The optimal shipment size and truck size choice- the allocation of trucks across hauls*

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Abstract

There has been a growing interest in understanding how firms allocate their trucks across hauls, and how this allocation changes under various economic environments. This study investigates how variations in route/haul, carrier and vehicle characteristics affect the optimal vehicle size choice and the associated choice of shipment size. We show that the two choices are derived from the same optimization problem. There can be a continuum of shipment sizes, but decision-makers in freight transport have to choose from a limited number of vehicle alternatives. Therefore, we use a discrete- continuous econometric model where shipment size is modeled as a continuous variable, and vehicle size/type choice as a discrete variable. The results indicate that when faced with higher demand, and during longer trips firms are more likely to use heavier vehicles and ship in larger quantities which suggest that firms are realizing economies of scale and economies of distance. The study also discusses the effect of vehicle operating cost on the vehicle selection process and its policy implications.

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1. Introduction

The demand for freight transport service has been growing rapidly, and is predicted to grow in the future. There has also been a proliferation of just-in-time inventory (JIT) practices, resulting in increased overall freight transport activity. From the side of policy makers, this growth has brought attention to the issues of allowing higher capacity vehicles on the roads, and the impact these vehicles have on safety, the environment, and efficiency.[1] As freight volume increases, it is expected that transport services will be provided by higher-capacity vehicles. Inventory practices such as JIT, however, suggest that part of the growth in volume may have to be met by increasing service frequency.

These trends in freight transportation raise interesting research questions. At a basic level, we can ask how freight operators choose a vehicle for a haul. It is also important to know how the pattern of vehicle use or vehicle size choice changes with policy interventions (such as a change in the permissible payload or road-pricing) or external shocks (such as an increase in fuel price). Answers to these questions help to clarify the implications of vehicle use patterns on traffic congestion, pavement deterioration, pollution and safety. This clarification becomes all the more important when we consider that different vehicles have different impacts on these externalities.

The objective of this study is to investigate how variations in route/haul, carrier and vehicle characteristics affect the optimal vehicle size choice in trucking. Previous studies have mainly focused on mode choice as opposed to the process by which firms make vehicle choices (the main topic here).[2] This study addresses two important issues in the economics of freight demand analysis. First, it outlines a conceptual framework based on shipment size optimization theory to identify the main determinants of firms' choice of vehicle and shipment size. Second, it provides a framework for modeling the interdependence between quantity shipped and vehicle choice using a discrete-continuous econometric model

[1] The US Congress recently debated a transportation bill that would increase the weight of trucks allowed on highways from 80,000 to 97,000 pounds (American Energy and Infrastructure Jobs Act of 2012). The congress didn't pass the bill; and it suggested that further studies on the impact of heavy-duty trucks are needed to implement the bill, among others. The EU has also been considering similar measures (TML, 2008; Christidis and Leduc, 2009; OECD, 2010; Significance and CE, 2010). In many emerging economies, leading truck manufacturers are also expecting the demand for medium and heavy-duty trucks to increase (Daimler, 2011; Mathyssek, 2009).

[2] Our modeling framework can also be applied in freight mode choice which is formally and economically similar to the vehicle choice problem.

developed by Dubin and McFadden (1984). For model estimation, a unique dataset from the Danish heavy trucks trip diary was used. The dataset has detailed one-week operational information on a trip-by-trip basis for about 2500 trucks in 2006 and 2007.

The results show that the main determinants of vehicle size choice are vehicle operating cost, vehicle age and carrier type. As operating cost increases, the probability of heavier vehicles being chosen also increases, while higher total cost leads to a gradual shift towards smaller vehicles. These seemingly contradictory effects of cost have important policy implications. For instance, in the face of policies (or exogenous shocks) which raise the variable cost of trucking operations (e.g. road pricing or increase in fuel price) firms prefer to use heavier vehicles. On the other hand, policies or other changes which increase fixed costs and therefore total cost (e.g. registration tax, permits, licenses, etc.) make firms use smaller vehicles.

In conformity with the predictions of shipment size optimization theory, we find that trip distance and total freight demand to have significant positive effects on shipment size choice. These findings suggest that firms realize economies of distance by using heavier vehicles for longer trips and economies of scale by hauling larger quantities. Commodity-type fixed effects and the density of a cargo were also shown to affect shipment size decisions. In general, the results imply that increases in freight volume and today's widespread business practice of sourcing products from distant places will lead to increased demand for higher capacity vehicles. The desire to have flexible and frequent services, however, may dampen this tendency to some extent.

The rest of the paper is organized as follows. Section 2 gives a brief background to theoretical and econometric studies on freight modeling. Section 3 develops the conceptual framework based on shipment size optimization theory; Section 4 presents a discrete-continuous econometric model that jointly estimates shipment size and vehicle size choice; Section 5 describes the data and presents the empirical results; Sections 6 concludes and summarizes the paper.

2. Background

This study is based upon and further contributes to several studies. It is well-documented in the literature that shipment size determines the choice of mode/vehicle and vice versa (see for example, McFadden et al. 1986; Inaba and Wallace, 1989; Abdelwahab and Sargious, 1992; Holguin-Veras 2002; Johnson and de Jong, 2011). In addition to recognizing this simultaneous decision process, these studies show that various haul, carrier, and commodity characteristics are important factors that affect the decision on the optimal shipment size and vehicle size.

The basic assumption of econometric studies of freight mode/vehicle choice is that mode/vehicle choice entails simultaneous decisions on how much to ship and by what mode, which implies the use of a discrete-continuous econometric framework.[3] McFadden et al. (1985) and Abdelwahab and Sargious (1992) provide the most complete formulation of the firm's simultaneous choice of mode and shipment size. However, the applicability of their models is rather limited when decision makers have to choose from more than two mode alternatives. Inaba and Wallace (1989) use a switching regression technique, arguing that shipment size and mode/destination choice are derived from the same optimization problem. Their analysis improved upon the approach of McFadden et al. by including spatial competition in the firm's decision and providing estimates of unconditional freight demand for more than two mode/destination choices. The econometric model of Inaba and Wallace, which is based on Lee (1983), assumes independent error structure across alternatives. Violation of this assumption would, therefore, seriously compromise the results and applicability of their model as a forecasting tool.

Recently, Holguin-Veras (2002) and Johnson and de Jong (2011) used an indirect approach to address the simultaneity problem. They model the discrete choice component (vehicle class choice in Holguin-Veras and mode choice in Johnson and de Jong) as the structural equation of interest, replacing actual shipment with prediction from a shipment size auxiliary regression. This approach is an interesting one when the main focus is the vehicle/mode choice because it is possible to apply advanced discrete choice models that overcome the IIA

[3] An alternative sometimes is discrete-discrete (by classifying shipment sizes to a number of size classes), as in de Jong and Johnson (2009) and Windisch et al. (2010).

problem that most selection models suffer from. But, unlike McFadden et al. (1985), this approach does not allow for testing for simultaneity bias.

The current study uses a basic econometric model developed by Dubin and McFadden (1984) to address the simultaneity bias in the context of a discrete-continuous choice. Their model relaxes the procedure suggested by Lee (1983), which imposes a strong assumption about the covariance between the error terms in the selection and the outcome equations.

We model the vehicle size/type choice process as a discrete choice, and the decision on shipment quantity as a continuous variable. Furthermore, as an alternative model specification for the main results, the paper presents estimates based on the indirect approach suggested by Holguin-Veras (2002) and Johnson and de Jong (2011).

3. Conceptual framework

When mode choice and shipment size choice are studied jointly, the determinants of these choices are usually derived from shipment size optimization theory (Baumol and Vinod, 1970; de Jong and Ben-Akiva, 2007). This framework can equally well be used as a theoretical foundation for the joint choice of vehicle type (trucks of different sizes) and shipment size. On the one hand, when the flexibility and frequency of a delivery are important, firms tend to choose smaller vehicles. High value products are also shipped in smaller quantities to save inventory holding costs (de Jong and Ben-Akiva, 2007; Shah and Brueckner, 2012). On the other hand, when firms have high freight demand, they are more likely to use their heavier vehicles and ship in larger quantities. Similarly, on longer trips firms tend to ship in larger quantities. This is because larger vehicles incur less than proportionally increased fuel/time cost per shipment, which in turn implies that as geographical distance increases, the shipper can reduce fuel/time costs per unit of cargo shipped, both by increasing the size of an individual shipment and by reducing shipment frequency (McCann, 2001).[4] Put differently, larger shipment size for higher demand and for longer trips is due to decreasing unit transport cost.

[4] In another strand of the literature, it is suggested that the choice of truck type is mainly explained by the monitoring technology capabilities of trucks such as Electronic Vehicle Management Systems (EVMS) and trip recorders (Hubbard, 2000; Barla et al., 2010). Although these capabilities clearly matter to some degree, a complete analysis should allow for more dimensions in vehicle heterogeneity, both observed and unobserved, when trying to explain the vehicle size choice process that takes place in reality.

To guide our empirical model, this section presents a conceptual framework that describes a firm's vehicle choice process. The main insight in the theoretical literature is that shipment size and vehicle/mode choice are derived from the same optimization problem. Baumol and Vinod (1970) developed a model based on inventory-theoretic considerations for the choice between 'abstract modes'. These are alternatives described solely on the basis of their attribute values. Inaba and Wallace (1989) used a spatial price competition model to show that there is simultaneity between the quantity shipped and the mode/destination choices. McFadden et al. (1985) and McCann (2001) used shipment size optimization theory to establish the simultaneous nature of the firm's choice of mode, shipment size, and frequency.

According to this theory, firms are assumed to minimize total logistics costs by trading off order costs, transport costs, capital costs on the inventory in transit and warehousing costs (in some formulations also with a safety stock to deal with variations in demand and lead time).[5] The solution to this minimization, which is referred to as the economic order quantity (EOQ), shows how the optimized shipment quantity is related to the total shipment quantity per period, haulage distances, and commodity characteristics (see for example, Baumol and Vinod, 1970; Blumenfeld et al., 1985; McFadden et al., 1985; McCann, 1996, 2001; Shirley and Winston, 2004; de Jong and Ben-Akiva, 2007; Combes, 2011, 2013).

Below we present the basic structure of the theory, based on Baumol and Vinod (1970).[6] Assume that the per-period (say: a year) total logistics cost (TLC) for firm *i* is given by the sum of the following four components (in respective order): order cost, transport cost,

[5] Decisions with regard to production technology, choice of input suppliers and/or receivers of their output, and location, are all assumed to be exogenous.

[6] An alternative formulation is the joint optimal shipment and vehicle size model of McCann (2001). We adopted a variant of the Baumol and Vinod (1970) formulation here, as advised by an anonymous referee, because this is more familiar in the transport and logistics literature (for instance Hall (1985), de Jong and Ben-Akiva (2007) and Combes (2013) used it), because unlike McCann (2001) it does not include the transport cost in the capital costs (which has no empirical support), and because it includes fewer parameters that are unobserved or relate to financial markets than in McCann (2001). We do however use the distance-based transport cost and the vehicle movement cost specification of McCann (2001), inserted in a more conventional framework.

capital cost on the inventory in transit and warehousing and capital costs on the inventory (at the sender and/or the recipient):[7]

$$\mathrm{TLC_i} = \frac{o_i\,\mathrm{Q_i}}{\mathrm{q_i}} + \; t_i\, d_i\, Q_i + u\, l_i\, v_i\, Q_i + (w_i + u\, v_i)\, \frac{q_i}{2} \tag{1}$$

where o_i is the unit cost of ordering and processing per shipment; Q_i is the total per-period shipment quantity (tonne/period); q_i is the individual shipment size (tonne/vehicle); t_i is the transport cost per tonne-kilometer and d_i the distance in kilometers between origin and destination, u is an implied interest rate, l_i is the transport time (as a fraction of a year) between origin and destination of the shipment, v_i is the value of the goods per tonne and w_i is the storage cost per tonne per year. The costs of keeping a safety stock can be added to Eq. (1) as a fifth component. Also physical deterioration of the goods during transport can be added.

Minimizing TLCi with respect to qi results in the following:

$$q_i^* = \sqrt{\frac{2\, Q_i\, o_i}{w_i + u\, v_i}} \tag{2}$$

This optimum shipment size is a variant of the economic order quantity, which basically goes back all the way to Harris (1913). Eq. (2) implies that the optimized shipment size q* is independent of the haulage distance d_i. But empirical evidence shows that on longer trips, larger shipment sizes and therefore larger vehicles are usually chosen (Kendall, 1972; Jansson and Shneerson, 1982). As pointed out by McCann (2001), the per tonne-kilometer transport cost t_i depends on the weight of the individual batch shipment: in reality t_i will also be a function of q_i, and q_i a function of t_i, so there is no closed form solution for the problem and it need to be solved iteratively. To incorporate this insight in the optimization problem, we first define vehicle movement cost (per vehicle per kilometer) as:

$$TC_i = a + b\, q_i \tag{3}$$

where a and b are the intercept and slope parameter values across the range of vehicle choices available (McCann, 2001). Assuming that the logistics planner has access to multiple

[7] This specification assumes that goods are delivered and consumed at a constant rate and there are no stock-outs (i.e. replenishments are instant). Note also that transport cost is specified in terms of a spatial measure, cost per tonne-kilometer, meaning that haulage distance is explicitly included as a variable.

vehicles and can always make sure that individual shipments take place as full-load shipments, a transport rate function (per tonne) can now be given as:[8]

$$t_i = \frac{a + b\, q_i}{q_i} = \frac{a}{q^*} + b \qquad (4)$$

If we replace t_i with the above definition in Eq. (1), we have a new logistics cost expression given as:

$$\mathrm{TLC_i} = \frac{o_i\, \mathrm{Q_i}}{\mathrm{q_i}} + \left(\frac{a}{q_i} + b\right) d_i\, Q_i + u\, l_i\, v_i\, Q_i + (w_i + u\, v_i)\frac{q_i}{2} \qquad (5)$$

Minimizing TLC_i with respect to q_i results in the following solution for optimal shipment/vehicle size:

$$q_i^* = \sqrt{\frac{2\, Q_i\, (o_i + a\, d_i)}{w_i + u\, v_i}} \qquad (6)$$

Eq. (6) gives the so-called 'square root laws' (Baumol and Vinod, 1970; Blumenfeld et al., 1985) which govern the relationship between the optimal shipment/vehicle size and the model's parameters.[9] First, q_i^* clearly increases with the total freight demand (Q_i). Second, q_i^* increases with distance if there are significant economies in vehicle movement cost (i.e. a > 0). This is because larger vehicles will incur less than proportionally increased fuel/time cost per shipment, implying that as geographical distance increases, the shipper can reduce fuel/time costs per unit of cargo shipped, both by increasing the size of an individual shipment and by reducing shipment frequency (McCann, 2001).[10] Third, as the

[8] If the planner has a single vehicle at her disposal, the rate function is defined as $t_i = TC_i/q_i$.

[9] Note that the solution given in Eq.(6) is the solution to both the optimum shipment size and the optimum vehicle size. This is because of the assumption that the logistics planner can always make sure that individual shipments take place as full-load shipments (i.e. load factor = 1). This assumption is not always valid, but is a common hypothesis in this kind of analysis (see Shah and Bruckner, 2011, who also assume that there is full utilization). An important reason why many trucks are not full in terms of tonnes is that the volume (m3) of the cargo often is the limiting factor, not the weight. A recent report for 13 European countries reveals that on about 30% of all trips made the trucks are empty, while the average load factor (the percentage of a truck'' carrying capacity filled with a cargo) remained stable at 50% over the period 1990-2008 (the European Environmental Agency, 2010).

[10] Although empirical evidence can be furnished to support this claim, it is also observed that carriers do not always operate with bigger vehicles on longer trips. For instance, a newer "small" vehicle might be cheaper to operate than an older "large" vehicle even for longer trips. So, the effect of a vehicle's age needs to be taken into account to find the true effect of distance on the optimal vehicle size. In our econometric model, we control for the effect of vehicle age.

value of a shipment (v_i) and its inventory storage cost (w_i) increase, the optimal shipment size decreases.

To test the main hypotheses of the model empirically, we can take the logarithm of Eq.(6) and add a stochastic component. This is possible for estimation of the optimal shipment size. However, we note that q_i^* is also the optimum vehicle size solution. So if q_i^* represents vehicle size it is not appropriate to treat it as a continuous variable for two reasons. First, due to vehicle design limitations and/or government regulations, a vehicle's size can neither be infinitely reduced nor infinitely increased, which means that there are always minimum and maximum capacity constraints. Second, vehicles differ not only in their carrying capacity, but also in their type/class (e.g. rigid truck, semi-trailers, articulated etc.). It is, therefore, more appropriate to treat q_i^* as a discrete variable if it represents vehicle capacity and as a continuous variable if it represents shipment size. The next section develops an empirical model in a discrete-continuous model framework to analyze the choice of optimal vehicle size and shipment size.

4. Econometric framework

As described in the conceptual framework section, freight vehicle choice is part of a larger joint decision process that includes choice of shipment sizes/frequency. Building on this insight, this section presents a discrete-continuous (D/C) econometric model to analyze the choice of optimal vehicle size and shipment size.[11] The firm's shipment size and the net benefits, conditional on vehicle choice are given respectively by

$$q_v^* = \beta_v X + u_v \tag{7}$$

$$U_v^* = \gamma_v Z + \varepsilon_v \tag{8}$$

[11] D/C models have been used to examine a wide range of topics, including transport mode/vehicle choice (Inaba and Wallace, 1989; McFadden et al., 1985; Holguín-Veras, 2002), car ownership and use (Train, 1986; de Jong, 1991), labour participation and wages (Heckman, 1979), labor productivity (Lindqvist and Vestman, 2010), and energy choice (Mansur et al., 2008).

where *X* denotes variables that affect shipment size, U_v^* is the reduced-form expression for the net-benefits from the choice of different vehicle types (*v=1...V*), and *Z* denotes observable factors that determine the net benefit function, while β_v and $\gamma_v$are parameters to be estimated, u_v and ε_v are idiosyncratic terms.

The conceptual framework section established that total freight demand (*Q*) and shipment distance (*d*), and various commodity characteristics determine the optimal shipment size. To capture the effect of these variables, *X* includes a firm's total freight demand, trip distance, and commodity fixed effects. Although Section 2 showed that the optimal shipment size and the optimal vehicle size depend on the same variables, in reality some variables will have bearing on the shipment size choice only through their impact on the vehicle choice process. Thus, *Z* contains all the variables in *X* and additional variables which describe the service attributes of a vehicle and its owner. These are vehicle age, per-tonne operating cost, and fleet size. The identifying assumption is that these variables affect shipment size choice only through preferences for different types of vehicle.

The firm computes its optimal shipment size q_v^* conditional on every feasible alternative. Thus conditional on *X*, it is observed to ship q_v^* by alternative *v* if the net-benefit of shipping by vehicle type *v* is greater than any type *j*, that is

$$\mathrm{U_v^*} > \max(\mathrm{U_j^*})$$

Note that the two error terms, u_v and ε_v , are correlated because of the possibility that the transport planner makes a choice between vehicle sizes, and at the same time decides how much to load on the chosen vehicle. As shown in Section 2, decisions on the optimal shipment size and vehicle are generated from the same optimization problem, which implies that the error terms are likely to be correlated. Ignoring this correlation would lead to a specification bias. For this reason we need to model vehicle choice and shipment size choice using a D/C model based on a two-step estimation method. A multinomial logit model (MNL) of vehicle choice is estimated in the first step, with vehicles classified into five different size and type categories to examine the determinants of the choice process. In the second step, we estimate shipment size given the vehicle choice. This step consists of using ordinary least squares (OLS) with selectivity correction terms constructed from the first step.

In the literature, we find two main approaches to estimating a selection model with multinomial choices. The first consists of using a selection correction term of the actual choice (Lee, 1983), while the second uses selection correction terms of the alternative choices (Dubin and McFadden, 1984).[12] Lee's model imposes strong restrictions on the covariance between the continuous demand and the selection model (Schmertmann, 1994; Bourguignon et al., 2007). What follows presents the basic structure of the Dubin and McFadden (1984) D/C model using the notation of Bourguignon et al. (2007).

As noted above, the two-step estimation is required due to the possible correlation of the idiosyncratic terms u_v and ε_v . The econometric problem is how to estimate the parameter vector β_v while taking into account this possible correlation. If we assume that $E(u_v\,|X,Z) = 0$ and $V(u_v\,|X,Z) = \delta^2$, where *V* denotes the variance, and ε_v is distributed extreme value type I, the probability that vehicle *v* is preferred is given by P_v

$$\mathrm{P_v} = \frac{\exp(\gamma_\mathrm{v}\mathrm{Z})}{\sum_\mathrm{v}\exp(\gamma_\mathrm{v}\mathrm{Z})} \tag{9}$$

The selectivity correction procedure involves using the parameter estimates from the choice model to construct the selectivity correction terms, appending these to Eq. (7) to get the following

$$\mathrm{q_v^*} = \beta_\mathrm{v}\mathrm{X} + \mu(\mathrm{P_1}, \dots, \mathrm{P_V}) + \mathrm{w_1} \tag{10}$$

where $w_1$is a residual that is mean-independent of the regressors. The intuition for appending the correction terms is that the original model Eq. (7) suffers from an omitted-variable problem. What is omitted is the effect of the vehicle choice selection process on the observed shipment quantity. One can remove the simultaneity bias by including the correction terms. Furthermore, depending on the sign and significance of these terms, we can tell whether the alternatives have been optimally or randomly chosen.

The various methods of estimating Eq. (10) differ in the kind of restrictions they impose on $\mu(P_1, \dots, P_V)$. Dubin and McFadden (1984) assume an important linearity condition

[12] A semi-parametric model which uses probability estimates from the first stage was suggested by Dahl (2002), but it is less used.

$$E(u_v|\varepsilon_1 \ldots \varepsilon_V) = \sigma \sum_{v=1\ldots V} r_v(\varepsilon_v - E(\varepsilon_v)) \tag{11}$$

where, where r_v is a correlation coefficient between u_v and ε_v, and by construction it sums to zero ($\sum_{v=1\ldots V} \gamma_v = 0$). They showed that OLS estimates of β_v from the following equation will be consistent:

$$q_1^* = \beta_v X_1 + \sigma \sum_{v=2\ldots V} r_v \left(\frac{P_v \ln(P_v)}{1-P_v} + \ln(P_1)\right) + w_1 \tag{12}$$

We use Eq. (12) for estimation.[13] Section 5.2.2 gives estimation results for an alternative model specification based on the Holguin-Veras (2002) approach which is commonly used in the literature. Results from this model will also be used to indirectly infer the importance of the IIA assumption implicit in the econometric framework presented in this section.

5. Data and empirical results

5.1. Data

The primary data source for this research is the Danish heavy trucks trip diary for 2006 and 2007 (Denmark Statistics, 2011). The diaries are filled out by truck owners, for-hire carriers and own-account shippers, across Denmark, for approximately 1200 vehicles each year and cover all trips undertaken during one week of operation. These data are used by Statistics Denmark to calculate national freight transport using heavy vehicles (above 6 tonnes gross weight). Data on the fleet size of companies and operating costs come from Statistics Denmark's database on companies' vehicle access (MOTV) and the Danish National Freight model, respectively. Together, these datasets provide detailed operational information for modeling the joint decision of shipment size and vehicle choice.

[13] Bourguignon et al. (2007) relax the linearity condition of Dubin and McFadden (1984), arguing that it imposes a specific form of linearity between u_v and the extreme value type I distribution, and thus restricts the class of allowed distributions of u_v. They suggest a variant of Dubin and McFadden's model that can make u_v linear in a set of normal distributions, allowing u_v in particular also to be normal. We considered both methods in this paper, and they gave comparable results. In the interest of brevity we only report results from the Dubin and McFadden method. The other results can be obtained from the authors upon request. The STATA 'selmlog' command developed by Bourguignon et al. (2007) was used to estimate the two D/C models.

Table 1 presents the main variables of interest, which include: vehicle attributes (age, vehicle class, and operating cost per tonne); carrier characteristics (fleet size and carrier type: own-account shipper or for-hire carrier); shipment characteristics (commodity classes, shipment weight, and cargo density (m^3); and haul characteristics (trip distance and origin-destination zones). A shipment is defined as the cargo carried by each vehicle in our sample.[14]

These datasets, however, do not include detailed information on the origin and destination of a trip, total shipment demand per year, or commodity price (for calculation of value density), all of which are important attributes to examine the economic considerations involved in the choice of vehicle and shipment size. To control for the effect of total shipment demand (Q) on shipment size (q), we constructed segments for shipment demand based on origin zone-commodity combinations.[15] We know the origin and destination of a trip at a zonal level (there are 15 zones in Denmark). There are 28 commodity classes based on NST/R, EU's standard goods classification for transport statistics. There are 840 possible combinations for the two years (15*28*2); however, there were only 581 positive observations. Our empirical work relates differences in total shipment demand across the demand segments to differences in shipment sizes across hauls. Furthermore, commodity fixed effects were included to control for unobserved characteristics of a shipment that might vary by commodity class.

Table 2 presents vehicle classification, distribution and attributes. Three types of vehicle choices appeared in the sample: rigid trucks, semi-trailers and articulated. For estimation purposes, the vehicles were further subdivided into 6 different classes.[16] The categorization was based on gross vehicle weight (GVW). Another classification based on the maximum legal carrying capacity (MCP) of a vehicle is also shown. Most trips were made by vehicles weighing more than 18 tonnes, revealing that the data is predominantly on heavy vehicles.

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[14] This definition could apply either to a certain quantity of a good that is ordered together and delivered together or a consolidated cargo of different owners on a vehicle. We cannot determine which of these definition hold for observations in our sample due to lack of data. However, since our sample comes from own-account shippers and for-hire carriers having such a general definition of shipment size helps us to account for both sources.

[15] An example is "hauls of food by trucks based in Copenhagen". Hubbard and Baker (2003) and Boyer and Burks (2009) used a somewhat similar segmentation of freight demand to account for the heterogeneity that exists in freight transportation.

[16] A similar classification is used for the National Freight model for Denmark.

The trip share of semi-trailers with 12-18-tonne capacity is rather small, so it was decided to treat all semi-trailers as one class of vehicle. Doing so reduced the vehicle choice set to 5. As shown the vehicle operating costs were positively correlated with size, which implies higher fuel and operating costs for heavier vehicles.

To achieve a better approximation of the actual vehicle choice-making process by carriers, the final sample for estimation was based on the following criteria. First, although the vehicles were observed making both loaded and empty trips, the analysis was based on loaded trips only. This made it possible to control for commodity characteristics. Second, only vehicles which belonged to a fleet size of 5 or more were considered. Note that the analysis assumes that for a given haul, carriers have access to at least one vehicle from each vehicle class. So, restricting the lower bound of the size of the fleet to which a vehicle belongs allows us to mimic the actual choice set a carrier had for a given haul.

5.2 Empirical results

The main estimation results are based on the D/C econometric model presented in Section 4. The first part of this section summarizes the results from the vehicle choice model, followed by the shipment size choice model. The final part of this section reports alternative results for a mixed MNL model based on an alternative model specification .

5.2.1. Main results

Table 3 presents coefficient estimates from Eq. (9), which was estimated by the multinomial logit MNL model. Vehicle type *V1* (rigid truck with less than 12-tonne capacity) is the base category where the normalization $\gamma_1 = 0$ is imposed. The estimates for cost per tonne show that it is statistically significant at the 1% level, and, as expected, reduces the probability of choosing a vehicle.[17] A vehicle's age has a significant negative effect for the heavier vehicle types, *V3*, *V4* and *V5*. This result implies that firms are less likely to choose older vehicles, especially if they are heavier. This is partly due to the fact that newer vehicles are usually equipped with better technological capabilities and partly due to the higher cost of

[17] Cost is defined as total cost (that is the per-kilometer vehicle operating cost (from Table 2) multiplied by the trip distance) divided by the payload (that is, the maximum legal carrying capacity) of the vehicle. Note that trip distance is indirectly included in this definition.

operating older and heavier vehicles. The effect of age for *V2* is, however, positive and unexpected. The effect of fleet size is positive and statistically significant at the 1% level. This result makes sense because bigger companies (in terms of vehicle ownership) are more likely to have the heavier vehicle types in their fleet, which in turn implies frequent usage.

Table 3 also reports the effect of total freight demand which is positive and statistically significant at the 1% level. Evidently, when faced with higher demand firms are more likely to use their heavier vehicles. The probability plots depicted in Figure 1 confirm this result. As total freight demand increases, the probability of selecting the smaller rigid trucks, *V1*, *V2* and *V3* declines. On the other hand, the probability of selecting the heavier vehicles, *V4* (semi-trailer truck) and *V5* (articulated truck), increases with freight demand.

The effect of cargo density (i.e. the voluminous cargo dummy variable) is negative and significant only for *V2* and *V3*.[18] This is an expected result, because heavier vehicles are more likely to be preferred for dense or bulk cargo. The parameter estimates for for-hire carrier dummy are positive and highly significant at the 1% level. This is expected because for-hire carriers are more capable of aggregating loads for a given trip compared to own-account shippers, which explains the former's preference for heavier vehicles. The commodity fixed effects[19] (for 28 commodity groups) and quarter dummies (8 quarters for 2006 and 2007) are not reported, but most of these variables were significant at least at the 5% level.

Table 4 reports semi-elasticities for selected variables from Table 3. These semi-elasticities are average marginal effects which show the percentage change in the probability of choosing a vehicle for a unit change in the continuous explanatory variables or a discrete change from the base category for the dummy variable. As shown, a one tonne increase in freight demand increases the probability of choosing vehicle V5 rather than *V1*, *V2*, *V3* and *V4* by 0.2%, which implies that the vehicle choice process is rather inelastic to changes in demand. In conformity with our earlier finding, an increase in cost/tonne (which refers to all vehicle types) implies a preference for smaller vehicles (*V1*, *V2*, and *V3*) as opposed to heavier vehicles (*V4* and *V5*). Note that the cost variable includes both the variable (fuel and

[18] The cargo density dummy indicates whether a cargo is voluminous or not based on the evaluation of truck drivers.
[19] The commodity fixed effects control for unmeasured characteristics that may vary by commodity type. For instance there might be a tendency to use articulated trucks for containerized products, and tankers for liquified products.

labor) and fixed costs of operating a vehicle per kilometer. In order to achieve a more informative interpretation of this result, we have to break the cost variable down into its components. But to do this, we need more data for each cost component. Unfortunately, our dataset does not have information on the various components of cost. One way to proxy the cost break down is to include trip distance and fuel cost in place of the cost variable.[20] It is reasonable to assume that both are positively correlated with the variable cost of operating a vehicle.

Table 5 presents parameter estimates from an alternative MNL vehicle choice model where trip distance and fuel cost are substituted for cost/tonne as a proxy for variable costs. Interestingly, the effect of cost is now somewhat reversed. As shown, firms prefer to use heavier vehicles over longer distances, and fuel price positively affects the probability of choosing *V3* and *V4*. The effects of the other explanatory variables are comparable to those in Table 3. Table 6 shows elasticity estimates for trip distance and fuel price for this MNL model. Although the effect is inelastic, an increase in trip distance increases the probability of choosing *V4* and *V5*. The effect of fuel price is mixed. It appears that *V4* and *V5* have inelastic but positive fuel price elasticity. On the other hand, the probability of choosing *V1*, *V2* and *V5* declines for higher fuel prices.

Figure 2 displays probability plots for total costs based on the MNL model estimated from Table 3. Similar plots are shown in Figures 3 and 4 for variable costs based on estimates from Table 5. Clearly, as variable costs increase (trip distance and fuel price), the probability of choosing *V4* and *V5* increases, while higher total cost leads to a preference for smaller vehicles, *V1* and *V2*. These apparently contradictory effects of cost have important policy implications. For instance, in the face of policies (or exogenous shocks) which raise the variable cost of trucking operations (e.g. a fuel price rise) firms prefer to use heavier vehicles. On the other hand, policies or other changes which increase fixed costs, and therefore total cost, (e.g. registration tax, permits, licenses, etc.), force firms to use smaller vehicles.

[20] To approximate fuel cost, we used the average monthly per-liter price of diesel fuel for the survey month in which each vehicle was observed. The source of this data is the Danish Oil Industry Association (EOF). See http://www.eof.dk/ for more details.

The estimates from the vehicle selection model in Table 3 were used to estimate the conditional shipment size for each vehicle using Eq. (10). The results from the Dubin and McFadden (1984) model are presented in Table 7. The overall result is consistent with the prediction of shipment size optimization theory: shipment size increases with trip distance and total freight demand. As indicated in Section 2, trip distance can have a positive effect on shipment size if there are significant economies in vehicle movement cost, which in turn implies that shipment sizes are larger for longer trips.[21]

Table 7 also shows that being a for-hire carrier results in a higher shipment quantity compared to being an own-account shipper. This result was expected since haulage firms are more likely to consolidate shipments and ship in larger quantities. Evidently, voluminous cargo (i.e. low density) results in lower shipment size. The commodity fixed effects are not reported, but many of them, up to 50% for some of the vehicles, are highly significant, which reveals inherent and handling requirement differences between commodities.

Table 7 also reports the effect of the bias that is introduced if the vehicle choice process is not taken into account. The signs and significance of the selectivity correction terms, Select *V1- V5*, reveal the direction and level of this bias. Almost all the correction terms are significant at least at the 5% level, which implies that there is simultaneity between shipment quantity and vehicle choice decisions and that misspecification bias will arise if Eq. (5) is not corrected for the vehicle selection process.[22]

The coefficient estimates of the correction terms tell us if a vehicle is carrying a larger or smaller shipment quantity when it is observed in the shipment size equation of another vehicle. For example, firms which for unobserved reasons employ a rigid truck with less than

[21] This hypothesis is based on McCann (2001), who suggests comparing parameters a and b from a transportation rate equation $t = \frac{a}{q^*} + b$. An OLS regression on the per-kilometer costs for each vehicle category and their maximum carrying capacity showed that $a > b$, which implies the existence of economies of capacity.

[22] We also estimated a shipment size model without taking the vehicle type selection process into account. The results for this model showed that most of the explanatory variables are significant at the 1% level and have the expected signs, but the point estimates are biased upward compared to those in Table 7 since no correction is made for selection.

12-tonne capacity (*V1*) instead of an articulated truck (*V5*) tend to carry larger shipment quantities.

5.2.2. Alternative estimation

An alternative approach to analyze the vehicle selection process is to model the vehicle selection, Eq. (9), as the main structural model of interest using a mixed MNL model while taking the effect of shipment size on the vehicle size choice process into consideration. This procedure was first proposed by Holguín-Veras (2002). In the present paper we extend this procedure to allow cross-alternative correlation and parameter heterogeneity, assuming normal mixing distributions over a dummy variable for rigid trucks, and over the cost variable. The next paragraphs outline this alternative modeling framework and estimation results.

As in our earlier framework, assume that the net benefit of using a vehicle is calculated across all interested parties (i.e. all carriers and shippers), the net benefit of using a vehicle, U_v^* is given as

$$U_v^* = \theta\mathrm{M} + \emptyset q_v + \epsilon_k + \varphi_v \tag{13}$$

where, *v=(1,…V)* represents vehicle sizes; *M* is a vector of explanatory variables that determine vehicle choice; q_v is the shipment size; ϵ_k is the unobserved vehicle characteristics and is assumed to be an independently and identically distributed (i.i.d.) extreme value. Vehicles are usually categorized based on their carrying capacity, but we note that vehicles may differ in their carrying capacity while being of the same type/class. The model is, therefore, set up in such a way as to allow correlation across alternatives which belong to the same vehicle class/type (*k*). This correlation is captured by ϵ_k , which is assumed to be distributed $\epsilon_k \sim N(0, \in)$. This specification mimics a vehicle class/type based nested logit model which is shown in Figure 5.[23]

When deciding which vehicle to use for a given shipment, the transport planner considers the operating cost per kilometer of a vehicle, and how closely it fits the shipment to be transported. To capture these decision criteria, *M* includes two alternative specific variables. The first one is $C_v/fleet_i$, where C_v is the vehicle operating cost per kilometer and fleet is

[23] The nest parameter is the dummy variable for rigid trucks. We estimated the standard deviation of the dummy, fixing the mean effect to zero.

the size of the fleet to which the vehicle belongs. Our specification implies that the effect of C_v is more pronounced for carriers with smaller fleets. This is intuitive, because a planner with smaller fleet at his disposal is more likely to optimize on a per-vehicle operating cost basis than one with a larger fleet. The latter is more likely to optimize vehicle use across the whole fleet, which implies that the cost of operating a single vehicle is less crucial.[24]

The second variable is a cargo-vehicle-fit variable which is defined as

$$L_v = |MC_v - q_v|$$

where MC_v is the maximum legal carrying capacity of a vehicle. L_v gives an indication of how appropriate a particular type of vehicle is for handling a given shipment. If there is a large difference between its maximum carrying capacity and the weight of a shipment, a vehicle is less likely to be selected (Holguín-Veras, 2002; Johnson and de Jong, 2011). Furthermore, *M* includes the age of a vehicle to allow for the possibility that carriers may tend to use their newer vehicles more often to rest older trucks, especially when faced with excess capacity (Abate, 2014; Hubbard, 2003).

As indicated in Section 3, we note that q_v may be correlated with the unobserved portion of U_v^*, which leads to an endogeneity problem. This correlation is caused by a simultaneity bias that comes from the possibility that the transport planner makes a choice among a set of vehicles, and at the same time decides how much to load on the chosen vehicle. To account for the endogenous nature of q_v, following Holguín-Veras (2002) we estimate the following auxiliary regression to predict shipment size:

$$q_v^* = \delta\mathrm{H} + \tau \tag{14}$$

where *H* is a vector that contains explanatory variables that determine shipment size. The q_v^* values predicted from Eq. (13) are then used to calculate the L_v variable which ultimately enters U_v^*. To estimate the mixed MNL model, 2357 trips (7% of the total trips) were randomly selected. This number is equivalent to the total number of individual vehicles in the sample, which roughly translates to one trip per vehicle.

Table 8 presents the results from the mixed MNL model presented above. In this model, random coefficients for the cost and cargo-vehicle-fit variables were allowed. As expected,

[24] As a side benefit, dividing cost by fleet size gives us more cross-sectional variation.

the mean effects of operating cost and L are negative and are statistically significant at the 1% level. The standard deviation of the random parameter for the L variable reveals that there is a significant heterogeneity around its mean effect. However, the standard deviation for the coefficient of the cost variable is not significant. Furthermore, older vehicles are less likely to be selected for a haul.

The MNL model in section 5.2.1 is based on the assumption that unobservable characteristics are not correlated across alternatives. The validity of this assumption can be indirectly tested from the nest parameter of Eq. (13) of the alternative model specification. To do this we added a random parameter which is assumed to be normally distributed to allow cross alternative correlation between vehicle types V1, V2 and V3, which are all rigid trucks. The hypothesis is that since they are all rigid trucks, they may share unobserved attributes. As shown in Table 9, the standard deviation of the nest parameter (rigid truck_std) was estimated, while its mean was fixed at zero. As it turns out, the standard deviation is not statistically different from zero, which implies that the three alternatives are rather dissimilar and there is no correlation between their unobserved attributes. This finding indirectly supports the IIA assumption used in the Dubin and McFadden (1984) selection model..

6. Conclusion and summary

In this paper we have developed a discrete-continuous model of shipment size (the continuous dependent variable, measured in tonnes per vehicle) and vehicle size class (represented as a multinomial choice). Similar models have been used before in freight transport, but mainly to study the shipment size and mode choice decisions. As exogenous variables we used characteristics of the route/haul, the shipment, the carrier and the vehicle.

The data used to estimate the model come from the Danish heavy trucks trip diary 2006/2007, which contain information on individual truck trips during one week of operation, supplied to Statistics Denmark by truck-owners, carriers and own-account shippers. Similar data exists in other European countries, but can rarely be used for disaggregate model estimation, because of confidentiality considerations.

We estimated the discrete-continuous model in two steps, taking account of the simultaneity bias since both choices are derived from the same decision problem of optimizing total logistics costs. Within the two-step models for the combination of a continuous and a multinomial choice we used a recent generalization (Bourguignon et al., 2007) as well as the original approach (Dubin and McFadden, 1984). Both methods gave similar results for the key influencing factors.

We found that increases in trip distance, increases in total demand for the origin-commodity combination per period, less voluminous goods and the decision-maker being a for-hire carrier lead to a larger shipment size. The first two effects indicate economies of distance and scale. Almost all of the selectivity correction terms are significant at least at the 5% level, which implies that ignoring the simultaneity of shipment size and truck size will lead to biased estimates.

Higher operating cost, lower total cost, higher total demand, dense and bulk cargo and the decision-maker being a for-hire carrier make the use of heavier vehicles more likely. Older vehicles are used less, especially for heavy vehicles. The first two effects on different types of costs lead to a remarkable policy conclusion on variabilization of freight transport costs. Variabilization means that fixed costs (such as road tax and purchase tax) are shifted to variable costs (such as fuel tax or road pricing). This would work as a two-edged sword, since both lowering fixed cost and increasing variable costs would lead to the use of heavier trucks (thereby reducing the vehicle kilometers for the same transport volume).

Furthermore, we estimated alternative models that allow for correlation between alternatives and unobserved heterogeneity in preferences by modeling the discrete choice as a mixed multinomial logit model suggested by Holguín-Veras (2002) and Johnson and de Jong (2011). We found evidence of significant unobserved heterogeneity but not of correlation between the error components of the vehicle size alternatives. A possible extension related to the models presented in this paper would be a simultaneous estimation (full information maximum likelihood) of the two-equation model. For models with multinomial choices and with continuous variable component, such a model would be a new territory.

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Table 1: Summary statistics the sample used for estimation

Variable	Definition	Mean (%)	Std. Dev.
Distance	Trip distance (km)	80.5	98.57
MC	Maximum legal carrying capacity (tonnes)	24.7	12.7
q	Shipment weight (tonnes)	13	10.14
Cost	Total operating cost/tonne (DKK) of a vehicle	39.5	52.75
Fleet	Total number of vehicles of a firm	85.3	144.47
Age	Age of vehicle (years)	4.4	3.95
Demand	Total shipment demand for origin-commodity combination (tonnes)	4338	5240.72
Fuel	Average month diesel fuel price per liter (DKK)	10.03	.73
L	Vehicle-cargo fit measure (tonnes)	12.1	10.98
For-hire	1 if vehicle is owned by a for-hire carrier	84%	
Voluminous	1 if cargo is voluminous	1%	

Source: The Danish Heavy Vehicles Trip Diary and MOTV vehicle registration data, 2006 & 07. The number of observations is 38,989. There are 581 observations for "Demand", which is defined at a origin zone and commodity combination. Fuel prices are from Danish Oil Industry Association (EOF).

Table 2: Vehicle classification

Vehicle Class		Gross Vehicle Weight (tonnes)	Average Payload (tonnes)	Trip Share (%)	Cost/km (DKK)
Rigid truck	V1	< 12	4.3	3.5	6.2
	V2	12 - 18	8.3	9.64	6.66
	V3	18 - 26	14.8	30.59	9.67
Truck with trailer	V4	12 - 18	8.2	0.01	7.29
	V4	> 18	31.1	22.65	10.74
Articulated	V5		38.02	33.6	13.89

Table 3: Vehicle Choice Model 1

	V2	V3	V4	V5
Log. Cost	-0.364***	-0.510***	-0.751***	-0.600***
	(0.037)	(0.036)	(0.037)	(0.036)
Age	0.118**	-0.212***	-0.493***	-0.695***
	(0.049)	(0.046)	(0.046)	(0.045)
Log. fleet	0.450***	0.505***	0.387***	0.465***
	(0.029)	(0.028)	(0.029)	(0.027)
Log. demand	0.065	0.076*	0.492***	0.515***
	(0.043)	(0.043)	(0.044)	(0.042)
Voluminous	-0.023	-0.409***	0.279**	0.337***
	(0.123)	(0.125)	(0.125)	(0.115)
For-hire	0.624***	1.369***	2.255***	2.783***
	(0.079)	(0.077)	(0.082)	(0.079)
Constant	1.377***	3.806***	1.820***	1.030**
	(0.445)	(0.428)	(0.437)	(0.428)
Observations	38,989			
Pseudo R-squared	0.21			

Note: Vehicle type 1 (solo truck with less than 12-tonne capacity) is the base choice. Commodity fixed effects and quarter dummy variables not shown. Robust standard errors in parentheses. *** p <0.01, ** p<0.05, * p<0.1.

Table 4: Elasticity Estimates from Model 1

	V1(%)	V2(%)	V3(%)	V4(%)	V5(%)
Cost	0.567***	0.203***	0.056***	-0.18***	-0.033***
	(0.034)	(0.018)	(0.008)	(0.009)	(0.007)
Age	0.404***	0.521***	0.191***	-0.089***	-0.291***
	(0.043)	(0.027)	(0.011)	(0.012)	(0.01)
Fleet	-0.443***	0.006	0.062***	-0.056***	0.022**
	(0.025)	(0.016)	(0.008)	(0.01)	(0.007)
Demand	-0.318***	-0.253***	-0.242***	0.174***	0.198***
	(0.039)	(0.022)	(0.01)	(0.013)	(0.01)

Note: Standard errors in parentheses are calculated by the Delta-method. *** p<0.01, ** p<0.05, *p<0.1

Table 5: Vehicle choice Model 2

	V2	V3	V4	V5
Log. distance	0.152***	0.131***	0.440***	0.530***
	(0.029)	(0.028)	(0.029)	(0.028)
Log. fuel price	-1.484**	1.124**	1.586***	0.611
	(0.641)	(0.563)	(0.578)	(0.571)
Log. Age	0.145***	-0.178***	-0.396***	-0.623***
	(0.047)	(0.043)	(0.044)	(0.043)
Log. fleet size	0.608***	0.699***	0.622***	0.703***
	(0.034)	(0.033)	(0.033)	(0.033)
Log. demand	0.031	0.060	0.454***	0.512***
	(0.041)	(0.040)	(0.042)	(0.041)
Voluminous	-0.117	-0.596***	0.005	0.039
	(0.129)	(0.130)	(0.131)	(0.123)
For-hire	0.501***	1.230***	2.059***	2.609***
	(0.079)	(0.076)	(0.081)	(0.079)
constant	2.563	-1.438	-6.35***	-4.929**
	(1.522)	(1.351)	(1.386)	(1.368)
Observations	38.989			
Pseudo R-squared	0.21			

Note: Vehicle type 1 (solo truck with less than 12-tonne capacity) is the base choice. Commodity fixed effects and quarter dummy variables were included but not shown. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Elasticity Estimates from Model 2

	V1 (%)	V2 (%)	V3 (%)	V4 (%)	V5 (%)
Distance	-0.33***	-0.18***	-0.20***	0.10***	0.19**
	(0.03)	(0.016)	(0.007)	(0.009)	(0.007)
Fuel price	-0.77***	-2.26***	0.34**	0.81***	-0.17
	(0.531)	(0.371)	(0.13)	(0.17)	(0.13)

Note: Standard errors in parentheses are calculated by the Delta-method. *** p<0.01, ** p<0.05, * p<0.1.

Figure1: Probability of vehicle choice and freight demand

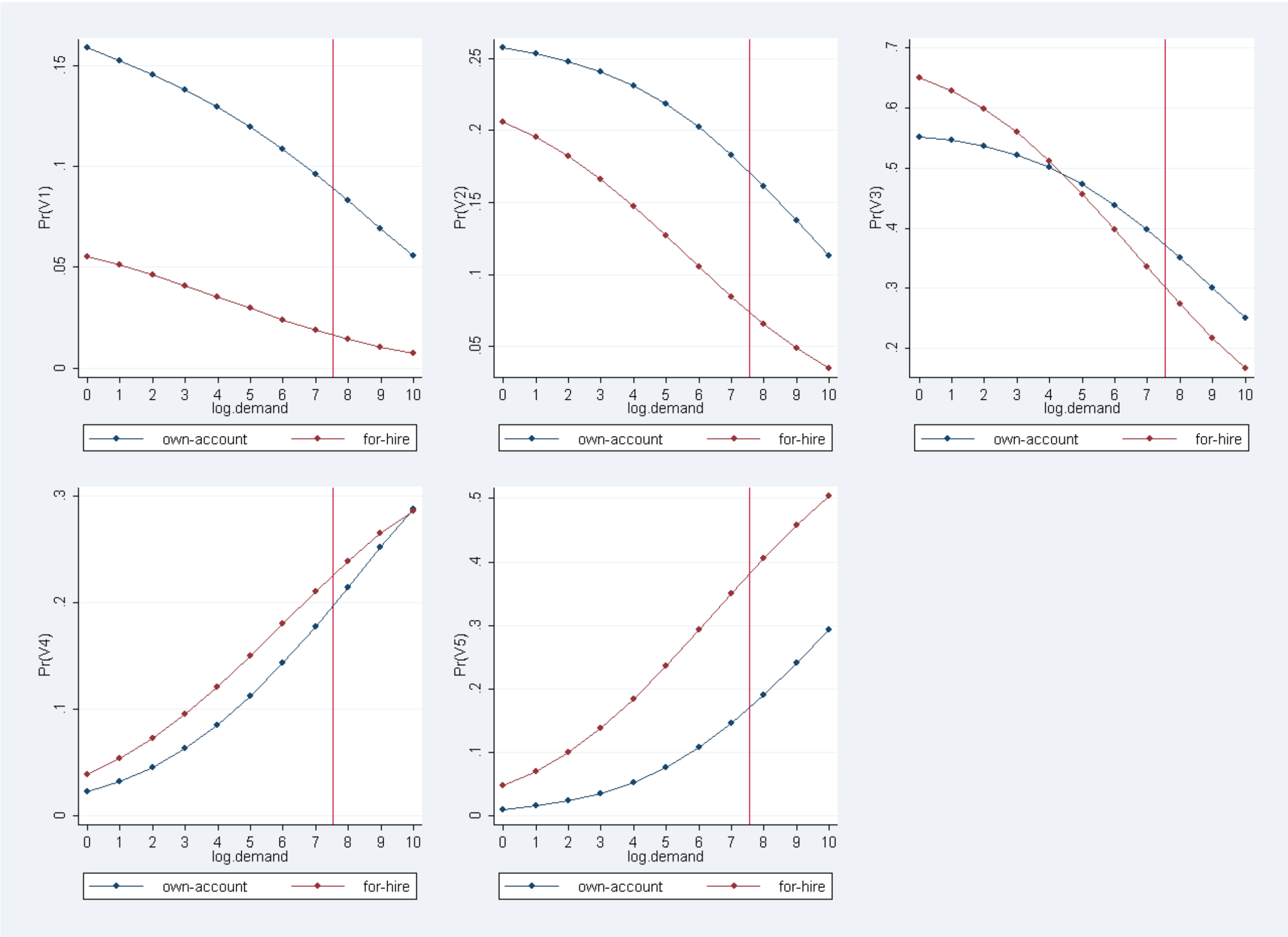

Figure 2: Probability of vehicle choice and total cost

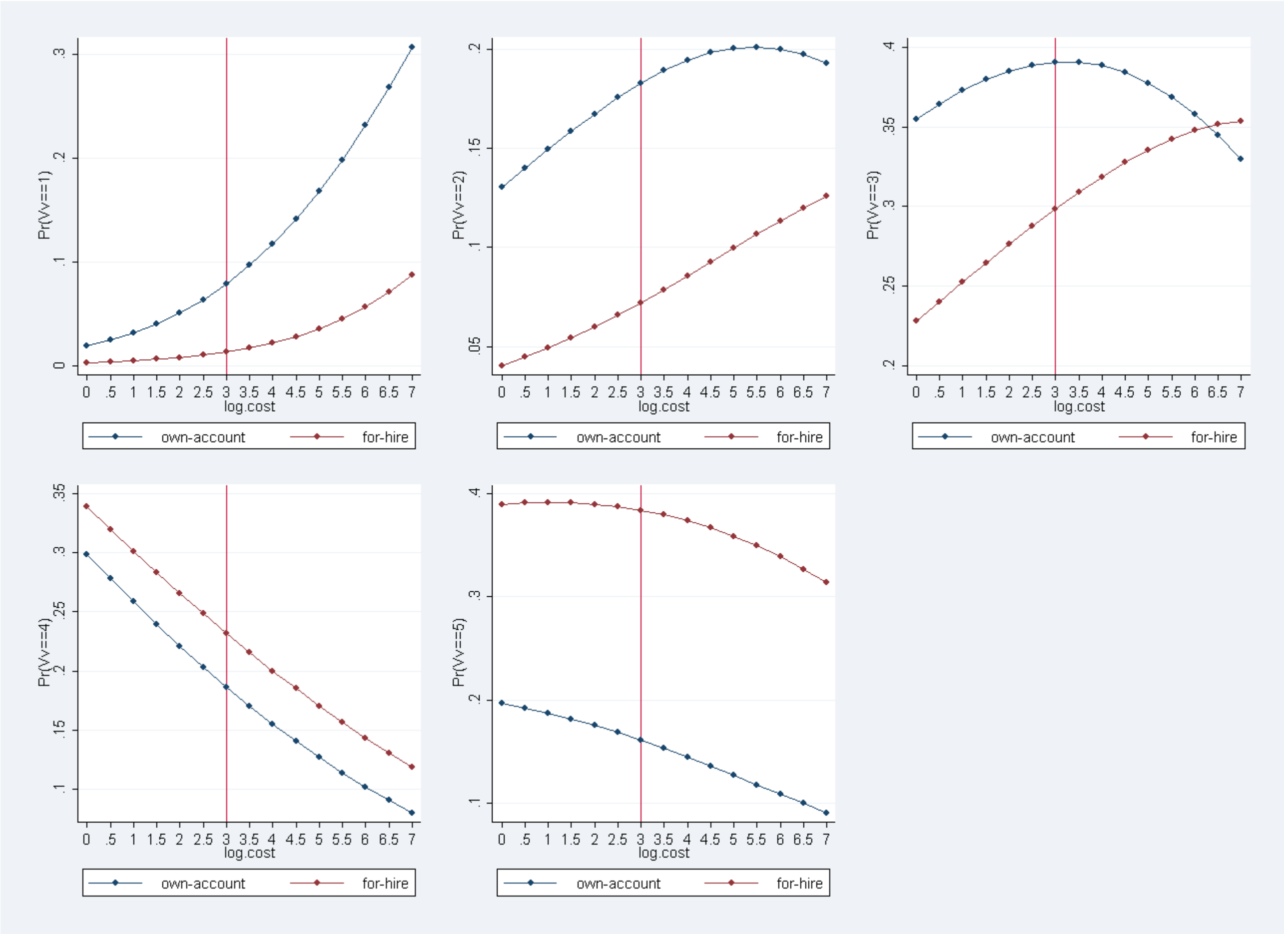

Figure 3: Probability of vehicle choice and fuel price

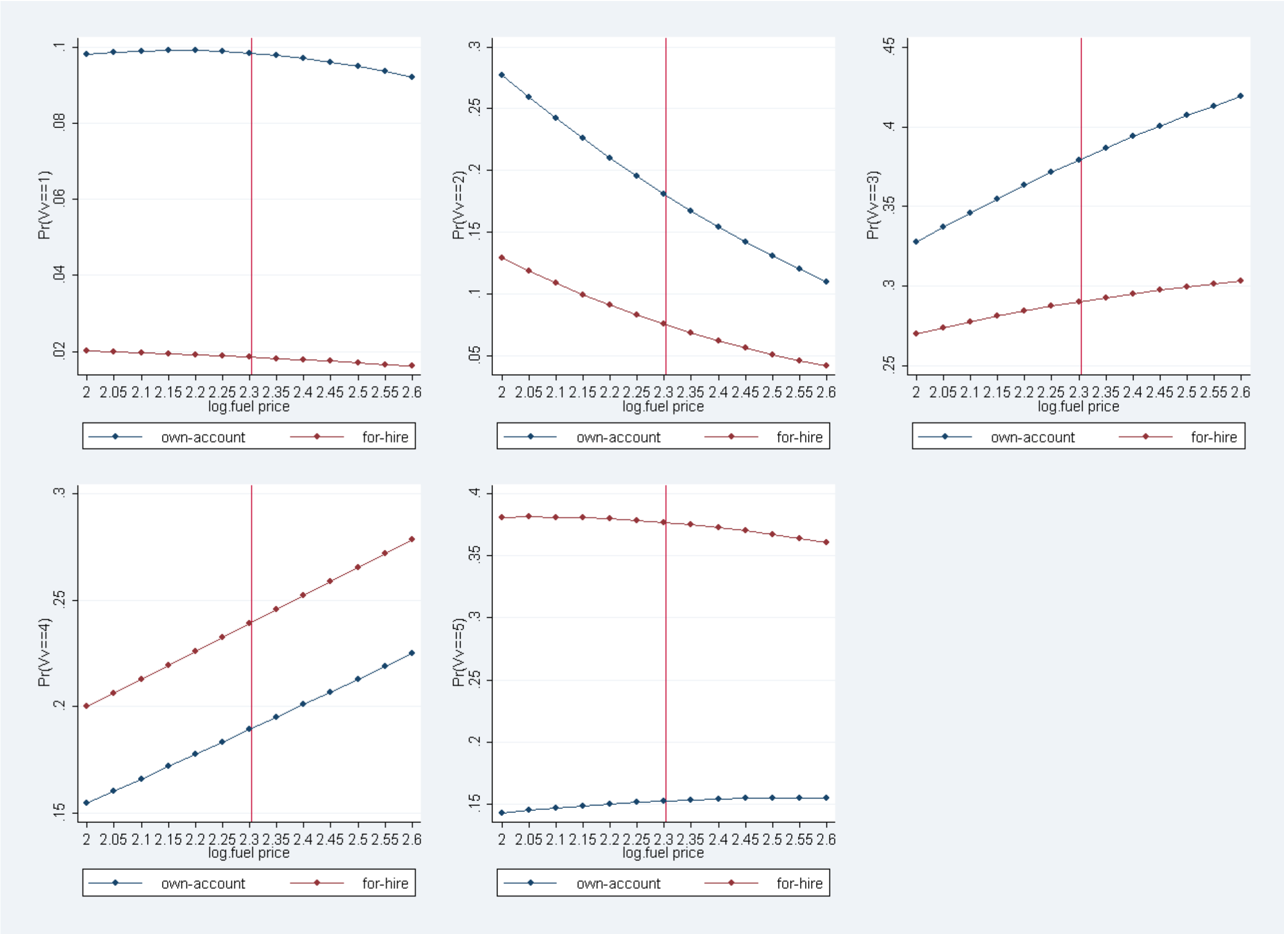

Figure 4: Probability of vehicle choice and trip distance

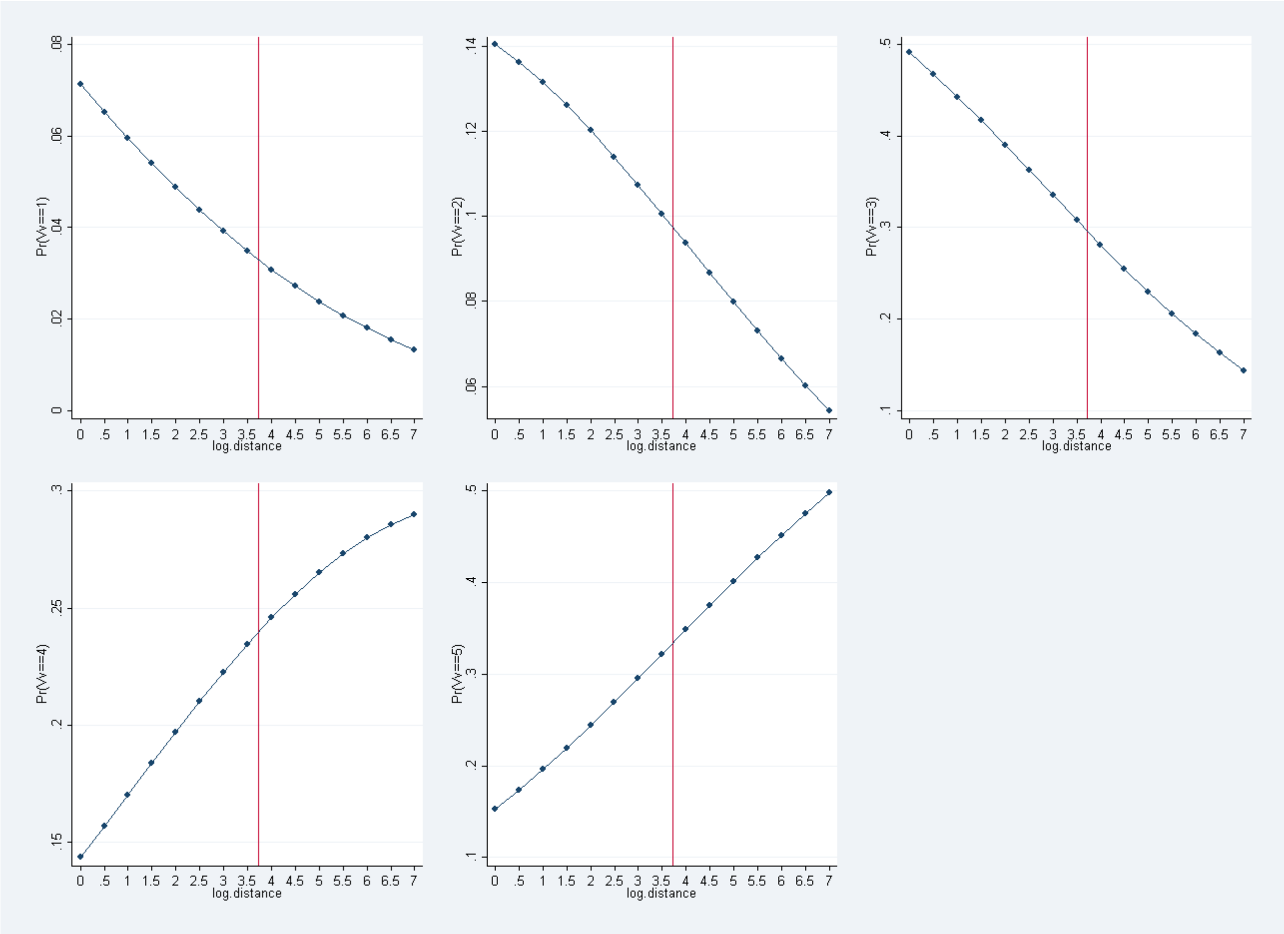

Table 7: Conditional shipment quantity model using the Dubin-McFadden Method

	q1	q2	q3	q4	q5
Log. Demand	0.144***	0.132***	0.078***	0.058***	0.097***
	(0.039)	(0.040)	(0.017)	(0.018)	(0.019)
Log. Distance	0.078**	0.170***	0.211***	0.273***	0.359***
	(0.037)	(0.025)	(0.013)	(0.016)	(0.023)
For-hire	0.198**	0.434***	0.103**	0.10	-0.079
	(0.101)	(0.067)	(0.044)	(0.34)	(0.055)
Voluminous	-0.051	-0.272***	-0.419***	-0.387***	-0.383***
	(0.094)	(0.095)	(0.073)	(0.046)	(0.045)
Select V1		-0.879***	0.738***	0.424	0.697***
		(0.202)	(0.194)	(0.262)	(0.252)
Select V2	0.811**		-0.132	-1.285***	0.406**
	(0.387)		(0.198)	(0.308)	(0.171)
Select V3	-2.176***	1.159**		0.941***	1.422***
	(0.500)	(0.567)		(0.178)	(0.204)
Select V4	0.063	1.060**	-1.328***		-2.886***
	(0.535)	(0.460)	(0.228)		(0.411)
Select V5	1.236***	-1.010***	0.667***	0.188	
	(0.448)	(0.326)	(0.141)	(0.147)	
Sigma2	6.112**	3.911***	2.718***	2.025***	8.378***
	(2.845)	(1.382)	(0.593)	(0.596)	(2.025)
Observations	1,233	3,623	11,888	9,011	13,235

Note: The dependent variable is shipment quantity in log(tonne) for the five vehicle types. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Vehicle choice nest structure

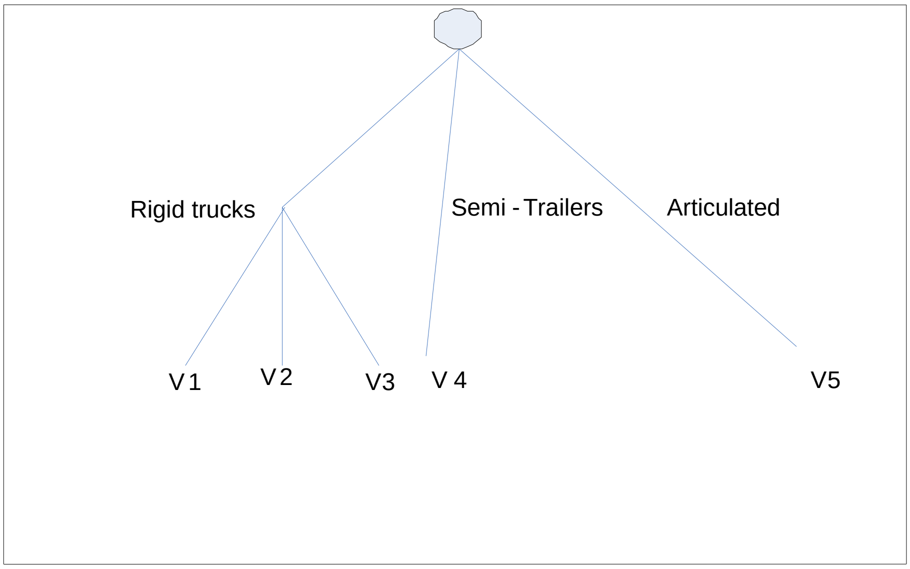

Table 8: Mixed MNL vehicle choice model

Variables	Estimates
L	-2.05***
	(0.13)
Standard deviation of L	1.66***
	(0.289)
Age	-0.06***
	(0.02)
Cost	-0.39***
	(0.107)
Standard deviation of Cost	0.01
	(0.01)
V2	0.64***
	(0.149)
V3	1.85***
	(0.212)
Rigid truck std.	0.03
	(0.153)
V4	3.30
	(0.236)
V5	4.11**
	(0.310)
Rho-square	0.10
Observations	2357
Number of Halton Draws	1000
Null Log-Likelihood	3172
Final Log-Likelihood	2860

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.2. 'Rigid truck std' denotes standard deviation of the dummy variable for rigid trucks. The normal distribution is assumed for the random coefficients.