Citizens in energy transition : analizing the case of biofuels acceptance

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Abstract

Renewable fuels development is an integral part of the public policies mix adopted by policy makers to decarbonize the transportation sector. Widespread deployment of energy transition technologies will largely depend on the attitudes of consumers and citizens. This paper investigates the acceptance by the French population to pay a new tax dedicated to the development of new biofuels in order to reduce greenhouse gas (GHG) emission in this sector. With a Discrete Choice Experiment conducted among about 1000 French citizens in 2018, we analyze preferences for different biofuels characteristics using both mixed logit and latent class models. According to our result, our sample can be split into two segments. The membership of one of these two classes depends on the age of the respondent and its localization (urban *vs.* rural). Whatever the segment of the population, respondents appear to be very sensitive to a potential increase in food prices due to biofuels production; highlighting their preference for second-generation biofuels based on non-food commodities. Respondents are willing to pay a positive mean amount for each percentage point of GHG reduction compared to the actual situation. The two classes differ in the amounts they are willing to pay and in their desire to support the agricultural sector. While the majority (65%) of respondents are willing to pay a mean amount of 2.64 Euros by percentage point of GHG reduction, a minority (35%) is rather willing to pay about 0.68 Euros. The former appears to accept the production of agricultural residuals-based biofuels, whereas the latter has a low acceptance for agricultural-based biofuels and would thus prefers wood residuals-based biofuels.

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1 Introduction

The French transportation sector is currently facing several major challenges: increasing its autonomy and energy efficiency, reducing its environmental footprint, in particular by reducing its dependence on fossil fuels, and integrating the notions of sustainable development.

Transportation sector accounts for 34% of the final energy consumed in France, 92% of which comes from petroleum products in 2015.[1] Oil is a non-renewable resource, and France imports all the oil it consumes. To that extent, policy makers attempt to diversify the transportation sector energy supplies in order to ensure its long-term independence from oil. The second challenge is related to environmental issues. In fact, 26.4% of national greenhouse gas (GHG) emissions in 2015 were due to the transport sector (excluding land use changes), making it the biggest emitter of GHGs at the French level. Road transport of goods or passengers represents more than 95% of these emissions. It is also one of the main contributor to the emissions of particulate matter (both $PM_{2.5}$ and PM_{10}), Polycyclic aromatic hydrocarbons ($PAHs$), copper, lead, or nitrous oxides. More globally environmental issues of transportation are not limited to GHG emissions.

Renewable fuels are one of the energy transition technologies considered by policy makers to decarbonize the transportation sector. Since 2006, their consumption has been multiplied by five in France. However, biofuels actually used are first-generation biofuels coming from agricultural crops. The use of agricultural raw materials for their production has largely called into question their sustainability. Indeed, these biofuels induce an additional demand for agricultural raw materials initially used for food, inducing at the same time a competition on the uses with the food (and thus potentially a rise of the prices) leading to the "food versus fuel" debate,[2] but also a competition on the uses of arable land and uses of water for irrigation. Several pathways exist to limit the environmental consequences of the transportation sector without using agricultural raw materials. One is the development of new types biofuels, also called second-generation biofuels, mainly relying on lignocellulosic biomass[3] or agricultural residues. In this regard, the "food *versus* fuel" debate leads to the adoption of the EU directive 2015/1513 to limit the use of first-generation biofuels to 7% of the final consumption of energy in the transport sector by 2020.[4]

[1] All these data come from Odyssee concerning energy and UNFCCC GHG profiles for emissions.

[2] In particular, it deals with the role of biofuels in the large increase in agricultural commodity prices during the 2000's, see, e.g., OECD (2008), Nazlioglu (2011), Nazlioglu and Soytas (2012) and Paris (2018).

[3] Biomass-based biofuels can be produced from wood residuals or energy crops as switchgrass or jatropha.

[4] Note that this limit will also concern biofuels produced from energy crop grown on agricultural land, except under specified conditions.

This support for second-generation biofuels is motivated by better score in GHG emissions reduction from Life Cycle Analysis (LCA) (Edwards et al., 2014) and a lower impact on agricultural prices. While second-generation biofuels have these advantages compared to the first one, it provides less opportunities for agricultural sector and have higher production costs. Note that effect of the second-generation biofuels on agricultural prices and agricultural activities could vary among feedstock used. Agricultural residuals-based biofuels can provide agricultural opportunities by valuing co-products without any impact on food prices. Energy crop-based biofuels can also provide agricultural opportunities. But they may yield to a rise in food prices, especially if energy crops used are in competition with food crops. On the contrary, wood residuals-based biofuels do not lead agricultural support and risk in food prices. The citizens' biofuels acceptance and the purchasing behavior of consumers could thereby depend on their preferences between the different characteristics of these two generations of biofuels, i.e., their respective advantages and disadvantages.

Despite their increasing role in the transport sector, the general public has low knowledge about biofuels (Van de Velde et al., 2009; Pacini and Silveira, 2011; Aguilar et al., 2015) and fuel-cell vehicles are seen as a better technology to replace fossil-fuel vehicles (Petrolia et al., 2010; Aguilar et al., 2015). However, according to various studies (e.g., Solomon and Johnson, 2009; Van de Velde et al., 2009; Farrow et al., 2011; Johnson et al., 2011; Dragojlovic and Einsiedel, 2015) citizens have a rather positive opinion about biofuels in term of environmental benefits but prefer biofuels from non-edible feedstock (Jensen et al., 2010; Farrow et al., 2011; Delshad and Raymond, 2013; Aguilar et al., 2015; Dragojlovic and Einsiedel, 2015). Note that wood residuals-based biofuels are not always considered as environmentally friendly due to the problem of deforestation (Jensen et al., 2010) but only without information about this feedstock (Farrow et al., 2011). Finally, people see the decrease of the energy dependence as one of main advantages of biofuels (Ulmer et al., 2004; Jensen et al., 2010; Farrow et al., 2011; Jensen et al., 2012).

Aiming at investigating these topical issues, this paper uses a Discrete Choice Experiment (DCE) to analyze the preference structure of French citizens about biofuels between their main characteristics: (i) the opportunities for the agricultural sector of the domestic economy, (ii) the ability to reduce GHG emissions of the transportation sector and (iii) the impact on the food prices. While Contingent Valuation methods (CV) allow to estimate a global willingness to pay (WTP), the DCE approach is able to disentangled WTPs by biofuels characteristic, named attributes. A payment vehicle is necessary to estimate these WTP. We choose to use a new tax paid by all French citizen and reused specifically to develop new biofuels. By this, we allow each citizen to finance the development of new biofuels and finally to fight against climate change. We also provide marginal rates of substitution (MRS) between the impacts on citizens' utility of the "agricultural support" and "the food prices increase" attributes. These MRS are proposed to investigate the citizens' trade-off between these two attributes in the "food versus fuel" debate.

To our knowledge, this study is the first one to apply a stated preference method to the case of biofuels in France. Contrary to the majority of the literature in the field, we are not interested in the extra fuel-price that consumers are willing to pay for the development of biofuels. The DCE presented here rather proposes to investigate citizens' preferences for supporting, or not, the financing of a biofuel deployment policy to support the decarbonization of the transportation sector. This seems relevant given the objectives that France has to achieve in terms of GHG reduction on the one hand and in term of biofuels consumption on the other hand. Currently, France is the fourth largest producer of biofuels in the world (2nd in Europe after Germany). Moreover, we go further than previous literature by highlighting spatial preference heterogeneity in biofuels acceptance. Results can be summarized as follows. A new tax to develop biofuels could be accepted by close to two-third of the French population. In addition, a potential risk in food prices increase is homogeneously seen as a disadvantage; revealing a strong preference for second-generation biofuels. However, regarding the "agricultural support" and the "reduction in GHG emissions" attributes, the French population preferences appear to be heterogeneous. Two-third of respondents have highest WTP for both attributes than the other third. Combined with other results presented in this paper, this tends to highlight a strong preference for second-generation biofuels based on agricultural residuals in the French population.

The rest of the paper is organized as follows. Section 2 provides literature review regarding WTP estimations about biofuels. Section 3 describes the theoretical framework of our methodology. Section 4 presents the design of the survey as well as data collected and the section 5 refers to econometric models used to analyze respondents' choice. Results are presented in the section 6 and the section 7 discusses about WTP and MRS. Finally, section 8 concludes.

2 Literature review

Savvanidou et al. (2010) analyze WTP for biofuels compared to fossil fuels in Greece with a CV survey and conclude to a mean premium of 0.079€ per liter. Petrolia et al. (2010) find a premium in the US between 0.06$ and 0.12$ per gallon for a 10% ethanol blend (E10) compared to gasoline. In addition, they estimate a premium in the range 0.13-0.15 per gallon for a 85% ethanol blend (E85). On the contrary, Liao and Pouliot (2016) highlight that consumers in Arkansas, Colorado, Iowa and Oklahoma accept to purchase E85 only if a discount exists in the price compared to E10. Only Californian consumers accept to pay a premium for E85.

The lack of willingness-to-pay for biodiesel is also found by Kallas and Gil (2015) in Barcelona province.

With a CV survey in Boston, Minneapolis and Portland, Li and McCluskey (2017) find a premium of 11% for second-generation biofuels compared to gasoline with a higher WTP for Portland followed by Minneapolis, and then Boston. Solomon and Johnson (2009) use the CV analysis in US Midwestern states to estimate the premium attributed to second-generation biofuels from different feedstock – agricultural residues, municipal solid wastes as well as wood and paper mill residues – compared to gasoline. They find an annual WTP between 252$ and 556$ depending on the treatment of non-respondents. In addition, no difference exists between the three feedstock proposed.

Table 9 in Appendix A presents a summary of the literature about the WTP for biofuels using the DCE approach. Giraldo et al. (2010) and Gracia et al. (2011) evaluate WTP in Zaragoza (Spain) for biodiesel. They find a WTP of 0.05€ and 0.07€ per liter for biodiesel compared to conventional diesel, respectively. Jensen et al. (2010, 2012) estimate preferences in the US between E10 and E85 from different sources. Biofuels from grass provide the higher WTP following by wood and then corn. In addition, the WTP is positively correlated with the GHG emissions reduction and negatively with the distance of the station (as in Gracia et al. (2011) in Zaragoza) and the quantity of biofuels imported. This last result are also found by Farrow et al. (2011) in the New England states and Bae (2014) in South Korea. The positive impact of GHG emissions reduction is also highlighted by Susaeta et al. (2010) for E10. In their studies in Arkansas, Florida and Virginia, they fail to find an impact on preferences of the enhancing biodiversity that can come from wood-based biofuels. Finally, Aguilar et al. (2015) find a positive effect of the blend rate in the US – despite some conflicting results according to the econometric model used – and of the energy contents, i.e., the number of miles per gallon. According to their results, consumers prefer corn- and cellulosic-based ethanol compared to ethanol without information about feedstock used. Note that in Barcelona, an increase in bread price accentuates the non-acceptance of biodiesel (Kallas and Gil, 2015). Finally, spatial heterogeneity in preferences is found in terms of reduction in GHG emission (Susaeta et al., 2010) and feedstock used in biofuel production (Jensen et al., 2010, 2012, Aguilar et al., 2015).

3 Theoretical framework

The choice experiment modeling framework relies on the characteristics theory of value (Lancaster, 1966) and the random utility theory (McFadden, 1974). According to Lancaster (1966), the value of a good is defined by the sum of values of each own characteristics. In a DCE approach, each attribute k provide a utility level for each respondent n and for each alternative i which the respondent is facing. The (indirect) utility $V_{n,i}$ of an alternative $i \in \{1, \dots, I\}$ for respondent $n \in \{1, \dots, N\}$, where I and N are given, possibly large, finite integers, is derived from the K observable attributes of the alternative, denoted as $X_i = (x_{i1}, \dots, x_{ik}, \dots, x_{iK})$, as well as of a set of A social, economic and attitudinal characteristics (socio-economic variables) characterizing the respondent, denoted as $Z_n = (z_{n1}, \dots, z_{na}, \dots, z_{nA})$:

$$V_{n,i} = V(X_i, Z_n) \quad \text{for } n = 1, \dots, N \text{ and } i = 1, \dots, I \ . \tag{1}$$

McFadden (1974) proposes to consider individual choices as a deterministic component and some degree of randomness. Combining these two approaches, the random utility of the i-th alternative for each individual n, $U_{i,n}$, can be divided into a deterministic part, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$, capturing the unsystematic and unobserved random element of individual n's choice (Louviere et al., 2000; Holmes and Adamowicz, 2003; Hanley et al., 2005).

$$U_{n,i} = V(X_i, Z_n) + \epsilon_{n,i} \tag{2}$$

Assuming the rationality of individuals, respondents choose the alternative i from a finite set of alternatives S, also called scenarios in the DCE context, if its utility, $U_{n,i}$, is greater than the utility derived from any other alternatives j, $U_{n,j}$:

$$U_{n,i} > U_{n,j} \Rightarrow V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall\, j \neq i \ ; \ i, j \in S \tag{3}$$

The probability to choose the alternative i is thus the same as the probability that the utility of alternative i is greater than the utility of any other alternative (Adamowicz et al., 1998). Following Train (2009), the probability that the respondent n chooses the alternative i is:

$$P_{n,i} = P\{U_{n,i} > U_{n,j} \quad \forall\, j \neq i; \ i, j \in S\} \tag{4}$$

$$\Leftrightarrow P_{n,i} = P\{V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall\, j \neq i; \ i, j \in S\} \tag{5}$$

$$\Leftrightarrow P_{n,i} = P\{\epsilon_{n,j} < V_{n,i} - V_{n,j} + \epsilon_{n,i} \quad \forall\, j \neq i; \ i, j \in S\} \tag{6}$$

4 Survey design and Data

The DCE allows us to estimate trade-off between different characteristics, called attributes, under hypothetical scenarios. After discussions with biofuels and fuels experts as well as with fuels consumers having knowledge of biofuels or not, we selected four main attributes: (i) the monetary vehicle, i.e., an annual fiscal contribution during five years, (ii) the support for agricultural sector, (iii) the variation in GHG emissions and (iv) the impact on food prices. We emphasize here our deliberate choice of using an annual fiscal contribution instead of a purchasing fuel-price as "monetary vehicle" attribute. It allows no-vehicle users to also express their preferences to participate, or not, to the development of biofuels and to finally finance an energy transition technology aiming at fighting climate change.[5] GHG emissions reduction is a traditional attribute in DCEs addressing biofuels issues (Jensen et al., 2010; Susaeta et al., 2010; Farrow et al., 2011; Jensen et al., 2012).[6] The two other attributes allow us to distinguish biofuels according to their type (i.e., first- or second-generation) and their feedstock without providing too many informations to respondents. Over-solicitation with unnecessary details are discouraged in DCEs (Bateman et al., 2002; Champ et al., 2017; Johnston et al., 2017), in order to avoid (i) investigations of information understanding and (ii) taking into account subjective perceptions (Johnston et al., 2017).

Three usual attributes in DCE analysis about biofuels are omitted in our work to limit the number of attributes. First, we do not include availability of biofuels in gas station. However, we mention to respondents that new biofuels will be available in all gas station. Second, we do not mention the blend rate of biofuels in fuel to avoid problem of motor compatibility. We provide information to respondents about the compatibility of biofuels in development with all vehicles. Third, we do not incorporate the biofuel price in the experiment as already explained.

Table 1: Attributes and levels used for survey

Attributes	Levels
Monetary contribution	0€ (only SQ); 15€; 50€; 100€; 150€
Support for agricultural sector	Yes; No (SQ)
Emissions variation	0% (only SQ); -5%; -20%; -30%; -50%
Impact on food prices	Yes; No (SQ)

Note: "SQ" refers to levels in the status quo (but also possible in the other options) and "only SQ" concerns levels only possible in the status quo option.

Levels for each attribute (see Table 1) were selected after discussions with biofuels and fuels experts. These focus groups lead us to specify the "Support for agricultural sector" and the "Impact on food prices" attributes as dichotomous choices – "Yes" or "No" – instead of continuous variables with different quantified levels. Indeed, imprecise or qualitative terms for levels need to be explained in a clearly and comprehensive manner (Johnston et al., 2012), which is difficult to achieve in the case of biofuels. After these discussions, the chosen attributes and levels are:

1. The monetary contribution paid by each household in Euros per year during five years: this attribute is the monetary attribute or cost attribute. The amount varies due to several factors including the biofuels generation, the feedstock used, the blend rate in the traditional fuel, etc. The maximal amount

[5] Note that a similar fiscal contribution exists in France to finance public audiovisual group, French households are thus familiar with this kind of public contribution.

[6] Note that the Table 9 in the Appendix A provides attributes and levels used by previous DCE on biofuels.

is based on the rounded amount of the audiovisual contribution paid by French citizens. The minimal level of this attributes is low – corresponding to 1.25€ per month – to allow low-income households to contribute without an high impact on their budgetary constraint. This attribute takes following values: 0€ (only for the status quo), 15€, 50€, 100€, 150€.

2. The support for agricultural sector: the increase of first-generation biofuels production yield to an additional demand for agricultural commodities used in its production rising the agricultural activity. The development of agricultural residuals- or energy crop-based biofuels (second-generation) could also lead to a support for the agricultural sector. On the contrary, development of wood residuals-based biofuels (second-generation) should not have impact on the agricultural activity. This attribute is qualitative and is expressed as the existence, or not, of an increase in agricultural activities compared to the situation without new biofuels development as: "No" (status quo), "Yes".

3. The variation in GHG emissions: the reduction in GHG emissions can vary based on the generation of biofuel developed, the feedstock used, and the blend rate of biofuels in the traditional fuel. Second-generation biofuels provide higher reduction in GHG emission compared to first-generation biofuels. Levels are based on LCA analysis (Edwards et al., 2014) and depend on various factors mentioned previously. This attribute is expressed in percentage of variation compared to the status quo: 0% (only for the status quo), -5%, -20%, -30%, -50%.

4. The impact on food prices: this attribute indicates how the food prices could be impacted by the development of biofuels. Development of first-generation biofuels will lead to an increase in food prices by using additional agricultural commodity in its production. Researches in second-generation biofuels has been encouraged to avoid a food prices increase based on an energetic use of food crops. This attribute is qualitative and is expressed as the existence, or not, of an increase in food prices compared to the situation without new biofuels development as: "No" (status quo), "Yes".

To select the optimal combinations of attributes' levels[7] in choices cards presented to respondents, we use the D-optimality criterion providing ten choices cards.[8] These were randomly blocked to two different blocks containing five choices cards. This first design has been administrated to a test sample comprising 42 respondents, i.e., 630 observations, to estimate[9] priors used in a second efficient design.

[7]The total number of scenarios is $4^2 \times 2^2 = 64$. Therefore, we cannot submit all choices to respondents.

[8]The design is done with *dcreate* package for STATA created by Arne Risa Hole.

[9]These estimations were done with Conditional Logit model presented in Appendix B.

This DCE has been administered in March 2018 thanks to an on-line survey addressed to 997 French people aged 18 years or older. The survey begins with some information about biofuels in terms of actual use, political determination to develop them, their advantages and disadvantages. In addition, we mention the potential impact of responses on political choices to improve consequentiality[10] and incentive-compatible[11] value elicitation (Herriges et al., 2010; Johnston et al., 2017). We also warn respondents about the negative impact of a new tax – with the monetary contribution – on their disposable income. This allows us to reduce the hypothetical bias.[12] We mention that various successive choices will be proposed between two scenarios – A and B – and a status quo option and used an example of choices card to explain each attributes (see Figure 1 for an example of choices card). We also give the number of successive choices tasks to respondents to reduce implications for sequencing (Bateman et al., 2004). We then randomly attribute to each respondent a block of choices set whose five choices card are given in a randomize order to avoid having a potential declining concentration (last choices) always affecting the same choice set. In addition, we follow advice of Börger (2016) by forcing respondents to stay on each choice task a minimum amount of time before being able to continue the survey. By this, we avoid negative effects of speedy responses. In order to detect protest answers, respondents choosing the status quo in all choice sets were asked the reasons of their choices. Respondents finish survey by responding to social and economic questions allowing us to analyze impact of these citizens' characteristics on their preferences structure.

We identified and removed 23 protest answers among 166 respondents choosing the status quo in all choice sets. The final sample size is thus 972. Its characteristics are presented in Table 2 and compared with the results of the last population survey in France provided by the national statistical institute (INSEE). According to Table 2, our sample is rather representative of the French population. Note however an under-representation of retired in the sample. This is especially due to a high quantity of retired among the 23 protest respondents removed from the sample. This leads to a highest quantity of workers in our sample than in the French population and potential overestimated WTPs.

[10]The consequentiality concerns a situation in which a respondent faces or perceives a nonzero probability that their responses will influence decisions and that they will have to pay for these decisions if these have a cost. Consequentiality is one necessary but not sufficient condition for incentive-compatibility of value elicitation (Herriges et al., 2010; Vossler et al., 2012; Carson et al., 2014).

[11]A mechanism is incentive-compatible when the respondent theoretically has the incentive to truthfully reveal private information asked for by the mechanism (Carson et al., 2014).

[12]The hypothetical bias refers to the possible overestimation of the WTP due to the hypothetic characteristic of scenarios.

Figure 1: Example of a choices card for survey

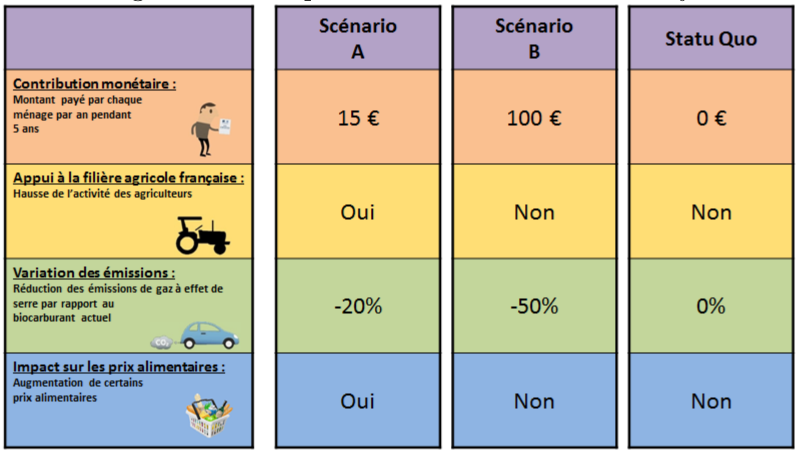


Table 2: Selected characteristics of study sample and the 2014 National Survey

Characteristics	2014 Survey	Sample
Size	-	972
Gender (% female)	51%	51.0%
Age		
Young (18 to 29)	20,6%	20.7%
Young adult (30 to 44)	27,9%	28.3%
Adult (45 to 59)*	28,6%	26.1%
Old (60 and older)	22,9%	24.9%
Professional activity		
Top socio-professional category**	13,7%	16.2%
Middle socio-professional category**	13,7%	16.2%
Low socio-professional category***	27,5%	32.2%
Retired***	32,6%	23.1%
Inactive	12,5%	12.2%

T-tests test shows significant differences * at 10% significance level; ** at 5% significance level, and *** at 1% significance level.

5 Econometric models

According to equation (2), the random utility $U_{n,i}$ is composed of a deterministic component, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$. Before estimating an econometric model, one needs to specify the deterministic part of the utility function, $V_{n,i} = V(X_i, Z_n)$. The linear specification is often chosen in the literature as it is the simplest to work with. We thus introduce the column vector of parameters $\beta_n = (\beta_{n1}, \ldots, \beta_{nK})'$, which are the coefficients quantifying the (linear) influence of the $K = 4$ attributes on utility, and may be specific to each respondent n.

We also introduce an Alternative Specific Constant (ASC) term to capture the effect of unobserved influences (omitted variables) on the utility function, which is a dummy variable taking the value 1 if none of the hypothetical alternatives is chosen (i.e., the status quo alternative is chosen), and 0 otherwise. Thus, the ASC defines a situation with no creation of a new monetary contribution, no additional support for agricultural sector, no reduction in GHG emission in the transportation sector and no increase in food prices. A negative and statistically significant coefficient η would indicate strong preferences for moving from the current situation, i.e., to accept a new monetary contribution to finance biofuels development in our case.

Hence, the model is specified so that the probability of selecting a particular biofuels development scenario i is a function of attributes X_i of that alternative, of the alternative specific constant ASC, and of the socio-economic characteristics Z_n of the respondent n. As the utility $V_{n,i}$ is assumed to be an additive function, equation (2) becomes:

$$U_{n,i} = \eta ASC + X_i(\beta_n + \alpha Z'_n) + \epsilon_{n,i} \tag{7}$$

where $Z'_n = (z_{1n}, .., z_{An})$ represents the vector of the A socio-demographic characteristics of the n-th respondent. X_i comprises all x_{ik} corresponding to the different level taken by the four attributes "Monetary contribution", "Emissions variation", "Support for agricultural sector" and "Impact on food prices". Note that in our case, "Monetary contribution" is the monetary vehicles allowing us to estimate WTP for each attributes. Thus specified, $\beta' = (\beta_{n1}, \beta_{n2}, \beta_{n3}, \beta_{n4})$ coefficients quantify the influence which the various levels of these attributes have on the utility that citizens associate with the different alternatives available, relative to the utility of the status quo option. The matrix α of size (K, A) is composed of coefficients $\alpha_{i,a}$ capturing the cross-effect of socio-economic characteristic a on attribute i.

The Conditional Logit (CL) model, also called the multinomial logit model, is the workhorse model for analyzing discrete choice data and is widely used in DCEs. Its mathematical specifications are presented in Appendix B. This model has several well-known limitations. An important drawback is that it assumes homogeneous preferences across respondents, meaning that the probability that an agent n chooses alternative i in a choice set S, is considered fixed across all individuals ($\beta_n = \beta$ for all n), while we can expect the preferences to vary among the respondents. Two other important drawbacks are the hypothesis of the independence of irrelevant alternatives (*IIA*) and uncorrelated unobserved components. *IIA* implies that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives (details are provided in Appendix B). If the *IIA* property is violated then the CL model does not fit the data. Results will be biased, leading to unrealistic predictions, and hence a discrete choice model that does not require the *IIA* property should be used.

Compared to the CL model, the Random Parameter Logit (RPL) model (McFadden and Train, 2000; Train, 2009), also called the mixed logit model, releases the *IIA* hypothesis and is more valuable to take into account the heterogeneity of preferences. Indeed, the preferences parameters β are allowed to vary randomly across respondents allowing for the fact that different decision makers may have different preferences: $\beta_n \neq \beta_m \;\; \forall\; n \neq m;\; n,\; m \;\in 1, \ldots, N$. As such, conditional on the individual-specific parameters and error components, we can define the logit[13] probability that respondent n chooses a specific alternative i for a given β:

$$P_{n,i}|\beta = L_{n,i}(\beta) = \frac{e^{V_{n,i}(\beta)}}{\sum_j e^{V_{n,j}(\beta)}} \tag{8}$$

Following this, the unconditional choice probability of choosing alternative i is the logit formula in equation (8) integrated over all values of β weighted by the density of β:

$$P_{n,i} = \int L_{n,i}(\beta) f(\beta|\Omega) d\beta \tag{9}$$

where $f(\beta)$ is the density function for β, describing the distribution of preferences over individuals, and Ω is the fixed parameter of the distribution.[14]

The choice probability in equation (9) cannot be calculated exactly because the integral does not have a closed form in general. This integral is approximated through simulations. For a given value of the parameters Ω, a value of β is drawn from its distribution. Using this draw, the logit formula in (8) is calculated. This process is repeated for many draws, and the mean of the resulting $L_{n,i}(\beta)$ is taken as the approximate choice probability yielding equation (10):

$$SP_{n,i} = \frac{1}{R} \sum_{r=1}^{R} L_{n,i}(\beta_r) \tag{10}$$

where R is the number of draws of β, and SP is the simulated probability that an individual n chooses alternative i.

Another way to relax the hypothesis of the *IIA* and to take account for the heterogeneity in respondents' preferences is to analyze the sample with a Latent Class (LC) model. In the latter, each respondent is sorted into a number of classes C in which preferences are assumed to be homogeneous with respect to attributes. In

[13] As the error term is assumed to be IID Type I Extreme Value. Note that Appendix B details calculation to obtain its probability.

[14] β is usually assumed to take on a multivariate normal distribution, with mean b and covariance ω where the off-diagonal elements of the covariance matrix are zero. Random parameters are generally supposed to be normally distributed in the RPL model because it is the most easily applied distribution allowing for both negative and positive preferences.

contrast, preferences are allowed to be heterogeneous between each latent class segment c ($c \in C$).

Compared to equation (8), the logit probability that respondent n prefers a specific alternative i over alternatives j is no more defined for a given β but becomes conditional on class c. Indeed, the βs are now assumed to follow a discrete distribution and belong to one class c of C classes. Thus, the conditional probability that respondents who are members of class c choose alternative i is:

$$P_{n,i}|\beta_c = \frac{e^{V_{n,i}(\beta_c)}}{\sum_j e^{V_{n,j}(\beta_c)}}; \quad \forall\ c \in \{1, \ldots, C\} \tag{11}$$

where β_c is the vector of preferences parameters specific to each class c, representing the average importance of each attribute for respondents belonging to c.

The unconditional probability of individual n selecting choice option i can be expressed as:

$$P_{n,i} = \sum_{c=1}^{C} (\Pi_{n,c} P_{n,i}|\beta_c) = \sum_{c=1}^{C} \left(\Pi_{n,c} \frac{e^{\beta_c' X_i}}{\sum_j e^{\beta_c' X_j}} \right) \tag{12}$$

where $\Pi_{n,c}$ is the probability of membership of respondent n in class c:

$$\Pi_{n,c} = \frac{e^{Z_n' \theta_c}}{\sum_{h=1}^{C} e^{Z_n' \theta_h}} \tag{13}$$

where Z_n is the vector of psychometric constructs and socioeconomic characteristics, and θ is the vector of parameters associated to Z_n (Boxall and Adamowicz, 2002).

According to equation (13), the probability of belonging to a class c with specific preferences is probabilistic, and depends on the social, economic and attitudinal characteristics of the respondents. Combining equation (12) and equation (13), it comes that the LC model assumes that respondent characteristics affect choice indirectly through their impact on segment membership. Note that θ_c includes $C - 1$ class membership parameters with θ_C being normalized to zero for identification. All other coefficients θ_c are thus interpreted relative to this normalized class.

6 Results and interpretation

Recall that we want to analyze citizen's motivation to reduce the GHG emissions in the transportation sector by developing new biofuels. We estimate the WTP associated with various biofuel characteristics. The DCE presented in the section 4 has been conducted among 972 respondents. Therefore, we obtained 4,860 elicited choices (thus corresponding to 14,580 observations).[15]

Table 3 presents results for the CL and RPL models. As expected, the RPL model is preferred to the CL model due to its highest value of the log-likelihood function. Note that applications of the RPL model have shown its superiority in terms of overall fit and welfare estimates (Lusk et al., 2003). Moreover, it is a flexible model able to approximate any discrete choice model (McFadden and Train, 2000) and relaxes the *IIA* assumption (Greene, 2008). We thus only comment results for the RPL models.[16] Here, ASC coefficient as well as the parameters of "Agricultural support", "Emissions variation" and "Food prices increase" are specified to be normally distributed. Their mean and standard deviation are then estimated by simulations based on 1000 Halton draws. The normal distribution is symmetric and unbounded leading few a priori assumption on respondents' preferences: positive as well as negative parameter values may be taken, in order to capture the heterogeneity in the population. The parameter of monetary vehicles is assumed to be constant as usual in the literature (Hensher and Green, 2003). For each model, socio-economic variables is used in interaction with "Agricultural support" and "Emissions variation" attributes. They give information on preferences heterogeneity in these attributes.

Let us first comment results from RPL models without socio-economic characteristics. The sign of the ASC coefficient is negative and significant at the 1% level, indicating that respondents value negatively the fact of staying in the status quo situation: respondents thus value positively a tax for biofuels development. As expected, the utility of the biofuel development for the French citizens decreases with the monetary contribution as their disposable income decreases. In addition, each percentage point of reduction in GHG emission increases the respondents' utility as its coefficient is positive. In terms of agricultural support and food prices increase, respondents' utility increases with biofuel production based on agricultural sector but decrease with production leading to an increase in food prices. These results highlight preferences for second-generation biofuels compare to the first one and are consistent with results in Jensen et al. (2010, 2012) and Farrow et al. (2011). In addition, there is a support for second-generation biofuels coming from agricultural input as agricultural residues and maybe energetic crops. Note that all coefficients' standard deviations are significant, indicating that the RPL model provides a better representation of the choices than a CL model as there is heterogeneity among respondents around the mean.

In the extended RPL model (Table 3, two last columns), the negative coefficient of the "young adult" variable indicates that people aged from 30 to 44 are less sensitive than other age classes to the reduction of GHG emissions attributes. This coefficient remains, in absolute value, inferior to the coefficient of the "Emissions variation"

[15] As we have 972 respondents with 5 choices cards between 3 alternatives, i.e., $972 * 5 * 3$.
[16] The CL models results are kept for robustness check.

Table 3: Results of the CL and RPL models

Attributes	CL model	CL model with interact.	RPL model Coefficient	RPL model Std. Deviat.	RPL model with interact. Coefficient	RPL model with interact. Std. Deviat.
Alter. Spec.	-0.189***	-0.191***	-0.891***	2.690***	-0.858***	2.694***
Constant	(0.053)	(0.053)	(0.120)	(0.144)	(0.118)	(0.143)
Monetary	-0.011***	-0.011***	-0.016***	-	-0.016***	-
contribution	(0.000)	(0.000)	(0.001)	-	(0.001)	-
Agricultural	0.451***	0.500***	0.640***	0.472***	0.720***	0.210
support	(0.042)	(0.050)	(0.055)	(0.132)	(0.066)	(0.290)
In high	-	-0.120*	-	-	-0.173*	0.638***
density area	-	(0.069)	-	-	(0.104)	(0.160)
Emissions	0.022***	0.020***	0.028***	0.043***	0.027***	0.045***
variation	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
In high	-	0.007***	-	-	0.012***	-
density area	-	(0.002)	-	-	(0.004)	-
For young	-	-0.005**	-	-	-0.009*	-
adult	-	(0.002)	-	-	(0.005)	-
Food prices	-0.451***	-0.451***	-0.582***	0.634***	-0.600***	0.735***
increase	(0.041)	(0.041)	(0.057)	(0.112)	(0.059)	(0.099)
N (Ind.)	972	972	972		972	
N (Obs.)	14,580	14,580	14,580		14,580	
McFadden R^2	0.065	0.067	-		-	
Log Likelihood	-4,990.93	-4,979.18	-4,187.74		-4,170.27	

Note: ASC mentions the Alternative Specific Constant and refers to the dummy variable equals to 1 if the status quo is chosen and 0 otherwise. For each variables, the first line concerns the estimated coefficient and the second line (in brackets) mentions the standard errors. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. "High density area" concerns city with more than 1,500 populations per square kilometers and "Young adult" refers to respondents aged from 30 to 44 years old.

attribute (-0.009 and 0.027, respectively. Even for this age class, these results indicate that the reduction of GHG keeps a positive impact on their utility. Regarding now respondents living in a densely populated city ($\geq 1500/km^2$), they are more positively impacted than others by a reduction of GHG emissions. On the contrary, this population of urban citizens appears to be a bit less sensitive than others to the question of supporting the agricultural sector in their preferences. These results are similar – but not perfectly – with results in Jensen et al. (2010, 2012) and Aguilar et al. (2015). Compared to these articles, no spatial heterogeneity in preferences is effectively found in term of French regions. Heterogeneity in preferences is here captured by the localization context, i.e., the city densities. As density of the cities is negatively correlated with the share of agricultural land in the department, this result confirms the idea that local environment in term of agricultural economy do have an impact on French's preferences for supporting the agricultural sector through biofuels production. Note that this spatial heterogeneity explains all the heterogeneity in preferences as the standard deviation of the "Agricultural support" becomes not statistically significant when including this localization variable. However, some heterogeneity remains among preferences in the "Agricultural support" attribute in high density areas as the standard deviation of this interaction variable is significant.

As explained in Section 5, another way to take into account the heterogeneity in respondents' preferences is to analyze the sample with a Latent Class (LC) model. In order to better understand citizen's preferences for the various attributes we thus now try to determine various classes of citizens whom have similar preferences.

Using a kernel density function, Figure 2 provides the distribution of the individual coefficients estimated by the RPL model with socio-economic variables.[17] Regarding the "Support for agricultural sector" and the "Impact on food prices" attributes, the distribution of these coefficients appears to be concentrated around a single value. On the contrary, the "Emissions variation" attribute coefficient seems to be distributed around two local maximum, both positive. Finally, there are at least three groups of preferences for the ASC coefficient. This latter point is of great interest with three distinct local maximums: (i) negative, (ii) positive and (iii) null. It tends to indicate that our sample of respondents can be split, at worst, in three distinct groups. A first group of respondents values negatively the fact of staying in the status quo situation (i.e., no development of new biofuels) while the second group values positively this situation. The last group seems to be indifferent among stay in or move away from the status quo.

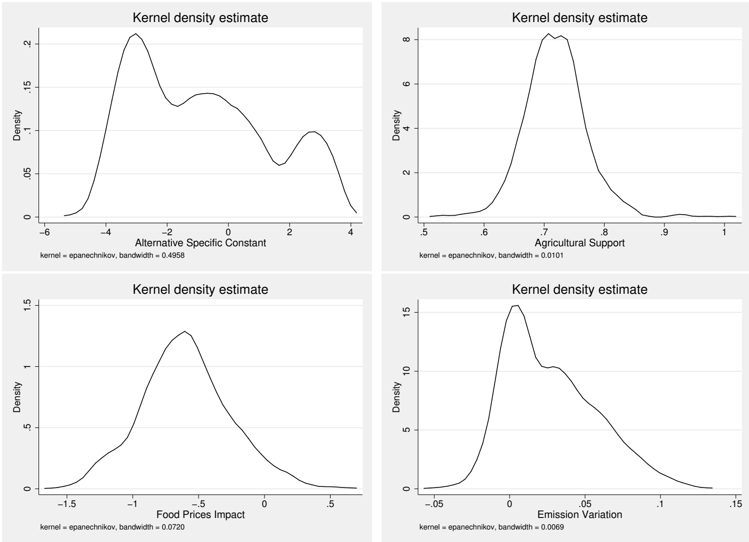
Though very useful and often revealing, inspecting graphs are always vulnerable to subjective interpretation and more objective statistical analysis is needed. Another way to choose the number of classes in the LC model is the use of information criterion as Consistent Akaike Information Criterion (CAIC) and Bayesian Information Criterion (BIC) presented in Table 4. Despite the three mode in the ASC coefficient distribution, we finally choose two classes due to the higher decrease in information criterion from models with one (CL model) to two classes compared to others.

Table 4: Criteria for determining the optimal number of segments

Nb. of classes	Parameters	Log Likelihood	CAIC	BIC
1	8	-4,979	10,043	10,035
2	10	-4,205	8,513	8,500
3	15	-4,027	8,219	8,198
4	20	-3,975	8,178	8,149
5	25	-3,957	8,206	8,169

[17]The distributions based on the RPL model without socio-economic variables are similar and available upon request to authors.

Figure 2: Kernel density of coefficients with RPL model



Results from LC models – with[18] and without socio-economic variables as Segment function – are presented in Table 5. The extended model displays utility parameters into two classes: (i) the Class 1 with 65.1% of the respondents and (ii) the Class 2 comprising 34.9% of them. As expected, these two classes differ widely in their preferences: while the first one has a strong utility to move from the status quo, with a negative and significant coefficient of the ASC, the second one has an utility to stay in the current situation. An interesting result from this model is the relative equality in the parameter linked to the GHG emissions reduction. Reduction in GHG emissions affected all respondents' utility in a similar way with preferences parameter of 0.028 and 0.022. Therefore, heterogeneity in respondents' behavior is linked to biofuel development and not to the fight against climate change through reduction in GHG emissions. In addition, a difference between these two classes concerns the "food versus fuel" debate. Compared to the Class 1, the second class has a stronger disutility to see an increase in food prices (-1.288, compared to -0.378) and a lower utility for an agricultural support due to a new biofuel development (0.284, compared to 0.552). On the contrary, the negative impact of the food prices on the utility seems to be lower than the positive effect of the agricultural support on utility for the first Class. Finally, note that respondents living in city with high density are more likely to be in the first class as well as young populations.

[18]Here, age of respondents and density are included as continuous variables.

Table 5: Results of the LC model with 2 classes

Attributes	without socio-eco. varia. Class 1	Class 2	with socio-eco. varia. Class 1	Class 2
ASC	-1.467***	0.512***	-1.464***	0.495***
	(0.091)	(0.162)	(0.090)	(0.162)
Monetary contribution	-0.011***	-0.031***	-0.011***	-0.032***
	(0.001)	(0.002)	(0.001)	(0.002)
Agricultural support	0.554***	0.279**	0.552***	0.284**
	(0.049)	(0.136)	(0.049)	(0.136)
Emissions variation	0.028***	0.022***	0.028***	0.022***
	(0.002)	(0.005)	(0.002)	(0.005)
Food prices increase	-0.377***	-1.302***	-0.378***	-1.288***
	(0.044)	(0.174)	(0.044)	(0.173)
Segment function				
Pop. density	-	-	-	-0.00003**
	-	-	-	(0.00001)
Age	-	-	-	0.0159***
	-	-	-	(0.0048)
Constant	-	-	-	-1.2707***
	-	-	-	(0.2518)
N (Ind.)	633	339	633	339
N (Obs.)	9,495	5,085	9,495	5,085
Class share (%)	65.1	34.9	65.1	34.9
Log Likelihood	-4,214		-4,205	

Note: ASC mentions the Alternative Specific Constant and refers to the dummy variable equals to 1 if the status quo is chosen and 0 otherwise. For each attributes, the first line concerns the estimated coefficient and the second line (in brackets) mentions the standard errors. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. Age of respondents and population density are included as continuous variables.

7 Willingness to pay and marginal rate of substitution

These WTP measure welfare in a monetary unit, i.e., in Euros by years during five years. There are determined by estimating the MRS between the considered attribute and the income. The marginal utility of income is represented by the cost attribute's coefficient, i.e., the monetary contribution.

Tables 6 and 7 present WTP estimates coming from respectively (i) the CL and RPL models results and (ii) the LC models results. As mentioned in the introduction, welfare measures can be determined in the form of marginal WTP by estimating the marginal rate of substitution (MRS) between the considered attribute and income. The marginal utility of income is represented by the cost attribute's coefficient, β_{cost}, which is assumed constant as mentioned before. Here it corresponds to the monetary contribution. As WTP are expressed in the monetary unit, those presented bellow are thus expressed in Euros by years during five years. Estimates of the WTP values are obtained for each of the non-monetary attributes using the Wald procedure (Delta method).[19] Since utilities are modeled as linear functions of the attributes, the marginal rate of substitution between two attributes is the ratio between the coefficients:[20]

$$WTP_k = -\frac{dx_{cost}}{dx_k} = -\frac{dU/dx_k}{dU/dx_{cost}} = -\frac{\partial V/\partial x_k}{\partial V/\partial x_{cost}} = -\frac{\beta_k}{\beta_{cost}} \tag{14}$$

Eq. (14) corresponds to the WTP for the attribute k with levels x.

For a LC model, the WTP for the individual n for a variation of the attribute k can be computed per class as

$$WTP_k^c = \Pi_{n,c}^* \cdot -\frac{\beta_k^c}{\beta_{cost}^c} \tag{15}$$

where c are the latent classes, β_k^c the parameter associated to attribute k for each latent class c, β_{cost}^c the parameter associated to the monetary attributes for each latent class c, and $\Pi_{n,c}^*$ the posterior estimate of the individual-specific class probability of membership of respondents n in class c. For each model, the estimated standard deviations and confidence intervals around the mean of the WTP estimates are obtained using the Krinsky and Robb parametric bootstrapping method (Krinsky and Robb, 1986).

To gain more insights into the extent to which respondents take place in the "food versus fuel" debate, we provide the MRS between "Impact on food prices" and "Support for agricultural sector" attributes. This MRS allows us to analyze the willingness to offset food price increasing with agricultural supporting and is calculated as:

$$MRS_{a,f} = -\frac{\beta_a}{\beta_f} \tag{16}$$

A $MRS_{a,f}$ significantly lower (resp. greater) than one indicates a stronger (resp. smaller) preference for the use of non-agricultural (resp. agricultural) commodities in biofuels production.

If we focus on the LC model with socio-economic variables in the Segment function (Table 7), results can be interpreted in the following way. French citizens in the first class (resp. second class) of our sample accept to pay 51.59 Euros (resp.

[19]The Delta method stipulates that the WTP for a unit change of a given attribute can be computed as the marginal rate of substitution between the quantity expressed by the considered attribute and the cost attribute (Louviere et al., 2000).

[20]It should be noted that the derivative of the unobserved part of the utility function is supposed to be zero with respect to both attributes.

8.98 Euros) per year to finance the development of a new biofuel allowing a support for the agricultural sector. On the contrary, they need to receive in average 35.30 Euros and 40.80 Euros per year to accept an increase in the food prices for the first and the second group, respectively. This result confirms a strong preference for second-generation biofuels, whatever the class under consideration. In addition, French citizens accept to pay in average 2.64 Euros or 0.68 Euros – for the Class 1 and 2, respectively – per year per percentage point of reduction in GHG emissions allowed by the new biofuels. Globally, we note that the risk in food prices increase seems to be a disadvantage in biofuels development for the respondents in the Class 2 with a MRS much lower than one. They are against biofuels produced from agricultural product and would appear to prefer wood residuals-based biofuels. On the contrary, majority of our sample accept to use agricultural product in biofuels production. However, they prefer agricultural residuals-based biofuels in line with its strong and negative WTP concerning the food prices increase.

Table 6: WTP estimates with CL and RPL models

Attributes	CL model	CL model with socio-eco. varia.	RPL model	RPL model with socio-eco. varia.
Agricultural support	41.13 [34.75 ; 47.52]	45.57 [37.91 ; 53.24]	40.07 [34.51 ; 45.64]	44.40 [37.69 ; 51.11]
In high density area	- -	-10.94 [-21.34 ; -0.54]	- -	-10.65 [-21.22 ; -0.76]
Emissions variation	1.99 [1.79 ; 2.20]	1.85 [1.60 ; 2.09]	1.77 [1.53 ; 2.01]	1.65 [1.32 ; 1.97]
In high density area	- -	0.67 [0.39 ; 0.95]	- -	0.77 [0.33 ; 1.21]
For young adult	- -	-0.44 [-0.74 ; -0.15]	- -	-0.57 [-1.05 ; -0.08]
Food prices increase	-41.15 [-47.29 ; -35.02]	-41.05 [-47.18 ; -34.92]	-36.42 [-42.20 ; -30.63]	-37.01 [-42.95 ; -31.09]
$MRS_{a,f}$	1.00 [0.82 ; 1.18]	1.11 [0.89 ; 1.33]	1.10 [0.90 ; 1.30]	1.20 [0.97 ; 1.43]

Note: The first line mentions the willingness to pay in Euros per years or the MRS between "Agricultural support" and "Food prices increase". The second line refers to the interval confidence at 90% level.

Last but not least, WTP estimates presented here allow us to deduce over the French population, the mean WTPs for the development of biofuels from various feedstock and incorporated in fuels with various blend rates. Table 8 presents these results with information about effects on attributes for each biofuel. WTP for high blended biofuels are obviously greater than low blend rates as they provide higher reduction in GHG emissions. However, high blended biofuels – as E85 or B100 – are not suitable as long as existing vehicles cannot accept these kinds of fuels. In addition, biofuels from wheat straw maximizes the WTP of French population by allowing agricultural support without any impact on food prices. This feedstock is followed by wood residuals and then food crops.

Table 7: WTP estimates with Latent Class models

Attributes	without socio-eco. varia. Class 1	Class 2	with socio-eco. varia. Class 1	Class 2
Agricultural support	51.67 [44.12 ; 59.22]	8.93 [1.61 ; 16.24]	51.59 [44.04 ; 59.15]	8.98 [1.75 ; 16.22]
Emissions variation	2.64 [2.38 ; 2.90]	0.71 [0.44 ; 0.98]	2.64 [2.38 ; 2.91]	0.68 [0.42 ; 0.95]
Food prices increase	-35.13 [-41.87 ; -28.39]	-41.63 [-51.83 ; -31.42]	-35.30 [-42.06 ; -28.55]	-40.80 [-50.81 ; -30.79]
$MRS_{a,f}$	1.47 [1.16 ; 1.78]	0.21 [0.05 ; 0.38]	1.46 [1.16 ; 1.76]	0.22 [0.06 ; 0.38]

Note: The first line mentions the willingness to pay in Euros per years or the MRS between "Agricultural support" and "Food prices increase". The second line refers to the interval confidence at 90% level.

Table 8: Mean WTP for various biofuels

Biofuels	Agricultural Support	Emission Variation	Food Prices Impact	WTP with RPL model	WTP with LC model
E20 sugar beet	Yes	-10.7%	Yes	22.36	20.48
E85 sugar beet	Yes	-45.4%	Yes	84.56	88.47
E10 wood residuals	No	-7.8%	No	13.98	15.28
E20 wood residuals	No	-15.5%	No	27.78	30.37
E85 wood residuals	No	-65.9%	No	118.13	129.12
E10 wheat straw	Yes	-8.9%	No	56.16	54.18
E20 wheat straw	Yes	-17.9%	No	72.29	71.81
E85 wheat straw	Yes	-75.9%	No	176.26	185.45
B20 rapeseed oil	Yes	-6.8%	Yes	15.37	12.84
B100 rapeseed oil	Yes	-33.8%	Yes	63.77	65.74
B10 wood residuals	No	-9.7%	No	17.39	19.01
B20 wood residuals	No	-19.3%	No	34.60	37.82
B100 wood residuals	No	-96.6%	No	173.16	189.27

Note: WTP come from model with socio-economic variables and are expressed in Euros per year during five years. Reductions in GHG emissions derive from Edwards et al. (2014).

8 Conclusion

This article investigates French population' motivations and obstacles to finance new biofuels development in the transportation sector. It uses a quantitative approach based on a Discrete Choice Experiment to measure the relative weight of various biofuels' characteristics in citizens' utility based on a sample of 972 respondents. We value respondents' willingness to pay for several components of their decision such as the agricultural support of a biofuel development, the reduction in greenhouse gas emissions from the transportation sector and the existence of an impact of the biofuel development on food prices. Regarding the latter, French behavior towards risk in food prices increase is a potential major component explaining their willingness to accept a tax to finance a new biofuel development.

Using three econometric models, namely the Conditional Logit, the Random Parameter Logit and the Latent Class models, we find that the risk in food prices increase is a prominent obstacle for respondents' fundings of biofuels development. All else being equal, approximatively two-third of respondents need to receive in average 35.30 Euros by year to accept an increase in food prices. Other part of French citizens need to receive 40.80 Euros. These two amounts are almost equal between themselves, highlighting a rather clear preference for a second-generation biofuels development.

Furthermore, the reduction in greenhouse gas emissions that may come along with new biofuels incorporation in the transportation sector is seen by respondents as an important reason to support its development. In particular, two-third accept to pay in average 2.64 Euros by year for each percentage point of greenhouse gas emissions reduction, all else being equal. On the contrary, one-third has a lower annual willingness to pay of 0.68 Euros. This difference depends, in part, on age of respondents and on whether or not they are living in high density cities.

Last, the impact of the biofuels development on the agricultural sector is a decisive factor for two-third of respondents accepting to pay 51.59 Euros to support agricultural sector with biofuels. The second part of French has a weak willingness to pay of 8.98 Euros per year. An heterogeneity in agricultural preferences exists thus among French population and can be explained by population density and thus by local agricultural environment of respondents.

Our results highlight the preference for second-generation biofuels produced by non-food commodities as in Jensen et al. (2010, 2012) and Farrow et al. (2011). Mores specifically, 65.1% of our sample appears to accept the production of agricultural residuals-based biofuels, whereas a minority, i.e., 34.9%, has a low acceptance for agricultural-based biofuels. These latter could prefer wood residuals-based biofuels or other technologies to reduce greenhouse gas emissions in the transportation sector. Agricultural residuals-based biofuels can thus maximize French population preferences as the wheat straw-based biofuels.

These results are of great interest for policy makers. Indeed, renewable fuels deployment is an integral part of the public policies mix adopted, both at the national and European level, to decarbonize the transportation sector. But widespread deployment of energy transition technologies will largely depend on the attitudes and preferences of consumers and citizens for these technologies. Regarding biofuels, the "food versus fuel" debate clearly dominates the issue of their acceptance by the civil society. In this regard, the EU directive 2015/1513 to limit the use of first-generation biofuels to 7% of the final consumption of energy in the transport sector by 2020 is heading in the right direction. Based on French citizens' preferences, this article comes to the conclusion that it is first the agricultural residuals-based biofuels and then the wood residuals-based biofuels which should be encouraged by policy makers.

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A Literature summary

Table 9: List of DCE about biofuels with details about attributes and levels

Authors	Country	Attributes	Levels
Susaeta et al. (2010)	US	Percentage reduction of CO_2 emissions (per mile traveled)	E10: 1-3% (low), 4-7% (medium), 8-10% (high) E85: 1-60% (low), 61-70% (medium), 71-90% (high)
		Percentage improvement of biodiversity by reducing wildfire risk and improving forest health	E10: 1-20% (low), 21-40% (medium), 41-60% (high) E85: 1-25% (low), 26-50% (medium), 51-75% (high)
		Increase of the fuel price of fuel at the pump per gallon	E10: $0.2, $0.5, $0.75, $1 E85: $0.3, $0.6, $1, $1.5
Giraldo et al. (2010)	Spain	Biodiesel	Biodiesel, conventional diesel
		Price	€0.99, €1.10, €1.21
		Brand	Big brand petrol stations, small or local petrol stations
		Proximity	Petrol station is close to everyday route (Yes), otherwise (No)
Jensen et al. (2010, 2012)	US	Fuel price (price per gallon)	E85: $1.34, $1.42, $1.50, $1.58, $1.66 (E10: $2.00)
		Feedstock for the ethanol	E85: corn, switchgrass, wood wastes (E10: corn)
		Percent of fuel from imported sources	E85: 10%, 33%, 50% (E10: 60%)
		Level of GHG emissions reductions compared with E10	E85: 10%, 50%, 73%
		Availability of the fuel nearby	E85: 'on your way', 2 min 'out of your way', 5 min 'out of your way' (E10: 2 min out of the way)
Gracia et al. (2011)	Spain	Price (€ per litre)	1.05, 1.1, 1.15, 1.20
		Type of diesel	Biodiesel, Biodiesel with a sustainable label, Conventional Diesel (SQ)
		Availability in a petrol station close to the everyday router	Yes, No
		Place of production	Europe, Outside Europe
Farrow et al. (2011)	US	Price (price per gallon)	Usual fuel: range of $1.50 to $4.50 with a mean of $2.50 Ethanol: range of $1.30 to $4.65 with a mean close to $2.50
		Feedstock for the ethanol	Corn, wood
		GHG emissions (pounds per gallon)	Usual fuel: range of 15 to 25 with a mean of 20 Corn based ethanol: reduction range of 5% to 60% with a mean of 23% Wood based ethanol: reduction range of 40% to 80% with a mean of 65%
		Import rate	Random
Bae (2014)	South Korea	Price changes of gasoline	+20 KRW, +80 KRW, +120 KRW
		Method of providing bioethanol	Use of domestic feedstock for domestic bioethanol: Domestic barley is used for producing domestic bioethanol Use of imported feedstock bioethanol: Tapioca is imported for producing domestic bioethanol Import of bioethanol: Bioethanol is imported
		Blending ratios of bioethanol to gasoline	3%, 5%, 10%
Aguilar et al. (2015)	US	Price/gallon	$2.75, $3.25, $3.75 (second round: $3.10, $3.45, $3.80)
		Miles per gallon	20 mpg, 25 mpg, 30 mpg
		Ethanol content	0%, 10%, 20%, 85%
		Ethanol source	corn-ethanol, cellulosic-ethanol, undisclosed feedstock
Kallas and Gil (2015)	Spain	Type of diesel	conventional diesel, B10, B20, B30
		Location of the petrol station	'usual route', 'outside the usual route'
		Type of the petrol station	'local petrol stations','multinational operator'
		Price of the bread	unchanged, +5%, +10%, +20%

B Mathematical details of the econometric models

Different discrete choice models are obtained from different assumptions about the distribution of the random terms.

Assuming $\epsilon_{n,i}$ being Independent and Identically Distributed (IID) and following a type I extreme-value distribution, i.e., a standard Gumbel distribution, the cumulative distribution function F and the density function f of each $\epsilon_{n,i}$ are given by:

$$F(\epsilon_{n,i}) = e^{-e^{-\epsilon_{n,i}}} \tag{17}$$

$$f(\epsilon_{n,i}) = e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}} \tag{18}$$

The equation (6) becomes therefore:

$$P_{n,i}|\epsilon_{n,i} = \prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+\epsilon_{n,i})}} \tag{19}$$

The non conditional probability for an agent n to choose the alternative i is therefore the integration of $P_{n,i}|\epsilon_{n,i}$ over the distribution of $\epsilon_{n,i}$:

$$P_{n,i} = \int \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+\epsilon_{n,i})}} \right) e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}} d\epsilon_{n,i} \tag{20}$$

By replacing $\epsilon_{n,j}$ with s, equation (20) becomes:

$$P_{n,i} = \int_{s=-\infty}^{+\infty} \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+s)}} \right) e^{-s} e^{-e^{-s}} ds \tag{21}$$

As $V_{n,i} - V_{n,i} = 0$, we have:

$$P_{n,i} = \int_{s=-\infty}^{+\infty} \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+s)}} \right) e^{-s} e^{-e^{-(V_{n,i}-V_{n,i}+s)}} ds \tag{22}$$

and the last term can be introduced into the product,

$$P_{n,i} = \int_{s=-\infty}^{+\infty} \left(\prod_{j} e^{-e^{-(V_{n,i}-V_{n,j}+s)}} \right) e^{-s} ds \tag{23}$$

By removing the first exponential from the product, we obtain:

$$P_{n,i} = \int_{s=-\infty}^{+\infty} exp\left(-\sum_{j} e^{-(V_{n,i}-V_{n,j}+s)} \right) e^{-s} ds \tag{24}$$

$$P_{n,i} = \int_{s=-\infty}^{+\infty} exp\Big(- e^{-s} \sum_j e^{-(V_{n,i}-V_{n,j})} \Big) e^{-s} ds \tag{25}$$

We now define $t = e^{-s}$. The expression $-e^{-s}ds$ therefore gives dt and note that t approaches zero (resp. positive infinity) if s tends to infinity (resp. negative infinity) as:

$$P_{n,i} = \int_{t=+\infty}^{0} exp\Big(- t \sum_j e^{-(V_{n,i}-V_{n,j})} \Big) (-dt) \tag{26}$$

that is to say:

$$P_{n,i} = \int_{t=0}^{+\infty} exp\Big(- t \sum_j e^{-(V_{n,i}-V_{n,j})} \Big) dt \tag{27}$$

This expression is now easy to integrate and allows us to obtain expression in equation (8).

$$P_{n,i} = \left. \frac{exp\big(- t \sum_j e^{-(V_{n,i}-V_{n,j})} \big)}{- \sum_j e^{-(V_{n,i}-V_{n,j})}} \right]_0^{+\infty} \tag{28}$$

$$P_{n,i} = 0 - \frac{1}{- \sum_j e^{-(V_{n,i}-V_{n,j})}} \tag{29}$$

$$P_{n,i} = \frac{1}{\sum_j e^{-(V_{n,i}-V_{n,j})}} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{30}$$

The CL model is estimated using maximum likelihood procedures. The probability that a respondent n chooses a particular alternative is $\prod_i (P_{n,i})^{y_{n,i}}$ with $y_{n,i} = 1$ if the alternative i is chosen and zero otherwise. Assuming the independence in choices of each respondent, the likelihood and log-likelihood functions are given by:

$$L(\beta) = \prod_{n=1}^{N} \prod_i (P_{n,i})^{y_{n,i}} \tag{31}$$

$$LL(\beta) = \sum_{n=1}^{N} \sum_i y_{n,i} ln(P_{n,i}) \tag{32}$$

with:

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{33}$$

where $P_{n,i}$ only depends on observable components. Here the β' vector contains the β_{ik} parameters from Eq. (1), and vector X_i holds the attribute content of alternative i.

The CL model assumes homogeneous preferences across respondents. In Eq. (33), the probability that an agent n chooses alternative i in a choice set C, β' is considered fixed across all individuals, while we can expect the preferences to vary among the respondents.

This model also requires the hypothesis of independence of irrelevant alternatives (IIA), which implies that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives. Indeed, according to Eq. (33), we have:

$$\frac{P_{n,i}}{P_{n,k}} = \frac{\frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}}}{\frac{e^{V_{n,k}}}{\sum_j e^{V_{n,j}}}} = \frac{e^{V_{n,i}}}{e^{V_{n,k}}} \tag{34}$$

C Results for Latent Class model with 3 classes

Table 10: Results of the LC model with 3 classes

Attributes	without socio-eco. variable			with socio-eco. variables		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
ASC	1.244***	-2.004***	-1.477***	1.303***	-1.985***	-1.473***
	(0.260)	(0.184)	(0.169)	(0.276)	(0.182)	(0.167)
Monetary contribution	-0.022***	-0.035***	-0.003**	-0.022***	-0.034***	-0.003***
	(0.004)	(0.002)	(0.001)	(0.004)	(0.003)	(0.001)
Agricultural support	0.193	0.403***	0.665***	0.200	0.398***	0.662***
	(0.211)	(0.130)	(0.065)	(0.219)	(0.130)	(0.065)
Emissions variation	0.013	0.036***	0.031***	0.014	0.034***	0.031***
	(0.009)	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)
Food prices increase	-1.393***	-0.992***	-0.389***	-1.404***	-0.993***	-1.142***
	(0.271)	(0.131)	(0.060)	(0.285)	(0.130)	(0.060)
Segment function						
Pop. density	-	-	-	-0.00003**	-0.00004***	-
	-	-	-	(0.00001)	(0.00001)	-
Age	-	-	-	0.0183***	-0.0005	-
	-	-	-	(0.0058)	(0.0062)	-
Constant	-	-	-	-1.1417***	0.0488	-
	-	-	-	(0.3296)	(0.3244)	-
N (Ind.)	258	337	377	254	337	381
N (Obs.)	3,870	5,055	5,655	3,810	5,055	5,715
Class share (%)	26.6%	34.7%	38.7%	26.1%	34.7%	39.2%
Log Likelihood		-4,039			4,027	

Note: ASC mentions the Alternative Specific Constant and refers to the dummy variable equals to 1 if the status quo is chosen and 0 otherwise. For each attributes, the first line concerns the estimated coefficient and the second line (in brackets) mentions the standard errors. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. Age of respondents and population density are included as continuous variables.