

# A data fusion approach for ride-sourcing demand estimation: A discrete choice model with sampling and endogeneity corrections

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## ABSTRACT

Ride-sourcing services offered by companies like Uber and Didi have grown rapidly in the last decade. Understanding the demand for these services is essential for planning and managing modern transportation systems. Existing studies develop statistical models for ride-sourcing demand estimation at an aggregate level due to limited data availability. These models lack foundations in microeconomic theory, ignore competition of ride-sourcing with other travel modes, and cannot be seamlessly integrated into existing individual-level (disaggregate) activity-based models to evaluate system-level impacts of ride-sourcing services. In this paper, we present and apply an approach for estimating ride-sourcing demand at a disaggregate level using discrete choice models and multiple data sources. We first construct a sample of trip-based mode choices in Chicago, USA by enriching household travel survey with publicly available ride-sourcing and taxi trip records. We then formulate a multivariate extreme value-based discrete choice model with sampling and endogeneity corrections to account for the construction of the estimation sample from multiple data sources and endogeneity biases arising from supply-side constraints and surge pricing mechanisms in ride-sourcing systems. Our analysis of the constructed dataset reveals insights into the influence of various socio-economic, land use and built environment features on ride-sourcing demand. We also derive elasticities of ride-sourcing demand relative to travel cost and time. Finally, we illustrate how the developed model can be employed to quantify the welfare implications of ride-sourcing policies and regulations such as terminating certain types of services and introducing ride-sourcing taxes.

## 1. Introduction

Ride-sourcing services like Uber, Lyft, Didi and Grab have expanded rapidly in the last decade and have attracted considerable ridership in many metropolitan areas worldwide (see [Goletz and Bahamonde-Birke, 2021](#)). Ride-sourcing is a disruptive transport mode with positive (provision of convenient, affordable on-demand transportation options) and negative (congestion, pollution, increased vehicle kilometres travelled, possible cannibalisation of public transport demand) impacts on transport systems (see [Tirachini, 2020](#)). To realise their advantages and inhibit their disadvantages, ride-sourcing services need to be planned, regulated and managed ([Goletz and Bahamonde-Birke, 2021](#); [Tirachini, 2020](#)). To that end, a rigorous understanding of ride-sourcing demand is essential. Specifically, it is crucial to (i) explain the characteristics of ride-sourcing demand, (ii) analyse the interaction of ride-sourcing with other transport modes and (iii) quantify the welfare implications of introducing ride-sourcing services or amending

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operational policies. To provide actionable, evidence-based decision support, ride-sourcing demand analysis calls for (i) powerful methods to leverage datasets with varying disaggregation and resolution and (ii) comprehensive datasets with user-level preferences and vehicle-level operations at an urban scale, yet both are currently found wanting.

In terms of methods, ride-sourcing demand analysis is currently dominated by approaches without adequate foundations in microeconomic theory. Aggregate models such as regression models for count and continuous data (e.g. Ghaffar et al., 2020; Marquet, 2020) estimate a statistical relationship between realised aggregate demand and aggregate explanatory variables. Ordered outcome models for explaining ride-sourcing use at the individual level (e.g. Alemi et al., 2019; von Behren et al., 2021) infer structural relationships between demand and individual-specific attributes. These methods disregard that ride-sourcing demand arises at the disaggregate level in the form of a mode choice involving trade-offs between various alternative-specific attributes (e.g. travel cost, time, reliability and safety).

Most applications of these statistical methods are driven by limited data availability. Commonly considered data sources exhibit significant weaknesses when they are analysed in isolation. Household travel surveys have a broad geographical coverage. However, they typically only include a small number of ride-sourcing trips, which precludes a thorough analysis of ride-sourcing demand. In principle, discrete choice experiments (DCEs) allow for a detailed analysis of ride-sourcing demand. However, data collected via DCEs may exhibit hypothetical biases. Also, DCEs are typically not repeated over time due to financial and logistical constraints. Recently, ride-sourcing trip records have been published under data sharing agreements between ride-sourcing companies and city authorities (e.g. Ghaffar et al., 2020). These trip records have a broad spatiotemporal coverage. However, in isolation, they cannot be used for the disaggregate analysis of ride-sourcing demand since they do not contain any information about the demand for other modes.

This research aims at improving ride-sourcing demand analysis. To that end, we present and apply an approach for estimating ride-sourcing demand using discrete choice models (DCMs) by fusing multiple data sources. DCMs are well suited for analysing ride-sourcing demand due to their solid foundations in microeconomic theory. DCMs estimate structural relationships between observed travel choices and various alternative- and individual-specific attributes. Due to their structural nature, DCMs produce stable and transferable predictions, which in turn makes DCMs suitable for analysing counterfactual pricing and service configuration scenarios.

We first construct an estimation sample of trip-based mode choices in Chicago by enriching household travel survey data with publicly available ride-sourcing and taxi trip records. By fusing the two data sources, we address the problems of (i) having too few ride-sourcing trip records in household travel survey data and (ii) having no information about other modes in ride-sourcing trip records. However, constructing an estimation sample from two revealed preference data sources creates two challenges in developing a DCM. First, a sampling correction is needed to account for the enrichment of the household travel survey data with ride-sourcing and taxi trip records. Second, the constructed mode choice dataset likely exhibits endogeneity biases, as the demand for the ride-sourcing options and their prices is simultaneously determined by supply-side constraints and surge pricing mechanisms (see e.g. Castillo et al., 2017). We address both challenges by formulating a multivariate extreme value (MEV)-based DCM with sampling and endogeneity corrections. To correct for sampling biases, we adopt a conditional maximum likelihood estimator (see Bierlaire and Krueger, 2020) due to its efficiency properties; and to correct for endogeneity biases, we adopt the control function approach (Petrin and Train, 2010) due to its simplicity. Ultimately, we apply the model to the constructed mode choice dataset to analyse the demand for ride-sourcing services in Chicago. The parameter estimates of the DCM are translated into the elasticity of ridesourcing demand relative to alternative-specific attributes like price and travel time. We also illustrate how the estimated model can be employed to quantify the welfare implications of ride-sourcing policies and regulations such as eliminating certain types of services and introducing taxes.

We organise the remainder of this paper as follows: In Section 2, we review related literature. In Section 3, we describe the construction of the estimation sample for the empirical application. In Section 4, we present the general formulation of the econometric model. In Section 5, we explain the model specification considered in the empirical application. In Section 6, we discuss the results of the empirical application, and in Section 7, we present the welfare analysis. Finally, we conclude in Section 8.

## 2. Related literature

The literature on ride-sourcing demand analysis evolves rapidly. In Table 9 in Appendix A, we present an overview of recently published ride-sourcing demand analysis studies. For reviews of earlier studies, the reader is directed to Tirachini (2020) and Wang and Yang (2019). The studies enumerated in Table 9 can be subsumed under five topics:

1. travel modes (mostly public transit) that are complemented or substituted by ride-sourcing services; impact of emerging on-demand mobility services on vehicle ownership;
2. association of built-environment, socio-demographics, weather and land use characteristics with ride-sourcing demand at a spatial level (e.g. census tract and census block groups);
3. association of attitudes, socio-demographic and economic characteristics with the usage of and preferences for ride-sourcing services;
4. determinants of preferences for the use of pooled ride-sourcing services;
5. impact of mode-specific attributes (e.g. travel time and wait time) on the demand for these services in the multi-modal transport system.

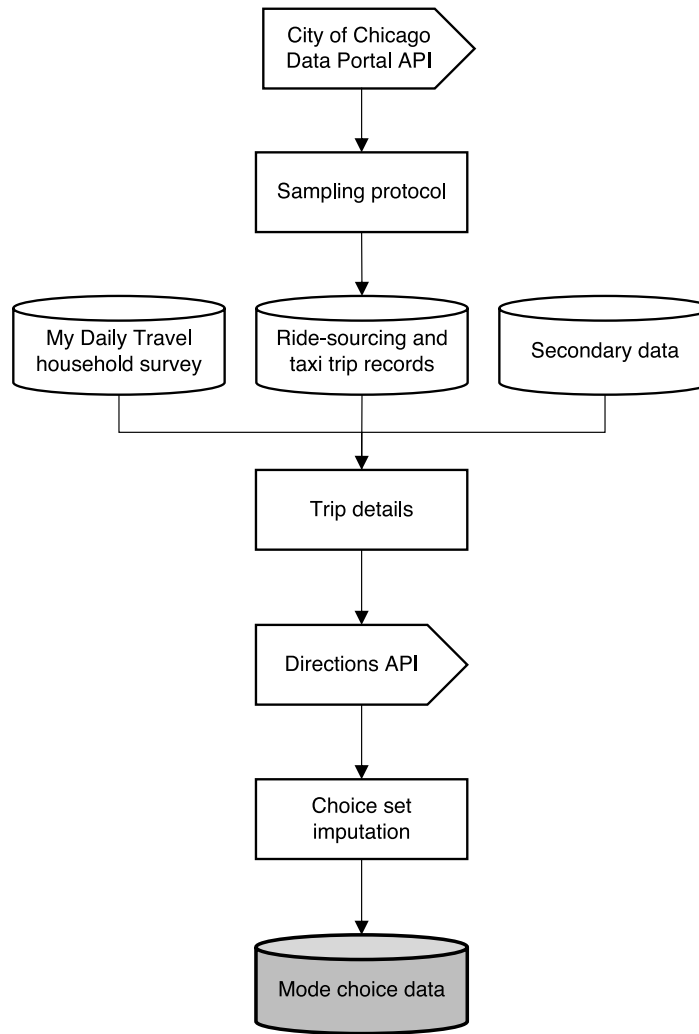


Fig. 1. Dataset construction.

The studies use mainly three types of data (see column “data type” in Table 9). First, trip records from ride-sourcing companies are merged with supplementary data about land use, weather and census tract attributes. These studies focus predominantly on the first two of the five topics enumerated above; only a few studies focus on the fourth topic. Second, household travel surveys with information about individuals’ travel patterns, socio-demographic characteristics and attitudes are considered for exploring the third topic; a handful of studies also focus on topics one and four. Third, DCEs are employed to investigate topics three to five.

In terms of methods, most studies that consider the first data type aggregate trips across space and time and then rely on geographically weighted and spatially lagged count or continuous data models with autoregressive structure or panel effects. A few studies use off-the-shelf machine learning algorithms such as random forest or gradient boosting decision trees. Studies considering household travel survey data use multinomial and ordered logit models. Several studies also develop joint models of continuous, count and ordered variables (i.e. generalised heterogeneous data models). Structural equation models are also used to analyse the relationship between ride-sourcing demand and latent attitudes. Finally, studies collecting data through DCEs naturally employ DCMs such as nested, latent class, error component or mixed logit models.

Only a few studies use DCMs and revealed preference data to analyse ride-sourcing demand. Habib (2019) considers revealed preference data from a household travel survey to investigate ride-sourcing demand using a semi-compensatory choice model with probabilistic choice set formation. The study finds that ride-sourcing demand mostly complements the demand for driving and transit and substitutes taxi demand. Furthermore, the probability of considering ride-sourcing varies by age, whereby young people are more likely to consider ride-sourcing, and older people are more likely to consider taxis. Lam et al. (2021) considered revealed preference data constructed from ride-sourcing trip records, field data and API queries to analyse ride-sourcing demand in New York City. The authors employ an aggregate logit model for market share data. The model includes endogeneity corrections for price and

wait times. The study finds that the distribution of ride-sourcing benefits varies substantially across space, with low accessibility areas experiencing comparatively higher benefits.

In summary, household travel surveys and trip records have been used in isolation. Both data sources exhibit significant weaknesses when used in isolation: Household travel surveys contain insufficient information about ride-sourcing demand; trip records cannot be used for disaggregate demand analysis, as they do not include information about individual-level preferences for other travel modes. This current study contributes to the literature with a DCM for disaggregate demand analysis of ride-sourcing services by fusing both datasets and addressing potential endogeneity issues. This data fusion framework leverages the richness of both data types while addressing the shortcomings of analysing them in isolation. We also control for demographics, transit accessibility, parking cost, land use characteristics, pedestrian friendliness, and weather conditions in the DCM, which may affect demand for ridesourcing services. The developed model can be used as a direct input to activity-based travel demand forecasting models to quantify the short- and long-term impact of policies and regulations related to ridesourcing services on the multi-modal transport system.

Finally, our study is also related to the literature on endogeneity and discrete choice analysis in various other applications, including but not limited to consumer choice (Petrin and Train, 2010), residential location choice (Guevara and Ben-Akiva, 2012), airline itinerary choice (Lurkin et al., 2017) and parking choice (Gopalakrishnan et al., 2020).

### 3. Data

We construct an estimation sample of trip-based mode choices in Chicago from November 2018 to May 2019, following the process visualised in Fig. 1. In what follows, we describe the construction of the estimation sample in detail.

#### 3.1. Primary data sources

Trip records for the construction of the estimation sample are gathered from two primary sources, namely (i) ride-sourcing and taxi trip records provided on the City of Chicago Data Portal<sup>1</sup> and (ii) the My Daily Travel household survey.

The City of Chicago Data Portal provides access to records of all ride-sourcing and taxi trips that transportation networking providers and taxi companies have reported to the City of Chicago for regulatory purposes since November 2018 and January 2013, respectively. The attributes of the trips are temporally and spatially aggregated to prevent a re-identification of individual trips. Each trip record includes information about the trip start and end times rounded to the nearest 15 min, the pick-up and drop-off community areas as well as the fare amount. The pick-up and drop-off census tracts are also available if at least three trips started or ended in the relevant census tract in the relevant 15-minute period. For ride-sourcing trips, it is also known if a pooled trip was requested. Thus, solo and pooled ride-sourcing trips can be distinguished.

The My Daily Travel household survey is a large-scale household travel survey that was conducted by the Chicago Metropolitan Agency for Planning (CMAP) between August 2018 and May 2019. The survey collected information about the daily travel behaviour of a representative sample of more than 12,000 households in North-eastern Illinois. More information about the survey is available in Westat (2020). The collected data include trip records with information about the chosen transport mode (car, transit, bike, walking, taxi, solo-ride-sourcing or pooled ride-sourcing), trip start and end times as well as origin and destination census tracts.

For the construction of the estimation sample, we exploit the temporal and spatial overlap of the ride-sourcing and taxi trip records from the City of Chicago Data Portal and the My Daily Travel household survey. Consequently, we limit our analysis to trip records produced between 1 November 2018 and 3 May 2019. Since we are interested in understanding ride-sourcing use in the context of general travel demand, we only consider trips on weekdays between 5:00 and 23:00. Furthermore, to make it possible to impute the attributes of non-chosen alternatives, we restrict our analysis to trips for which the reported start and end locations are distinct. The start and end points of a trip are given by the centroids of the origin and destination census tracts or community areas. We exclude trips that start or end outside of the City of Chicago.

After applying these inclusion criteria, we are left with 12,593 trip records from the My Daily Travel household travel survey. For our analysis, we consider all trips from the My Daily Travel household survey that satisfy the inclusion criteria. 18,784,655 solo ride-sourcing, 7,290,921 pooled ride-sourcing and 3,821,709 taxi trips from the City of Chicago Data Portal satisfy the inclusion criteria.

We briefly describe the ride-sourcing and taxi trip records that meet the inclusion criteria. Fig. 2 shows the average weekday ride-sourcing and taxi trip counts by pick-up community area. It can be seen that the demand for ride-sourcing and taxi trips is concentrated in central zones (i.e. the Northeast) of the study area. In addition, Fig. 3 shows the average proportion of ride-sourcing trips requested as pooled trips by pick-up community area. We observe that the proportion of ride-sourcing trips requested as pooled trips is larger in the peripheral areas of the study area. Finally, Fig. 4 visualises the average ride-sourcing and taxi trip count in the whole study area by time of day. Whereas the demand for taxi is relatively balanced throughout the day, the demand for solo and pooled ride-sourcing trips exhibits pronounced morning and evening peaks.

<sup>1</sup> <https://data.cityofchicago.org>.



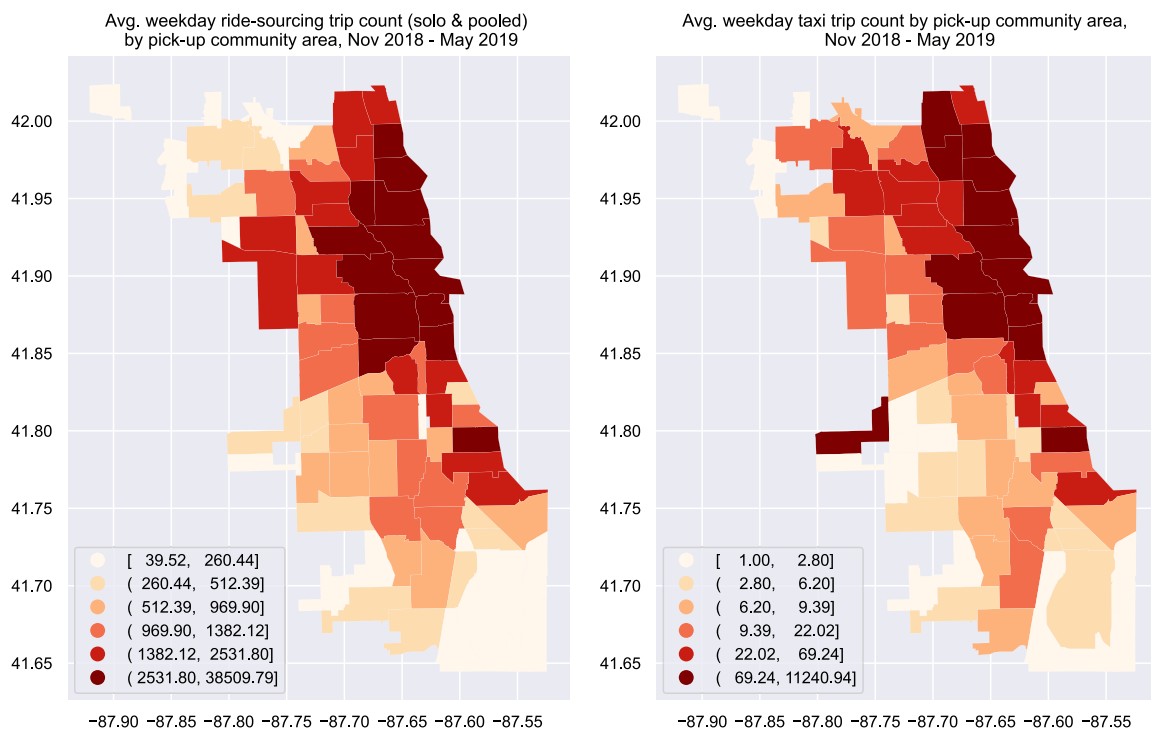


Fig. 2. Average weekday ride-sourcing and taxi trip counts by pick-up community area.

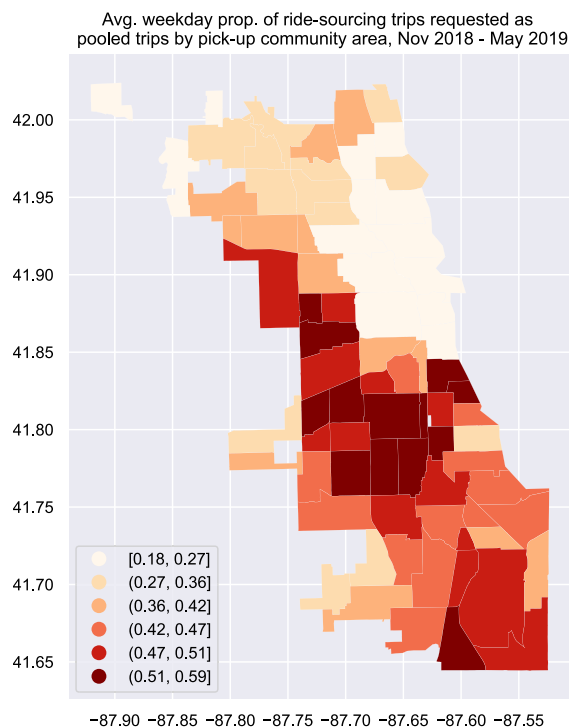


Fig. 3. Average proportion of ride-sourcing trips requested as pooled trips by pick-up community area.

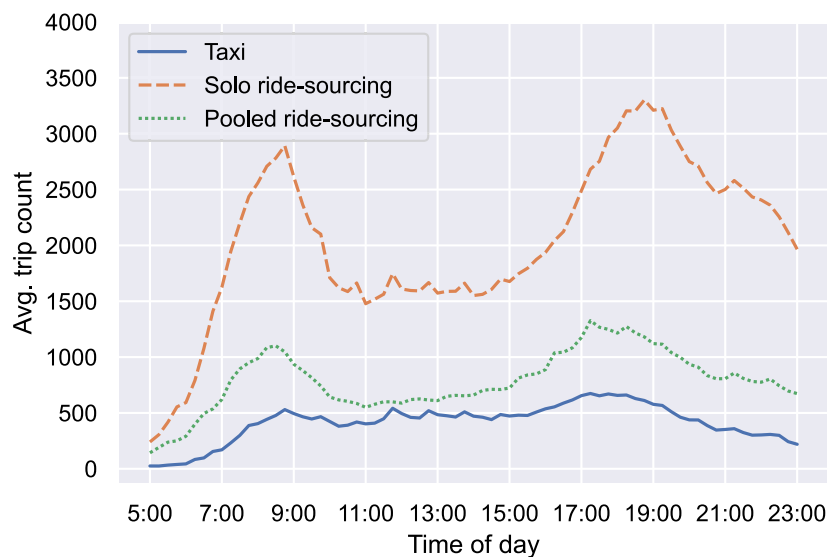


Fig. 4. Average ride-sourcing and taxi trip count by time of day.

**Table 1**  
Population and sample mode choice frequencies.

Mode	Population	My Daily Travel		Trip records		Estimation sample	
	Share	Count	Share	Count	Share	Count	Share
Car	0.521	4 781	0.380	0.000	0.000	4 781	0.066
Transit	0.200	4 275	0.339	0.000	0.000	4 275	0.059
Walk	0.200	2 737	0.217	0.000	0.000	2 737	0.038
Bike	0.050	334	0.027	0.000	0.000	334	0.005
Taxi	0.004	45	0.004	20 000	0.333	20 045	0.276
Solo ride-sourcing	0.016	285	0.023	20 000	0.333	20 285	0.279
Pooled ride-sourcing	0.009	136	0.011	20 000	0.333	20 136	0.277
Sum	1.000	12 593	1.000	60 000	1.000	72 593	1.000

### 3.2. Sampling protocol

If all eligible ride-sourcing and taxi trip records were considered, the resulting estimation sample would be too large to be processed. Therefore, we employ a choice-based sampling strategy to select ride-sourcing and taxi trips from the City of Chicago Data Portal. More specifically, we randomly select 20,000 records each from the sets of eligible solo ride-sourcing, pooled ride-sourcing and taxi trips. Table 1 shows the absolute and relative frequencies of the observed mode choices in the two subsamples and the final estimation sample.

We use the My Daily Travel household survey to estimate the population mode share. In line with the sample design, the population quantity of interest is the mode share for trips between distinct census tracts in Chicago on weekdays between 5:00 and 23:00. To that end, we calculate average person trip rates of the population of Northeastern Illinois using the person-specific sampling weights provided in the My Daily Travel household survey. The calculated population mode share is shown in the column “Population—Share” in Table 1.

### 3.3. Secondary data sources

After merging the two subsamples, we supplement the resulting dataset with information from secondary data sources.

The median household income and median age of each census tract are obtained from the American Community Survey (United States Census Bureau, 2021). The spatial distributions of the two quantities are visualised in Fig. 5.

We source various census tract attributes pertaining to employment and housing (employment density, residential density, employment and housing diversity), pedestrian friendliness (pedestrian network density, intersection density), transit supply (average proximity to transit, average transit service frequency) and car ownership (proportion of households with zero cars) from the Smart Location Database maintained by the US Environmental Protection Agency (US Environmental Protection Agency, 2021). Employment and housing diversity is an entropy-based diversity index accounting for employment numbers in five categories (retail, office, industrial, service and entertainment) and occupied housing from the database. Figs. 5–10 show the spatial distributions of the extracted quantities.

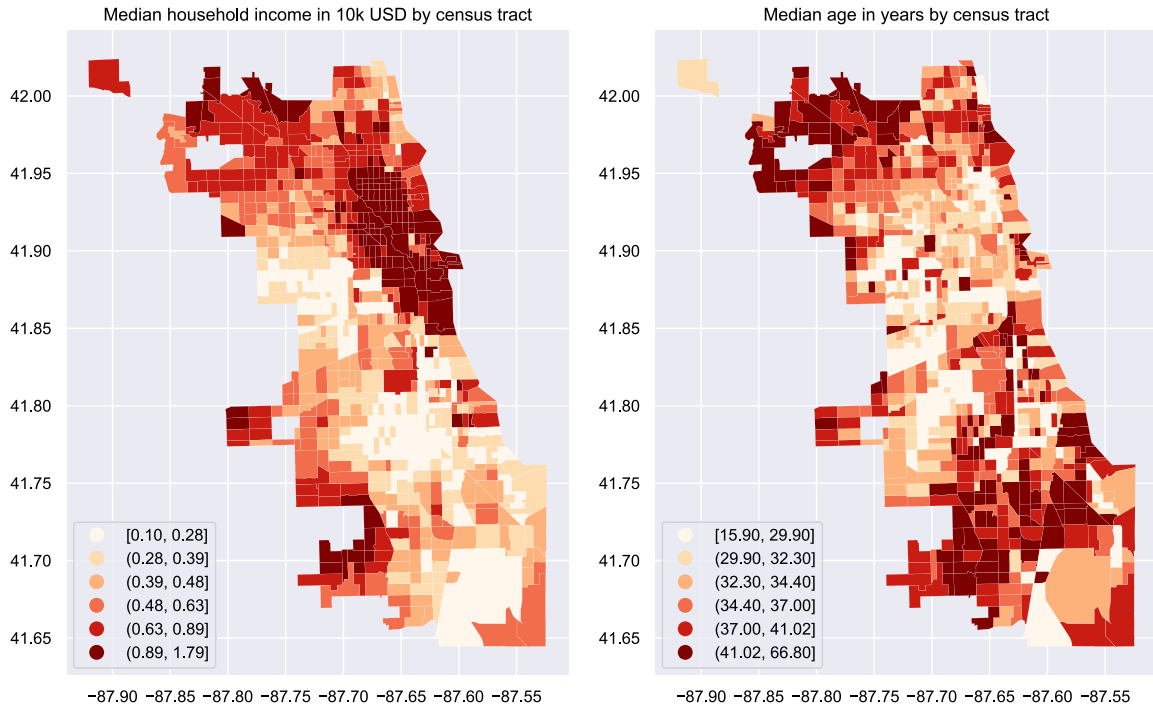


Fig. 5. Median household income and median age by census tract.

Furthermore, information on seven land use categories (residential, commercial, institutional, industrial, transportation/communication/utilities/waste, agricultural, open space) is gathered from the 2013 CMAP Land Use Inventory ([Chicago Metropolitan Agency for Planning, 2015](#)). For each census tract in the study area, we calculate an entropy-based land use diversity index of the form  $D = (\sum_{c \in \mathcal{C}} p_c \ln p_c) / |\mathcal{C}|$ , where  $\mathcal{C}$  denotes the set of considered land use categories, and  $p_c$  is the proportion of land use classified as category  $c$ . The right panel of [Fig. 7](#) shows the spatial distribution of the calculated diversity index.

In addition, information about park fees are sourced from the CMAP Parking Inventory (see [Ghaffar et al., 2020](#)). The spatial distribution of the average hourly park rate is shown in the right panel of [Fig. 10](#).

Finally, weather information is taken from daily meteorological summaries for O'Hare International Airport provided by [National Centers for Environmental Information \(2021\)](#). The average daily temperature and total daily precipitation during the observation period are shown in [Fig. 11](#).

### 3.4. Imputation of choice sets and mode attributes

Lastly, we impute choice sets and the attributes of the mode choice alternatives. Driving times and distances, transit connections as well as walking and bicycling travel times are obtained from the HERE Routing Application Programming Interface (API).<sup>2</sup>

A mode is assumed to be available in the choice set of a trip, unless the HERE Routing API indicates that the mode in question is not available for the given origin–destination pair. We specify the choice sets in this way, as the constructed mode choice data do not contain sufficient information to determine with certainty whether a mode is feasible and available for a given trip. Car, bike, taxi, solo ride-sourcing and pooled ride-sourcing are available in 100% of the trips, transit is available in 99.0% of the trips, and walking is available in 93.8% of the trips.

For the calculation of the cost of the driving alternative, we consider two variable cost components, a vehicle running cost component of 0.20 \$/mile and a fuel cost component. To compute the latter, we assume a fuel economy of 20 miles per gallon. Weekly average retail gasoline prices are sourced from [US Energy Information Agency \(2021\)](#). [Fig. 12](#) shows the evolution of the unit price of gasoline during the observation period. We approximate transit fares using agency-specific revenue information provided in the 2019 National Transit Database ([Federal Transit Administration, 2021](#)). Based on this information, we assume a fare of 0.50 \$/mile for bus and a fare of 0.30 \$/mile for rail and metro. Taxi fares are calculated using official fare information ([City of Chicago, 2020](#)).

Since passenger wait times for ride-sourcing and taxi are not observed, we assume a fixed wait time of two minutes for solo ride-sourcing, pooled ride-sourcing and taxi. These waiting times are included in the total travel times of these alternatives. To

<sup>2</sup> <https://developer.here.com/products/routing>.

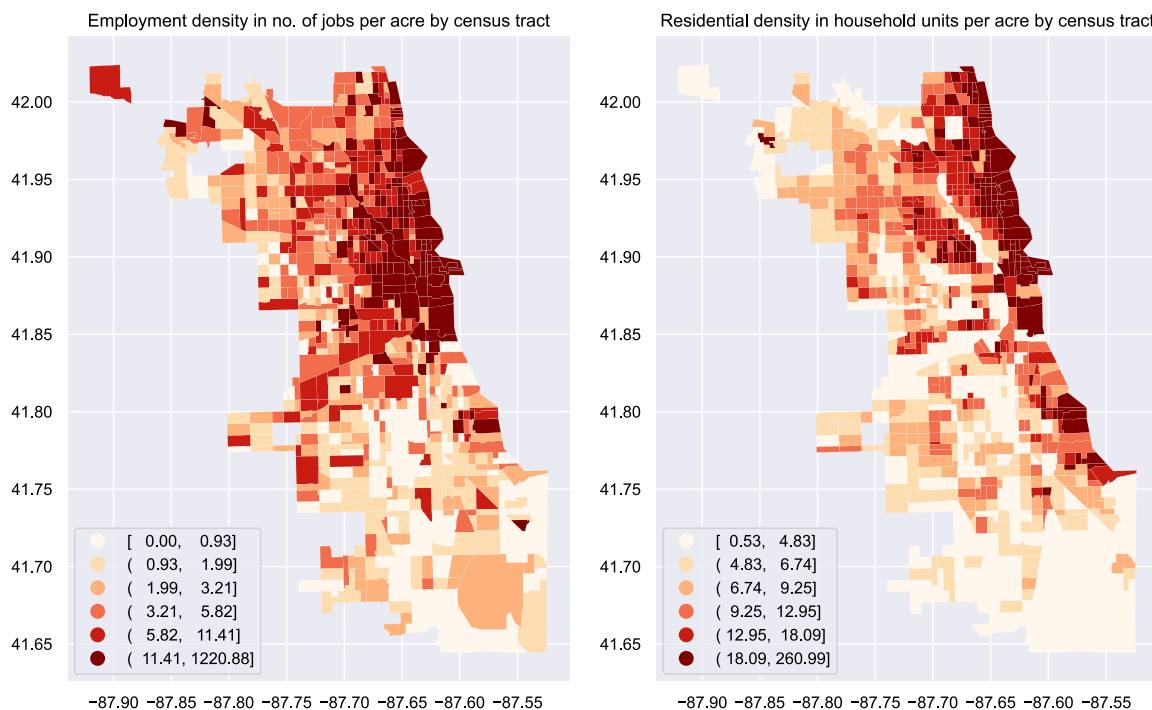


Fig. 6. Employment and residential densities by census tract.

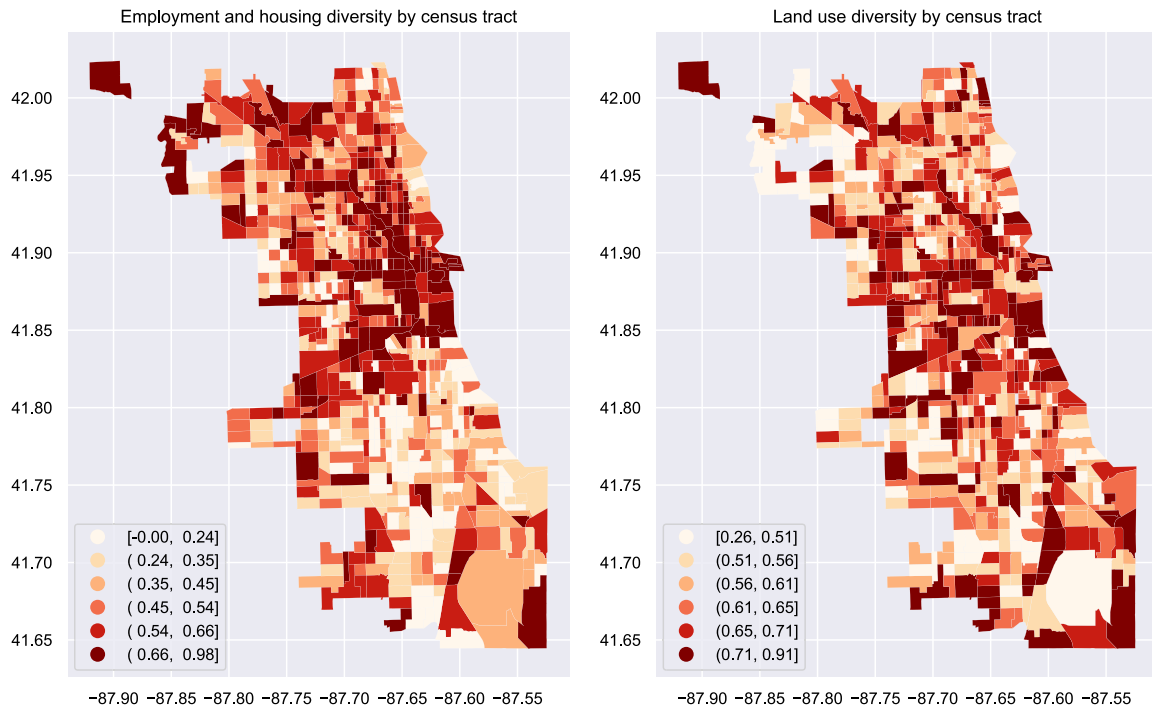


Fig. 7. Employment and housing diversity and land use diversity by census tract.

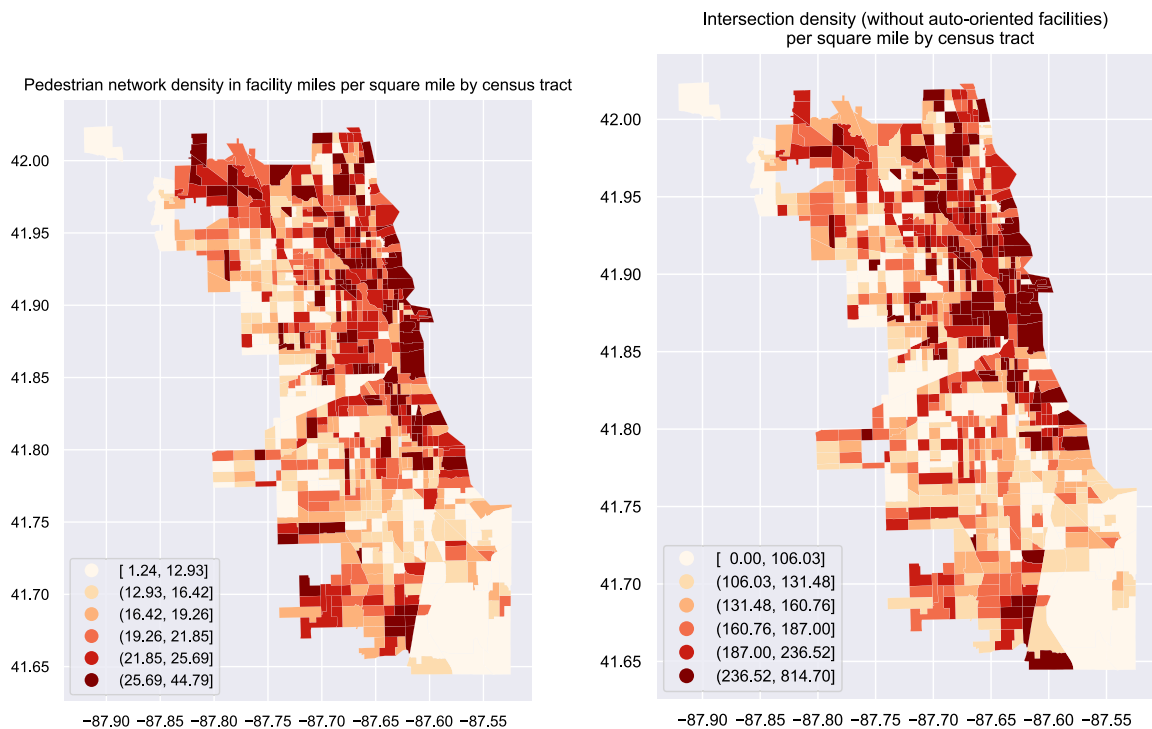


Fig. 8. Pedestrian network and intersection densities by census tract.

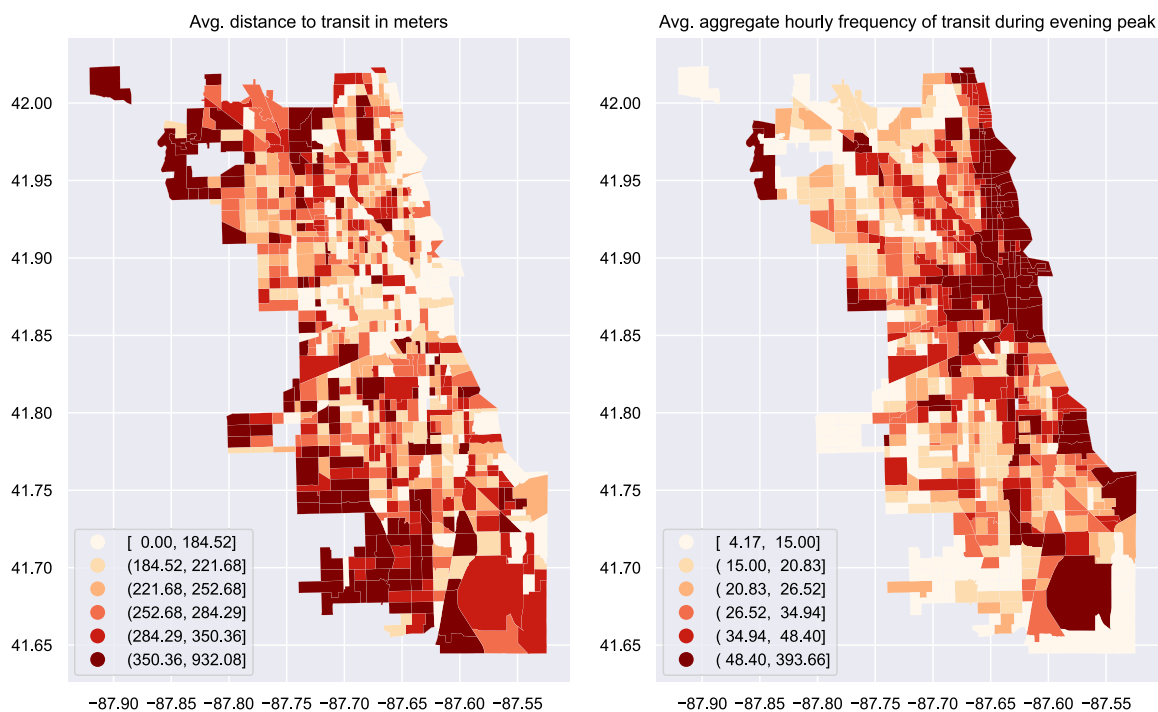


Fig. 9. Average proximity to transit and average transit service frequency by census tract.

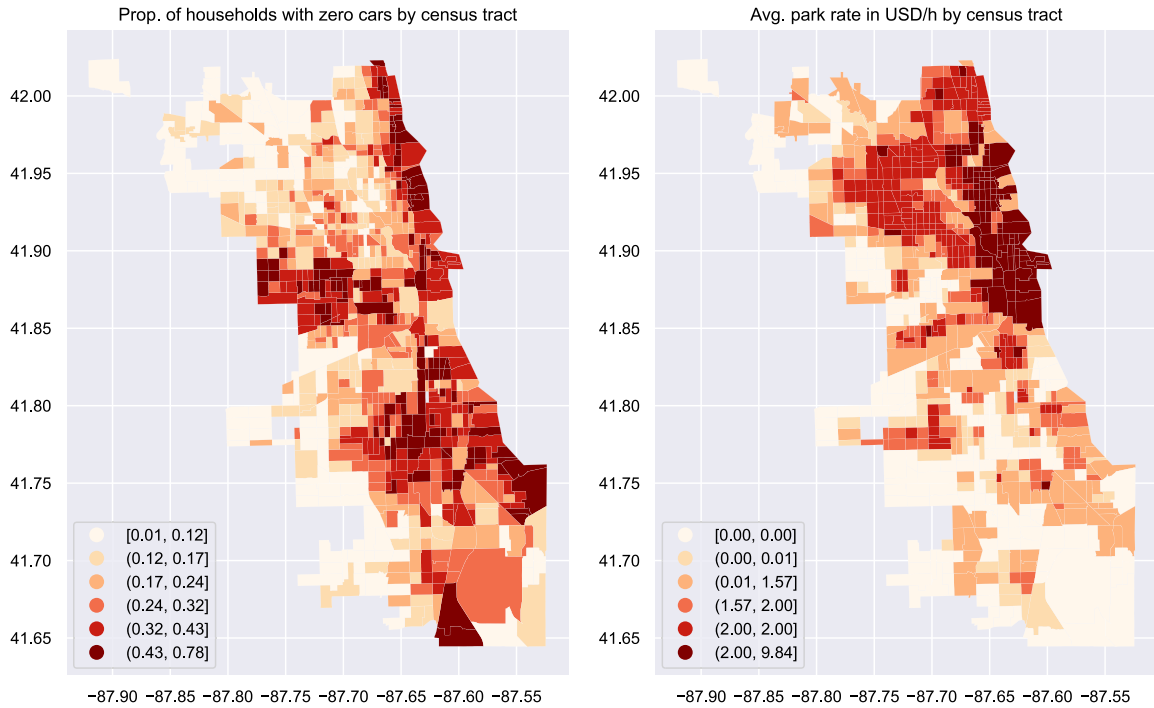


Fig. 10. Proportion of households with zero cars and average park rate by census tract.

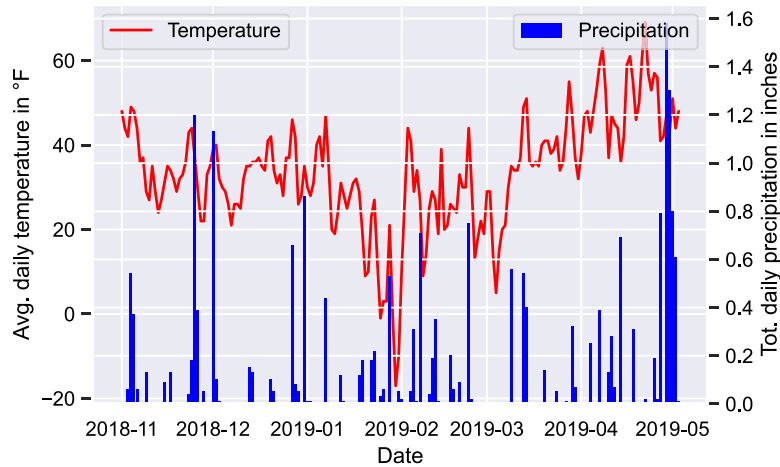


Fig. 11. Average daily temperature and total daily precipitation at O'Hare International Airport during the observation period.

account for possible detours for picking up other passenger during pooled ride-sourcing trips, we add a ten percent travel time penalty to the driving time of pooled ride-sourcing.

We use random forests (Breiman, 2001) to impute solo and pooled ride-sourcing fares. The random forest models take into account various predictors, namely trip attributes (driving distance and time, start time, the day of the week) and lagged fare information (the 25th, 50th and 95th percentiles of the per kilometre fare in the whole network during the 30-minute time period preceding the start time of the trip), weather data (average daily temperature and daily precipitation amount) and characteristics of the origin and destination census tracts (median income, median age, proportion of households with zero cars, employment density, residential density, land use, employment and housing diversity). The hyperparameters of the random forest models are tuned using a grid search with five-fold cross-validation. The selected hyperparameters are reported in Appendix B. We implement the random forest models using scikit-learn (Pedregosa et al., 2011).

We evaluate the predictive performance of the random forest models using five-fold cross-validation (see Table 2). The predictive accuracy is measured in terms of the mean squared error between observed and predicted values and in terms of the coefficient of



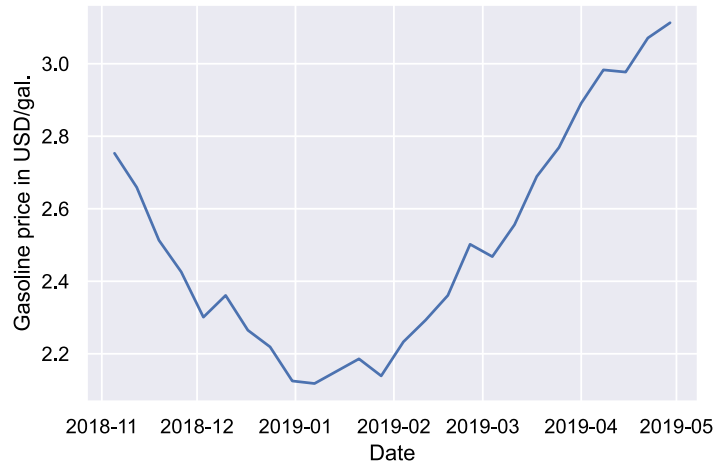


Fig. 12. Gasoline price during the observation period.

**Table 2**  
5-fold cross-validation of fare imputation models.

	Mean squared error		R-squared	
	Mean	Std.	Mean	Std.
Solo ride-sourcing				
Linear regression	−10.10	1.38	0.64	0.03
Random forest	−8.76	1.29	0.69	0.03
Pooled ride-sourcing				
Linear regression	−8.72	0.31	0.46	0.01
Random forest	−8.47	0.32	0.47	0.01

determination  $R^2$ . For comparison, we also evaluate the predictive accuracy of linear regression models, which consider the same set of predictors as the random forest models.

Finally, Table 3 provides a summary of the attributes of the chosen alternatives.

#### 4. Econometric model

Constructing the estimation sample from two revealed preference data sources creates two challenges in the development of a DCM. First, a sampling correction is needed to account for the enrichment of the household travel survey data with ride-sourcing and taxi trip records. Second, the constructed revealed preference mode choice dataset is likely to exhibit endogeneity biases, as the demand for the ride-sourcing options and the price of the ride-sourcing options are simultaneously influenced by supply-side constraints and surge pricing mechanisms.

In this section, we present a MEV-based DCM with sampling and endogeneity corrections to address these challenges. First, we present the sampling correction (Section 4.1). Here, we adopt a conditional maximum likelihood estimator due to its superior efficiency properties. Then, we describe the endogeneity correction (Section 4.2). Here, we employ the control function approach due to its simplicity. The reader is directed Bierlaire and Krueger (2020) for a recent review of sampling correction approaches in discrete choice analysis and to Mcfadden (1999) for an earlier synthesis of the topic. Guevara (2015) provides a review of endogeneity correction approaches.

##### 4.1. Discrete choice analysis under non-random sampling

We consider a sample of  $N$  individuals indexed by  $n = 1, \dots, N$ . Every individual  $n$  is observed to choose an alternative  $y_n$  from the set  $\mathcal{M} = \{1, \dots, J\}$ . We stipulate a parametric model which generates the probability that individual  $n$  chooses alternative  $j \in \mathcal{M}$  given explanatory variables  $\mathbf{x}_n$  and the unknown parameter  $\theta$ :

$$P(j|\mathbf{x}_n; \theta). \quad (1)$$

Random utility theory (McFadden, 1981) posits that a rational decision-maker  $n$  chooses the option  $y_n$  with the highest utility from  $\mathcal{M}$ , i.e.

$$U_{ny_n} > U_j \quad \forall j \in \mathcal{M} \setminus \{y_n\}, \quad (2)$$

**Table 3**  
Summary of attributes of chosen alternatives.

Alternative								
Attribute	Count	Mean	Std.	Min.	25%	50%	75%	Max.
<b>Driving</b>								
Cost [USD]	4 781	1.43	1.36	0.06	0.49	0.94	1.89	9.62
Travel time [min]	4 781	17.34	13.03	0.97	7.67	13.67	22.83	91.00
Avg. park rate at destination [USD/h]	4 781	1.89	2.11	0.00	0.05	1.99	2.00	9.84
<b>Transit</b>								
Walking time [min]	4 275	17.30	6.70	0.00	12.00	16.00	22.00	52.00
On-vehicle time [min]	4 275	18.82	12.26	0.00	9.00	17.00	26.00	86.00
Fare [USD]	4 275	1.84	1.37	0.05	0.77	1.56	2.57	10.44
Transfers	4 275	0.72	0.77	0.00	0.00	1.00	1.00	3.00
<b>Walking</b>								
Travel time [min]	2 737	28.89	37.06	3.88	13.85	20.37	28.77	595.62
<b>Bike</b>								
Travel time [min]	334	22.21	15.96	2.70	9.78	18.18	30.26	75.20
<b>Taxi</b>								
Travel time [min]	20 045	14.20	7.40	2.82	9.85	12.23	16.12	77.53
Fare [USD]	20 045	13.24	7.97	3.78	8.93	10.79	14.61	90.08
<b>Solo ride-sourcing</b>								
Travel time [min]	20 285	18.13	9.30	2.87	11.52	15.83	22.75	76.70
Fare [USD]	20 285	9.19	5.26	2.50	5.00	7.50	12.50	122.50
<b>Pooled ride-sourcing</b>								
Travel time [min]	20 136	22.81	11.55	2.94	14.34	20.11	28.76	95.78
Fare [USD]	20 136	7.10	4.00	2.50	5.00	5.00	10.00	40.00

whereby

$$U_{nj} = V_{nj}(\mathbf{x}_{nj}, \theta) + \varepsilon_{nj} \quad (3)$$

denotes the utility of alternative  $j \in \mathcal{M}$ . The utility  $U_{nj}$  is decomposed into a deterministic aspect  $V_{nj}(\mathbf{x}_{nj}, \theta)$  and a stochastic aspect  $\varepsilon_{nj}$ , which is unknown to the analyst.

We further suppose that the sample considered in the analysis is obtained using non-random sampling. Thus, the sample consists of  $S$  subsamples indexed by  $s = 1, \dots, S$ . Each subsample  $s$  is characterised by a sampling protocol involving endogenous and exogenous stratification. Under an exogenous sampling protocol, the analyst selects observations based on exogenous variables  $\mathbf{x}$ .<sup>3</sup> Under an endogenous sampling protocol, the analyst selects observations based on realised choices.

Discrete choice analysis under non-random sampling can be performed using a conditional maximum likelihood estimator (Manski and McFadden, 1981) of the form

$$\hat{\mathcal{L}}(\theta; \mathbf{y}, \mathbf{x}) = \sum_{n=1}^N \ln \frac{P(y_n | \mathbf{x}_n; \theta) \alpha_{ny_n}}{\sum_{j \in \mathcal{M}} P(j | \mathbf{x}_n; \theta) \alpha_{nj}}, \quad (4)$$

Here, the term  $\alpha_{nj}$  corrects for non-random sampling. It is defined as

$$\alpha_{nj} = \sum_{s=1}^S \frac{R_s(j, \mathbf{x}_n) H_s}{Q_s}. \quad (5)$$

$R_s(j, \mathbf{x}_n)$  is the probability that a population member with configuration  $\{j, \mathbf{x}_n\}$  qualifies for the subpopulation from which subsample  $s$  is drawn.  $H_s = \frac{N_s}{N}$  is the share of subsample  $s$  in the total sample. It is an estimator of the probability of drawing an observation belonging to subsample  $s$  from the total sample.  $Q_s$  is the population share of the subpopulation from which subsample  $s$  is recruited. It is an estimator of the probability of drawing an observation that qualifies for subsample  $s$  from the population.

The term

$$\frac{P(y_n | \mathbf{x}_n; \theta) \alpha_{ny_n}}{\sum_{j \in \mathcal{M}} P(j | \mathbf{x}_n; \theta) \alpha_{nj}} \quad (6)$$

in (4) needs to be adapted to the stipulated parametric form of the choice model (1). In the MEV family of DCMs (McFadden, 1978), the probability of choosing alternative  $j \in \mathcal{M}$  conditional on explanatory variables  $\mathbf{x}_n$  and parameters  $\theta$  is given by

$$P(j | \mathbf{x}_n; \theta) = \frac{\Lambda_j(\mathbf{x}_n, \theta)}{\sum_{j' \in \mathcal{M}} \Lambda_{j'}(\mathbf{x}_n, \theta)}, \quad (7)$$

<sup>3</sup> Note that the exogenous variables  $\mathbf{x}$  in the exogenous sampling protocol need not be the same as the explanatory variables  $\mathbf{x}$  in the choice model.

where

$$\Lambda_{nj}(\mathbf{x}_n, \theta = \{\beta, \lambda\}) = e^{V_{nj}(\mathbf{x}_n, \beta) + \ln G_{nj}(\psi_{n1}, \dots, \psi_{nJ}; \lambda)} \quad (8)$$

with  $\psi_{nj} = e^{V_{nj}(\mathbf{x}_n, \beta)}$  and  $G_{nj}(\psi_{n1}, \dots, \psi_{nJ}; \lambda) = \frac{\partial G}{\partial \psi_{nj}}(\psi_{n1}, \dots, \psi_{nJ}; \lambda)$ .  $V_{nj}$  is the deterministic aspect of utility, which depends on explanatory variables  $\mathbf{x}_n$  and parameter  $\beta$ .  $G(\psi_{n1}, \dots, \psi_{nJ}; \lambda)$  is a MEV generating function with parameter  $\lambda$ .

To evaluate (6) under the MEV assumption, the result presented in Bierlaire et al. (2008) is generalised from purely choice-based samples to a wider class of enriched samples. We have

$$P(y_n | \mathbf{x}_n; \theta) \alpha_{ny_n} = \frac{\Lambda_{ny_n}(\mathbf{x}_n, \theta) \alpha_{ny_n}}{\sum_{j \in \mathcal{M}} \Lambda_{nj}(\mathbf{x}_n, \theta)} \quad (9)$$

and define

$$\Lambda_{nj}(\mathbf{x}_n, \theta) = e^{V_{nj}(\mathbf{x}_n, \beta) + \ln G_{nj}(\psi_{n1}, \dots, \psi_{nJ}; \lambda) + \ln \alpha_{nj}}. \quad (10)$$

Consequently, we obtain

$$\frac{P(y_n | \mathbf{x}_n; \theta) \alpha_{ny_n}}{\sum_{j \in \mathcal{M}} P(j | \mathbf{x}_n; \theta) \alpha_{nj}} = \frac{e^{V_{ny_n}(\mathbf{x}_n, \beta) + \ln G_{ny_n}(\psi_{n1}, \dots, \psi_{nJ}; \lambda) + \ln \alpha_{ny_n}}}{\sum_{j \in \mathcal{M}} e^{V_{nj}(\mathbf{x}_n, \beta) + \ln G_{nj}(\psi_{n1}, \dots, \psi_{nJ}; \lambda) + \ln \alpha_{nj}}}. \quad (11)$$

Thus, a conditional maximum likelihood estimator for the MEV family of DCMs under non-random sampling is given by

$$\hat{\mathcal{L}}(\theta; \mathbf{y}, \mathbf{x}) = \sum_{n=1}^N \ln \frac{e^{V_{ny_n}(\mathbf{x}_n, \beta) + \ln G_{ny_n}(\psi_{n1}, \dots, \psi_{nJ}; \lambda) + \ln \alpha_{ny_n}}}{\sum_{j \in \mathcal{M}} e^{V_{nj}(\mathbf{x}_n, \beta) + \ln G_{nj}(\psi_{n1}, \dots, \psi_{nJ}; \lambda) + \ln \alpha_{nj}}} \quad (12)$$

with  $\theta = \{\beta, \lambda\}$ .

#### 4.2. Control function correction of endogeneity

We partition the explanatory variables  $\mathbf{x}_{nj}$  into exogenous explanatory variables  $c_{nj}$  and an endogenous explanatory variable  $p_{nj}$  such that  $\mathbf{x}_{nj} = \{c_{nj}, p_{nj}\}$ . Then, the utility of alternative  $j \in \mathcal{M}$  is

$$U_{nj} = V(\mathbf{x}_{nj}, \beta) + \varepsilon_{nj} \quad (13)$$

with

$$p_{nj} = \mathbf{z}_{nj}^\top \boldsymbol{\gamma}_j + \xi_{nj}. \quad (14)$$

Here,  $\mathbf{z}_{nj}$  are explanatory variables which include a set of instruments  $\mathbf{m}_{nj}$  and the exogenous explanatory variables  $c_{nj}$  such that  $\mathbf{z}_{nj} = \{\mathbf{m}_{nj}, c_{nj}\}$ .  $\boldsymbol{\gamma}_j$  is an unknown parameter, and  $\xi_{nj}$  is an error term. The error term  $\xi_{nj}$  captures the influence of unobserved attributes of alternative  $j$  which impact  $p_{nj}$  but are not included in  $\mathbf{z}_{nj}$ . The instruments  $\mathbf{m}_{nj}$  and exogenous explanatory variables  $c_{nj}$  are independent of the stochastic aspect of utility  $\varepsilon_{nj}$  and the stochastic disturbance  $\xi_{nj}$ . Yet, the endogenous explanatory variable  $p_{nj}$  is correlated with  $\varepsilon_{nj}$ , i.e.  $\text{Cov}(p_{nj}, \varepsilon_{nj}) \neq 0$  and thus  $\text{Cov}(\xi_{nj}, \varepsilon_{nj}) \neq 0$ . Ignoring the endogeneity of  $p_{nj}$  in the estimation of the choice model parameters  $\theta$  leads to inconsistent parameter estimates (Train, 2009).

The control function correction of endogeneity (Petrin and Train, 2010) consists of constructing a control variable, which is included as an additional explanatory variable into the utility equation. Including the control variable in the utility equation creates a new utility error which is uncorrelated with all other explanatory variables, including  $p_{nj}$  (Wooldridge, 2015). The utility error is decomposed as

$$\varepsilon_{nj} = C(\xi_{nj}, \phi_j) + \tilde{\varepsilon}_{nj}, \quad (15)$$

where  $C(\xi_{nj}, \phi)$  is the control function with parameter  $\phi_j$ .  $\tilde{\varepsilon}_{nj}$  is the residual error, which remains after conditioning out the aspect of  $\varepsilon_{nj}$  that is correlated with  $p_{nj}$ . The simplest specification of the control function is

$$C(\xi_{nj}, \phi_j) = \phi_j \xi_{nj}, \quad (16)$$

whereby  $\phi_j$  is an unknown scalar parameter. Then, the utility (13) writes

$$U_{nj} = V(\mathbf{x}_{nj}, \beta) + \phi_j \xi_{nj} + \tilde{\varepsilon}_{nj}. \quad (17)$$

A choice model with a control function correction may be estimated in one or two stages (Guevara, 2015). The one-stage estimation approach is more efficient, but also more demanding from a computational point-of-view, as it necessitates the approximation a multidimensional integral in the calculation of the choice probabilities (Guevara, 2015). The two-stage estimation approach is computationally simpler but less efficient (Guevara, 2015). Here, we adopt the two-stage estimation approach, as we deal with a large dataset, a circumstance which exacerbates the limitations of the one-stage approach and reduces the effects of lower efficiency in the two-stage approach. In the two-stage approach, we first regress the endogenous variable  $p_j$  on the instruments  $\mathbf{z}_j$  and exogenous variables  $c_{nj}$ . The residuals  $\hat{\xi}_{nj}$  from this regression are used to calculate the control function. In the second stage, the

choice model is estimated, with the control function being included in the utility equation. Using the two-step estimation approach, standard errors of the second stage need to be computed via bootstrapping.<sup>4</sup>

## 5. Model specification

### 5.1. Second stage: Discrete choice model

In our analysis of the mode choice dataset described in Section 3 using the modelling approach explained in Section 4, we consider two choice model specifications, namely multinomial logit and nested logit.<sup>5</sup> The choice models assume a specification of the random utility of the following form: We let

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad \forall j \in \{\text{car, transit, bike, walk, taxi}\} \quad (18)$$

$$U_{nj} = V_{nj} + \phi_j \hat{\varepsilon}_{nj} + \tilde{\varepsilon}_{nj} \quad \forall j \in \{\text{solo ride-sourcing, pooled ride-sourcing}\} \quad (19)$$

with

$$V_{nj} = \mathbf{x}_{nj}^{(\text{alt.-spec.})} \boldsymbol{\beta}^{(\text{alt.-spec.})} + \mathbf{x}_{nj}^{(\text{trip-spec.})} \boldsymbol{\beta}_j^{(\text{trip-spec.})} \quad \forall j \in \mathcal{M}. \quad (20)$$

Here,  $\mathbf{x}_{nj}^{(\text{alt.-spec.})}$  and  $\mathbf{x}_{nj}^{(\text{trip-spec.})}$  denote alternative- and trip-specific attributes, respectively. The corresponding parameters are denoted by  $\boldsymbol{\beta}^{(\text{alt.-spec.})}$  and  $\boldsymbol{\beta}_j^{(\text{trip-spec.})}$ , respectively. Whereas alternative-specific attributes vary across alternatives and trips (e.g. travel time, travel cost etc.), trip-specific attributes only vary across trips (e.g. census tract attributes at the origin and destination). The parameters  $\boldsymbol{\beta}_j^{(\text{trip-spec.})}$  pertaining to trip-specific attributes are necessarily alternative-specific. For identification, we fix  $\beta_{\text{car}}^{(\text{trip-spec.})}$  to zero. The parameter pertaining to transit cost is divided by the median household income in 10,000 USD in the origin census tract to account for systematic heterogeneity in the sensitivity to transit cost.

We also incorporate alternative-specific departure time preferences in the utility specification. Following earlier studies on air-travel itinerary choices (Koppelman et al., 2008; Lurkin et al., 2017; Wen et al., 2020), we consider continuous representations of departure time preferences using a weighted sum of sine and cosine functions. The specification has the following form:

$$V_{nj} = \dots + \beta_{j,1} \sin\left(\frac{2\pi t_n}{1440}\right) + \beta_{j,2} \sin\left(\frac{4\pi t_n}{1440}\right) + \beta_{j,3} \sin\left(\frac{6\pi t_n}{1440}\right) \\ + \beta_{j,4} \cos\left(\frac{2\pi t_n}{1440}\right) + \beta_{j,5} \cos\left(\frac{4\pi t_n}{1440}\right) + \beta_{j,6} \cos\left(\frac{6\pi t_n}{1440}\right) \quad (21)$$

Here,  $\beta_{j,1}, \dots, \beta_{j,6}$  are unknown parameters.  $t_n$  is the observed departure time of trip  $n$  in minutes past midnight, 1440 is the total number of minutes in a day. Compared to discrete representations, continuous representations of departure time preferences produce more realistic demand predictions due to their smoothing properties (Koppelman et al., 2008; Lurkin et al., 2017).

In accordance with the model formulation put forward in the previous section,  $\phi_j \hat{\varepsilon}_{nj}$  in (19) is the control function, and  $\phi_j$  is the corresponding coefficient.  $\varepsilon_{nj}$  and  $\tilde{\varepsilon}_{nj}$  are error terms, which are assumed to be independent and identically distributed according to  $\text{EV}_1(0, 1)$  across  $n, t$ .  $\tilde{\varepsilon}_{nj}$  is the residual utility error that remains after conditioning on the aspect of  $\varepsilon_{nj}$  that is correlated with the endogenous variable.

In nested logit, the utility error  $\varepsilon_{nj}$  (and analogously  $\tilde{\varepsilon}_{nj}$ ) is further decomposed as  $\varepsilon_{nj} = \tilde{\varepsilon}_{nm(j)} + \check{\varepsilon}_{nj}$  with  $\tilde{\varepsilon}_{nm(j)} \sim \text{EV}_1(0, \mu_m)$  and  $\mu_m \geq 1$ .  $m(j)$  maps alternatives to nests such that  $m(j) = m$  if alternative  $j$  is in nest  $m$ . Nested logit induces positive correlation

across the utility errors of alternatives within the same nest with  $\text{Corr}(\varepsilon_{nj}, \varepsilon_{nj'}) = \begin{cases} 1 & \text{if } j = j' \\ 1 - \frac{1}{\mu_m} & \text{if } m(j) = m(j') = m. \\ 0 & \text{otherwise} \end{cases}$ . In our analysis of

the mode choice dataset, we consider two nests, namely one nest containing the ride-sourcing modes solo and pooled ride-sourcing and a second nest containing all other modes. The nest parameter of the first nest is fixed to one, which implies that the correlation across the random utilities of the ride-sourcing alternatives is zero. We fixed the nest parameter to one after estimations of model specifications in which both nest parameters were freely estimated subject to the constraint  $\mu_{\text{other}, \mu_{\text{ride-sourcing}}} \geq 1$  indicated an active bound for  $\mu_{\text{ride-sourcing}}$ , suggesting that  $\mu_{\text{ride-sourcing}}$  should be fixed to one.

<sup>4</sup> We also implemented a joint model using maximum simulated likelihood estimation. The considered joint model includes an estimable parameter capturing the correlation between the utility error and the endogenous variable error. We implemented the model in PandasBiogeme (Bierlaire, 2018) and used 200 modified Latin hypercube sampling draws (Hess et al., 2006) to simulate the choice probabilities of the model. The model did not converge within 24 h of estimation time on a high-performance computing cluster. For comparison, using the two-stage estimation approach, the logit and nested logit models presented in the paper converged within 1 and 9 h, respectively. We regard an estimation time of more than 24 h as prohibitive for exploring many different model specifications, especially considering that a computationally efficient alternative (i.e. the two-stage approach) is available. Estimation times may be different with other estimation software. However, the relative estimation times are likely in the same order of magnitude even with different software. The fact that we were unable to estimate a joint model within a reasonable amount of time on the given dataset further underlines the practical relevance of the two-stage estimation approach. The two-stage estimation approach is statistically less efficient but offers faster computation. Using a high-performance computing cluster, the apparent drawback that standard errors need to be computed via bootstrapping is not critical, since the estimation runs for the bootstrap samples can be parallelised. Nonetheless, we acknowledge a need for further investigations into the relative benefits of different approaches for correcting for endogeneity in discrete choice models, especially for large datasets. A description of the joint model and estimation code are available from the authors upon request.

<sup>5</sup> Cross-nested logit specifications were also explored but no meaningful nesting structures emerged.

We note that the considered choice models assume deterministic choice sets, even though the actual choice sets may differ from the imputed choice sets, especially in that fewer modes than assumed may actually be available at the moment of choice. In the implemented choice models, eventual differences between actual and imputed choice sets are reflected in the estimated choice probabilities and specifically the estimates of the parameters pertaining to interactions between alternative-specific constants and context variables (i.e. census tract attributes, weather conditions and departure times). Consequently, the developed choice models are able to predict mode choice probabilities but do not capture if a mode has low a probability of being selected for a given trip because it is perceived as unattractive by the decision-maker or because it is unavailable or infeasible.

### 5.2. First stage: Control function

We hypothesise that the prices of solo and pooled ride-sourcing are endogenous, because the demand for the ride-sourcing options and their prices are co-determined by supply-side constraints and surge pricing mechanisms. We employ the control function approach described in Section 4.2 to correct for this price endogeneity. To form the control function, we must find suitable instruments that are (i) correlated with the endogenous variable (i.e. price) and (ii) independent of the error term of the demand equation (Guevara, 2015). Nevo (2000) distinguishes three types of demand-side instrument, namely (i) cost shifters, (ii) non-price attributes of other alternatives—also referred to as BLP-type instruments (Berry et al., 1995)—and (iii) prices of the same alternative in other markets—also referred to as Hausman-type instruments (Hausman et al., 1994; Hausman, 1996). In this work, we consider the product of the retail price of gasoline in USD per gallon and the driving distance in miles as cost-shifting instrument for the prices of solo and pooled ride-sourcing. If more than one instrument were available, instrument validity could be assessed using the tests described in Guevara (2018).

### 5.3. Estimation practicalities

The choice models are estimated using the conditional maximum likelihood estimator given in (12). Note that the presented estimator is fully general in that it can account for both endogenous and exogenous stratification. In the current application, the sampling protocol is purely choice-based and does not involve stratification by an exogenous variable. Thus, we have  $\ln \alpha_{nj} = \ln \alpha_j \forall n \in \{1, \dots, N\}$ .  $\alpha_j$  is given by the sampling protocol defined in Table 1. Specifically, we have  $\alpha_j = H_j/Q_j$ , whereby  $H_j$  is the share of observations in the sample choosing alternative  $j$  (see column “Estimation sample—Share” in Table 1), and  $Q_j$  is the share of the population choosing alternative  $j$  (see column “Population—Share” in Table 1).

We implement the conditional maximum likelihood estimator using PandasBiogeme (Bierlaire, 2018). Standard errors are bootstrapped using 100 resamples. The first-stage regressions of the two-stage models are estimated using ordinary least squares.

## 6. Results

In Table 4, we provide the estimation results of four models, namely

- Model 1a: an uncorrected multinomial logit (MNL) model (without control function correction of endogeneity but with sampling correction),
- Model 1b: a corrected MNL model (with endogeneity and sampling corrections),
- Model 2a: the nested counterpart of model 1a, and
- Model 2b: the nested counterpart of model 1b.

The first-stage results of models 1b and 2b are presented in Table 5. Summary statistics for the first-stage regressions, namely  $F$ -statistics, the associated  $p$ -values and the coefficients of determination  $R^2$  are given in Table 6. Summary statistics for the choice models are given in Table 7.

First, we test for the presence of endogeneity. Under the null hypothesis that the prices of the ride-sourcing alternatives are exogenous, the second-stage coefficients  $\phi_{\text{solo ride-sourcing}}$  and  $\phi_{\text{pooled ride-sourcing}}$  on the first-stage residuals are zero. Note that the uncorrected models 1a and 2a are nested within their corrected counterparts 1b and 2b, respectively. This is because the uncorrected model can be obtained from the corrected model by setting  $\phi_{\text{solo ride-sourcing}}$  and  $\phi_{\text{pooled ride-sourcing}}$  equal to zero. Under the null hypothesis that the prices of the ride-sourcing alternatives are exogenous, the restrictions imposed by the uncorrected model are supported by the observed data. Table 7 shows that the log-likelihood values of the corrected models 1b and 2b are higher than the log-likelihood values of their respective uncorrected counterparts 1a and 2a. For example, the log-likelihood of model 2b is  $-96133.77$ , whereas the log-likelihood of model 2a  $-96147.08$ . Log-likelihood ratio tests indicate that the improvement in fit offered by the corrected models is statistically significant. We have  $-2(-96185.02 - (-96167.69)) = 34.66 > \chi^2_{2,0.05} = 5.99$  and  $-2(-96147.08 - (-96133.77)) = 26.62 > \chi^2_{2,0.05} = 5.99$ . Thus, we reject the constraints of the uncorrected models and conclude that the prices of the ride-sourcing alternatives are endogenous.

Furthermore, the  $F$ -statistics of both price equations are high with  $F = 17268.265$  for solo ride-sourcing and  $F = 7266.419$  for pooled ride-sourcing, and the associated  $p$ -values are less than 0.001 (see Table 6). Thus, we can conclude that the selected instruments are fairly strong. More advanced testing approaches for detecting weak identification (see Frazier et al., 2020) may also be leveraged. However, they are not needed here, because the inferences derived using the traditional test hold at a high confidence level.

**Table 4**  
Second stage estimation results.

	Model 1a		Model 1b		Model 2a		Model 2b	
	MNL uncorrected		MNL corrected		Nested logit uncorrected		Nested logit corrected	
	Est.	z-stat.	Est.	z-stat.	Est.	z-stat.	Est.	z-stat.
<b>ASCs</b>								
ASC <sub>transit</sub>	−1.661***	−31.415	−1.604***	−25.776	−1.455***	−26.991	−1.436***	−26.428
ASC <sub>walk</sub>	0.444***	5.487	0.472***	5.480	0.118	1.145	0.161	1.484
ASC <sub>bike</sub>	−2.983***	−27.417	−2.939***	−26.862	−2.488***	−23.839	−2.504***	−21.759
ASC <sub>taxi</sub>	−6.424***	−55.213	−6.379***	−56.057	−5.123***	−20.661	−5.201***	−21.838
ASC <sub>solo ride-sourcing</sub>	−3.841***	−35.125	−3.734***	−37.039	−4.019***	−36.069	−3.925***	−36.673
ASC <sub>pooled ride-sourcing</sub>	−4.330***	−39.596	−4.001***	−35.892	−4.484***	−40.002	−4.210***	−35.837
<b>Mode attributes</b>								
$\beta_{\text{cost, car}}$	0.033	0.809	−0.126***	−3.115	−0.105**	−2.101	−0.200***	−5.392
$\beta_{\text{cost, transit}}$	−0.194***	−2.977	−0.273***	−4.007	−0.225***	−4.086	−0.279***	−4.873
$\beta_{\text{cost, taxi}}$	−0.051***	−15.286	−0.081***	−14.311	−0.045***	−12.830	−0.067***	−10.704
$\beta_{\text{cost, solo ride-sourcing}}$	−0.036***	−6.169	−0.106***	−8.584	−0.032***	−5.576	−0.083***	−6.607
$\beta_{\text{cost, pooled ride-sourcing}}$	−0.019***	−3.486	−0.121***	−6.256	−0.023***	−4.302	−0.106***	−5.814
$\beta_{\text{time, car}}$	−0.074***	−15.027	−0.063***	−12.266	−0.050***	−7.020	−0.045***	−7.725
$\beta_{\text{time, transit}}$	−0.019***	−6.441	−0.022***	−7.515	−0.016***	−6.121	−0.019***	−7.305
$\beta_{\text{time, walk}}$	−0.060***	−26.362	−0.060***	−24.974	−0.046***	−11.752	−0.047***	−12.205
$\beta_{\text{time, bike}}$	−0.053***	−11.997	−0.055***	−12.384	−0.042***	−9.737	−0.045***	−10.817
$\beta_{\text{time, taxi, solo ride-sourcing}}$	−0.050***	−13.387	−0.024***	−4.298	−0.038***	−8.585	−0.020***	−4.175
$\beta_{\text{time, pooled ride-sourcing}}$	−0.042***	−13.690	−0.025***	−5.679	−0.029***	−6.911	−0.016***	−3.529
$\beta_{\text{park rate at destination, car}}$	−0.249***	−38.433	−0.249***	−36.259	−0.228***	−29.709	−0.230***	−31.096
$\beta_{\text{no. of transfers, transit}}$	−0.145***	−5.107	−0.144***	−5.095	−0.100***	−3.891	−0.103***	−3.966
<b>Socio-economic attributes</b>								
$\beta_{\text{median age at origin, taxi}}$	−0.085***	−5.418	−0.084***	−5.510	−0.061***	−4.974	−0.062***	−5.099
$\beta_{\text{median age at origin, solo ride-sourcing}}$	0.043***	3.165	0.043***	3.066	0.038***	2.779	0.038***	2.724
$\beta_{\text{median age at origin, pooled ride-sourcing}}$	−0.021	−1.580	−0.010	−0.758	−0.024*	−1.773	−0.014	−1.011
$\beta_{\text{median age squared at origin, taxi}}$	0.080***	9.101	0.082***	11.458	0.062***	7.682	0.064***	9.644
$\beta_{\text{median age squared at origin, solo ride-sourcing}}$	−0.013	−1.472	−0.010	−1.170	−0.010	−1.176	−0.008	−0.980
$\beta_{\text{median age squared at origin, pooled ride-sourcing}}$	−0.021**	−2.526	−0.021***	−2.662	−0.018**	−2.229	−0.019**	−2.333
$\beta_{\text{median income at origin, taxi}}$	0.575***	22.234	0.580***	21.889	0.444***	14.774	0.458***	14.971
$\beta_{\text{median income at origin, solo ride-sourcing}}$	0.567***	25.587	0.574***	24.621	0.556***	25.721	0.562***	24.448
$\beta_{\text{median income at origin, pooled ride-sourcing}}$	0.160***	8.432	0.149***	7.156	0.147***	7.978	0.138***	6.833
$\beta_{\text{median income squared at origin, taxi}}$	−0.087***	−8.111	−0.088***	−8.405	−0.067***	−7.457	−0.069***	−7.741
$\beta_{\text{median income squared at origin, solo ride-sourcing}}$	−0.103***	−12.678	−0.100***	−9.950	−0.100***	−12.499	−0.098***	−9.743
$\beta_{\text{median income squared at origin, pooled ride-sourcing}}$	−0.031***	−3.681	−0.026***	−3.028	−0.027***	−3.262	−0.023***	−2.692
$\beta_{\text{prop. of households with zero cars at origin, car}}$	−0.435***	−22.016	−0.440***	−24.637	−0.367***	−16.787	−0.377***	−18.823
<b>Land use and built environment</b>								
$\beta_{\text{residential density at origin, taxi}}$	0.412***	33.337	0.413***	36.041	0.309***	14.931	0.318***	14.470
$\beta_{\text{residential density at origin, solo ride-sourcing}}$	0.158***	15.876	0.166***	16.984	0.160***	16.504	0.166***	17.192
$\beta_{\text{employment density at origin, taxi}}$	0.067***	20.569	0.067***	21.339	0.052***	12.964	0.053***	12.898
$\beta_{\text{employment density at origin, solo ride-sourcing}}$	−0.015***	−4.660	−0.014***	−3.810	−0.014***	−4.365	−0.013***	−3.655
$\beta_{\text{employment density at origin, pooled ride-sourcing}}$	−0.037***	−10.424	−0.037***	−11.203	−0.035***	−10.193	−0.036***	−10.896
$\beta_{\text{land use diversity at origin, taxi}}$	−1.392***	−7.007	−1.421***	−8.786	−1.121***	−6.713	−1.164***	−8.241
$\beta_{\text{land use diversity at origin, solo ride-sourcing}}$	−0.553***	−3.654	−0.520***	−3.788	−0.480***	−3.151	−0.465***	−3.395
$\beta_{\text{land use diversity at origin, pooled ride-sourcing}}$	−0.447***	−3.077	−0.486***	−3.937	−0.376***	−2.583	−0.415***	−3.391
$\beta_{\text{pedestrian network density at origin, transit}}$	−0.247***	−8.639	−0.243***	−7.748	−0.215***	−8.479	−0.217***	−8.332
$\beta_{\text{pedestrian network density at origin, taxi}}$	−0.504***	−19.705	−0.500***	−20.313	−0.401***	−13.632	−0.407***	−14.661
$\beta_{\text{pedestrian network density at origin, solo ride-sourcing}}$	−0.239***	−9.794	−0.237***	−9.124	−0.226***	−9.339	−0.226***	−8.898
$\beta_{\text{pedestrian network density at origin, pooled ride-sourcing}}$	−0.321***	−13.127	−0.332***	−12.765	−0.307***	−12.817	−0.318***	−12.366
$\beta_{\text{intersection density at origin, transit}}$	0.245***	11.600	0.237***	10.321	0.194***	8.928	0.194***	9.411
$\beta_{\text{intersection density at origin, taxi}}$	0.398***	19.094	0.394***	19.673	0.314***	12.873	0.319***	13.782
$\beta_{\text{intersection density at origin, solo ride-sourcing}}$	0.146***	7.174	0.140***	6.438	0.129***	6.313	0.127***	5.963
$\beta_{\text{intersection density at origin, pooled ride-sourcing}}$	0.192***	9.190	0.194***	9.598	0.175***	8.542	0.180***	8.878

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Next, we assess the nesting structure of the nested logit models. According to Table 7, the nested logit models 2a and 2b produce higher log-likelihood values on the sample data than the multinomial logit models 1a and 1b. For example, the log-likelihood of model 2b is −96 133.77, whereas the log-likelihood of model 1b −96 167.69. Log-likelihood ratio tests indicate that the improvement in fit offered by the nested logit models is statistically significant. For model 1b versus 2b, we have  $-2(-96\ 167.69 - (-96\ 133.77)) = 67.84 > \chi^2_{1,0.05} = 3.84$ . Thus, we reject the restrictions imposed by the simpler multinomial logit models. From Table 4, it can be seen that in model 2b, the estimate of the nest parameter for the nest containing the non-ride-sourcing alternatives is 1.251. This implies a moderate degree of correlation across the random utilities of the alternatives in the nest. In our subsequent discussion, we thus focus primarily on model 2b due to its superior statistical performance.



Table 4 (continued).

	Model 1a		Model 1b		Model 2a		Model 2b	
	MNL uncorrected		MNL corrected		Nested logit uncorrected		Nested logit corrected	
	Est.	z-stat.	Est.	z-stat.	Est.	z-stat.	Est.	z-stat.
<b>Weather conditions</b>								
$\beta_{\text{avg. temperature, taxi}}$	0.163***	9.508	0.165***	8.414	0.124***	7.787	0.128***	7.017
$\beta_{\text{avg. temperature, solo ride-sourcing}}$	0.150***	9.127	0.150***	9.744	0.148***	9.064	0.149***	9.613
$\beta_{\text{avg. temperature, pooled ride-sourcing}}$	0.119***	7.261	0.110***	6.741	0.116***	7.134	0.110***	6.748
$\beta_{\text{daily precipitation, taxi}}$	0.916***	12.374	0.917***	12.944	0.715***	10.852	0.731***	10.786
$\beta_{\text{daily precipitation, solo ride-sourcing}}$	0.909***	12.519	0.959***	14.961	0.900***	12.510	0.936***	14.696
$\beta_{\text{daily precipitation, pooled ride-sourcing}}$	0.979***	14.764	1.032***	14.403	0.975***	14.839	1.018***	14.371
$\beta_{\text{avg. temperature} \times \text{daily precipitation, taxi}}$	1.486***	11.207	1.489***	11.905	1.156***	8.651	1.184***	9.879
$\beta_{\text{avg. temperature} \times \text{daily precipitation, solo ride-sourcing}}$	1.576***	11.473	1.563***	12.607	1.569***	11.486	1.559***	12.705
$\beta_{\text{avg. temperature} \times \text{daily precipitation, pooled ride-sourcing}}$	1.695***	13.657	1.686***	14.424	1.690***	13.687	1.681***	14.489
<b>Departure time</b>								
$\beta_{\sin\left(\frac{2\pi \cdot \text{dep. time in min.}}{1440}\right), \text{taxi}}$	0.076	1.419	0.083	1.532	0.055	1.309	0.062	1.412
$\beta_{\sin\left(\frac{2\pi \cdot \text{dep. time in min.}}{1440}\right), \text{solo ride-sourcing}}$	0.113***	2.611	0.095**	2.128	0.125***	2.893	0.111**	2.495
$\beta_{\sin\left(\frac{2\pi \cdot \text{dep. time in min.}}{1440}\right), \text{pooled ride-sourcing}}$	0.023	0.539	0.026	0.593	0.033	0.785	0.035	0.809
$\beta_{\cos\left(\frac{2\pi \cdot \text{dep. time in min.}}{1440}\right), \text{taxi}}$	0.596***	8.399	0.599***	8.953	0.472***	8.147	0.484***	8.025
$\beta_{\cos\left(\frac{2\pi \cdot \text{dep. time in min.}}{1440}\right), \text{solo ride-sourcing}}$	0.903***	14.394	0.870***	15.244	0.900***	14.539	0.877***	15.572
$\beta_{\cos\left(\frac{2\pi \cdot \text{dep. time in min.}}{1440}\right), \text{pooled ride-sourcing}}$	0.910***	15.288	0.906***	15.712	0.904***	15.327	0.901***	15.623
$\beta_{\sin\left(\frac{4\pi \cdot \text{dep. time in min.}}{1440}\right), \text{taxi}}$	0.176***	2.935	0.180***	2.916	0.140***	2.986	0.146***	2.878
$\beta_{\sin\left(\frac{4\pi \cdot \text{dep. time in min.}}{1440}\right), \text{solo ride-sourcing}}$	0.094*	1.915	0.070	1.379	0.092*	1.887	0.074	1.490
$\beta_{\sin\left(\frac{4\pi \cdot \text{dep. time in min.}}{1440}\right), \text{pooled ride-sourcing}}$	0.152***	3.124	0.158***	3.436	0.147***	3.049	0.153***	3.315
$\beta_{\cos\left(\frac{4\pi \cdot \text{dep. time in min.}}{1440}\right), \text{taxi}}$	0.615***	18.915	0.618***	19.522	0.484***	14.779	0.497***	13.515
$\beta_{\cos\left(\frac{4\pi \cdot \text{dep. time in min.}}{1440}\right), \text{solo ride-sourcing}}$	0.462***	14.992	0.438***	13.310	0.459***	15.040	0.442***	13.565
$\beta_{\cos\left(\frac{4\pi \cdot \text{dep. time in min.}}{1440}\right), \text{pooled ride-sourcing}}$	0.441***	14.792	0.445***	13.998	0.437***	14.821	0.440***	13.836
$\beta_{\sin\left(\frac{6\pi \cdot \text{dep. time in min.}}{1440}\right), \text{taxi}}$	0.149***	4.115	0.152***	4.090	0.118***	4.086	0.123***	3.984
$\beta_{\sin\left(\frac{6\pi \cdot \text{dep. time in min.}}{1440}\right), \text{solo ride-sourcing}}$	0.139***	4.208	0.157***	5.012	0.138***	4.218	0.151***	4.819
$\beta_{\sin\left(\frac{6\pi \cdot \text{dep. time in min.}}{1440}\right), \text{pooled ride-sourcing}}$	0.164***	5.214	0.169***	5.534	0.164***	5.261	0.168***	5.516
$\beta_{\cos\left(\frac{6\pi \cdot \text{dep. time in min.}}{1440}\right), \text{taxi}}$	-0.082***	-3.010	-0.083***	-3.386	-0.063***	-2.896	-0.065***	-3.253
$\beta_{\cos\left(\frac{6\pi \cdot \text{dep. time in min.}}{1440}\right), \text{solo ride-sourcing}}$	-0.103***	-4.861	-0.069***	-2.726	-0.101***	-4.774	-0.076***	-3.068
$\beta_{\cos\left(\frac{6\pi \cdot \text{dep. time in min.}}{1440}\right), \text{pooled ride-sourcing}}$	-0.046**	-2.178	-0.041*	-1.769	-0.041*	-1.954	-0.038	-1.636
<b>Control function</b>								
$\phi_{\text{solo ride-sourcing}}$			0.073***	5.266			0.054***	4.109
$\phi_{\text{pooled ride-sourcing}}$			0.106***	5.191			0.087***	4.444
<b>Nest parameter</b>								
$\mu_{\text{other}}$					1.280***	20.408	1.251***	20.061

\*Significance level:  $p < 0.1$ .\*\*Significance level:  $p < 0.05$ .\*\*\*Significance level:  $p < 0.01$ .

In model 2b, the estimates of the parameters pertaining to mode attributes have the expected signs and are significantly different from zero. More precisely, the mode-specific travel time parameters are all negative and statistically significant. As expected, a larger number of transfers appears to decrease the propensity of choosing public transit, and a higher hourly park rate at the destination appears to decrease the propensity of choosing car.

In Table 8, we compare the weighted direct aggregate arc elasticities with respect to travel cost and time of models 2a and 2b. It can be seen that in the corrected model 2b, the demand for taxi as well as for solo and pooled ride-sourcing is substantially more elastic with respect to price than in the uncorrected model 2a. For example, the estimated direct aggregate arc elasticity with respect to the cost of pooled ride-sourcing is  $-0.171$  in the uncorrected model 2a and  $-0.780$  in the corrected model 2b. The corrected model 2b further reveals that the direct aggregate arc elasticities of the demand for solo- and pooled ride-sourcing with respect to travel time are in the same order of magnitude as the corresponding direct aggregate arc elasticities of the demand for car, transit and taxi. As expected, walking and biking exhibit the highest elasticities with respect to travel time.

Fig. 13 visualises the estimated continuous departure time preferences in model 2b. While there are minor differences in departure time preferences across the three modes in the morning, afternoon and evening hours, solo and pooled ride-sourcing appear to be comparatively less likely to be chosen mid-day.

We also observe that weather conditions affect the demand for taxi and ride-sourcing. Our utility specification includes both main and interaction effects of the average daily temperature and the daily precipitation amount. To facilitate the interpretation

**Table 5**  
First stage estimation results.

	Price: solo r.-s.		Price: pooled r.-s.	
	Est.	z-stat.	Est.	z-stat.
$\gamma_{\text{constant}}$	1.354***	20.319	3.104***	49.359
$\gamma_{\text{driving distance} \times \text{gas price}}$	0.188***	93.702	0.137***	71.114
$\gamma_{\text{driving time (solo ride-sourcing)}}$	0.207***	89.622		
$\gamma_{\text{driving time (pooled ride-sourcing)}}$			0.052***	24.366
$\gamma_{\text{residential density at origin}}$	0.142***	20.284	0.018***	3.328
$\gamma_{\text{employment and housing diversity at origin}}$	-0.450***	-8.323	-0.061	-1.217
$\gamma_{\text{median income at origin}}$	-0.014	-0.980	-0.182***	-12.912
$\gamma_{\text{median income squared at origin}}$	0.066***	10.732	0.067***	12.511
$\gamma_{\text{median age at origin}}$	-0.021**	-2.390	0.089***	10.457
$\gamma_{\text{median age squared at origin}}$	0.030***	8.009	-0.019***	-5.961
$\gamma_{\text{daily precipitation}}$	0.572***	8.925	0.412***	10.063
$\gamma_{\text{avg. temperature}}$	-0.271***	-20.146	-0.292***	-28.362
$\gamma_{\text{avg. temperature} \times \text{daily precipitation}}$	-0.626***	-6.309	-0.441***	-6.083
$\gamma_{\text{employment density at origin}}$	0.033***	19.301	-0.000	-0.190
$\gamma_{\text{land use diversity at origin}}$	0.893***	8.255	-0.020	-0.214
$\gamma_{\text{pedestrian network density at origin}}$	0.002	0.160	-0.125***	-11.532
$\gamma_{\text{intersection density at origin}}$	-0.053***	-6.463	0.048***	7.680
$\gamma_{\sin\left(\frac{2 \times \text{dep. time in min.}}{1440}\right)}$	-0.321***	-11.497	-0.018	-0.608
$\gamma_{\cos\left(\frac{2 \times \text{dep. time in min.}}{1440}\right)}$	-0.506***	-13.622	-0.062*	-1.776
$\gamma_{\sin\left(\frac{4 \times \text{dep. time in min.}}{1440}\right)}$	-0.391***	-11.887	0.035	1.137
$\gamma_{\cos\left(\frac{4 \times \text{dep. time in min.}}{1440}\right)}$	-0.355***	-21.450	0.018	1.175
$\gamma_{\sin\left(\frac{6 \times \text{dep. time in min.}}{1440}\right)}$	0.235***	12.263	0.030*	1.733
$\gamma_{\cos\left(\frac{6 \times \text{dep. time in min.}}{1440}\right)}$	0.506***	34.451	0.066***	4.995

\*Significance level:  $p < 0.1$ .

\*\*Significance level:  $p < 0.05$ .

\*\*\*Significance level:  $p < 0.01$ .

**Table 6**  
First stage estimation summary.

	Price: solo r.-s.	Price: pooled r.-s.
F-stat.	17 268.265	7266.419
p-val. (F-stat.)	0.000	0.000
R-squared	0.833	0.678

**Table 7**  
Second stage estimation summary.

Model	No. of parameters	Log-lik.
Model 1a: MNL uncorrected	77	-96 185.02
Model 1b: MNL corrected	79	-96 167.69
Model 2a: Nested logit uncorrected	78	-96 147.08
Model 2b: Nested logit corrected	80	-96 133.77
Null log-lik.: -157 407.73		

**Table 8**  
Aggregate direct point elasticities.

	Car	Transit	Walk	Bike	Taxi	Solo r.-s.	Pooled r.-s.
Model 2a: Nested logit uncorrected							
Cost	-0.060	-0.065	NaN	NaN	-0.795	-0.301	-0.171
Time	-0.356	-0.244	-1.025	-1.160	-0.710	-0.686	-0.674
Model 2b: Nested logit corrected							
Cost	-0.113	-0.079	NaN	NaN	-1.160	-0.784	-0.780
Time	-0.315	-0.276	-1.033	-1.209	-0.376	-0.370	-0.378

of the effects, we standardised the former and kept the latter on its original scale. The estimates of these effects are statistically significant for taxi as well as solo and pooled ride-sourcing. Since the estimated effects have the same signs and are in the same order of magnitude, the same interpretation applies to the estimated effects for all three modes. At the mean average daily temperature in the observation period, positive precipitation increases the demand for taxi and ride-sourcing. On dry days, a higher temperature leads to increased demand for taxi and ride-sourcing.

**Table 9**

Overview of recently published ride-sourcing demand analysis studies.

Study	Location	Modelling approach	Data type	Study type	Key findings
<a href="#">Acheampong et al. (2020)</a>	Ghana	Structural equation	2	1, 3	Perceived benefits, ease of use, perceived safety risks, and car-dependent lifestyles are associated with the adoption and use of ride-hailing services. Ride-hailing is used alone for full door-to-door journeys, instead of complementing other travel modes.
<a href="#">Alonso-González et al. (2020)</a>	Netherlands	Mixed and latent class logit	3	4	Value of in-vehicle travel time for pooled on-demand services is 7.88–10.80 euro per hour. Value of reliability is around half of the value of wait time and in-vehicle travel time.
<a href="#">Asgari and Jin (2020)</a>	USA	Error component logit	3	3, 4, 5	This study creates a habit index based on past usage frequency of a mode. They find that habits and private vehicle expenses (e.g., parking cost and time spent in finding it) are highly associated with the preferences towards rider-sourcing services.
<a href="#">Azimi et al. (2021)</a>	USA	Error component nested logit	3	3, 4, 5	Generation Xers and Millennials have distinct preferences for on-demand shared mobility. Whereas the perceived time and cost benefits of shared mobility affect Generation Xers' preferences for shared mobility, Millennials' choices are more likely to be influenced by their attitudes towards on-demand services.
<a href="#">Baker (2020)</a>	San Francisco, USA	Geographically weighted regression	1	1, 2	This study finds positive relationships between ride-sourcing use and public transport ridership, as well as between ride-sourcing demand and choice rider (i.e., not transit dependent) neighbourhoods.
<a href="#">Bansal et al. (2020b)</a>	USA	Multinomial logit	2	3, 4	10% of ride-sourcing users in the USA postponed the purchase of a new car due to availability of ride-sourcing services. Older ride-sourcing users with higher vehicle ownership are less likely to pool rides. Ride-sourcing drivers with a postgraduate degree who drive daily and live in metropolitan regions are more likely to switch to fuel-efficient vehicles.
<a href="#">Bi and Ye (2021)</a>	Chengdu, China	Latent dirichlet allocation	1	1, 2	Ride-sourcing in Chengdu is mostly used for non-work trips. Ride-sourcing is more extensively used in areas with lack of public transit access.
<a href="#">Dean and Kockelman (2021)</a>	Chicago, USA	Poisson-Gamma negative binomial and linear regression	1	2, 4	Longer trips in Chicago are likely to be requested as shared rides. Census tracts with higher shares of young, unemployed, and non-White persons, and vehicle-free households have higher proportions of shared rides. Shared ride-hail demand decreases with the increase in density of pedestrian infrastructure.
<a href="#">Dey et al. (2021)</a>	New York City, USA	Negative Binomial and fractional split	1	1, 2	Job density, employment density, bike infrastructure and transit service significantly affect ride-hailing demand. This study also provides a prediction framework for predicting future ride-hailing trends.
<a href="#">Dong et al. (2021)</a>	Boston and Philadelphia, USA	Mixed logit	3	1, 3, 4, 5	Carless households are likely to delay or forgo car purchasing decisions due to ride-sourcing services. TNCs are likely to substitute transit more than complementing it. Willingness to pay to save 10 min of wait time for transit is US\$5 in Boston and US\$8 in Philadelphia, compared to below US\$3 and US\$2 for TNCs.

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Model 2b also provides insights into the influence of census tract attributes on travel demand. Due to the inclusion of quadratic terms in the utility specification, we are able to capture non-linear income and age effects on the demand for taxi as well as solo and pooled ride-sourcing. These effects are visualised in [Fig. 14](#) over their respective realised ranges in the training dataset. For all three modes, the non-linear income effects are concave down, whereby the curvature is more pronounced for taxi and solo ride-sourcing than for pooled ride-sourcing. The demand for pooled ride-sourcing appears to be less sensitive to income compared to the demand for taxi and solo ride-sourcing. Increasing income initially has a positive effect on the demand for taxi and solo ride-sourcing, but the effect of income becomes negative for median annual household incomes above USD 140,000. This suggests that the demand for taxi and solo ride-sourcing is comparatively lower in census tracts with high median household incomes.

Next, we consider the estimated age effects in model 2b. For solo and pooled ride-sourcing, the age effects are concave down, while they are concave up for taxi. The curvature of the age effect on demand for taxi is substantially more pronounced than for

Table 9 (continued).

Study	Location	Modelling approach	Data type	Study type	Key findings
Dong (2020)	Philadelphia, USA	Mixed logit	3	1, 3, 5	Higher-income females with age over 30 years, who are less frequent transit users, are increasingly willing to choose ride-hailing over transit. Time spent on walking to transit stop is found to be more burdensome than in-vehicle travel time and wait time.
Edwards (2020)	Austin, USA	Linear regression	1	2	Nonstandard (expansive variants) ride-sourcing services are preferable by airport travellers and those living in carless and low-density neighbourhoods, but are less preferred in low-income neighbourhoods.
Ghaffar et al. (2020)	Chicago, USA	Random-effects negative binomial regression	1	1, 2	Higher ride-sourcing demand is experienced in Chicago on days with lower temperature. Census tracts with higher household income, high proportion of carless households, higher employment and population density, and fewer parking spots have higher demand for ride-sourcing services.
Gomez et al. (2021)	Madrid, Spain	Generalised heterogeneous data	2	1, 3	Young, well-educated, wealthy individuals, who are familiar with new technologies, have more inclination towards ride-hailing services. Environment-conscious respondents are less inclined towards ride-hailing. Ride-hailing has substituted transit for leisure and errand trips.
Hasnine et al. (2021)	Toronto, Canada	Autoregressive moving average	1	1, 2	Lagged demand is a good predictor of the future demand for ride-sourcing services. Households that rent their dwelling have positive association with ride-sourcing demand. Bike-sharing and transit trip counts are negatively correlated with the ride-sourcing demand, but precipitation has a positive relationship.
Hou et al. (2020)	Chicago, USA	Linear regression and machine-learning	1	2,4	Ride-sourcing trips starting or ending at Chicago-area airports have a smaller ratio for shared trips, perhaps due to time, luggage, and other constraints.
Kang et al. (2021)	Austin, USA	Generalised heterogeneous data	3	3, 4, 5	Women, older adults, and non-Hispanic/non-Latino Whites have a low propensity to pool rides in Austin. Austin residents are willingness to pay to not pool a ride is on averages about 62 cents for commute, US\$1.70 for shopping and US\$1.32 for leisure travel.
Lazarus et al. (2021)	California, USA	Multinomial logit	3	3, 4, 5	High-frequency ride-sourcing users are more likely to share rides. Average values of in-vehicle travel time for Los Angeles, Sacramento, San Diego, and San Francisco are US\$29.2, US\$27.3, US\$25.9, and US\$34.5.
Li et al. (2021)	Toronto, Canada	Random-effects panel data and log-log regression	1	2	Ride-sourcing and public transit demand varies by transit mode, time of day and transit level-of-service. The demand for ride-sourcing services is positively associated with subway station ridership during the mid-day and early evening, while negatively correlating with surface transit demand during peak commuting hours.
Loa et al. (2021)	Toronto, Canada	Structural equation	2	1, 3	Students, persons from lower-income households, and transit pass owners are more likely to substitute ride-sourcing for public transit.
Loa and Habib (2021)	Toronto, Canada	Binary logistic and zero-inflated ordered probit	2	3, 4	Transit pass ownership positively influences the frequency of ride-hailing usage (i.e., complementary relationship). The factors affecting preference for shared and single-occupancy ride-hailing differ, and therefore, both modes need to be studied separately.

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the other two modes. In comparison to the age effect for taxi, solo and pooled ride-sourcing do not appear sensitive to age. The effect of age on taxi demand increases sharply for median ages above 35 years, which suggests that taxi demand is comparatively higher in census tracts with older residents.

Various land use and built environment characteristics also influence the demand for taxi and ride-sourcing. For example, a higher residential density increases the propensities of choosing taxi and solo ride-sourcing. A higher employment density increases the propensity of choosing taxi but decreases the propensity of choosing ride-sourcing. A higher land use diversity decreases the propensities of choosing taxi and ride-sourcing. A denser network of pedestrian-oriented links decreases the propensities of choosing

Table 9 (continued).

Study	Location	Modelling approach	Data type	Study type	Key findings
Malik et al. (2021)	California, USA	Integrated choice and latent variable	2	1, 3	Omission of variables related to residential location and vehicle ownership could bias the results on the linkage between transit ridership and ride-hailing. To discourage the replacement of active mode through ride-hailing services, pricing strategies should be employed to reduce the use of ride-hailing for short trips.
Marquet (2020)	Chicago, USA	Truncated Poisson	1	1, 2	Walkable and diverse neighbourhoods attract and generate more ride-sourcing trips. Areas with lower car ownership generate fewer ride-sourcing trips but attract more trips.
Nugroho et al. (2020)	Indonesia	Ordered logit	2	1, 3	Lack of car access encourages the adoption of ride-sourcing services. Ride-sourcing services complement the local public transport system.
Sabogal-Cardona et al. (2021)	Mexico city	Multinomial and ordered logit	2	3	Ride-hailing is mainly used for leisure and health trips. Young travellers with higher education and higher income are more inclined to adopt ride-hailing. Due to perception of crime and sexual harassment in Mexico city, women depend more on ride-sourcing than men.
Sabouri et al. (2020)	USA	Multi-level linear	1	1, 2	Census block level population, employment, activity, and transit density are positively associated with the Uber demand, but intersection density and destination accessibility by auto and transit has negative effect.
Shen et al. (2020)	Nanjing, China	Nested logit	3	3, 5	Young travellers are naturally inclined to use ride-sourcing, but age does not make difference in preference of the service type (premier vs. regular). The demand for ride-sourcing services is elastic to in-vehicle travel time and waiting time, but much highly elastic to travel cost.
Soltani et al. (2021)	Adelaide, Australia	Multinomial logit	2	2, 3	Younger travellers with higher levels of education and income, who live in dense areas with higher property prices, are more inclined towards ride-hailing services. Car ownership, ethnic background, gender, and household size have no association with the propensity to use ride-hailing services.
Sweet (2021)	Ontario, Canada	Mixed logit	3	3, 4, 5	An individual is willing to pay US\$1 to US\$4 for not sharing trip with other passenger. The analysis provides mixed evidence about the potential of integrating transit with ride-sourcing to solve the last mile problem.
Toman et al. (2020)	New York City, USA	Multivariate time series	1	1	This study explored substitution effects between ride-sourcing, shared bike, taxi, and subway. The relationship varies across weekdays and weekends, and also during holidays.
Tu et al. (2021)	Chengdu, China	Gradient boosting decision trees	1	2, 4	Distance to city centre, land use diversity and road density are the main determinants of the proportion of shared ride-sourcing trips. Whereas the first two factors positively affect the proportion of shared trips, the last one and public transport density has negative affect.
von Behren et al. (2021)	China	Integrated choice and latent variable	2	1, 3	Ride-hailing services are more attractive in tier-2 cities due to poor public transport infrastructure. Ride-hailing substitutes other modes for medium-distance trips (5–10 km). Women with higher income are more likely to use ride-sourcing services than men.

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taxi and ride-sourcing. However, a higher intersection density at the trip origin increases the propensities of choosing taxi and ride-sourcing.

## 7. Welfare analysis

We also use the corrected nested logit model 2b to analyse the welfare implications of ride-sourcing. More specifically, we consider three scenarios in which we simulate welfare losses due to the removal of (i) all ride-sourcing, (ii) solo ride-sourcing and (iii) pooled ride-sourcing services from the choice sets of observations in which the removed mode is the chosen mode. In addition,

Table 9 (continued).

Study	Location	Modelling approach	Data type	Study type	Key findings
Ward et al. (2021)	USA	Difference-in-difference	1	1	Entry of ride-sourcing services led to an increase of 0.7% in vehicle registrations. The effect varies across urban areas. There is no significant effect of the entry of ride-sourcing services on the transit use.
Wang et al. (2022)	Michigan, USA	Latent class cluster analysis	2	3, 4	Males, college graduates, and car owners have a higher inclination towards ride-sourcing services. Vehicle owners have lesser interest in sharing ride-sourcing trips than their demographic counterparts.
Yan et al. (2020)	Chicago, USA	Random forest	1	2	Among the built-environment variables, employment density and walkability at trip origin have high correlation with ride-sourcing demand. Among the transit-supply factors, frequencies of bus and rail services have the strongest correlation with ride-sourcing demand.
Yan et al. (2021)	Michigan, USA	Ordered logit	2	1, 3	Male college graduates with poor transit access are more inclined to use mobility-on-demand transit services, but people with lack of access to mobile data have significantly lower preference for such services. Disability does not seem to be associated with the preference for mobility-on-demand services.
Yu and Peng (2020)	Austin, Texas	Structural equation	1	2	Population/employment/road density, and transit accessibility have positive association with ride-sourcing demand, but walk accessibility have a negative effect. These effects vary across the time-of-day.

**Note 1:** In column “data type”, 1: spatial trip level, census, weather, land use data, 2: household travel survey, 3: discrete choice experiment.

**Note 2:** In column “study type”, 1: substitution/complementary effect of ride-sourcing on other travel modes and vehicle ownership, 2: correlation between a spatial unit’s characteristics (e.g., population density) and ride-sourcing demand, 3: relation of individual-level attitudes and socio-economic attributes with preference for ride-sourcing services, 4: factors affecting preference for shared ride-sourcing services 5: effect of mode-specific attributes on the demand for ride-sourcing services.

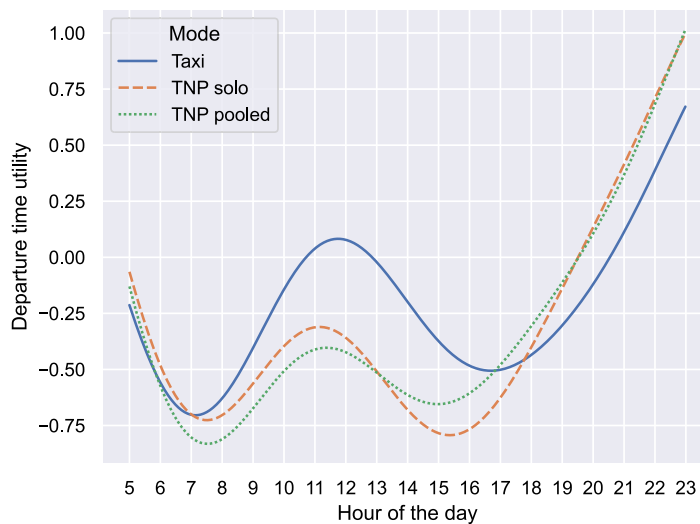


Fig. 13. Departure time utility in model 2b.

we analyse the welfare implications of ride-sourcing taxes, inspired by a congestion tax implemented in Chicago in 2020 (McMahon, 2020). More specifically, we consider two taxation scenarios in which a tax is added to the fare of trips in which solo ride-sourcing is selected. In the first scenario, we impose a fixed tax of USD 3 on solo ride-sourcing trips, and in the second scenario, we apply a variable tax of 20% added to solo ride-sourcing fares.

For each scenario and trip, we compute compensating variations, i.e. the monetary compensations that offset the alteration of the choice sets. Compensating variations are straightforward to compute in MEV-based DCMs if the considered model specification contains a generic cost parameter. In this case, the compensating variation for an observation is given by the difference in consumer



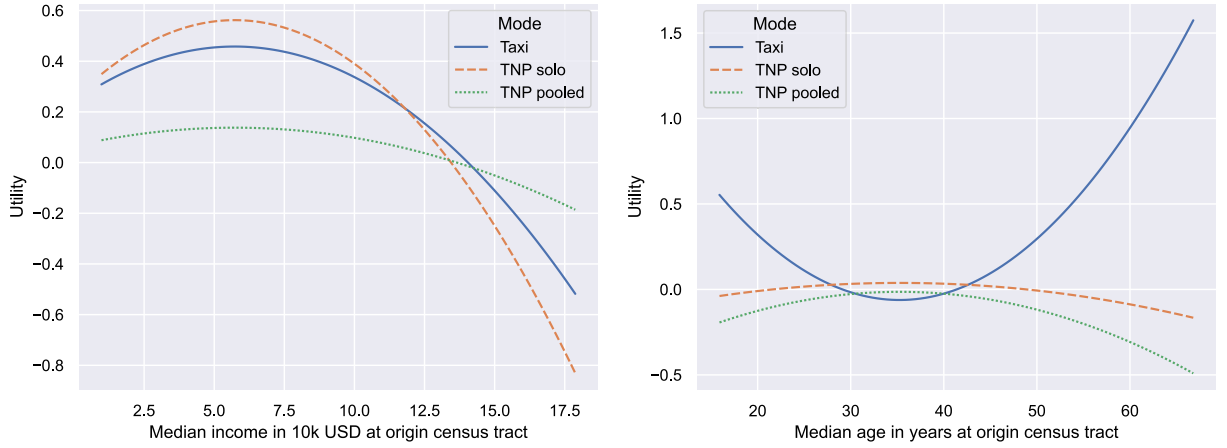


Fig. 14. Income and age effects in model 2b.

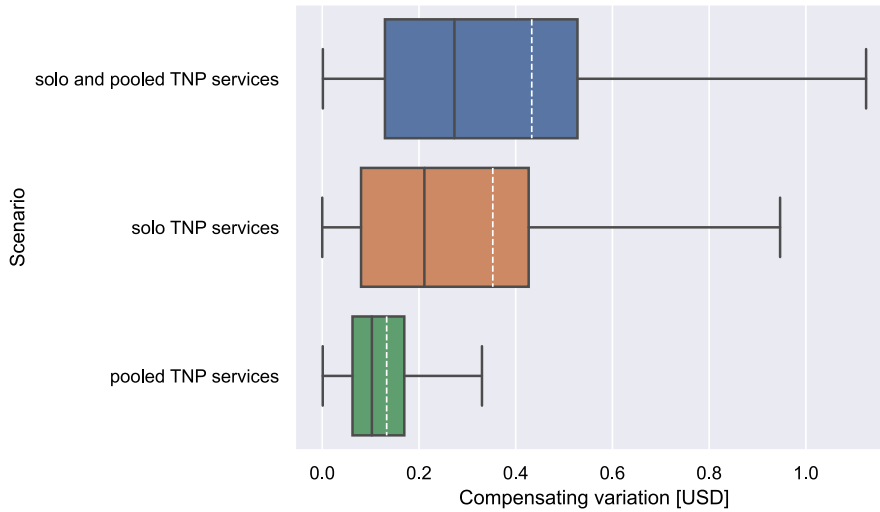


Fig. 15. Box plots of compensating variations in elimination scenarios (dashed white lines indicate means).

surplus divided by the cost parameter estimate. The difference in consumer surplus in MEV-based models is given by

$$\ln G(e^{V_n^1}) - \ln G(e^{V_n^0}), \quad (22)$$

where it is assumed that a policy changes the choice set from  $\mathcal{C}^0$  to  $\mathcal{C}^1$ , prices from  $p_{nj}^0$  to  $p_{nj}^1$  and non-cost attributes from  $X_n^0$  to  $X_n^1$  such that the utilities change from  $V_n^1$  to  $V_n^0$ . Furthermore,  $G$  is the MEV generating function of the considered model. In the current application, it is not possible to analytically compute compensating variations, as the considered model specification contains alternative-specific cost parameters. Therefore, we adopt the simulation approach presented in McFadden (2012) to compute compensating variations in the considered scenarios.

In Figs. 15 and 16, we show box plots of the computed compensating variations in the elimination and taxation scenarios, respectively. Fig. 15 suggests that welfare losses are largest due to the elimination of all ride-sourcing services, closely followed by the removal of only solo ride-sourcing services, whereas welfare losses due to the removal of pooled ride-sourcing services are comparatively small. While the mean compensating variations for the first two elimination scenarios are USD 0.43 and USD 0.35, respectively, the compensating variation in the third scenario, in which only pooled ride-sourcing services are eliminated, is only USD 0.13. As expected, welfare losses in the taxation scenarios are smaller compared to the elimination scenarios (see Fig. 16). This is because in the taxation scenarios, alternatives are made less attractive through the introduction of a tax but are not entirely removed from choice sets. It can be seen that welfare losses are higher in the scenarios with a fixed tax compared to the scenarios with a variable tax. Whereas the mean compensating variation is USD 0.12 in the first taxation scenario, the mean compensating variation in the second scenario is USD 0.07. In all scenarios, the distributions of the compensating variations exhibit a considerable spread and a heavy right tail. For example, in the first elimination scenario, the interquartile range of the compensating variations is

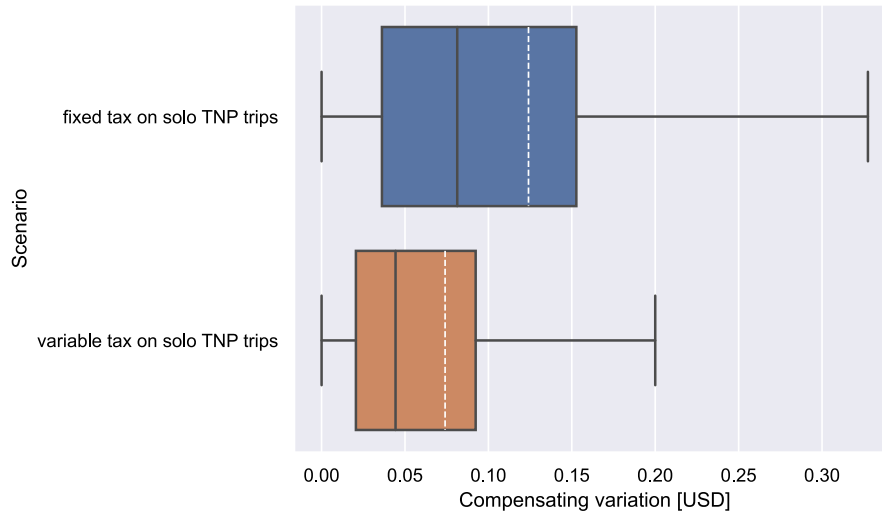


Fig. 16. Box plots of compensating variations in taxation scenarios (dashed white lines indicate means).

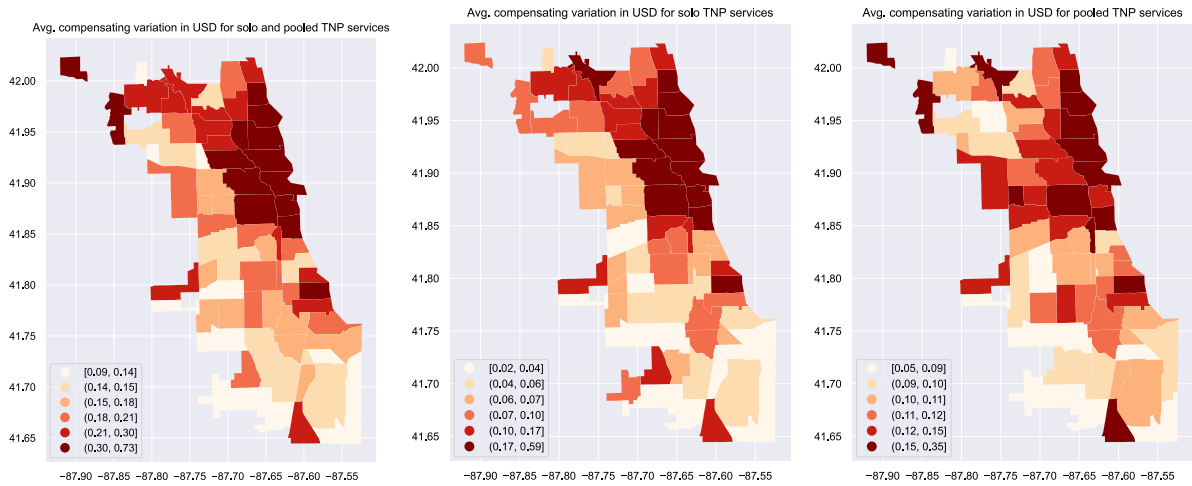


Fig. 17. Average compensating variations by community area in elimination scenarios.

USD 0.40, and in the first taxation scenario the interquartile range is USD 0.12. In all scenarios, the mean is larger than the median. These results suggest that the distribution of ride-sourcing benefits is highly heterogeneous. Overall, the compensating variations appear small. However, this can be explained by the fact that the ride-sourcing alternatives have comparatively small probabilities of being selected compared to other alternatives, such as car and public transit.

In Fig. 17, we present the average compensating variations by community area for the elimination scenarios, in which services are removed from choice sets. The figure reveals substantial heterogeneity in the distributions of the computed compensating variations in the three considered scenarios across the community areas of the study region. In all three scenarios, ride-sourcing benefits are valued higher in central areas. The average compensating variations in the community areas of the study area in the first scenario range from USD 0.09 to 0.73. Benefits of solo ride-sourcing are valued higher than the benefits of pooled ride-sourcing. Whereas the average compensating variations in the second scenario range from USD 0.02 to 0.59, the average compensating variations in the third scenario range from USD 0.05 to only 0.35.

Finally, in Fig. 18, we present the average compensating variations by community area for the taxation scenarios. The average compensating variations range from USD 0.01 to 0.19 in the fixed tax scenario and from USD 0.01 to 0.11 in the variable tax scenarios. The spatial distributions of the compensating variations appear similar in both scenarios and are consistent with the spatial distributions obtained in the elimination scenarios.

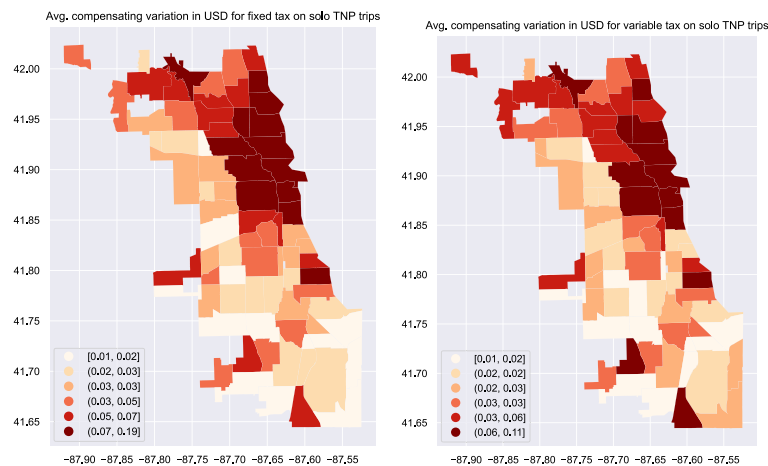


Fig. 18. Average compensating variations by community area in taxation scenarios.

## 8. Conclusion

In this paper, we presented and applied an approach for estimating ride-sourcing demand at a disaggregate level from multiple data sources using DCMs. In sum, our research makes four contributions to the literature. First, we demonstrate how ride-sourcing demand estimation with DCMs can be performed by fusing multiple disaggregate data sources. Second, we show how traditional household travel surveys can be enriched with emerging sources of big data (i.e. trip records). Third, we highlight the importance of controlling for endogeneity biases in ride-sourcing demand estimation. Finally, we provide a methodology for incorporating emerging mobility options (such as ride- and bike-sharing etc.) into disaggregate activity-based travel demand forecasting models.

There are several ways in which our work could be extended. First, an important avenue for future research is to compare different methods for correcting for endogeneity in discrete choice models, especially for large datasets. Such an analysis may include one- and two-stage approaches as well as alternative estimation approaches in addition to maximum (simulated) likelihood such as maximum approximate composite marginal likelihood (Bhat and Sidharthan, 2011) as well as Markov chain Monte Carlo and Variational Bayes methods (see e.g. Bansal et al., 2020a; Hawkins and Habib, 2022). Second, the constructed mode choice dataset could be enriched with trip records providing information about other emerging transport modes such as bike-sharing. Third, the temporal structure of the data could be explicitly considered to investigate the temporal stability of the structural relationship between travel demand and the various explanatory variables. Finally, a fourth direction for future research is to circumvent the deterministic definition of choice sets by adopting a choice model in which the availability of alternatives is treated in a probabilistic manner (see Habib, 2019).

## CRedit authorship contribution statement

**Rico Krueger:** Conceptualisation, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualisation. **Michel Bierlaire:** Conceptualisation, Methodology, Writing – review & editing. **Prateek Bansal:** Conceptualisation, Methodology, Investigation, Writing – original draft.

## Data availability

The authors do not have permission to share data

## Appendix A. Overview of ride-sourcing demand analysis studies

See Table 9.

## Appendix B. Random forest hyperparameters

See Table 10.

**Table 10**  
Hyperparameters of random forest models.

Parameter	Price: solo r.-s.	Price: pooled r.-s.
No. of trees	100	100
Prop. of features to consider on split	$\frac{1}{3}$	$\frac{1}{2}$
Max. tree depth	$\infty$	10
Min. no. of samples to split internal node	5	40
Min. no. of samples to be at a leaf node	5	1

## References

- Acheampong, R.A., Siiba, A., Okyere, D.K., Tuffour, J.P., 2020. Mobility-on-demand: An empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. *Transp. Res. C* 115, 102638.
- Alemi, F., Circella, G., Mokhtarian, P., Handy, S., 2019. What drives the use of ridehailing in California? Ordered probit models of the usage frequency of uber and lyft. *Transp. Res. C* 102, 233–248.
- Alonso-González, M.J., van Oort, N., Cats, O., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2020. Value of time and reliability for urban pooled on-demand services. *Transp. Res. C* 115, 102621.
- Asgari, H., Jin, X., 2020. Incorporating habitual behavior into mode choice modeling in light of emerging mobility services. *Sustainable Cities Soc.* 52, 101735.
- Azimi, G., Rahimi, A., Jin, X., 2021. Exploring the attitudes of millennials and generation xers toward ridesourcing services. *Transportation* 1–35.
- Baker, D.M., 2020. Transportation network companies (TNCs) and public transit: examining relationships between TNCs, transit ridership, and neighborhood qualities in San Francisco. *Case Stud. Transp. Policy* 8 (4), 1233–1246.
- Bansal, P., Krueger, R., Bierlaire, M., Daziano, R.A., Rashidi, T.H., 2020a. Bayesian estimation of mixed multinomial logit models: Advances and simulation-based evaluations. *Transp. Res. B* 131, 124–142.
- Bansal, P., Sinha, A., Dua, R., Daziano, R.A., 2020b. Eliciting preferences of TNC users and drivers: evidence from the United States. *Travel Behav. Soc.* 20, 225–236.
- von Behren, S., Chlond, B., Vortisch, P., 2021. Exploring the role of individuals' attitudes in the use of on-demand mobility services for commuting—a case study in eight Chinese cities. *Int. J. Transp. Sci. Technol.*
- Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. *Econometrica* 841–890.
- Bhat, C.R., Sidharthan, R., 2011. A simulation evaluation of the maximum approximate composite marginal likelihood (MACML) estimator for mixed multinomial probit models. *Transp. Res. B* 45 (7), 940–953.
- Bi, H., Ye, Z., 2021. Exploring ridesourcing trip patterns by fusing multi-source data: A big data approach. *Sustainable Cities Soc.* 64, 102499.
- Bierlaire, M., 2018. PandasBiogeme: a short introduction. Report TRANSP-OR: Lausanne, Switzerland, 181219.
- Bierlaire, M., Bolduc, D., McFadden, D., 2008. The estimation of generalized extreme value models from choice-based samples. *Transp. Res. B* 42 (4), 381–394.
- Bierlaire, M., Krueger, R., 2020. Sampling and discrete choice. Technical Report TRANSP-OR 201109, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland.
- Breiman, L., 2001. Random forests. *Mach. Learn.* 45 (1), 5–32.
- Castillo, J.C., Knoepfle, D., Weyl, G., 2017. Surge pricing solves the wild goose chase. In: *Proceedings of the 2017 ACM Conference on Economics and Computation*. pp. 241–242.
- Chicago Metropolitan Agency for Planning, 2015. Land use inventory 2013.
- City of Chicago, 2020. Chicago taxicab fare rates and fees.
- Dean, M.D., Kockelman, K.M., 2021. Spatial variation in shared ride-hail trip demand and factors contributing to sharing: Lessons from chicago. *J. Transp. Geogr.* 91, 102944.
- Dey, B.K., Tirtha, S.D., Eluru, N., Konduri, K.C., 2021. Transformation of ridehailing in new york city: A quantitative assessment. *Transp. Res. C* 129, 103235.
- Dong, X., 2020. Trade uber for the bus? An investigation of individual willingness to use ride-hail versus transit. *J. Am. Plan. Assoc.* 86 (2), 222–235.
- Dong, X., Guerra, E., Daziano, R.A., 2021. Impact of TNC on travel behavior and mode choice: a comparative analysis of boston and philadelphia. *Transportation* 1–21.
- Edwards, M., 2020. Nonstandard ridehail use in austin. *J. Transp. Geogr.* 86, 102746.
- Federal Transit Administration, 2021. National transit database: 2019 data tables.
- Frazier, D.T., Renault, E., Zhang, L., Zhao, X., 2020. Weak identification in discrete choice models. *arXiv preprint arXiv:2011.06753*.
- Ghaffar, A., Mitra, S., Hyland, M., 2020. Modeling determinants of ridesourcing usage: A census tract-level analysis of chicago. *Transp. Res. C* 119, 102769.
- Goletz, M., Bahamonde-Birke, F.J., 2021. The ride-sourcing industry: status-quo and outlook. *Transp. Plan. Technol.* 44 (6), 561–576.
- Gomez, J., Aguilera-García, Á., Dias, F.F., Bhat, C.R., Vassallo, J.M., 2021. Adoption and frequency of use of ride-hailing services in a European city: The case of madrid. *Transp. Res. C* 131, 103359.
- Gopalakrishnan, R., Guevara, C.A., Ben-Akiva, M., 2020. Combining multiple imputation and control function methods to deal with missing data and endogeneity in discrete-choice models. *Transp. Res. B* 142, 45–57.
- Guevara, C.A., 2015. Critical assessment of five methods to correct for endogeneity in discrete-choice models. *Transp. Res. A* 82, 240–254.
- Guevara, C.A., 2018. Overidentification tests for the exogeneity of instruments in discrete choice models. *Transp. Res. B* 114, 241–253.
- Guevara, C.A., Ben-Akiva, M.E., 2012. Change of scale and forecasting with the control-function method in logit models. *Transp. Sci.* 46 (3), 425–437.
- Habib, K.N., 2019. Mode choice modelling for hailable rides: An investigation of the competition of uber with other modes by using an integrated non-compensatory choice model with probabilistic choice set formation. *Transp. Res. A* 129, 205–216.
- Hasnine, M.S., Hawkins, J., Habib, K.N., 2021. Effects of built environment and weather on demands for transportation network company trips. *Transp. Res. A* 150, 171–185.
- Hausman, J.A., 1996. Valuation of new goods under perfect and imperfect competition. In: *Bresnahan, T.F., Gordo, R.J. (Eds.), The Economics of New Goods*. University of Chicago Press, pp. 207–248.
- Hausman, J., Leonard, G., Zona, J.D., 1994. Competitive analysis with differentiated products. *Ann. Econ. Stat.* 159–180.
- Hawkins, J., Habib, K.N., 2022. Bayesian estimation of discrete choice models: a comparative analysis using effective sample size. *Transp. Lett.* 14 (10), 1091–1099.
- Hess, S., Train, K.E., Polak, J.W., 2006. On the use of a modified latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. *Transp. Res. B* 40 (2), 147–163.
- Hou, Y., Garikapati, V., Weigl, D., Henao, A., Moniot, M., Sperling, J., 2020. Factors influencing willingness to pool in ride-hailing trips. *Transp. Res. Rec.* 2674 (5), 419–429.
- Kang, S., Mondal, A., Bhat, A.C., Bhat, C.R., 2021. Pooled versus private ride-hailing: A joint revealed and stated preference analysis recognizing psycho-social factors. *Transp. Res. C* 124, 102906.

- Koppelman, F.S., Coldren, G.M., Parker, R.A., 2008. Schedule delay impacts on air-travel itinerary demand. *Transp. Res. B* 42 (3), 263–273.
- Lam, C.T., Liu, M., Hui, X., 2021. The geography of ridesharing: A case study on new york city. *Inf. Econ. Policy* 57, 100941.
- Lazarus, J.R., Caicedo, J.D., Bayen, A.M., Shaheen, S.A., 2021. To pool or not to pool? Understanding opportunities, challenges, and equity considerations to expanding the market for pooling. *Transp. Res. A* 148, 199–222.
- Li, W., Shalaby, A., Habib, K.N., 2021. Exploring the correlation between ride-hailing and multimodal transit ridership in toronto. *Transportation* 1–25.
- Loa, P., Habib, K.N., 2021. Examining the influence of attitudinal factors on the use of ride-hailing services in toronto. *Transp. Res. A* 146, 13–28.
- Loa, P., Mashrur, S.M., Nurul Habib, K., 2021. What influences the substitution of ride-sourcing for public transit and taxi services in toronto? An exploratory structural equation model-based study. *Int. J. Sustain. Transp.* 1–14.
- Lurkin, V., Garrow, L.A., Higgins, M.J., Newman, J.P., Schyns, M., 2017. Accounting for price endogeneity in airline itinerary choice models: An application to continental US markets. *Transp. Res. A* 100, 228–246.
- Malik, J., Bunch, D.S., Handy, S., Circella, G., 2021. A deeper investigation into the effect of the built environment on the use of ridehailing for non-work travel. *J. Transp. Geogr.* 91, 102952.
- Manski, C.F., McFadden, D., 1981. Alternative estimators and sample designs for discrete choice analysis. *Struct. Anal. Discret. Data Econom. Appl.* 2.
- Marquet, O., 2020. Spatial distribution of ride-hailing trip demand and its association with walkability and neighborhood characteristics. *Cities* 106, 102926.
- McFadden, D., 1978. Modeling the choice of residential location. *Transp. Res. Rec.* (673).
- McFadden, D., 1981. Econometric models of probabilistic choice. *Struct. Anal. Discret. Data Econom. Appl.* 198272.
- McFadden, D., 1999. Chapter 2. sampling and selection 1. In: *Lecture Notes of Economics* 240B, Second Half, pp. 1–21.
- McFadden, D., 2012. Computing willingness-to-pay in random utility models. In: *Trade, Theory and Econometrics*. Routledge, pp. 275–296.
- McMahon, K., 2020. City's new congestion tax puts burden on Uber and Lyft drivers.
- National Centers for Environmental Information, 2021. Daily Summaries Chicago o'Hare International Airport, IL US.
- Nevo, A., 2000. A practitioner's guide to estimation of random-coefficients logit models of demand. *J. Econ. Manage. Strategy* 9 (4), 513–548.
- Nugroho, S.B., Zusman, E., Nakano, R., 2020. Explaining the spread of online taxi services in semarang, bogor and bandung, Indonesia; a discrete choice analysis. *Travel Behav. Soc.* 20, 358–369.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: Machine learning in python. *J. Mach. Learn. Res.* 12, 2825–2830.
- Petrin, A., Train, K., 2010. A control function approach to endogeneity in consumer choice models. *J. Mar. Res.* 47 (1), 3–13.
- Sabogal-Cardona, O., Oviedo, D., Scholl, L., Crotte, A., Bedoya-Maya, F., 2021. Not my usual trip: Ride-hailing characterization in Mexico city. *Travel Behav. Soc.* 25, 233–245.
- Sabouri, S., Park, K., Smith, A., Tian, G., Ewing, R., 2020. Exploring the influence of built environment on uber demand. *Transp. Res. D* 81, 102296.
- Shen, H., Zou, B., Lin, J., Liu, P., 2020. Modeling travel mode choice of young people with differentiated E-hailing ride services in nanjing China. *Transp. Res. D* 78, 102216.
- Soltani, A., Allan, A., Khalaj, F., Pojani, D., Mehdizadeh, M., 2021. Ridesharing in adelaide: Segmentation of users. *J. Transp. Geogr.* 92, 103030.
- Sweet, M.N., 2021. User interest in on-demand, shared, and driverless mobility: Evidence from stated preference choice experiments in southern ontario. *Travel Behav. Soc.* 23, 120–133.
- Tirachini, A., 2020. Ride-hailing, travel behaviour and sustainable mobility: an international review. *Transportation* 47 (4), 2011–2047.
- Toman, P., Zhang, J., Ravishanker, N., Konduri, K.C., 2020. Dynamic predictive models for ridesourcing services in New York city using daily compositional data. *Transp. Res. C* 121, 102833.
- Train, K.E., 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press.
- Tu, M., Li, W., Orfila, O., Li, Y., Gruyer, D., 2021. Exploring nonlinear effects of the built environment on ridesplitting: Evidence from chengdu. *Transp. Res. D* 93, 102776.
- United States Census Bureau, 2021. American community survey 2018 5-year estimates.
- US Energy Information Agency, 2021. Chicago weekly retail gasoline and diesel prices.
- US Environmental Protection Agency, 2021. Smart location database.
- Wang, X., Yan, X., Zhao, X., Cao, Z., 2022. Identifying latent shared mobility preference segments in low-income communities: ride-hailing, fixed-route bus, and mobility-on-demand transit. *Travel Behav. Soc.* 26, 134–142.
- Wang, H., Yang, H., 2019. Ridesourcing systems: A framework and review. *Transp. Res. B* 129, 122–155.
- Ward, J.W., Michalek, J.J., Samaras, C., Azevedo, I.L., Henao, A., Rames, C., Wenzel, T., 2021. The impact of uber and lyft on vehicle ownership, fuel economy, and transit across US cities. *Science* 24 (1), 101933.
- Wen, C.-H., Huang, C.-J., Fu, C., 2020. Incorporating continuous representation of preferences for flight departure times into stated itinerary choice modeling. *Transp. Policy* 98, 10–20.
- Westat, 2020. 2018-19 My Daily Travel Methods and Final Survey Report. Technical report, Chicago Metropolitan Agency for Planning, Prepared for.
- Wooldridge, J.M., 2015. Control function methods in applied econometrics. *J. Hum. Resour.* 50 (2), 420–445.
- Yan, X., Liu, X., Zhao, X., 2020. Using machine learning for direct demand modeling of ridesourcing services in chicago. *J. Transp. Geogr.* 83, 102661.
- Yan, X., Zhao, X., Han, Y., Van Hentenryck, P., Dillahun, T., 2021. Mobility-on-demand versus fixed-route transit systems: An evaluation of traveler preferences in low-income communities. *Transp. Res. A* 148, 481–495.
- Yu, H., Peng, Z.-R., 2020. The impacts of built environment on ridesourcing demand: A neighbourhood level analysis in austin, texas. *Urban Stud.* 57 (1), 152–175.