Socio-economic and driving experience factors affecting drivers' perceptions of traffic crash risk

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SOCIO-ECONOMIC AND DRIVING EXPERIENCE FACTORS AFFECTING DRIVERS´ PERCEPTIONS OF TRAFFIC CRASH RISK

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ABSTRACT

Drivers are estimated to contribute an overwhelming proportion to the burden of traffic crashes, as factors that increase crash risk are frequently due to unsafe driving behaviours. The relationship between risk perceptions and people's risky driving behaviours is still not well understood. This paper aims to further analyze the potential effect of risky driving behaviours on drivers' perceptions of crash risk and differences in perceptions among drivers.

Crash risk perceptions in an inter-city, two-way road context of 492 drivers were measured by using a Stated Preference (SP) ranking survey. Rank-ordered Logit models were used to evaluate the impact on risk perception of five unsafe driving behaviours and to identify differences in drivers' risk perceptions. The five unsafe driving behaviours considered in the analysis were respectively related to whether or not the driver follows the speed limits, the rules of passing another car and the safe distance, whether or not the driver is distracted, and whether or not she/he is driving under optimal personal conditions.

All risky driving behaviours showed a significant potential effect ($p<0.001$) on crash risk perceptions, and model´s results allowed to differentiate more important from less important unsafe driving behaviours based on their weight on perceived crash risk. Additionally, this paper further analyses the potential differences in risk perception of these traffic violations between drivers of different characteristics, such as driving experience, household size, income and gender.

The SP technique could be applied to further analyse differences in perceptions of risky driving behaviours among drivers. Future research should consider the potential effect of driving skill on perceptions of risky driving behaviours.

Keywords: road crashes risk; SP survey; rank-ordered logit model; gender; driving experience; income; number of people in household.

1. - INTRODUCTION

Road safety is an issue of a huge importance across the world. According to data of the World Health Organization, approximately 1.24 million people die on the world´s roads every year, which is estimated to be the 8th main cause of death globally (WHO, 2013).The most frequent causes that lead to traffic crashes are the infrastructure, the environment, the vehicle and human factors (such as excessive speed, driver fatigue and traffic rules violation) (Penden et al., 2004); however, an overwhelmingly proportion of traffic crashes are estimated to be mainly due to the human factor (between 70% and 90%) (Blanco, 2013).

It has been reported the evidence-based hypothesis that driving behaviour is a central human factor that contributes to road crashes (Sabey & Taylor, 1980). Driver behaviour, also known as driving style, refers to the manner in which people choose to drive or driving habits that have developed over time (Elander, West, & French, 1993). For instance, the most frequent traffic violation is speeding, which is related to increased risk of a crash (Delhomme, Verlhiac, & Martha, 2009; Parker, West, Stradling, & Manstead, 1995; West, Elander, & French, 1992).

Similarly, lack of thoroughness in decision making (e.g., making decisions without considering all the implications) has been found to be a driving behaviour associated with crash involvement (Parker et al., 1995; West et al., 1992). Furthermore, several authors have provided grounds for believing that self-reported risky driving behaviours were linked to increased crash involvement for inexperienced drivers (Ivers et al., 2009; Stevenson & Palamara, 2001).

Road users´ risk perception is essential in the process of driving because it affects their driving behaviour and how they perform tasks such as receive and process information coming from the driving environment and act based on her/his judgment on predictions about possible actions (Wang, Hensher, & Ton, 2002). In fact, research has shown that risk perception can be a predictor of unsafe driving behaviour (Glendon, McNally, Jarvis, Chalmers, & Salisbury, 2014; Rhodes & Pivik, 2011).

In the decision making literature, two different concepts of risk perception can be differentiated: risk as feelings and risk as analysis (Kinnear et al., 2013). Risk as feelings, or affect, has been defined by Slovic, Finucane, Peters, & MacGregor (2002) as the specific quality of "goodness" or "badness" experienced as a feeling state, implying or not consciousness; and that is related to a positive or negative quality of a stimulus. According to a thorough literature review conducted by Kinnear et al. (2013), dual-process theories of information processing consider that the analytical processing of risk is developed in the analytical system, whereas affect is processed in a different and underlying system, the experiental system. Within the domain of neurological theory, the Somatic Marker Hypothesis (SMH) embeds the position adopted in the literature that these two systems work in parallel (Kinnear et al., 2013). The SMH considers that the feedback from the experiental system allows for decision speed and accuracy when the completely rational analytic system faces complex decisions, which otherwise would be time consuming and incomplete due to working memory limitations (Kinnear et al., 2013). Additionally, the rational decision-making could process options biased by somatic markers that are caused by prior experience (Kinnear et al., 2013). With this regard, there is reported evidence in the literature that there are dissociations between cognitive risk estimates and psycho-physiological measures of hazard awareness such as skin conductance responses, which supports the hypothesis that risk perceptions are processed by two separate systems (Kinnear et al., 2013).

According to the existing literature, drivers´ risk perception is believed to be a complex phenomenon and the difference between risk as feelings and risk as analysis has not been frequently introduced in a clear manner. Individual risk perceptions are unique, that is, any two individuals will perceive a given risk differently (Dixit, Harrison, & Rutström, 2014; Iragüen & Ortúzar, 2004). Moreover, risk perception of drivers may depend on several factors, such as transportation mode (Noland, 1995), geometric characteristic of the road and traffic (Wang et al., 2002) and if the person travels with another person (Iragüen & Ortúzar, 2004). Additionally, risk perception of individuals in the driving environment may depend on socio-economic characteristics such as gender and age. There are reported evidences that men tend to have a lower level of perceived risk in the driving environment than women (Deery, 1999; Glendon et al., 2014; Iragüen & Ortúzar, 2004; Ivers et al., 2009; Parker, Manstead, Stradling, & Reason, 1992; Rhodes & Pivik, 2011; Wang et al., 2002). Rhodes and Pivik (2011) found evidence that risk perception was a stronger predictor of risky driving for females and adults than for males and young drivers respectively, when compared to positive affect. In regards to the possible effect of age in risk perception, it is commonly acknowledged that young drivers are more likely to underestimate their risk of crash in a variety of traffic situations (Deery, 1999; Rhodes & Pivik, 2011).

Furthermore, risk perception of road users may be biased by their driving skill, which is concerned with performance limitation on aspects of the driving task (Elander et al., 1993). It has been reported in the literature that optimism is associated with risk perceptions of an accident, and this optimism may be due to people's overestimations of the degree of control that they have over events (DeJoy, 1989). Moreover, Dixit et al. (2014) identified risk attitudes, risk perceptions and driving skills of drivers by using a controlled experimental elicitation method, and they reported differences in subjective risk perceptions between higher skilled drivers and lower skilled drivers. They used a driving simulator to induce a driving context on the decision environment in which respondents were presented risky alternatives and made choices over left-hand turns into incoming traffic at an intersection. They found evidence that higher skilled drivers, when compared to lower skilled drivers, showed a higher subjective probability of turning successfully at shorter gaps (space between incoming cars), and lower subjective probability of success at longer gaps. The concept of calibration may allow explaining the subjective judgment bias in the driving environment. According to Horrey, Lesch, Mitsopoulos-Rubens, and Lee (2015), the concept of calibration has been used to discuss whether or not non-realistic evaluations of our own skills and abilities, and simultaneously, good feelings and self-worth and esteem, could lead us to dangerous situations. Horrey et al. (2015) further developed calibration models by making use of momentary demand regulation, information processing, and lens models for information selection and utilization. In this model, the way in which the drivers assess the state of the world is described by a lens model, in which the driver uses information cues to make a subjective estimate of "current performance", or any other environmental criterion such as task demands. Similarly, a second lens model explains the calibration of ability as the degree of correspondence between the driver's perceived abilities and actual abilities.

The ability of a driver to detect dangerous situations (i.e., hazards) on the road ahead is the only skill specific to driving that has been found to correlate with crash risk (Wetton, Hill, & Horswill, 2011). In fact, computer-based hazard perception tests are being created for licensing purposes in countries such as the UK, Australia (Wetton et al., 2011) and Spain (Castro et al., 2014). These hazard perception tests measure driver skill by considering hazard perception as the "situation awareness" of potentially hazardous incidents while driving, which involves not only perceiving the hazard but also understanding the situation and anticipating what will follow (Castro et al., 2014). Although further research on the mechanisms underpinning hazard perception is needed, there is reported evidence that it consists of a cognitive and visual search components (Kinnear et al., 2013). Furthermore, driving skill is expected to improve with practice or training (Elander et al., 1993), which is a hypothesis that has been supported with evidences reported in the literature. For instance, Castro et al. (2014) reported that less experienced drivers showed lower ability to correctly identify hazardous traffic situations.

Differences in risk perceptions in the driving environment have been described in the existing literature, however, the relationship between risky driving behaviour and risk perception is still not clearly understood and more research is needed on this area (Blanco, 2013; Deery, 1999; Glendon et al., 2014; Ivers et al., 2009; Rhodes & Pivik, 2011; Ulleberg & Rundmo, 2003). This paper focuses on drivers' subjective risk perceptions of risky driving behaviours and its objective is twofold. Firstly, the aim of this paper is to further study drivers' subjective risk perceptions of dangerous situations in the driving environment that are characterized by certain unsafe driving behaviours. These unsafe driving behaviours are related to whether the driver follows the speed limits, the rules of passing another car and the safe distance, whether the driver is distracted, and whether or not she/he is driving under optimal personal conditions. Secondly, this work helps to further understand the differences in risk perception of these traffic violations between drivers of different characteristics such as driving experience, household size, income and gender.

In order to further research road users' risk perceptions, this paper conducted a non-experimental study by using the Stated Preference (SP) approach, which has been previously used in road safety. The SP technique can be a useful tool to study risk perception in the driving environment and provides for flexible means to study data that cannot be found as when gathered as revealed preference data (Eboli & Mazzulla, 2008; Iragüen & Ortúzar, 2004; Rizzi & Ortúzar, 2006; Wang et al., 2002).The data were collected through face-to-face interviews that gathered information about risk perception, driving experience and socio-economic characteristics of the 492 drivers who participated in the study. Moreover, in order to understand drivers' behaviour and determine the impact of different behaviours on crash risk perception, a rank-ordered logit model was used to calibrate the collected data. We captured heterogeneity among road users' risk perceptions by working with different categories of drivers defined by gender, income, household size and driving experience in terms of number of years holding a driving licence and kilometres annually driven on average for the last three years. This paper further develops the work of de Oña, de Oña, Eboli, Forciniti, and Mazzulla (2014) by providing evidence that there could be statistically significant effects of socio-economic characteristics and driving experience on perceived risk of unsafe driving behaviours. Furthermore, in a different manner to the existing literature, rank-ordered logit modelling was used to analyze rank data with regards to drivers' crash risk perceptions. Rank-ordered logit modelling considers the nature of rank data in its formulation and can be a superior model to analyze this type of data when compared to other approaches (Calfee, Winston, & Stempski, 2001; Kockelman, Podgorski, Bina, & Gadda, 2012).

We describe the methodology used for data collection and discrete choice models in Sections 2 and 3. Section 4 shows the results of our analysis. A discussion of the results is conducted in Section 5, and, finally, Section 6 summarizes the main conclusions and limitations of this study.

2. -SURVEY INSTRUMENT AND SAMPLE CHARACTERISTICS

The main attractions of the SP approach are that it provides researchers for the ability to control choice context and the independent variables that will enter the model (Ortúzar & Willumsen, 1994). In our case, the SP survey allowed the potential main effects of the perceived risk of unsafe driving behaviours on overall risk perception of a driving situation to be identified in an inter-city, two-way road context. That is, we measured how drivers perceived the risk of crashing in different driving situations that were characterized by different unsafe driving behaviours of the driver. As a result, participants' response provides a detailed measurement of the potential effect of each risky driving behaviour (factor) on crash risk perception. This SP survey consisted of a ranking task of unlabeled alternatives; therefore, respondents were only presented with scenarios in the driving environment that were defined by the driver's behaviour. The SP survey consisted of 5 factors, each varying into two levels: (1) travel speed limits (respecting/violating); (2) safe distance (respecting/violating); (3) rules of passing another car (respecting/violating); (4) driver distraction (attentive/inattentive driver); (5) driver psychophysical state (not optimal/optimal). Four choice sets with four alternatives each were obtained from the equivalent full factorial of thirty-two scenarios (2^5=32) by using a fractional factorial based on orthogonal design. The five behavioural factors included in the SP survey were chosen based on the literature review conducted by the authors of this article and their experience in road safety; a more detailed description of the questionnaire design can be found in Cardamone, Eboli, and Mazzulla (2014).

Therefore, each scenario is a hypothetical driving situation that is characterized by differing types of driving behaviours that follow the five factors that were just described above. Respondents had to rank the four driving situations in a choice set according to their perception of crash risk, considering that rank 1st corresponds to the most dangerous situation and rank 4th the least dangerous. The four unlabeled scenarios in each choice set were called A, B, C or D independently of their characteristics. Table 1 shows one of the choice sets that respondents had to rank; for instance, Scenario A in the choice set describes a driver who respects the speed limits, does not respect the safe distance, does not respect the rules of passing another car, who is attentive and altered (not optimal conditions). Additionally, since the ranking task required considerable time and cognitive effort, respondents were asked to do only two ranking tasks.

(Insert TABLE 1)

Two researchers of the University of Granada collected a pilot survey and the final survey through face-to-face interviews. The pilot survey consisted of 20 respondents and it was conducted in order to test the questionnaire instrument and train the interviewers. Once the survey questionnaire was improved, a total of 492 respondents were interviewed. The interviews took place in different locations throughout the city of Granada, Spain. The survey instrument consisted of three sections. The first section was targeted towards collecting data regarding the socio-economic characteristics of the respondents: age, gender, employment (status, sector and occupational status), income and number of members of the household. Section 2 collected information about the experience of the driver in terms of years with a driving licence and average km driven in the last three years, car crashes caused by the respondent in the last three years and the consequences of the worst crash that she/he ever had. Lastly, Section 3 of the questionnaire contains the SP survey previously described.

A choice context was designed in order to help respondents to similarly understand the type of risk that they were introduced in the SP survey and obtain meaningful results, following the experience of other authors (Carson et al., 1994; Iragüen & Ortúzar, 2004; Wang et al., 2002). As previously discussed, risk perception might be affected by several factors such as geometric and traffic characteristics of the road and whether the respondent travels alone or with someone else. For this reason, prior to the ranking task, a concise descriptive text was presented to respondents, which asked them to assume that they were driving a car without a travel companion on an inter-city, two-way road. The context was designed to encourage the respondent to imagine him/herself in the described situation in order to evoke a mental picture with sufficient detail to give respondents a clear image of the scenario (Parker et al., 1992). Pictures of interurban roads with similar characteristics in the metropolitan area of Granada were used to help respondents understand the exercise and to increase their familiarity with the driving context. Figure 1 shows the graphic resources used to conduct the SP survey. Additionally, respondents had available information describing the attributes of the driving scenarios while doing the ranking task. This information came in the form of glossaries with detailed descriptions of the attributes. Both the context and the choice sets were presented to respondents on laminated sheets that could be handled by the interviewee while she/he was doing the ranking task. Although advance web-based survey design have been proved to allow for interactive questionnaires that limit bias due to questionnaire complexity (Iragüen & Ortúzar, 2004), we decided to conduct a face-to-face data collection in order to overcome other on-line sampling biases such as coverage bias (Cardamone et al., 2014; Duffy, Smith, Terhanian, & Bremer, 2005).

(Insert FIGURE 1)

In order to limit potential fatigue and boredom bias, the SP survey was placed at the beginning of the survey (Carson et al., 1994) after two introductory questions about respondent's frequency of driving (every day, every week, few times per month or never) and after they were asked how many years they had held a driving licence. Additionally, following the work of Cameron, DeShazo, and Stiffler (2010), we decided to ask the respondents for a subjective difficulty evaluation of each ranking task, in order to assess if road users were able to easily perform this task. This question was measured using a 5-point Likert scale from 1- Very easy, to 5- Very difficult.

Granada is a medium-sized city in the Southeaster region of Spain, with a total population of 237,818 inhabitants and a surface area of 88 squared-kilometres, according to data of the Statistics and Cartography Institute of Andalucía in 2013. The population of Granada consists of 46.5% men and 53.5% women according to data from 2013. Furthermore, of the total population approximately 18.8% of people were younger than 20 years old, 62.3% were between 20 and 65 years and 18.9% people were older than 65 years.

In regards to the characteristics of the collected sample (see Table 2), there were more male drivers (62.0%) than female drivers (38.0%). Additionally, most drivers in the sample were 26 to 40 years old (37.6%), while there were less drivers between 41 to 65 years of age (35.4%), 18 to 25 years of age (25.2%) and older than 65 years of age (1.8%). Moreover, most drivers in the sample were employed (57.3%) or students (22.6%). In relation to household size, respondents most frequently lived in a dwelling of 3-4 people (58.1%), and the remaining people lived in a dwelling of 1-2 people (23.8%), or in a dwelling of 5 people or more people (18.1%). The most frequent monthly net family income was between 1,001 and 2,000 euro (32.9%) for sampled people, and there were also respondents who stated they had a monthly family income between 2,001 to 3,000 euro (25.8%), between 3,001 to 4,000 euro (14.6%), over 4,000 euro (9.8%) and up to 1,000 euro (9.5%).

Looking into sample characteristics concerning driving experience, drivers most often held a licence for 8 to 22 years (37.4%). Also in the sample, there were drivers holding a licence between 0 and 7 years (33.5%), and drivers holding an older licence between 23 and 47 years (27.0%) and over 47 years (2.0%). Additionally, most drivers drove up to 10,000 km annually (40.2%) and from 10,001 to 30,000 km annually on average for the last three years (37.6%). Lastly, 13.8% of the respondents had a traffic crash in the last three years while they were driving.

(Insert TABLE 2)

(Insert TABLE 3)

Finally, the average perception of difficulty of each ranking exercise showed that respondents stated more often that their perceived level of difficulty was "3- Neutral" (in a 5-point Likert scale) for all the choice sets (see Table 3). Respondents were presented only two ranking tasks, that is, they had to rank the alternatives of either Choice Set 1 and Choice Set 2 or Choice Set 3 and Choice Set 4. Furthermore, it should be highlighted that respondents tend to consider the first ranking task that they did to be more difficult than the second ranking task. The average value of the subjective difficulty of Choice Set 1 vs. Choice Set 2 and Choice Set 3 vs. Choice Set 4 was 3.00 vs. 2.89 and 3.12 vs. 3.01 respectively.

3. -METHODOLOGY

A dataset recording how each individual ranks each alternative includes much more information than simply knowing which alternative is most preferred within a sample. In fact, this is the main reason why ranking data are used. Several models have been used to analyze ranked data, but the most common is the Rank-Ordered Logit model (ROL model), also known as Exploded Logit model (Kockelman et al., 2012). The ROL modelling approach makes use of the extensive information in ranked responses and respondent characteristics, allowing one to draw more meaningful conclusions than cross-tabulations or other approaches (Kockelman et al., 2012). The ROL model was first applied by Beggs, Cardell, and Hausman (1981) to assess the potential demand for electric cars and it has been subsequently used in fields such as transportation studies (Calfee et al., 2001; Kockelman et al., 2012) and marketing (Ahn, Lee, Lee, & Kim, 2006; Dagsvik & Liu, 2009). The ROL model can be derived from an underlying random utility model, the same random utility model which can be used to justify the standard Multinomial Logit model (Allison & Christakis, 1994). The utility of respondent n for each item j can be expressed as $U_{j,n}$, where j runs from 1 through J, the total number of items. $U_{j,n}$ can be seen as the sum of a systematic component ($V_{j,n}$), and a random term $e_{j,n}$.

$$U_{j,n} = V_{j,n} + e_{j,n} \tag{1}$$

where $V_{j,n}$ refers to the observable component of the utility of individual n from alternative j, which is a function of the measured attributes defining the alternatives, and the $e_{j,n}$ are independently and identically distributed with an extreme-value distribution. It is assumed that the respondent breaks down the task of ranking J alternative products into a sequence of J-1 choices, and he/she selects the product profile associated with maximum utility in each choice occasion (Hess, Shires, & Jopson, 2013). This ranking can be expressed as:

$$U\xi_j^1 \geq U\xi_j^2 \geq \ldots U\xi_j^J \tag{2}$$

where U represents utility, ξ represents the profile of attributes, the number in the superscript indicates the rank, and the subscript j indicates the generic alternative. The deterministic part of the utility may be written as:

$$V_{j,n} = \sum_{h}^{H} \beta_h x_{j,h,n} \tag{3}$$

β_h is a parameter that can be estimated and indicates the effect of attribute h on individual utility. $x_{j,h,n}$ is the attribute h under alternative j observed by respondent n and whose value is known. Finally, the expression of the model can be stated as:

$$\Pr(U_{j^1,n} \geq U_{j^2,n} \geq \ldots \geq U_{j^3,n}) = \prod_{i=0}^{J-1} \frac{\exp(\mathbf{x},_{j,h,n})}{\sum_{j\in(J-i)} \exp(\mathbf{x},_{j,h,n})} \quad (4)$$

where **x** is a row vector (1 x h) of attribute parameters. Therefore, the attributes of the rank exercise will compose this vector **x** of alternative-specific variables. The vector of estimated parameters $\hat{\beta}$ can be derived with the maximum-likelihood method. These estimated parameters represent the effect of the attributes on the utility. In fact, $\hat{\beta}$ can be interpreted as an indicator of the underlying drivers' risk perception and it describes how each attribute affects risk perception, considering everything else constant.

The formulation of this model is possible just by making strong assumptions; one of them is the well-known independence from irrelevant alternatives (IIA) assumption. It is frequent to encounter situations in which the underlying assumptions of the model are less plausible such as the possibility that pseudo-observation of the same individual are not independent of each other and that respondents do not pay the same level of attention to all the steps of the ranking exercise. Attempts to relax this assumption can lead to complications of the computation of the model and difficulty in issues related to identification (Allison & Christakis, 1994). Additionally, some tests of the IIA assumption exist, such as the Hausman test and Small and Hsiao test, however, they often give inconsistent results and are not helpful to determine violations of the IIA assumption (Long & Freese, 2006). Therefore, we consider that it is reasonable to employ the ROL model as an approximation to what may sometimes be a more complex phenomenon (Allison & Christakis, 1994). Furthermore, we replaced standard errors with robust standard errors, which provide with correct standard errors in the presence of violations of the assumptions of the model. In this case, the ROL coefficients are considered to be minimum ignorance estimators since the estimator provide the best possible approximation to the true probability density function (Long & Freese, 2006).

In order to capture some of the heterogeneity that may exist among drivers' perceptions of risk we worked with different categories of drivers. We estimated a ROL model that explicitly included gender, income, household size and driver experience by interacting them with the five alternative-specific variables corresponding to the risky driving behaviours that described the alternatives. The statistical software package STATA 12.1 was used to calibrate the ROL models.

4. -ESTIMATED MODELS

Two ROL models (ROL_1 and ROL_2) were used in estimating the relative bearing of each variable on the perceived crash risk. ROL_1 was calibrated including five dummy variables corresponding to the five risky driving behaviours that described the alternatives presented to respondents in the SP survey. Each of these dummy variables allowed us to model the potential effect on the utility of a discrete change from the safest level of a driving behaviour to the riskiest level of that driving behaviour, considering everything else constant (Long & Freese, 2006). That is, the estimated parameters in the model describe the impact on overall risk perception of crash risk in relation to each risky driving behaviour respectively and considering everything else constant. For instance, we modelled the potential effect of risky driving behaviours in regards to speeding by using the dummy variable *Speed Limits (SL)*, which took the value of 1 if the driver did not respect the speed limits in the driving scenario and took the value of 0 if the driver respected the speed limits. The same applied to the remaining dummy variables: *Safe Distance (SD)* (1-not respect, 0-respect)*; Passing Rules (PR)* (1-not respect, 0-respect)*; Distracted Driver (DD)* (1-inattentive, 0-attentive)*;* and *Personal Conditions While Driving (PC)* (1-not optimum, 0-optimum). These variables modelled the potential effect on the utility of risky driving behaviours in regards to the safe distance, the rules of passing another car, the distraction of the driver and the driver's personal conditions while driving, respectively.

It is possible that the effect of the five risky driving behaviours on perceived crash risk vary with socio-economic characteristics and driver experience. To allow this possibility we estimated ROL_2 that included, in addition to the five variables considered in ROL_1, the interactions of gender, income, household size and driver experience with the five risky driving behaviours. The analysis with interactions seeks to determine interactions with a certain statistical significance within each user characteristic, which may allow us to identify potential divergent drivers' risk perception of the five risky driving behaviours among drivers of different characteristics. After a very exhaustive work carried out via stepwise addition, combination and deletion, only the interaction effects of the variables gender, income, household size and driver experience with the five risky driving behaviours were found to give significant results. Therefore, these are the only categories reported in this paper.

Different groups of drivers within socio-economic and driving experience characteristics were defined and considered in the model. In regards to the variable gender, male drivers were used as the base category and the interactions of *FEMALE* with *SL, SD, PR, DD* and *PC* were included in the model. Three groups of drivers were used based on income: drivers with a monthly net family income up to 1,000 euro (variable *INCOME_≤1k€* in the model), between 1,001 and 2,000 euro (*INCOME_1k€_to_2k€*), and over 2,000 euro. This last class was used as the base category. The interactions of household size with the five risky driving behaviours were estimated considering household size as a continuous variable (*HOUSEHOLD*). Additionally, three groups of drivers holding a licence for differing numbers of years were used: driving licence between 0 to 7 years (*LIC_0_to_7_YRS*), between 8 to 22 years (base category) and over 22 years (*LIC_OVER_22_YRS*). Lastly, the experience of the drivers in terms of annual average of kilometres driven in the last three years was studied by using two groups of drivers: one of drivers who drove up to 10,000 km (*ANNUAL_KM_≤10,000*) and the other of drivers who drove over 10,000 km. The group of more experienced drivers was chosen as the base category. The number of cases of these groups of drivers can be found in Table 4.

(Insert TABLE 4)

Table 5 summarizes the parameters for both models estimated with the whole sample of drivers. *Pseudo-observations* represent the number of observations that resulted from the SP survey conducted for the 492 respondents. ROL_1 model is satisfying, with significant coefficients (at a 0.1% significance level) for all the five explanatory variables, and adequate values of the chi-squared test (*p-value*), which allow us to reject the null hypothesis that all the coefficients associated with independent variables are simultaneously equal to zero. The coefficients of the five dummy variables related to the risky behaviours considered in the SP survey had correct signs (column *Value*), reflecting that a change from the safer level of the behaviour (for example, respect of the speed limits) to the worst level (not respecting the speed limits) results in an increase in the probability of ranking that alternative as riskier, considering everything else constant.

ROL_2 model's results show that the parameters related to the five risky driving behaviours also had correct signs and significant coefficients (at a 0.1% level), once the interactions of socio-economic and driving experience characteristics have been taken into account (Table 5). It is worth noting that ROL_2 results show that driving under not optimum personal conditions (β=1.560), when compared to the other four risky driving behaviours, had the largest effect on the perception of crash risk for the whole sample, followed by distracted driver (β=1.422), not respect of the rules for passing another car (β=1.303), not respect of the speed limits (β=1.293) and not respect of the safe distance (β=0.870).

We found interesting results concerning differences in risk perceptions of drivers. The interactions of variables allowed us to succeed in capturing statistically significant effects of some drivers' characteristics on the weight of risky driving behaviours in crash risk perceptions. Although all interactions of variables above described were part of the formulation of the model ROL_2, for the sake of clarity and brevity, only the interactions of variables with statistically significance ($p<0.05$) or with a certain trend towards statistical significance ($p<0.10$) are shown in Table 5. It can be observed that *Personal Conditions While Driving* (β_{men}=1.560, β_{women}=1.560-0.369) has more weight for men than for women ($p<0.04$). On the other hand, the opposite occurs with the variable *Safe Distance* (β_{men}=0.870, β_{women}=0.870+0.145; $p<0.088$).

In regard to differences between drivers having differing monthly incomes per household, *Personal Conditions* ($\beta_{>2k€}$=1.560, $\beta_{\leq 1k€}$=1.560-0.458, $\beta_{1k\text{-}2k€}$=1.560-0.316) had lower weight for drivers in the sample with a monthly income per household up to 1,000 euro ($p<0.078$) and drivers with 1,001-2,000 euro/month per household ($p<0.066$) than drivers earning more than 2,000 euro/month per household. In addition to *Personal Conditions*, several risky driving behaviours tended to have lower weight for drivers with 1,001-2,000 euro/month per household than drivers earning more than 2,000 euro/month per household, these were *Speed Limits* ($\beta_{>2k€}$=1.293, $\beta_{1k\text{-}2k€}$=1.293-0.343; $p<0.045$), *Safe Distance* ($\beta_{>2k€}$=0.870, $\beta_{1k\text{-}2k€}$=0.870-0.138; $p<0.088$) and *Passing Rules* ($\beta_{>2k€}$=1.303, $\beta_{1k\text{-}2k€}$=1.303-0.139; $p<0.100$).

Looking into differences between drivers having differing household sizes, the interaction of *Passing Rules* and *HOUSEHOLD* (β=-0.093; $p<0.003$) shows that the associated weight of not respecting the rules of passing another car tends to be lower as the number of people in a household increases.

In regards to driving experience in terms of number of years holding a driving licence, it is worth noting that *Passing Rules* ($\beta_{\text{licence 8-22y}}$=1.303, $\beta_{\text{licence 0-7y}}$=1.303-0.289) had less weight for drivers holding a licence between 0 to 7 years than drivers holding a licence from 8 to 22 ($p<0.004$). Additionally, the associated weight of *Speed Limits* ($\beta_{\text{licence 8-22y}}$=1.293, $\beta_{\text{licence over 22y}}$=1.293-0.323; $p<0.081$) and *Distracted Driver* ($\beta_{\text{licence 8-22y}}$=1.422, $\beta_{\text{licence over 22y}}$=1.422-0.386; $p<0.097$) is lower for more experienced drivers (holding a licence over 22 years) than drivers holding a licence between 8 to 22 years. Looking into the effect of driving experience in terms of annual average of kilometres driven in the last three years, we found that *Speed Limits* ($\beta_{>10{,}000\text{ km}}$=1.293, $\beta_{\leq 10{,}000\text{km}}$=1.293+0.342; $p<0.068$) tended to have a lower weight for more experienced drivers (>10,000 km annual average driven in the last three years) than less experienced drivers (≤10,000 km annual average driven in the last three years). It is worth noting that interactions of both driving experience measures (number of years holding a licence and annual average of kilometres driven in the last three years) and *Speed Limits* successfully captured a statistically significant effect of driving experience on the weight of *Speed Limits*, which indicates that the risky behaviour related to not respect of the speed limits tended to have less weight for more experienced drivers.

(Insert TABLE 5)

5. -DISCUSSION

The ranked SP data were interpreted by using Rank-Ordered Logit models calibrated with the 492 drivers in the sample. The results of the models showed positive and significant coefficients at a 0.1% level in regard to the considered five driving behaviours, indicating that the unsafe condition of these factors could increase the perceived level of crash risk. Once the potential effects of socio-economic characteristics and driving experience of drivers were taken into account, we were able to infer from model's results that "driving under not optimum personal conditions" tended to be the risky driving behaviour with the greatest weight in crash risk perception of drivers in the sample, when compared to the other considered four risky driving behaviours. "Distracted driver", "not respect the rules of passing another car" and "not respect the speed limits" were the second, third and fourth risky driving behaviours in order of importance based on their weight in crash risk perceptions. In addition, not respect the safe distance showed the lowest weight in crash risk perception.

Moreover, ROL_2 model's results showed statistically significant support for potential variations across risk perceptions of different groups of drivers. The associated weight of not respecting the safe distance in crash risk perception tended to be greater for women, when compared to men. On the other hand, men showed notably greater weight of driving under not optimal personal conditions in their crash risk perceptions than women. Differences in risk perceptions between female and male drivers have been reported in the existing literature, which generally show that women tend to have higher levels of perceived risk than men (Deery, 1999; Glendon et al., 2014; Iragüen & Ortúzar, 2004; Ivers et al., 2009; Parker et al., 1992; Rhodes & Pivik, 2011; Wang et al., 2002). Our results reported evidences that women and men could differ in their perceived risk of different unsafe driving behaviours and that certain risky driving behaviours could be considered more dangerous by men than by women and vice versa.

ROL_2 model's results showed potential differences in risk perceptions of unsafe driving behaviours between groups of drivers of different monthly net family income. Drivers who had a higher income level (over 2,000 euro/month) showed a notably greater weight of not respecting the speed limits, not respecting the safe distance, not respecting the rules of passing another car and driving under not optimum personal conditions on their perceived crash risk than drivers with monthly net family incomes between 1,001 and 2,000 euro. Drivers with the lowest income level (up to 1,000 euro) also showed a considerably lower weight of driving under not optimum personal conditions on their perceived risk of crash than did drivers with an income level over 2,000 euro/month. Concerning the relationship between income level and perceived risk, several authors have reported a positive effect of income on willingness to pay for reducing crash risk (Iragüen & Ortúzar, 2004). Although our results are not directly comparable, income might similarly increase the relative importance of crash risk due to certain unsafe driving behaviours.

In regards to potential differences in risk perception between drivers who have households of different sizes, results show that the associated weight of not respecting the rules of passing another car in crash risk perception tends to be significantly lower as the number of people in a household increases. Iragüen and Ortúzar (2004) found that people with children younger than 18 showed markedly increased intentions to contribute economically towards reducing the traffic crash rate. Therefore, risk perceptions of drivers with a household of different sizes might be affected by the age distribution of members in the household. Unfortunately, our study did not consider further information about characteristics of the household and thus this result, though interesting, could not be interpreted further.

Moreover, our results show that driving experience could significantly affect risk perceptions of drivers. Less experienced drivers (holding a licence between 0 to 7 years) showed a lower weight of not respecting the rules of passing another car on perceived crash risk, which has been similarly reported in another study concerning younger drivers (Parker et al., 1992). On the other hand, in the case of medium-level experienced drivers (holding a licence between 8 to 22 years), "not respecting the speed limits" and "distracted driver" tended to show a considerable higher weight on perceived crash risk than in the case of more experienced drivers (holding a licence over 22 years). Lastly, driving experience potential effect on risk perceptions was analyzed in terms of annual average km driven in the last three years. Similarly, results show that less experienced drivers (up to 10,000 annual avg. km) could consider not respecting the speed limits to be a notably more important risky dangerous behaviour than did drivers with more experience (over 10,000 avg. km). These results might indicate that drivers of increased experience tend to consider certain risky driving behaviours such as "not respecting the speed limits" and "distracted driver" to be less dangerous.

6. -CONCLUSIONS

The stated preference approach and the analysis with logistic regression models conducted in an non-experimental study allowed us to measure risk perceptions of unsafe driving behaviours by estimating the potential effect of behavioural factors on perceived crash risk. This is especially important because other types of data such as traffic crashes statistics are relatively scarce and this technique provides researchers with information that could not be obtained otherwise (Wang et al., 2002). Furthermore, the response scale approach to measure risk perceptions, in which respondents rate several items as a measure of overall risk perception, has been questioned. Additionally, reported risk perceptions may be context dependent. Therefore, response scales may not be sensitive enough to determine stronger associations between risk perceptions and other factors such as crash risk or risky driving behaviours (Ivers et al., 2009).

In our case, the SP approach allowed us to identify in detail the potential effect of risky driving behaviours on crash risk perceptions in a inter-city, two-way road context and to describe potential differences in these risk perceptions between drivers having different gender, income, household size and driving experience. This paper provides evidences that the SP technique, which has been previously used to measure risk perception of drivers in the road environment (Eboli & Mazzulla, 2008; Iragüen & Ortúzar, 2004; Rizzi & Ortúzar, 2006; Wang et al., 2002), can be also applied to further analyzing differences in risk perceptions of risky driving behaviours among drivers. Therefore, the main practical application of this paper is an alternative measure of subjective risk perception, which is more detailed than response scale data and considers that risk perceptions are context dependent.

As a limitation of this study, it is worth noting that driving skill may affect risk perceptions of road users (Dixit et al., 2014) and this factor was not directly considered in our analysis. We could incorrectly consider that driving skill, which is expected to improve with practice or training (Elander et al., 1993), is somehow measured indirectly with the variables used to describe driving experience (number of years holding a licence and average annual km driven in the last three years) and assume that more experienced drivers also tend to be higher skilled as it has been reported in the existing literature (Castro et al., 2014; Wetton et al., 2011). However, we encourage future research to take into account the potential effect of driving skill on risk perceptions of unsafe driving behaviours by using alternative measures such as scores of hazard perception tests, which have been successfully used to measure driving skills (Castro et al., 2014; Wetton et al., 2011). In a similar manner, risky driving behaviours may have an effect on drivers decision making, since they could provide drivers with feedback that is processed in the experiental system (Kinnear et al., 2013), and affect "current performance" (or state of the world) and how drivers perceive their actual abilities (Horrey et al., 2015). Therefore, future research should aim to find associations between subjective perceptions of risky driving behaviours and reported risky driving behaviours or crash risk by using the SP approach to measure risk perceptions of risky driving behaviours.

Furthermore, the difficulty and length of the survey could lead to response bias. Therefore, face-to-face interviews were considered as the most appropriate data collection method to increase the probability of collecting reliable responses, and to avoid coverage bias of web-based surveys. Additionally, warming-up questions, detailed descriptive texts and glossaries, graphic resources and a subjective difficulty evaluation of each ranking task were included in the SP survey in order to limit and evaluate potential boredom and fatigue bias (Cameron et al., 2010; Carson et al., 1994; Ortuzar & Willumsen, 1994). Since respondents are required a considerable cognitive effort while doing the SP survey, special attention should be paid to these potential bias while designing future SP surveys to measure subjective risk perceptions of unsafe driving behaviours in order to ensure the reliability of the SP data.

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FIGURE 1. Example of graphic resources used to help respondents to understand the SP experiment.

TABLE 1. Choice set of the stated preference experiment.

Scenario	Speed limits	Safe distance	Rules of passing another car	Driver's distraction	Personal Conditions
A	Respect	Not Respect	Not Respect	Attentive	Not Optimum
B	Not Respect	Not Respect	Respect	Inattentive	Optimum
C	Respect	Respect	Respect	Attentive	Not Optimum
D	Not Respect	Respect	Not Respect	Inattentive	Optimum

TABLE 2. Sample Characteristics

Part	Variable		Cases	Percent
PART 1. SOCIO-ECONOMIC CHARACTERISTICS	Gender	Female	187	38.01%
		Male	305	**61.99%**
	Age	From 18 to 25 years	124	25.20%
		From 26 to 40 years	185	**37.60%**
		From 41 to 65 years	174	35.37%
		Over 65 years	9	1.83%
	Occupational status	Employed	282	**57.32%**
		Unemployed	61	12.40%
		Student	111	22.56%
		Other	38	7.72%
	Qualification	No Studies	8	1.63%
		Diploma of secondary	63	12.80%
		Diploma of high school	127	25.81%
		Diploma of job training	66	13.41%
		Degree	176	**35.77%**
		Postgraduate (Master or	52	10.57%
	Household size	1-2 people	117	23.78%
		3-4 people	286	**58.13%**
		5 people or more	89	18.09%
	Net family income level	Up to 1.000 euro	47	9.55%
		From 1.001 to 2.000 euro	**162**	**32.93%**
		From 2.001 to 3.000 euro	127	25.81%
		From 3.001 to 4.000 euro	72	14.63%
		Over 4.000 euro	48	9.76%
		Non response	36	7.32%
PART 2. DRIVING EXPERIENCE	How many years do you have your driving licence?	From 0 to 7	165	33.54%
		From 8 to 22	184	**37.40%**
		From 23 to 47	133	27.03%
		Over 47 years	10	2.03%
	How many annual km did you cover on average in the last three years?	Up to 10.000	198	**40.24%**
		From 10.001 to 30.000	185	37.60%
		From 30.001 to 50.000	56	11.38%
		Over 50.000	52	10.57%
		Non response	1	0.20%
	Did you have any traffic accidents in the last three years while you were	Yes	68	13.82%
		No	424	**86.18%**
	The most dangerous accident have had:	No damage (No accident)	329	**66.87%**
		Only material damages	125	25.41%
		Injures	37	7.52%
		Dead persons	1	0.20%

TABLE 3. Subjective difficulty of the ranking tasks (experiments). Means, frequencies and percentages.

	Avg.	Non Resp.	1. Very Easy	2. Easy	3. Neutral	4. Difficult	5. Very Difficult
How difficult was the previous ranking exercise?							
Experiment 1	3.00	24	0.40% (1)	22.00% (55)	**47.60% (119)**	17.60% (44)	2.80% (7)
Experiment 2	2.89	24	1.60% (4)	26.00 (65)	**44.40% (111)**	17.20% (43)	1.20% (3)
Experiment 3	3.12	24	0.83% (2)	19.09% (46)	**43.57% (105)**	21.99% (53)	4.56% (11)
Experiment 4	3.01	26	1.24% (3)	23.55% (57)	**42.15% (102)**	18.18% (44)	4.13% (10)

TABLE 4. Categories of drivers within socio-economic characteristics and driving experience.

Variable		Cases	Percent
Gender	Female	187	38.01%
	Male	305	**61.99%**
Net family income level	Up to 1.000 euro	47	9.55%
	From 1.001 to 2.000 euro	162	32.93%
	Over 2.000 euro	247	**50.20%**
	Non response	36	7.32%
How many years do you have your driving licence?	From 0 to 7	165	33.54%
	From 8 to 22	184	**37.40%**
	Over 22 years	143	29.07%
How many annual km did you cover on average in the last three years?	Up to 10.000	198	40.24%
	Over 10.000	108	**59.55%**
	Non response	1	0.20%

TABLE 5. ROL models calibrated with the whole sample of drivers. Estimated parameters that model the effects of risky driving behaviours on crash risk perceptions and interactions of socio-economic characteristics, driving experience and risky driving behaviours.

	ROL_1				ROL_2			
Explanatory Variables	**Value**		**RSE**	**p-value**	**Value**		**RSE**	**p-value**
SL	0.800	***	0.073	0.000	1.293	***	0.267	0.000
SD	0.712	***	0.037	0.000	0.870	***	0.132	0.000
PR	0.762	***	0.039	0.000	1.303	***	0.143	0.000
DD	0.850	***	0.087	0.000	1.422	***	0.338	0.000
PC	0.872	***	0.078	0.000	1.560	***	0.306	0.000
SD x FEMALE					0.145		0.085	0.088
PC x FEMALE					-0.369	*	0.180	0.040
PC x INCOME_≤1k€					-0.458		0.260	0.078
SL x INCOME_1k€ _to_2k€					-0.343	*	0.171	0.045
SD x INCOME_1k€ _to_2k€					-0.138		0.081	0.088
PR x INCOME_1k€ _to_2k€					-0.139		0.084	0.100
PC x INCOME_1k€ _to_2k€					-0.316		0.172	0.066
PR x HOUSEHOLD					-0.093	**	0.031	0.003
PR x LIC_0_to_7_YRS					-0.289	**	0.099	0.004
SL x LIC_OVER_22_YRS					-0.323		0.185	0.081
DD x LIC_OVER_22_YRS					-0.386		0.233	0.097
SL x ANNUAL_KM_≤10,000					0.342		0.187	0.068
chi-squared	6,606.026				6,985.532			
p-value (chi-squared)	0.000				0.000			
log-likelihood	-2,693.939				-2,659.274			
Pseudo-observations	3,932				3,932			

*Note: RSE. Robust Standard Error; *(p<0.05), **(p<0.01), ***(p<0.001)*