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Residential migration and the Covid-19 crisis : Towards an urban exodus in France ? [1]

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Résumé

Plus de 18 mois après le début de la crise de la Covid-19, l'exode urbain a fait couler beaucoup d'encre dans la presse. Mythe ou réalité ? Les ménages recherchent-ils davantage des logements plus grands, particulièrement des maisons, dans des endroits où la densité de population est plus faible et où il y a plus d'aménités vertes ?

Si l'envie de quitter les zones urbaines denses (D'Alessandro et al, 2021) pour aller dans les zones rurales moins denses n'est pas nouvelle, la crise de la Covid-19 a pu lever certains freins qui empêchaient le passage à l'acte. En particulier, le télétravail, d'abord contraint puis devenu plus fréquent depuis la crise, permet à une part des actifs français de s'éloigner de leur lieu de travail.

Outre les données de recensement de la population et de la prochaine enquête logement disponibles avec délai, les données de plateformes immobilières constituent une mine d'informations sur les comportements de recherche et d'achat des Français. La plateforme immobilière Meilleurs Agents (2021) souligne ainsi une demande croissante pour l'immobilier dans les zones rurales. Entre septembre 2020 et 2021, les prix à l'achat des logements ont augmenté de 6,4% dans les

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zones rurales et de 4,1% dans les 10 plus grandes villes françaises alors que durant les dix dernières années, les hausses de prix concernaient surtout Paris et les grandes villes. De même, Meilleurs Agents (2021) estime l'augmentation des volumes de vente de 13% dans les zones rurales depuis mars 2020.

Ce dynamisme du marché immobilier dans les zones rurales ne suffit pas pour affirmer que la crise de la Covid-19 a donné naissance à un exode urbain. Ce papier étudie les changements dans le choix de localisation résidentielle des Français suite à la crise, avec un focus sur les relocalisations des zones urbaines vers les zones rurales.

Pour ce faire, nous utilisons les données issues du comportement des utilisateurs de la plateforme Meilleurs Agents. Les estimations de prix de biens immobiliers faites sur la plateforme nous permettent d'identifier des intentions de migrations résidentielles entre des communes françaises. L'utilisation de ces données présente deux avantages majeurs. Premièrement, comme la plateforme attire deux millions de visiteurs uniques qui réalisent 500 000 estimations par mois, nous avons accès à un échantillon de taille importante. Deuxièmement, cette donnée récoltée au jour le jour permet d'étudier les migrations résidentielles au fil de la crise de la Covid-19, et plus particulièrement sur la période allant de janvier 2019 à août 2021. Nous sommes ainsi en mesure de lier les estimations faites sur le site aux différents épisodes de confinement et déconfinement.

Nous mobilisons des modèles de choix discrets, i.e., des modèles Logit et Logit Multinomiaux emboîtés, pour établir un lien entre les intentions de relocalisation résidentielle et la crise sanitaire en prenant en compte les caractéristiques des logements occupés et recherchés ainsi que les caractéristiques des villes d'origine et de destination.

Nous montrons que la pandémie a modifié l'intention de déménager, tant par le choix de l'aire d'attraction des villes que par le positionnement sur le gradient urbain-rural. En particulier pour la probabilité de rester dans la même aire d'attraction, l'effet Covid-19 varie avec la temporalité de la pandémie, c'est-à-dire qu'il n'est significatif que dans les périodes intermédiaires entre deux confinements et après la fin du troisième confinement. De plus, l'attrait pour les autres aires d'attraction et les villes rurales est plus fort après la fin du dernier confinement. Par ailleurs, depuis mars 2020, la probabilité qu'un résident urbain recherche une résidence dans une ville urbaine plutôt que dans une ville rurale est 0,911 fois plus faible, alors qu'elle n'a aucun impact sur le choix d'un résident rural.

Ces résultats montrent donc réellement un exode urbain depuis le début de la crise sanitaire, en cohérence avec le dynamisme croissant du marché de l'immobilier dans les zones rurales. L'augmentation des prix à l'achat dans ces zones pourrait conduire à un accès à la propriété plus difficile pour les locaux. La croissance démographique dans ces zones pourrait toutefois ˆtre source de développement économique.

Abstract en Anglais

Much has been written about the potential effect of the Covid-19 crisis on residential mobility. Based on owner and buyer estimates performed from January 2019 to September 2021 on the platform Meilleurs Agents, we are able to build mobility flows and analyze, using logit and nested logit models, how the pandemic has changed the probability that both urban and rural residents relocate. We find that after a time of shock during the first lockdown, the desire to migrate, both to rural municipalities and 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.

Introduction

Since the first lockdown was implemented 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 recent survey by Meilleurs Agents[2], among those who have changed their primary residence since July 2020 or plan to do so before January 2022, half of them changed their search criteria to have a garden (for 39% of them) to be closer to nature (for 34% of them) or to live in a smaller city (for 19% of them).

Attraction to rural areas is not a new phenomenon. Over the previous three decades, a report from Observatoire des Territoires (2018) concludes that France has experienced a decrease in population concentration, with big centers losing attractiveness while the surrounding areas attract new inhabitants. According to D'Alessandro et al. (2021), between 2007 and 2017, average annual population growth was 0.66% in rural areas, yet only around half of that (0.38%) in urban areas. The attraction of rural areas seems to mainly concern rural suburban cities.

In 2017, 26.9% of people moving from an urban area to a rural area moved to a city in the catchment zone of a center (D'Alessandro et al. (2021)). In addition, though French people move more than their neighbors, with 11% of the French population moving each year compared to 9% on average in Europe, Observatoire des Territoires (2018) notes that French people move less and less further 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 is conditioned to age and education level. In particular, mobility decreases with age and increases with education level. Similarly, the type of move depends on the individual's socio-professional category. Executive professions, higher intellectual professions and intermediate professions tend to move further, between Paris and other big cities, while employees are more concerned by smaller moves. 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[3] 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, first widespread and mandatory and then more balanced and negociated between workers and employers, could remove this third obstacle to urban exodus, at least partially[4]. Since March 2020, Meilleurs Agents has observed a 13% increase in transaction volume in rural areas[5]. It also seems to be reflected in the evolution of prices[6] : in 2020, Paris experienced a decline in prices, unlike rural areas that experienced a greater increase in prices than the largest cities. The increase mainly concerns rural suburban

2. Toluna study for Meilleurs Agents 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

3. https://www.ifop.com/publication/le-retour-a-la-campagne/

4. In their survey, Meilleurs Agents see 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.

5. 2021 Meilleurs Agents Press Conference :"Quelles sont les nouvelles tendances pour le marché immobilier ?" https://backyard-static.meilleursagents.com/press/6b615242cec200af47aec27515746e25a8174bf6.pdf

6. Meilleurs Agents Real Estate Price Index of September 1, 2021

areas[7] with a 9.7% increase in 2020 and rural areas with a large proportion of secondary homes.

To understand if we are really facing an urban exodus with Covid-19, we need to link each mover's place of departure and place of destination, i.e., to observe residential mobility paths, over the recent period. In the next two or three years, INSEE data from the population census and INSEE's next housing survey will make it possible to observe this precisely. In the meantime, processing traces left by users on real estate platforms is a font of information, which we exploit in this article. Our objective is to provide some early answers to establish whether the Covid-19 crisis has modified the residential location behavior of French people, by analyzing users' behaviour on the Meilleurs Agents website. We reconstruct the residential mobility path for users that first estimate a real-estate good with an owner status and then subsequently estimate another one with a buyer status, tracking them with their userID. The estimate tool also provides information on the characteristics of the dwelling estimated, beyond its location. As users need specific information to fill in the form, they generally use it to estimate the price of a dwelling that they visited or they are going to visit, in order to make an offer close to market price. This is a more advanced indicator that we can track to get information on migrations almost in real time.

We first estimate logit models, separately on urban resident and rural resident sub-samples, for two different dependent variables : the probability of staying in the same catchment area (as defined by INSEE and based on the intensity of commuting to the employment cluster) and the probability of choosing an urban destination. We then estimtate a nested logit model to analyze the intentions of residents to move from a set of mutually exclusive alternatives and allowing certain alternatives in the choice set to be correlated. At the root node, residents choose whether to stay in the same catchment area or to move to another one and in each subset, they choose whether to go to an urban or rural municipality. In each one of these models, we focus on the sign and coefficient of the variable capturing the Covid effect. We first consider the binary variable pre- and post-Covid-19 and then decompose the timing of the post-Covid period. The selection of control variables is done by elastic net.

In discrete choice models (see the seminal paper by McFadden, 1978), the location choice is the dependent variable. The choice is made among a set of mutually exclusive alternatives and decision makers choose the alternative that gives them the highest level of utility. Independent variables describe the alternative itself with location characteristics (socio-economic environment) and dwelling characteristics (area, number of rooms, etc.). As we cannot observe all 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 group in which IIA assumption holds but 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 will be performed relative to this alternative (Aissaoui, 2016).

Discrete choice models are used by 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

7. Rural suburban areas are rural cities that are part of catchment areas of cities with more than 50,000 inhabitants.

to employment (Waddell, 1993 ; Srour et al., 2002 ; Rivera and 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 family 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 and 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 and Schaeffer, 2013). The last group of determinants is household characteristics, i.e., income and household size (Waddel, 1993) and life cycle (Walker and Li, 2007 ; Habib and Miller, 2007). Regarding all these determinants, Schirmer et al. (2014) noticed 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 and Miller, 2009 ; Lee and Waddell, 2010).

How the Covid-19 crisis has changed the determinants of residential mobility is obviously an emerging subject for the literature. Ramani and 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 city CBDs and dense areas experience relative price decreases compared with less dense areas. They interpret it as a donut effect for prices, which seems to be limited to highly populated, dense cities. Additionally, they found that migrations across metropolitan areas is a smaller phenomenon than migration 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 telecommuting will mainly be part-time and thus, there remains a significant distance to employment location. 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 work-from-home imposes capital losses on real estate owners in high-productivity cities and capital gains to renters. Furthermore, as remote working reduces commuting cost, they found that it increases disutility for places with high crime rates and high taxes. This phenomenon makes the suburbs more attractive.

We contribute to this literature by carrying out the first study about the consequences of Covid-19 on residential mobility in France. We show that the pandemic modified the intention to relocate, through both the choice of the catchment area and the location on the urban-rural gradient. Especially for the probability of staying in the same catchment area, the Covid-19 effect varies with the timing of the pandemic, i.e., it is only significant in the intermediate periods between two lockdowns and after the end of the third lockdown. In addition, the appeal for other catchment areas and rural cities was the strongest after the end of the last lockdown. Moreover, since March 2020, the odds that an urban resident searches for a residence in an urban city rather than in a rural city is 0,911 times lower, whereas it has no impact on the choice of a rural resident.

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

1 Data

1.1 Platform Data Description

The Meilleurs Agents platform is the leader in online real estate estimates and information in France and attracts 2.4 million unique visitors per month. 500,000 online estimates per month are done by these users[8]. The use of these day-to-day data in the academic literature is very recent and promising, since it makes it possible to explore users' behaviour by following users at each step of their home-buying project. Traffic data from the Meilleurs Agents platform has already been used in a thesis by Pierre Vidal (2021) to analyze matching and pricing mechanisms on the real estate market. Van Dijk et Francke (2018), Rae et 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 that login to the Meilleurs Agents platform with their user ID, which is required for dwelling estimates (but not for consulting ads for instance). The estimate tool takes the shape of a form in which users give information on their status (owner, owner-seller or buyer), the characteristics of the dwelling estimated and its location. In the end, the tool returns a price range for the dwelling. For users that fill in the form with the buyer's status, this tool intervenes at an advanced stage of the 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, it is the most advanced indicator along the buying process that we can follow. It reveals a strong intention to buy before the purchase.

In order to reconstruct a mobility path, in our database we select the users that make both an estimate with the owner status and then an estimate with a buyer status. We thus have information on the starting location (from the owner estimate) and on the desired arrival location (from the buyer estimate). Moreover, we have information on the features of the current residence and of the searched one, detailed in Table 9 in appendix.

Unfortunately, we do not have information about users (e.g. age or income) and 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 can capture part of this effect because it is likely to be correlated with family size. Another data limitation is that Meilleurs Agents is not equally well-known everywhere in France, with activity being mainly driven by the Paris area and areas of other big cities. We also need to keep in mind that the increase in website traffic is simultaneous to our period of study. Additionally, our users may be not representative of all people moving.

1.2 Platform data processing

We process the data from our database in several ways. Firstly, we remove the outliers. Estimates of dwellings with a very small or a very big area have been eliminated to keep those with an area between 9 and 250 square meters. In addition, we ensure consistency between the area and the number of rooms. We also remove estimates that return a very low price or a very high price, i.e., for which the price is above the half of the first percentile and under twice the 99^{th} percentile of prices estimated. Then, to avoid automated estimates in our data set, we remove the percentile of users that made the highest number of estimates in the period.

8. Figures for November 2021.

Secondly, we account for multiple estimates by the same user. Regarding buyer estimates, if a user makes several estimates of the same dwelling, we keep only the most recent one. Regarding owner estimates, if a user makes several estimates in the same city of the same address (or of another address but with an identical area or an identical number of rooms), we keep the oldest one because it represents the first intention to move. In the event of several searches within 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.[9]

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 location and characteristics of the desired property).[10] In the latter case, the rows are links between an estimate as an owner and an estimate as a buyer.

Finally, in order to avoid searches for investment purposes, we removed observations when dwelling size between the property and the desired dwelling were too different. We removed observations when the area difference was greater than 100 square meters and where the difference of number of rooms was greater than 5 rooms.

Our database contains all owner estimates from February 22, 2012, to September 20, 2021, and all buyer estimates from January 1, 2019, to September 20, 2021, which provides relatively similar periods before and after the beginning of Covid-19. Overall, our database contains 96,807 observations establishing a link between an estimate of a principal residence owned and a dwelling searched to buy.

1.3 Characteristics of the location

With regards to location, a key factor to address our issue is whether the dwelling is located in a rural or an urban area. We use the rural zoning from the Observatoire des Terriroires[11], which splits French cities between 4,193 urban cities and 30,772 rural cities based on their density. Figures 2 and 3 in appendix map the territorial coverage of our owners and buyers estimates.

We also use the INSEE zoning in catchment areas[12] to more precisely characterize the nature of 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. Inside a catchment area, there is a "pôle" (cluster) and "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 that send at least 15% of their workers to work in the pôle constitute the "couronne" of the area. Figure 4 in appendix maps

9. We also removed links when owner and buyer estimates are done for the same dwelling.
10. We are not interested in cases where the owner estimate follows the buyer estimate, because we focus on the intention to move from owners.
11. https://www.observatoire-des-territoires.gouv.fr/typologie-urbain-rural
12. Aire d'Attraction des Villes in French.

this split. Additionally, catchment areas are ranked according to their population size. Figure 5 in appendix maps this zoning.

Furthermore, we characterize municipalities using a large range of socioeconomic data from INSEE, specifically, the median population income, services and equipment levels, age distribution of the population and structure of the housing stock.

The list of all variables can be seen in Table 9 in appendix.

1.4 Descriptive Statistics

Our dataset contains 96,807 observations of people with the intention to move from 01/01/2019 to 20/09/2021 through an estimation of a property to buy on the platform. Table 1 shows that 41.6% of our sample concern dwelling searches between January 2019 and the announcement of the first lockdown (12 March 2020) and 58.2% after. A detailed decomposition of the timing after Covid-19 shows that our sample splits into 2.6%, 1.9% and 4.4% respectively for each of the three lockdowns, 18.2% in the intermediate period between the first two lockdowns, 13.3% in the intermediate period between the last two lockdowns, and 18% afterwards. More interestingly, after dividing the number of estimates with respect to the number of days in the period considered, we show that the first lockdown was a time of shock leading to a decrease by more than half of the number of buyer estimates on the platform. It then sharply increased just after the first lockdown to such an extent that it exceeded the level before Covid-19, with 104.2 estimates per day against 92.5. 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.

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

	Number of days	Number of buyers estimates	%tage of buyers estimates	Average number of estimates per day
Before	435	40232	41,6%	92.5
Lockdown 1	59	2535	2.6%	43.0
Intermediate 1	169	17616	18.2%	104.2
Lockdown 2	217	1805	1.9%	106.2
Intermediate 2	1104	12863	13.3%	123.7
Lockdown 3	32	4295	4.4%	134.2
After	140	17461	18.0%	124.7
Sum	956	96807	100.0%	

Regarding the place of origin of people with the intention to move, we see almost no difference before and after Covid-19. By contrast, we observe an effect on choice of destination. Searches in rural areas represented 17% before the Covid-19 crisis and have increased to 20.8% since the beginning of the pandemic. If we look at the timing of the crisis (Table 2), we observe that the rate of searches in rural areas is the highest during the first lockdown, with 23% of searches. It then slightly dropped (still remaining above the pre-Covid level) during the period from the end of the first lockdown to the end of second lockdown. Since then, rural appeal has been persistent, showing moderate growth.

The demand for houses follows a similar trend with respect to the timing of the crisis, as shown by Table 3, which reveals an increasing desire to live in a house.

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	0.170	0.830
Lockdown 1	12/03/2020	10/05/2020	0.230	0.770
Intermediate 1	11/05/2020	27/10/2020	0.201	0.799
Lockdown 2	28/11/2020	15/12/2020	0.183	0.817
Intermediate 2	16/12/2020	30/03/2021	0.203	0.797
Lockdown 3	1/03/2021	02/05/2021	0.208	0.792
After	03/05/2021	20/09/2021	0.217	0.783

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

	Flats (%)	Houses (%)
Before	0.518	0.482
Lockdown 1	0.444	0.556
Intermediate 1	0.463	0.537
Lockdown 2	0.509	0.491
Intermediate 2	0.477	0.523
Lockdown 3	0.458	0.542
After	0.463	0.537

The analysis of trajectories of intention to migrate (see Table 4) shows urban-urban trajectories were largely predominant before the crisis with three-quarters of intentions, followed by urban-rural (9.26%) and almost equal for rural-rural (7.75%) and rural-urban (7.27%) trajectories. During the first lockdown, urban-urban trajectories decreased to two-thirds, essentially due to the simultaneous rise of rural-rural and urban-rural trajectories.

Table 4 – Analysis of trajectories of intention to migrate

	Stay rural (%)	Stay urban (%)	Rural to urban (%)	Urban to rural (%)
Before	0.078	0.757	0.073	0.092
Lockdown 1	0.102	0.679	0.091	0.128
Intermediate 1	0.085	0.729	0.070	0.117
Lockdown 2	0.078	0.748	0.069	0.105
Intermediate 2	0.086	0.723	0.074	0.117
Lockdown 3	0.091	0.721	0.071	0.117
After	0.089	0.707	0.076	0.128

The biggest increase over the period concerns urban to rural migrations, from 9.3% to 12.8%.

Lastly, we combine the categorization of catchment areas with the intention to move to a rural versus urban zone. Before the Covid-19 crisis, 61.3% of users had the intention to move to an urban city in the same catchment area, whereas this decreases to 56% from the beginning of the crisis, as shown by 5.

TABLE 5 – Evolution of the decision to move to another catchment area combined with the destination choice "rural versus urban"

	Diff. area Rural	Diff. area Urban	Same area Rural	Same area Urban
Search before Covid	0.091	0.216	0.073	0.613
Search after Covid	0.120	0.232	0.088	0.556

2 Empirical specifications

We estimate two simple logit models and then a nested logit model. These models are run on two different sub-samples, one for urban residents and the other for rural residents. We also alternatively consider the effect of a binary variable that distinguished between pre-Covid and post-Covid periods. In addition, we use elastic net to select input variables that are relevant for our specifications.

2.1 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 :

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

The discrete choice model is :

$$y_i = x_i'\beta + \mu_i \tag{1}$$

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 :

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

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

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

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 :

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

2.2 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 (Davidson 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 2 limbs that represent the choice of staying in the same catchment area or changing to another one and, conditionally on it, the choice of a rural or a urban municipality is done.

FIGURE 1 – Diagram of decision tree

In a general framework (see Cameron and 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 :

$$p_{jk} = p_j * p_{k|j} = \frac{e^{\mathbf{z_j'}\alpha+\rho_j I_j}}{\sum_{m=1}^{J} e^{\mathbf{z_m'}\alpha+\rho_m I_m}} * \frac{e^{\mathbf{x_{jk}'}\beta_\mathbf{j}/\rho_j}}{\sum_{l=1}^{K_j} e^{\mathbf{x_{jl}'}\beta_\mathbf{j}/\rho_j}} \tag{5}$$

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 $\beta_\mathbf{j}$. Finally, ρ_j is a scale parameter equal to $\sqrt{1 - Cor[\epsilon_{jk}, \epsilon_{lk}]}$. In the case $\rho_j = 1$, which corresponds to independence of ϵ_{jk} and ϵ_{lk}, we obtain a multinomial logit model.

3 Results

We first analyze the intention to change one's catchment area (Aire d'attraction des villes)[13]. Most intentions to move, i.e. two-thirds, are in 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 results of logit models where the binary 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. The first two columns correspond to logit models run on the sub-sample of urban residents, whereas the last two columns give the results for logit models run on the sub-sample of rural residents. In columns (1) and (3), we analyse how the Covid-19 crisis, which started in March 2020, has modified searches afterwards. We show that since the beginning of the crisis, the odds of an urban resident searching for a residence in the same catchment area rather than in another one is 0.868 times lower. The pandemic has thus led to a greater desire to relocate outside of the catchment area. If we detail the timing of the crisis, we show that the effect of Covid-19 pandemic is only significant in the

13. There are about 700 "aires d'attraction des villes". These sets of municipalities (in a single block and without enclaves) are based on the intensity to commuting in the employment pole.

intermediate periods between two lockdowns and after the end of the third lockdown. Lockdown periods thus appear as periods of inaction, where people either have difficulties projecting into the future or are waiting for the end of the lockdown to start a real estate project, probably due to the possibility to visit properties again. It should be noted that the more we advance in time, the lower the probability of staying in the same catchment area is for an urban resident. The coefficient goes from 0.916 between the first two lockdowns to 0.791 after the end of the third lockdown. The prolongation of the crisis results in a reinforced desire for mobility.

TABLE 6 – Logit estimation results for the probability of staying in the same catchment area ; Odds Ratios

	Dependent variable : probability of staying in the same catchment area			
	Urban origin		Rural origin	
search_after_covid	0.868***		0.916**	
	(0.019)		(0.036)	
covidconf1		0.933		0.939
		(0.059)		(0.100)
covidinter1		0.916***		0.948
		(0.026)		(0.050)
covidconf2		0.940		0.990
		(0.069)		(0.134)
covidinter2		0.869***		0.977
		(0.029)		(0.055)
covidconf3		0.933		0.875
		(0.047)		(0.087)
covidafter		0.791***		0.858***
		(0.026)		(0.048)
Controls	Yes	Yes	Yes	Yes
Observations	81,646	81,646	15,161	15,161
Log Likelihood	−36,247.950	−36,232.510	−9,543.136	−9,540.378
Akaike Inf. Crit.	72,611.900	72,591.020	19,152.270	19,156.760
Note :				*p<0.1 ; **p<0.05 ; ***p<0.01

The last two columns of Table 6 give the results of logit models run on the sub-sample of rural residents. For these inhabitants of rural municipalities, the post-Covid decrease in the probability of staying in the same area is less pronounced. We estimate that since the beginning of the crisis, the odds that a rural resident searches for a residence in the same catchment area rather than in another one is 0.916 times lower. This post-Covid effect is essentially driven by what happens after the end of the third lockdown as only the coefficient associated to the last period after May 2, 2021 is significant. Table 10 in appendix presents the full results with all control variables selected by elastic net.

We complete the analysis by estimating logit models where the binary dependent variable is equal to 1 when the resident has the intention to move to an urban city and 0 to a rural city. Table 7 reports the results for the two variables of interest related to Covid-19 alone, and Table 11 in appendix gives the results with all control variables selected by elastic net.

The odds that a urban resident searches for a residence in an urban city rather than in a rural city is 0,911 times lower since the beginning of the pandemic. The succession of lockdowns has created this appeal for the countryside as shown in the second column, as only the coefficient

TABLE 7 – Logit estimation results for the probability of choosing urban over rural ; Odds Ratios

	Dependent variable : choose urban over rural			
	Urban origin		Rural origin	
search_after_covid	0.911**		1.041	
	(0.044)		(0.070)	
covidconf1		0.887		1.293
		(0.126)		(0.192)
covidinter1		0.959		0.982
		(0.060)		(0.100)
covidconf2		1.110		1.140
		(0.167)		(0.270)
covidinter2		0.909		0.998
		(0.067)		(0.108)
covidconf3		0.916		0.882
		(0.104)		(0.167)
covidafter		0.857***		1.138
		(0.060)		(0.097)
Controls	Yes	Yes	Yes	Yes
Observations	81,646	81,646	15,161	15,161
Log Likelihood	−36,247.950	−36,232.510	−9,543.136	−9,540.378
Akaike Inf. Crit.	72,611.900	72,591.020	19,152.270	19,156.760
Note :				*p<0.1 ; **p<0.05 ; ***p<0.01

associated to the last period after the third lockdown is significant.
By contrast, the Covid-19 crisis has no impact on the probability of choosing urban over rural municipalities for rural residents. This strong result thus establishes that a change in preferences of location has been generated by the Covid-19 crisis, but only for urban residents.

Finally, we analyze the estimation results of the nested logit model. At the top level, residents choose whether to stay in the same catchment area or to move to another one. Conditionally to the choice of the catchment area, they choose to relocate to an urban municipality or 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 changing the catchment area to buy property in the countryside. Table 8 reports the results for the two variables of interest related to Covid-19 alone, and Table 12 in appendix gives the results with all control variables selected by elastic net.

Since the beginning of the crisis, the odds that an urban resident searches for a residence in the same catchment area rather than in a rural city in another catchment area is 0.848 times lower for a rural destination and even lower for an urban destination, with a coefficient equal to 0.802. This means that since the beginning of the crisis, urban residents are more likely to change of catchment area to go to a rural area and even more likely to change of catchment area to go to rural area rather than stay in the same catchment area to buy a dwelling in an urban city. These changes are mainly driven by what happens after the third lockdown as shown by the results of the second columns. The coefficient is particularly significant and low for the joint choice of moving to an urban city in the same catchment area.
Results are less significant for rural residents, although we still show a reduction in the probability of staying in the same catchment area since the Covid-19 crisis, ever more pronounced after the end of the last lockdown.

Table 8 – Nested logit estimation results

	Dep. variable : staying in the same attraction area and choosing urban over rura			
	Urban origin		Rural origin	
search_after_covid :diff_aav_urb	0.915		0.975	
	(0.091)		(0.069)	
search_after_covid :same_aav_rur	0.848***		0.901**	
	(0.057)		(0.048)	
search_after_covid :same_aav_urb	0.802**		0.926	
	(0.089)		(0.071)	
covidconf1 :diff_aav_urb		0.859		1.406*
		(0.261)		(0.182)
covidconf1 :same_aav_rur		0.953		1.064
		(0.162)		(0.133)
covidconf1 :same_aav_urb		0.788		1.110
		(0.253)		(0.195)
covidinter1 :diff_aav_urb		0.942		0.957
		(0.124)		(0.097)
covidinter1 :same_aav_rur		0.862*		0.918
		(0.077)		(0.066)
covidinter1 :same_aav_urb		0.872		0.930
		(0.120)		(0.100)
covidconf2 :diff_aav_urb		0.981		0.969
		(0.325)		(0.252)
covidconf2 :same_aav_rur		0.622**		0.827
		(0.220)		(0.176)
covidconf2 :same_aav_urb		0.997		1.238
		(0.314)		(0.250)
covidinter2 :diff_aav_urb		0.904		0.903
		(0.137)		(0.106)
covidinter2 :same_aav_rur		0.865*		0.916
		(0.087)		(0.073)
covidinter2 :same_aav_urb		0.795*		1.001
		(0.133)		(0.111)
covidconf3 :diff_aav_urb		0.935		0.964
		(0.209)		(0.161)
covidconf3 :same_aav_rur		1.029		0.882
		(0.132)		(0.114)
covidconf3 :same_aav_urb		0.856		0.915
		(0.203)		(0.176)
covidafter :diff_aav_urb		0.909		1.000
		(0.120)		(0.094)
covidafter :same_aav_rur		0.811***		0.873**
		(0.076)		(0.064)
covidafter :same_aav_urb		0.725***		0.848*
		(0.117)		(0.098)
Controls	Yes	Yes	Yes	Yes
Observations	81,646	81,646	15,161	15,161
Log Likelihood	−36,247.950	−36,232.510	−9,543.136	−9,540.378
Akaike Inf. Crit.	72,611.900	72,591.020	19,152.270	19,156.760
Note :				*p<0.1 ; **p<0.05 ; ***p<0.0

4 Conclusion

Thanks to owner and buyer estimations on the Meilleurs Agents platform, we were able to construct desired mobility paths over the January 2019 to September 2021 period, and thus to analyze how the Covid-19 crisis has changed the location preferences in France. Our 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 "pôles", "couronnes" and outside of the attraction pole has increased relatively significantly since the beginning of the pandemic while it is the reverse for centers 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 trend towards urban exodus, although it is moderate, as the odds that an urban resident searches for a residence in an urban city rather than in a rural city is 0,911 times lower since the beginning of the pandemic. 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 teleworking. Finally, we show that since the beginning of the crisis, urban residents are more likely to choose to go to a rural city in a different catchment area than to go to an urban city in the same catchment area since the odds is of 0.802.

As a next step, we would like to extend this analysis to renters and first home buyers, who are not in our sample, and take into account concerns of representativity, as knowledge of the Meilleurs Agents website varies over time and across the French territory. 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 better exploit catchment area zoning in order to challenge results from Ramani and Bloom (2021) results in the case of France.

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Appendix

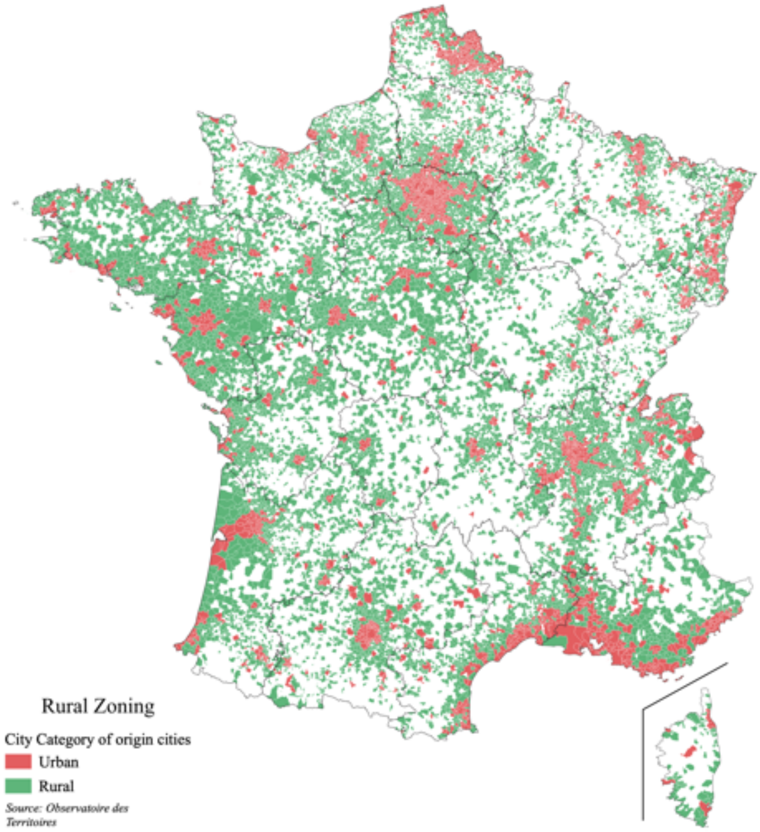

FIGURE 2 – Owners estimates

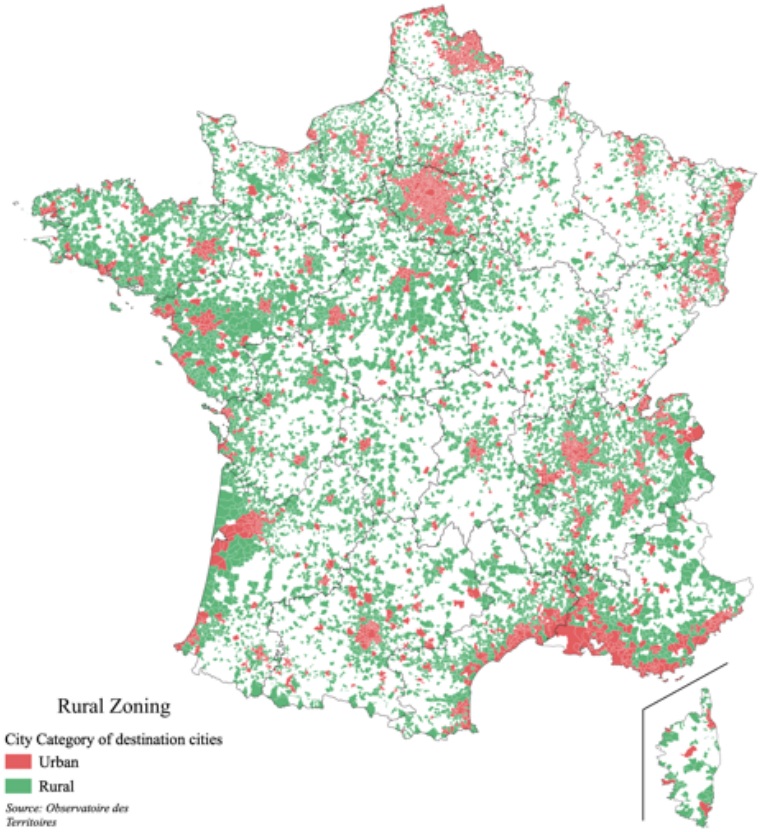

FIGURE 3 – Buyers estimates

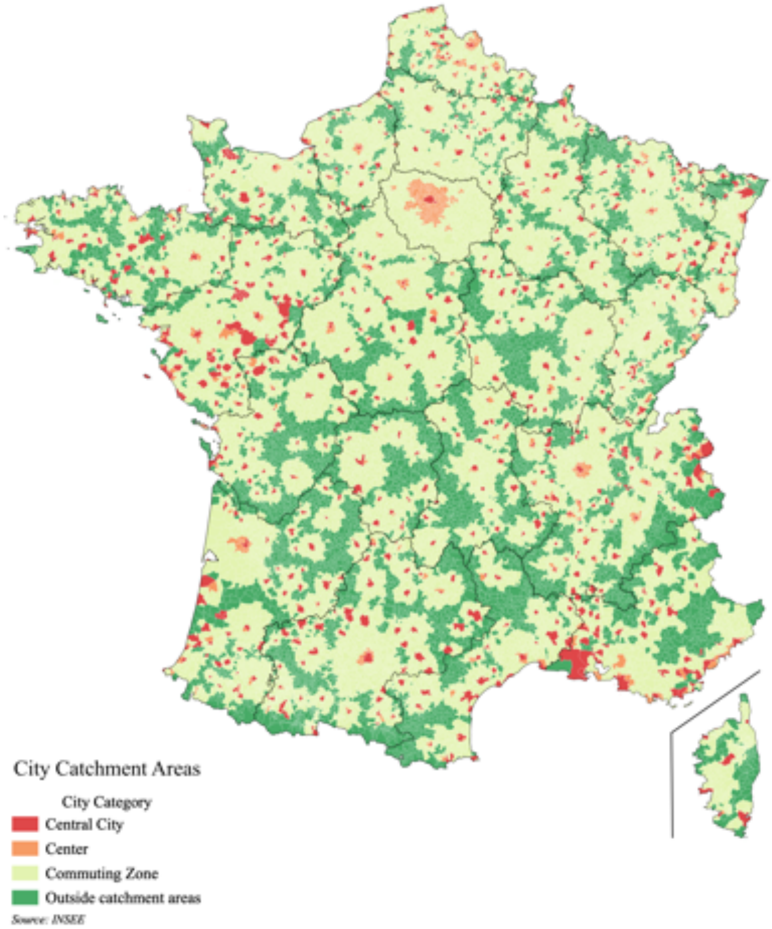

Figure 4 – Composition of catchment areas

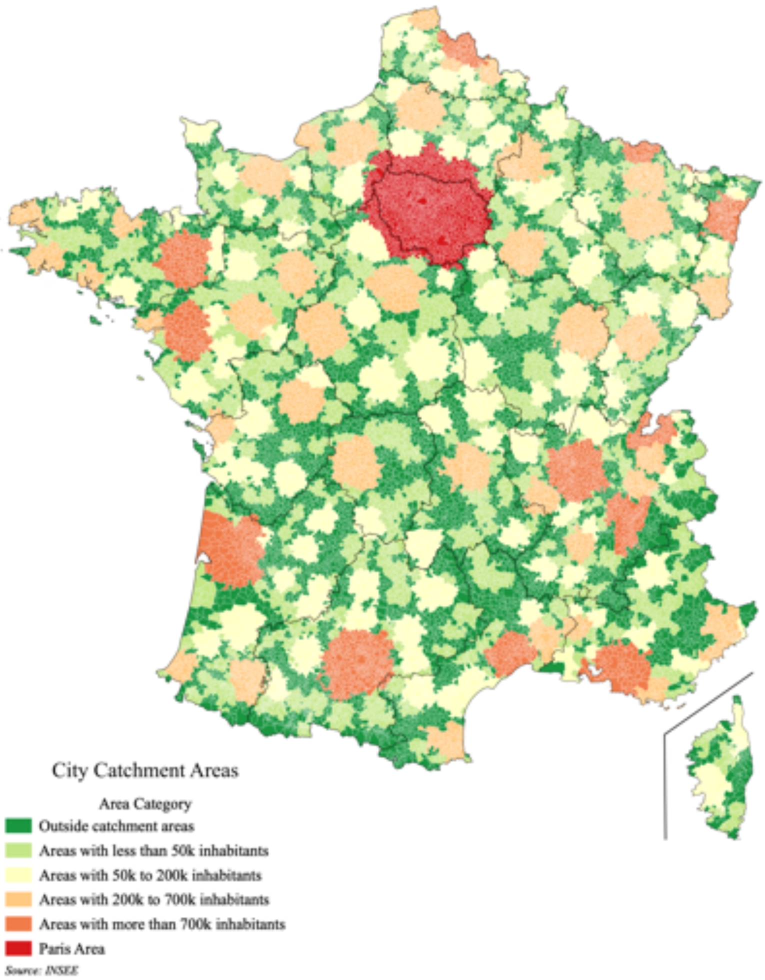

FIGURE 5 – Catchment areas by size

Table 9 – List of Variables

Variable	Unit	Observations
Search done Since March 2020		1 if yes ; 0 if No
Search done before the first lockdown		1 if search is done between 1/1/2019 and 3/11/2020 ; 0 if No
Search done during first lockdown		1 if search is done between 3/12/2020 and 5/10/2020 ; 0 if No
Search done during the first period between two lockdowns		1 if search is done between 5/11/2020 and 10/27/2020 ; 0 if No
Search done during second lockdown		1 if search is done between 11/28/2020 and 12/15/2020 ; 0 if No
Search done during the second period between two lockdowns		1 if search is done between 12/16/2020 and 3/30/2020 ; 0 if No
Search done during third lockdown		1 if search is done between 3/31/2021 and 5/2/2021 ; 0 if No
Search done after the third lockdown		1 if search is done between 5/3/2021 and 9/20/2021 ; 0 if No
Search in the same catchment area		1 = yes ; 2 = No
Search in Urban Area		1 = yes ; 2 = No
Origin City Category		1= Central City ; 2= Commuting Zone ; 3 = Outside Catchment Areas ; 4 = Center
Destination City Category		1= Central City ; 2= Commuting Zone ; 3 = Outside Catchment Areas ; 4 = Center
Housing type of the property		1 = Apartment ; 2 = House
Area of the property	Square Meters	
Number of rooms of the property		
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
Value of the property at the time of the search	Thousands Euros	
Housing type of the wanted dwelling		1 = Apartment ; 2 = House
Area of the wanted dwelling	Square Meters	
Number of rooms type of the wanted dwelling		
The wanted dwelling has a swimming-pool		1 if yes ; 0 if No
The wanted dwelling has a shared walls		1 if yes ; 0 if No
The wanted dwelling has a terrace or a balcony		1 if yes ; 0 if No
The wanted dwelling has a ground garden		1 if yes ; 0 if No
Difference of number of rooms between wanted dwelling and the property		
Share of vacant dwellings in Origin City	%	
Share of second homes in Origin city	%	
Share of multi-unit housing in Origin city	%	
Share of dwellings built before 1946 in Origin city	%	
Share of owners in Origin city	%	
Share of renters in Origin city	%	
Residential Surface of Origin city	Ha	
Surface dedicated to economic activities in Origin city	Ha	
Number of inhabitants in the Origin city		
Population density (population / residential surface) in Origin city	inhabitants / Ha	
Share of 65+ in the total population in Origin city	%	
Share of 18-24 in the total population in Origin city	%	
Share of 0-10 in the total population in Origin city	%	
Unemployment rate of population aged of 15-64 years old in Origin City	%	
Number of jobs per inhabitants in Origin City		
Share of the not in school population aged 15 years or more with a âCAPâ or a âBEPâ in Origin city	%	
Median income of consumption units in Origin city	Thousands €	
Spending in amenities of the agglomeration of the Origin city	Euros per inhabitant	
Number of amenities to find a job in Origin City		
Number of educational amenities other than schools in Origin city		
Number of health amenities in Origin city		
Number of childcare centers in Origin city		
Number of amenities for disabled persons in Origin city		
Number of amenities for elderly persons in Origin city		
Number of social amenities in Origin city		

Number of sport, culture and leisure amenities in Origin city	
Share of vacant dwellings in Destination City	%
Share of second homes in Destination city	%
Share of multi-unit housing in Destination city	%
Share of dwellings built before 1946 in Destination city	%
Share of houses in Destination city	%
Share of owners in Destination city	%
Share of renters in Destination city	%
Residential Surface of Destination city	Ha
Surface dedicated to economic activities in Destination city	Ha
Number of inhabitants in the Destination city	
Population density (population / residential surface) in Destination city	inhabitants / Ha
Share of 65+ in the total population in Destination city	%
Share of 18-24 in the total population in Destination city	%
Share of 11-17 in the total population in Destination city	%
Share of 0-10 in the total population in Destination city	%
Shares of foreigners in Destination city	%
Number of jobs per inhabitants in Destination City	
Spending in amenities of the agglomeration of the Destination city	Euros per inhabitant
Number of amenities to find a job in Destination City	
Number of higher education amenities in Destination city	
Number of educational amenities of first and second degree in Destination city	
Number of educational amenities other than schools in Destination city	
Number of childcare centers in Destination city	
Number of amenities for elderly persons in Destination city	
Number of amenities for disabled persons in Destination city	
Number of social amenities in Destination city	
Number of security amenities in Destination city	
Number of sport, culture and leisure amenities in Destination city	
Difference in the shares of foreigners between destination city and origin city	%
Difference in number of childcare amenities destination city and origin city	%

TABLE 10 – Logit estimation results for the probability of staying in the same attraction area ; Odds Ratios

	Dependent variable : staying in the same attraction area			
	Urban origin		Rural origin	
search_after_covid	0.868***		0.916**	
	(0.019)		(0.036)	
covidconf1		0.933		0.939
		(0.059)		(0.100)
covidinter1		0.916***		0.948
		(0.026)		(0.050)
covidconf2		0.940		0.990
		(0.069)		(0.134)
covidinter2		0.869***		0.977
		(0.029)		(0.055)
covidconf3		0.933		0.875
		(0.047)		(0.087)
covidafter		0.791***		0.858***

Continued on next page

Table 10 – continued from previous page

	Dependent variable : staying in the same attraction area			
	Urban origin		Rural origin	
		(0.026)		(0.048)
own_commune_category12	1.258***	1.259***	0.954	0.957
	(0.044)	(0.044)	(0.307)	(0.307)
own_commune_category13	1.281***	1.279***		
	(0.090)	(0.090)		
own_commune_category20	1.524***	1.525***	3.277***	3.283***
	(0.047)	(0.047)	(0.129)	(0.129)
own_commune_category30	0.480*	0.481*	1.553***	1.557***
	(0.412)	(0.412)	(0.135)	(0.135)
buy_commune_category12	2.987***	2.981***	1.604***	1.610***
	(0.041)	(0.041)	(0.081)	(0.081)
buy_commune_category13	2.536***	2.531***	2.526***	2.519***
	(0.093)	(0.093)	(0.200)	(0.200)
buy_commune_category20	2.361***	2.358***	2.853***	2.852***
	(0.043)	(0.043)	(0.062)	(0.062)
buy_commune_category30	0.023***	0.023***	2.471***	2.476***
	(0.306)	(0.306)	(0.083)	(0.083)
own_area	0.998***	0.998***	0.998**	0.998***
	(0.0005)	(0.0005)	(0.001)	(0.001)
own_room_count	0.960***	0.960***	0.942***	0.942***
	(0.011)	(0.011)	(0.015)	(0.015)
own_swimming_poolTrue	1.220***	1.221***	1.097*	1.095*
	(0.042)	(0.042)	(0.050)	(0.050)
own_parkingTrue	0.858***	0.858***	0.897***	0.895***
	(0.020)	(0.020)	(0.037)	(0.037)
own_shared_wallTrue	1.220***	1.220***	1.382***	1.385***
	(0.027)	(0.027)	(0.044)	(0.044)
own_exterieur1	1.115***	1.115***		
	(0.023)	(0.023)		
buy_item_type2	1.200**	1.199**		
	(0.072)	(0.072)		
buy_area	0.997***	0.997***		
	(0.0005)	(0.0005)		
buy_room_count	1.026**	1.026**		
	(0.011)	(0.011)		
buy_ground_garden1	1.231***	1.230***		
	(0.054)	(0.054)		
buy_swimming_poolTrue	0.659***	0.659***		
	(0.038)	(0.038)		
buy_shared_wallTrue	1.110***	1.112***		
	(0.029)	(0.029)		
buy_sell_price	1.000***	1.000***		
	(0.00000)	(0.00000)		
buy_jardin1	1.330***	1.331***		
	(0.065)	(0.065)		
buy_exterieur1	1.074**	1.076**		
	(0.029)	(0.029)		
buy_parkingTrue			0.902***	0.902***
			(0.036)	(0.036)
estima_value			1.000***	1.000***
			(0.00000)	(0.00000)
own_DEPEQUIP_EPCI	1.001***	1.001***	1.000**	1.000**
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
own_CHOM1564	1.028***	1.028***		
	(0.004)	(0.004)		
own_VACANT	1.019***	1.018***	0.980***	0.980***
	(0.005)	(0.005)	(0.006)	(0.006)
own_RESECOND	0.997*	0.997*	0.995**	0.995**
	(0.002)	(0.002)	(0.002)	(0.002)
own_PROPRIO	1.045***	1.045***		
	(0.011)	(0.011)		
own_COLLECTIF			1.008***	1.008***
			(0.002)	(0.002)
own_LOCATAIRE	1.038***	1.038***	0.991***	0.991***
	(0.011)	(0.011)	(0.003)	(0.003)
own_CONS45	0.995***	0.995***	0.994***	0.994***
	(0.001)	(0.001)	(0.002)	(0.002)
own_POP65P	1.017***	1.017***	0.988**	0.988**
	(0.003)	(0.003)	(0.005)	(0.005)

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Table 10 – continued from previous page

	Dependent variable : staying in the same attraction area			
	Urban origin		Rural origin	
own_POP1824	1.023***	1.023***		
	(0.006)	(0.006)		
own_AUTRSERVEDUC	0.989**	0.989**		
	(0.005)	(0.005)		
own_POP0010			0.969***	0.969***
			(0.010)	(0.010)
own_ETABSANTE	0.993***	0.993***	1.038*	1.039*
	(0.001)	(0.001)	(0.021)	(0.021)
own_CRECHE	1.002**	1.002**		
	(0.001)	(0.001)		
own_ACTIONSOCIALHANDI	1.006***	1.006***		
	(0.002)	(0.002)		
own_AUTREACTSOCIALE	1.007***	1.007***		
	(0.003)	(0.003)		
own_surfres	1.000***	1.000***		
	(0.00002)	(0.00002)		
own_surfact	1.000***	1.000***		
	(0.0001)	(0.0001)		
own_denspop			1.014***	1.014***
			(0.003)	(0.003)
buy_DEPEQUIP_EPCI	0.999***	0.999***	0.999***	0.999***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
buy_VACANT	0.920***	0.920***		
	(0.004)	(0.004)		
buy_RESECOND	0.951***	0.951***	0.985***	0.985***
	(0.001)	(0.001)	(0.001)	(0.001)
buy_MAISON	0.942***	0.942***		
	(0.009)	(0.009)		
buy_COLLECTIF	0.972***	0.972***		
	(0.009)	(0.009)		
buy_LOCATAIRE	0.955***	0.955***		
	(0.002)	(0.002)		
buy_ETRANGER	1.042***	1.042***		
	(0.004)	(0.004)		
buy_POP1117	1.157***	1.157***		
	(0.010)	(0.010)		
buy_POP1824	1.069***	1.069***	1.057***	1.057***
	(0.005)	(0.005)	(0.008)	(0.008)
buy_SUPUN	1.005***	1.005***		
	(0.001)	(0.001)		
buy_AUTRSERVEDUC	0.973***	0.973***		
	(0.004)	(0.004)		
buy_ACTIONSOCIALAGE	1.005***	1.005***		
	(0.001)	(0.001)		
buy_ACTIONSOCIALHANDI	0.992***	0.992***		
	(0.002)	(0.002)		
buy_AUTREACTSOCIALE			1.012***	1.013***
			(0.003)	(0.003)
buy_surfres	1.000***	1.000***	1.000***	1.000***
	(0.00002)	(0.00002)	(0.00005)	(0.00005)
buy_surfact			1.001***	1.001***
			(0.0001)	(0.0001)
buy_denspop	1.003***	1.003***	0.992***	0.992***
	(0.0003)	(0.0003)	(0.001)	(0.001)
buy_slc	1.002***	1.002***		
	(0.0004)	(0.0004)		
ETRANGER_diff	1.020***	1.020***		
	(0.003)	(0.003)		
Constant	0.896	0.884	0.582*	0.579**
	(1.422)	(1.423)	(0.277)	(0.277)
Observations	81,646	81,646	15,161	15,161
Log Likelihood	−36,247.950	−36,232.510	−9,543.136	−9,540.378
Akaike Inf. Crit.	72,611.900	72,591.020	19,152.270	19,156.760
Note :			*p<0.1 ; **p<0.05 ; ***p<0.01	

Table 11 – Logit estimation results for the probability of choosing urban over rural ; Odds Ratios

	Dependent variable : choose urban over rural			
	Urban origin		Rural origin	
search_after_covid	0.911**		1.041	
	(0.044)		(0.070)	
covidconf1		0.887		1.293
		(0.126)		(0.192)
covidinter1		0.959		0.982
		(0.060)		(0.100)
covidconf2		1.110		1.140
		(0.167)		(0.270)
covidinter2		0.909		0.998
		(0.067)		(0.108)
covidconf3		0.916		0.882
		(0.104)		(0.167)
covidafter		0.857***		1.138
		(0.060)		(0.097)
own_commune_category12	1.105	1.103	0.226***	0.226***
	(0.077)	(0.077)	(0.545)	(0.547)
own_commune_category13	1.309	1.304		
	(0.185)	(0.185)		
own_commune_category20	1.428***	1.427***	1.095	1.086
	(0.083)	(0.083)	(0.222)	(0.222)
own_commune_category30	5.502***	5.552***	1.114	1.098
	(0.559)	(0.559)	(0.239)	(0.239)
buy_commune_category12	14.799***	14.813***	16.133***	15.978***
	(0.189)	(0.189)	(0.268)	(0.268)
buy_commune_category13	20,185.150	20,446.860	98,361.360	99,400.470
	(121.748)	(122.004)	(184.504)	(184.828)
buy_commune_category20	0.456***	0.455***	0.694**	0.693**
	(0.103)	(0.103)	(0.150)	(0.150)
buy_commune_category30	0.044***	0.043***	0.062***	0.061***
	(0.205)	(0.205)	(0.357)	(0.358)
buy_area	0.994***	0.994***		
	(0.001)	(0.001)		
buy_swimming_poolTrue	0.689***	0.689***		
	(0.065)	(0.065)		
buy_sell_price	1.000***	1.000***	1.000***	1.000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
own_EMPHAB	0.780**	0.780**		
	(0.106)	(0.106)		
own_CAPBEP	0.986***	0.986***		
	(0.005)	(0.005)		
own_VACANT	1.032***	1.032***		
	(0.010)	(0.010)		
own_RESECOND	1.005**	1.005**		
	(0.002)	(0.002)		
own_PMUN			1.000***	1.000***
			(0.0001)	(0.0001)
own_PROPRIO	1.006***	1.006***	0.987***	0.987***
	(0.002)	(0.002)	(0.004)	(0.004)
own_CONS45	1.017***	1.017***	1.012***	1.012***
	(0.003)	(0.003)	(0.003)	(0.003)
own_ACTIONSOCIALAGE	1.006***	1.006***		
	(0.002)	(0.002)		
own_EMPLOI	1.024*	1.024*		
	(0.014)	(0.014)		
own_AUTREACTSOCIALE			0.713**	0.711**
			(0.156)	(0.157)
own_surfres			1.002***	1.002***
			(0.001)	(0.001)
own_denspop			0.981**	0.981**
			(0.008)	(0.008)
buy_PMUN	1.001***	1.001***	1.001***	1.001***
	(0.00003)	(0.00003)	(0.00005)	(0.00005)
buy_DEPEQUIP_EPCI	1.001***	1.001***		
	(0.0002)	(0.0002)		
buy_VACANT	0.900***	0.900***	0.906***	0.905***
	(0.010)	(0.010)	(0.015)	(0.015)

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Table 11 – continued from previous page

	Dependent variable : choose urban over rural			
	Urban origin		Rural origin	
buy_RESECOND	0.963***	0.963***	0.970***	0.970***
	(0.002)	(0.002)	(0.004)	(0.004)
buy_COLLECTIF	1.036***	1.036***	1.041***	1.041***
	(0.003)	(0.003)	(0.004)	(0.004)
buy_PROPRIO	1.086***	1.086***	1.051***	1.051***
	(0.018)	(0.018)	(0.006)	(0.006)
buy_LOCATAIRE	1.044**	1.044**		
	(0.018)	(0.018)		
buy_CONS45	0.981***	0.981***	0.964***	0.964***
	(0.003)	(0.003)	(0.005)	(0.005)
buy_ETRANGER	1.076***	1.076***		
	(0.008)	(0.008)		
buy_POP65P	1.081***	1.081***	1.099***	1.099***
	(0.008)	(0.008)	(0.012)	(0.012)
buy_POP0010	0.884***	0.884***	0.922***	0.922***
	(0.016)	(0.016)	(0.026)	(0.027)
buy_POP1117	1.043**	1.043**		
	(0.020)	(0.020)		
buy_POP1824	1.102***	1.101***	1.125***	1.124***
	(0.018)	(0.018)	(0.027)	(0.027)
buy_ACTIONSOCIALAGE	0.844***	0.844***	0.845***	0.845***
	(0.023)	(0.023)	(0.033)	(0.033)
buy_POLICE	0.549***	0.550***	0.529***	0.530***
	(0.066)	(0.066)	(0.106)	(0.106)
buy_EMPLOI			2.222***	2.225***
			(0.135)	(0.135)
buy_surfres	0.996***	0.996***	0.994***	0.994***
	(0.0003)	(0.0003)	(0.001)	(0.001)
buy_denspop	1.066***	1.066***	1.069***	1.069***
	(0.004)	(0.004)	(0.007)	(0.007)
own_slc	0.996***	0.996***		
	(0.001)	(0.001)		
buy_slc	0.951***	0.951***	0.920***	0.919***
	(0.005)	(0.005)	(0.008)	(0.008)
ETRANGER_diff			1.056***	1.056***
			(0.013)	(0.013)
CRECHE_diff			1.188***	1.185***
			(0.057)	(0.058)
Constant	0.00005***	0.00005***	0.001***	0.001***
	(1.764)	(1.763)	(0.997)	(1.000)
Observations	81,646	81,646	15,161	15,161
Log Likelihood	−6,985.357	−6,983.255	−2,780.011	−2,777.741
Akaike Inf. Crit.	14,050.710	14,056.510	5,626.023	5,631.482
Note :				*p<0.1 ; **p<0.05 ; ***p<0.01

Table 12 – Nested logit estimation results ; Odds Ratios

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
(Intercept) :diff_aav_urb	0.000***	0.000***	12.375***	12.469***
	(6.744)	(6.689)	(0.873)	(0.873)
(Intercept) :same_aav_rur	0.128	0.114	3.775**	3.711**
	(3.970)	(3.964)	(0.573)	(0.573)
(Intercept) :same_aav_urb	0.000***	0.000***	1.946	1.937
	(6.383)	(6.329)	(0.890)	(0.892)
search_after_covid1 :diff_aav_urb	0.915		0.975	
	(0.091)		(0.069)	
search_after_covid1 :same_aav_rur	0.848***		0.901**	
	(0.057)		(0.048)	
search_after_covid1 :same_aav_urb	0.802**		0.926	
	(0.089)		(0.071)	
covidconf1 :diff_aav_urb		0.859		1.406*

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Table 12 – continued from previous page

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
		(0.261)		(0.182)
covidconf1 :same_aav_rur		0.953		1.064
		(0.162)		(0.133)
covidconf1 :same_aav_urb		0.788		1.110
		(0.253)		(0.195)
covidinter1 :diff_aav_urb		0.942		0.957
		(0.124)		(0.097)
covidinter1 :same_aav_rur		0.862*		0.918
		(0.077)		(0.066)
covidinter1 :same_aav_urb		0.872		0.930
		(0.120)		(0.100)
covidconf2 :diff_aav_urb		0.981		0.969
		(0.325)		(0.252)
covidconf2 :same_aav_rur		0.622**		0.827
		(0.220)		(0.176)
covidconf2 :same_aav_urb		0.997		1.238
		(0.314)		(0.250)
covidinter2 :diff_aav_urb		0.904		0.903
		(0.137)		(0.106)
covidinter2 :same_aav_rur		0.865*		0.916
		(0.087)		(0.073)
covidinter2 :same_aav_urb		0.795*		1.001
		(0.133)		(0.111)
covidconf3 :diff_aav_urb		0.935		0.964
		(0.209)		(0.161)
covidconf3 :same_aav_rur		1.029		0.882
		(0.132)		(0.114)
covidconf3 :same_aav_urb		0.856		0.915
		(0.203)		(0.176)
covidafter :diff_aav_urb		0.909		1.000
		(0.120)		(0.094)
covidafter :same_aav_rur		0.811***		0.873**
		(0.076)		(0.064)
covidafter :same_aav_urb		0.725***		0.848*
		(0.117)		(0.098)
estima_value2 :diff_aav_urb	1.000	1.000	1.001***	1.001***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
estima_value2 :same_aav_rur	0.999***	0.999***	1.001***	1.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
estima_value2 :same_aav_urb	1.000	1.000	1.004***	1.004***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
own_item_type2 :diff_aav_urb	1.353**	1.356**	1.006	1.008
	(0.152)	(0.151)	(0.165)	(0.165)
own_item_type2 :same_aav_rur	0.808**	0.812**	0.754**	0.756**
	(0.091)	(0.091)	(0.118)	(0.118)
own_item_type2 :same_aav_urb	1.186	1.190	0.754*	0.756*
	(0.148)	(0.147)	(0.164)	(0.164)
own_area :diff_aav_urb	1.000	1.000	0.999	0.999
	(0.002)	(0.002)	(0.001)	(0.001)
own_area :same_aav_rur	1.000	1.000	1.000	1.000
	(0.001)	(0.001)	(0.001)	(0.001)
own_area :same_aav_urb	0.998	0.998	0.993***	0.993***
	(0.002)	(0.002)	(0.002)	(0.002)
own_room_count :diff_aav_urb			0.959	0.958
			(0.030)	(0.030)
own_room_count :same_aav_rur			0.938***	0.938***
			(0.019)	(0.019)
own_room_count :same_aav_urb			0.905***	0.905***
			(0.032)	(0.032)
own_swimming_poolTrue :diff_aav_urb	1.085	1.079	1.111	1.108
	(0.173)	(0.171)	(0.099)	(0.099)
own_swimming_poolTrue :same_aav_rur	1.071	1.074	1.107	1.106
	(0.112)	(0.112)	(0.069)	(0.069)
own_swimming_poolTrue :same_aav_urb	1.357*	1.351*	1.339***	1.337***
	(0.166)	(0.165)	(0.102)	(0.102)
own_parkingTrue :diff_aav_urb	1.001	0.999	1.111	1.113
	(0.093)	(0.093)	(0.071)	(0.071)
own_parkingTrue :same_aav_rur	0.846***	0.847***	0.870***	0.870***
	(0.058)	(0.058)	(0.047)	(0.047)

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Table 12 – continued from previous page

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
own_parkingTrue :same_aav_urb	0.880	0.879	1.000	1.001
	(0.091)	(0.090)	(0.074)	(0.074)
own_shared_wallTrue :diff_aav_urb	0.765**	0.765**	0.988	0.987
	(0.126)	(0.125)	(0.089)	(0.089)
own_shared_wallTrue :same_aav_rur	1.026	1.026	1.459***	1.461***
	(0.078)	(0.078)	(0.058)	(0.058)
own_shared_wallTrue :same_aav_urb	1.001	1.000	1.336***	1.339***
	(0.121)	(0.120)	(0.092)	(0.092)
buy_item_type2 :diff_aav_urb	0.752	0.750	0.500***	0.498***
	(0.335)	(0.333)	(0.125)	(0.125)
buy_item_type2 :same_aav_rur	1.151	1.156	0.960	0.959
	(0.247)	(0.246)	(0.097)	(0.097)
buy_item_type2 :same_aav_urb	0.896	0.893	0.659***	0.656***
	(0.329)	(0.328)	(0.126)	(0.127)
buy_area :diff_aav_urb	0.998	0.998		
	(0.002)	(0.002)		
buy_area :same_aav_rur	1.000	1.000		
	(0.001)	(0.001)		
buy_area :same_aav_urb	0.996**	0.996**		
	(0.002)	(0.002)		
buy_ground_garden1 :diff_aav_urb	1.448	1.440		
	(0.348)	(0.345)		
buy_ground_garden1 :same_aav_rur	1.051	1.054		
	(0.324)	(0.323)		
buy_ground_garden1 :same_aav_urb	1.814*	1.803*		
	(0.343)	(0.341)		
buy_jardin1 :diff_aav_urb	1.009	1.007		
	(0.267)	(0.265)		
buy_jardin1 :same_aav_rur	0.904	0.901		
	(0.160)	(0.160)		
buy_jardin1 :same_aav_urb	1.490	1.490		
	(0.260)	(0.258)		
buy_exterieur1 :diff_aav_urb	0.710	0.709		
	(0.257)	(0.255)		
buy_exterieur1 :same_aav_rur	0.887	0.887		
	(0.239)	(0.238)		
buy_exterieur1 :same_aav_urb	0.819	0.819		
	(0.256)	(0.254)		
rc_diff :diff_aav_urb	0.960	0.960		
	(0.037)	(0.037)		
rc_diff :same_aav_rur	0.984	0.984		
	(0.022)	(0.022)		
rc_diff :same_aav_urb	1.006	1.005		
	(0.036)	(0.036)		
own_DEPEQUIP_EPCI :diff_aav_urb	0.999**	0.999**		
	(0.0003)	(0.0003)		
own_DEPEQUIP_EPCI :same_aav_rur	1.000*	1.000**		
	(0.0002)	(0.0002)		
own_DEPEQUIP_EPCI :same_aav_urb	1.001***	1.001***		
	(0.0003)	(0.0003)		
own_EMPHAB :diff_aav_urb	0.801	0.801		
	(0.228)	(0.226)		
own_EMPHAB :same_aav_rur	1.211	1.208		
	(0.148)	(0.148)		
own_EMPHAB :same_aav_urb	0.706	0.707		
	(0.220)	(0.218)		
own_CHOM1564 :diff_aav_urb	0.978	0.978		
	(0.019)	(0.019)		
own_CHOM1564 :same_aav_rur	0.956***	0.956***		
	(0.012)	(0.012)		
own_CHOM1564 :same_aav_urb	0.990	0.990		
	(0.018)	(0.018)		
own_VACANT :diff_aav_urb	1.092***	1.092***	1.079***	1.079***
	(0.022)	(0.022)	(0.014)	(0.014)
own_VACANT :same_aav_rur	1.045***	1.044***	0.991	0.991
	(0.013)	(0.013)	(0.008)	(0.008)
own_VACANT :same_aav_urb	1.084***	1.084***	1.040***	1.040**
	(0.022)	(0.022)	(0.015)	(0.015)
own_RESECOND :diff_aav_urb	1.044***	1.044***	1.022***	1.022***

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Table 12 – continued from previous page

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
	(0.007)	(0.007)	(0.004)	(0.004)
own_RESECOND :same_aav_rur	0.995	0.995	1.008***	1.008***
	(0.005)	(0.005)	(0.002)	(0.002)
own_RESECOND :same_aav_urb	1.035***	1.035***	0.995	0.995
	(0.007)	(0.007)	(0.004)	(0.004)
own_PROPRIO :diff_aav_urb	0.950	0.951	1.000	1.000
	(0.049)	(0.049)	(0.005)	(0.005)
own_PROPRIO :same_aav_rur	1.103***	1.103***	1.000	1.000
	(0.032)	(0.032)	(0.003)	(0.003)
own_PROPRIO :same_aav_urb	0.970	0.972	1.028***	1.028***
	(0.047)	(0.047)	(0.005)	(0.005)
own_CONS45 :diff_aav_urb	1.043***	1.043***	0.996	0.996
	(0.007)	(0.007)	(0.003)	(0.003)
own_CONS45 :same_aav_rur	0.985***	0.985***	0.994***	0.994***
	(0.004)	(0.004)	(0.002)	(0.002)
own_CONS45 :same_aav_urb	1.038***	1.038***	0.991**	0.991**
	(0.007)	(0.007)	(0.004)	(0.004)
own_LOCATAIRE :diff_aav_urb	0.940	0.942		
	(0.050)	(0.049)		
own_LOCATAIRE :same_aav_rur	1.107***	1.107***		
	(0.032)	(0.032)		
own_LOCATAIRE :same_aav_urb	0.956	0.958		
	(0.048)	(0.047)		
own_POP0010 :diff_aav_urb			0.974	0.974
			(0.020)	(0.020)
own_POP0010 :same_aav_rur			0.973**	0.974*
			(0.014)	(0.014)
own_POP0010 :same_aav_urb			0.935***	0.935***
			(0.021)	(0.021)
own_POP1824 :diff_aav_urb	0.941***	0.941***	0.938**	0.939**
	(0.023)	(0.023)	(0.028)	(0.028)
own_POP1824 :same_aav_rur	1.012	1.012	1.007	1.007
	(0.013)	(0.013)	(0.018)	(0.018)
own_POP1824 :same_aav_urb	0.959*	0.959*	0.973	0.974
	(0.023)	(0.023)	(0.027)	(0.027)
own_POP65P :diff_aav_urb	0.946***	0.947***	0.977**	0.977**
	(0.013)	(0.013)	(0.011)	(0.011)
own_POP65P :same_aav_rur	1.049***	1.049***	0.993	0.993
	(0.008)	(0.008)	(0.007)	(0.007)
own_POP65P :same_aav_urb	0.969**	0.970**	0.936***	0.936***
	(0.013)	(0.013)	(0.012)	(0.012)
own_REVUC :diff_aav_urb	1.039**	1.038**		
	(0.017)	(0.017)		
own_REVUC :same_aav_rur	1.000	0.999		
	(0.012)	(0.012)		
own_REVUC :same_aav_urb	1.040**	1.040**		
	(0.017)	(0.017)		
own_AUTRSERVEDUC :diff_aav_urb	1.081***	1.081***		
	(0.019)	(0.019)		
own_AUTRSERVEDUC :same_aav_rur	1.020*	1.020*		
	(0.010)	(0.010)		
own_AUTRSERVEDUC :same_aav_urb	1.069***	1.068***		
	(0.019)	(0.019)		
own_ETABSANTE :diff_aav_urb	1.014***	1.014***		
	(0.004)	(0.004)		
own_ETABSANTE :same_aav_rur	0.999	0.999		
	(0.003)	(0.003)		
own_ETABSANTE :same_aav_urb	1.012***	1.012***		
	(0.004)	(0.004)		
own_surfres :diff_aav_urb	1.000	1.000	0.998***	0.998***
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
own_surfres :same_aav_rur	1.000***	1.000***	1.000	1.000
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
own_surfres :same_aav_urb	1.000	1.000	0.999***	0.999***
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
own_surfact :diff_aav_urb	1.000*	1.000*		
	(0.0003)	(0.0003)		
own_surfact :same_aav_rur	1.000**	1.000**		
	(0.0002)	(0.0002)		

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Table 12 – continued from previous page

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
own_surfact :same_aav_urb	1.000*	1.000*		
	(0.0003)	(0.0003)		
own_denspop :diff_aav_urb	0.995***	0.995***	1.007	1.008
	(0.001)	(0.001)	(0.006)	(0.006)
own_denspop :same_aav_rur	0.997***	0.997***	1.015***	1.015***
	(0.001)	(0.001)	(0.005)	(0.005)
own_denspop :same_aav_urb	0.995***	0.995***	1.031***	1.031***
	(0.001)	(0.001)	(0.006)	(0.006)
own_slc :diff_aav_urb	0.987***	0.987***		
	(0.002)	(0.002)		
own_slc :same_aav_rur	1.000	1.000		
	(0.001)	(0.001)		
own_slc :same_aav_urb	0.988***	0.988***		
	(0.002)	(0.002)		
buy_DEPEQUIP_EPCI :diff_aav_urb	1.003***	1.003***	1.002***	1.002***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
buy_DEPEQUIP_EPCI :same_aav_rur	0.999***	0.999***	1.000	1.000
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
buy_DEPEQUIP_EPCI :same_aav_urb	1.001***	1.001***	1.002***	1.002***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
buy_VACANT :diff_aav_urb	0.734***	0.736***	0.714***	0.714***
	(0.032)	(0.032)	(0.035)	(0.035)
buy_VACANT :same_aav_rur	0.920***	0.920***	0.954***	0.954***
	(0.011)	(0.011)	(0.008)	(0.008)
buy_VACANT :same_aav_urb	0.664***	0.666***	0.706***	0.705***
	(0.032)	(0.031)	(0.035)	(0.035)
buy_RESECOND :diff_aav_urb	0.890***	0.891***	0.946***	0.946***
	(0.010)	(0.010)	(0.006)	(0.006)
buy_RESECOND :same_aav_rur	0.958***	0.959***	0.985***	0.985***
	(0.003)	(0.003)	(0.002)	(0.002)
buy_RESECOND :same_aav_urb	0.855***	0.855***	0.911***	0.910***
	(0.010)	(0.010)	(0.008)	(0.008)
buy_PROPRIO :diff_aav_urb	1.173***	1.171***	0.953***	0.953***
	(0.044)	(0.043)	(0.007)	(0.007)
buy_PROPRIO :same_aav_rur	0.970	0.971	1.011***	1.011***
	(0.021)	(0.021)	(0.003)	(0.003)
buy_PROPRIO :same_aav_urb	1.175***	1.172***	0.966***	0.966***
	(0.042)	(0.042)	(0.006)	(0.006)
buy_MAISON :diff_aav_urb	1.076**	1.076**		
	(0.033)	(0.033)		
buy_MAISON :same_aav_rur	0.964**	0.964**		
	(0.015)	(0.015)		
buy_MAISON :same_aav_urb	0.940**	0.940**		
	(0.031)	(0.031)		
buy_COLLECTIF :diff_aav_urb	1.207***	1.206***		
	(0.034)	(0.034)		
buy_COLLECTIF :same_aav_rur	0.990	0.990		
	(0.015)	(0.015)		
buy_COLLECTIF :same_aav_urb	1.085**	1.083**		
	(0.032)	(0.032)		
buy_LOCATAIRE :diff_aav_urb	1.104**	1.103**		
	(0.043)	(0.043)		
buy_LOCATAIRE :same_aav_rur	0.897***	0.898***		
	(0.021)	(0.021)		
buy_LOCATAIRE :same_aav_urb	1.039	1.037		
	(0.042)	(0.041)		
buy_CONS45 :diff_aav_urb	0.927***	0.927***		
	(0.008)	(0.008)		
buy_CONS45 :same_aav_rur	1.004	1.004		
	(0.003)	(0.003)		
buy_CONS45 :same_aav_urb	0.940***	0.941***		
	(0.008)	(0.008)		
buy_ETRANGER :diff_aav_urb	1.143***	1.141***		
	(0.019)	(0.019)		
buy_ETRANGER :same_aav_rur	1.005	1.005		
	(0.014)	(0.014)		
buy_ETRANGER :same_aav_urb	1.199***	1.197***		
	(0.019)	(0.019)		
buy_POP65P :diff_aav_urb	1.375***	1.372***	1.091***	1.091***

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Table 12 – continued from previous page

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
	(0.026)	(0.025)	(0.012)	(0.012)
buy_POP65P :same_aav_rur	0.953***	0.953***	0.979***	0.979***
	(0.008)	(0.008)	(0.005)	(0.005)
buy_POP65P :same_aav_urb	1.299***	1.295***	1.109***	1.110***
	(0.025)	(0.025)	(0.013)	(0.013)
buy_POP1117 :diff_aav_urb	1.239***	1.236***		
	(0.050)	(0.050)		
buy_POP1117 :same_aav_rur	1.024	1.024		
	(0.020)	(0.020)		
buy_POP1117 :same_aav_urb	1.368***	1.365***		
	(0.047)	(0.047)		
buy_POP1824 :diff_aav_urb	1.656***	1.649***	1.171***	1.169***
	(0.046)	(0.046)	(0.029)	(0.029)
buy_POP1824 :same_aav_rur	1.180***	1.181***	1.015	1.014
	(0.020)	(0.020)	(0.018)	(0.018)
buy_POP1824 :same_aav_urb	1.641***	1.634***	1.222***	1.221***
	(0.046)	(0.045)	(0.030)	(0.030)
buy_SUPUN :diff_aav_urb	0.701**	0.703**	0.754	0.756
	(0.176)	(0.175)	(0.229)	(0.231)
buy_SUPUN :same_aav_rur	0.967	0.967	1.020	1.021
	(0.216)	(0.215)	(0.288)	(0.289)
buy_SUPUN :same_aav_urb	0.707**	0.709**	0.765	0.768
	(0.176)	(0.175)	(0.229)	(0.231)
buy_ACTIONSOCIALAGE :diff_aav_urb	1.001	1.000	0.973	0.974
	(0.045)	(0.045)	(0.031)	(0.031)
buy_ACTIONSOCIALAGE :same_aav_rur	1.005	1.004	1.055*	1.055*
	(0.040)	(0.040)	(0.028)	(0.028)
buy_ACTIONSOCIALAGE :same_aav_urb	0.996	0.995	0.965	0.966
	(0.045)	(0.045)	(0.031)	(0.031)
buy_AUTREACTSOCIALE :diff_aav_urb			1.367***	1.369***
			(0.101)	(0.101)
buy_AUTREACTSOCIALE :same_aav_rur			0.958	0.960
			(0.102)	(0.102)
buy_AUTREACTSOCIALE :same_aav_urb			1.385***	1.387***
			(0.101)	(0.101)
buy_CRECHE :diff_aav_urb			1.609***	1.605***
			(0.078)	(0.078)
buy_CRECHE :same_aav_rur			0.982	0.981
			(0.056)	(0.056)
buy_CRECHE :same_aav_urb			1.596***	1.592***
			(0.078)	(0.078)
buy_POLICE :diff_aav_urb	0.417***	0.419***	0.521***	0.520***
	(0.146)	(0.145)	(0.118)	(0.118)
buy_POLICE :same_aav_rur	0.849	0.851	1.224**	1.223**
	(0.103)	(0.103)	(0.079)	(0.079)
buy_POLICE :same_aav_urb	0.417***	0.420***	0.543***	0.543***
	(0.147)	(0.145)	(0.118)	(0.118)
buy_EMPLOI :diff_aav_urb			1.477***	1.479***
			(0.150)	(0.150)
buy_EMPLOI :same_aav_rur			1.371*	1.370*
			(0.174)	(0.174)
buy_EMPLOI :same_aav_urb			1.426**	1.427**
			(0.151)	(0.151)
buy_surfres :diff_aav_urb	1.009***	1.009***	1.000	1.000
	(0.001)	(0.001)	(0.0003)	(0.0003)
buy_surfres :same_aav_rur	0.999***	0.999***	1.000	1.000
	(0.0004)	(0.0004)	(0.0002)	(0.0002)
buy_surfres :same_aav_urb	1.009***	1.009***	1.000	1.000
	(0.001)	(0.001)	(0.0003)	(0.0003)
buy_surfact :diff_aav_urb	1.002	1.002	1.001	1.001
	(0.001)	(0.001)	(0.001)	(0.001)
buy_surfact :same_aav_rur	1.001	1.001	0.999	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
buy_surfact :same_aav_urb	1.002	1.002	1.002*	1.002*
	(0.001)	(0.001)	(0.001)	(0.001)
buy_denspop :diff_aav_urb	1.411***	1.408***		
	(0.024)	(0.023)		
buy_denspop :same_aav_rur	1.064***	1.064***		
	(0.007)	(0.007)		

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Table 12 – continued from previous page

	Dependent variable : staying in the same attraction area and choosing urban over rural			
	Urban origin		Rural origin	
buy_denspop :same_aav_urb	1.417***	1.413***		
	(0.024)	(0.023)		
buy_slc :diff_aav_urb	0.996	0.997		
	(0.009)	(0.009)		
buy_slc :same_aav_rur	0.997	0.997		
	(0.010)	(0.010)		
buy_slc :same_aav_urb	0.995	0.995		
	(0.009)	(0.009)		
buy_ens :diff_aav_urb			1.368***	1.369***
			(0.038)	(0.037)
buy_ens :same_aav_rur			0.994	0.994
			(0.021)	(0.021)
buy_ens :same_aav_urb			1.368***	1.368***
			(0.038)	(0.037)
ETRANGER_diff :diff_aav_urb			1.098***	1.098***
			(0.014)	(0.014)
ETRANGER_diff :same_aav_rur			1.002	1.002
			(0.008)	(0.008)
ETRANGER_diff :same_aav_urb			1.109***	1.109***
			(0.015)	(0.015)
iv :same_aav	7.835***	7.667***	2.718***	2.718***
	(0.181)	(0.179)	(0.091)	(0.091)
iv :diff_aav	9.976***	9.804***	2.718***	2.718***
	(0.161)	(0.159)	(0.109)	(0.108)
Observations	81,643	81,643	15,161	15,161
R^2	0.424	0.424	0.353	0.353
Log Likelihood	−45,013.890	−44,996.180	−13,486.740	−13,478.280
LR Test	66,142.780***	66,178.180***	14,688.570***	14,705.470***
	(df = 152)	(df = 167)	(df = 107)	(df = 122)
Note :				*p<0.1 ; **p<0.05 ; ***p<0.01

[1] Elston Lafata J., Koch G.G., Weissert W.G., Estimating activity limitation in the non-institutionalized population : a method for small areas, American Journal of Public Health, vol 84, n ? 11, pp 1813-1817, november 1994.

[2] Erathosth ?ne, un algorithme de d ?termination du PGCD par le crible ?ponyme, IIIe si ?cle avant J-C.

[3] Molkogorov A., un th ?or ?me central limite universel.