# Citizens in energy transition: Highlighting the role played by spatial preference heterogeneity in public acceptance of biofuels

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**Abstract**

Renewable fuels development is an integral part of the public policies mix highlighted 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 annual tax to finance the development of new biofuels in order to reduce greenhouse gas (GHG) emission in this sector. With a Discrete Choice Experiment conducted among about 997 French citizens in 2018, we analyze preferences for different biofuel development policies. Using a two-stage method, we are particularly interested in the heterogeneity of these preferences. The first stage uses a random parameters logit model. It highlights the heterogeneity of preferences for the attributes within our sample. The means of marginal willingness to pay stemming from the random parameter model are 71, 105 and 142 euros for 20%, 30% and 50% reduction in GHGs emissions compared to 5% reduction. In addition, the support to agricultural sector and the avoidance of food price increase are valued, in mean, respectively at 60 euros and 39 euros. The second stage model uses a panel random-effect regression to estimate the influence of socioeconomic and spatial characteristics on marginal willingness to pay for each of the choice experiment attributes except for emissions reduction.

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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 and dependence on fossil fuels. Renewable fuels are one of the energy transition technologies considered by policy makers to decarbonize the transportation sector. This article studies the French preferences for financing an industrial sector producing a new type of biofuel, with particular attention to the spatial heterogeneity of preferences. These preferences are estimated by conducting a nation-wide choice experiment survey.

In France, transportation sector accounts for 34% of the final energy consumed and 26.4% of national greenhouse gas (GHG) emissions (excluding land use changes).[1] It is the biggest emitter of GHGs at the French level. To reduce dependence on oil imports and tackle climate change, policy makers want to shift consumption behaviour towards local "greener" energies. This is why biofuels are often presented as one of the ways to reduce GHGs emissions in the transport sector. Since 2006, the consumption of biofuels 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 well-known "*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]

This support for second-generation biofuels is motivated by better score in GHGs emissions reduction from Life Cycle Analysis (LCA) (Edwards et al., 2014) and a lower impact on agricultural prices. While second-generation biofuels have these

[1]All these data come from Odyssee concerning energy and UNFCCC GHG profiles for emissions. Road transport of goods or passengers represents more than 95% of these 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.

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).

In this article, we estimate the preferences of the French for policies aimed at developing biofuels that emit less GHGs. Our results can provide support for the implementation of such policies. This seems relevant given the objectives that France has to achieve in terms of GHGs 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). To our knowledge, this is the first study of stated preferences for biofuels in France. In addition, unlike previous studies of this type, we are not interested in preferences for a biofuel at the gas pump but rather in preferences for the development of biofuels as a solution to reduce GHGs emissions in transport. We use 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 GHGs emissions of the transportation sector (iii) the impact on the food prices and (iv) a new tax paid by all French citizens.

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. Thus, rather than simply deriving estimates of willingness to pay for a given policy scenario, we study the determinants of the variation in these estimates within our sample. The main objectives of this article are: (i) identify the factors that influence the individual preferences for the financing of a new biofuel sector; and (ii) estimate the determinants of the spatial heterogeneity of preferences, with a special attention to the types and importance of agricultural activities in the areas where respondents are located. Following Campbell (2007), Campbell et al. (2009) and Yao et al. (2014), we use a two-step method. Firstly, we estimate a model that includes random parameters and an error component. This step highlights the heterogeneity of preferences. The means of marginal willingness to pay stemming from random parameter model are 71, 105 and 142 euros for 20%, 30% and 50% reduction in GHGs emissions compared to 5% reduction. In addition, the support to agricultural sector is valued, in mean, at 60 euros and 39 euros for the avoidance of food price increase. Secondly, we use a panel random effects regressions models to identify the determinants influencing WTPs for the biofuel policy. Our results highlight various spatial determinants for preferences among between two groups of respondents who are distinguished by the dominant type of agriculture at the local level. For one group, preferences vary according to local population density. For the other group, preferences vary according to the share of agricultural land on a larger scale. Other determinants such as tax burden perception and income also influence preferences.

The rest of the paper is organized as follows. Section 2 provides literature review regarding WTP estimations about biofuels. Section 3 presents our experiment and sample. Section 4 describes our methodology with the theoretical framework, the model specification and econometric methods used to analyse respondents' choices. Results are presented in the section 5 and the section 6 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 U.S. 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 U.S. 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 6 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 U.S. 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 GHGs 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 GHGs 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 U.S. – 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 – standing for food price impacts due to biofuel production – accentuates the non-acceptance of biodiesel (Kallas and Gil, 2015).

Concerning spatial heterogeneity in preferences about biofuels, some CV surveys exhibit various WTP among American states or cities (Liao and Pouliot, 2016; Li and McCluskey, 2017). Some differences are also highlighted by DCE studies. Susaeta et al. (2010) highlight a significant greater valuation for E85 – and not for E10 – in Florida and Virginia compared to Arkansas. Citizens coming from states in Midwest and south of U.S. exhibit lower preferences for E85 compared to E10 but not concerning corn based ethanol (Jensen et al., 2010). The heterogeneous valuation is also analyzed by Jensen et al. (2012) among all U.S. states. They found greater WTP to consume biofuels in order to reduce oil imports in Arkansas, Kentucky, Tennessee and West Virginia than other states. A higher WTP is also highlighted in rural area compared to metropolitan locality. Note that only Aguilar et al. (2015) study heterogeneous preferences in terms of feedstocks. They highlight greater valuation for cellulosic biofuels in west coast states compared to others U.S. states. This result is explained by differences in the periods of public debate about biofuels among U.S. states. However, they also mention the need of studies analyzing spatial heterogeneity focus on location specific differences.

# 3 The choice experiment

The DCE approach relies on the economic theory of consumer choice and non-market valuation. In a DCE survey, respondents must choose from several options defined by their attributes ( i.e., fundamental characteristics of the respondents' situation). Often, three options are presented: nothing changes ( i.e., the status quo) and two alternative options. The use of an opt-out option (status quo) is known to improve realism in choices (Adamowicz and Boxall, 2001; Kontoleon and Yabe, 2003). Respondents then choose their favorite option. Each option has different levels of the attributes. One of these attributes usually represents the monetary contribution of the respondents. Other attributes can include environmental or social implications of the issue under consideration. See Louviere et al. (2000) for a detailed description of the method. The DCE framework has the advantage of considering several attributes of the issue, delivering more detailed information than other stated preference methods. Especially, it makes it possible to estimate the marginal rates of substitution between different attributes. When one attribute is expressed in monetary terms, these marginal rates of substitution can be interpreted as the willingness to accept (WTA) or willingness to pay (WTP) for changes in the attributes levels.

The DCE allows us to then estimate trade-off between different biofuels 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 GHGs 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] GHGs 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 infor-

[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 6 in the Appendix A provides attributes and levels used by previous DCE on biofuels.

mations 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, quantitative 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 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 euro 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 GHGs emissions: the reduction in GHGs 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 GHGs emissions 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 priors used in a second efficient design.

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[9] and incentive-

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

[8]The experimental design was generated using *dcreate* package for STATA created by Arne Risa Hole.

[9]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).

compatible[10] 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.[11] 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.

Figure 1: Example of a choices card for survey

| | Scenario A | Scenario B | Status Quo |
|---|---|---|---|
| **Monetary contribution:** Amount paid by each household in Euros per year during five years | 15 € | 100 € | 0 € |
| **Support for agricultural sector:** Increase agricultural activities | Yes | No | No |
| **Variation in GHG emissions:** Reduction in GHG emissions compared to actual biofuels | -20% | -50% | 0% |
| **Impact on food prices:** Increase in some food prices | Yes | No | No |

We identified and removed 23 protest answers among 166 respondents choosing the status quo in all choice sets. The size of the final sample is 972.[12] Its characteristics are presented in Table 2 and compared with those of the French population using

[10] 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).

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

[12] A respondent living in an overseas department has been removed as we focus our analysis on

the data from The National Institute of Statistics and Economic Studies (INSEE). According to Table 2, our sample is rather representative of the French population aged 18-75 years.

Table 2: Selected characteristics of study sample

| Characteristics | French population | Sample |
|---|---|---|
| Size | - | 972 |
| Gender (% female) | 51.1% | 51.0% |
| Age | | |
| Young (18 to 29) | 19.8% | 20.7% |
| Young adult (30 to 44) | 26.8% | 28.3% |
| Adult (45 to 59) | 28.6% | 26.1% |
| Old (60 to 75) | 24.8% | 24.9% |
| Professional activity | | |
| Top socio-professional category | 15.7% | 16.2% |
| Middle socio-professional category | 16.4% | 16.2% |
| Low socio-professional category | 33.7% | 32.2% |
| Retired | 20.0% | 23.1% |
| Inactive | 14.2% | 12.2% |

# 4 Modelling framework

Following Campbell (2007), Abildtrup et al. (2013) and Yao et al. (2014), we use a two-stage estimation procedure to identify and quantify the determinants of the individual-specific WTP estimates. We first estimate a Random Parameters Logit (RPL) Model to obtain the individual-specific parameters for the biofuels attributes. We then infer individual-specific marginal WTP for each attribute. Random-effects models for panel data are then used to analyze the heterogeneity of these estimated individual-specific WTPs and determine their main determinants.

## 4.1 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

metropolitan France as well as a respondent who have done a mistake during survey.

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 (socioeconomic 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:

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

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

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

## 4.2 Model specifications

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 $\beta_n = (\beta_{n1}, \dots, \beta_{nK})'$, which are the coefficients quantifying the (linear) influence of the $K$ attributes on utility, and may be specific to each respondent $n$. The attributes ("*support for agricultural sector*", "*variation in GHGs emissions*", "*impact on food prices*"), were entered in the form of dummy coded variables. When there is support for agricultural sector, the corresponding variable takes the value of 1 and 0 otherwise. A positive coefficient associated with this variable indicates a preference for support for the agricultural sector. When there is no increase in food prices, the corresponding variable takes the value of 1 and 0 otherwise. A positive coefficient associated with this attribute indicates a preference for no increase in food prices. For the GHGs emissions' attribute, three levels of reduction are represented (20%, 30%, 50%). The variables take the value of 1 if the reduction level is present in the alternative and 0 otherwise. The effect of a level is interpreted in comparison with the reference level: "5% reduction in GHGs emissions compared to actual biofuels". The attribute "*monetary contribution*" is a continuous variable.

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 in the status quo alternative 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 GHGs emissions in the transportation sector and no increase in food prices. A negative and statistically significant coefficient $\eta$ for the $ASC$ dummy variable (see equation (7) below) 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 socioeconomic 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 $Z'_n = (z_{n1}, \ldots, z_{na}, \ldots, z_{An})$ 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 that appeared on every choice card. The matrix $\alpha$ of size $(K, A)$ is composed of coefficients $\alpha_{i,a}$ capturing the cross-effect of socioeconomic characteristic $a$ on attribute $i$.

Furthermore, as in Abildtrup et al. (2013), an error component is incorporated into the model to capture any remaining status quo effects in the stochastic part of the utility. The error component, which is implemented as a zero-mean normally distributed random parameter, is exclusively assigned to the two non-status quo alternatives. By specifying a common error component across these two alternatives, correlation patterns in the utility over these alternatives are induced. It therefore captures any additional variance associated with the cognitive effort of evaluating experimentally-designed hypothetical alternatives (Greene and Hensher, 2007; Scarpa et al., 2007b, 2008). This results in the following general utility structure:

$$U_{n,i} = \begin{cases} V_{n,i} + \epsilon_{n,i} = V(X_i, Z_n, \beta_n, \mu_n) + \epsilon_{n,i}, & \forall\ i = 1, 2 \\ V_{n,i} + \epsilon_{n,i} = V(ASC, X_i, Z_n, \beta_n) + \epsilon_{n,i}, & i = SQ \end{cases} \tag{8}$$

where the indirect utility, $V$, is a function of the vectors of explanatory variables,$X_i$ and $Z_n$, as well as the vectors of individual-specific random parameters, $\beta_n$. For the two experimentally-designed policy alternatives, the common individual-specific error component $\mu_n$ enters the indirect utility function, while it is replaced by the $ASC$ for the status quo alternative. The unobserved error term $\epsilon_{n,i}$ remains assumed to be Gumbel-distributed.

### 4.3 Random Parameters Logit Model

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. 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. 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.

Here, we used a Random Parameter Logit (RPL) model, also called the mixed logit model, to analyze our data. 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 $\beta$ 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 $\beta_n$:

$$P_{n,i}|\beta_n = L_{n,i}(\beta_n) = \frac{e^{V_{n,i}(\beta_n)}}{\sum_j e^{V_{n,j}(\beta_n)}} \tag{9}$$

[13] As the error term is assumed to be IID Type I Extreme Value variable.

Following this, the unconditional choice probability of choosing alternative $i$ is the logit formula in equation (9) integrated over all values of $\beta_n$ weighted by the density of $\beta_n$:

$$P_{n,i} = \int L_{n,i}(\beta_n) f(\beta_n|\Omega) d\beta_n \tag{10}$$

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

The choice probability in equation (10) 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 $\Omega$, a value of $\beta_n$ is drawn from its distribution. Using this draw, the logit formula in (9) is calculated. This process is repeated for many draws, and the mean of the resulting $L_{n,i}(\beta_n)$ is taken as the approximate choice probability yielding equation (11):

$$SP_{n,i} = \frac{1}{R} \sum_{r=1}^{R} L_{n,i}(\beta_{n,r}) \tag{11}$$

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

$\beta_n$ varies over individuals in the population with density $f(\beta_n|\Omega)$, where $\Omega$ is a vector of the true parameters of the taste variation, e.g., representing the mean and standard deviation of the $\beta_n$'s in the population. Assumptions concerning the distribution of each of the random parameters, i.e., the density function $f(\beta_n|\Omega)$, are necessary. The true distribution is unknown, so, in principle, any distribution could be applied (Carlsson et al., 2003; Hensher and Greene, 2003). In the present paper the parameters associated with all biofuels attributes, except the cost attribute, are supposed to be normally distributed random parameters, as commonly assumed in the literature (Hensher and Green, 2003). On the contrary, the coefficient associated with the cost attribute is usually kept fixed in valuation studies in order to avoid a ”wrong” sign ( i.e. negative) for a share of respondents. We believe that it may be important in the current case to let the monetary contribution be specified as a random variable because of spatial preference heterogeneity. A log-normal distribution is thus assumed for this attribute.

As explained by Burton (2018), econometric models that include categorical variables (as here) are not invariant to the choice of the “base” category when random parameters are estimated, unless they are allowed to be correlated. When

[14] $\beta_n$ is usually assumed to take on a multivariate normal distribution, with mean $b$ and covariance $\omega$ 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.

not taken into account, the invariance can lead to significant increases in Type I errors. To avoid this bias, all results for the RPL models presented in this article are estimated with a full covariance matrix structure in which the random coefficients are supposed to be correlated.

### 4.4 Panel Data Regression of marginal WTPs

One important interest of the RPL model is the ability to calculate the means of attributes marginal WTP (mWTP) distributions for each respondent conditional on observed choice: their known sequence of choices (within sample).

Welfare measures can be determined in the form of mWTP by estimating the marginal rate of substitution (MRS) between the considered attribute and income (Louviere et al., 2000). The marginal utility of income is represented by the cost attribute's coefficient, $\beta_{cost}$. Since utilities are modeled as linear functions of the attributes, the MRS between two attributes is the ratio between the corresponding coefficients.[15]

For quantitative attributes, the WTP for a marginal variation of the level of attribute $k$ for respondent $n$ is

$$W_{n,k} = -\frac{dx_{cost}}{dx_k} = -\frac{dU/dx_k}{dU/dx_{cost}} = -\frac{\partial V/\partial x_k}{\partial V/\partial x_{cost}} = -\frac{\beta_k}{\beta_{cost}} \qquad (12)$$

For attributes modeled as effect-coded dummy variables, the $W^l_{n,k}$ associated with attribute $k$ and category $l$ is

$$W^l_{n,k} = -\frac{\beta^l_k}{\beta_{cost}} \qquad (13)$$

representing the willingness to pay to move from the status quo category of attribute $k$ to category $l$ for respondent $n$.

Once calculated, we wish to try and see how the variation of these WTPs estimates can be explained on the basis of socio-economic characteristics of respondents, taking into account the fact that these conditional means estimates are correlated when they pertain to the same respondent. Panel data procedures are thus used to account for systematic group effects. Here the sub-groups within the data are created by pooling the WTP estimates for each of the category $l$ for attribute $k$ held by each of the respondents. The econometric specification of the model is:

$$W^l_{n,k} = \psi_n + \gamma D^l_{n,k} + \lambda Z_n + \epsilon^l_{n,k} \qquad (14)$$

[15]The derivative of the unobserved part of the utility function is supposed to be zero for both attributes.

Where $W^l_{n,k}$ represents a 5-period panel of WTP for the $l$ level of the attribute $k$ for respondent $n$, $\psi_n$ represents independent random variables with constant mean and variance, $D^l_{n,k}$ is a vector of indicator variables for $k$ minus one attribute levels $l$, $Z_n$ represents a vector of socio-economic characteristics, attitude and affiliations of respondent n, while $\gamma$, $\lambda$ and $\epsilon$ are unknown parameters to be estimated. Assuming that the same factors influence WTP for each respondent, subject to an additional error term that differs for each individual respondent, implies the random-effects panel data model, which assumes $\psi_n = \psi + \nu_n$. The $\alpha_n$ values represent independent random variables with the same mean ($\psi$) and variance ($\sigma^2_\nu$).

# 5 Results and interpretation

Recall that we want to analyze citizens' motivation to reduce the GHGs emissions in the transportation sector by developing new biofuels with a two step procedures. We first estimate the WTP associated with various biofuel characteristics. The DCE presented in the section 3 has been conducted among 972 respondents. Therefore, we obtained 4,860 elicited choices (thus corresponding to 14,580 observations).[16] We then analyzed heterogeneity in French citizens preferences and determined determinants of their preferences with a panel econometric model on marginal WTPs.

## 5.1 Conditional Logit Results

Let us first briefly comment the results from the Conditional Logit model presented in the Table 3. As expected, monetary contribution affects negatively the respondent's utility with a positive coefficient as the contribution monetary is used in negative form. In addition, results highlight non linearity in preferences concerning the emission reduction attribute with a significant and different impact on respondents utility for 20%, 30% and 50% reduction in GHGs emissions compared to the 5% level. This reduction in emissions positively impacts the utility confirming previous in previous studies (Susaeta et al., 2010; Jensen et al., 2010, 2012; Gracia et al., 2011). 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 biofuel development. Concerning others biofuel characteristics, results are in line with our expectation. The utility of the biofuel development for the French citizens increases with biofuel production supporting agricultural sector and avoiding an increase in food prices. This last result is in line with the negative impact of the bread price increase on the utility found by Kallas and Gil (2015). However, the Conditional Logit model requires the IIA hypothesis that we are checked with the Hausman test applied to each

[16] As we have 972 respondents with 5 choices cards between 3 alternatives, i.e., $972 \times 5 \times 3$.

alternative and the statu-quo. This hypothesis is rejected highlighting the necessity of using the Random Parameter Logit estimation.

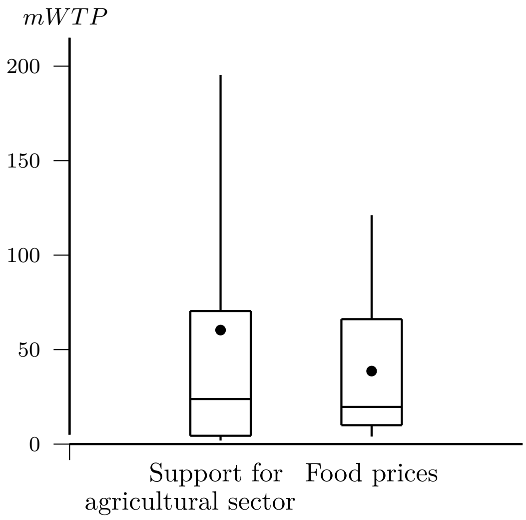
Table 3: Results for the Conditional Logit and Random Parameter Logit models

| | CL model | RPL model | |
|---|---|---|---|
| | | Coef. | Std. Deviation |
| Alternative Specific Constant | -0.251*** | -2.143*** | - |
| | (0.057) | (0.185) | - |
| Monetary contribution | 0.012*** | -4.008*** | 1.737*** |
| | (0.000) | (0.087) | (0.090) |
| Agricultural support | 0.509*** | 0.742*** | 0.662*** |
| | (0.044) | (0.084) | (0.137) |
| Food prices increase | 0.453*** | 1.113*** | 1.130*** |
| | (0.041) | (0.090) | (0.116) |
| Emissions variation | | | |
| 20% reduction | 0.336*** | 0.675*** | 1.732*** |
| | (0.063) | (0.123) | (0.193) |
| 30% reduction | 0.856*** | 1.458*** | 1.380*** |
| | (0.073) | (0.145) | (.204) |
| 50% reduction | 0.985*** | 1.693*** | 2.476*** |
| | (0.041) | (0.162) | (0.210) |
| Error Component | - | - | 3.481*** |
| | - | - | (0.223) |
| N (Ind.) | 972 | 972 | |
| N (Obs.) | 14,580 | 14,580 | |
| McFadden $R^2$ | 0.0679 | 0,2669 | |
| Log Likelihood | -4,976.61 | -3,914.10 | |
| | Alt. 1 Alt. 2 S.Q. | | |
| Hausman tests | 77.84 43.5 62.94 | | |
| for IIA hypothesis | 0.001 0.001 0.001 | | |

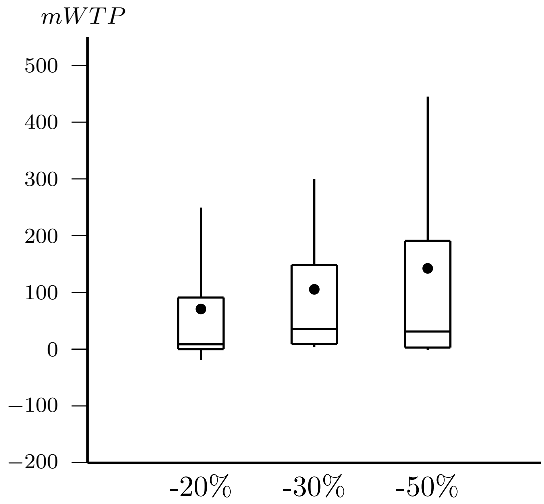
Note: For each variables, the first line concerns the estimated coefficient and the second line (in brackets) mentions the standard errors. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. The Hausman test lines mention test statistics and p-value for Independence of each alternative. For the Random Parameter Logit, the coefficient of the monetary contribution follows a log-normal distribution.

## 5.2 Random Parameter Logit Results

Table 3 also presents results from the RPL estimations. 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). All mean coefficients are significant at the 1% level, are of the expected sign confirming results from the CL model. French citizens utility increases with the development of a new biofuel as the ASC is negative. The support of the agricultural sector and the avoidance of food prices with the new biofuel also increase the utility confirming results from the CL model and highlighting the interest of the “food versus fuel” debate. Indeed, French citizens have interest in agricultural based biofuel – to provide activities in agricultural sector – but prefer to avoid an inflationary impact on food prices. In addition, reductions in GHGs emissions by 20%, 30% and 50% with the new biofuel have more positive impact on French citizens utility compared to 5% reduction. These result highlights their willingness to fight against climate change through effort in the transport sector. Note that the estimated parameter for the monetary contribution is the mean of the natural logarithm of the real coefficient (Train, 2009). The mean and the median of the real coefficient are thus 0.083 and 0.018, respectively. This positive coefficient highlights the preference of respondents for lower monetary contribution. Finally, all coefficients for standard deviations are significant at the 1% level highlighting the heterogeneity in French citizens' preferences concerning all biofuel characteristics analyzed here.[17]




(a) Box plots for the marginal willingness to pay for the support for agricultural sector and impact on food prices




(b) Box plots for the marginal willingness to pay for the GHGs emissions reduction

Figure 2a and 2b present the distribution for the marginal willingness to pay of French citizens for each biofuel attributes stemming from the RPL estimation. Boxplots present the mean, the median, the interquartile range of the data as well as the first and ninth decile. They reflect sample variability regarding preferences for each attribute. The mean (resp. median) for mWTPs concerning GHGs emissions reduction of 20%, 30% and 50% – compared to 5% – are 71, 105 and 142 euros (resp. 8.50, 36 and 31 euros), respectively. Concerning agricultural and food characteristics of biofuels, the mean (resp. median) for mWTPs of French citizens are 60 and 39 euros

[17] Note that the real coefficient for standard deviation concerning the monetary contribution is 0.365.

(resp. 24 and 20 euros), respectively. These two latter mWTPs exhibit heterogeneity with a range between the first and third quartile (resp. first and ninth quantile) close to 66 and 56 euros (resp. 197 and 125 euros).[18] This heterogeneity in French citizens preferences concerning these two biofuel characteristics can now be analyzed.

## 5.3 Panel regression

Turning now to the second step of our analysis, Table 4 reports the estimation of our panel model for the marginal WTPs of our 972 respondents concerning the 20%, 30% and 50% emission reductions – compared to the 5% emission reduction – as well as for the agricultural support and food price impact. As mentioned in subsection 4.4, we include indicator variables for all but one biofuel characteristics for the different types of marginal WTP. We explore the role of the agricultural environment of respondents with dummies referring to the agricultural specialization of the city for each respondent compared to cities without agricultural activities. In addition, we also analyze impact of local and departmental importance of agricultural sector, through the share of agricultural land and the local population density on the mWTPs, as well as socioeconomic variables as income and the perception of tax burden. Note that the individual mWTPs are not known with certainty as they stem from a previous estimation. We should thus interpret coefficients significance with caution. Keeping in mind this limitation, we used this methodology allowing to determine marginal WTPs determinant following Greene et al. (2005), Campbell et al. (2008, 2009) and Train (2009), among others.

The first column in the Table 4 presents impacts of the local agricultural specialization on the mWTP compared to area without agricultural activity. This last one mainly corresponds to urban area. Two types of area appear to be distinct in term of preferences. Indeed, respondents living in area with local agricultural specialization in livestock farming, poly-culture and market gardening have a significant lower mWTP – for all attributes together – of 43, 31 and 29 euros compared to the reference area, respectively. These differences are significant at the 1% (resp. 10%) level for the two first areas (resp. for the last one) and motivate the separation of our sample into two sub-samples through a dummy variable clustering respondents living in area with agricultural specialization in livestock farming, poly-culture and market gardening.

The second column mentions results with the agricultural specialization dummy variable in interaction with attributes dummies to analyze impacts of this local agricultural variable on the mWTP of each biofuel characteristics. French citizens from

[18] Note that mWTPs for emissions reductions also exhibit heterogeneity but we focus our analysis on the biofuels characteristics linked to the “food versus fuel” debate.

Table 4: Marginal WTPs panel regression model

| | (1) | (2) | (3) |
|---|---|---|---|
| Attributes | | | |
| Constant | 92.53*** | 85.71*** | 40.52** |
| | (8.677) | (7.287) | (19.78) |
| 30% reduction | 34.62*** | 35.46*** | 34.62*** |
| | (4.432) | (6.527) | (4.432) |
| 50%reduction | 71.58*** | 82.59*** | 71.58*** |
| | (4.432) | (6.527) | (4.432) |
| Agricultural support | -10.42** | -18.82*** | -10.42** |
| | (4.432) | (6.527) | (4.432) |
| Food price impact | -32.11*** | -45.82*** | -32.11*** |
| | (4.432) | (6.527) | (4.432) |
| Socioeconomic and locational variables | | | |
| Local population density | | | 0.002*** |
| | | | (0.001) |
| Dptmt. agricultural surface share | | | 0.566** |
| | | | (0.234) |
| Income | | | 0.008*** |
| | | | (0.003) |
| Tax burden | | | -20.65* |
| | | | (12.07) |
| Agricultural specialization | | | |
| No agricultural area | ref. | | |
| | - | | |
| Biofuel crops area | -19.86 | | |
| | (13.15) | | |
| Livestock farming area | -43.02*** | | |
| | (13.89) | | |
| Market gardening area | -30.67* | | |
| | (15.87) | | |
| Poly-culture area | -28.96*** | | |
| | (10.90) | | |
| Viticulture area | -16.88 | | |
| | (18.95) | | |
| Agricultural specialization subgroups | | -27.58*** | -14.57* |
| | | (9.896) | (8.818) |
| Attributes crossed with *Agr. spec. subgroups* | | | |
| 30% reduction | | -1.543 | |
| | | (8.864) | |
| 50% reduction | | -20.30** | |
| | | (8.864) | |
| Agricultural support | | 15.49* | |
| | | (8.864) | |
| Food price impact | | 25.28*** | |
| | | (8.864) | |
| N (Ind.) | 972 | 972 | 972 |
| N (Obs.) | 4860 | 4860 | 4860 |
| $R^2$ | 0.061 | 0.061 | 0.072 |
| $\chi^2(5)$ | | 39.61 | |
| | | 0.001 | |

Note: 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. Indicator for agricultural specialization subgroups is equal to one for livestock farming, market gardening and poly-culture areas. Dptmt. agricultural surface share refers to the share of land used for agricultural purpose in the department that the respondent comes from. The $\chi^2(5)$ lines mention test statistic and p-value of the Chow test applied on interaction between the agricultural indicator and attribute indicators.

livestock farming, poly-culture and market gardening areas have lower mWTP to reduce emissions by 50% as the interaction with the variable *Agricultural specialization subgroups* is negative and significant. In addition, these citizens are more sensible to the agricultural support and to avoid the food price pressure. Respondents from these agricultural areas seem to be more influenced by the agricultural support due to biofuel production compared to respondents living in area specialized in cereal crops. Biofuel crops areas could be nonetheless the main recipients of the agricultural support by the biofuel development. This result also highlights difference between American and French citizens about agricultural-based biofuels. Indeed, Jensen et al. (2010) show that citizens from Midwest – comprising the corn belt –

seem to have greater WTP for corn-based E85 compared to others American areas. Note that all interaction coefficients concerning livestock farming, poly-culture and market gardening areas are significant as a whole according to the result from the Chow test.

Results for some socioeconomic variables are presented in the last column highlighting the role played by the local population density, the income, the agricultural land share in the department – with a positive impact on the mWTP – and the perception of tax burden – with a negative effect. These results allow us to analyze the difference in the influence of these socioeconomic variables for both agricultural areas already found as mWTP influencing factor.

Table 5: Panel regression for both area

| | Livestock farming, market gardening and poly-culture areas | | | Biofuel crops, viticulture and non agricultural areas | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Attributes | | | | | | |
| 30% reduction | 33.92*** | 33.92*** | 33.92*** | 35.46*** | 35.46*** | 35.46*** |
| | (5.397) | (5.397) | (5.395) | (7.225) | (7.225) | (7.215) |
| 50% reduction | 62.29*** | 62.29*** | 62.29*** | 82.59*** | 82.59*** | 82.59*** |
| | (5.397) | (5.397) | (5.395) | (7.225) | (7.225) | (7.215) |
| Agricultural support | -3.330 | -3.330 | 21.04 | -18.82*** | -18.82*** | -10.76 |
| | (5.397) | (5.397) | (14.45) | (7.225) | (7.225) | (8.27) |
| Food price impact | -20.54*** | -20.54*** | 3.497 | -45.82*** | -45.82*** | -35.22*** |
| | (5.397) | (5.397) | (14.45) | (7.225) | (7.225) | (8.27) |
| Constant | 35.91 | 55.16** | 88.47*** | 32.99 | 47.95*** | 54.48*** |
| | (26.03) | (22.70) | (16.03) | (28.73) | (14.68) | (14.28) |
| Socioeconomic and locational variables | | | | | | |
| Income | 0.005 | | | 0.011** | 0.011** | 0.012*** |
| | (0.004) | | | (0.004) | (0.004) | (0.004) |
| Tax burden | -33.37** | -32.84** | -33.86** | -10.47 | | |
| | (16.58) | (16.54) | (16.56) | (17.70) | | |
| Dptmt. agricultural surface share | 0.720** | 0.625** | | 0.423 | | |
| | (0.311) | (0.304) | | (0.352) | | |
| Local population density | 0.003 | | | 0.002** | 0.001** | |
| | (0.003) | | | (0.001) | (0.001) | |
| Agricultural support *in interaction with* | | | | | | |
| Dptmt. agricultural surface share | | | -0.470* | | | |
| | | | (0.259) | | | |
| Local population density | | | | | | -0.001** |
| | | | | | | (0.001) |
| Food price impact *in interaction with* | | | | | | |
| Dptmt. agricultural surface share | | | -0.463* | | | |
| | | | (0.259) | | | |
| Local population density | | | | | | -0.001*** |
| | | | | | | (0.001) |
| N (Ind.) | 527 | 527 | 527 | 445 | 445 | 445 |
| N (Obs.) | 2,625 | 2,625 | 2,625 | 2,225 | 2,225 | 2,225 |
| $R^2$ | 0.056 | 0.056 | 0.046 | 0.084 | 0.081 | 0.072 |

Note: 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. Dptmt. agricultural surface share refers to the share of land used for agricultural purpose in the department that the respondent comes from.

Last but not least, Table 5 presents results from panel regression for both agricultural areas with socioeconomic variables. First, we can note that each groups of French citizens represent close to the half of the sample. The livestock farming, market gardening and poly-culture areas regroup 54.1% of the whole sample against 45.9% for the second group. Second, these two areas seem to be influenced by different factors. While mWTPs of French citizens living in livestock farming, market gardening and poly-culture areas seem to be impacted by their global agricultural environment – through the departmental agricultural land share presented in the Figure 3 –, respondents from areas without agricultural activities or with biofuel crops and viticulture is influenced by local environment with the local population density viewable on the Figure 4. For the first one, the agricultural surface share impacts positively the mWTP as the whole, with a positive coefficient in the column (2), but negatively the agricultural support and the food price avoidance through the negative coefficients in the column (3). French citizens from these areas have thus higher mWTP for agricultural support by biofuel production than others areas but the range of this difference decreases in departments with a large agricultural activity. Rather, the mWTP of the second one is positively influenced by the population density – which might reflects the local agricultural environment –, with a positive parameter in the column (5), but inversely considering these two biofuel attributes with two negative coefficients. The difference in mWTP for agricultural support previously highlighted decreases concerning citizens from these areas living in a dense city. In addition, the mWTPs is negatively impacted by the perception of tax burden for the first group of respondents and positively influenced by the income for the second one.

Figure 3: Agricultural surface by department

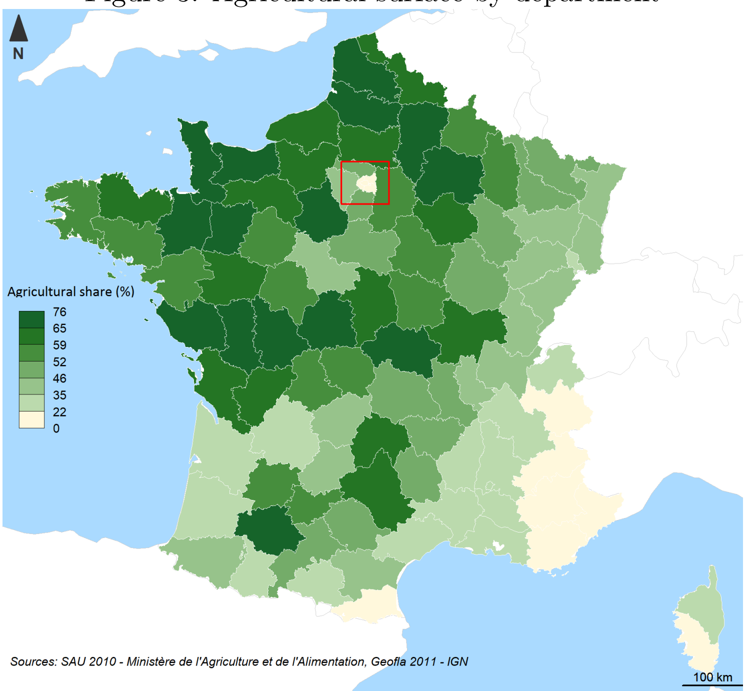
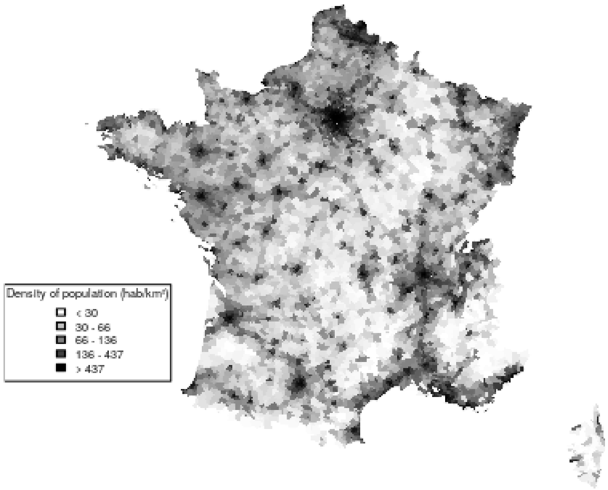


Figure 4: Population density




# 6 Conclusion

This article investigates French population's motivations and obstacles to finance new biofuels development in the transportation sector. It uses a two-step approach – following Campbell (2007), Campbell et al. (2009) and Yao et al. (2014) – based on a nation-wide discrete choice experiment to (i) identify the influencing factors in individual preferences concerning a new biofuel development; and (ii) analyze the determinants of the spatial heterogeneity of preferences, with a special attention to the types and importance of agricultural activities around respondents localization.

Based on a sample of 972 respondents, we first value respondents' willingness to pay for several non market 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. The means of marginal willingness to pay stemming from random parameter model are 71, 105 and 142 euros for 20%, 30% and 50% reduction in GHGs emissions compared to 5% reduction. In addition, the support to agricultural sector is valued, in mean, at 60 euros and 39 euros for the avoidance of food price increase. Finally, our results highlight heterogeneity in French citizens preferences.

Second, we use random-effects models for panel data to understand the heterogeneity of individual-specific willingness to pay stemming from the random parameter model. We show that French citizens can be split into two categories depending on the agricultural specialization of its localization. Respondents living in area specialized in livestock farming, poly-culture and market gardening have greater marginal willingness to pay to support agricultural sector and avoid food price increase compared to French citizens coming from area with biofuel crops or viticulture specialization or without agricultural activity. In addition, we highlight various spatial determinants for preferences among these two groups of French citizens. While marginal willingness to pay for agricultural support and food price increase avoidance of respondents coming from areas with livestock farming, poly-culture and market gardening activities are negatively impacted by the size of the agricultural sector in the department, these willingness to pay for other French citizens are negatively affected by the local population density. Finally, we found two other distinct determinants among these two groups of French citizens. The marginal willingness to pay of the first one is negatively linked to the perception of tax burden while the income is a determinant for the second one.

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. Our results show that individual preferences vary spatially depending on the agricultural context in which respondents live. This spatial variability of preferences could be taken into consideration when setting its policy.

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# A Literature summary

Table 6: List of DCE about biofuels with details about attributes and levels

| Authors | Country | Attributes | Levels |
|---|---|---|---|
| Susaeta et al. (2010) | U.S. | Percentage reduction of $CO_2$ emissions (per mile traveled) | E10: 1-3% (low), 4-7% (medium), 8-10% (high)<br>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)<br>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<br>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) | U.S. | 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 GHGs 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) | U.S. | Price (price per gallon) | Usual fuel: range of \$1.50 to \$4.50 with a mean of \$2.50<br>Ethanol: range of \$1.30 to \$4.65 with a mean close to \$2.50 |
| | | Feedstock for the ethanol | Corn, wood |
| | | GHGs emissions (pounds per gallon) | Usual fuel: range of 15 to 25 with a mean of 20<br>Corn based ethanol: reduction range of 5% to 60% with a mean of 23%<br>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<br>Use of imported feedstock bioethanol: Tapioca is imported for producing domestic bioethanol<br>Import of bioethanol: Bioethanol is imported |
| | | Blending ratios of bioethanol to gasoline | 3%, 5%, 10% |
| Aguilar et al. (2015) | U.S. | 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% |