dECON
Facultad de Ciencias Sociales
UNIVERSIDAD DE LA REPÚBLICA

Documentos de Trabajo

Determinants of urban mobility with a focus on gender: a multilevel analysis in the Metropolitan Area of Montevideo, Uruguay

Cecilia Olivieri (Universidad de la República, Uruguay)
& Xavier Fageda (University of Barcelona)

Documento No. 04/19
Setiembre 2019

ISSN 0797-7484

Determinants of urban mobility with a focus on gender: a multilevel analysis in the Metropolitan Area of Montevideo, Uruguay

Cecilia Olivieri (Universidad de la República, Uruguay)
& Xavier Fageda (University of Barcelona)

Abstract: This study analyzes the determinants of urban mobility in the Metropolitan Area of Montevideo. By applying multilevel regression models, it provides estimates of the impact of individual and contextual factors on travel behavior. The paper's findings lend support to the household responsibility hypothesis, which claims that women's travel patterns are affected by the type of household in which they live and the consequent responsibilities or roles they assume. Furthermore, gender differences in travel patterns are reinforced across census tracts. The results indicate that policy makers need to consider gender differences when seeking to enhance urban planning decisions.

Keywords: Urban mobility, Travel behavior, Built environment, Gender, Household responsibility hypothesis

JEL: R41, R23, O18, J16

Resumen: El presente estudio analiza los determinantes de la movilidad urbana en el Área Metropolitana de Montevideo. Al aplicar modelos de regresión multinivel, proporciona estimaciones del impacto de los factores individuales y contextuales en el comportamiento del viaje. Los hallazgos respaldan la hipótesis de responsabilidad del hogar, que afirma que los patrones de viaje de las mujeres se ven afectados por el tipo de hogar en el que viven y las consecuentes responsabilidades o roles que asumen. Además, las diferencias de género en los patrones de viaje se refuerzan en las áreas de residencia. Los resultados indican que los formuladores de políticas deben tener en cuenta las diferencias de género al tratar de mejorar las decisiones de planificación urbana.

Palabras clave : Movilidad urbana, Patrones de desplazamiento, Entorno construido, Género, Hipótesis de responsabilidad del hogar

1. Introduction

People’s commuting patterns are influenced and limited both by their personal characteristics and factors related to place of residence (Hanson, 1982; Hanson & Johnston, 1985) These elements can operate in different ways depending on gender and the type of household in which the individual lives (Silveira Neto et al., 2015).

In this regard, several studies claim that gender differences in travel behavior arise from differences in the way women and men participate in household- related activities. The household responsibility hypothesis (Johnston-Anumonwo, 1992) relies on the notion that women – owing perhaps to perceptions of values and roles – tend to take greater responsibility for childcare and household chores than men. Furthermore, women have to reconcile these activities with paid work. As space and time are constrained, competing demands for time result in a reduction of women’s mobility (Crane, 2007).

Empirical papers have sought to provide evidence in support of the household responsibility hypothesis by focusing on the time and distance dimensions of travel behavior. While there is a broad consensus that women’s trips are shorter than men’s, explanations as to how the household responsibility operates vary in the literature. Indeed, there is no consensual understanding of the influence of the presence of children (Lee & McDonald, 2003, Gordon et al., 1989, Hanson & Johnston, 1985, Johnston-Anumonwo, 1992) or the marital status and partner’s employment (Johnston-Anumonwo, 1992; Lee & McDonald, 2003; Crane, 2007; Fan, 2017, Silveira Neto et al. , 2015)

The number of daily trips has also been studied as a relevant dimension of travel behavior (Best & Lanzendorf, 2005; Hanson, 1982; Kim & Wang, 2015) on the assumption that it will highlight differences related to typical gender roles and the presence of children in the household. Individuals reporting fewest trips are usually those who make single-purpose daily trips, such as the commute to work. In contrast, a greater number of trips are reported by those who perform other types of activities, such as home and care duties.

Several quantitative studies have identified significant gender differences in car use as well. The more infrequent use of cars and the more frequent use of slower modes of transport by women have been associated with women’s time poverty (Turner & Grieco, 2000) although the increasing availability of licenses and cars have led to a convergence over time. In this regard, findings about gender differences on car use are not conclusive either (Gordon et al., 1989; Best & Lanzendorf, 2005; Crane, 2007; Frändberg & Vilhelmson, 2011; Scheiner & Holz-Rau, 2012)

In the analysis of gender differences in urban mobility patterns, it is important to take into account that the attributes of the built environment are recognized as being a major contributor to household activity-travel decisions (see Ewing and Cervero, 2010 for an in-depth review).[1] The built environment can be described in terms of various dimensions: density, diversity, design and destination accessibility (eg; Cervero, 2013; Sun et al., 2017; Kim & Wang, 2015; Zahabi et al., 2015). While it is generally recognized the importance of the contextual environment, very few studies consider the interactions between individual and neighborhood factors. A number of more recent analyses, however, show the effectiveness of incorporating multi-level models so as to control for level interactions (Bottai et al., 2006; Silveira Neto et al., 2007; Mercado & Paez; 2009; Antipova et al., 2011; Ding et al., 2014; Ding et al., 2017; Sun et al., 2017)

This paper seeks to illustrate the factors that influence travel patterns in the Metropolitan Area of Montevideo, with a specific focus on social gender roles and relations. Accounting for the interactions between the individual and their zone of residence, it specifically analyzes whether there are differences between male and female travel patterns that can be linked to the household responsibility hypothesis. Our results show the importance of family structure in accounting for gender differences in commuting patterns. Specifically, the interaction between the presence of a partner and the presence of children in the household appear to be key factors in accounting for these differences, pointing to the validity of the household responsibility hypothesis.

The methodology we adopt is based on multilevel regression models to provide accurate estimates of both individual and contextual effects on travel behavior. Its adoption allows us to contribute to the extant literature by providing a link between research on commuting gender differentials and research on the impacts of neighborhood environment on travel behavior.

Note also that most studies of urban mobility have been undertaken in developed countries and, so, there is little evidence on this subject for the middle-income economies. This study seeks to fill this gap by conducting a case study of Montevideo, the capital city of Uruguay. Interestingly, while the sociodemographic characteristics of Montevideo are

[1] It is worth stressing that the concepts of the built environment, urban form and neighborhood environment characteristics are used interchangeably in the literature

similar to those of developed countries, its transport infrastructure and the characteristics of its built environment are more similar to those of a city in the developing world.[2]

Furthermore, the study undertakes a joint consideration of the various attributes or dimensions of urban mobility, while most previous studies have focused on just one specific aspect of urban mobility. Third, the study analyzes in detail the interaction between gender, family organization and contextual factors while the previous literature has tended to focus on just one of these aspects in isolation.

The rest of this article is organized as follows: Section 2 describes the study area, it outlines the data sources and the variables included in the analysis; section 3 describes the methodological approach; and, section 4 reports the results. Finally, the last section presents the conclusions and discusses the main empirical findings.

2. Data sources and variable specification

This study focuses on the Metropolitan Area of Montevideo (MAM) which comprises the entire *departmento* of Montevideo and parts of the border *departmentos* of San José and Canelones (see Figure 1).

The main data source is the household mobility survey for the MAM (*Encuesta de movilidad del Área Metropolitana de Montevideo*) carried out in 2016. The purpose of the survey is to record information about all the daily trips made by each individual in every sampled household. Specifically, it inquires about trips (made between 4 a.m. on the previous day and 4 a.m. on the day of the survey, including the trip’s purpose, time, origin and destination) and all the stages making up those trips (including the mode of transport and specific information about each mode). Households were only surveyed when the day of reference (i.e. the previous day) was a working day. No interviews were conducted when the reference days were holidays.

In addition, the survey records information about households (housing conditions, home comforts, vehicle ownership, household composition and income) and the individual

[22] Uruguayan women have on average 10.2 years of schooling and their participation rate is 67%, whereas the Latin American averages are, respectively, 8.7 years and 55% (ECLAC, 2016; World Bank, 2016). Moreover, as the ageing process is more advanced in Uruguay, there is a relatively high incidence of one person households (mostly elderly) as well as couples without children. In contrast, average annual investment in the road subsector in Latin America was 0.7% in 2008-2015, while road investment in Uruguay was just 0.4% of GDP (OECD, 2016). In this same period, dividing annual road investment by a country’s total population yields an average for Latin America of US$ 64 per capita (at 2010 constant prices); in the case of Uruguay, this figure fell below US$ 50 per capita

members (education, employment status and mobility for each household member over the age of three). The survey includes 307 census tracts in Montevideo, 201 in Canelones and 27 in San José, making a total of 535 census tracts for the MAM. The overall sample comprises 2,230 households and 5,946 individuals of whom only 4,255 reported trips. Some observations were eliminated in order to ensure that every census tract incorporated had at least 5 individuals. Thus, the final sample includes 2,943 observations. The spatial distribution of the sample is shown in Figure 2.

Secondary sources of data used included the 2011 National Census and the Montevideo Municipality Open Data catalogue, which provide information about population density, aggregate educational attainment, number of bus stops and land use categories for calculating a land use mixture index, all of them referenced by census tract.

The last national census, conducted in 2011, recorded a total population of 3.3 million people, of whom around 1.9 million resided in the MAM, with 1.3 million residents in the capital. Within the MAM, the areas with the highest population density are those near the center of the capital city and that extend out along the coastline (see Figure 2). The financial center, the most important government offices and the higher education institutions are located primarily in and around the city center. Exceptions include some large commercial areas, free zones and technology parks of recent development, which are located in the periphery. This could have served to relocate high value-added jobs that were previously located in the city center.

The MAM public transport network is based primarily on bus services, provided by private companies but regulated by the government (about 1 million trips a day in 2016). A key feature of Montevideo's bus network is that the city center acts as a hub with most of the lines converging on that area. There are three railroad lines operated by the state railways administration which connect Montevideo primarily with other regions in the country, but demand is marginal (fewer than 1000 passengers a day in 2016).

On average, each household in the study area has 0.53 automobiles, 0.17 motorcycles and 0.64 bicycles. Of the total trips reported, the participation of the private car is relatively high (32.2% either as a driver or as a passenger) compared to 25.2% of journeys made by bus.

Dependent variables

We focus on four dimensions of trip behavior: 1) *Trip time* is measured as the average overall travel time spent by an individual on trips made with a frequency greater than 1 or 2 days a week; 2) *Trip distance* is measured as an individual's average travel distance (trips made with a frequency greater than 1 or 2 days a week); 3) *Mode choice* is a binomial logit variable (1: automobile; 2: bus, walk, bicycle or combined) and 4) *Trip count* is the sum of the number of trips that are made with a frequency greater than 1 or 2 days a week.

Explanatory variables

Table 1 outlines the explanatory variables used in the analysis, which are nested in two levels: that is, the individual and census tract levels. The individual attributes included in the study are gender, age, income (included in the survey as a socioeconomic index), employment status, purpose of the trip and household type. We attempted to include other characteristics of an individual's economic activity but they were found to distort the model's fit.

As the specific focus of our study is to capture gender differences, we classified households on the basis of the employment status of their members and the presence of children below the age of 15. The "Male breadwinner" category includes households (with or without children) in which only men work; around 25% of individuals live in this type of household. The "Female breadwinner" category includes households in which only women work; around 18.7% of individuals live in this type of household. The "Dual earner" type corresponds to households in which both men and women work. This category is the most frequent, accounting for 36.8% of individuals. Households without workers are classified as "Non-employed" and account for 19.7% of the sample. In line with previous studies, mobility is associated with the working population and it is reflected in the lower mobility of the non-employed households, which present greater differences in their mobility patterns in relation to those of the other categories.

The study includes the following census tract level attributes: population density, the percentage of people educated to *baccalaureate* or degree level, the total number of bus stops and an entropy measure representing the evenness of distribution of several land use types.

3. Methodology

We use multilevel regression models as proposed in geographical research to provide accurate estimates of the effects of individual and contextual factors on travel behavior (eg; Kim & Wang, 2015; Duncan & Jones, 2000; Paez & Scott, 2004; Mercado & Paez, 2009). The primary motive for using multilevel models is to be able to take into account the hierarchical structure of the data, in order to model their spatial heterogeneity.

In this context, we assume that individuals within a zone of residence (census tract) have certain characteristics in common and that these attributes differ from those residents in other zones. Thus the data are nested, that is, individuals (level 1) are grouped into zones (level 2).

In modes of this type the analysis is carried out in stages (Raudenbush & Bryk, 2002; Rabe-Hesketh & Skrondal, 2012). In the first stage, we estimate a null or "empty" model, with no explanatory variables included:

$$Y_{ij} = \beta_{0j} + r_{ij} \tag{1}$$

$$\beta_{0j} = \gamma_{00} + \mu_{0j} \tag{2}$$

where Y_{ij} is the outcome value for individual *i* in zone *j*, β_{0j} the average outcome within zone *j* and r_{ij} the deviation of the outcome of individual *i* from the mean outcome within zone *j*. Equation (2) discriminates the average outcome of the population (γ_{00}) from μ_{0j}, the deviation of the mean outcome of zone *j* from the grand mean across all zones. Combining (1) and (2), we obtain the random effect equation to be estimated:

$$Y_{ij} = \gamma_{00} + \mu_{0j} + r_{ij} \tag{3}$$

$$Var(Y_{ij}) = Var(\mu_{0j} + r_{ij}) = \tau_{00} + \sigma^2 \tag{4}$$

Equation (4) shows that the total variance of Y_{ij} is composed of the variance between zones (τ_{00}) and the variance within a given zone (σ^2).

We then gradually incorporate the different explanatory variables ($\beta_{1j}, \beta_{2j}, \ldots, \beta_{nj}$). In a second stage, we include the level 1 variables and, finally, incorporate the level 2 variables. The models detailed above are known as "random intercept" models because only the intercept has a random component. However, the random variations between the different zones can also be found on the slope, giving rise to "random slope" models.

Several indicators can be employed to evaluate and compare multilevel models. The most widely used is the intraclass correlation coefficient (ICC) which determines the proportion of the total variability that is attributable to differences between zones: $\rho = \tau_{00}/(\tau_{00} + \sigma^2)$. A comparison of the models' ICC enables us to assess whether the addition of variables accounts for the zone variation. This is commonly expressed as a percentage and only applies to random intercept models.

The likelihood-ratio test compares the log-likelihoods of two models, one contained in the other: $L = 2(l_1 - l_0)$. In our framework, the conventional regression model is a reduced form of the multilevel model (when the random components are removed); thus, we test the hypothesis that the variables that appear in just one of the models are jointly statistically equal to zero. Specifically, to select the best models we estimate multilevel models and test for significance relative to their respective multiple regression models.

4. Results

In this section we present the outcomes of our application of multilevel models to the analysis of urban mobility in the metropolitan area of Montevideo. As outlined above, urban mobility is considered as comprising the following four dimensions: trip time, trip count, trip distance and mode choice. In addition, the determinants are considered at two levels: the individual (level-1) and the geographical (census tract) (level-2). The tables below show the estimated coefficients for the three specifications (the Null model, Model 1, and Model 2) of each dependent variable. All the specifications include a random intercept across census tracts. To compare the models, we present the intraclass correlation coefficient and the likelihood-ratio test results. For the goodness of fit, we present the typical statistics (AIC and BIC).

4.1. Multilevel regression analysis for trip time

Table 2 shows the estimated results of the multilevel regression analysis for trip time. Each model was estimated using the maximum likelihood method fitted with the *xtmixed* Stata command. The first specification is the Null model in which no explanatory variables are included. In Model 1 we add the individual-level variables and in Model 2 the contextual variables described above. We also include an alternative specification for Model 2 (*Model 2b*) that incorporates the variable *Mode of transport*.

On average, we estimate that daily travel time is about 30 minutes (see Null model). The variance component corresponding to the random intercept is 68.44, while the variance between census tracts is 629.31. The ICC for the Null model indicates that 9.81% of the variance is attributable to the geographical level.

The estimation results of Model 1 indicate that, on average, commuting time is differentiated by gender. The variable *Female* is positive and significant, which means that women's travel times are longer than men's, given the same individual characteristics. This outcome, however, is not supported by the literature reviewed herein. For that reason, we opted to estimate the alternative model (Model 2b), which includes mode of transport as a control variable. The intuition behind this outcome is that regardless of the distance, men and wealthier residents tend to travel by faster means of transport. Indeed, in Model 2b the variable *Female* loses its significance, reflecting the differentiated use of transport modes according to an individual's gender (we return to this question in greater detail below).

The model's specification also incorporates eight dummy variables that distinguish four types of family organization, each broken down between "with children" and "without children" categories. Table 2 reports the estimated coefficients of *Household type* corresponding to the "Dual earner without children" category. It can be seen that, on average, households with children present shorter travel times. A comparison of the four main types of family organization shows that the presence of children reduces the travel time in all categories (see the expected difference in Table A1 of the Annex). However, the effect is stronger for dual earner types; moreover, they maintain their significant effect when controlling for the mode of transport in Model 2b.

Households with children are particularly relevant for understanding gender inequalities in mobility patterns. To refine our analysis, we examine the interaction between the variables *Female* and *Household type*. A comparison of the four main household categories shows that the presence of children significantly reduces women's travel time in all household types, with the exception of the non-employed. The changes in men's trip times are not significant (see Table A2 in the Annex). This pattern is considered as being evidence in support of the household responsibility hypothesis (Fan, 2017; Lee & McDonald, 2003; Silveira Neto et al., 2015) and may indicate that women in such households take on additional family responsibilities that foster relocation strategies that seek a greater proximity between work and home.

Figure 3 shows the expected gender difference (contrast of prediction if *Female* equals 1 minus prediction if *Female* equals 0) in trip time by household type. The white bar shows the Model 1 estimation, the light gray bar the Model 2 estimation, and the dark gray bar the Model 2b estimation; in all three, a straight line indicates the 95% confidence interval of the estimation. This information is also presented in table format in the Annex (Table A3).

Figure 3 shows that only the male breadwinner with children type presents a negative and significant difference in travel time. In other words, women's trip times are shorter than male's when they live in households with children and in which only men work. Male breadwinner types are represented primarily by the traditional family of a working man and a woman who does not go out to work (82%), which contrasts with the female breadwinner types composed primarily by single mothers (55%). This distribution of household types is evidence of the continuing existence of traditional gender roles in Uruguayan society.

In contrast, dual earner without children households present a positive and significant difference in travel time. This result can be attributed to the use of different transport modes by women and men from the same household (women traveling on public transport and men in their own vehicles). Unlike the previous models, Model 2b shows that women make significantly shorter trips in the "Dual earner with children" category, in line with the household responsibility hypothesis (see Figure 3).

According to the Model 2 estimates, of the contextual factors only *Transportation accessibility* cannot explain the significant zone-level variation. In general, most of the areas with high population density and high land-use diversity are close to jobs, shopping centers and educational establishments, which cuts trip times. Thus, women's options in terms of access to public transport are likely to be poorer when they live away from the city center; this aspect of social inequality leaves them especially vulnerable. Moreover, the educational attainment of residents in an area is highly correlated with their socioeconomic status. The negative coefficient presented by the variable *Baccalaureate or degree level* is not in line with the literature, since in general the richest people make longer commutes from residential areas to the city center. However, the results do reflect the polycentric urban-territorial structure described above. In this same region, Silveira Neto et al. (2015) evidence the same pattern for Brazilian cities, in this case due to centralization of income.

As mentioned above, when we control for mode of transport (Model 2b), our time differences are smoothed because public transport tends to be much slower. Indeed, some level-1 variables lose their significance, which reflects the differentiated use of transport modes according to certain attributes of individuals. In particular, the variables *Female* and *Full time* and the category "Study" present these changes. The zone-related variables reinforce the above results, with the novelty of *Transport accessibility* which presents a negative and significant sign as expected. Once we control for the means of transport, the greater availability of public transport reduces travel time.

4.2. Multilevel regression analysis for trip distance

Table 3 shows that the average daily distance traveled in the MAM is about 7,130 meters (see Null model). The high ICC (15.18%) and the statistically significant variance suggest that the variation in travel distance can be explained by both individual and neighborhood attributes.

In the estimations, the variable *Female* presents a negative and significant sign. Thus, in line with previous research and unlike trip time, women on average travel less distance than men.

Table 3 reports the estimated coefficients of *Household type* relative to the "Dual earner without children" category. As expected, households with children travel shorter distances on average. However, while the point estimates point to these shorter distances, the presence of children only significantly reduces travel distance in the female breadwinner category (see expected difference in Table A4 of the Annex). Given that the presence of children significantly reduces travel times in all household types but does not reduce travel distance, it could be argued that the strategy of households is based, at least in part, on a shift towards faster means of transport. The exceptions here are the dual earner and female breadwinner households.

If we examine gender roles in each category (that is, by analyzing the interaction between the *Female* and *Household type* variables), it can be seen that in the presence of children, the women in female breadwinner households reduce their trip distance while men in male breadwinner households increase this distance. As the household responsibility hypothesis argues, in households with children, the gender difference in trip distance is sensitive to spouse/partner presence. In households where the woman does not work, the presence of children increases the distance travelled by the man. In contrast, in households with a single female breadwinner, the presence of children leads to a relocation of the residence or workplace towards zones of greater proximity to that household's daily activities (see Table A5 of the Annex).

Figure 4 shows the expected gender difference (contrast of prediction if *Female* equals 1 minus prediction if *Female* equals 0) in trip distance by household type. The figure shows that women travel shorter distances in the male breadwinner with children and dual earner with children households (this information is also presented in table format in the Annex, Table A6). This evidence reinforces the argument presented above that females in dual earner with children households seem to prefer working nearer to home or opt for part-time jobs.

In the case of the level-1 control variables, socioeconomic status, job type and trip purpose are significant factors in explaining travel distance on weekdays. The signs of these impacts, moreover, are as expected.

At the zone level, transport accessibility and population density both seem to impact on the distance travelled by MAM residents (see Model 2). The level-2 results show that individuals residing in the most densely populated zones, with the greatest public transport accessibility and land-use diversity, travel shorter distances. This evidence is consistent with findings in the literature related to travel distance (eg; Kim & Wang, 2015).

Here again, the evidence presented in this section suggests that more densely populated areas with greater accessibility to public transport and greater diversity of land use are associated with shorter trips. Therefore, women's options in terms of access to public transport are likely to be poorer in less central areas, making them especially vulnerable to this aspect of social inequity. Similarly, it is more likely that female breadwinner with children and dual earner with children households are located in more densely populated areas, while male breadwinner with children households are more likely to be located in less central areas, where women's travel distances are shorter and men's are longer.

We conducted an additional estimate including the variable *Mode of transport* but the results did not change substantially and so opted not to include them here.

4.3. Multilevel regression analysis for trip count

We assume that the number of trips can be explained by both family structure and gender roles. In general, trips made on weekdays are not solely single-purpose (for example, trips just to undertake household-related activities) but are likely to be multiple-purpose (for example, work, school run, or shopping). Given that household-related activities are mainly the preserve of women, the latter can be expected to complete more multiple-purpose trips. As Table 4 shows, the average number of daily trips made by MAM residents is about 2.71. The inter-individual variation is about 0.18, while the inter-zone variation is about 1.74, with an ICC of 9.48%.

According to our estimations, the variable *Female* presents a negative coefficient which means fewer trips, on average, for women. This outcome runs contrary to expectations but is in line with findings published elsewhere, including Bottai et al. (2006). However, if we consider the purpose of the trips made – in particular, those to complete household-related activities – then we can see that they are associated with a greater number of trips than the daily commute to work. Indeed, trips associated with household-related activities are important in explaining the trip count. Moreover, as expected, the presence of children is related to a significant increase in the number of trips made in the "Male breadwinner", "Dual earner" and "Non-employed" categories (see Table A6 in the Annex).

As for gender roles within each household category, the presence of children is significant in explaining the greater number of trips made by women in all household types. In the case of men, we document a significant increase in the number of trips in the dual earner and non-employed households. Our evidence suggests that in traditional family units only the mobility of women increases in the presence of children, albeit with a reduction in travel time. In contrast, in male breadwinner households the travel distance of men increases but not the number of trips.

Figure 5 shows the differences (contrast of prediction if *Female* equals 1 minus prediction if *Female* equals 0) in trip count between women and men by household type. Trip frequency is significantly higher for women only in male breadwinner households with children. In contrast, in male breadwinner households without children and in dual earner and non-employed households with children the number of trips is significantly lower for females. This result reinforces our previous findings: that is, women are more likely to present a lower frequency of mobility with the exception of those residents in "Male breadwinner with children" households. This higher number of trips can probably be attributed to their specific purposes, i.e. an association with activities of care and/or domestic chores.

Model 2 includes the zone-related variables. As shown in Table 5, transport accessibility and population density are associated with a greater frequency of trips, though the impact is very small. As expected, the most densely populated residential areas with better supplies of public transport enable residents to access a greater diversity of services and activities, which may be associated with a greater number of trips.

The inclusion of the variable "Mode of transport" supports, in the main, the Model outcomes and, so, these results are not reported here.

4.4. Multilevel regression analysis for mode choice

The probability of an individual traveling by car (*Mode choice* equals 1 when automobile and 0 if other means of transport) is estimated using a binomial logit multilevel model fitted with the *melogit* Stata command. In non-linear multivariate models, such as logit, the impact of the independent variables can be analyzed using alternative measures. We display the estimated coefficients, whose signs allow us to analyze the positive or negative association with the individual's car use, that is, it shows the direction of the change but not its size. In addition, we examine the marginal effects, which show the effect on the probability of traveling by car when changing exogenous variables. Finally, we perform the likelihood-ratio test to compare each model using ordinary logistic regression, and find high statistical significance in all cases.

Table 5 reports the fixed effects estimated coefficients and the estimated variance components of the binomial logit multilevel models. According to our results, the estimated intercept of the Null model is -1.107, indicating that the average probability of travelling by car is about 24.8%. The ICC, which denotes how much of the total variation in the probability of choosing a car is accounted for by the zone of residence, is quite large, almost 20%. When controlling for the level-1 variables (Model 1), women are 24.5% less likely, on average, than men to travel by car.

Household types also play an important role in determining the individual's mode choice. Controlling for all other variables, the "Male breadwinner with children", "Dual earner with children" and "Female breadwinner with children" households are more likely to use an automobile than their counterparts without children, a finding that is in line with the literature. In the case of "Non-employed with children", the expected difference is not statistically significant, but as discussed above these households present a number of atypical characteristics in relation to the other categories (see Table A10 in the Annex).

When we interact the household type with gender, no differences are found in the behavior of males and females. The presence of children suggests that both women and men are more likely to travel by car, with the exception of non-employed households (see Table A11 in the Annex).

As for gender differences by household type, women present a significantly lower probability of travelling by car in "Dual earner" and "Female breadwinner" households with and without children and in "Non-employed" households without children (see Figure 6 and Table A12 in the Annex).

As Table 7 shows, the likelihood of using a private vehicle increases with age. Moreover, and as expected, the probability of traveling by car is significantly and positively related to socioeconomic status. To illustrate this, Figure A1 (Annex) displays the predicted probabilities of choosing to travel by car by household type and gender and for selected values of the income variable. It is worth noting that in all types of household, the predicted gender difference in the probability of travelling by car increases in medium-high positions of the income distribution (see Figure A2 in the Annex).

In model 2, in which we include the contextual variables, only the estimated coefficient of the *Population density* variable is statistically significant, indicating that an individual's mode choice is not so strongly influenced by the attributes of their zone of residence. This result is in line with previous studies; in general, the need of those living in the most densely populated areas to use a car is not so great because of the greater service supply within the same neighborhood.

5. Discussion and concluding remarks

In this paper, we have taken a multilevel approach to examine the determinants of commuting patterns in the Metropolitan Area of Montevideo, with a specific focus on social gender roles and relations. The methodology allows us to contribute to the previous literature by providing a link between research on commuting gender differentials and studies examining the impact of the neighborhood environment on travel behavior.

This study has tested the household responsibility hypothesis by seeking to identify interactions between an individual's attributes and the contextual factors of their zone of residence, links that have previously gone unexplored. We have considered four aspects of trip behavior: namely, trip time, distance, and frequency and the choice of transport mode, while the travel data we employ are stratified in two levels: that of the individual and that of the zone of residence (census tract).

Overall, we present evidence pointing to the existence of differences in the commuting patterns of males and females resident in the MAM. On average, women travel shorter distances and make fewer trips. Travel time does not differ significantly between genders, because women tend to use slower means of transport, as demonstrated by their less frequent use of cars.

Women's lower mobility may be associated, among other factors, with the unequal internal distribution of domestic chores within households (corresponding to the household responsibility hypothesis). Women, who traditionally spend more time undertaking domestic work than do men (owing perhaps to perceptions of values and roles), have to reconcile these activities with paid work. Given the limited number of hours in each day, women are obliged to adopt a strategy: either they choose to live close to their workplace or, in cases where the residential choice is made jointly with other members of the household, they choose to work closer to home. In either case, however, the outcome is the same: women's mobility is not as great as men's.

Households with children are particularly important for understanding gender inequalities related to mobility patterns. The results show that women in all types of household with children tend to have shorter commute times than those of their counterparts in households without children. In the case of women in female breadwinner households, this shorter commute is apparent both in terms of time and distance. Similarly, the presence of children increases the frequency of trips for women in all households, while the probability of travelling by car increases with the presence of children in all household types and for both genders. Meanwhile, men present higher travel distances in male breadwinner households with children and a higher frequency of trips in dual earner households with children.

Besides the presence of children, the presence of a spouse/partner in the household also has an effect on mobility patterns. Our findings indicate that the behavior of women in dual earner households is similar to that of women in male breadwinner households, regardless of the fact that in the former they participate in the labor market. In couple households, the presence of children has a marked effect on the mobility of women, who tend to reduce their travel time by incorporating faster means of transport (increased car use), increase the number of trips by assuming a greater number of tasks associated with care, while maintaining their total travel distance (probably reflecting the net effect of a decrease in distance associated with the relocation of their workplace, compensated by an increase in distance due to their taking on more domestic chores and activities related to care).

In contrast, in couple households where only men participate in the labor market, their travel distance increases in the presence of children. However, this increase in distance is not accompanied by an increase in trip time or frequency of travel. Thus, it seems that men in households of this type fail to assume part of the responsibilities of childcare and, moreover, they extend the time they spend outside the home. In the case of men in dual earner households, the significant increase in the frequency of their trips, together with a greater probability of travelling by car, may be indicative of their undertaking some childcare activities.

In households where the presence of couples is lower and women undertake paid work (i.e. female breadwinner type), the relocation strategy of daily activities takes on considerable relevance insofar as trip and total travel time both fall. This behavior occurs despite the greater use of faster means of transport and an increase in trip frequency.

In the case of expected gender differences within each household type, our results reinforce the above findings: women are less mobile than men above all in couple households with children. We should also stress that the probability of travelling by car is significantly lower for females (in dual earner and female breadwinner households). Here, there would appear to be broader cultural and environmental factors that lie outside the scope of enquiry of the present study that might help explain this pattern.

As for the specific zone of residence, most of the contextual variables provide a significant explanation of the variation between census tracts. In the case of the trip time and distance variables, our findings suggest that residing in the most densely populated zones, with the greatest degree of public transport accessibility and land-use diversity, is associated with shorter trip distances and time. Transport accessibility and population density variables are associated with a greater frequency of trips, though the impact is very small. As expected, the most densely populated residential areas with the best supply of public transport enjoy better access to a wider diversity of services and activities, which may be associated with a greater number of trips.

In the final regression, only the estimated coefficient of the *Population density* variable is statistically significant, indicating that the individual's mode choice is less influenced by the attributes of the zone of residence. However, most areas of high population density have a weakened need to use automobiles due to a greater supply of services in the same neighborhood.

According to our results, women's options in terms of access to public transport are likely to be poorer in less centrally located areas of residence, an aspect of social inequality to which they are especially vulnerable. Overall, our evidence suggests that women make more intensive use of public transport; thus, in residential areas with less access to public transport, women's mobility in particular will be affected. This finding has obvious implications for public policy, given that the promotion of public transport in less central areas could help reduce the negative consequences of gender inequality.

In short, this study demonstrates the presence of multiple gender differences (conditioned by the type of family organization) that should be taken into account in policies aimed at improving urban mobility. A possible limitation of the study is the

References

Antipova, A., Wang, F. & Wilmot, C. (2011). Urban land uses, socio-demographic attributes and commuting: A multilevel modeling approach. *Applied Geography*, 31(3), 1010-1018.

Best, H., & Lanzendorf, M. (2005). Division of labour and gender differences in metropolitan car use: an empirical study in Cologne, Germany. *Journal of Transport Geography*, 13(2), 109-121.

Bottai, M., Salvati, N. & Orsini, N. (2006). Multilevel models for analyzing people's daily movement behavior. *Journal of Geographical Systems*, 8(1), 97-108.

Cervero, R. (2013). Linking urban transport and land use in developing countries . *Journal of Transport and Land Use*, 6(1), 7-24.

Crane, R. (2007). Is there a quiet revolution in women's travel? Revisiting the gender gap in commuting. *Journal of the American Planning Association*, 73: 298–316.

Ding, C., Lin, Y. & Liu, C. (2014). Exploring the influence of built environment on tour-based commuter mode choice: A cross-classified multilevel modeling approach. *Transportation Research Part D: Transport and Environment*, 32, 230-238.

Ding, C., Mishra, S., Lu, G., Yang, J. & Liu, C. (2017). Influences of built environment characteristics and individual factors on commuting distance: a multilevel mixture hazard modeling approach. *Transportation Research Part D: Transport and Environment*, 51, 314-325.

Duncan, C. & Jones, K. (2000). Using Multilevel Models to Model Heterogeneity: Potential and Pitfalls. *Geographical Analysis*, Vol. 32, No. 4.

ECLAC. (2016). CEPALSTAT Databases. Accessed April,2019.

ECLAC. (2018). CEPALSTAT Databases. Accessed April, 2019.

Ewing, R. & Cervero, R. (2010). Travel and the built environment. *Journal of the American Planning Association*, 76(3), 265-294.

Fan, Y. (2017). Household structure and gender differences in travel time: spouse/partner presence, parenthood, and breadwinner status. *Transportation*, 44(2), 271-291.

Frändberg, L., Vilhelmson, B. (2011). More or less travel: personal mobility trends in the Swedish population focusing gender and cohort. *Journal of Transport Geography* , 19 (6), 1235–1244.

Gordon, P., Kumar, A., & Richardson, H. (1989). Gender differences in metropolitan travel behaviour. *Regional Studies*, 23(6), 499-510.

Hanson, S. (1982). The determinants of daily travel-activity patterns: relative location and sociodemographic factors. *Urban Geography, 3,* 179 - 202.

Hanson, S., & Johnston, I. (1985). Gender differences in work-trip lengths: Explanations and implications. *Urban Geography*, 6(3), 193-219.

Johnston-Anumonwo, I. (1992). The influence of household type on gender differences in work. *The Professional Geographer*, 44(2), 161-169.

Kim, C., & Wang, S. (2015). Empirical examination of neighborhood context of individual travel behaviors. *Applied Geography*, 60, 230-239.

Lee, B., & McDonald, J. (2003). Determinants of commuting time and distance for Seoul residents: The impact of family status on the commuting of women. *Urban Studies*, 40(7), 1283-1302.

Mercado, R. & Páez, A. (2009). Determinants of distance traveled with a focus on the elderly: a multilevel analysis in the Hamilton CMA, Canada . *Journal of Transport Geography*, 17, 65–76.

OECD. (2016). *Development Pathways Multi-dimensional Review of Uruguay Volume 2. In-depth Analysis and Recommendations.* OECD Publishing: ISBN 9264251669, 9789264251663.

Páez, A. & Scott, D.M. (2004). Spatial statistics for urban analysis: A review of techniques with examples. *GeoJournal*, 53–67.

Rabe-Hesketh, S. & Skrondal, A. (2012). *Multilevel and Longitudinal Modeling Using Stata.* (3rd Edition) College Station TX: Stata Press.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods.* (Vol. 1): Sage.

Scheiner, J. & Holz-Rau, C. (2012). Gendered travel mode choice: a focus on car deficient households. *Journal of Transport Geography*, 24, 250-261.

Silveira Neto, R., Duarte, G. & Páez, A. (2015). Gender and commuting time in São Paulo metropolitan region. *Urban Studies, 52(2),* 298-313.

Sun, B., Ermagun, A., & Dan, B. (2017). Built environmental impacts on commuting mode choice and distance: Evidence from Shangha. *Transportation research part D: transport and environment*, 52, 441-453.

Turner, J., & Grieco, M. (2000). Gender and time poverty: the neglected social policy implications of gendered time, transport and travel. *Time & Society*, 9(1), 129-136.

W. B. (2016). World Bank Open Data. "https://data.worldbank.org/" Accessed April, 209.

Zahabi, S., Miranda-Moreno, L., Patterson, Z., & Barla, P. (2015). Spatio-temporal analysis of car distance, greenhouse gases and the effect of built environment: A latent class regression analysis. *Transportation Research Part A: Policy and Practice*, 77, 1-13.

Tables

Table 1. Explanatory variables

Level	Variable name	Description
Individual	Female	1 for female ; 0 for male
	Age	min: 18; max: 99; mean: 43.9
	Income (socioeconomic index)	min: 5; max: 82; mean: 42.2
	Full-time	1 for full-time employee; 0 for part-time employee, unemployed or inactive
	Household type	11 Male breadwinner 12 Male breadwinner with children 21 Female breadwinner 22 Female breadwinner with children 31 Dual earner 32 Dual earner with children 41 None employed 42 None employed with children
	Purpose of the trip	1 Return to home 2 Work 3 Study 4 Household related activities 5 Leisure
Zone	Population density	Population per square kilometer (in hundreds)
	Baccalaureate above percent	Percentage of adults (> 18 years old) who acquire baccalaureate´s or above degrees
	Transportation accessibility	Total number of bus stops
	Land use mixture	Diversity index expressed by entropy (0-100)

Source: Own elaboration

Table 2. Estimated coefficients for Trip time

	Null model	Model 1	Model 2	Model 2b
Fixed effects				
Intercept	29.547***	40.788***	45.138***	36.256***
	(0.63)	(3.8)	(3.86)	(3.37)
Level-1 variables				
Age		-0.078	-0.102	0.056
		(0.16)	(0.16)	(0.13)
Age2		0.000	0.000	0.000
		(0.00)	(0.00)	(0.00)
Income		-1.473***	-0.572	-0.671**
		(0.32)	(0.36)	(0.31)
Female		1.747*	1.779*	-0.924
		(0.97)	(0.96)	(0.80)
Full time		4.123***	4.103***	1.230
		(1.21)	(1.20)	(0.98)
Purpose				
Home return		4.230***	4.369***	1.988**
		(1.13)	(1.12)	(0.91)
Work		#	#	#
Study		8.009***	8.889***	1.544
		(2.53)	(2.52)	(2.05)
HH related activities		-16.471***	-16.615***	-6.881***
		(1.43)	(1.42)	(1.18)
Leisure		-10.598***	-10.334***	-4.521***
		(1.90)	(1.88)	(1.53)
Mode of transport				
Foot (less than 10 blocks)				-11.890***
				(1.18)
Foot/bike/motorbike				-7.476***
				(1.23)
Payed vehicle				14.081***
				(3.38)
Car				#
Bus				26.498***
				(1.04)
Household type				
MaleBreadwinner		-2.747*	-2.437	-1.732
		(1.63)	(1.62)	(1.31)
MaleB_children		-5.657***	-5.096***	-2.481
		(1.93)	(1.92)	(1.56)

Table 2. Estimated coefficients for Trip time (cont)

	Null model	Model 1	Model 2	Model 2b
FemaleBreadwinner		2.52	3.058*	-1.610
		(1.84)	(1.83)	(1.48)
FemaleB_children		-6.530***	-6,065***	-4.601***
		(1.99)	(1.97)	(1.60)
DualEarner		#	#	#
DualE_children		-3.659**	-3.281**	-2.641**
		(1.47)	(1.46)	(1.18)
NoneEmployed		-1.852	-1.459	-0.313
		(2.11)	(2.10)	(1.70)
NoneE_children		-8.379**	-7.416**	-2.524
		(3.39)	(3.37)	(2.73)
Level-2 variables				
Transport_access			0.123	-0.179*
			(0.15)	(0.12)
Baccalaureate _above			-9.939***	-6.653***
			(3.58)	(2.86)
Pop_density			-0.030***	-0.038***
			(0.01)	(0.01)
Land_use mixture			-0.514**	-4.992**
			(2.82)	(2.24)
Random effects				
var(Intercept)	68.438***	55.640***	44.050***	25.992***
	(11.68)	(10.16)	(9.02)	(5.77)
var(Residual)	629.309***	536.727***	534.099***	349.957***
	(17.70)	(15.26)	(15.12)	(9.93)
ICC	9.81%	9.39%	7.62%	6.91%
-2LL	-13773.64	-13388.54	-13363.52	-12714.58
AIC	27553.29	26815.07	26773.05	25483.16
BIC	27571.25	26928.62	26910.50	25644.47
N	2,943	2,911	2,911	2,905

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1, # indicates the reference category

Table 3. Estimated coefficients for Trip distance

	Null model	Model 1	Model 2
Fixed effects			
Intercept	7129.56***	6573.10***	9500.96***
	(245.90)	(1378.90)	(1382.84)
Level-1 variables			
Age		44.91	34.35
		(56.11)	(55.36)
Age2		-0.83	-0.72
		(.61)	(.60)
Income		204.75*	421.79***
		(120.68)	(128.90)
Female		-595.11*	-573.46*
		(344.48)	(342.14)
Full time		1723.73***	1733.19***
		(435.40)	(429.71)
Porpose			
Home return		621.3	715.18*
		(403.93)	(398.01)
Work		#	#
Study		3339.75***	3620.90***
		(909.17)	(896.79)
HH related activities		-4528.47***	-4653.75***
		(512.27)	(504.76)
Leisure		-2327.833***	-2117.76***
		(685.45)	(675.10)
Household type			
MaleBreadwinner		-495.411	-227.48
		(593.79)	(577.87)
MaleB_children		-100.219	91.98
		(702.43)	(684.61)
FemaleBreadwinner		970.07	1320.06**
		(666.87)	(650.28)
FemaleB_children		-1667.028**	-1486.92**
		(721.32)	(701.55)
DualEarner		#	#
DualE_children		-404.274	-298.05
		(535.82)	(520.43)
NoneEarner		-580.271	-255.57
		(763.10)	(745.88)

Table 3. Estimated coefficients for Trip distance (cont.)

	Null model	Model 1	Model 2
NoneE_children		-1267.006	-923.4
		(1214.45)	(1193.87)
Level-2 variables			
Transport_access			-333.768***
			(57.31)
Bachelor_above			-738.16
			(1319.77)
Pop_density			-31.353***
			(3.87)
Land_use mixture			-1902.235*
			(1046.32)
Random effects			
var(Intercept)	13579204***	14229988***	7112882***
	(1909777.00)	(1877188.00)	(1339810.79)
var(Residual)	75879380***	65826516***	65917348***
	(2176580.00)	(1908166.00)	(1903009.43)
ICC	15.18%	17.77%	9.74%
-2LL	-30629.17	-30131.18	-30061.39
AIC	61264.34	60300.37	60168.78
BIC	61282.26	60413.67	60305.94
N	2,904	2,874	2,874

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1, # indicates the reference category

Table 4. Estimated coefficients for Trip count

	Null model	Model 1	Model 2
Fixed effects			
Intercept	2.705***	1.787***	1.661***
	(.03)	(.21)	(.21)
Level-1 variables			
Age		0.030***	0.030***
		(.01)	(.01)
Age2		-0.000***	-0.000***
		.00	.00
Income		0.057***	0.043**
		(.02)	(.02)
Female		-0.102*	-0.104*
		(.05)	(.05)
Full time		-0.03	-0.029
		(.07)	(.07)
Porpose			
Home return		0.054	0.048
		(.06)	(.06)
Work		#	#
Study		0.204	0.181
		(.14)	(.14)
HH related activities		0.499***	0.507***
		(.08)	(.08)
Leisure		0.381***	0.372***
		(.10)	(.10)
Household type			
MaleBreadwinner		-0.016	-0.027
		(.09)	(.09)
MaleB_children		0.232**	0.219**
		(.11)	(.11)
FemaleBreadwinner		0.049	0.024
		(.10)	(.10)
FemaleB_children		0.339***	0.328***
		(.11)	(.11)
DualEarner		#	#
DualE_children		0.317***	0.312***
		(.08)	(.08)
NoneEarner		-0.254**	-0.276**
		(.12)	(.12)
NoneE_children		0.326*	0.31
		(.19)	(.19)

Table 4. Estimated coefficients for Trip count (cont.)

	Null model	Model 1	Model 2
Level-2 variables			
Transport_access			0.015*
			(.01)
Bachelor_above			-0.053
			(.20)
Pop_density			0.001**
			.00
Land_use mixture			0.118
			(.16)
Random effects			
var(Intercept)	0.182***	0.163***	0.150***
	(.03)	(.03)	(.03)
var(Residual)	1.738***	1.642***	1.641***
	(.05)	(.05)	(.05)
ICC	9.48%	9.02%	8.38%
-2LL	-5100.256	-4958.333	-4950.911
AIC	10206.51	9954.666	9947.822
BIC	10224.47	10068.21	10085.28
N	2,943	2,911	2,911

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1, # indicates the reference category

Table 5. Estimated coefficients for Mode choice

	Null model	Model 1	Model 2
Fixed effects			
Intercept	-1.107***	-6.683***	-6.564***
	(.07)	(.52)	(.52)
Level-1 variables			
Age		0.096***	0.094***
		(.02)	(.02)
Age2		-0.001***	-0.001***
		0	0
Income		0.744***	0.775***
		(.04)	(.05)
Female		-1.113***	-1.098***
		(.12)	(.12)
Full time		0.419***	0.420***
		(.15)	(.15)
Purpose			
Home return		-0.294**	-0.283**
		(.13)	(.13)
Work		#	#
Study		-0.912**	-0.829**
		(.36)	(.36)
HH related activities		0.373**	0.350**
		(.16)	(.16)
Leisure		0.803***	0.821***
		(.21)	(.21)
Household type			
MaleBreadwinner		-0.006	0.025
		(.18)	(.18)
MaleB_children		1.294***	1.339***
		(.22)	(.22)
FemaleBreadwinner		-0.055	-0.013
		(.21)	(.21)
FemaleB_children		0.839***	0.849***
		(.24)	(.24)
DualEarner		#	#
DualE_children		0.957***	0.966***
		(.16)	(.16)
NoneEmployed		-0.085	-0.045
		(.25)	(.25)
NoneE_children		0.178	0.204
		(.52)	(.52)

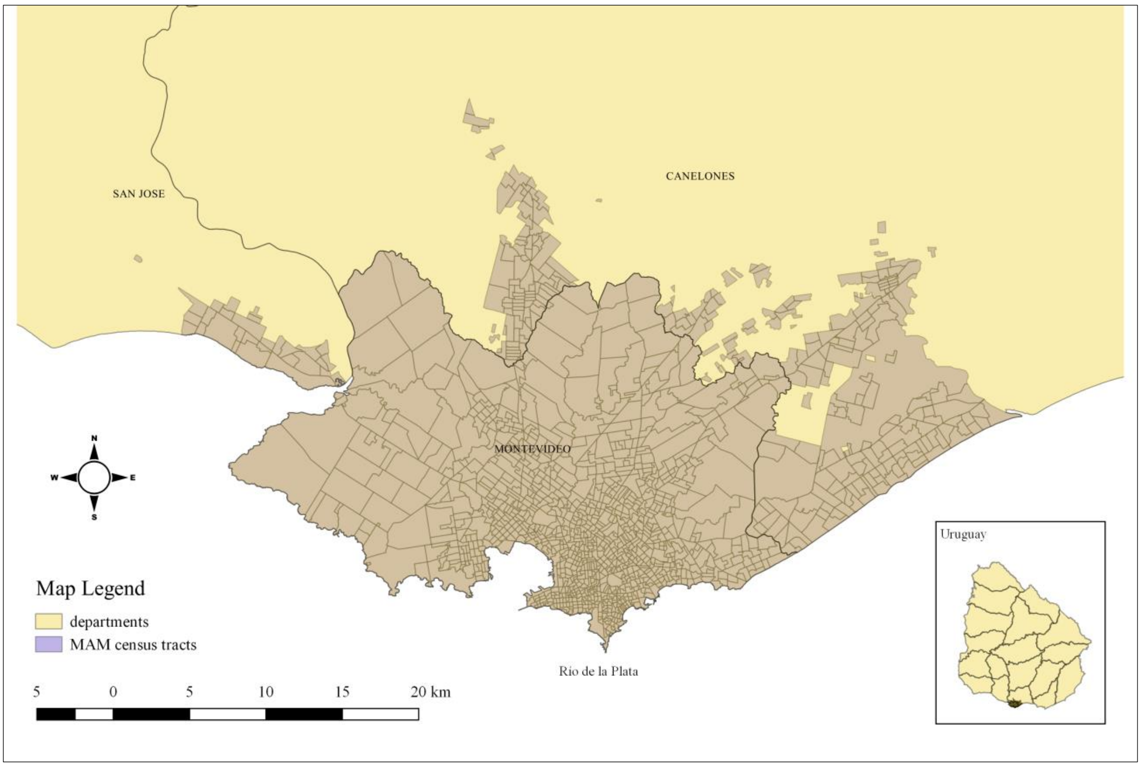
Table 5. Estimated coefficients for Mode choice (cont.)

	Null model	Model 1	Model 2
Level-2 variables			
Transport_access			-0.017
			(.02)
Baccalaureate _above			-0.137
			(.39)
Pop_density			-0.003***
			(.00)
Land_use mixture			0.329
			(.32)
Random effects			
var(Intercept)	0.816***	0.507***	0.455***
	(.15)	(.13)	(.13)
ICC	19.87%	13.34%	12.14%
-2LL	-1677.671	-1337.985	-1332.091
AIC	3359.342	2711.969	2708.182
BIC	3371.312	2819.505	2839.615
N	2,937	2,905	2,905

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1, # indicates the reference category

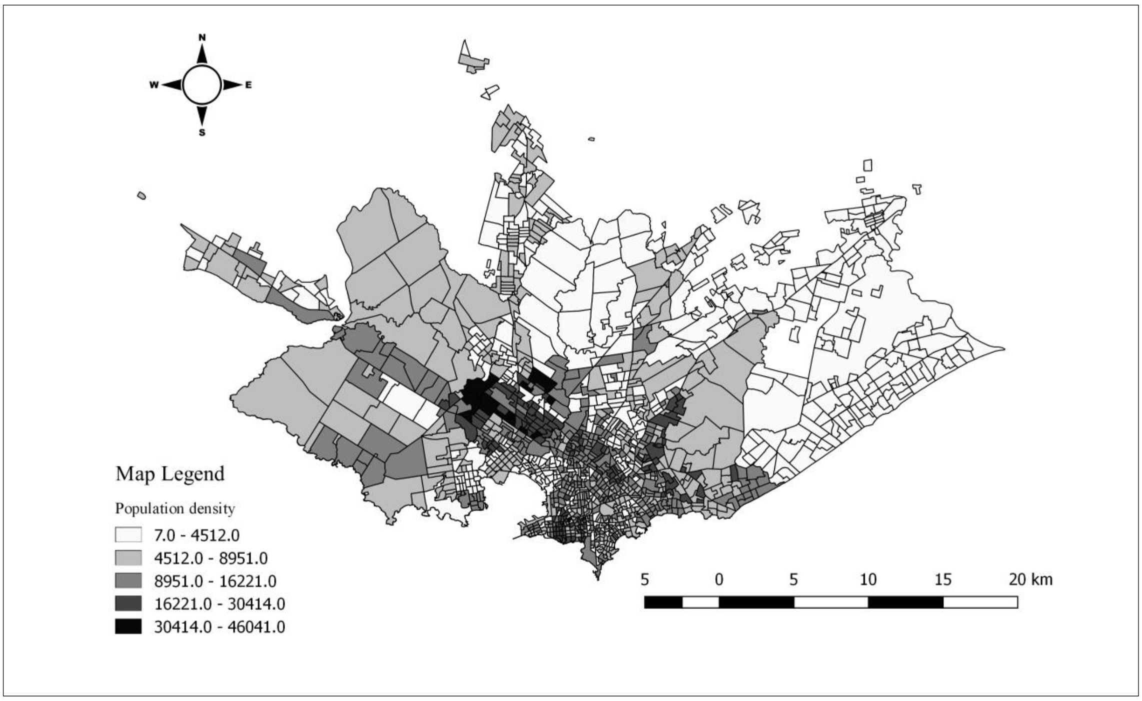
Figures

Figure 1. Census tracts of the Metropolitan Area of Montevideo



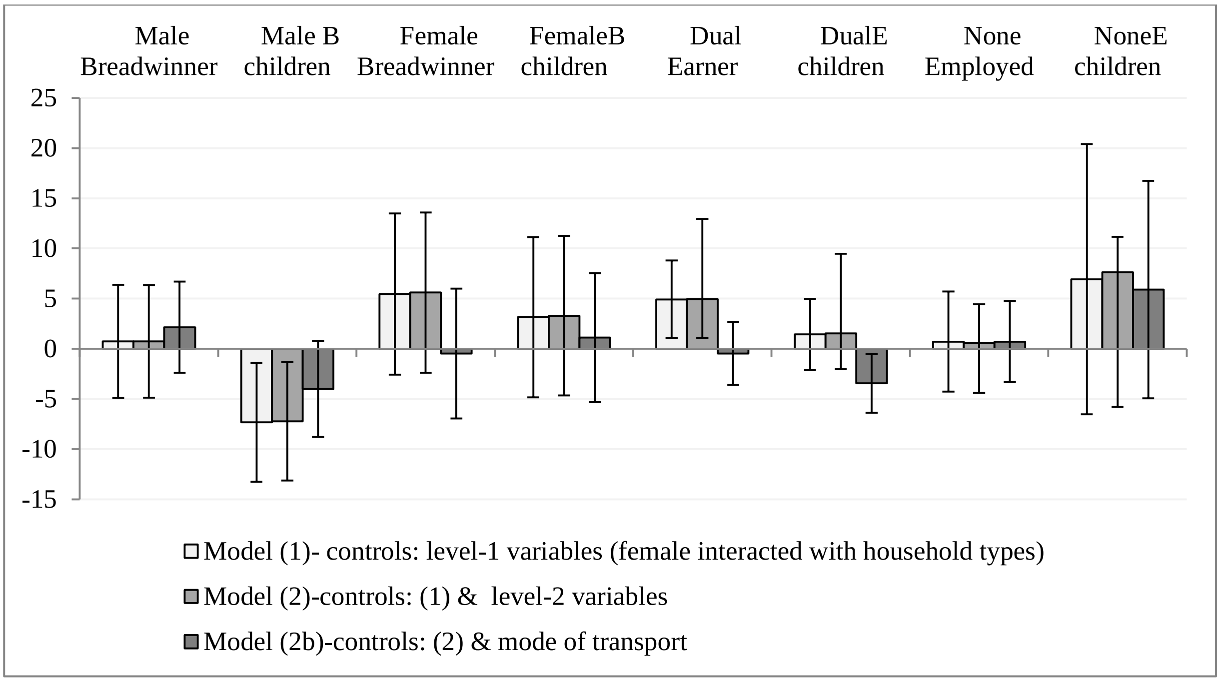
Source: Own elaboration

Figure 2. Population density in the Metropolitan Area of Montevideo's census tracts



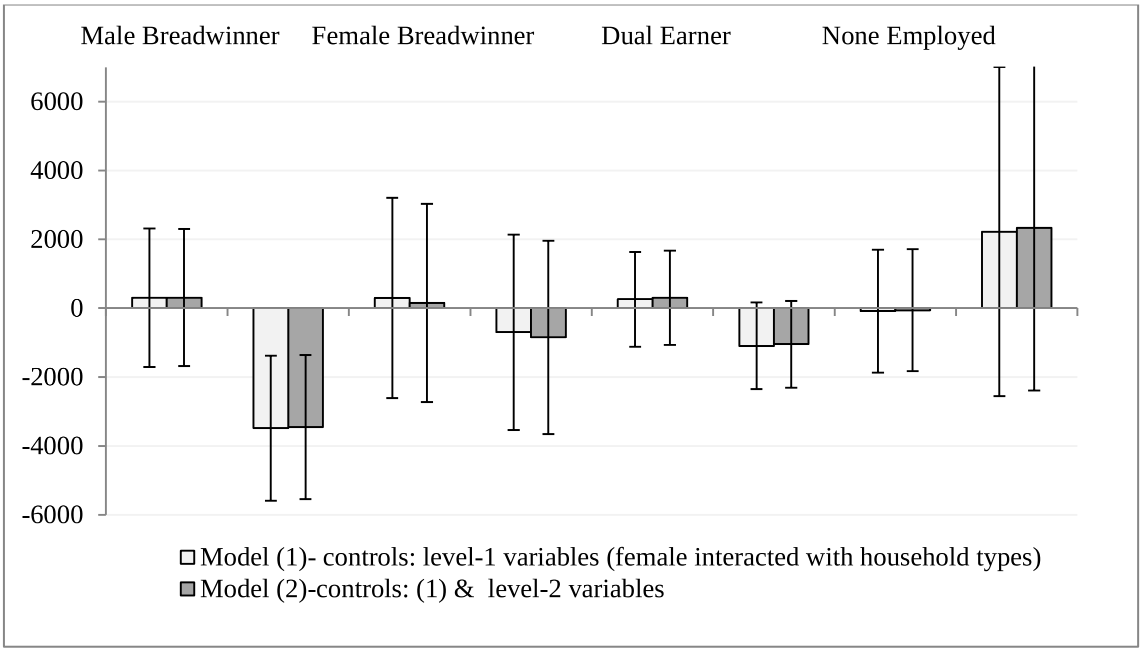
Source: Own elaboration

Figure 3. Differences in trip-time between women and men (prediction of Female – prediction of Male), by household type



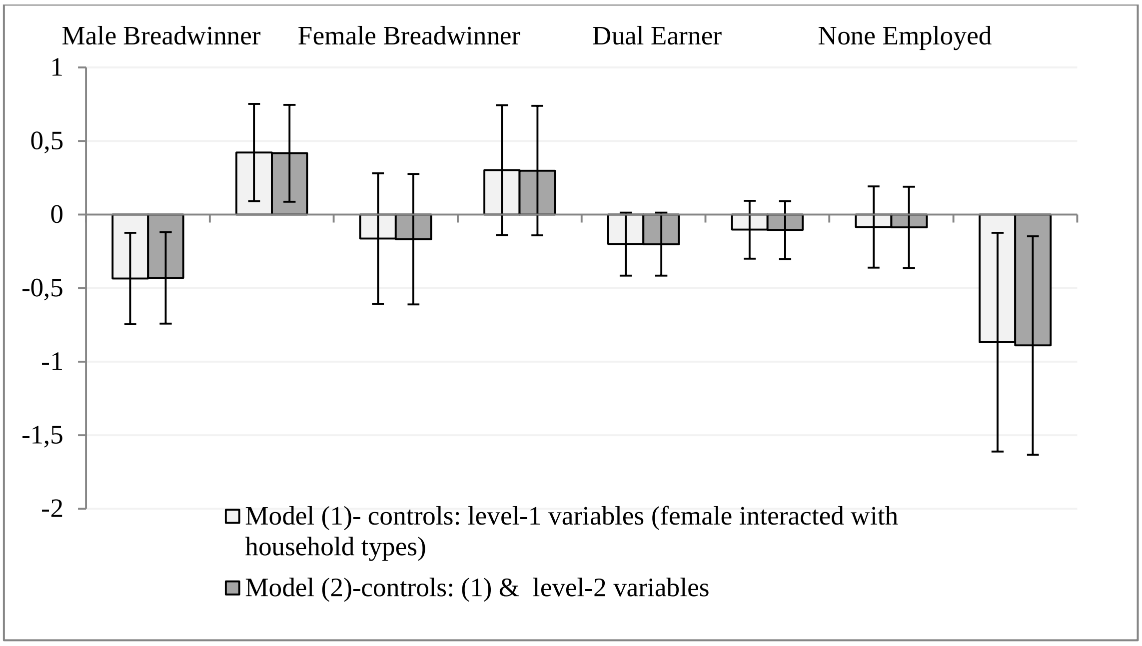
Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: Contrast of predictive margins, the straight line indicates the 95% confidence interval

Figure 4. Differences in trip distance between women and men (prediction of Female – prediction of Male), by household type



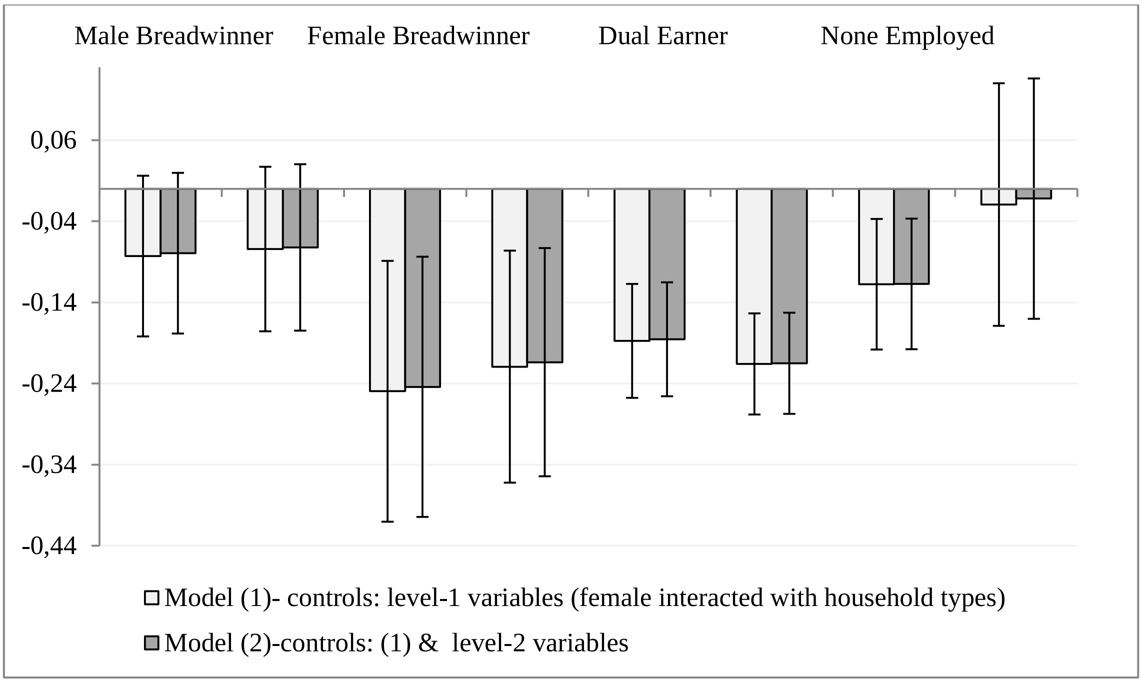
Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016. Note: Contrast of predictive margins, the straight line indicates the 95% confidence interval

Figure 5. Differences in trip count between women and men (prediction of Female – prediction of Male), by household type



Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016
Note: Contrast of predictive margins, the straight line indicates the 95% confidence interval

Figure 6. Differences in mode-choice between women and men (prediction of Female – prediction of Male), by household type



Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016. Note: Contrast of predictive margins, the straight line indicates the 95% confidence interval

Annex

Table A1. Differences in trip-time between households with children and households without children, by household type.

Household type	Model 1	Model 2	Model 2b
MaleBreadwinner	-3.84*	-3.52*	-2.50
	(2.11)	(2.09)	(1.69)
FemaleBreadwinner	-7.77***	-7.86***	-3.73
	(2.86)	(2.84)	(2.29)
DualEarner	-3.53**	-3.16**	-2.63**
	(1.46)	(1.44)	(1.17)
NoneEmployed	-6.40*	-6.02	-4.02
	(3.70)	(3.67)	(2.96)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A2. Differences in trip-time between households with children and households without children, by household type and gender.

Household type # Gender	Model 1	Model 2	Model 2b
MaleBreadwinner # Man	0.36	0.60	0.90
	(2.25)	(2.23)	(1.80)
MaleBreadwinner # Woman	-7.71**	-7.31**	-5.64**
	(3.34)	(3.31)	(2.68)
FemaleBreadwinner # Man	-6.57	-6.74	-4.28
	(5.26)	(5.22)	(4.21)
FemaleBreadwinner # Woman	-8.87***	-8.90***	-3.22*
	(2.34)	(2.32)	(1.89)
DualEarner # Man	-1.71	-1.41	-1.04
	(1.98)	(1.97)	(1.60)
DualEarner # Woman	-5.21***	-4.77**	-4.09***
	(1.96)	(1.95)	(1.58)
NoneEmployed # Man	-9.64	-9.71	-6.40
	(6.27)	(6.24)	(5.03)
NoneEmployed # Woman	-3.42	-2.63	-1.82
	(3.96)	(3.94)	(3.18)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A3.Gender differences in trip-time (prediction of Female – prediction of Male), over household types.

Household type	Model 1	Model 2	Model 2b
MaleBreadwinner	0.74	0.74	2.15
	[-4.89 ; 6.37]	[-4.87 ; 6.34]	[-2.39 ; 6.69]
MaleB_children	-7.33**	-7.24**	-4.02*
	[-13.26 ; -1.40]	[-13.14 ; -1.33]	[-8.81 ; 0.76]
FemaleBreadwinner	5.45	5.60	-0.47
	[-2.57 ; 13.48]	[-2.38 ; 13.58]	[-6.94 ; 5.99]
FemaleB_children	3.15	3.30	1.11
	[-4.84 ; 11.14]	[-4.65 ; 11.24]	[-5.33 ; 7.54]
DualEarner	4.92**	4.95**	-0.46
	[1.05 ; 8.80]	[1.09 ; 8.81]	[-3.61 ; 2.68]
DualE_children	1.42	1.52	-3.45**
	[-2.14 ; 4.99]	[-2.03 ; 5.07]	[-6.36 ; -0.55]
NoneEmployed	0.72	0.59	0.72
	[-4.28 ; 5.72]	[-4.39 ; 5.56]	[-3.32 ; 4.75]
NoneE_children	6.94	7.61	5.89
	[-6.54 ; 20.41]	[-5.79 ; 21.02]	[-4.94 ; 16.73]

Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Contrast of predictive margins, 95% confidence intervals in brackets

Table A4. Differences in trip-distance between households with children and households without children, by household type.

Household type	Model 1	Model 2
MaleBreadwinner	-72.80	-136.15
	(766.87)	(748.44)
FemaleBreadwinner	-1933.09*	-2112.28**
	(1035.84)	(1012.37)
DualEarner	-268.21	-178.56
	(531.51)	(516.39)
NoneEmployed	-230.81	-260.43
	(1317.80)	(1297.13)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A5. Differences in trip-distance between households with children and households without children, by household type and gender.

Household type # Gender	Model 1	Model 2
MaleBreadwinner # Man	1911.00**	1832.29**
	(813.47)	(797.76)
MaleBreadwinner # Woman	-1880.21	-1929.55
	(1196.15)	(1177.80)
FemaleBreadwinner # Man	-1412.90	-1588.27
	(1902.52)	(1870.43)
FemaleBreadwinner # Woman	-2407.03***	-2589.69***
	(840.54)	(824.03)
DualEarner # Man	438.99	530.34
	(715.68)	(703.74)
DualEarner # Woman	-912.53	-824.43
	(706.49)	(694.27)
NoneEmployed # Man	-1439.67	-1516.42
	(2233.13)	(2205.06)
NoneEmployed # Woman	870.56	883.87
	(1414.22)	(1394.03)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A6. Gender differences in trip-distance (prediction of Female – prediction of Male), over household types.

Household type	Model 1	Model 2
MaleBreadwinner	309.98	310.29
	[-1702.02 ; 2321.98]	[-1681.10 ; 2301.67]
MaleB_children	-3481.23***	-3451.55***
	[-5588.00 ; -1374.46]	[-5546.04 ; -1357.07]
FemaleBreadwinner	297.14	156.76
	[-2614.14 ; 3208.42]	[-2719.96 ; 3033.48]
FemaleB_children	-696.99	-844.66
	[-3535.56 ; 2141.58]	[-3651.82 ; 1962.51]
DualEarner	260.56	311.30
	[-1110.55 ; 1631.67]	[-1055.15 ; 1677.75]
DualE_children	-1090.97*	-1043.48*
	[-2353.57 ; 171.64]	[-2303.21 ; 216.26]
NoneEmployed	-81.12	-58.89
	[-1871.95 ; 1709.71]	[-1828.15 ; 1710.37]
NoneE_children	2229.10	2341.41
	[-2554.29 ; 7012.50]	[-2389.88 ; 7072.70]

Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Contrast of predictive margins, 95% confidence intervals in brackets

Table A7. Differences in trip-count between households with children and households without children, by household type

Household type	Model 1	Model 2
MaleBreadwinner	0.43***	0.43***
	(0.12)	(0.12)
FemaleBreadwinner	0.15	0.16
	(0.16)	(0.16)
DualEarner	0.32***	0.32***
	(0.08)	(0.08)
NoneEmployed	0.77***	0.78***
	(0.21)	(0.21)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A8. Differences in trip-count between households with children and households without children, by household type and gender

Household type # Gender	Model 1	Model 2
MaleBreadwinner # Man	-0.01	-0.01
	(0.12)	(0.12)
MaleBreadwinner # Woman	0.84***	0.84***
	(0.19)	(0.19)
FemaleBreadwinner # Man	-0.09	-0.08
	(0.29)	(0.29)
FemaleBreadwinner # Woman	0.37***	0.39***
	(0.13)	(0.13)
DualEarner # Man	0.27**	0.26**
	(0.11)	(0.11)
DualEarner # Woman	0.37***	0.36***
	(0.11)	(0.11)
NoneEmployed # Man	1.18***	1.20***
	(0.35)	(0.35)
NoneEmployed # Woman	0.39*	0.39*
	(0.23)	(0.23)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A9.Gender differences in trip-count (prediction of Female – prediction of Male), over household types

Household type	Model 1	Model 2
MaleBreadwinner	-0.43***	-0.43***
	[-0.75 ; -0.12]	[-0.74 ; -0.12]
MaleB_children	0.42**	0.42**
	[0.09 ; 0.75]	[0.09 ; 0.75]
FemaleBreadwinner	-0.16	-0.17
	[-0.61 ; 0.28]	[-0.61 ; 0.28]
FemaleB_children	0.30	0.30
	[-0.14 ; 0.74]	[-0.14 ; 0.74]
DualEarner	-0.20*	-0.20**
	[-0.41 ; 0.01]	[-0.42 ; 0.01]
DualE_children	-0.10	-0.11
	[-0.30 ; 0.09]	[-0.30 ; 0.09]
NoneEmployed	-0.08	-0.09
	[-0.36 ; 0.19]	[-0.36 ; 0.19]
NoneE_children	-0.87**	-0.89**
	[-1.61 ; -0.12]	[-1.63 ; -0.15]

Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Contrast of predictive margins, 95% confidence intervals in brackets

Table A10. Differences in mode-choice between households with children and households without children, by household type

Household type	Model 1	Model 2
MaleBreadwinner	0.20***	0.20***
	(0.04)	(0.04)
FemaleBreadwinner	0.13**	0.13**
	(0.05)	(0.05)
DualEarner	0.14***	0.14***
	(0.02)	(0.02)
NoneEmployed	0.02	0.01
	(0.08)	(0.08)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A11. Differences in mode-choice between households with children and households without children, by household type and gender

Household type # Gender	Model 1	Model 2
MaleBreadwinner # Man	0.21***	0.21***
	(0.04)	(0.04)
MaleBreadwinner # Woman	0.19***	0.20***
	(0.06)	(0.06)
FemaleBreadwinner # Man	0.17*	0.16*
	(0.10)	(0.10)
FemaleBreadwinner # Woman	0.10***	0.10***
	(0.04)	(0.04)
DualEarner # Man	0.18***	0.18***
	(0.03)	(0.03)
DualEarner # Woman	0.10***	0.10***
	(0.03)	(0.03)
NoneEmployed # Man	-0.03	-0.04
	(0.13)	(0.13)
NoneEmployed # Woman	0.06	0.06
	(0.09)	(0.09)

Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets, Contrast of predictive margins: prediction of household type with children minus prediction of household type without children.

Table A12.Gender differences in mode-choice (prediction of Female – prediction of Male), over household types

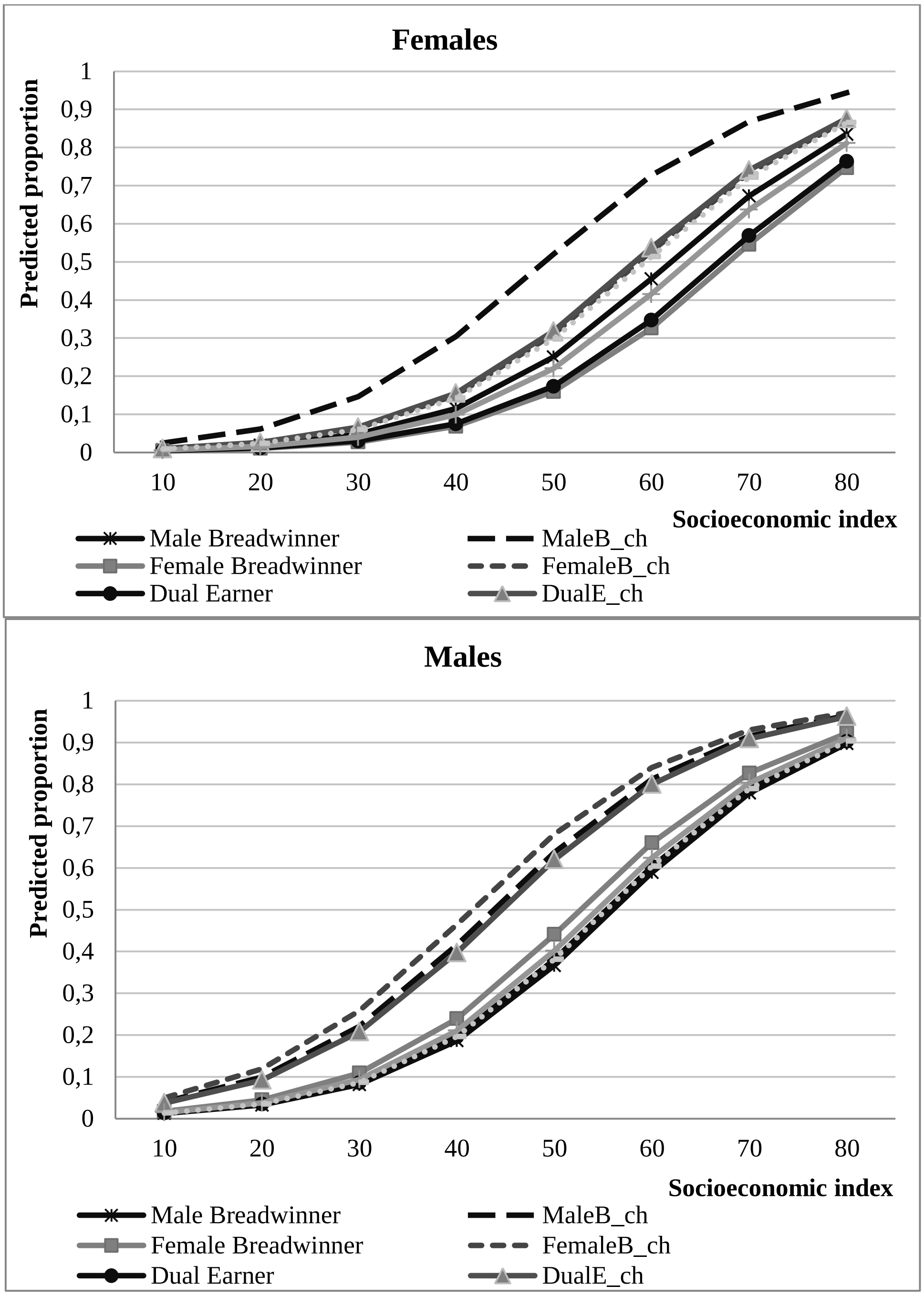
Household type	Model 1	Model 2
MaleBreadwinner	-0.08	-0.08
	[-0.18 ; 0.02]	[-0.18 ; 0.02]
MaleB_children	-0.07	-0.07
	[-0.18 ; 0.03]	[-0.17 ; 0.03]
FemaleBreadwinner	-0.25***	-0.24***
	[-0.41 ; -0.09]	[-0.40 ; -0.08]
FemaleB_children	-0.22***	-0.21***
	[-0.36 ; -0.08]	[-0.35 ; -0.07]
DualEarner	-0.19***	-0.19***
	[-0.26 ; -0.12]	[-0.26 ; -0.12]
DualE_children	-0.22***	-0.21***
	[-0.28 ; -0.15]	[-0.28 ; -0.15]
NoneEmployed	-0.12***	-0.12***
	[-0.20 ; -0.04]	[-0.20 ; -0.04]
NoneE_children	-0.02	-0.01
	[-0.17 ; 0.13]	[-0.16 ; 0.14]

Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016

*** p<0.01, ** p<0.05, * p<0.1

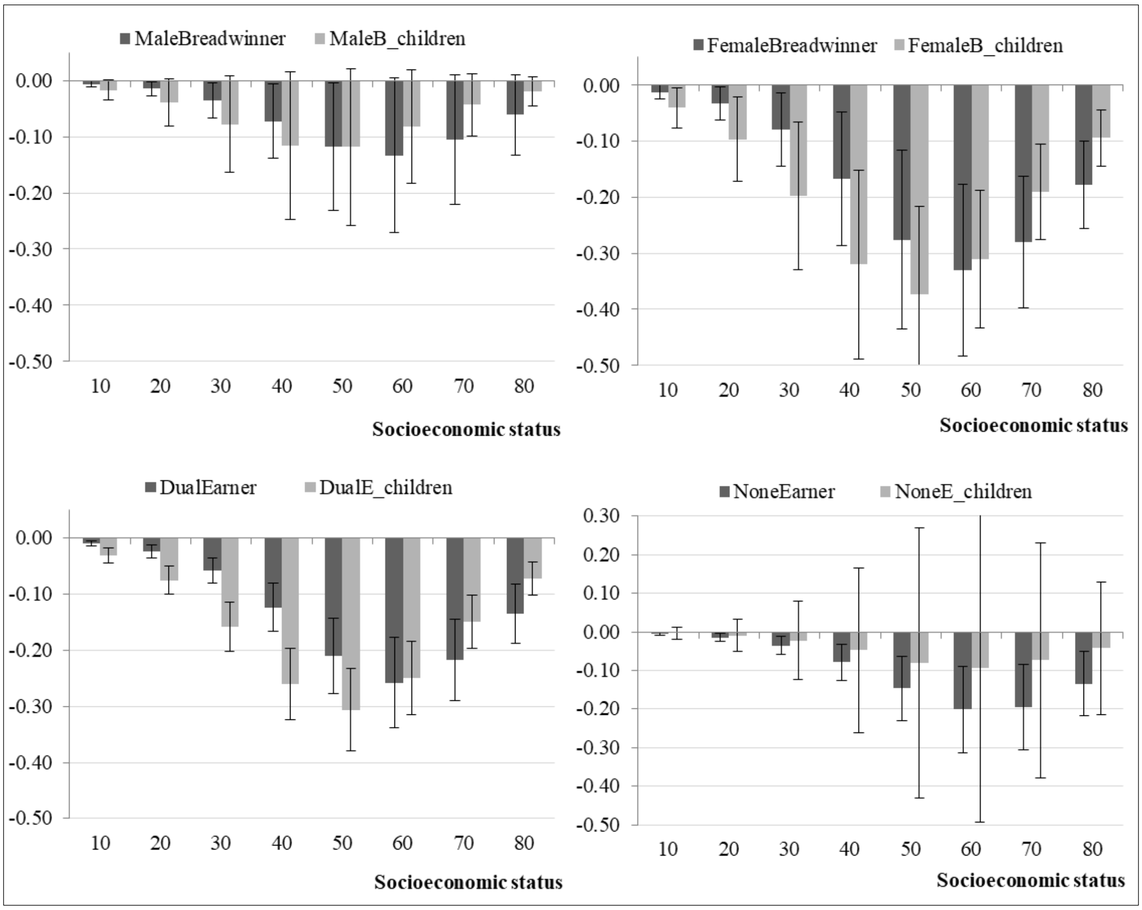
Note: Contrast of predictive margins, 95% confidence intervals in brackets

Figure A1. Predicted probabilities of choosing automobile, by household type and gender. Selected values of the income variable



Source: Authors' estimations based on Encuesta de Movilidad del Área Metropolitana de Montevideo, 2016

Figure A2. Gender differences in mode-choice (prediction of Female – prediction of Male) for selected values of income variable, by household types



Source: Authors' estimations based on *Encuesta de Movilidad del Área Metropolitana de Montevideo*, 2016. Note: Contrast of predictive margins, the straight line indicates the 90% confidence interval