



# Heterogeneity in marginal value of urban mobility: evidence from a large-scale household travel survey in the Greater Toronto and Hamilton Area

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## Abstract

The value of mobility is an unresolved question in transportation economics literature. The advent of ride-hailing services and the emergence of mobility as a service (MaaS) place increased pressure on the research community to develop methods to consider this question. We provide one of the first efforts to quantify the value of mobility using a consistent econometric approach. A series of discrete choice models are estimated for car ownership and residential density choices. The decision to purchase an additional vehicle is a concrete manifestation of the marginal value of travel vis-a-vis the desire to make additional trips. The proposed framework has the benefit of employing a single utility function, thus removing the need to set a reference alternative. Models are estimated with a large household travel survey for the Greater Toronto and Hamilton Area, which provides a close approximation to the true population. We estimate separate values of mobility by household composition, providing evidence for a high degree of heterogeneity. Results are examined in the context of MaaS and it is found that the value of mobility is much higher in suburban areas than suggested in previous research. Model results provide strong evidence for potential social exclusion with the widespread adoption of MaaS. The methods explored in this paper show great promise for quantifying the value of mobility and we present recommendations for additional research in this direction.

**Keywords** Value of mobility · Count variable models · Mobility as a service · Social equity

## Introduction

A paradigm shift is underway in the urban transportation sector. There is a growing sense that, in the coming years, households will begin moving from a system of personal car ownership, with large upfront capital costs, towards one of mobility as a service (MaaS).

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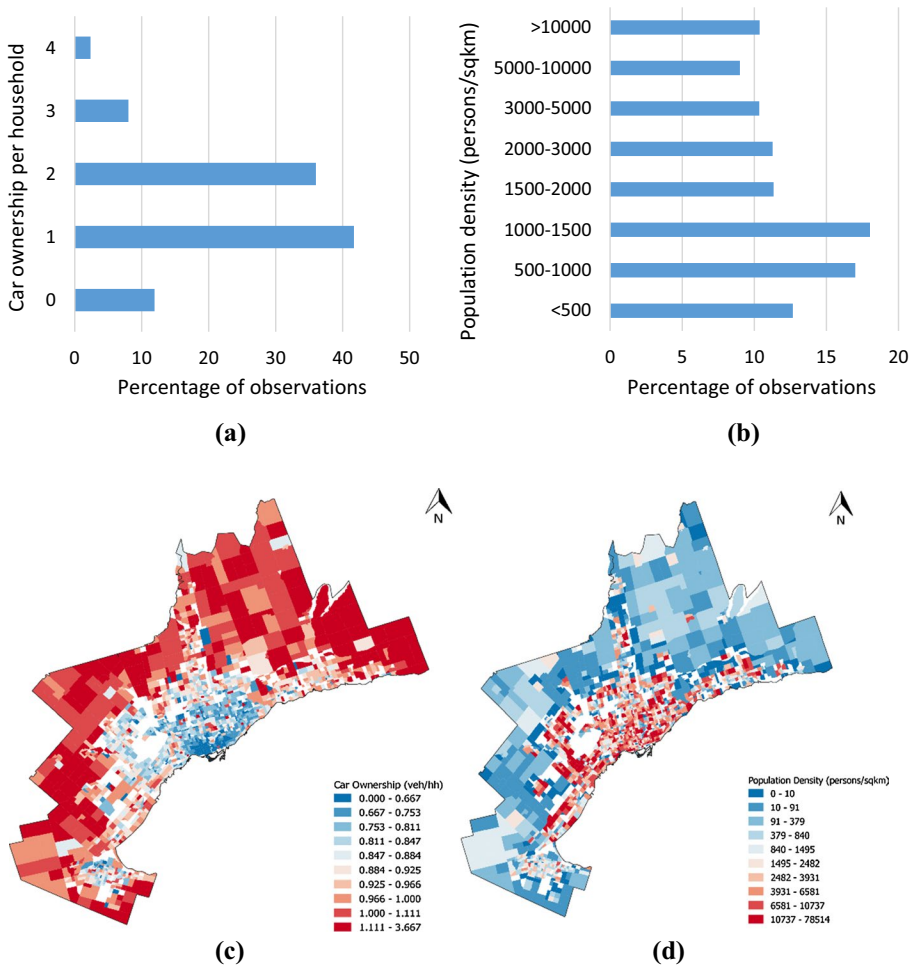
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The emergence of transportation network companies (TNCs), such as Uber and Lyft, has brought about a surge in technological development within the transportation sector. This has led many, such as Jeremy Rifkin in his book “The Zero Marginal Cost Society” (Rifkin 2014), to predict that these developments will eventually reduce the marginal cost of travel to zero. It is speculated that the rise of new business models, in the form of car sharing, ride sharing, and driverless cars will eliminate car ownership—reducing the importance of car manufacturing. However, as argued by Ehret (2015), it is probable that the market will simply move away from the sale of products and towards the sale of services. This is captured in the concept of MaaS, which involves the replacement of ownership of the physical capital by the individual with the purchase of mobility from a service provider. MaaS can be viewed as analogous to the purchase of a mobile phone plan. Each household purchases a *package* of mobility services, which might include personal vehicles, mass transit, fleets of bicycles, and shared autonomous taxis. The individual will no longer own the means of transport, but rather lease it from a private or public operator.

In such a future, transportation costs shift from the high upfront capital expenditure associated with purchasing a personal car and towards a high marginal cost for individual trips. A critical question we see arising from these changing patterns of mobility is: what is the marginal value of mobility? We define mobility as the ability to make additional trips and therefore the value of mobility is equivalent to the value of travel. The monetization of travel is not a foreign concept in the field of transportation economics. It is common to calculate the value of travel from, for example, the parameters of a mode choice model. The analyst will generally take the ratio of the parameters for in-vehicle travel time and some measure of monetary value (e.g. vehicle operating value or transit fare). However, there are several limitations to these methods of monetizing travel. First, the value obtained is mode-specific and does not represent a generalized value of travel time. Second, the result is an average value and not the marginal value of travel. Metz (2008) provides a strong argument against the appropriateness of such average values in the valuation of long-term infrastructure investments. He states that short-term average travel time savings are not necessarily maintained in the long-term, with the induction of additional trips by the associated reduction in congestion. A similar argument can be made in the case of MaaS in that the average value of travel does not provide an accurate picture of the willingness to purchase an additional trip. Convex preferences, meaning a diminishing marginal utility with an increasing marginal cost, is associated with each of our additional trips. Finally, it is rare that any distinction is made between the value of mobility by socioeconomic group. With the deployment of MaaS, such considerations become important in the pricing of the service.

We include the distance to the central business district (CBD) in the model specification to capture the spatial distribution of potential MaaS prices. Its inclusion gives an a posteriori notion of the flexibility of demand to the value of mobility services. A major consideration in the assessment of MaaS is its equity impacts. Private operators will seek to maximize their profit and, while remaining agnostic to this capitalist philosophy in our analysis, policymakers need tools to quantify the effects this might have on poor and mobility tool deficient households. Using examples of known goods consumed by the household, MaaS might be considered like food as contrasted with entertainment. It is generally accepted that a household has a minimal requirement for food, beyond which additional consumption is deemed a luxury decision, whereas consumption of entertainment is a pure luxury good. Similarly, a household might have a minimum level of MaaS that the government would subsidize, beyond which households would pay the marginal value for additional trips. Setting this threshold is a complex task. We need to know at what level to begin pricing households and which households to price at each level of trip making.



**Fig. 1** Sample distribution of **a** household car ownership and **b** home-zone population density. TTS distribution of **c** household car ownership and **d** home zone population density

In this paper, we present among the first attempts to address these questions using consistent econometric techniques. The problem is presented as a Poisson multinomial logit (MNL) discrete choice using the number of cars owned by the household as a countable dependent variable. This model specification allows us to develop a single model for all alternatives (i.e. 0, 1, 2, 3... vehicles), thus representing a consistent measure of the marginal value of mobility. Marginal values are differentiated along the dimensions of the number of household workers, the presence of children in the household, and the distance of the home location from the CBD. A secondary set of models is developed for a count variable representing the residential density of the home traffic analysis zone (TAZ). This provides a contrasting perspective on the problem. In the case of car ownership, there is a positive correlation with household income, whereas residential density tends to decrease with increasing income (Palm et al. 2014). This inverse relationship is evident in Fig. 1, which plots each variable on a map of the study region based on TAZ-level statistics. For

both car ownership and residential density, we develop models for each of (1) a marginal trip and (2) a marginal km of travel. The first case, number of trips, provides a value measure for a trip as a discrete unit, which can be contrasted between household and trip configurations (i.e. household size and vehicle ownership). The second case, trip distance (in km), provides a continuous measure of the value of mobility by distance.

## Literature review

There is an extensive literature on the economics of transportation, but the only similar studies (of which we are aware) that directly examine the quantification of the marginal value of mobility are by Stanley and Hensher (2011; Stanley et al. 2011). The focus of their work is the link between mobility and social exclusion (SE). In their original study, Stanley and Hensher (2011) define SE according to 5 criteria: household income below a threshold, employment status, political activity, social network strength, and participation in public activities. They present the problem as a generalized ordered logit model, with the dependent variable being the number of SE criteria met by each household participating in their survey. A strength of their approach is that they explicitly capture household incomes as a continuous variable in the survey. They take the ratio of the marginal utility of trips to that of household income to obtain the marginal rate of substitution between trips and income (or marginal value of a trip). Stanley and Hensher (2011) estimate this value at AUD\$18.40 and offer the interpretation that it represents the value to the household of an additional trip made possible by increased accessibility resulting from a transportation improvement. We find several issues with their methods, largely arising from the choice of dependent variable and model structure. The ordered logit model is classified by Stanley and Hensher as a *choice model* in their publications. However, this is not the case, and it would be more accurate to classify the model as an *ordered regression*. The estimation procedure provides a latent variable structure into which households are classified by their level of SE and not a random utility maximizing (RUM) outcome. Mathematically, the difference manifests as an *ordered logit regression* being a series of binary logistic regressions with threshold intercepts. In contrast, an *ordered logit choice model* takes a standard MNL form, with all alternatives in the denominator, and correlation in the error terms between alternatives. Along a similar vein, we argue that it is problematic to characterize social exclusion as a choice. It is more accurately described as an undesired outcome of social forces. In addition, the criteria for SE included in the dependent variable levels are fairly subjective and do not provide a clear connection with the value of mobility. We propose that car ownership or residential location choice provide more robust and objective measures to estimate the marginal value of mobility. Finally, these variables represent clear household purchasing decisions and provide a stronger basis for RUM-based discrete choice models.

Kryvobokov and Bouzouina (2014) consider the question in terms of willingness to pay (WTP) for accessibility under conditions of residential segregation. They frame residential segregation as an inevitable outcome of the monocentric city model, wherein segregation of households occurs according to differential WTP. This can be partially captured through residential density, where it is assumed that density correlates with differences in household composition and income (Palm et al. 2014). Employing a bid-rent function with two income categories, they provide an empirical analysis for Lyon, France. They confirm previous results by Korsu and Wenglenski (2010) finding that the two major drivers of poor employment accessibility in French cities are locating in remote neighborhoods with few

jobs and low rates of car ownership (Kryvobokov and Bouzouina 2014). This supports the choice of car ownership and residential density as dependent variables in our models.

In the context of discrete choice experiments and WTP for emerging modal alternatives, there are several studies focused on the purchase of electric vehicles. Kochhan and Horner (2015) performed a choice experiment in which they explicitly ask respondents to make a choice between a conventional vehicle and electric vehicle, given a set of attributes (time savings, reliability, convenience, cleanliness, flexibility, and operating value). They find that the cost of electric vehicles is much higher than the WTP (i.e. perceived value), relative to a conventional vehicle, as elicited in their experiment. We highlight their focus on the total value of ownership compared with the WTP for an electric vehicle. A similar study of MaaS should include a comparison of the total cost of car ownership to fully capture the gap between the cost and the WTP for each alternative. The results can be context specific. For example, Kochhan and Horner (2015) performed their study in Singapore, which has an exceptionally high cost of car ownership. A similar study conducted in different jurisdictions would likely produce quite different results. Jacobs et al. also consider the WTP for electric vehicles, but in their case, the focus is on owners of energy-efficient homes (2016). They find that these homeowners are willing to pay around €4500 more for a plug-in hybrid electric vehicle and €5600 more for a battery electric vehicle, as compared with owners of conventional homes (Jacobs et al. 2016). This highlights the differential WTP between different segments of the population. A similar pattern likely exists in the case of WTP for MaaS. A key insight from these results is that one should avoid associating a single value of mobility to the heterogeneous population of a large region.

The final field of literature reviewed is research specifically focused on the economics and demand for MaaS. Wong et al. (2017) see MaaS as a probable outcome of emerging patterns of collaborative consumption. They cite ride-hailing, ridesharing, micro transit, carsharing, and autonomous vehicles as examples of new and next generation modal alternatives that will interact (with traditional modes) to form a mobility service network. Wong et al. (2017) discuss two streams of thought on the potential for reduced car ownership in the coming years. The first being the continued automation of vehicles strengthening ride-hailing as a mode. The second reason given is the declining status of obtaining a driver's license (Wong et al. 2017). Although the evidence is unclear on both accounts, this does support a shift towards MaaS and a diminishing rate of car ownership. The shift from a transportation system of high capital cost to one of high marginal costs features prominently in their research. Wong et al. (2017) and Matyas and Kamargianni (2018) have conducted stated preference experiments to elicit the WTP for MaaS, but they do not provide details on these numbers. In defining MaaS, we use the definition of Kamargianni et al. (2018, p. 3) that it is “a user-centric, intelligent mobility management and distribution system, in which an integrator brings together offerings of multiple mobility service providers, and provides end-users access to them through a digital interface, allowing them to seamlessly plan and pay for mobility”.

## Methods

We begin the development of our econometric models from the work of Stanley and Hensher (2011 and Stanley et al. 2011). Our objectives are to improve upon the choice of dependent variable and differentiate the value of mobility into market segments. Using a

RUM behavioural framework, we apply recent developments in count model specifications to develop a consistent measure of trip value, irrespective of mode choice.

Considering RUM assumptions for discrete choice modelling, the utility of choice of a discrete alternative is:

$$U_j = V_j + \varepsilon_j; j \in C_i \tag{1}$$

where  $U$  is the total random utility,  $V$  is the total systematic utility, and  $\varepsilon$  is the random error term. The subscript  $j$  indicates a specific alternative, which is a part of the choice set  $C$  of an individual choice maker,  $i$ .

Under an independent and identical distribution (IID) type I extreme value distribution assumption for the random utility component, the choice probability becomes the classical multinomial logit model (MNL):

$$Pr(j) = \frac{\exp(V_j)}{\sum_{k \in C_i} \exp(V_k)} \tag{2}$$

This specification requires a reference alternative to ensure the mathematical identification of the model that is necessary for model parameter estimation. A generic linear-in-parameter specification of the systematic utility component can avoid taking any arbitrary alternative as the reference, but the generic specification is only possible for the attributes of the choice alternatives. Attributes of choice makers (e.g. income) cannot have a generic coefficient in the specification of the systematic utility and so, at least for one of the choice alternatives, they must have a fixed (preferably 0) effect in the utility function. This makes the use of MNL or any similar discrete choice model problematic in estimating a generic marginal value of mobility. An alternative possibility would be specifying the systematic utility function of choice alternatives as a function of a generic function of all choice alternative. In this paper, we propose to consider the choice alternative as a count variable. Let us assume that the choice alternative (also a count variable)  $j$  follows a flexible Negative Binomial (NB) distribution. So, the resulting choice probability becomes an NB probability as follows:

$$Pr(j) = \left(\frac{r}{r + \lambda}\right)^r \frac{\Gamma(r + y)}{\Gamma(1 + y)\Gamma(r)} \left(\frac{\lambda}{r + \lambda}\right)^y \tag{3}$$

As presented by Paleti (2016), this specification can be further manipulated into an MNL-style specification as follows:

$$Pr(j) = \left(\frac{r}{r + \lambda}\right)^r \frac{\Gamma(r + y)}{\Gamma(1 + y)\Gamma(r)} \left(\frac{\lambda}{r + \lambda}\right)^y = \left(1 - \frac{\lambda}{r + \lambda}\right)^r \frac{\Gamma(r + y)}{\Gamma(1 + y)\Gamma(r)} \left(\frac{\lambda}{r + \lambda}\right)^y \tag{4}$$

$$Pr(j) = \frac{\frac{\Gamma(r+y)}{\Gamma(1+y)\Gamma(r)} \left(\frac{\lambda}{r+\lambda}\right)^y}{\left(1 - \frac{\lambda}{r+\lambda}\right)^{-r}} \tag{5}$$

Using the NB expansion (Paleti 2016):

$$\left(1 - \frac{\lambda}{r + \lambda}\right)^{-r} = \sum_{k=0}^{\infty} \binom{-r}{k} \left(\frac{-\lambda}{r + \lambda}\right)^k \approx \sum_{k=0}^{\infty} \frac{\Gamma(r + k)}{\Gamma(1 + k)\Gamma(r)} \left(\frac{\lambda}{r + \lambda}\right)^k \tag{6}$$

the NB probability converges into an MNL specification:

$$Pr(j) = \frac{\frac{\Gamma(r+y)}{\Gamma(1+y)\Gamma(r)} \left(\frac{\lambda}{r+\lambda}\right)^y}{\sum_{k=0}^{\infty} \frac{\Gamma(r+k)}{\Gamma(1+k)\Gamma(r)} \left(\frac{\lambda}{r+\lambda}\right)^k} = \frac{\exp(V_j)}{\sum_{k=1}^K \exp(V_k)} = \frac{\exp(V_j)}{\sum_{k \in C_i} \exp(V_k)} \tag{7}$$

which assumes that the systematic utility of a specific count alternative  $j$  is:

$$V_j = \ln \left( \frac{\Gamma(r+y)}{\Gamma(1+y)\Gamma(r)} \left(\frac{\lambda}{r+\lambda}\right)^y \right) \tag{8}$$

Under this specification, if  $j$  is a discrete alternative, but also count in nature, the systematic utility varies by three parameters:

1.  $y$ , which is actual count (0,1,2,... N)
2.  $r$ , which is the dispersion parameter of the NB distribution. For a very large value of  $r$  (i.e.  $r \rightarrow \infty$ ), the NB distribution converges into a Poisson distribution
3.  $\lambda$ , which is the mean systematic utility of the choice process

It is very interesting to note that the mean systematic utility is generic across the choice alternatives ( $j \in C_i$ ) and we can further specify this as an exponential of the linear-in-parameter functional form:

$$\lambda = \exp\left(\beta_0 + \sum \beta x\right) \tag{9}$$

where  $\beta_0$  is the constant mean of systematic utility that captures any systematic utility not explained by available variables,  $X$  is a vector of attributes of choice makers and/or choice contexts, and  $\beta$  is the corresponding coefficient vector.

One can further extend the MNL formulation of NB model into an ordered generalized extreme value distribution, which eventually converges into an MNL formulation of zero correlations between successive ordered (count) discrete alternatives (Habib and Hasnine 2017). All these formulations (NB-MNL, Poisson-MNL, NB-OGEV, Poisson-OGEV) are of the closed form and can be estimated by using the classical maximum likelihood estimation technique. In this investigation, we programmed this model in GAUSS and estimated it by using the maximum likelihood estimation technique (Aptech 2018). Empirical estimation of the model reveals a very large (with low confidence) value of dispersion,  $r$ . Also, investigation of an OGEV formulation reveals that the correlations between two consecutive ordered (count) discrete alternatives is not significantly different from zero. So, the final model specification that is presented here is of the Poisson-MNL formulation where the mean utility is defined by:

$$\lambda = f(V) = \exp \left[ \beta_0 + \beta_{income} \left( \frac{\beta_{trips}}{\beta_{income}} trips + income \right) + \sum \beta x \right] \tag{10}$$

In this formulation, the marginal value of mobility is explicitly estimated as the ratio of  $\beta_{trips}$  by  $\beta_{income}$  in what is termed the WTP-space. This method is recommended by Hess and Train (2017), among others, to avoid the need to calculate an implicit measure from parameters estimated in the preference-space. Separate parameters can be estimated for

each market segment of interest. It is also appealing if one employs a mixed logit formulation, as it allows for the direct estimation of the distribution of WTP across individuals.

Count and ordered logit models are common methods to model car ownership choice (see Anowar et al. (2014) for a summary of the literature). We have chosen this as our main dependent variable for considering the marginal utility of trips. Car ownership was chosen because it allows us to use a count model, specifically Poisson MNL, which contains a single mean utility function for all alternatives. This removes the mode-specific components of the marginal value of mobility and constitutes a related decision to that of MaaS. A household would almost certainly consider the utility of MaaS when making the decision to purchase an additional vehicle. The countable nature of the model provides a direct connection with the marginal value objectives of this research effort. We also know that a higher household income will allow the household to make additional discretionary trips. Put differently, it is a direct manifestation of the household WTP for marginal trips. As noted by Ehret (2015), most aspects of developed economies have moved past the stage of personal ownership of capital. In most of these countries, the service sector (where *service* is defined as “the transfer of benefits without the transfer of ownership” (Ehret 2015, p. 123)) accounts for 70–90% of GDP.

The second dependent variable considered is residential density, which we define as a count variable to maintain consistency with the model structure. Bhat et al. (2014) employ a similar assumption in the context of a multiple discrete–continuous travel behaviour choice model. This provides an approximation to residential location choice, whereby residential densities for each of the locations (zones) are placed in evenly sized bins defining a monotonically increasing discrete variable. A total of 8 density categories are defined in the model (as outlined in Fig. 1). This dependent variable also provides a measure of residential segregation and tests the hypothesis that higher income households will tend to locate in lower density areas. These lower densities generally mean a higher number of trips by modes most readily substitutable for MaaS (e.g. car and low-frequency transit).

## Data for empirical investigations

Data for empirical investigation of this study is derived from a large-scale household travel survey conducted in the Greater Golden Horseshoe (GGH) of Southern Ontario, called the Transportation Tomorrow Survey (TTS<sup>1</sup>). This is an approximately 5 percent sample (of households) survey of the GGH region, which is one of the largest (if not the largest) household travel survey in North America. The 2016 TTS, the latest cycle of the survey, consists of travel diaries of around 162,000 households in the region (Malatest and DMG 2018). The TTS has been a regular 5-year cycle household travel survey in the region since 1996, but only the 2016 TTS collected information on household income along with other household socio-demographic variables and travel diaries of the household members. One of the main reasons for moving in this direction with the TTS is to provide data with quantitative economic implications for travel behaviour. This study is the first effort to leverage these new data to examine such economic questions.

The study area of the TTS includes the Greater Toronto and Hamilton Area (GTHA) and some other areas of the GGH. Even though the total study area of the TTS changed

<sup>1</sup> <http://dmg.utoronto.ca/transportation-tomorrow-survey/tts-introduction>.



**Table 1** Descriptive statistics for TTS sample (Malatest and DMG 2018)

	Census/other statistical reference	Unweighted TTS Sample
Sex (% of the sample)		
Male	48.6	48.0
Female	51.4	52.0
Income category (% of the sample)		
<\$15,000	5.6	4.9
\$15,000–\$40,000	18.2	18.1
\$40,000–\$60,000	14.9	17.6
\$60,000–\$100,000	24.5	25.7
\$100,000–\$125,000	10.9	12.1
\$125,000+	25.8	21.5
Average HH size	2.66	2.43
Dwelling type (% of the sample)		
House	55.1	61.2
Apartment	35.4	29.2
Townhouse	9.5	9.6
Average vehicles per household	Not given	1.50
Driver license (% of sample 16+)	84.0	84.0

slightly between the cycles of TTS, the GTHA has always been the core areas within the GGH in all TTS. This study focuses on the GTHA part of the 2016 TTS that includes a sample of around 124,000 households. However, for the empirical investigation, a sample of 83,938 households are selected after cleaning for missing/unreported household income, zero trip making households and faulty home location (zero population and household density zones). Figure 1 presents the two key variables (household car ownership, home location population density) that are used as dependent variables to estimate the marginal values of mobility in this study.

In terms of other household-specific socio-demographic variables, the sample provides information on household income, household size, number of adults, number of children, number of workers, home location relative to downtown Toronto (distance from the CBD), dwelling type, etc. Home locations (traffic analysis zone) of the households in the sample are also used to generate information on land use type and combinations, employment density, the proportion of various population groups, etc. based on secondary sources of land use and 2016 census data.

A frequent challenge in the specification of WTP measures that arise from access to continuous income data. For reasons of sensitivity, in the 2016 TTS, annual household income data were collected as a categorical variable. A summary is provided in Table 1, along with additional descriptive statistics and comparison to Statistics Canada data for validation.

Since the empirical model requires a continuous variable specification of household income, we must make an assumption about how to treat the income variable. Aiew et al. (2004) provide an empirical comparison of three common methods: (1) income as dummy variables, (2) median of income categories, and (3) income as category value. Their analysis suggests that there is no statistically significant difference in the WTP between each specification (Aiew et al. 2004). We explored the use of the lower or upper income bound

of income categories, before settling upon the median as a reasonable approximation to income from which to calculate marginal values of mobility.

## Empirical investigations and policy relevance

The results of model estimation are presented in Tables 2, 3, 4 and 5 below. The first point to make about these results is that the parameter for income comes out as positive in the case of car ownership and negative in the case of residential density. This provides a basic check of the results with a priori expectations. One would generally expect additional income to allow a household to purchase additional vehicles and reside in a lower density area (i.e. larger dwelling). This density effect is also captured in the distance from the CBD parameter, which is negative and significant with increasing residential density. Looking at the parameters, excluding those considering marginal trip values, it is found that additional adults have a stronger effect than additional children on the number of vehicles owned by the household. We also find that higher car ownership is positively correlated with the area of land devoted to parks and recreation. This is reasonable and fits with the residential density model outcome of higher density being negatively correlated with parks and recreation.

Considering car ownership choice and total daily trips (Table 2), we estimate a total of 40 marginal trip value parameters. There is a general trend of increasing trip value with distance from the CBD. This acts as a benchmark in our analysis and suggests that households making trips further from the CBD incur additional costs (relative to households closer to the CBD) to maintain the same level of access to shops and services. By considering a fixed household income, one can see that making an additional trip is positively correlated with the purchase of an additional car. An increasing marginal trip value, with distance from the CBD, suggests that additional trips are more highly valued the further one moves away from the CBD. These households would pay a higher value for MaaS because they exhibit stronger captivity to the car to maintain their mobility and access to services. The presence of children in the household tends to lower the marginal value of a trip. An overall consideration of Table 2 illustrates the high variation in the marginal value of travel. At the low end, 2 worker households residing within 5 km of the CBD have a marginal value of CA\$2.43, while households with 3+ workers and residing > 25 km from the CBD have a marginal value of CA\$91.95. This variation is not captured in transportation economics literature. Consider that Stanley and Hensher (2011) provide a single value of AUD\$18.40 per trip, which is well below the upper bound of what we find in this study.

Table 2 suggests that MaaS may not be used in the congested CBD, where there is a variety of mobility alternatives available. Rather, the high-profit trips desired by a private operator would be outlying areas where household are willing to pay considerably more to make an additional trip. Contrasting this result with Table 4, which summarizes the results for travel distance, there is less variation in the WTP between households in CBD and outlying communities. This indicates that trips in these communities may not be long. Taken in combination, Tables 2 and 4 suggest that suburban areas (with high segregation of land uses and lower densities) are the highest profit areas for marginal trip providers, but that these trips may not be long. The combination of factors may produce a MaaS service characterized by a high number of car trips, rather than the desired effect of facilitating a mixed mode system. Public management of the system could help to encourage MaaS deployment that alleviates congestion in central areas and encourages use across trip distances.

**Table 2** Household car ownership choice model: considering total daily trips

	Parameter	<i>t</i> stat	<i>p</i> value
Constant	−0.89	−4.47	0
Income	0.006	15.94	0
Value of an additional trip by the household			
0 worker, no children, and location within 5 km or less from the CBD	5.84	2.12	0.03
0 worker, having children, and location within 5 km or less from the CBD	5.84	2.12	0.03
1 worker, no children, and location within 5 km or less from the CBD	5.84	2.12	0.03
1 worker, having children, and location within 5 km or less from the CBD	5.43	1.10	0.27
2 worker, no children, and location within 5 km or less from the CBD	2.43	1.08	0.28
2 worker, having children, and location within 5 km or less from the CBD	2.43	1.08	0.28
3+ worker, no children, and location within 5 km or less from the CBD	37.52	2.25	0.025
3+ worker, having children, and location within 5 km or less from the CBD	16.14	3.61	0.0003
0 worker, no children, and location within 5–10 km from the CBD	16.14	3.61	0.0003
0 worker, having children, and location 5–10 km from the CBD	10.74	1.14	0.25
1 worker, no children, and location within 5–10 km from the CBD	15.51	4.38	0
1 worker, having children, and location within 5–10 km from the CBD	5.46	1.29	0.20
2 worker, no children, and location within 5–10 km from the CBD	9.14	2.91	0.004
2 worker, having children, and location within 5–10 km from the CBD	9.08	2.35	0.019
3+ worker, no children, and location within 5–10 km from the CBD	49.51	2.01	0.045
3+ worker, having children, and location within 5–10 km from the CBD	41.47	1.25	0.21
0 worker, no children, and location within 10–15 km from the CBD	24.35	4.66	0
0 worker, having children, and location 10–15 km from the CBD	16.76	1.77	0.08
1 worker, no children, and location within 10–15 km from the CBD	30.76	5.70	0
1 worker, having children, and location within 10–15 km from the CBD	14.74	2.69	0.010
2 worker, no children, and location within 10–15 km from the CBD	24.45	4.74	0
2 worker, having children, and location within 10–15 km from the CBD	17.17	3.11	0.002
3+ worker, no children, and location within 10–15 km from the CBD	76.86	1.50	0.14
3+ worker, having children, and location within 10–15 km from the CBD	76.86	1.49	0.14
0 worker, no children, and location within 15–25 km from the CBD	29.99	6.32	0
0 worker, having children, and location 15–25 km from the CBD	8.16	1.09	0.28
1 worker, no children, and location within 15–25 km from the CBD	37.40	6.99	0
1 worker, having children, and location within 15–25 km from the CBD	17.18	3.33	0.0009
2 worker, no children, and location within 15–25 km from the CBD	51.39	5.96	0

**Table 2** (continued)

	Parameter	<i>t</i> stat	<i>p</i> value
2 worker, having children, and location within 15–25 km from the CBD	29.15	4.23	0
3+ worker, no children, and location within 15–25 km from the CBD	86.94	1.81	0.07
3+ worker, having children, and location within 15–25 km from the CBD	86.94	1.81	0.07
0 worker, no children, and location farther than 25 km from the CBD	18.86	4.43	0
0 worker, having children, and location farther than 25 km from the CBD	18.86	4.43	0
1 worker, no children, and location within farther than 25 km from the CBD	23.66	4.40	0
1 worker, having children, and location within farther than 25 km from the CBD	14.66	2.84	0.005
2 worker, no children, and location within farther than 25 km from the CBD	81.40	4.40	0
2 worker, having children, and location within farther than 25 km from the CBD	57.63	3.38	0.0007
3+ worker, no children, and location within farther than 25 km from the CBD	91.95	1.41	0.16
3+ worker, having children, and location within farther than 25 km from the CBD	91.95	1.41	0.16
Number of adults in the household	0.51	14.59	0
Total number of children in the household	0.077	1.69	0.092
Dwelling type: apartments/condominiums	−0.49	−10.11	0
Relative (to the sample mean) distance of the home from the CBD	0.32	5.53	0
Log of the proportion of land (of the home zone) dedicated to parks & recreations	0.42	2.17	0.030
Log of population density of the home zone	0	−	
Log of dwelling density of the home zone	−0.11	−6.12	0
Entropy of youth population (16–19 years old) proportion in the home zone	−1.55	−2.663	0.0077
Zonal average income per day	0.0009	1.985	0.047
Loglikelihood of the full model	−120,651		
Loglikelihood of the constant-only model	−141,194		
Adjusted rho-squared value	0.146		

We include a graphical representation of the WTP for Table 2 via a set of WTP curves in Fig. 1. For 2 and 3+ worker households, the increasing WTP with distance from the CBD is consistent, while it tends to stabilize for 0 and 1 worker households past the 10–15 km range. We suggest that the higher income associated with more workers in the household leads to an increased WTP, particularly since more household members must make work trips. The constraint of a single home location and multiple work locations likely leads to more trips being made by the household.

Moving onto residential density (Tables 3 and 5), the distance category for the marginal value of a trip is replaced by car ownership, which provides the link between the two sets

**Table 3** Household location choice (residential density) model: considering total daily trips

	Parameter	<i>t</i> stat	<i>p</i> value
Constant	7.09	60.36	0
Income	−0.006	−23.81	0
Value of an additional trip by the household			
0 worker, no car, and no children	9.61	2.26	0.02
0 worker, have car(s), and no children	14.36	14.62	0
1 worker, no car, and no children	8.46	8.89	0
1 worker, have car(s), and no children	8.46	8.89	0
2 worker, no car, and no children	2.55	3.39	0.0007
2 worker, have car(s), and no children	2.55	3.39	0.0007
3+ worker, no car, and no children	2.55	3.39	0.0007
3+ worker, have car(s), and no children	2.55	3.39	0.0007
0 worker, no car, and have children	19.20	3.39	0.0007
0 worker, have car(s), and have children	11.03	5.23	0
1 worker, no car, and have children	9.18	10.60	0
1 worker, have car(s), and have children	9.18	10.60	0
2 worker, no car, and have children	8.12	11.59	0
2 worker, have car(s), and have children	8.12	11.59	0
3+ worker, no car, and have children	11.88	1.88	0.0599
3+ worker, have car(s), and have children	2.35	2.88	0.004
Number of adults in the household	−0.33	−23.45	0
Relative (to the sample mean) distance of the home from the CBD	−1.41	−64.48	0
Log of the proportion of land (of the home zone) dedicated to parks and recreations	−1.61	−12.73	0
Entropy of the youth population (16–19 years old) proportion in the home zone	8.13	25.88	0
Zonal average income per day	−0.0072	−14.34	0
Loglikelihood of the full model	−164,360		
Loglikelihood of constant-only mode	−238,448		
Adjusted rho-squared value	0.311		

of dependent variables. These results do not show the same obvious pattern of variation across categories. Considering similar densities, households have a similar WTP, or marginal value of trips, regardless of their car ownership status. In general, households without children have a lower marginal value of trips (Fig. 2).

We also present models for the value of travel by total travel daily travel distance (in km). These models also suggest that trips made to a destination further from the CBD and by larger households have a higher value associated with them. This trend supports the finding that the urban form in these regions forces households into a state of mobility deprivation. The lower density associated with these outlying areas means households must purchase additional vehicles to maintain their mobility. They exhibit a willingness to pay a higher travel value to maintain a residence in these communities. Comparing the values obtained on per trip and per km bases illustrates the difference in trip distance associated with trips made in the CBD and those made in the suburbs. The per km values are fairly similar between the two distance extrema, but per trip, values are significantly higher in

**Table 4** Household car ownership choice model: considering total daily km travel

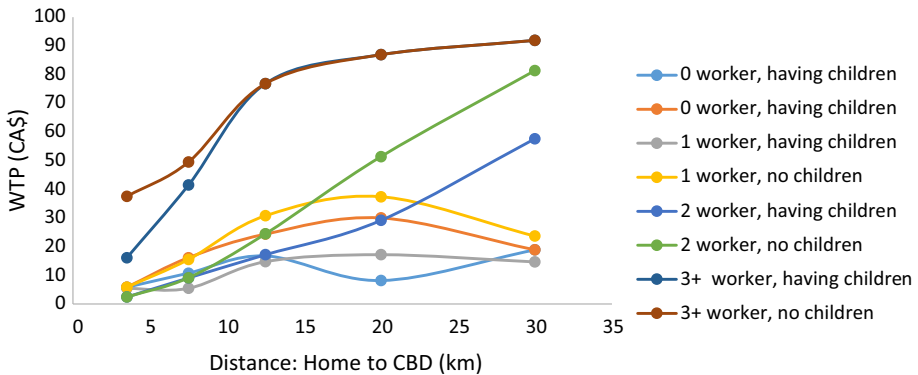
	Parameter	<i>t</i> stat	<i>p</i> value
Constant	−0.94	−3.55	0.0004
Income	0.0066	16.98	0
Value of an additional km distance travel by the household			
0 worker, no children, and location within 5 km or less from the CBD	0.62	1.71	0.087
0 worker, having children, and location within 5 km or less from the CBD	0.62	1.71	0.087
1 worker, no children, and location within 5 km or less from the CBD	0.82	3.33	0.0009
1 worker, having children, and location within 5 km or less from the CBD	0.46	2.59	0.0096
2 worker, no children, and location within 5 km or less from the CBD	0.46	2.59	0.0096
2 worker, having, children and location within 5 km or less from the CBD	0.46	2.59	0.0096
3+ worker, no children, and location within 5 km or less from the CBD	2.03	1.58	0.11
3+ worker, having children, and location within 5 km or less from the CBD	2.03	1.58	0.11
0 worker, no children, and location within 5–10 km from the CBD	0.81	1.98	0.048
0 worker, having children, and location 5–10 km from the CBD	0.81	1.98	0.048
1 worker, no children, and location within 5–10 km from the CBD	1.14	4.04	0.0001
1 worker, having children, and location within 5–10 km from the CBD	0.49	1.07	0.29
2 worker, no children, and location within 5–10 km from the CBD	0.66	2.63	0.0085
2 worker, having children, and location within 5–10 km from the CBD	0.74	1.86	0.063
3+ worker, no children, and location within 5–10 km from the CBD	2.17	1.92	0.055
3+ worker, having children, and location within 5–10 km from the CBD	1.79	1.24	0.21
0 worker, no children, and location within 10–15 km from the CBD	0.66	1.88	0.06
0 worker, having children, and location 10–15 km from the CBD	0.66	1.88	0.06
1 worker, no children, and location within 10–15 km from the CBD	1.23	3.76	0.0002
1 worker, having children, and location within 10–15 km from the CBD	0.74	1.33	0.18
2 worker, no children, and location within 10–15 km from the CBD	2.46	5.12	0
2 worker, having children, and location within 10–15 km from the CBD	2.04	3.15	0.002
3+ worker, no children, and location within 10–15 km from the CBD	4.35	1.53	0.12
3+ worker, having children, and location within 10–15 km from the CBD	3.71	1.57	0.12
0 worker, no children, and location within 15–25 km from the CBD	0.65	2.25	0.025
0 worker, having children, and location 15–25 km from the CBD	0.65	2.25	0.025
1 worker, no children, and location within 15–25 km from the CBD	1.33	4.60	0
1 worker, having children, and location within 15–25 km from the CBD	0.75	1.83	0.067
2 worker, no children, and location within 15–25 km from the CBD	2.63	4.94	0
2 workers, having children, and location within 15–25 km from the CBD	2.09	3.36	0.0008
3+ worker, no children, and location within 15–25 km from the CBD	4.38	2.00	0.046
3+ worker, having children, and location within 15–25 km from the CBD	3.74	1.41	0.16
0 workers, no children, and location farther than 25 km from the CBD	0.26	1.90	0.058
0 workers, having children, and location farther than 25 km from the CBD	0.26	1.90	0.058
1 worker, no children, and location within farther than 25 km from the CBD	0.26	1.90	0.058
1 worker, having children, and location within farther than 25 km from the CBD	0.65	1.79	0.07
2 worker, no children, and location within farther than 25 km from the CBD	2.89	3.62	0.0003
2 worker, having children, and location within farther than 25 km from the CBD	2.34	2.91	0.004
3+ worker, no children, and location within farther than 25 km from the CBD	4.43	1.43	0.15

**Table 4** (continued)

	Parameter	<i>t</i> stat	<i>p</i> value
3+ worker, having children, and location within farther than 25 km from the CBD	3.76	1.14	0.26
Number of adults in the household	-0.12	-3.25	0.0012
Total number of children in the household	-0.21	-5.19	0
Dwelling type: apartments/condominiums	0.57	16.05	0
Relative (to the sample mean) distance of the home from the CBD	0.24	5.17	0
Log of the proportion of land (of the home zone) dedicated to parks and recreations	-0.43	-8.67	0
Log of population density of the home zone	0.45	9.84	0
Log of dwelling density of the home zone	0.56	2.89	0.0039
Entropy of the youth population (16–19 years old) proportion in the home zone	0.25	2.49	0.013
Zone average income per day	-0.37	-4.05	0.0001
Loglikelihood of the full model	-120,532		
Loglikelihood of constant-only model	-141,185		
Adjusted rho-squared value	0.147		

**Table 5** Household location choice (residential density) model: considering total daily km travel

	Parameter	<i>t</i> stat	<i>p</i> value
Constant	5.69	81.53	0
Income	-0.008	-30.42	0
Value of an additional trip by the household			
0 worker, no children	0.17	8.50	0
1 worker, no children	0.094	5.68	0
2 worker, no children	0.14	7.37	0
3+ worker, no children	0.091	4.98	0
0 worker, have children	0.055	2.00	0.046
1 worker, have children	0.055	2.00	0.046
2 worker, have children	0.14	9.15	0
3+ worker, have children	0.058	3.09	0.002
Number of workers in the household	0.18	10.93	0
Number of adults in the household	0.048	2.66	0.008
Number of students in the household	-0.39	-25.59	0
Number of children in the household	-0.22	-11.87	0
Relative (to the sample mean) distance of the home from the CBD	-1.49	-71.16	0
Log of the proportion of land (of the home zone) dedicated to parks and recreations	-1.40	-11.06	0
Loglikelihood of the full model	-164,748		
Loglikelihood of constant-only model	-238,433		
Adjusted rho-squared value	0.309		



**Fig. 2** Willingness to pay curve for household car ownership choice model: considering total daily trips

the greater than 25 km range than less than 5 km range. This suggests that the difference in values is largely a function of the average trip length.

The adoption of MaaS provides an excellent avenue for exploring model results. Service providers will require a means of pricing trips based on the origin, destination, length, number of passengers, among other metrics. Local governments may play a part in service provision but will certainly have a regulatory role. In the absence of MaaS, public transit provides a means of applying the model results to public policy. The models suggest that values will be higher in areas further from the CBD, which fits with patterns observed in transit. It is typical that transit fares cover a smaller portion of operating costs in areas of low transit ridership. High car ownership, low-density developments, and greater distances from the CBD characterize such areas. In the case of transit, the government agency will generally subsidize fares to provide a service for car deficient households. The adoption of MaaS will place a similar cost burden on service providers, who may not have the same objectives as providing low-cost mobility options. Government intervention, through subsidies, is one method to address this potential issue.

## Conclusions and further research

In this paper, we have made the first approximation to the marginal value of mobility. Four models are presented to capture the many dimensions of this measure. The multinomial logit model formulation proved to provide the best results (compared to ordered discrete choice model), considering car ownership as a count variable, and allows for the specification of multiple marginal trip value parameters. We find that the marginal value of travel varies between CA\$2.43 and CA\$91.95, depending upon the household characteristics and the location of the trip. This raises serious concerns about the equity of future mobility access. In an environment of MaaS, regulatory measures will likely be required to ensure equal access to transportation for all. Multi-worker households in outlying areas bear most of the cost burden because they lack the variety of mobility alternatives of areas around the CBD and must purchase additional cars to make commuting trips to, potentially, dispersed work locations.

The high marginal value of mobility in low-density communities also suggests an inefficiency in the distribution of home and work locations. Mobility can be provided at



a significantly lower price point in higher density areas closer to the CBD. Our results indicate that trips in low-density suburbs may not be long, but are heavily reliant on car ownership. The combination of car dependence and high WTP makes these communities desirable for private MaaS operators from the perspective of maximizing marginal revenue—assuming replacement of car ownership by purchase of MaaS membership. However, this environment is not conducive to streamlining the provision of a mixed mode system of transportation. The present MaaS picture is one of high cost, single mode, trips in suburban communities and low cost, streamlined, trips in the denser communities around the CBD. On the one hand, households in low density communities may be penalized with high subscription costs. This would send a price signal that encourages denser, mixed, development but at the risk of disproportionately affecting low income households. In the bleaker case, the price is set below the marginal cost of travel in these communities and households are encouraged to make more trips by car—increasing congestion and air pollution. Public investment in transit, cycling, and walking infrastructure will be vital. Our results suggest policies to encourage the mixing land uses will also remain important to decrease the marginal cost of travel in these communities. This will help to alleviate what we foresee as a major issue of unequal MaaS quality and use frequency.

There is substantial scope for further research in this space. We estimated a large number of individual parameters to capture market segmentation in a closed form MNL model. The model could be specified with a mixing distribution to capture this heterogeneity with a single continuous variable. The direct estimation of the ratio of  $\beta_{trips}$  by  $\beta_{income}$  provides for this extension without significant changes to the model structure. A question that remains to be more fully answered is the distinction between the WTP for increased mobility and the cost of increased mobility. These terms are used interchangeably in the literature, but this is largely a function of an inability to disentangle their distinction. We postulate that the distinction is captured in the difference between factors endogenous to the household and those that are exogenous. WTP is a function of the household's willingness to pay for an additional discretionary trip based on their income and internal utility function. The cost of increased mobility is additionally a function of land use patterns that are only partially an outcome of decisions by the individual household. We have attempted to separate these effects through the estimation of models for car ownership (a household-level decision) and residential density (an aggregate outcome of household, firm, and government decisions). However, this remains a problem requiring further research.

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