French Association of Energy Economists

Personal car or shared car? Predicting potential modal shifts from multinomial logit models and bootstrap confidence intervals

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Abstract

Households' daily mobility in France is characterized by the preponderance of the automobile. Passenger cars, mainly used by households but not only, are thus responsible for more than a half of fuel consumption in road transport (CGDD/SoES, July 2013) and more than a half of CO_2 emissions in the transport sector (SoES/CDC, December 2012). The main objective of this paper is thus to explain the modal choice of French households for their local daily trips, particularly the importance of the car, and to predict potential shifts from personal car to shared car. A multinomial logit model is estimated and reveals the particular importance of car equipment on modal choices and specifically on car use. Simulations by 2020 are thus conducted under three scenarios depending on the household's motorization (no car, one car, two cars or more) and per different mobility profiles. Personal car should remain the main mode of transportation by 2020 except if households have no car. In that case, modal shares would be more balanced, public transport would become the main transport mode and the shift to shared car would be at a maximum. Modal share of shared car could thus reach 16% for "exclusive motorists". A conditional logit model is also estimated and shows no particular importance of the means of transportation's costs in the modal choices. These results show that the increase in distances between 2010 and 2020 makes motorized modes more necessary. Thus, personal car and public transport should remain the main modes of transportation by 2020. Moreover, expected changes in costs and travel time by 2020 does not seem to have any effect on the deployment of shared car, its modal share being constant (in an average) between 2010 and 2020.

Keywords: Modal choice; personal car; shared car; multinomial logit model; conditional logit model; bootstrap confidence intervals.

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Introduction

Households' daily mobility in France is characterized by the preponderance of the automobile. Passenger cars, mainly used by households but not only, are thus responsible for more than a half of fuel consumption in road transport (CGDD/SoES, July 2013) and more than a half of CO_2 emissions in the transport sector (SoES/CDC, December 2012). But in recent years, inflections in car use are observed. Households try to adapt to the high cost of car by travelling less kilometers by car each year and by pooling its use thanks to new mobility services such as carpooling and carsharing.

These services can be considered as empirical applications of the business model of the functional service economy. According to some researchers, the new business model consisting of the substitution of the sale of the product's function to the sale of its property, which is the concept behind the new individual mobility services we mentioned, allows for a decrease in production, lower consumption of natural resources, in addition to encouraging companies to design products that consume fewer resources in their production, use, maintenance, recycling and reuse (Bourg and Buclet, 2005; Du Tertre, 2007). Fourcroy and Chevalier (2012) show that great energy savings can be achieved by these services only if they replace car ownership and do not add a new need of car. That is the reason why the main objective of this paper is to explain the modal choice of French households for their local daily trips (especially from motorization), particularly the importance of the car, to predict potential shifts from personal car to shared car.

From survey data (Mobility Observatory, BIPE, October 2010), we base on households' activities, ie their need for mobility, their car equipment, and socio-economic variables that could impact their modal choices. We estimate a multinomial logit model from these variables and a conditional logit model from characteristics of each mean of transportation (cost and travel time). From these estimations, we simulate modal choices by 2020 and apply a pairs bootstrap method to predict modal shares with confidence intervals.

In a first part of the paper, we present a brief review of the literature. Then we describe the method and the data we use in this paper. Our results are then presented. The fourth section is devoted to the simulations of modal shares by 2020 and the last section to the discussion of our results.

1. Literature review

The decision of an individual among several unordered alternatives is generally modelled through multinomial logit models. As an example of such a decision, the choice between means of transport is modelled in this way. Modal choice models such as those estimated by Train (1977), Carson (1994) and more recently Hensher (2008) are mainly built from quantitative data describing the characteristics of the various modes (costs, transfer or transport time, etc.). They can then be used to test the effects of a transport policy (construction of a new road, creation of a new line of transport, etc.). Thus, from a sample interviewed before the introduction of the Bay Area Rapid Transit (BART) in San Francisco in 1973, Train (1977) developed a model to measure the effect of the service in terms of modal split. From the same type of model, Carson (1994) wanted to know how can change the modal share of the car if its cost increases. More generally, research on modal choices show that they are influenced by the level of service (travel time and cost diffrerentials), but also by the characteristics of individuals and households, such as the level of income, car equipment, area of residence and place of work (Stopher and Meyberg 1975, Koppelman and Pas, 1980 Kanafani, 1983, Ben-Akiva and Lerman, 1985; Wachs, 1991).

Moreover, the choice of a mode of transportation can be studied for a particular type of trip, most often commuting. This is particularly what study Train (1977) in San Francisco, Hensher (2008) in six Australian cities, Liu (2007) in Shanghai, Khattak and Palma in Brussels (1997).

Some are also interested in the impact of unexpected events on the modal choice. Thus, Khattak and The Colletter (1994), and Khattak et al. (1995) show that longer travel time on road may encourage motorists to use public transport. Moreover, Khattak and Palma (1997) show that adverse weather conditions encourage half of motorists in Brussels to change their departure time or their itinerary.

It can also be question of interdependence between the choice of transport mode and trip purpose, more precisely the organization of trips depending on the schedule of the day. Thus one part of the literature focuses on modal choices on the basis of household's activities (activity-based demand model). Damm (1983), Golob and Golob (1983), Kitamura (1988) and Etterna (1996) conduct literature reviews on this subject. We mainly retain that Pas (1984) shows that demographic factors such as employment status, gender, or the presence of children in the household have a significant impact on the activities and trips. In addition, Kitamura (1984) identifies the interdependence between the choice of destinations in travel chains and the choice of the mode of transportation.

Moreover, Baht and Koppelman (1993) propose an analytical model based on the organization of activities. More specifically and always on the basis of households' activities, the first models of travel chains were mainly developed in the 70's and 80's in the Netherlands (Daly et al, 1983; Gunn et al, 1987; Hague Consulting Group, 1992; Gunn, 1994). They were then used to model the movements in different cities and countries: Stockholm (Algers et al, 1995), Salerno, Italy (Cascetta et al, 1993), Boise, Idaho (Shiftan, 1995), New Hampshire (Shiftan and Rossie, 1997) or Boston (Bowman and Ben-Akiva, 2000). A key finding highlighted by Krygsman et al. (2007) is that there are variations in the order of choice of travel mode and trip purpose. But in most cases, the travel pattern is done before the modal chioice. This therefore indicates that it rather depends on the choice of the pattern and the travel chain considered. t is precisely on this need for mobility we base to try to explain the modal choice, as well as on variables describing individuals and households and variables that are characteristics of the different modal choices (travel costs and time).

2. Data and method

2.1. Data and descriptive statistics

To explain modal choice, we base on a sample of 1,517 people (representative of the French population) involved in the Mobility Observatory (BIPE, October 2010) which describes mobility practices of French households.

The variable to explain is the modal choice on a normal week day. It has six categories: personal car (including company car), shared car (carpooling and carsharing), motorcycle, bike, walking and public transport. The modal distribution of the sample is described in figure 1. About 60% of individuals use personal car which is the main mode of transportation to travel each day. The second mode is public transport used by 20% of the sample, followed by walking for 15%. Bike and motorcycle are used by only 3% of the population and shared car by only 1% (homogeneous groups of people for carpooling and carsharing).

A multiple correspondence analysis performed in a preliminary work on the same data set shows that the most discriminating variables distinguishing mobility profiles are: the travel need / distances (in km / pattern), the type of the municipality of residence (density), the marital status (single, couples, cohabitation / roommate), the motorization, the age, the employment status and the income. Thus we use these variables to estimate a multinomial logit model to explain modal choice. Moreover, this work led to the construction of mobility profiles described in figure 2.

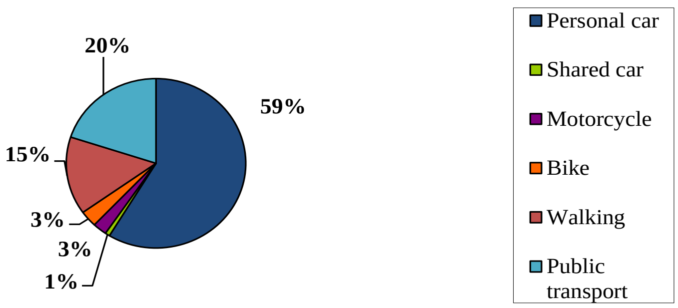

Figure 1 – Modal distribution of the sample (Mobility Observatory, BIPE, October, 2010)

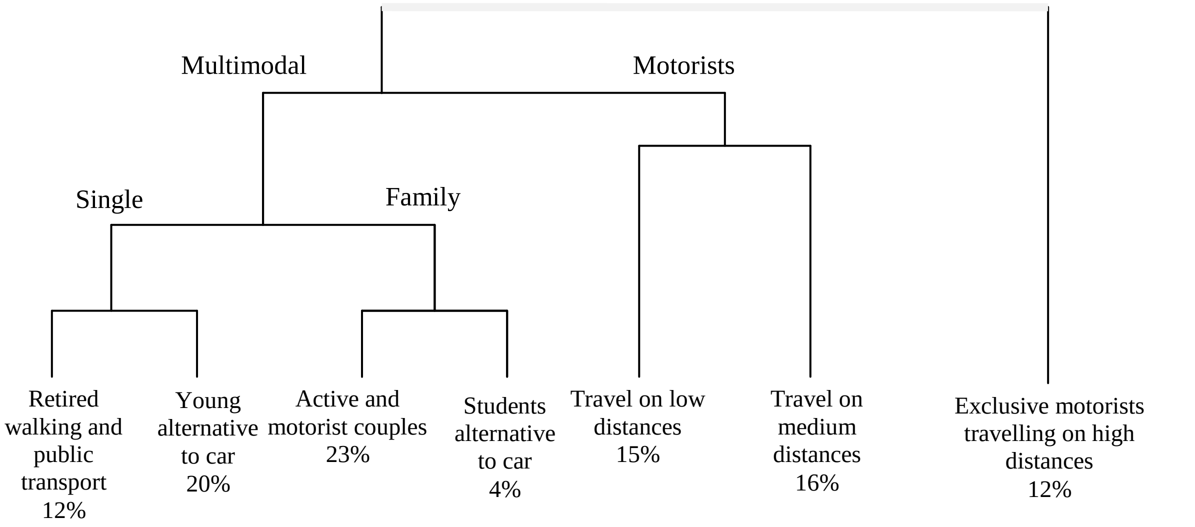

Figure 2 – Mobility profiles, from Mobility Observatory, BIPE, October, 2010

The first level of partition distinguishes “exclusive motorists” from others. These individuals have the highest travel needs for all patterns and move exclusively by car. They are from 30 to 60, are active, live in couple and have children. They live in low density areas and are motorized. The rest of the population is then cut in two classes: people using their car (exclusively or in combination with one or more other modes) and people being “multimodal”. The third level of partition occurs between individuals using the car (the “motorists”), some travelling on low distances, others having higher travel needs and living in lower density areas. Within the group of “multimodal” we then distinguish people living alone (rather inactive or workers, under 30 or over 60, without children, with modest incomes, living in large city-center, non-motorized and travelling by motorcycle, walking and public transport), from people living in family (with two active persons, under 60, with children, living in Paris area and large city-center, motorized and travelling by car, motorcycle, walking or public transport). Within the “singles” we distinguish “retired” of more than 60, living alone and travelling by walking, from “young” inactive or low-skilled labour, living alone or with roommates, and travelling by motorcycle, walking or public transport. Finally, within the “families” we distinguish “active couples” of more than 30 and travelling by car, from “students” of less than 30 travelling by motorcycle, walking or public transport.

In addition, it is possible to model modal choices from their own characteristics: their costs and travel time. The expenditure incurred by the travellers to the use of car and public transport in France was calculated for the National Federation of Transport Users by Beauvais consultants (2012). The costs of two-wheelers (motorcycle and bike) correspond to the average costs taken from different specialized websites and Internet forums.
The travel time with each mode of transport is also taken into account to explain modal choice. It is calculated from the distance to travel and the average speed associated with each of the transportation mode shown in table 1 (the average speed is that observed in the Mobility Observatory in October 2010).

Table 1 – Average speed associated with different means of transport in km/hour

Mode	Average speed (km/hour)
Personal car	42
Shared car	42
Motorcycle	42
Bike	23
Walking	8
Public transport	33

Source: Mobility Observatory, BIPE, October, 2010

2.2. Multinomial logit model

We are in a situation where each individual i has a choice between six unordered alternatives j. As this dependent variable is a qualitative one with a limited number of unordered terms, we use a discrete choice model: the multinomial logit model (MLN). More specifically, we use two types of logit models: single or independent multinomial and conditional. The distinction between these two types of models is primarily based on the nature of the selected explanatory variables. The first includes variables that are characteristics of individuals, while the second includes variables that are characteristics of the different means of transportation and differ according to the dependent variables and individuals as well. In the case of modal choice, individual i compares the different levels of utility associated with different choices and chooses the one that maximizes his utility from the j choices. For individual i, the utility of the choice j is:

$$U_{ij} = f\,(\beta\, X_{ij}) + \varepsilon_{ij} \qquad (1)$$

Where β is a vector of unknown parameters, X_{ij} is a vector of the individuals' or households' characteristics and ε_{ij} a random error term.
As MLN are probabilistic models, their results reflect the utility maximization. Thus the probability that the individual i chooses the alternative j is the probability that the value of j is greater than that associated with all other modes:

$$P\,(U_{ij} > U_{ik}\,)\ \textit{pour}\ k \neq j \qquad (2)$$

The models are estimated using the SAS software through Logistic and Mdc procedures.

2.3. Bootstrap prediction intervals

From these models estimations, we realize simulations to estimate the modal shares by 2020. But from logit model, it is only possible to perform simulations from ''case study''. Thus, we set the main explanatory variables according to their most probable evolution by 2020 in an average. However, the probability distribution being not linear, the average probabilities predicted by the models are not equal to the probability at the average of the variables. It is therefore imperative to provide predictions with confidence intervals. To do this, we use the method of bootstrap prediction intervals.
The principle of the bootstrap, as described in figure 3, is to approximate the theoretical distribution of a statistic of interest from the empirical distribution obtained from B random samples of size N in the sample of the original data. In our case, we repeat 1,000 times a random drawing with replacement of 1,517 individuals of the original population to get 1,000 bootstrap samples. We then estimate the models on each of the 1,000 samples to obtain an empirical distribution of the probabilities predicted by the models.
The bootstrap method is realized using the SAS software through the surveyselect procedure.

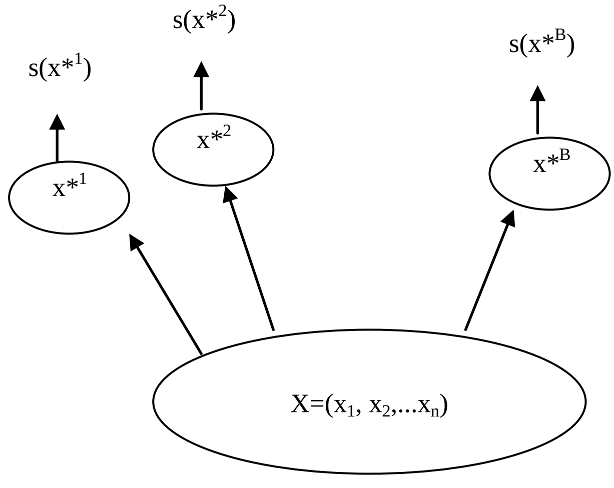

Figure 3 – Bootstrap process (from Efron and Tibshirani, 1993, p.13)

3. Results

3.1. Independent logit model

3.1.1. Estimated parameters

We seek to estimate a multinomial logit model explaining the modal choice between six different modes (personal car, shared car, motorcycle, bike, walking and public transport) by the explanatory variables distance, density, motorization, age, marital status, employment status and income.
Quality indicators of the model are good enough (ρ^2 McFadden: 0.58 and Estrella indicator: 0.95), but the indicators of significance associated with activity status and income are too high so that we can say that they have an effect on the modal split in the sample we study. This conclusion cannot be generalized to the total population in that the significance of the parameters depends on the sample size. We decide anyway to remove the employment status and income variables, which does not deteriorate the quality of the model.

Table 2 – Estimated parameters

Variable	Shared car	Motorcycle	Bike	Walking	Public transport
Constant	-3.8070** (1.9152)	3.6326*** (1.0709)	6.1623*** (0.9501)	5.8934*** (0.6520)	4.5689*** (0.5291)
Distance	-0.2625 (0.2946)	-0.6165*** (0.2174)	-1.8559*** (0.2151)	-2.3348*** (0.1451)	-0.7297*** (0.0920)
Density (1=Paris to 7=rural area)	0.3062 (0.1879)	-0.2449** (0.1145)	-0.2455** (0.1059)	-0.2080*** (0.0655)	-0.4802*** (0.0544)
Motorization	-2.6028*** (0.5760)	-3.8533*** (0.4233)	-3.0637*** (0.3527)	-1.6787*** (0.2157)	-2.0262*** (0.1811)
Age	-0.0107 (0.0170)	-0.0722*** (0.0140)	-0.0519*** (0.0102)	-0.0121* (0.006302)	-0.0233*** (0.005149)
Marital status	1.1477** (0.5057)	1.1749*** (0.2767)	0.8464*** (0.2909)	0.6427*** (0.2084)	0.8741*** (0.1534)
Number of observations			1413		
Log-likelihood			-1079		

Personal car is the reference
Standard deviation in parenthesis
****: significant at 1% ; **: significant at 5% ; *: significant at 10%*

Table 2 shows that the distance has a negative effect on the use of alternatives to the personal car: the longer the distance to travel, the greater the probability to choose the personal car. Similarly, the lower the density of the residence area, the higher the household is motorized, the older the person and the more there are people in the household, and the more the alternatives to the car are used.
Only variables of motorization and marital status appear to have an effect on the choice between personal and shared car. Obviously, non-motorized people have no choice than using shared car. Contrary to intuition, age does not seem to have any effect on the choice between personal car and shared car. In addition, motorization seems to be crucial. However, it is important to remain vigilant with these findings in that, on the observed sample, we have very few individuals using shared car.

3.1.2. Odds ratio

The interpretation of estimated parameters can be specified by measuring the magnitude of a change in explanatory variables on the probability to use each mode of transportation through odds ratio presented in table 3.

Table 3 – Odds ratio

Variable	Shared car	Motorcycle	Bike	Walking	Public transport
Distance	0.769	0.540	0.156	0.097	0.482
Density	1.358	0.783	0.782	0.812	0.619
Motorization	0.074	0.021	0.047	0.187	0.132
Age	0.989	0.930	0.949	0.988	0.977
Marital stats	3.151	3.238	2.331	1.902	2.397

Personal car is the reference

Increasing the distance to travel of one unit decreases the probability of using alternative modes to personal car of 0.23 points (1-0.769) for shared car, 0.46 points for motorcycle, 0.84 points for bike, 0.90 points for walking and 0.52 points for public transport. Concerning shared car, this result shows that for a given level of distance to travel, it is better to own a private car than sharing a car when needed so that individuals are quite rational.
Similarly, the decrease in the density of the residential area decreases the same probability from 0.38 points for public transport to 0.19 for walking, but increases the probability to use shared car, which means that it should rather develop in low density areas. But we must be careful with this conclusion which is mainly explained by the fact that shared car is mainly used in the less dense area in our sample.
To be older of one year also decreases this probability: from 0.07 points for motorcycle to 0.01 points for shared car.
An extra car owned by the household also decreases this probability: from 0.98 points for motorcycle to 0.81 points for walking. The motorization is crucial: its effect on the probability of choosing the different modes of transportation is the largest. Once purchased, the car is thus used almost exclusively. This conclusion has been already widely demonstrated in the literature.
Finally, with an additional person in the household, it is 1.9 times more likely to choose walking than personal car or 3.24 times more likely to choose motorcycle. Thus, the more in the household (even if it is motorized), the less likely to use the personal car.

3.1.3. Independence of Irrelevant Alternatives (IIA) assumption test

To test the independence of irrelevant alternatives assumption necessary to validate the multinomial logit model, we realize the test proposed by Hausman and McFadden (1984). Thus, we calculate the test statistic s for five different sub-groups in which we removed each time a modality (except personal car which is the reference category).
As shown by Hausman and McFadden (1984), the test statistic can be negative, especially in the case of small samples. This does not then challenge the IIA property. As shown in table 4, in the case of subgroups excluding motorcycle, walking and public transport, the test statistic follows a law of χ^2 to 24 degrees of freedom. In the subgroup excluding motorcycle, the test statistic is less than the critical value (at 99.5%) so we accept H_0. P-value = 1 also tells us that there are 100% chance of being wrong in rejecting the null hypothesis of independence. The IIA assumption is indeed satisfied in this case. Similarly, in the subgroup excluding walking, the test statistic is less than the critical value (at 99.5%) so we accept H_0, p-value = 0.99 also indicates that there are 99% chance of being wrong in rejecting the null hypothesis of independence. Finally, in the subgroup excluding public transport, p-value = 0.87 indicates that there are 87% chance of being wrong in rejecting the null hypothesis. Thus we accept the IIA hypothesis at 87% and have 13% chance that our model does not respect this property.

Table 4 – Results of the IIA assumption test

	Test statistic	p-value
S_1 : shared car excluded	Negative	
S_2 : motorcycle excluded	2.6645332	1
S_3 : bike excluded	Negative	
S_4 : walking excluded	6.0857236	0.99
S_5 : public transport excluded	16.570484	0.87

3.2. Conditional logit model

To take into account the economic rationality of individuals in their modal choices, we estimate a conditional logit model, taking into account variables that are characteristics of choices: the cost and travel time. In addition, we also introduce specific constants for each mode of transport to take into account their own characteristics hardly captured elsewhere (including comfort for example).
Table 5 shows that parameters associated with the constants are all negative which confirms the preference for personal car compared to all other means of transportation for its comfort, flexibility… In addition, the parameters associated with the cost and travel time are negative which means that a high cost a and long travel time do not encourage the use of alternative modes to the personal car. This result shows that mobility is an arbitrable need on the basis of its cost. Thus, odds ratios show that an increase in the cost of a transport mode (of a cent per kilometer) decreases by 0.05 points the probability of its use (1-0995). Similarly, an increase in the travel time of one minute of a mode of transport decreases by 0.06 points the probability of its use.

Table 5 – Conditional logit model: estimated parameters and odds ratio

Variable	Estimated parameters	Odds ratio
Cs_shared car	-4.2780*** (0.2939)	0.014
Cs_motorcycle	-2.1148*** (0.1705)	0.044
Cs_bike	-2.6564*** (0.1581)	0.070
Cs_walking	-0.4410*** (0.1157)	0.643
Cs-public transport	-0.9843*** (0.0712)	0.374
Cost	-0.005489** (0.002859)	0.995
Travel time	-0.005580*** (0.00670)	0.994
Number of observations	1414	
Log-likelihood	-1573	
ρ^2 McFadden	37.93	
Estrella indicator	81.6	

Personal car is the reference
Standard deviation in parenthesis
****: significant at 1% ; **: significant at 5% ; *: significant at 10%*

4. Simulations by 2020 and bootstrap prediction intervals

4.1. Independent logit model

4.1.1. Hypothesis

The objective of the simulations is to try to predict the modal choice in 2020 from the estimated models. But from logit model, it is only possible to perform simulations from ‘‘case study’’. Thus, we set the main explanatory variables according to their most probable evolution, in an average, by 2020 to try to approach the closest to reality.

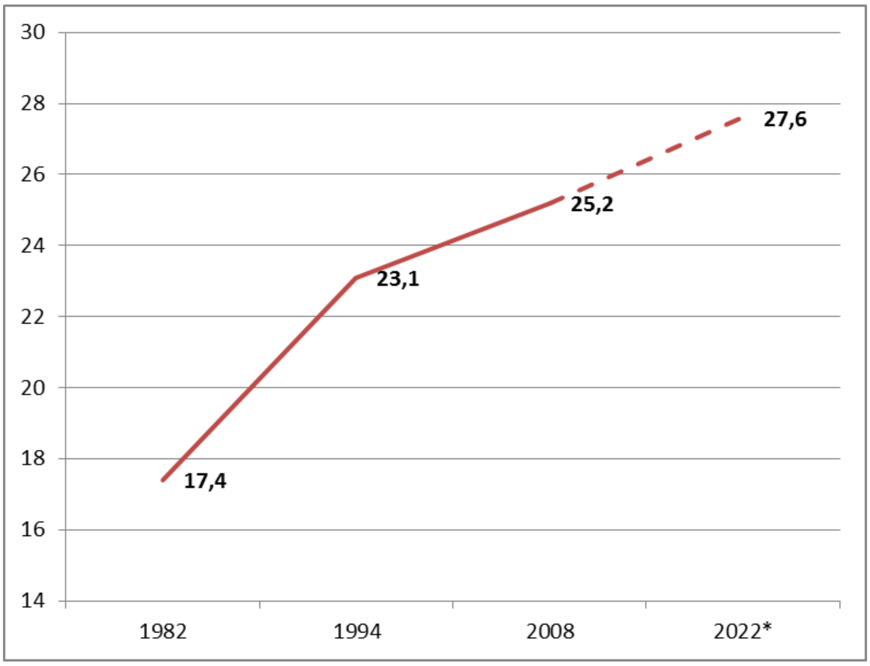

Figure 4 – Average distance travelled each day, projection from National Survey of Transport and Travel (1982, 1994, 2008)

The multinomial logit model explaining modal choices is estimated using the following variables: the distance, the category of the municipality of residence (density), age, motorization and marital status.

About the distance to travel, we base on figures from the National Survey of Transport and Travel (1982, 1994, 2008) to realize a projection to 2020 based on a logarithmic adjustment on previous data as shown in figure 4. These evolutions are applied to the data in our sample. Therefore, the log of the distance to travel in 2010 was 3.029 and will be 3.102 in 2020. This result is that applying on an average of the sample, but the trend between 2010 and 2020 is applied to the average distances observed in each subgroup used to perform simulations (different mobility profiles) and that is the case for all other explanatory variables. In our sample, the mean age is 47.2 years in 2010. According to population projections made by the BIPE (Residential Migration), the average age is expected to increase in 2020 and should be 48.7 years. In our sample, people living in a couple are the majority. According to the BIPE projections, this mode of cohabitation should remain dominant in 2020 but the number of households of one person is expected to grow as shown in table 6.

Table 6 – Marital status evolution, projection form OMA and Residential Migration, BIPE (2010)

Year	2010	2020
Single	42%	45%
Couple	55%	52%
Cohabitation/roommate	3%	3%

Concerning the evolution of the distribution of households between urban and rural areas, projections of the BIPE (Residential Migration) show no significant changes by 2020. Therefore, we do not change the structure depending on the category of municipality of residence. Finally, as motorization is a key explanatory variable of modal choice, we perform simulations according to three scenarios: the household has no car, the household has one car (current situation on average and therefore central scenario) and the household has two cars or more.

4.1.2. Simulations and bootstrap confidence intervals

To obtain results close from reality, we realize our simulations according to different mobility profiles presented in section 2.1 and three motorization scenarios. The aggregated results provide the modal split described in the figure 5.

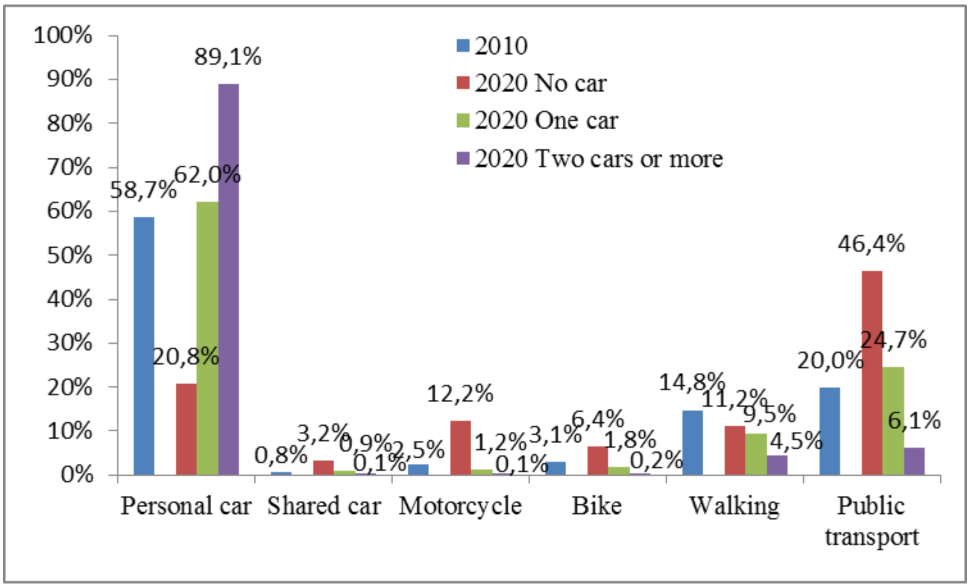

Figure 5 – Changes in modal shares in France between 2010 and 2020 according to three scenarios of motorization

In the original sample, 18% of households are not motorized, 62% have one car and 20% have two cars or more. The results show a wide variation depending on the motorization scenario. Personal car should remain the main mode of transportation by 2020 except if households have no car. In that case, public transport would become the main mode of transportation, the modal distribution would be more balanced and shared car would deploy. More specifically, these general conclusions should be specified by discussing the results per mobility profile.

We choose to provide the detailed results of two extreme profiles, the others being just discussed.
The “retired walking and public transport” mainly includes people with no car. That is why we study only one alternative: the equipment (one car), as shown in table 7. In this case, the probability of using the private car increases while that of all other modes decreases. Being by nature not very motorists “retired walking and public transport” do not constitute an important target for car-sharing: 2.37% at a maximum as shown by bootstrap confidence intervals.

Table 7 – Changes in modal shares of “retired walking and public transport” between 2010 and 2020

Year	Personal car	Shared car	Motorcycle	Bike	Walking	Public transport
2010	26.38%	1.84%	0%	3.07%	35.58%	33.13%
2020 No car	16.43%	1.12%	1.49%	7.3%	42.9%	30.76%
Bootstrap CI	[12.53 ; 20.94]	[0.19 ; 2.37]	[0.53 ; 2.8]	[3.75 ; 10.7]	[35.82 ; 50.1]	[24.89 ; 37.66]
2020 One car	56.87%	0.27%	0.1%	1.19%	27.59%	13.98%
Bootstrap CI	[50.06 ; 63.41]	[0.06 ; 0.55]	[0.04 ; 0.19]	[0.55 ; 2.06]	[22.01 ; 33.98]	[10.74 ; 17.49]

Similarly “young alternative to car” use less car (personal and shared) than the average population and more motorcycle, bike and public transport. They are mainly motorized (one car). The shared car could only grow in the case of a household with no car to 3.93% at a maximum.
“Active and motorist couples” however use more personal car than the average population and are an attractive target for car-sharing, especially in the case of a household without a car. In that scenario the use of public transport could also develop significantly, especially since they mainly live in urban areas (Paris and its region and city centers of more than 100,000 inhabitants).
“Students alternative to car” mainly use public transport and motorcycle. They are also the second shared car users. But their low car use (personal as shared) does not make them a prime target for shared car. Thus, a decrease in the use of personal car is accompanied by an increase of motorcycle, bike and walking.

"Motorists" on the contrary use more personal car than the average population. The more their travel needs are important, the more they use it. They are preferred targets for car-sharing, but also for motorcycle and public transport, primarily in a scenario of a household not motorized.

Table 8 – Changes in modal shares of "exclusive motorists travelling on high distances" between 2010 and 2020

Year	Personal car	Shared car	Two-wheelers	Bike	Walking	Public transport
2010	80.37%	2.45%	0.61%	0.00%	9.20%	7.36%
2020 No car	41.35%	8.36%	12.71%	1.48%	0.87%	35.22%
Bootstrap CI	[32.99 ; 49.89]	[1.84 ; 16.33]	[5.64 ; 21.92]	[0.39 ; 3.16]	[0.33 ; 1.61]	[25.86 ; 43.74]
2020 One car	87.93%	1.24%	0.55%	0.14%	0.34%	9.79%
Bootstrap CI	[85.02 ; 90.80]	[0.33 ; 2.16]	[0.26 ; 0.94]	[0.04 ; 0.30]	[0.14 ; 0.62]	[7.20 ; 12.43]
2020 2 cars or +	98.34%	0.11%	0.01%	0.01%	0.07%	1.46%
Bootstrap CI	[97.65 ; 98.99]	[0.01 ; 0.26]	[0.00 ; 0.03]	[0.00 ; 0.02]	[0.02 ; 0.13]	[0.85 ; 2.13]

"Exclusive motorists travelling on high distances" (table 8) are the first users of shared cars and the main target for developing its use for local daily trips. This share could even reach 16% of the modal share of this mobility profile. But even in that case, shared car would not become the main mode of transportation, which would remain personal car (obviously company car) and public transport would represent a third of modal shares.

4.2. Conditional logit model

4.2.1. Hypothesis

The conditional model is estimated from the variables of cost and travel time.
Concerning transportation costs, we base on the calculation of expenses incurred by the travellers by car and public transport between 1970 and 2010 conducted for the National Federation of Transport Users by Beauvais consultants (2012). In 2020, these costs correspond to the projection of the linear fit of the observed costs between 1970 and 2010. The evolution observed on the car costs (total cost) is then applied to the cost of other modes of transportation (motorcycle and bike). The transportation costs to 2020 will therefore continue to increase as shown in table 9.

Table 9 – Cost associated with different means of transport in 2020 - costs per passenger in (constant €cents/km)

Mode	2010	2020
Personal car	25 (total cost)	26 (total cost)
Shared car	18 (variable cost)	18 (variable cost)
Motorcycle	33	35
Bike	15	16
Walking	0	0
Public transport		
Paris area	11	12
Other cities	13	14
Inter-urban train	6	6

Source: Beauvais consultants (2012), websites and Internet forums specialized in motorcycle and bicycle (consulted in June 2013), projections from Beauvais consultants (2012)

In addition, we propose a scenario in which we apply a carbon tax. Indeed, at the environmental conference on 20 and 21 September 2013, the entry into force of a Climate-Energy Contribution (CEC) in 2014 was announced (Le Figaro, September 20, 2013). The price of a ton of carbon is 7 € in 2014 and then increases to 14.5€ in 2015 and 22 € in 2016. In 2020, we retain a CO_2 price at 22 € / ton. At this price, the impact of the tax on the user cost

per kilometer of the car or motorcycle is almost zero (0.4 € cents / km). We also apply a tax to 100€/ ton and 1,000 €/ton in order to observe potential inflections in use behaviour of different modes of transport.
Finally, the transport time to 2020 depends on the evolution of distances whose assumptions were presented in section 4.1.1, the speed remaining constant. Therefore, the average transport time will increase by 6% by car and motorcycle, 6.7% by bike, 7.6% by walking and 8.1% by public transport.

4.2.2. Simulations and bootstrap confidence intervals

The simulations are performed at the average point of the sample and give the modal distribution shown in figure 6. These results show that the increase in distances between 2010 and 2020 makes motorized modes more necessary. Thus, personal car and public transport should remain the main modes of transportation by 2020. In addition, costs of the different means of transport increasing linearly, differentials of cost do not vary. Arbitrations are thus rather realised in terms of travel time than costs.
Concerning shard car more precisely, expected changes in costs and travel time by 2020 does not seem to have any effect on its deployment, its modal share being constant (in an average) between 2010 and 2020. It will be 1.23% at a maximum as shown in table 10.
Simulations have also been realized taking into account a carbon tax. At different prices of the carbon (22€/ton, 100€ and 1,000€), costs do not really differ from the situation without a carbon tax and no modal shift is observed. Moreover, even if the car costs are doubled, we do not observe modal shifts or a significant increase in the use of shared car.

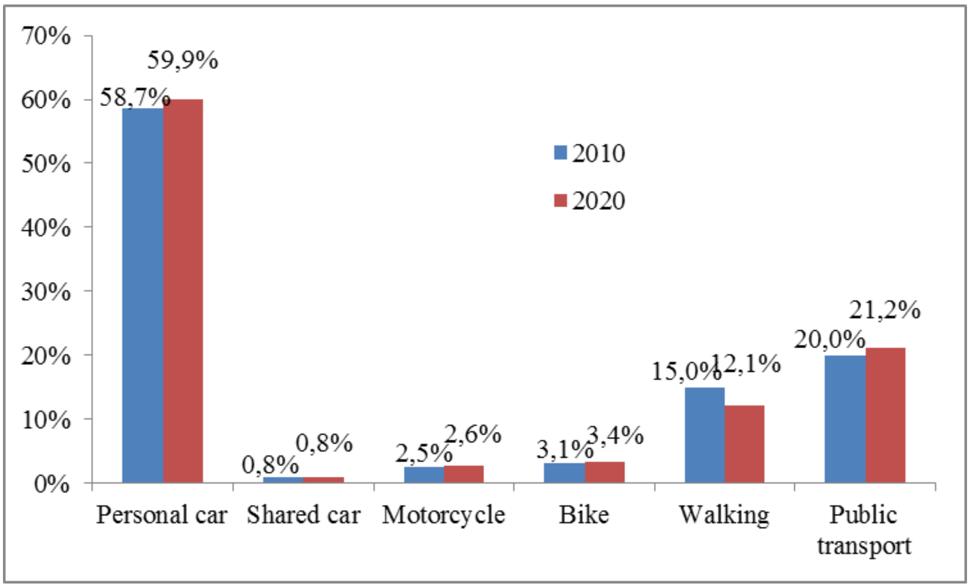

Figure 6 – Changes in modal shares in France between 2010 and 2020

Table 10 – Changes in modal shares in France and bootstrap confidence intervals between 2010 and 2020

Year	Personal car	Shared car	Motorcycle	Bike	Walking	Public transport
2010	58,7%	0,8%	2,5%	3,1%	15,0%	20,0%
2020	59,9%	0,8%	2,6%	3,4%	12,1%	21,2%
Bootstrap CI	[57,06 ; 67,23]	[0,44 ; 1,23]	[1,92 ; 3,3]	[2,55 ; 4,17]	[0,58 ; 15,17]	[18,91 ; 25,91]

5. Discussion

From the independent logit model, simulations by 2020 have been conducted by mobility profiles to reflect the diversity of mobility habits. However, application of the conditional logit model by these mobility profiles does not allow assessing correctly the modal distribution observed in 2010. As a consequence, simulations from the conditional logit model have been performed at the average point. That means that, apart from purely rational considerations (cost and time of transport), modal choices are driven by other factors that are characteristics of households and their travel needs. Those two approaches are thus complementary and show that personal car should remain the main mean of transportation by 2020 with public transport.

Moreover, conclusions about shared car have to be taken with caution because there are few observations concerning the use of shared car for local daily trips in our original sample, but it seems that this use corresponds to specific profiles.

Thus personal car and public transport should remain the main modes of transportation by 2020, which implies that the supply of them should be available and sufficient everywhere.

In addition, forecasts from the conditional logit model could be achieved by income deciles to highlight the weight of the transport budget (as shown by Merceron and Theuliere, 2010) and the implications of a potential carbon tax on households more or less wealthy and dependent on their car, that is hidden by the prediction from a midpoint.

Finally, methods used in this paper to measure the potential development of shared cars in daily local trips do not take into account diffusion phenomena or learning effects. Simulations realized in this paper are thus floor values for the use of shared car by 2020.

6. Conclusion

This paper shows that the main drivers of modal choices are the distance to travel, the density, the age, the marital status, the household’s motorization, and travel cost and time. In an independent multinomial logit model, we confirm that motorization is the most determining factor of modal choices of French households in general and car use in particular. Thus the results of simulations by 2020 show a wide variation depending on the motorization scenario. In addition, the longer the distance to travel, the more we use motorized modes. However, an increase in the distance to travel results in a decrease of the probability to use shared car. This probably means that people with the highest needs to travel are motorized (what is then more profitable than carsharing) and suggests that shared car can hardly become a mean of transportation used exclusively. Thus the simulations show that personal car should remain the main mode of transportation by 2020, except if households have no car, which is the only case in which shared car could deploy, but in which public transport would become the main mode of transportation. Moreover, “motorists” are the main target for shared car, which means that we could observe shift from personal to shared car. But “motorists” are also those with the highest travel needs and the most motorized.

In addition, the estimation of a conditional logit model based on variables characteristics of the different modes of transportation (travel cost and time) shows that the two approaches are complementary and that the only economic rationality does not explain alone modal choices. Moreover, the increase in distances between 2010 and 2020 makes motorized modes more necessary. Thus, personal car and public transport should remain the main modes of transportation by 2020. Only very high values of carbon tax could influence modal choices. However, expected changes in costs and travel time by 2020 does not seem to have any effect on the deployment of shared car, its modal share being constant (in an average) between 2010 and 2020. It could be 1.23% at a maximum.

Therefore, the use of shared car seems to corresponds to a specific profile and be essentially driven by the motorization of the households. But the relationship between motorization and shared car use being not very simple, that is the reason why it will be determinant to work on the future of households’ motorization and to connect the results with the simulations realized here.

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