Australasian Transport Research Forum 2015 Proceedings
30 September - 2 October 2015, Sydney, Australia
Publication website: http://www.atrf.info/papers/index.aspx

Modelling Sydney's light commercial service vehicles

Richard B. Ellison[1], Collins Teye[1], David A. Hensher[1]

[1] Institute of Transport and Logistics Studies, The University of Sydney Business School, The University of Sydney, Sydney, NSW, Australia
E-Mail for correspondence: richard.ellison@sydney.edu.au

Abstract

One frequently overlooked source of trips in Sydney (and elsewhere) is light commercial vehicles (LCVs) used by tradesmen and other service workers to travel to customers to provide commercial services. Although these trips have substantial differences from other types of trips (and vehicles), they are frequently included either as standard passenger vehicles or, alternatively, as freight, if they are considered at all. However, light commercial vehicle trips used for commercial services comprise a substantial number of vehicle trips, particularly in areas with large concentrations of businesses such as the Sydney CBD and other growing business precincts, and for this reason should be included in travel demand models. As part of a large project involving the development of a comprehensive model system for predicting passenger, service and freight travel in Sydney (MetroScan-TI), this paper outlines the estimation and application of a set of models for service vehicles. The model system includes four models, a tour generation model, a tour type model, an SLA choice model and a destination (or travel zone) choice model. These models are estimated using data from a small subset of the Sydney Household Travel Survey (HTS) involving work trips using LCVs, as well as detailed land-use and employment data from the 2011 Australian Census. We obtain a set of behaviourally rich and geographically detailed models that incorporate feedback through the use of several inclusive value (logsum) parameters. In addition to the overview of the model system, this paper discusses the estimation results and their application to policies.

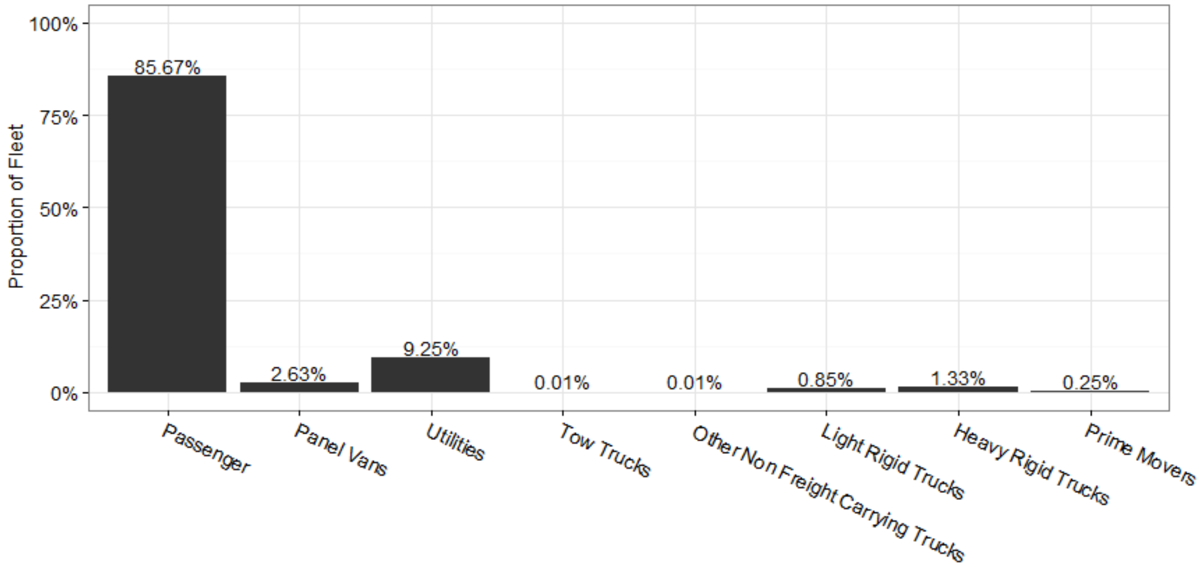
1. Introduction

Light commercial vehicles are some of the most common vehicles on the roads of many cities, but they are also among the vehicles of which relatively little is known about their use. Light commercial vehicles (LCVs), or to be more accurate in the context of this paper, light commercial service vehicles as opposed to light goods vehicles (LGVs), include small vans and utility vehicles frequently used by tradespeople and other service workers to travel between different customers where they provide an on-site service. Typically these services require specialist, heavy or large tools and parts that are difficult to carry in passenger cars. The nature of the services provided by these workers means that their travel patterns are neither consistent with commuting trips and other work-related trips (e.g., travel to meetings) nor with the trips made by freight vehicles delivering goods (Mei, 2013). However, despite these differences, LCV trips by service workers are typically either modelled as part of passenger travel or, occasionally, freight models, as well as frequently ignored altogether. This has been the case despite the large number of trips that are made by LCVs. This paper describes the structure, estimation and application of a set of behavioural models for service vehicles. This is followed by a discussion on the application of the results to policy.

2. Background and motivation

Passenger vehicles dominate the Sydney Greater Metropolitan Area's (GMA) vehicle fleet with approximately 86% of the fleet of cars, LCVs and heavy vehicles (see Figure 1). However, "panel vans" and utility vehicles together account for 12%, most of the remaining vehicles on the road after passenger cars (Australian Bureau of Statistics, 2014). Although not all of these vehicles are used for service trips and those that are will likely also be used for other purposes, they are a significant proportion of the fleet. Furthermore, it is known that LCVs tend to be used for more trips than passenger vehicles (Mei, 2013). Trips from LCVs are also increasing at a higher rate than thoseof passenger vehicles and heavy vehicles (Hebes et al., 2013). For these reasons, it was considered important to develop a model that was optimised for service trips rather than including these trips in either the passenger or freight models that are being developed as part of a large project involving the development of a comprehensive model system for predicting travel in Sydney (MetroScan-TI).

Figure 1: Proportion of car, LCV and heavy vehicle fleet in Sydney by class



It is important to emphasise that the focus of the models described in this paper are service trips made by light vehicles rather than freight-carrying trips, regardless of the vehicle class. Although it is acknowledged that some of the increase in trips from LCVs is a result of freight-carrying activities being switched from heavier vehicles to light vehicles (Ellison et al., 2013), the behavioural drivers of these trips are likely to be different to those of service trips, and as a result are not considered in these models. The focus of the LCV models described in this paper are primarily on the types of tours (i.e., number of stops in a tour) and the destinations within the tours.

3. Literature review

Many studies on commercial vehicle movements either ignore the differentiation between goods-carrying LGVs and other LCVs, if they are not ignored altogether. Nonetheless, some studies have attempted to model LCVs separately from freight-carrying vehicles. These studies broadly fall into two categories. The first of these categories includes studies that apply gravity models and other methods that have typically been applied to freight vehicles. The second, but smaller, category of studies are those that attempt to develop behavioural models to explain LCV trips.

One study of LCVs in Sydney used data collected primarily from two surveys from the Transport Data Centre (now Bureau of Transport Statistics, Transport for NSW) that included LCVs (Mendigorin and Peachman, 2005). Mendigorin and Peachman (2005) used a dataset from an earlier study that measured the attraction rates of LCVs to both businesses and households, and a dataset from the Commercial Transport Survey (CTS). Using a gravity model, a trip matrix for LCVs in Sydney was estimated (Mendigorin and Peachman, 2005). A similar study in Germany used data from earlier studies as well as business registration and employment data to generate vehicle locations (by vehicle class including LCVs) and through these, trip matrices (Steinmeyer and Wagner, 2006).

These studies are useful for providing an estimate of the likely LCV trips generated in an area and can provide some insights into how LCV trips are distributed around a city. Given the relatively little data available on LCV trips, these estimates can be very useful and provide information that can be used to differentiate LCV trips from both passenger and freight trips (Elaurant et al., 2007). However, these models do not have much predictive power as they generally lack a behavioural basis and rely primarily on averages and data on the origin and destination zones, and lack any data on the individual LCVs.

There are a limited number of studies that have studied the behavioural drivers of service trips and related decisions. For example, a German study used data from a survey on general vehicle traffic as well as data on service-related trips specifically (Hebes et al., 2013). Hebes et al. (2013) used a combination of multinomial logistic regression on the general vehicle data and multiple linear regression on the service-related data to identify how different firm characteristics affected the service trips they made. Although this study included work-related trips by car as well as service-related trips using LCVs, the study found that the industry of the firm, the size of the firm and the location of the firm were also significant predictors of VKT for service trips. As could reasonably be expected, their results showed that the location of customers was important to total vehicle kilometres of travel (VKT), but they also found that the location of a firm in an agglomeration substantially reduces their average VKT. Another study that looked at both goods and service vehicles used discrete choice models to model likely destinations of LCVs for goods and service-related trips in North Carolina (Mei, 2013).

4. Data and overview of model system

As discussed in the brief literature review, modelling of LCV trips has primarily focused on the use of gravity models for generating origin-destination flows of trips based on employment and population patterns in each area. In contrast, the structure chosen for the models described here uses several nested discrete choice models with disaggregate data. The reasons for this are two-fold. First, the primary purpose for developing the models was to provide forecasts of the likely changes to service trips given new infrastructure projects and changes to transport and land-use policies at a strategic level. Discrete choice models can be used to estimate behavioural changes based on underlying demographic (or firm-level) characteristics as opposed to gravity models that are intended to provide estimates of aggregate flows given exogenous zone-level data. Second, the use of the LCV models, as just one set of models within a larger framework that includes both passenger and freight-related models, required that the models be generally consistent with the form of the other models (albeit with some necessary adjustments). Since the other models have been estimated using discrete choice models for use with synthetic households (or firms), these LCV models use a similar form (Hensher, 2008). It should be emphasised that the model structures themselves are by necessity different due to the different nature of decisions made by households, service firms and freight transport firms but all retain the use of synthetic agents as the decision makers.

4.1. Data

The dataset used for estimating the models includes a small subset of the Sydney Household Travel Survey (HTS) as well as a dataset of zone-level data sourced from the Australian census, various Australian Bureau of Statistics (ABS) surveys and publications, and the GeoScience Australia NEXUS database. The data (and the resulting models) cover the Sydney Greater Metropolitan Area (GMA).

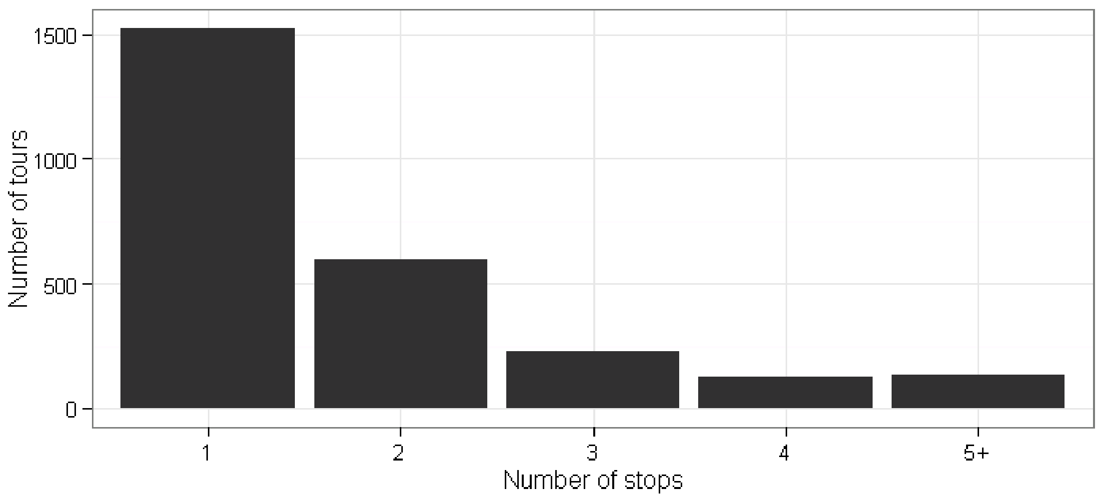
The HTS dataset that was used is a subset of the HTS including only individuals involved with work-related trips using LCVs. A combination of several HTS variables were used to identify if the purpose of the trip was likely to be a "service" trip including the industry and occupation as well as frequency of work-related trips made by LCV. The HTS data was used to ensure that relevant demographic characteristics were available for estimating the models that were also available (through other sources) for the later development of synthetic households (and in particular the service workers within them) (Hensher, 2008).

The zone-level data used includes data on employment by industry and occupation from the Australian census, ABS business counts by both employment and revenue, and land-use data derived from ABS meshblock data. Also used was data from the GeoScience Australia NEXUS database that provided details on the existing number of physical structures of various types (such as warehouses, factories, and office and residential buildings). Some of these data are available for both the SLA-level model and the travel-zone model but some is available only for the SLA-level model.

4.2. Model system

The proposed LCV demand model system (LCVDM) consists of a series of sub-models connected together in a tree structure such that sub-models at one stage influence models at other stages higher up in the hierarchy through accessibility measures. Conversely, sub-models at the lower stage are conditioned by models at higher stages. The first model is the tour-type model (TTM) that determines the number of stops in a given tour. The number of alternatives in this model are tours with 1, 2, 3, 4, and 5+ (5 or more) stops with the distribution presented in Figure 2. A tour with 1 stop means a driver starts his tour from an origin (e.g., his home) visits only one stop and returns to his origin. This model uses data from the HTS (occupation in particular) for each individual service worker (vehicle driver).

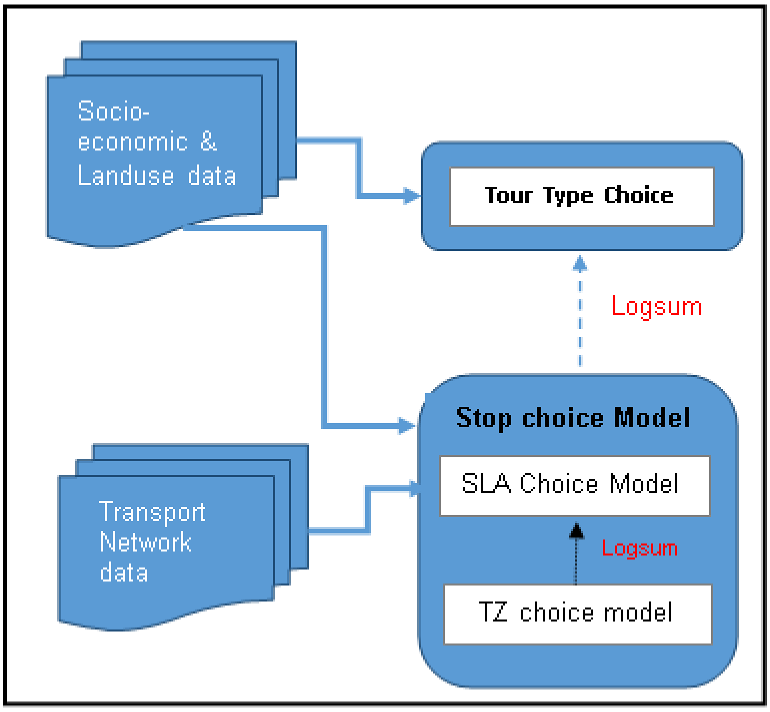
Figure 2: Number of tours in sample by number of stops



The second model is the stop choice model (SCM) which determines the actual stop(s) (destinations) for each tour type. The SCM is a Nested Logit (NL) model where each nest is a Statistical Local Area (SLA) zone and the number of nests equals the number of SLA zones in the Sydney Greater Metropolitan Area (GMA). The elementary alternatives in each nest are the travel zones within that nest (SLA). Thus the unconditional probability of stopping at a travel zone along a tour is the product of the probability of choosing the nest (SLA) in which the travel zone is in and the probability of choosing the travel zone within that nest. The stop choice modelling technique allows us to make use of some additional explanatory variables that are available at the SLA-level without these variables having to be available at the travel-zone level. Furthermore, the nested structure means that the zones used in the lower level (travel zones) are logically consistent with the tour type model that predicts the number of stops while maintaining predictive power for inter-SLA trips.

In addition to these models, the model system incorporates the micro-simulation techniques used with the synthetic households (and synthetic firms) as are used in TRESIS (Hensher, 2008) to apply these models. This is used for selecting the number of stops to visit based on the probabilities, and constructing a tour linking the stops together as well as factoring the results up to the population. A simplified version of the model architecture dealing with how the logit models were estimated is presented in Figure 3.

Figure 3: Overview of model system



5. Methodology and estimation

All models are logit models estimated using the NLogit software package (Hensher et al., 2015). The first estimated model is the NL model for stop choice followed by the tour-type model.

5.1. Stop Choice Model

The stop choice model, developed as part of the MetroScan-TI project, is a Nested Logit model with the alternatives on the lower level being travel zones and those in the upper level being SLAs. Starting with the lower level, the unconditional probability of stopping at travel zone *j* from origin *i* under tour type *t* is mathematically expressed as:

$$\mathrm{P_{ijt} = P_{it}(m)P_{it}(j/m)}$$

where $\mathrm{P_{it}(m)}$ is the probability of choosing nest $\mathrm{m = \{1,2, \dots, M\}}$ (i.e., the SLAs) and $\mathrm{P_{it}(j/m)}$ is the probability of stopping at travel zone *j* given that it is within nest *m* for origin *i* and tour type *t* and where *M* is the number of nests. These probabilities are mathematically expressed as shown in the equations below:

$$\mathrm{P_{it}(m) = \frac{e^{U_{imt}}}{\sum_{m \in N_t} e^{U_{imt}}}}$$

$$\mathrm{P_{it}(j/m) = \frac{e^{U_{it}(j/m)}}{\sum_{j \in N_m} e^{U_{it}(j/m)}}}$$

$\mathrm{U_{imt}}$ and $\mathrm{U_{it}(j/m)}$ are the utilities for nest m and travel zone *j* or origin *i* and tour type *t* respectively:

$$\mathrm{U_{it}(j/m) = \beta \cdot GT_{ijt} + \alpha \cdot \ln(Pop_j) + \sum_{l=1}^{E} \gamma_l \cdot \ln(E_{jl})}$$

$\mathrm{GT_{ijt}}$ is the generalised time[1] of traveling from origin zone *i* to stop *j* along tour type *t*, $\ln(\mathrm{Pop_j})$ is the natural logarithm of the population in travel zone *j*, and $\ln(\mathrm{E_{jl}})$ is the natural logarithm of the number of people employed in industry *l* in travel zone j and *E* is the number of industry types. The generalised time was constructed as follows:

$$\mathrm{GT_{ijt}} = \mathrm{T_{ijt}} + \frac{\mathrm{voc}}{\mathrm{vtts}} \mathrm{D_{ijt}} + \cdots$$

where $\mathrm{T_{ijt}}$ is the travel time (in minutes) of traveling from origin zone *i* to stop *j* along tour type *t*, voc is the vehicle operating cost ($/km), vtts is the value of travel time savings ($/min) and $\mathrm{D_{ijt}}$ is the corresponding travel distance (km). The VTTS used is one derived from several confidential studies on non-commuting work-related travel so the exact value is not reported here but it is in range of those used elsewhere of between $25/hr and $40/hr (Mackie et al., 2003; Batley 2014).

The utility of each nest can then be expressed as:

$$\mathrm{U_{imt}} = \theta_\mathrm{t} \cdot \mathrm{L_{imt}} + \varphi$$

where $\mathrm{L_{imt}}$ is the logsum or expected utility over all the travel zones within nest m under tour type *t*, θ_t are structural parameters with different estimated values for each tour type t, and φ is a constant for zones in the Sydney Inner City SLA relative to tour type 1. The logsum was expressed as:

$$\mathrm{L_{imt}} = \ln \sum_{\mathrm{j \in N_m}} \mathrm{e}^{\mathrm{U_{it}(j/m)}}$$

5.2. Tour Type Choice Model

The tour type model is a logit model in which the logsums from the stop choice models are used. Once the parameters in the SCM are estimated, the logsums are computed for each tour type, and these are then fed up into the tour type model as variables in the following utility equation:

$$\mathrm{U_{it}} = \delta \cdot \mathrm{L_{it}} + \sum_{\mathrm{l=1}}^{\mathrm{C}} \eta_\mathrm{l} \cdot (\mathrm{Occ_l}) + \rho_\mathrm{t}$$

where $\mathrm{L_{it}}$ is computed over all stops for each tour type t with associated structural parameter δ to be estimated, ρ_t are the constants for each tour type estimated relative to tour type 5+, $\mathrm{Occ_l}$ is an indicator variable which equals 1 if the tour type was made by a driver with occupation l, and zero otherwise, with parameters η_l which were estimated relative to tour types 2, 3, 4 and 5+ and *C* is the number of occupation types. The logsums were computed using the equation:

$$\mathrm{L_{it}} = \ln \sum_{\mathrm{m \in N_t}} \mathrm{e}^{\mathrm{U_{imt}}}$$

The parameter estimates for both the stop choice models and the tour type model are discussed in the following section.

6. Results

6.1. Stop choice model results

The estimation results for the stop choice models are reported in Table 1 (for the travel zone level) and Table 3 (for the SLA-level) showing that all estimated parameters except employment type 1 (employment in the mining and agriculture industries) are significant at the

[1] Generalised time (GT) is a linear combination of time and monetary costs expressed in time units.

95% confidence interval (the full list of employment categories are provided in Table 2). As expected, the results showed negative marginal utilities for increases in generalised travel time. Also, the higher the tour type (i.e., the number of stops on a tour), the larger the (negative) parameter of generalised cost[2], implying that service workers generally prefer using tours with a higher number of stops as transport costs increase. This is particularly pertinent to policies such as congestion charging or road pricing suggesting that these policies may result in a shift to longer (and arguably more efficient) tours. The estimated population and employment variables are all positive, as expected, and indicate that service workers are more likely to stop at zones with higher levels of employment and population. Employment type 5 (accommodation and food services) has the highest weight indicating the likelihood of more stops at zones with a higher number of jobs in those sectors, all other things being equal. Furthermore, the estimated structural parameters, or logsum parameters, are all positive and are within the expected range of 0 and 1 (see Hensher et al. 2015). The results also show that the higher tour types have fewer degrees of correlation among their alternatives. In other words, travel zones (or stops) available to lower tour types are better substitutes of each other than those under higher tour types.

Table 1: Results of travel zone stop choice model

Generalised time variables	Parameter	Z-Stat	Employment Industry[3]	Parameter[4]	Z-Stat
Gen Time TR1 (Min)	-0.0819	23.77	1	0.0178	1.24
Gen Time TR2 (Min)	-0.0687	18.22	2	0.0311	2.34
Gen Time TR3 (Min)	-0.0539	11.20	4	0.0747	3.95
Gen Time TR4 (Min)	-0.0394	6.64	5	0.0839	5.52
Gen Time TR5 (Min)	-0.0359	7.14	6	0.0690	4.72
Log (Population)	0.0202	2.42	7	0.0422	3.22
			9	0.0341	3,22
			12	0.0519	1.89
No of Estimated Parameters	14.00				
No of observations	4749				
Null log likelihood	-19679				
Model log likelihood	-15598				
Rho bar squared	20%				
Inf.Cr.AIC	30170.00				

Table 2: Industry classifications

Employment industry	Code	Employment industry	Code
Agriculture and mining	1	Financial and insurance services	7
Manufacturing	2	Media, Professional, Scientific and ICT services	8
Construction	3	Public administration	9
Wholesale and retail trade	4	Education and training	10
Accommodation and food services	5	Health care and social assistance	11
Transport and warehousing	6	Real estate, administration and other services	12

[2] Generalised cost (GC) is a linear combination of time and monetary costs expressed in monetary units. Generalised time (GT) can be converted into GC by multiplying GT by the value of travel time savings ($/min). Thus higher GT implies higher GC and vice versa.
[3] See Table 2 for meaning of the codes
[4] These are estimated parameters for the natural logarithm of each employment type.

Table 3: Results of SLA stop choice model

Logsums and variables	Parameter	Z-Stat
Tour type 1 Logsum	0.6634	46.03
Tour type 2 Logsum	0.7120	41.42
Tour type 3 Logsum	0.7222	31.27
Tour type 4 Logsum	0.8285	26.59
Tour type 5 Logsum	0.8063	32.15
CBD TR2+TR3+TR4+TR5	0.6034	8.07
No of Estimated Parameters	6	
No of observations	4750	
Null log likelihood	-19972	
Model log likelihood	-12107	
Rho bar squared	39%	
Inf.Cr.AIC	24227	

6.2. Tour type choice model results

Table 4 contains the estimation results for the tour type model, and also shows that all estimated parameters are significant at the 95% confidence interval. Again as expected, the results showed that the logsum parameter is positive and is within the expected range of 0 and 1. The smaller logsum parameter relative to those in the stop choice models indicates that tour type choice is less sensitive to changes in transport level of service (LOS) variables than stop choice. In other words, service workers are more likely to change a visited stop than to change the tour length (measured by the number of stops) as a result of changes in transport LOS. The change in visited stops here is likely due to re-ordering of the tour such that the first visited place may be the second or last stop.

The estimated occupation variables are all negative, implying all things being equal, workers in these occupations are more likely to use tours with only a single stop. For example, the negative value (-0.3028) associated with 'Managers' indicates that managers generally prefer tours with one stop rather than those with two or more stops. This is also true for the rest of the occupation variables included in the model. The results also reveal that those who are employed as 'machinery operators and drivers' are most likely to undertake tours with one stop, followed by 'professionals' while those in managerial positions are the least likely to do so of the occupations included in the model but more likely than those of other occupations. The positive constant for tour type 1 further supports these conclusions.

Table 4: Results of tour type model

Variable	Parameter	Z-Stat	Constant	Parameter	Z-Stat
Logsum	0.5528	1.59	Tour 1	1.7834	20.58
Managers	-0.3028	2.23	Tour 2		
Professionals	-0.4643	2.73	Tour 3	-0.4458	5.77
Technicians and Trades Workers	-0.4387	4.42	Tour 4	-1.0938	10.98
Machinery Operators and Drivers	-0.4686	2.82	Tour 5+		
Labourers	-0.3839	2.53			
No of Estimated Parameters	9				
No of observations	2609				
Null log likelihood	-4199.02				
Model log likelihood	-3178.43				
Rho bar squared	24%				
Inf.Cr.AIC	6374.90				

6.3. Discussion

Many of the results of these models are consistent with those expected *a priori*. However, there are a few interesting results. One of these is the difference in the parameters for generalised time conditioned by the tour type. Although in large part, the differences in the parameters for generalised time for the different tour types are expected because of the higher total costs and travel times associated with longer tours, this does not fully explain the differences as evidenced by the estimates of the logsums in the upper models. Instead, the significance of the different generalised time parameters in the travel-zone model suggests that tours involving more stops are less likely to change destinations than less complex tours. Furthermore, the logsums in the upper models indicate that these differences also have an effect on the likelihood of choosing a particular type of tour that, as stated above, suggests that higher costs would likely lead to an increase in more complex tours. However, although changes to the generalised costs appear to have an effect on the type of tour, the results suggest that service workers are likely to first reorganise the order and combination of stops they make in each tour as generalised cost increases. These results make intuitive sense because the largest proportion of travel time is likely to be interzonal (between SLAs) rather than intrazonal (within SLAs), and as a result, any additional stops within the same zone offset any increase in the generalised cost of travelling to the SLA.

7. Policy implications

The results of the models have several implications for policy makers. Perhaps most importantly, the effect of changes to costs or travel time, which are accounted for through the generalised time function in the model, are related to the tour type. The results suggest that increasing the generalised cost (likely through financial costs rather than time) will lead to a greater number of trips tours containing multiple stops, particularly if a congestion charge (or other charge) is levied only in specific SLAs. Although not directly comparable to the results of Hebes et al. (2013) who focused on total distance rather than the complexity of tours, the results are consistent with their findings of shorter distances given higher costs and agglomeration (i.e., clusters of customers in a single location).

Also of importance to policy makers are the results that different occupations for service workers have an effect on the types of tours. Although service workers are frequently characterised exclusively as tradespersons (or related occupations), both the sample dataset and the results show how different occupations are involved in "service trips". These include managers and professionals (e.g., engineers) making site visits in addition to the more common trips made by tradesmen. The differences between how the different occupations within the service sector choose a tour type suggests that any policy or infrastructure project is likely to affect tours made by each occupation differently, with managers and labourers more likely to have tours with more than one stop than professionals and machinary operators and as a result are likely to be less substantially affected from increases in generalised costs. The results suggest those in other occupations would likely make changes to their trips in an attempt to maximise the number of stops and potentially split up any increase in costs between multiple customers.

Of particular interest is that together, the results of these models further support the benefits of agglomeration in cities by extending the benefits to service workers (and the firms they work for) who gain a benefit from the reduced negative effects of changes to generalised costs when fewer complex tours can be made rather than many point-to-point tours.

7.1. Application

It is important to emphasise that these models have been estimated for use with a micro-simulation technique that uses synthetic individuals (including service workers), households and firms to simulate the decisions made by real individuals and firms in the population (Hensher, 2008). This means that applying these models in practice requires some disaggregate data on service workers in the population from which synthetic individuals (and the firms and households they are part of) can be constructed and their weights (representing their incidence in the population) calculated. Crucially, before being used for prediction, the models are calibrated to ensure the results in the base year match the flows and other aggregate statistics available on service workers and their trips.

8. Conclusions and further research

This paper has described the estimation and results of a model system for LCV service trips in the Sydney GMA. These results suggest that policies that change the generalised costs, and by extension the types of tours made by service workers, are likely to change how service workers make trips around a metropolitan area. In particular, the results show that an increase in generalised cost (or travel time) is likely to lead to service workers first reorganising their tours such that they change the order of their stops (perhaps to maximise efficiency), and if generalised costs increase above a certain threshold, to then change the type of tours they make. However, although the models presented here provide evidence of the likely effects of policies on service trips, they would benefit from including more firm-level covariates as previous studies have shown this to have an effect on the types of trips made (Hebes et al., 2013). Nonetheless, these models provide a good basis from which the likely behavioural responses of light commercial vehicle users can be modelled separately but incorporated into a larger model system encompassing both passenger and freight models.

References

Australian Bureau of Statistics. (2014). *Australian Motor Vehicle Census*. Canberra: Australian Bureau of Statistics.
Retrieved from http://www.abs.gov.au/ausstats/abs@.nsf/mf/9309.0

Batley, R. (2014). The Hensher Equation: Derivation, Interpretation and Implications for Practical Implementation. *Transportation*, 42, 257–275.

Elaurant, S., Ashley, D., Bates, J. and Merz, S. K. (2007). Future Directions for Freight and Commercial Vehicle Modelling. *30th Australasian Transport Research Forum*, 3, 1–14.

Ellison, R. B., Greaves, S. P. and Hensher, D. A. (2013). Five years of London's low emission zone: Effects on vehicle fleet composition and air quality. *Transportation Research Part D: Transport and Environment*, 23, 25–33.

Hebes, P., Menge, J. and Lenz, B. (2013). Service-related traffic: An analysis of the influence of firms on travel behaviour. *Transport Policy*, 26, 43–53.

Hensher, D. A. (2008). Climate change, enhanced greenhouse gas emissions and passenger transport - What can we do to make a difference? *Transportation Research Part D: Transport and Environment*, 13(2), 95–111.

Hensher, D. A., Rose, J. M. and Greene, W. H. (2015). *Applied Choice Analysis*. 2nd edition, Cambridge: Cambridge University Press.

Mackie, P. J., Wardman, M., Fowkes, A. S., Whelan, G., Nellthorp, J. and Bates, J. (2003). *Values of Travel Time Savings in the UK: Report to Department for Transport*. Working Paper 567, Institute of Transport Studies, University of Leeds, Leeds.

Mei, B. (2013). A Destination Choice Model for Commercial Vehicle Movements in the Metropolitan Area. *Transportation Research Record: Journal of the Transportation Research Board*, (2344), 126–134.

Mendigorin, L. and Peachman, J. (2005). Estimation of small-area commercial vehicle movements in the Sydney Greater Metropolitan Area: development, estimation issues addressed and enhancements to the estimation method. *Australasian Transport Research Forum (Atrf), 28Th, 2005, Sydney, New South Wales, Australia*, 28, 1–14.

Steinmeyer, I. and Wagner, T. (2006). Using National Behavioral Data on Commercial Traffic for Local and Regional Applications, in: *Proceedings of the 85th annual meeting of the transportation research board*. Washington D. C.: Transportation Research Board.