$

with x_i the vector of explanatory variables, β the vector of parameters and μ_i the error term.

The conditional probability that the dependent variable y_i takes the value 1 is modeled as:

$$p_i = P(y_i = 1 | x_i) = F(x_i^{'}\beta) \quad (2)$$

After the logistic transformation of the function F that maps $x_i^{'}\beta$ into the interval [0,1], we get the response probabilities:

$$P(y_i = 1 | x_i) = \frac{e^{x_i^{'}\beta}}{1 + e^{x_i^{'}\beta}} = \frac{1}{1 + e^{-x_i^{'}\beta}} \quad (3)$$

We estimate this logit model with maximum likelihood.

Since the parameters β cannot directly be interpreted as marginal effects on the dependent variable y_i, we calculate the marginal effect of a change in x_{ik} for every explanatory variable x_k on the expected value of the response variable y_i:

$$\frac{\partial E(y_i | x_i)}{\partial x_{ik}} = \frac{\partial P(y_i = 1 | x_i)}{\partial x_{ik}} = \frac{e^{x_i^{'}\beta}}{\left(1 + e^{x_i^{'}\beta}\right)^2} \beta_k \quad (4)$$

2.2. The Nested Logit Model

We then estimate a nested logit model, which has the advantage of allowing for dependence across responses by grouping alternatives into groups called nests (Thurston *et al.*, 2009). It allows for some correlation in the error terms in the same nest, while still assuming that error terms of different nests are uncorrelated. In other words, the assumption of independence of irrelevant alternatives holds within each nest. The choice of the location is such that each individual first chooses among the two limbs that represent the choice of intending to stay in the same catchment area or to change to another one and, conditionally on it, the choice of a rural or an urban municipality is made (Figure I).

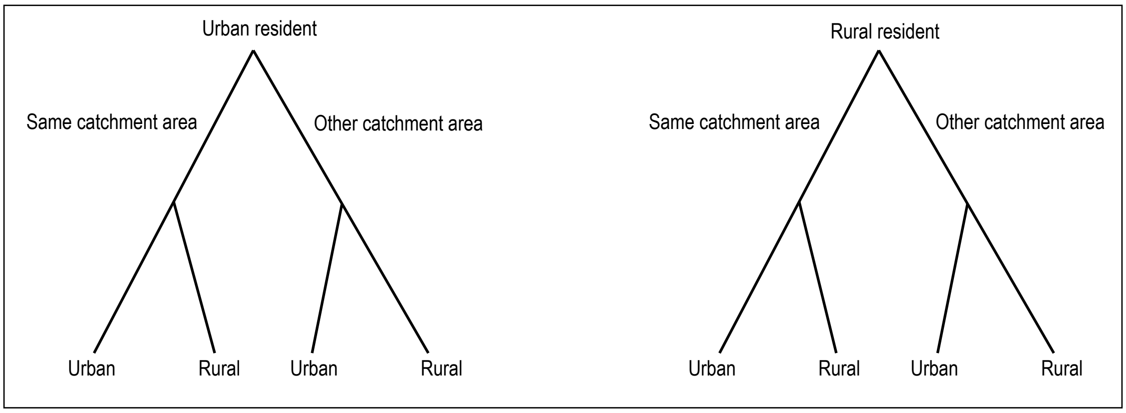
In a general framework (Cameron & Trivedi, 2005), with J limbs indexed by j and K_j branches indexed by k in each limb j, the joint probability p_{jk} of being on limb j and branch k amounts to the probability p_j of choosing limb j multiplied by the probability $p_{k|j}$ of choosing branch k conditional on being on limb j, i.e.: $p_{jk} = p_j * p_{k|j}$.

Using the generalized extreme value (GEV) distribution, we get:

$$p_{jk} = p_j * p_{k|j} = \frac{e^{z_j^{'}\alpha + \rho_j \rho I_j}}{\sum_{m=1}^{J} e^{z_m^{'}\alpha + \rho_m I_m}} * \frac{e^{x_k^{'}\beta_j / \rho_j}}{\sum_{l=1}^{K_j} e^{x_l^{'}\beta_j / \rho_j}} \quad (5)$$

where the vector of explanatory variables $\mathbf{z_j}$ varies only over limbs and the vector of explanatory variables $\mathbf{x_{jk}}$ varies over both limbs and branches. The respective vectors of parameters are α and β_j. Finally, ρ_j is a scale parameter equal to $\sqrt{1 - Cor\left[\varepsilon_{jk}, \varepsilon_{lk}\right]}$. In the case $\rho_j = 1$, which corresponds to independence of ε_{jk} and ε_{lk}, we obtain a multinomial logit model.

Figure I – **Decision tree**



3. Results

We first analyze the intention to move to another catchment area ("*Aire d'attraction des villes*"). Our dependent variable is a binary variable reflecting a change of "state" (i.e. from one catchment area to another one) so that the estimated coefficients capture the impact of the variables on the probability of this change of state. The control of numerous characteristics of the origin and destination cities enables a precise understanding of the structural and locational characteristics of housing that households look for in another catchment area. Most intentions to move, i.e. two-thirds, target the same catchment area, as shown by descriptive statistics over the whole period, which reflects a strong attachment to the territory of origin because of family, friends or work.

Table 6 reports the estimation results (odds ratios) for the main variables of interest of binary logit models where the dependent variable is equal to 1 when residents have the intention to stay in the same catchment area and 0 if they have the intention to move to another one.

Table 6 – **Probability of staying in the same catchment area. Binary logit model (Odds Ratios)**

	Urban origin			Rural origin		
	(1)	(2)	(3)	(4)	(5)	(6)
Search since March 12 2020	0.870***(0.019)	0.815***(0.033)		0.892***(0.035)	1.296 (0.222)	
Search during 1^{st} lockdown			0.924 (0.059)			0.917 (0.098)
Search between lockdowns 1 and 2			0.929***(0.026)			0.905** (0.048)
Search during 2^{nd} lockdown			0.886***(0.045)			0.818** (0.085)
Search between lockdowns 2 and 3			0.883***(0.029)			0.958 (0.053)
Search during 3^{rd} lockdown			0.910***(0.046)			0.876 (0.083)
Search after 3^{rd} lockdown			0.776***(0.027)			0.846***(0.049)
Origin:						
commune du pôle	1.275***(0.044)	1.221***(0.053)	1.257***(0.043)	1.129 (0.295)	2.763** (0.434)	1.134 (0.295)
commune du pôle secondaire	1.195** (0.086)	1.218 (0.136)	1.179* (0.085)			
couronne	1.522***(0.047)	1.437***(0.057)	1.508***(0.046)	3.545***(0.122)	4.433***(0.178)	3.552***(0.122)
hors attraction des pôles	0.343** (0.430)	0.200** (0.719)	0.347** (0.430)	1.646***(0.127)	1.863***(0.190)	1.649***(0.127)
Destination:						
commune du pôle	2.525***(0.043)	2.495***(0.053)	2.513***(0.043)	1.472***(0.082)	1.445***(0.113)	1.478***(0.082)
commune du pôle secondaire	2.406***(0.091)	2.416***(0.142)	2.399***(0.091)	2.316***(0.190)	1.811** (0.287)	2.317***(0.190)
couronne	2.295***(0.044)	2.239***(0.052)	2.287***(0.043)	2.464***(0.069)	2.480***(0.087)	2.470***(0.069)
hors attraction des pôles	0.022***(0.338)	0.021***(0.583)	0.022***(0.338)	2.013***(0.087)	2.237***(0.122)	2.019***(0.087)
Interaction Search since March 12 2020 × Origin						
commune du pôle		1.073 (0.046)			0.209***(0.599)	
commune du pôle secondaire		0.970 (0.169)				
couronne		1.100* (0.053)			0.679* (0.219)	
hors attraction des pôles		2.416 (0.893)			0.798 (0.237)	
Interaction Search since March 12 2020 × Destination						
commune du pôle		1.022 (0.051)			1.027 (0.128)	
commune du pôle secondaire		0.995 (0.174)			1.522 (0.368)	
couronne		1.042 (0.047)			0.994 (0.086)	
hors attraction des pôles		1.120 (0.712)			0.853 (0.134)	
Controls[(a)]	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,991	83,991	83,991	16,202	16,202	16,202
Log Likelihood	−37.496	−37.492	−10.105	−10.091	−10.085	−10.088
AIC	75.113	75.121	20.332	20.256	20.258	20.260

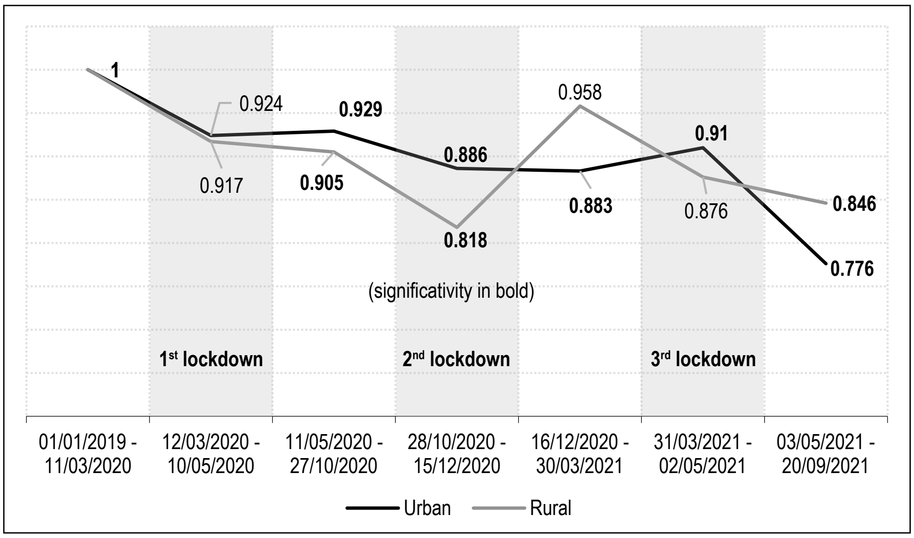
[(a)] The full results with all control variables selected by elastic net are available from the authors upon request.
Note: *p<0.1; **p<0.05; ***p<0.01.

The models are estimated for the sub-sample of urban residents (columns 1 to 3) and for the sample of rural residents (columns 4 to 6). For each sub-sample, we estimate the effect of the COVID-19 crisis first since March 2020 overall, then detailing the sub-periods defined by the lockdowns.

For urban residents, the results show that, since the beginning of the crisis, the odds of searching for a residence in the same catchment area rather than in another one is 0.87 times lower (column 1). The pandemic has thus led to a greater desire to move out of the initial catchment area. The category of the municipality of origin or destination has highly significant effects on the intention to stay in the same catchment area, with suburban residents (origin: "*couronne*") being the most attached to their catchment area, but almost no role on the intensity of the COVID-19 effect, as shown by the interaction terms (see column 2). The detailed timing of the crisis shows that the effect of the pandemic is strongly significant in all sub-periods (column 3), except during the first lockdown, which appears as a period of inaction, where people may either have had difficulties projecting into the future or been waiting for the end of the lockdown to start a real estate project, probably due to the possibility to visit properties again.

As shown in Figure II, the probability of intending to stay in the same catchment area decreases over time, the coefficient dropping from 0.929 between the first two lockdowns to 0.776 after the end of the third lockdown. The

Figure II – **Probability of staying in the same catchment area (Odds ratios)**



continuing crisis results in a reinforced desire for mobility for urban residents.

For the residents of rural municipalities (col. 4 to 6 of Table 6), the decrease in the probability to stay in the same area is less pronounced in the period since March 2020 overall. We estimate that since the beginning of the crisis, the odds for a rural resident to search for a dwelling in the same catchment area rather than in another one is 0.892 times lower. This effect is essentially driven by searches made after the end of the third lockdown, the only period for which the associated coefficient is significant at the 1% threshold.

We complete the analysis by estimating logit models where the binary dependent variable is the intention to move to an urban *vs* a rural city, still separately for the urban and rural sub-samples. Table 7 reports the results for the variables of interest related to COVID-19 and the category of the municipality of origin or destination (the detailed results are available from the authors).

For urban residents, the odds to search for a residence in an urban rather than a rural city is 0.923 times lower since the beginning of the pandemic (Table 7, col. 1); it drops to 0.644 for a resident from a *pôle* searching for a residence in the *pôle* also when interactions are introduced between the COVID-19 dummy variable and the category of the municipality of origin or destination (col. 2). This appeal for rural areas is more pronounced since the end of the second lockdown (col. 3), as reflected by the decrease in the odds ratios (Figure III).

By contrast, the crisis has no impact on the probability of choosing urban over rural

Figure III – **Probability of choosing urban over rural (Odds ratios)**

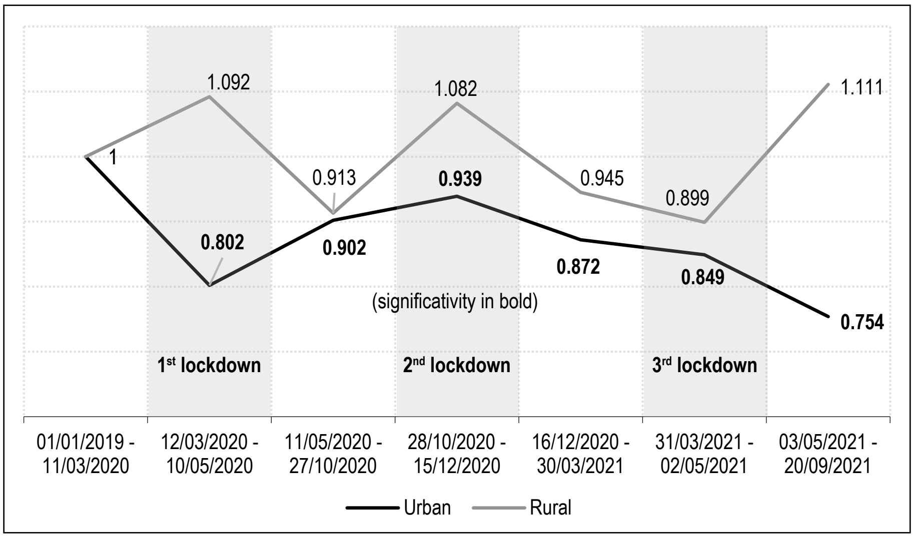


Table 7 – **Probability of choosing urban over rural. Binary logit (Odds Ratios)**

	Urban origin						Rural origin					
	(1)		(2)		(3)		(4)		(5)		(6)	
Search since March 12 2020	0.923*	(0.045)	0.644***	(0.167)			0.991	(0.071)	1.016	(0.412)		
Search during 1st lockdown					0.802**	(0.094)					1.092	(0.196)
Search between lockdowns 1 and 2					0.902**	(0.042)					0.913	(0.101)
Search during 2nd lockdown					0.939	(0.076)					1.082	(0.171)
Search between lockdowns 2 and 3					0.872***	(0.047)					0.945	(0.108)
Search during 3rd lockdown					0.849**	(0.074)					0.899	(0.160)
Search after 3rd lockdown					0.754***	(0.044)					1.111	(0.102)
Origin:												
commune du pôle	1.128	(0.077)	0.965	(0.107)	1.246***	(0.055)	0.186***	(0.560)	0.241*	(0.773)	0.187***	(0.560)
commune du pôle secondaire	1.425*	(0.186)	1.426	(0.301)	1.347**	(0.134)						
couronne	1.366***	(0.085)	1.331***	(0.109)	1.949***	(0.059)	0.962	(0.225)	1.361	(0.333)	0.962	(0.225)
hors attraction des pôles	3.056**	(0.565)	25.277***	(1.065)	3.187**	(0.579)	0.837	(0.244)	0.971	(0.368)	0.834	(0.245)
Destination:												
commune du pôle	10.069***	(0.181)	8.163***	(0.306)	3.822***	(0.148)	13.705***	(0.281)	7.431***	(0.417)	13.529***	(0.282)
couronne	0.378***	(0.100)	0.311***	(0.149)	0.023***	(0.063)	0.493***	(0.159)	0.348***	(0.220)	0.490***	(0.160)
hors attraction des pôles	0.033***	(0.203)	0.023***	(0.364)	0.0001***	(0.202)	0.047***	(0.380)	0.039***	(0.573)	0.047***	(0.381)
Interaction Search since March 12 2020 × Origin												
commune du pôle			1.282	(0.116)					0.819	(1.122)		
commune du pôle secondaire			1.011	(0.376)								
couronne			1.047	(0.110)					0.560	(0.411)		
hors attraction des pôles			0.044**	(1.265)					0.773	(0.458)		
Interaction Search since March 12 2020 × Destination												
commune du pôle			1.383	(0.368)					2.786*	(0.542)		
commune du pôle secondaire			0.962	(6.676)					0.0001	(0.243)		
couronne			1.339*	(0.165)					1.735**	(0.242)		
hors attraction des pôles			1.583	(0.431)					1.375	(0.745)		
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	83,991		83,991		83,991		16,202		16,202		16,202	
Log Likelihood	−6.956		−6.949		−13.902		−2.735		−2.730		−2.733	
AIC	13.994		13.996		27.873		5.546		5.551		5.552	

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

municipalities for rural residents (Table 7, col. 4 to 6). This strong result thus establishes that the COVID-19 crisis generated a change in preferences of location, but only for urban residents.

To complete the analysis, we have also estimated a multinomial logit model detailing the category of the city of destination (centre, periurban area – *couronne* – and rural zone – *hors attraction des pôles*) to explore whether it influences the intention to move (the results, not presented here, are available from the authors). The interaction of the category of city with the COVID-19 dummy appears significant only for the subsample of urban residents, for periurban areas (*couronne*) *vs* centre. This means that, since the COVID-19 crisis, urban residents living in city centres are more inclined to move than those living in periurban areas.

Finally, we analyze the estimation results of the nested logit model. The first level choice is between staying in the same catchment area or moving to another one. Conditionally to the choice of catchment area, the choice is then between moving to an urban or to a rural municipality. In other words, residents decide whether to stay close to their job and conditionally position themselves on the urban-rural gradient. The reference category is moving from the initial catchment area to a rural area. Table 8 reports the results for the variables of interest related to COVID-19 and the category of municipality of origin or destination (the detailed results with

Table 8 – **Probability of staying in the same catchment area and choosing urban over rural. Nested logit estimation results (Odds Ratios)**

	Urban origin		Rural origin	
	(1)	(2)	(3)	(4)
Search since March 12 2020				
× in urban city in another catchment area	0.979 (0.081)		0.937 (0.068)	
× in rural city in the same catchment area	0.887*** (0.056)		0.901** (0.048)	
× in urban city in the same catchment area	0.861* (0.079)		0.813*** (0.07)	
Search during 1st lockdown				
× in urban city in another catchment area		1.161 (0.277)		1.13 (0.177)
× in rural city in the same catchment area		1.035 (0.165)		1.042 (0.132)
× in urban city in the same catchment area		1.043 (0.267)		0.781 (0.194)
Search between lockdowns 1 and 2				
× in urban city in another catchment area		1.045 (0.127)		0.852 (0.096)
× in rural city in the same catchment area		0.885 (0.078)		0.882* (0.065)
× in urban city in the same catchment area		0.978 (0.123)		0.764*** (0.098)
Search during 2nd lockdown				
× in urban city in another catchment area		1.168 (0.223)		0.949 (0.16)
× in rural city in the same catchment area		0.816 (0.143)		0.766** (0.113)
× in urban city in the same catchment area		1.05 (0.215)		0.83 (0.163)
Search between lockdowns 2 and 3				
× in urban city in another catchment area		0.91 (0.141)		0.844 (0.104)
× in rural city in the same catchment area		0.896 (0.086)		0.91 (0.072)
× in urban city in the same catchment area		0.809 (0.136)		0.846 (0.108)
Search during 3rd lockdown				
× in urban city in another catchment area		0.936 (0.216)		0.967 (0.153)
× in rural city in the same catchment area		1.028 (0.132)		0.933 (0.11)
× in urban city in the same catchment area		0.838 (0.208)		0.806 (0.165)
Search after 3rd lockdown				
× in urban city in another catchment area		0.941 (0.129)		1.075 (0.096)
× in rural city in the same catchment area		0.837 (0.079)		0.919 (0.067)
× in urban city in the same catchment area		0.737* (0.125)		0.838* (0.101)
Controls	Yes	Yes	Yes	Yes
Observations	83,991	83,991	16,202	16,202
R^2	0.4	0.394	0.361	0.362
Log Likelihood	48.395	48.91	14.23	14.221
LR Test	64.631*** (df = 86)	63.600*** (df = 86)	16.093*** (df = 107)	16.112*** (df = 122)

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

all control variables selected by elastic net are available from the authors).

Since the beginning of the crisis, the odds that a resident from an urban area searches for a residence in the same catchment area rather than in a rural city in another catchment area is 0.887 times lower for a rural destination and even lower for an urban destination, with an odds ratio of 0.861 (Table 8, col. 1). In other words, since the beginning of the crisis, urban residents are less likely to intend to stay in the same catchment area, especially to buy in an urban area, rather than change catchment area to buy in a rural area. These changes are mainly driven by searches after the third lockdown (Table 8, col. 2). Indeed, the only significant and low coefficient appears for the joint choice of moving to an urban city in the same catchment area. The strongest effect after the third lockdown could be explained by the increased awareness that the sanitary crisis and the associated restrictions could settle durably. Another explanation could be that there was less compliance with the restrictions related to the second and third lockdowns than during the first lockdown, which may have questioned the authorities' ability to manage the health crisis and generated a feeling of anxiety about the future, and in turn, a greater desire for change.

The results are less significant for rural residents, although they still show a reduction in the probability of intentions to stay in the same catchment area since the COVID-19 crisis, even more pronounced after the end of the last lockdown.

* *
*

Using owner and buyer estimates from the MeilleursAgents platform, we were able to reconstruct migration intentions over the period from January 2019 to September 2021, and thus to analyze how the COVID-19 crisis has changed the location preferences in France. Descriptive statistics show that after a time of shock during the first lockdown, the number of buyer estimates exceeded the pre-COVID level and has continued to grow afterwards, which might reveal more intentions to move. The demand for houses and real estate located in secondary locations ("*pôles*", "*couronnes*") and outside of the attraction poles has increased relatively significantly since the beginning of the pandemic while it is the reverse for city centres that may appear less attractive. Our estimations of logit and nested logit models make it possible to isolate the post-COVID effect on both the intention to change one's catchment area and to move to rural areas. We indeed observe a clear trend towards an urban exodus, as the odds that an urban resident searches for a residence in an urban city rather than in a rural city is 0.644 times lower since the beginning of the pandemic for households coming from a pole and searching for a residence in a pole. Both urban and rural residents are also more inclined to leave their catchment area to relocate further away, which may have been facilitated by the development of telework. Finally, we show that since the beginning of the crisis, urban residents are more likely to seek housing in a rural city in a different catchment area.

While our data provide advanced information on migration intentions in real time, they provide no information about users and reflect an activity on the website mainly driven by the Paris area and areas of other big cities. Our sample is reasonably representative, but the analysis could also be extended to renters and first home buyers, who were not included in this analysis. Next steps would also consist in carrying out an inference causal analysis of COVID-19 and better characterizing migrations using a gravity model. Finally, we could use the catchment area zoning in greater detail in order to test whether the results from Ramani & Bloom (2021) hold in the case of France. ☐

Link to the Online Appendix:
www.insee.fr/en/statistiques/fichier/6667537/ES536-37_Breuille-et-al_Online-Appendix.pdf

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APPENDIX

1 – Key dates – Sequence of lockdowns since the start of COVID-19 and associated restrictions.

- “Before” from 01/01/2019 to 11/03/2020: No restrictions, except ban on gatherings from 5/03/2020
- “Lockdown 1” from 12/03/2020 to 10/05/2020. On 12/03/2020, announcement of closure of nurseries, schools, colleges, high schools and universities until further notice. On 16/03/202, announcement of the first national lockdown. Closure of all non-essential public places. From 17/03/2020, ban on all travels except for professional activity, buying essential goods, health or family reasons or exercise for less than one hour. Requirement to carry identification and signed and dated declaration for any travel.
- “Intermediate 1” from 11/05/2020 to 27/10/2020: Progressive lifting of most restrictions. Extension of mask-wearing rules. From 17/10/2020, overnight curfew in Paris and suburbs, Marseille, Lyon, Lille, Saint-Etienne, Rouen, Toulouse, Grenoble and Montpellier. From 24/10/2020, overnight curfews extended to 38 French departments.
- “Lockdown 2” from 28/10/2020 (announcement) to 15/12/2020: Second national lockdown, which was similar to the first one in terms of restrictions, except that primary and secondary schools were open.
- “Intermediate 2” from 16/12/2020 to 30/03/2021: Lifting of most restrictions. Curfew hours nationally. From 20/03/2021, daily lockdowns imposed in 16 departments.
- “Lockdown 3” from 31/03/2021 (announcement) to 02/05/2021: Third national lockdown with daily lockdown rules extended to Metropolitan France.
- “After” from 03/05/2021 to 20/09/2021: Lifting of most restrictions. From 21/07/2021, all people over 12 require a health pass to access some places.

2 – List of variables

Variable	Modalities / (Unit)
Search since March 12 2020	1 if yes; 0 if No
Search before the 1st lockdown	1 if search between 01/01/2019 and 11/03/2020; 0 if No
Search during 1st lockdown	1 if search between 12/03/2020 and 10/05/2020; 0 if No
Search during the first period between two lockdowns	1 if search between 11/05/2020 and 27/10/2020; 0 if No
Search during 2nd lockdown	1 if search between 28/10/2020 and 15/12/2020; 0 if No
Search during the second period between two lockdowns	1 if search between 16/12/2020 and 30/03/2020; 0 if No
Search during 3rd lockdown	1 if search between 31/03/2021 and 02/05/2021; 0 if No
Search after the 3rd lockdown	1 if search between 03/05/2021 and 20/09/2021; 0 if No
Search in the same catchment area	1 = yes; 2 = No
Search in urban area	1 = yes; 2 = No
City category	11=*commune centre*; 12=*commune du pôle*; 13=*commune du pôle secondaire*; 20=*couronne*; 30=*hors attraction des pôles*
Housing type	1 = Apartment; 2 = House
Property surface	(Square meters)
Number of rooms	
The property has a swimming-pool	1 if yes; 0 if No
The property has shared walls	1 if yes; 0 if No
The property has a terrace or a balcony	1 if yes; 0 if No
The property has a parking	1 if yes; 0 if No
The property has a ground garden	1 if yes; 0 if No
Value of the property at the time of the search	(Thousands €)
Difference in number of rooms between wanted dwelling and the property	
Share of vacant dwellings	(%)
Share of second homes	(%)
Share of multi-unit housing	(%)
Share of dwellings built before 1946	(%)
Share of owners	(%)
Share of renters	(%)
Share of foreigners	(%)

➔

(contd.)

Variable	Modalities / (Unit)
Residential surface	(Ha)
Surface dedicated to economic activities	(Ha)
Number of inhabitants	
Population density	(Inhabitants/residential surface)
Share aged 65+ in the total population	(%)
Share aged 18-24 in the total population	(%)
Share aged 11-17 in the total population	(%)
Share aged 0-10 in the total population	(%)
Unemployment rate of population aged 15-64	(%)
Number of jobs per inhabitant	
Share aged 15+ not in school holding a 2nd degree diploma (CAP or BEP)	
Share aged 15+ not in school holding a baccalaureate	
Median income (by consumption units)	(Thousand €)
Spending in amenities of the agglomeration	(€/Inhabitant)
Number of amenities to find a job	
Number of educational facilities other than schools	
Number of health facilities	
Number of childcare centres	
Number of facilities for disabled persons	
Number of facilities for elderly persons	
Number of social facilities	
Number of sport, culture and leisure amenities	
Number of universities/higher education facilities	
Number of security stations (police and *gendarmerie*)	
Number of back-to-work assistance facilities	
Distance to closest *centre d'équipement local / intermédiaire / structurant majeur*	(km)
Difference in shares of foreigners destination *vs* origin	(%)
Difference in number of childcare facilities destination *vs* origin	(%)