Reading a Paper with Purpose – Data Tables

Example 1

Literature review of vehicle ownership models with data requirements, strengths and shortcomings.

Purpose: Decide on the appropriate vehicle ownership model to use.

Table 1: Exogenous static models.

Study example	**Modeling approach**	**Data requirements**	**Strengths**	**Shortcomings**
Potoglou and Kanaroglou (2008)	***2 models:*** Multinomial logit (MNL) and ordered logit (OL)	Internet-survey in the Census Metropolitan Area of Hamilton (CIBER-CARS survey) with two stages: Past and current vehicle ownership, and stated choices experiment on future vehicle preferences. Combined with GIS data.	***Both***: Closed form (i.e., computational simplicity). ***OL***: Easier parameter estimation. ***MNL***: Better representation than ordered logit. Less restriction on the household attributes to include	***Both***: Dynamics associated with the random unobserved variables are not handled. Assume proportional substitution across alternatives which is not always suitable (i.e., changes in one alternative probability lead to proportional adjustments of other alternative probabilities). Assume independence of irrelevant alternatives (IIA) property (i.e., the unobserved factors of the alternative utilities are independent). Population homogeneity assumption (i.e., exogenous variables are the same for the entire population). ***OL***: Only appropriate when small number of categories. ***MNL***: More parameters to estimate than ordered logit.
Mohammadian and Miller (2003)	Nested logit with two levels	Retrospective survey (Toronto Area Car Ownership Study). Information on household vehicle transactions from 1990	Do not require IIA property. Generalization of the multinomial logit model. Allow for correlation of alternative utilities in common nests. Vehicle ownership with vehicles size.	Alternatives in a common nest have equal cross-elasticities. Population homogeneity assumption.

		to 1998 in Toronto. Vehicle attributes from Canadian Vehicle Specification System and fuel consumption from Fuel Economy Guide Database.		
Mohammadian and Miller (2002)	Multilayer perceptron artificial neural network	Same than previous study (A. K. Mohammadian and Miller 2003)	Quicker than traditional discrete choice models. Better predictive potential than Nested logit model. Vehicle ownership with vehicles size.	Black box. Lack of explicit sensitivity measures due to the lack of transparency. Difficult to integrate artificial neural network into larger framework (compared to nested models). Population homogeneity assumption.
Shay and Khattak (2012)	Poisson regression	Two cross-sectional datasets from the Charlotte metro area (U.S.) providing household descriptions, travellers and trips.	Rely on single-equation models, more simple to settle with a closed form solution.	Only vehicle ownership without vehicle type. Assume that number of automobiles owned by household is independently Poisson distributed (i.e., mean equal to the variance), which is unjustified: It does not adequately represent over- or under-dispersed data. Has non-zero probability for values higher than 3 vehicles per household, which is very unlikely. Population homogeneity assumption.
Anowar et al. (2014)	***2 models:*** Latent segmentation based ordered logit (LSOL) and latent segmentation based multinomial logit (LSMNL)	Origin–Destination (O–D) surveys of Quebec City (2001)	***Both:*** Can deal with systemic heterogeneity of observed variables through set of exogenous variables for each population segment. Include land use characteristics and household demographics. Latent models outperform traditional models. ***LSMNL***: Higher predictive performance than LSOL	Only vehicle ownership without vehicle type. Prone to stability issues in the estimation process.

Endogenous static models

Study example	Modeling approach	Data requirements	Strengths	Shortcomings
Weinberger and Goetzke (2010)	Multinomial probit	2000 US census 5 % public use micro sample (PUMS) of major U.S. cities.	Can jointly model vehicle ownership along with other attributes to account (e.g., residential location) for simultaneity of the attributes. Relaxation of IIA assumption and allow substitution pattern of alternatives.	Only vehicle ownership without vehicle type. No closed form (i.e., computational intensive). Cannot be used with continuous travel attribute.
Bhat (2008)	Multiple discrete continuous extreme values (MDCEV)	2000 San Francisco Bay Area Travel Survey (BATS)	Model vehicle ownership decision along with discrete (e.g., types of vehicles) and continuous (i.e., VKT) decisions. Can capture many vehicle classifications. Can handle complementarity as well as substitution among goods. No constraint of additive separability. Closed form solution.	Do not consider the current household attributes by the process of acquiring a vehicle as instantaneous. Cannot capture the vehicle transactions.
Fang (2008)	Bayesian multivariate ordered probit and tobit	2001 National Household Travel Survey data	Combine vehicle type choice (2 sizes) with vehicle usage. Closed form solution. Similar results to MDCEV (Bhat 2008) but easier to solve and faster. No constraint on total travelled distance.	Computational intensive with increasing vehicle categories because equation increases proportionally.

Dynamic models

Study example	**Modeling approach**	**Data requirements**	**Strengths**	**Shortcomings**
Mohammadian and Rashidi (2007)	Competing hazard-based duration	Toronto Area Car Ownership Study (TACOS) survey	Can capture probability of occurrence at a specific time. Vehicle ownerships along vehicle transaction behavior.	Only vehicle ownership without vehicle type. Require time-series data, not always available. Assume independence among hazard events, which is unlikely. Cannot handle heterogeneity effects.
Paleti et al. (2011)	Copula-based joint GEV-based logit-regression model	Residential survey component of the California Vehicle Survey data: Revealed choice on the current household vehicle fleet and usage. Stated Intention data on vehicle replacement and future vehicle characteristics. Then stated preference data on future vehicle types and technology.	Closed form solution. One module that simulates vehicle ownership (by size and technology) along decision of residential choice and vehicle usage. One module that simulates the fleet over time including replacement, acquisition and disposal.	It requires longitudinal data on the dynamics of household vehicles. Assume independence of irrelevant alternatives (IIA) property.

Table 1: Examples of vehicle ownership models with data requirements, strengths and shortcomings.

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Example 2

Literature review of land-use regression models

Purpose: Decide on the appropriate protocol.

Table 2: Summary of land-use regression (LUR) model protocols for Ultrafine Particles (UFP)

Study	**Location**	**Type of data collection**	**Number of segments/points sampled**	**Time spent per point/segment and/or number of visits**	**R^2 of the LUR model (* means adjusted R^2)**
Hankey and Marshall [2]	Minneapolis (U.S.A.)	Mobile (bike)	1,101 aggregation locations (spatial resolution: 100m, temporal resolution: 1s)	200 seconds (afternoon), and less than 100 seconds (morning) on average	0.50 (morning) and 0.48 (afternoon)
Sabaliauskas et al. [3]	Toronto (Canada)	Mobile (pedestrian)	112 road segments	5 to 10 minutes	0.72
Patton et al. [4]	Boston (U.S.A.)	Mobile (car)	Each one-second measurement was kept	1 second	0.23 to 0.42 (depending on neighbourhood considered)
Kerckhoffs et al. [5]	Amsterdam and Rotterdam (Netherlands)	Mobile (electric car)	2,964 road segments (745 visited twice)	18 seconds on average	0.13 (all segments) 0.18 (segments visited twice)
Farrell et al. [6]	Montreal (Canada)	Mobile (bike)	4,058 road segments	Between 1 and 52 visits	0.3812
Weichenthal et al. [7]	Montreal (Canada)	Mobile (bike in summer, cars in winter)	414 road segments	405 seconds on average (always more than 200)	0.62
Weichenthal et al. [8]	Toronto (Canada)	Mobile (car)	405 road segments	10 minutes on average (always more than 250 seconds)	0.67*
Rivera et al. [9]	Girona and close cities (Spain)	Fixed	644 fixed sites	15 minutes	0.36*
Saraswat et al. [10]	New Delhi (India)	Fixed	18 (morning) 37 (afternoon)	More than 1h	0.28 (morning) 0.23 (afternoon)
Ghassoun et al. [11]	Braunschweig (Germany)	Fixed	27 fixed points	45 minutes	0.74 (summer) 0.85 (winter)

Montagne et al. [12]	Amsterdam and Rotterdam (Netherlands)	Fixed	161 sites	90 minutes	0.37
Kerckhoffs et al. [5]	Amsterdam and Rotterdam (Netherlands)	Fixed	128 fixed sites	60 minutes	0.36
van Nunen et al. [1]>	Basel (Switzerland), Heraklion (Greece), Amsterdam, Maastricht, and Utrecht ("The Netherlands"), Norwich (United Kingdom), Sabadell (Spain), and Turin (Italy)	Fixed	160 in general, 240 sites for "The Netherlands"	90 minutes	0.28 to 0.48

Example 3

Table 3. Optimization of automated external defibrillator placement and retrieval literature.

Study	**Target population**	**Models**	**Outcomes**	**Result**
Tsai et al. 2012, Huang and Wen 2014	Public OHCA	Genetic algorithm covering model (spatial and temporal weights)	Spatiotemporal OHCA coverage	spatiotemporal model provided a relative increase in spatiotemporal OHCA coverage of 18.0%-26.2% over the spatial model; AED configurations vary by model weights
Chan et al. 2013	Public out-of-hospital cardiac arrest (OHCA)	Maximum coverage location problem (MCLP), Population guided heuristic	Spatial OHCA coverage	MCLP provided significantly more spatial OHCA coverage compared to the population guided heuristic, regardless of the number of AEDs placed
Siddiq et al. 2013	Public OHCA	MCLP – varying coverage radius	Spatial OHCA coverage	Quantified relationship between coverage radius and spatial coverage
Chan et al. 2016	Public OHCA	Probabilistic MCLP	Probability of AED retrieval	Quantified impact of differing bystander AED retrieval behaviors on probability and configuration.
Sun et al. 2016,	Public OHCA	Spatiotemporal MCLP, MCLP	Spatiotemporal OHCA coverage	DMCLP can reverse the negative effects of limited

Sun et al. 2018				temporal accessibility on spatiotemporal coverage of AED placements based on MCLP; DMCLP generalizable from NA to EU
Boutilier et al. 2017	Private and public OHCA	MCLP and queuing model	Drone AED delivery response time	Quantified relationship between number of drone bases and drones to reach a target OHCA response time.
Tierney et al. 2018	Public OHCA	Relocation - MCLP	Spatial OHCA coverage	Relocation models have been shown to have relative increases in spatial OHCA coverage between 11.5% - 121.9%
Chan et al. 2018	Public OHCA	Robust MCLP – uncertainty in demand, MCLP	Spatial OHCA coverage	Robust MCLP improved spatial coverage under typical and worst-cases of demand uncertainty. Performed nearly as well as ex-post MCLP.
Lee et al. 2019	In-hospital cardiac arrest	P-median, Simulated demand	Distance to AED	Optimal placements decreased the average distance of simulated arrest to a defibrillator by 77.8%, compared to existing placements
Sun et al. 2019	Public OHCA	Multi-period spatiotemporal MCLP, Logistic regression	Spatiotemporal OHCA coverage, bystander defibrillation, 30-day survival	Relative increase in spatiotemporal OHCA coverage of 52.0-95.9% over the existing AED network, corresponding to an estimated 52.9-83.5% relative increase in bystander defibrillation and estimated 11.0-13.3% relative increase in 30-day survival

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