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Analyzing the characteristics of the residential relocation phenomenon through the willingness of households to move

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Abstract

To face the challenges of reducing the footprint of daily travel, a sustainable solution for cities could be to propose strategies that affect the spatiotemporal structure of travel, by addressing residential location. Understanding how households choose where to live is therefore essential to help politicians and planners encourage people to select their place of residence more wisely in relation to their travel needs. This research aims to define the characteristics of households willing to move, and to examine the reasons given for this choice, using data from two Montreal CMA-wide surveys on changes in habits caused by the Covid-19 pandemic. Results show that the household typology has a strong influence on relocation reflection, with young couple households having a lower probability of wanting to stay in their housing than other household types. Proximity to services in the area of residence is also found to have a strong impact on willingness to relocate, good proximity to secondary education and employment fostering the desire to relocate, and good proximity to groceries supporting staying in current housing. Results show that getting closer to nature is the most common reason why households want to relocate.

Keywords: residential location choice ; household relocation ; reasons to relocate

1. Introduction

For several decades, and even more so in recent years due to the Covid-19 pandemic, the phenomenon of urban sprawl has been increasing. Households are leaving city centers to move to the suburbs where land prices are generally more affordable. According to Allard et al.(2014) , this remoteness results in an increase in travel distances and

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dependence on the automobile, generating significant transportation costs. In this context, cities face the challenges of reducing the footprint of daily travel, and the solutions that often arise focus on reducing car dependence, which amounts to trying to change the way trips are made. However, it would also be possible, and perhaps more sustainable, for these municipalities to propose strategies to generate changes that affect the spatio-temporal structure of travel. One such structural change is the choice of residence since it is well known that location is one of the main drivers of travel behaviour. For Morency & Verreault (2020), understanding how households choose their place of residence is therefore essential in order to help politicians and planners propose strategies that encourage people to select their place of residence more wisely in relation to their travel needs.

This research aims to determine how households' choices about their residential location are articulated. It aims to define the characteristics of households that express a desire to move, and to examine the reasons given for this choice. It uses data from two Montreal CMA-wide surveys on changes in habits caused by the Covid-19 pandemic, to develop typologies of households wishing to relocate. The 2020 and 2021 COVID-19 surveys, which collect data from more than 2,000 households, are used in conjunction with proximity variables developed by Statistics Canada to segment households into types, while controlling for location-related characteristics. This paper first presents some results of studies on the households' choice to relocate and the key factors influencing this decision. The methodology used in this study is then detailed. The characteristics of households wishing to relocate, as well as the reasons expressed to justify this choice are then presented as results. A conclusion, some limitations and perspectives follow.

2. Background

A significant portion of the literature focuses on modeling and describing residential location choice behavior. However, the study of factors influencing the decision to move or not is not as extensive and would benefit from further research.

Several categories of factors influence the choice of whether to change residence. The first category is household demographic and socioeconomic factors. Household structure is an important factor (Kortum et al., 2012; Lee & Waddell, 2010; Vandersmissen et al., 2009). Households composed of younger adults have a higher probability of moving than those composed of older adults (Clark, 2013; Kortum et al., 2012; Lee & Waddell, 2010; Rashidi et al., 2011). Kortum et al. (2012) observe that households with children are more likely to move, which they attribute to the fact that these households are at a stage in their life cycle when they are actively looking for attractive housing and neighborhoods in which to settle permanently. These findings are not shared by all authors, however. Several authors have found that the number of children strongly decreases the likelihood of moving (Clark, 2013; Vandersmissen et al., 2009), as does the addition of a new member to the household (Rashidi et al., 2011). The number of workers in the household is also a factor influencing the decision to relocate (Kortum et al., 2012; Lee & Waddell, 2010; Yu Jianhui et al., 2015). Household income also influences residential mobility, with an increase in household income leading to a greater propensity to move (De Groot et al., 2011; Kortum et al., 2012).

Housing characteristics are a second category of attributes influencing the likelihood of relocation, with tenure being the most important determinant (Clark, 2013; De Groot et al., 2011; Lee & Waddell, 2010; Rashidi et al., 2011; Vandersmissen et al., 2009; Yi & Lee, 2014; Yu Jianhui et al., 2015). Indeed, De Groot et al. (2011) have shown that renters are about twice as likely to move as homeowners. Housing price is also an important factor on the choice to move (Kortum et al., 2012; Lee & Waddell, 2010).

Regarding residential location characteristics, Rashidi et al. (2011) focus on commuting distance and show that it positively influences the likelihood of moving, as relocation can reduce these daily distances and thus reduce transportation expenditures and time spent commuting. Conversely, Vandermissen et al. (2009) observe that a large distance between home and work is poorly correlated with an increase in the probability of moving, which they attribute to the low importance households place on reducing commuting distances. Rashidi et al. (2011) find that households residing in TAZs, where there are more real estate, leasing, and rental jobs, are more likely to relocate. Kortum et al. (2012) find that households considering proximity to work or family and friends as the main reason for choosing a place to live are more likely to move than others, as opposed to those who consider neighborhood quality as very important.

As for the reasons for choosing to move, various studies have identified trends that are common to all households and others that are specific to certain types of households. For example, older people appear to value proximity to family and friends and to shopping (Dittrich-Wesbuer & Osterhage, 2008; L. Wang et al., 2022). Younger couples with children tend to purchase homes, particularly in neighborhoods with lower public facility density and higher diversity scores (Lee & Waddell, 2010; L. Wang et al., 2022). These results are consistent with those of Dittrich-Wesbuer and Osterhage (2008), who show that environmental criteria (child-friendliness, green and open space, accessibility to care and education) are the primary considerations of households with children. Neighborhood composition and accessibility are also important factors in choosing where to live (Lee & Waddell, 2010; F. Wang et al., 2020; Yi & Kim, 2018; Yi & Lee, 2014). A household will be attracted to a home with better job accessibility than the one in which it is currently staying (Lee & Waddell, 2010; Yi & Kim, 2018). Population density, school density, accessibility to public transportation, and accessibility to hospitals in a census tract have significant positive effects on its attractiveness (L. Wang et al., 2022). Although according to some studies moving closer to one's workplace is considered an important attribute examined by the household in evaluating different alternatives (Hunt, 2010; Rashidi & Mohammadian, 2011; Yi & Lee, 2014), it seems that in general, in their relocation process, households prioritize factors such as larger housing units, in greener neighborhoods, and closer to services over reducing commuting time and costs (Smith & Olaru, 2011).

When we look at the models developed to explain and understand how the choices made during the relocation process are articulated, we observe a great diversity of approaches. Eluru et al. (2009) tested three models to investigate the reasons and timing of residential relocation in Zurich: an ordered independent multinomial (OIM) model (simple multinomial logit model for reason for relocation and an independent clustered response model for length of stay), an ordered independent random multinomial (IRMO) model (multinomial logit model with random coefficients for the reason for the move and an independent random coefficient clustered response model for the length of stay), and a correlated random multinomial ordered (CRMO) model (multinomial logit model with random coefficients for the reason for the move and a clustered response model with correlated random coefficients for the length of stay). A likelihood ratio test shows that the CRMO model provides significantly better goodness of fit at all significance levels. Yi and Kim (2018), who studied residential moving distances, show that the decision tree regression model has better explanatory power performance than the ordinary least squares regression model. The moving distances estimated by decision tree are also more realistic. Finally, this method exposes not only the diversity of structures that determine distances, but also the key features that form these diverse structures. To better understand the interdependencies between the choice to move and the reasons for that choice, Kortum et al. (2012) formulated a bivariate multinomial probit choice model to jointly model the decision to move/stay and the main reasons for that decision. Such a system effectively treats the main reasons for residential location choice as endogenous to the choice to relocate. To estimate the impact of life cycle stages and other independent variables on the annual probability of moving, De Groot et al. (2011) use two logistic regression models, one for households that do not intend to move and one for those that do intend to move.

Regarding the variables used to model the relocation phenomenon in the various previous works, the choices generally involve variables related to the individual characteristics of the respondent (age, gender and employment/education status), household characteristics (household size, household type, household income, and vehicle ownership), as well as commuting characteristics (mode of travel and commuting distance) and characteristics of the origin and destination location (accessibility, density, proportion of new construction, proportion of homeowners, rail and bus availability) (Eluru et al., 2009; Yi & Kim, 2018). Because household composition and needs change over time, several studies have categorized the households studied by type to assess the impact of life cycle and family structure on willingness to move (Clark, 2013; Hunt, 2010; Lee & Waddell, 2010; F. Wang et al., 2020; Yi & Lee, 2014).

3. General methodology

3.1. Data and variables

In 2020 and 2021, the Mobility Chair of Polytechnique Montreal conducted a survey in the Montreal CMA on the changes in habits caused by the Covid-19 pandemic. The questionnaire includes questions on household characteristics (household size, motorization, income, address), on housing (type of dwelling, type of property/rental), on the persons composing the household (gender, age, occupation, possession of a driver's license), on the impacts of the pandemic on travel habits (motorization, online shopping, travel and use of modes of transportation) and on the reflexion on the place and type of residence. It is on this last point that the study focuses. Indeed, the data offer useful and important insights on the impact of the pandemic on household location choice behaviour.

Because the survey was shared on social networks, the resulting response sample is an opportunistic sample. The sample collected in 2020 includes 1620 households, while the 2021 sample has 936 respondents. In the study, these two samples were combined to form an aggregated sample of 2539 observations. Non-qualitative observations for our study were removed and a variable containing the survey year information was created.

The household typologies used in this study (Clark, 2013; Hunt, 2010; Lee & Waddell, 2010; F. Wang et al., 2020; Yi & Lee, 2014) were developed by Fabre (2018) using data from Montreal household surveys. This typology includes eight distinct household types that are mutually exclusive types. It is based on the structure of the household and the socio-demographic characteristics of its members. The variables used in the process are the average age, age range and size of the household, as well as the number of children under 12 years of age and the number of people aged 75 years and over. The eight household types and their characteristics are presented in Table 1.

Table 1. Household Type Description and Sample

Household type description	% of total sample		Household average							
			Size		Age		Number of children under 12		Number of 75 years and older	
	2020 and 2021 COVID-19 survey	2018's OD survey	2020 and 2021 COVID-19 survey	2018's OD survey	2020 and 2021 COVID-19 survey	2018's OD survey	2020 and 2021 COVID-19 survey	2018's OD survey	2020 and 2021 COVID-19 survey	2018's OD survey
Sixty-years old households	16,1	26,2	1,6	1,5	63,4	64,1	0,0	0,0	0,0	0,0
Multi-generational family	2,7	3,0	4,1	3,8	37,8	39,2	0,7	0,6	0,1	0,1
Young couples	30,0	15,2	1,9	1,6	30,1	30,5	0,0	0,0	0,0	0,0
Adults and seniors	2,3	3,7	2,8	2,6	58,5	59,6	0,0	0,0	0,2	0,3
Retired	2,6	14,5	1,6	1,4	75,0	78,4	0,0	0,0	0,5	0,6
Very young families	21,2	14,3	4,0	3,9	23,3	22,9	1,5	1,5	0,0	0,0
Fifty-years old households	12,2	11,5	1,4	1,5	48,2	49,9	0,0	0,0	0,0	0,0
Young families	12,9	11,7	3,4	3,2	36,8	37,4	0,1	0,1	0,0	0,0

As this study is based on an opportunistic sample, it seemed important to compare this sample to the more commonly used data in the literature. Thus, the same clustering process was applied to the Origin-Destination (OD) data (the OD survey is a travel survey conducted every five years in the Greater Montreal area), allowing us to compare the two samples to determine if our sample can be considered representative. The most important differences between the two samples lie in the proportion of each household typology in the total sample. In the COVID-19 survey, "Very young families" and "Young couples" represent 21.2% and 30.0% of the sample, respectively, while they represent only 14.3% and 15.2% in the travel survey. Conversely, households in their sixties and retired people are

underrepresented in our sample. This under-representation of older households seems logical since the COVID-19 survey was conducted only via Internet. Considering such differences, our sample cannot be considered representative. However, the under-represented categories are categories of households that should have lower residential mobility than others, so the results of our study can still be used to explain the residential mobility of young households.

In order to characterize the respondents' residential location (Eluru et al., 2009; Yi & Kim, 2018), we used Statistics Canada's proximity measurement work. Statistics Canada (2020) has published a database that contains 10 proximity measures. Each measure is based on a gravity model that considers the distance between a reference dissemination block (DB) and all DBs in which the service is located (at a given distance) and the size of the services. These measures are presented as nationally normalized values, varying on a scale of 0 to 1, with 0 indicating the lowest proximity and 1 the highest proximity in Canada. The descriptive analysis of the ten proximity variables used is presented in Table 2.

Table 2. Descriptive analysis of proximity variables

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum	NA's
Employment	0.0000	0.0300	0.1020	0.1183	0.1975	0.5999	1
Pharma	0.0051	0.0255	0.0667	0.0913	0.1310	0.5010	466
Childcare	0.0010	0.1197	0.2534	0.2800	0.4120	0.9574	62
Healthcare	0.0000	0.0067	0.0246	0.0401	0.0598	0.4044	37
Grocery	0.0070	0.0509	0.1238	0.1677	0.2380	0.7903	656
Primary education	0.0074	0.0880	0.2015	0.2286	0.3435	0.8364	313
Secondary education	0.0095	0.0514	0.1013	0.1192	0.1608	0.7387	1022
Library	0.0300	0.0635	0.1020	0.1227	0.1526	0.7685	1154
Parks	0.0050	0.0465	0.0846	0.1167	0.1371	0.9831	175
Transit	0.0001	0.0124	0.0314	0.03476	0.0488	0.2139	137

To make the study of the impact of these proximity variables on the willingness of households to relocate more explicit, we have chosen in our model to normalize these variables at the level of the Montreal CMA. The new statistical analysis is presented in Table 3.

Table 3. Descriptive analysis of proximity variables standardized at the Montreal CMA level

	Mean	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Employment	0.20	0.00	0.05	0.17	0.33	1.00
Pharma	0.17	0.00	0.04	0.12	0.25	1.00
Childcare	0.29	0.00	0.12	0.26	0.43	1.00
Healthcare	0.10	0.00	0.02	0.06	0.15	1.00
Grocery	0.21	0.00	0.06	0.15	0.29	1.00
Primary education	0.27	0.00	0.10	0.23	0.41	1.00
Secondary education	0.15	0.00	0.06	0.13	0.21	1.00
Libraries	0.13	0.00	0.05	0.10	0.17	1.00
Parks	0.11	0.00	0.04	0.08	0.14	1.00
Transit	0.16	0.00	0.06	0.15	0.23	1.00

A summary of the variables used in our study is presented in the Table 4.

Table 4. Summary of variables used in our models

	Variable	Data Type	Descriptive analysis		Description
Dependent	Plan to move	Binary	Move : Stay :	35.5% (889) 64.5% (1613)	The household responded “yes” or “no” to the question : “Does the pandemic and the different confinement periods make you think about your home location and your type of residence ?”.
Independent	Year 2020	Binary	Year 2020 : Year 2021 :	63.2% (1582) 36.8% (920)	The observation is from the 2020 survey, as opposed to the 2021 survey
	Typology of household	Categorical	See Table. 1		The eight typologies of household developed by Fabre
	Household car ownership	Continuous	Minimum : 1st Quartile : Median : Mean : 3rd Quartile : Max :	0.0 0.0 1.0 1.1 2.0 7.0	The number of personal cars possessed by family members.
	Number of driving licenses	Continuous	Minimum : 1st Quartile : Median : Mean : 3rd Quartile : Max :	0.0 1.0 2.0 1.8 2.0 6.0	The number of driver's licenses held by persons in the household
	Owner	Binary	Owner : Tenant :	60.4% (1510) 39.6% (992)	The household owns the dwelling as opposed to a household that rents its dwelling.
	Dwelling type	Binary	Condominium : Plex : Row town house : Semi-detached house : Single-detached house : Other : Don’t know :	40.0% (1002) 14.7% (367) 6.4% (161) 8.2% (204) 29.7% (743) 0.7% (17) 0.3% (8)	The type of dwelling the household lives in
	Annual income	Categorial	Less than 30,000CAD : Between 30,000 and 60,000 CAD : Between 60,000 and 90,000 CAD : Between 90,000 and 120,000 CAD : Between 120,000 and 150,000 CAD : Between 150,000 and 180,000 CAD : Between 180,000 and 210,000 CAD : More than 210,000 CAD : Don’t know : Refusal : NA’s :	7.8% (194) 13.4% (336) 17.3% (434) 14.5% (362) 10.5% (262) 7.1% (178) 5.4% (136) 6.3% (157) 1.7% (43) 6.5% (162) 9.5% (238)	The annual income of the household
	Proximity measures to services	Continuous	See Table. 3		The proximity index developed by Statistic Canada

3.2. Analysis methods

Although the design of a joint model of the willingness to relocate and the reasons influencing this choice is quite relevant when focusing on the relocation phenomenon (Eluru et al.; Kortum et al.), two separate studies were chosen. Joint modeling of the decision to move/stay and the main reason for that decision indeed allows treating the reasons

as endogenous to the choice to relocate (Kortum et al., 2012), but in our case, the reasons are present only for the 889 households considering relocating, the question on the reasons not being asked to the households that answered that they did not wish to relocate. Analyzing separately the decision to move or not and then the reasons for choosing to relocate allows, first, to keep a large number of observations and not to neglect the study of the characteristics that influence the fact of wanting to stay in one's current dwelling. In the second stage, only households wishing to relocate are studied, which makes it possible to highlight trends within this particular group.

The method chosen to analyze the correlations between the explanatory variables and the variable on willingness to move is decision tree regression (Yi & Kim, 2018). A decision tree is a systematic data mining method that creates a set of leaves and branches based on segmentation rules. The goal of the study is to identify the characteristics of households and their residences that are most determinant of willingness to relocate but also to reveal combinations of variables relevant to the study of these choices. Decision trees were chosen because generally they produce results that are easy to explain and provide a visualization capability that supports the interpretation of the model's decisions (Rudd & Priestley, 2017). Another advantage of this method is that it allows for both continuous and categorical variables, the latter being common in our study. Furthermore, this method exposes not only the diversity of structures that influence the decision to relocate, but also the key characteristics that form these diverse structures (Yi & Kim, 2018).

In this study, the recursive partitioning decision tree method is used, using the rpart() function in R software. This function constructs a tree that minimizes the Gini impurity index, while checking three stopping criteria: a split can only be attempted if the current node contains at least 20 observations and the resulting nodes have at least 7 observations and the overall Gini index improves by c_p, the complexity parameter. The impurity of a decision tree node is defined as follows:

$$Gini(node) = 1 - p_{Stay}^2 - p_{Move}^2$$

The Gini impurity index of a tree is derived from the impurity of each node:

$$Gini(tree) = \sum_{each\ node} \frac{number\ of\ observations\ in\ the\ node}{number\ of\ observations\ in\ the\ tree} * Gini(node)$$

The rpart() function also allows to measure, for all the parameters of complexity c_p, and thanks to the cross-validation, the predictive performances of the corresponding trees (i.e. the proportion of observations for which the predicted choice does not correspond to the observed choice). The model with the smallest c_p is therefore the one that generates the largest number of splits, and consequently the largest number of leaves in the tree. To reconcile the predictive power and the relevance of the model results, we chose to retain the largest tree for which the relative cross-validated error is less than the sum of the standard error and the relative cross-validated error of the c_p with the lowest relative cross-validated error. This sum is represented by a dotted line on the graphs of the predictive performance of the tested trees (Foley, n.d.).

Once the best model has been selected, the results are analyzed based on the decision tree's visualization and measures of the importance of each of the variables included in the model. Indeed, the importance of the variables is measured by the overall improvement in the Gini index produced by the nodes in which it appears, in contrast to the decisions to split the tree, which are made based on impurity. Thus, the variables at the nodes are not necessarily the most important variables for the full model.

The part of the study that focuses on the reasons for wanting to move is based on a method of exploring sets of frequent items and learning association rules using Python software. The Apriori algorithm (2021), present in the mlxtend (machine learning extension) library of Python, works by identifying the frequent individual elements encountered in the database and extends them to larger and larger sets of elements, provided that the frequency of appearance of these combinations of elements is sufficiently important.

4. Results

4.1. Willingness to relocate

In order to get an estimate of the distribution of households wishing to relocate within the Montreal CMA, we mapped the rate of respondents expressing a desire to relocate. Responses were aggregated at the municipal sector level, and only those sectors with more than 10 respondents were displayed. The results are presented in Fig.1.

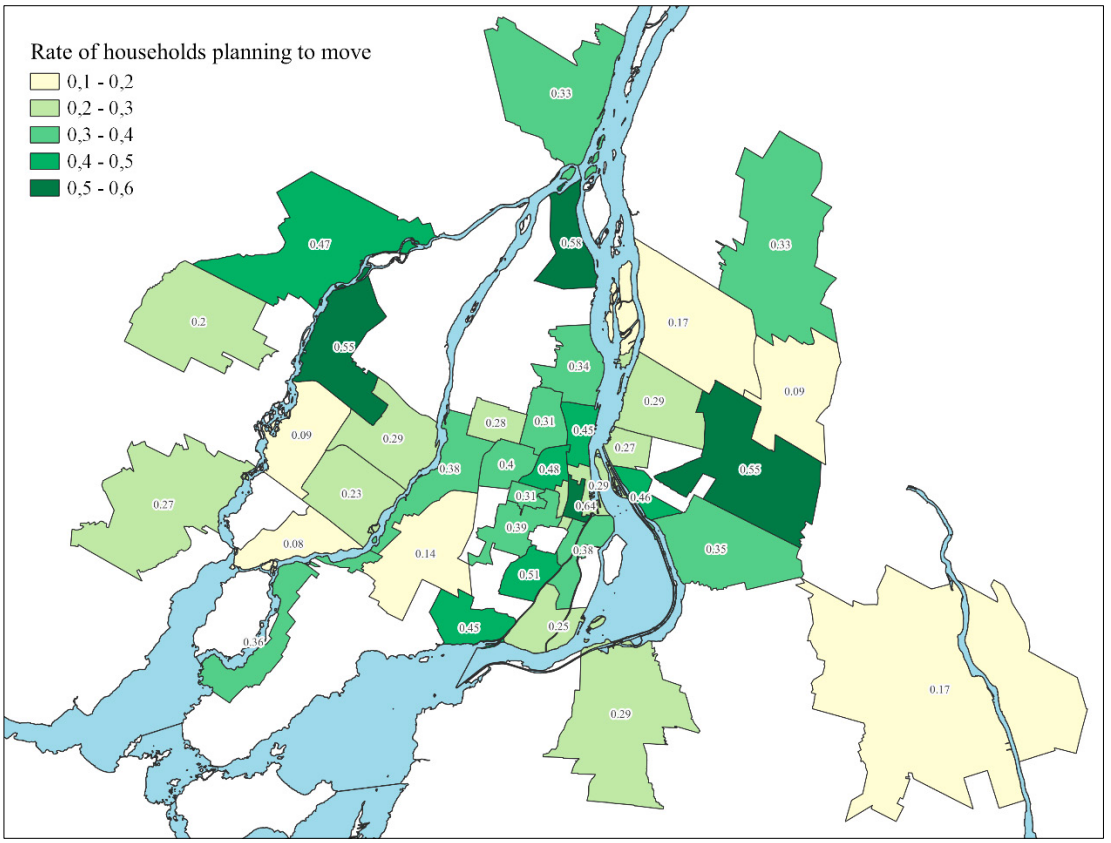

Fig. 1. Willingness of households to relocate by municipal area of residence (source: COVID-19 survey, Mobility Chair of Polytechnique Montréal)

The areas with the highest willingness to relocate are downtown Montreal (101), Pointe-aux-Trembles (113), Longueuil: Saint-Hubert (307) and Laval: Vimont, Auteuil (405). The decision trees calculated below will allow us to determine which characteristics of these sectors and their inhabitants are causing them to want to relocate. The first decision tree we computed has five leaves, this size allowing a satisfactory relative error rate while keeping relevant results to analyze, as presented in Fig 2.

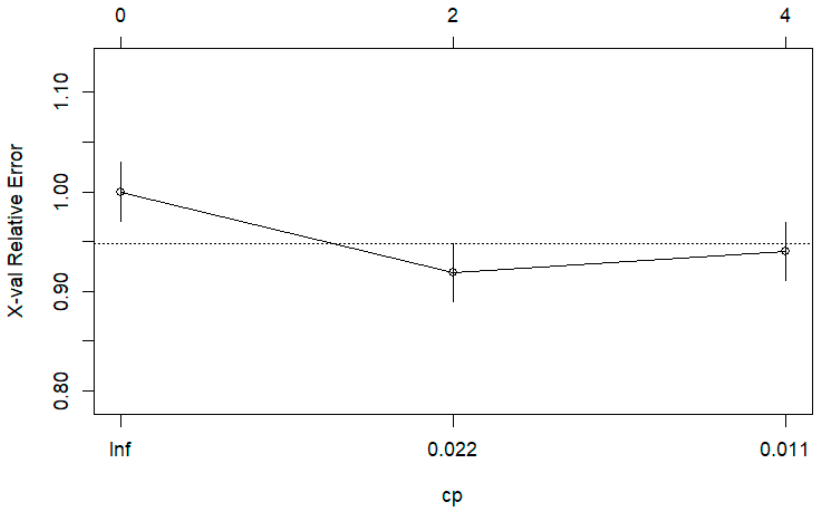

Fig 2. Relative cross-validated error of a first decision tree as a function of the cp and the number of divisions

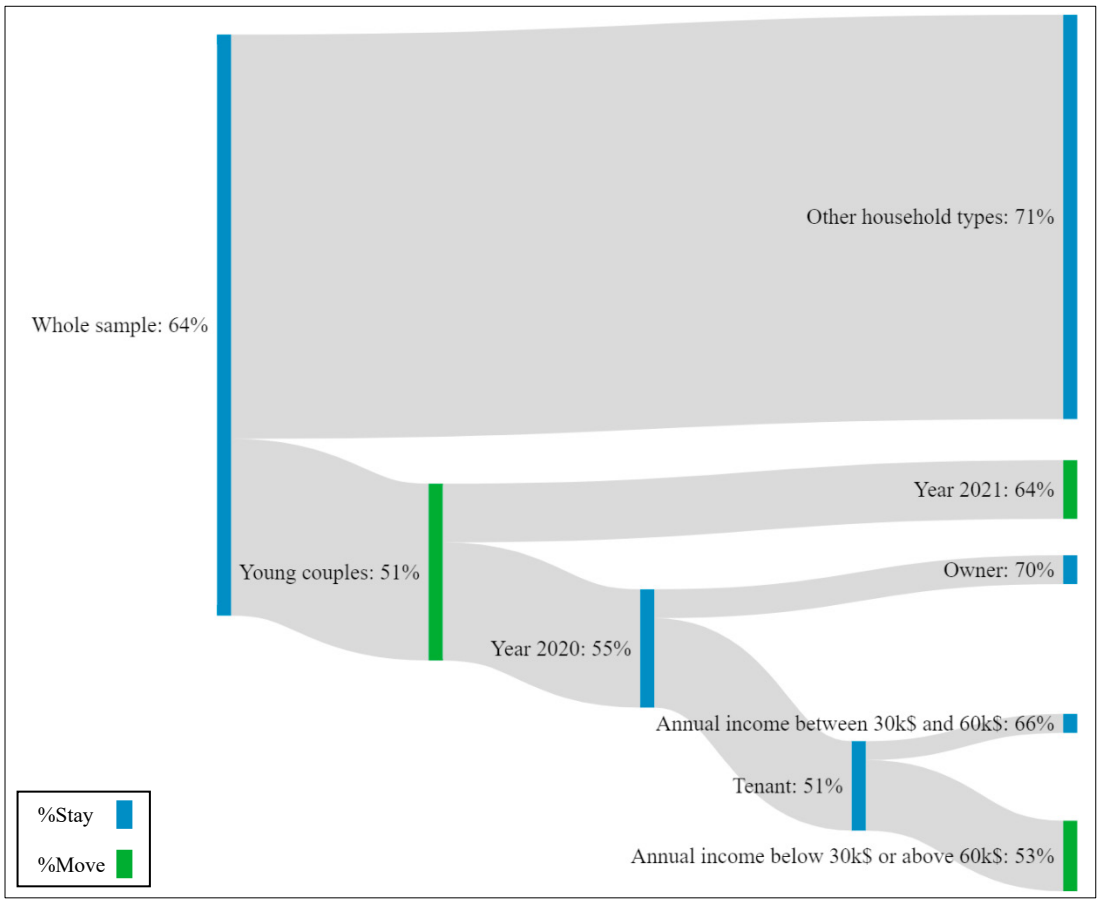

Fig. 3. Decision tree on households' willingness to move

Figure 2 shows the decision tree on willingness to move for households responding to the 2020 and 2021 surveys. At the top, the main node groups 100% of the sample of respondents. The first variable that separates this population is household type. For “Young Couples” households, two groups are then formed: 2021 respondents and 2020 respondents. The latter are then distinguished by their type of housing ownership (owner or renter). Finally, the group of renters is separated into two parts: households with annual incomes between 30,000 and 60,000 CAD and those with incomes below 30,000CAD or above 60,000CAD. This decision tree is thus composed of five "leaves".

- Households other than “Young couples” (1392 households) who have a 71% probability of remaining in their current house;
- Young couples who responded to the survey in 2021 (202 households) who have a 64% probability of moving;
- Young couples who responded to the survey in 2020 and who currently own their home (99 households), who have a 70% probability of staying;
- Young couples' responding to the 2020 survey who are renting and earning between 30,000 and 60,000 CAD per year (65 households) who are 66% more likely to stay in their current home;
- Young couples' responding to the 2020 survey, living in rentals and earning less than CAD 30,000 or more than CAD 60,000 per year (243 households) who have a 53% probability of moving.

The importance of the variables is presented in Table 5.

Table 5. Level of importance of decision tree variables on willingness to move

Variable	Young couples	Owner	Year 2020	Income between 30,000 and 60,0000CAD	Number of cars	Proximity to employment	Condominium	Proximity to childcare	Single-detached house
Importance	52	16	13	6	5	4	3	1	1
	51,49%	15,84%	12,87%	5,94%	4,95%	3,96%	2,97%	0,99%	0,99%

In the light of the importance of the household type and size of the non-“Young couple” group, it seems appropriate to run a decision tree regression for this group to determine which variables explain this type of households’ willingness to move. The database used for this new regression is composed of 1754 observations. The presented decision tree has three divisions, with a satisfactory relative error rate, as can be seen in.

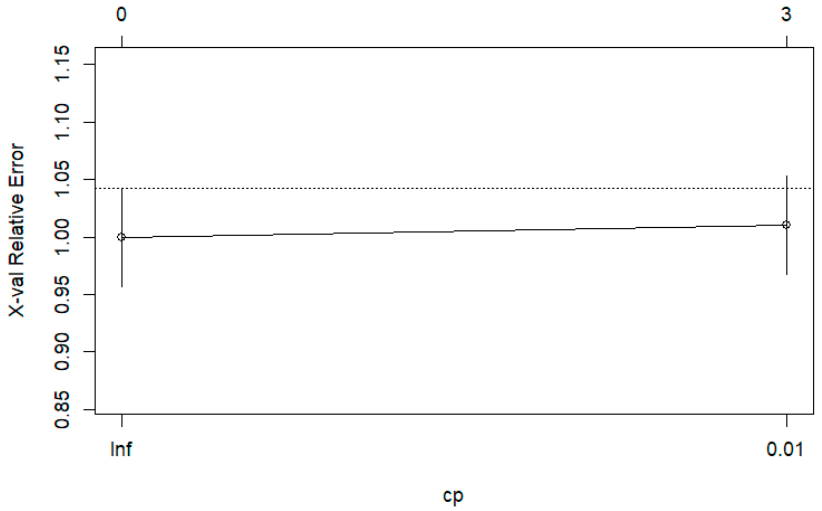

Fig 4. Relative cross-validated error of a second decision tree as a function of the cp and the number of divisions

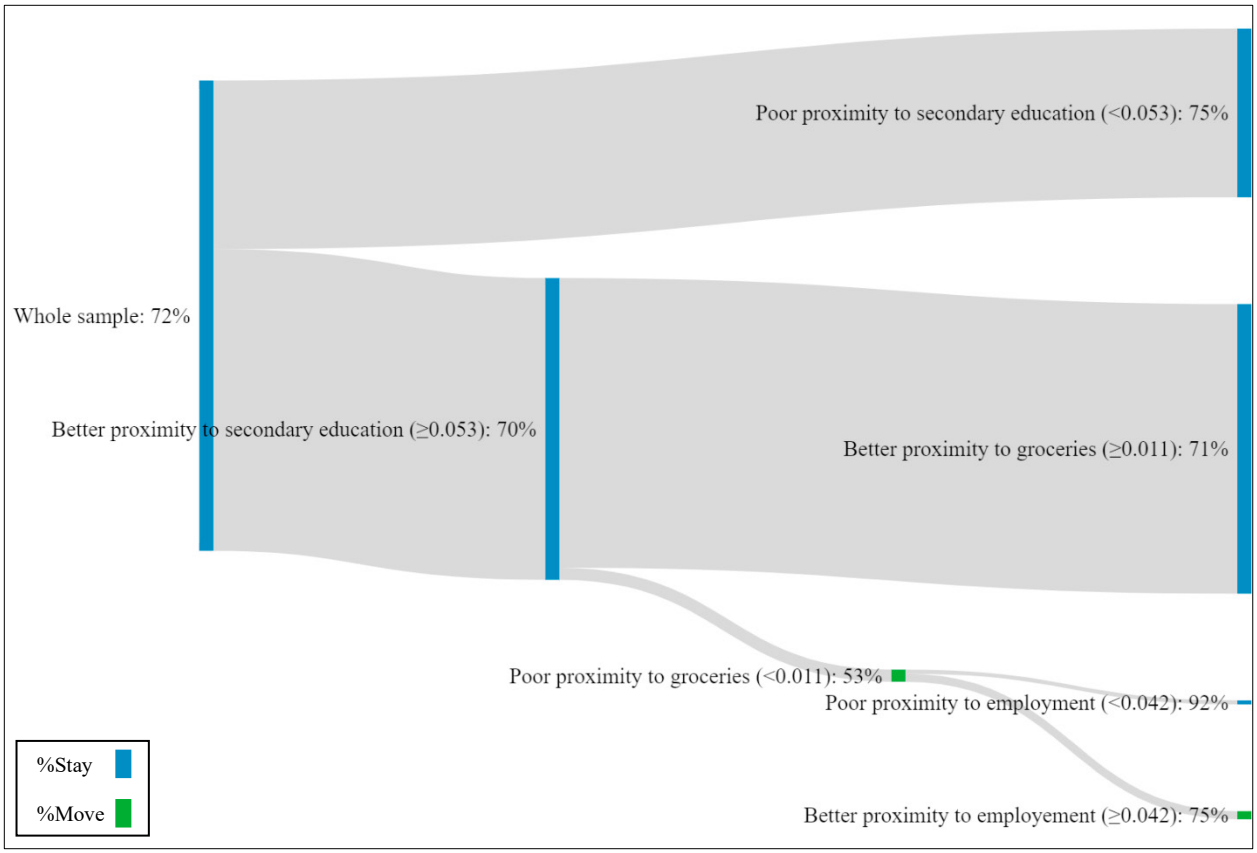

Fig. 5. Decision tree on willingness to move of households other than “Young couples”

Fig. 3 illustrates the decision tree on willingness to move for this sub-sample. The first variable that separates the sample of respondents is proximity to secondary schools. Two groups are formed: households domiciled in a census tract with a proximity index to secondary schools below 0.053 and those with better proximity. The households with the best proximity are then separated into two groups by their proximity to supermarkets. The group with poor proximity to supermarkets (below 0.011) is then split into two groups by proximity to employment. This tree is thus composed of four "leaves" that identify four types of households:

- Households located in a diffusion block with proximity to high schools <0.053 (503 households) who have a 75% probability of remaining in their current housing;
- Households located in a diffusion block with proximity to high schools ⩾0.053 and proximity to supermarkets ⩾0.011 (864 households), who have a 71% probability of remaining in their current housing;
- Households located in a diffusion block with proximity to high schools ⩾0.053, proximity to supermarkets <0.011, and proximity to employment <0.042 (12 households), who have a 92% probability of remaining in their current housing;
- Households located in a diffusion block with proximity to high schools ⩾0.053, proximity to supermarkets <0.011, and proximity to employment ⩾0.042 (24 households), who have a 75% probability of moving.

Since simple observation of the tree does not really determine which variables have the most influence on willingness to move, the importance of the variables is presented in Table 6.

Table 6. Importance of variables on willingness to move for households other than “Young couples”

Variable	Proximity to employment	Proximity to groceries	Proximity to secondary education	Proximity to healthcare	Proximity to transit	Proximity to primary education
Importance	34	21	17	11	11	5
	34,34%	21,21%	17,17%	11,11%	11,11%	5,05%

Only the residential environment variables are important in the willingness of households to relocate. In Table 6, we see that proximity to employment is the most important variable. We also observe the importance of proximity to healthcare, primary schools and transit, variables that are not present in the decision tree.

4.2. Reasons for wanting to relocate

In the survey, each respondent who indicated that he or she was considering moving was asked to select the reasons for that consideration. The reasons suggested were: become a homeowner, become a renter, move closer to friends and family, move closer to nature, move closer to school and shops, move closer to public transportation, move closer to work, larger home, larger lot, limit common areas, reduce expenses, reduce housing costs, reduce number of rooms, reduce commuting costs, smaller home and “other”. The occurrence of selection of each of the listed responses is presented in Fig. 4.

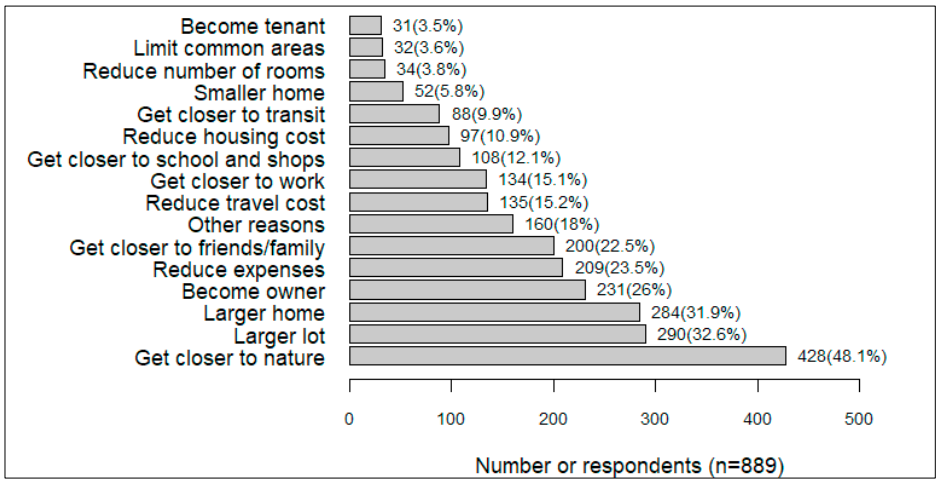

Fig. 6. Occurrence of reasons to move

Since almost half of the sample of respondents selected the reason "Get closer to nature", it seemed interesting to study the characteristics that differentiate households that selected this reason from those that did not.

Table 7. Comparison of household characteristics according to whether they selected the "Get closer to nature" reason

		Selected “Get closer to nature” (% of the sample)	Did not select “Get closer to nature” (% of the sample)
Household motorization	Motorised :	69.2	65.3
	Non-motorised :	30.8	34.7
Owner	Owner :	49.3	48.2
	Tenant :	50.7	51.8
Type of dwelling	Condominium :	50.7	48.2
	Plex :	13.6	14.5
	Row town house :	6.1	6.5
	Semi-detached house :	7.9	5.9
	Single-detached house :	20.3	23.9
	Other :	1.4	1.1
Year	2020 :	61.0	55.1
	2021 :	39.0	44.9
Type of household	Sixty-years old households :	10,3	9,8
	Multi-generational family :	2,3	1,7
	Young couples :	42,3	44,3
	Adults and seniors :	1,6	2,2
	Retired :	0,9	2,6
	Very young families :	20,6	17,8
	Fifty-years old households :	11,0	10,4
	Young families :	11,0	11,1

Households that selected "Get closer to nature" as one of the proposed reasons are overall more motorized than those that did not select this reason. Another important difference between these two samples is the proportion of "Very young families" households, this type being more represented among households considering proximity to nature. Conversely, “Young couples” household give less importance to proximity to nature than other household types in their relocation process. Households living in condominiums are more likely to select this reason than households living in houses. These observations seem to describe a type of household that considers closeness to nature important: families with children, already owning one or more vehicles and living in apartments or attached houses with no, or less, space than households living in single-detached houses, which generally have their own yard. We also note that there are significantly more people who selected this reason in 2020 than in 2021. This could be explained by the fact that in the study area (Montreal), the 2020 lockdown was more restrictive than the 2021 lockdown, and therefore people were perhaps more sensitive to being close to open spaces during these strict confinement periods.

Since each respondent could select any number of responses, it seemed important to observe the number of reasons selected by each. The number of reasons selected by respondents in this survey is presented in Fig. 5. Note that one respondent selected all 16 reasons, but because some of them are contradictory ("Get a smaller home" and "Get a larger home"), we chose to remove this observation from the data set.

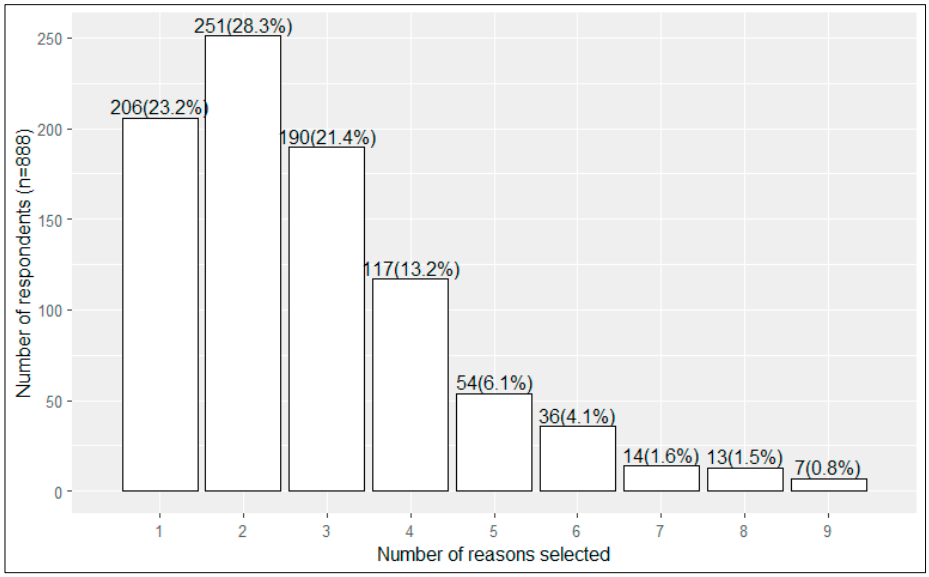

Fig. 7. Number of reasons selected by the respondents

The large number of respondents who selected one, two or three responses allowed us to study which reasons are often selected together. The Apriori algorithm allowed us to obtain the results presented in Table 8.

Table 8. Occurrence of combinations of reasons, depending on the number of responses selected

Number of reasons selected	Most frequent reason or combination of reasons	Frequency of response
1 (n=206)	Get closer to nature	28,6% (n=59)
	Larger home	17,5% (n=36)
	Become owner	14,6% (n=30)
2 (n=251)	Get closer to nature & Larger lot	12,0% (n=30)
	Get closer to nature & Other	9,2% (n=23)
	Larger home & Larger lot	6,0% (n=15)
3 (n=190)	Get closer to nature & Larger lot & Larger home	11,6% (n=22)
	Become owner & Larger lot & Larger home	8,4% (n=16)
	Get closer to nature & Larger lot & Become owner	7,4% (n=14)

We note that the reasons selected together are suggestive of the motives that characterize moves to the suburbs of the city. Access to larger properties in less dense areas is indeed more common when moving away from the city centre. Lower land prices away from downtown also encourage homeownership.

5. Conclusion

Before drawing any conclusions from the results presented in this study, it is important to present the limitations of interpretation. The main limitation is the type of sample used. Because the survey was distributed over the Internet, it is an opportunistic sample, and we cannot safely assume that our sample is representative of the Greater Montreal population and that the results are generalizable. However, we believe that the unique data collected during this pandemic period, which disrupted household patterns, allows us to explore the thought process of choosing a new place of residence. In addition, there is a reasonable match between the sample and the Montreal travel survey data. Therefore, the full sample results are considered reasonably accurate indications of household attitudes in the Greater

Montreal area. Finally, the results are consistent with the findings of other work on residential relocation process. Although the study has limitations, this adds substantial credibility to the results.

Residential location and household commuting are intrinsic. As large cities face the challenge of reducing the ecological impact of commuting trips, understanding how households' relocation choices are articulated is crucial. This study developed a methodological framework to try to explain how households' desire to relocate is articulated, through a survey of willingness to move conducted during the Covid-19 pandemic. The study of these decisions to move first examined the household characteristics influencing a willingness to move before analysing the reasons supporting that intention.

This study first estimated the characteristics of households wishing to relocate and found that 1) household typology has a strong influence on relocation reflection, with young couple households having a lower probability of wanting to stay in their housing than other household types (49% vs. 71% respectively); 2) proximity to services in the area where households live has a strong impact on willingness to relocate for all household types except young couples, the factors influencing the latter being housing ownership type, survey response year, and income; 3) households (other than "Young Couples") living in areas with good proximity to secondary schools and employment are more likely to want to relocate than households with poorer proximity, while good proximity to grocery stores will support staying in current housing. Overall, the decision tree results are consistent with the high rates of willingness to relocate for the more central and densely urbanized municipal areas highlighted in Fig. 1.

The study then examined the reasons why households intend to relocate. The conclusions we were able to draw from our database are, first, that getting closer to nature is the most common reason (48.1% of our sample). Households that selected this reason from those available were generally families with children, already owning one or more vehicles, and living in housing types with little or no outdoor space. Proximity to nature is also more considered during periods of very restrictive lockdown, since people were perhaps more sensitive to being close to open spaces during the time they were confined to their homes. This reason is often accompanied by a desire to have access to a larger house or lot and to become a homeowner. These recurring reasons are fairly typical of a relocation to the outskirts of cities, since moving away from the city centre brings one closer to nature and gives one the opportunity to access larger homes with gardens. Access to property is also easier when one moves away from the city centre. Consistent with the findings of the previous section, proximity to services is not a reason for moving, nor is reduced commuting expense. This demonstrates some ignorance of the impact on household budgets of choosing a residential location in an area with poor proximity to services.

The purpose of this article was to determine the factors considered by households when choosing to relocate. The context of the global pandemic has led households to question their mobility habits and their residential location choices. It is also, for municipalities, a period of great change in urban mobility. In the context of a desire by municipalities to slow or even reverse the trend of urban sprawl in order to limit its social and environmental consequences, these findings provide information on the households to be targeted by potential policies. They also highlight the consequences of periods of strict containment that made people realize the importance of access to green and open space. To ensure that this realization does not result in an acceleration of the peri-urbanization phenomenon, communication and information campaigns about the presence of such spaces in the city and the consequences of relocating to the periphery on daily mobility could help guide relocation choices toward a more sustainable model.

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References

Algorithme APriori. (2021). In *Wikipédia*. https://fr.wikipedia.org/w/index.php?title=Algorithme_APriori&oldid=179912531

Allard, M., Feyt, G., Fourny, M.-C., & Talandier, M. (2014). Raising Awareness on Mobility Costs for Households : A Lever for Changing Residential Choices and Improving Local Governance? Experimentation in the French Alpine Metropolitan Area. *Transportation Research Procedia*, *4*, 255-270. https://doi.org/10.1016/j.trpro.2014.11.020

Clark, W. A. V. (2013). Life course events and residential change : Unpacking age effects on the probability of moving. *Journal of Population*

Research, *30*(4), 319-334. https://doi.org/10.1007/s12546-013-9116-y
De Groot, C., Mulder, C., Das, M., & Manting, D. (2011). Life Events and the Gap Between Intention to Move and Actual Mobility. *Environment and Planning A*, *43*, 48-66. https://doi.org/10.1068/a4318
Dittrich-Wesbuer, A., & Osterhage, F. (2008). Wohnstandortentscheidungen in der Stadtregion : Das Beispiel „Bergisches Land". *ILS – Institut für Landes - und Stadtentwicklungsforschung*, *02/08*.
Eluru, N., Sener, I. N., Bhat, C. R., Pendyala, R. M., & Axhausen, K. W. (2009). Understanding Residential Mobility. *Transportation Research Record Journal of the Transportation Research Board*, *2133*(1), 64-74. https://doi.org/10.3141/2133-07
Fabre, L. (2018). *Développement d'une typologie de ménages pour enrichir la prévision de la demande de transport* [Masters, École Polytechnique de Montréal]. https://publications.polymtl.ca/3192/
Government of Canada, S. C. (2020, avril 17). *Proximity Measures Database*. https://www150.statcan.gc.ca/n1/pub/17-26-0002/172600022020001-eng.htm
Hunt, J. D. (2010). Stated Preference Examination of Factors Influencing Residential Attraction. In F. Pagliara, J. Preston, & D. Simmonds (Éds.), *Residential Location Choice : Models and Applications* (p. 21-59). Springer. https://doi.org/10.1007/978-3-642-12788-5_2
Kortum, K., Paleti, R., Bhat, C. R., & Pendyala, R. M. (2012). Joint Model of Residential Relocation Choice and Underlying Causal Factors. *Transportation Research Record*, *2303*(1), 28-37. https://doi.org/10.3141/2303-04
Lee, B. H. Y., & Waddell, P. (2010). Residential mobility and location choice : A nested logit model with sampling of alternatives. *Transportation*, *37*(4), 587-601. https://doi.org/10.1007/s11116-010-9270-4
Morency, C., & Verreault, H. (2020). Assessing the Efficiency of Household Residential Location Choices. *Transportation Research Record*, *2674*(11), 455-465. https://doi.org/10.1177/0361198120946023
Rashidi, T. H., & Mohammadian, A. (2011). Behavioral housing search choice set formation : A hazard-based screening model of property value and work distance. *T and DI Congress 2011: Integrated Transportation and Development for a Better Tomorrow - Proceedings of the 1st Congress of the Transportation and Development Institute of ASCE*, 919-937. https://doi.org/10.1061/41167(398)88
Rashidi, T. H., Mohammadian, A., & Koppelman, F. S. (2011). Modeling interdependencies between vehicle transaction, residential relocation and job change. *Transportation*, *38*(6), 909-932. https://doi.org/10.1007/s11116-011-9359-4
Smith, B., & Olaru, D. (2011). Validating stated preference surveys through the use of hedonic regression models with an application to housing prices around transit oriented developments. *17th International Conference on Urban Transport and the Environment - UT 2011, June 6, 2011 - June 8, 2011*, *116*, 303-313. https://doi.org/10.2495/UT110261
Vandersmissen, M.-H., Séguin, A.-M., Thériault, M., & Claramunt, C. (2009). Modeling propensity to move after job change using event history analysis and temporal GIS. *Journal of Geographical Systems*, *11*(1), 37-65. https://doi.org/10.1007/s10109-009-0076-x
Wang, F., Mao, Z., & Wang, D. (2020). Residential relocation and travel satisfaction change : An empirical study in Beijing, China. *Transportation Research Part A: Policy and Practice*, *135*, 341-353. https://doi.org/10.1016/j.tra.2020.03.016
Wang, L., Miwa, T., Jiang, M., & Morikawa, T. (2022). Household Lifecycle, Daily Travel Behavior, and Residential Location : Case in Aichi, Japan. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4227683
Yi, C., & Kim, K. (2018). A Machine Learning Approach to the Residential Relocation Distance of Households in the Seoul Metropolitan Region. *Sustainability*, *10*(9), 2996 (19 pp.). https://doi.org/10.3390/su10092996
Yi, C., & Lee, S. (2014). An empirical analysis of the characteristics of residential location choice in the rapidly changing Korean housing market. *Cities*, *39*, 156-163. https://doi.org/10.1016/j.cities.2014.03.002
Yu Jianhui, Dong Guanpeng, Zhang Wenzhong, & Li Jiaming. (2015). Study on the synergy between intra-urban resident's migration and job change in Beijing. *Journal of Geographical Sciences*, *25*(8), 978-990. https://doi.org/10.1007/s11442-015-1214-7