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Essays on capacity utilization, vehicle choice, and networks in the trucking industry

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ESSAYS ON CAPACITY UTILIZATION, VEHICLE CHOICE, AND NETWORKS IN THE TRUCKING INDUSTRY

By

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PhD Thesis

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Table of Contents

Acknowledgment

Introduction and Summary

Chapter I..............................Capacity Utilization of Vehicles for Road Freight Transport- a review

Chapter II......................................Determinants of Capacity Utilization in Road Freight Transport

Chapter III.......The Optimal Shipment Size and Truck Size Choice- the allocation of trucks across hauls

Chapter IV......................The effect of Fuel Prices on Trucking Industry's Network Characteristics

Exploratory assessment using Danish HGV data

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Megersa Abera Abate

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Introduction and Summary

In recent years there has been a growing interest to understand the drivers and the limits of road freight demand in many countries. Behind this interest lies a strong desire to improve operational performance in road freight transport, which has remained stable for many years. A recent report for 13 European countries reveals that on about 30 per cent of all trips made the trucks are empty, while the percentage of a truck's carrying capacity filled with a cargo (that is, the load factor) remained stable at an average of 50 percent over the period 1990-2008 (European Environmental Agency, 2010). The overall objective of this PhD thesis is to provide economic analyses of some of the drivers and limits of road freight transport, and their implication on the trucking industry's performance. It is composed of four self-contained chapters which can be read independently. Each chapter addresses this objective from various angles to provide economic perspectives and policy recommendations.

Chapter 1 sets the stage by reviewing studies on capacity utilization in road freight transport from the economics and engineering literature. It draws important lessons and sheds light on potential gains that can be achieved by combining the two strands of studies. Chapter 2 looks at two aspects of capacity utilization, namely the extent of empty running and the load factor. It shows that they are explained as a function of truck, haul and carrier characteristics. Chapter 3 analyzes how firms choose the optimal truck size and shipment size. Chapter 4 looks at the effect of fuel price on the operating characteristics of the trucking industry.

Data background

The main source of data for the thesis is the Danish heavy trucks trip diary. It is a unique dataset, and as such it is worth giving a short introduction to it from the outset. The diaries have been collected as part of a wider European Union (EU) initiative, in accordance with Council Regulation (EC) 1172/98 on statistical returns in respect of the carriage of goods by road. Access to this data is limited to aggregate statistics in many member countries. In the Danish case, it has been possible to get access to the data at the most detailed level. The Danish data is also the first, to the author's knowledge, to be used for a detailed microeconometric analysis. With the cancelation of the Vehicle Inventory and Use Survey (VIUS) in the US back in 2006, and the difficulty of getting data from freight carriers due to confidentiality issues in many countries, the Danish data give a rare opportunity to study the performance of the trucking industry rigorously. Furthermore, trucking is the major mode of freight transport in Denmark, and as such studying its performance provides interesting lessons that can be of use for countries where trucking is also the dominant mode of freight transport.

The travel diaries contain information on the movements of approximately 1000 trucks every year for one week's operation. All the trips undertaken by the trucks are recorded and the diaries report the trip length, the load carried, the type of good carried, and special information if the good is considered a voluminous good. Moreover, background information about the type of vehicle, age, owner, size is provided. Although there have been some difficulties with the collection and the representativeness of the recorded transports, it is still believed to be a very strong data set in relation to understanding the variation in Danish trucking. The data is also used for producing aggregate statistics in accordance with the above EU directive, but there are some concerns about the precision in this regard.

Based on the identification number of truck owners, it is possible to link the trip diary data to other register data in Denmark to get further information on firm characteristics. The thesis exploited this possibility to enrich its data source to investigate a number of interesting issues concerning the use of heavy vehicles. The following paragraphs give a more detailed summary of each chapter.

Chapter 1 (a joint work with Ole Kveiborg) gives an overview of the literature on capacity utilization in road freight transport. It groups previous contributions into two segments according to their analytical approach and origin of research. The first approach looks at capacity utilization based on economic theories such as a firm's objective to maximize profitability and considers how firm and haul characteristics influence utilization. The second approach stems from the transport modeling literature and mainly focuses on the modeling of trip-chain and its implication on the level of capacity utilization. A key lesson from the reviewed studies is that it is important to take into account the commercial activity that initiates vehicle movements to evaluate performance. Various suggestions are also made on how to calculate capacity utilization measures in this chapter. *(A version of* *this chapter is forthcoming in **Freight Transport Modeling** book edited by Eddy Van de Voorde, Moshe Ben-Akiva, and Hilde Meersman, which will be published by Emerald in the first half of 2013.)*

Chapter 2 looks at two aspects of capacity utilization, namely the extent of empty running and the load factor. It shows that they can be explained as a function of truck, haul and carrier characteristics. The study employs an econometric model that simultaneously estimates a market access decision (empty or loaded movement decision) and the load factor (the level of capacity utilization during a loaded trip). A unique dataset from the Danish heavy trucks trip diary for 2006 and 2007 is used for analysis.

The results show that trip distance, truck size, fleet size and carrier type are the main determinants of capacity utilization. In particular, trucks on longer trips tend to have higher levels of load factor, and are more likely to be loaded. The analysis consistently shows that trucks owned by for-hire carriers are better utilized than those owned by own-account shippers, which suggests that specialization in haulage service helps carriers to optimize resource use. But the effect of a trucks' size on utilization is not straightforward; while an increase in truck size contributes to excess capacity to some extent; its overall effect appears to be positive. This result adds an interesting insight into the current policy debate in Europe regarding whether increasing the maximum legal carrying capacity of trucks is beneficial or not. *(A version of this chapter is accepted for publication in **Journal of Transport Economics and Policy**)*

Chapter 3 takes an in-depth look at the truck size/type and shipment size choice process of firms. This is a timely topic as the demand for freight transport has been growing rapidly, and is predicted to grow in the future. There has also been a proliferation of just-in-time inventory practices by shippers and receivers, 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.

The objective of this chapter is to investigate how variations in route/haul, carrier and vehicle characteristics affect the optimal vehicle size choice in trucking. Little is known about this choice process and its underlying determinants. Previous studies mainly focus on mode choice as opposed to the vehicle choice process of firms. This chapter addresses two important issues in econometric 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 simultaneity between quantity shipped and vehicle choice using a discrete continuous econometric model 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. Results show that the main determinants of vehicle size choice are vehicle operating cost, vehicle age and carrier type. It is also shown that as operating cost increases the probability of choosing heavier vehicles increases, while higher total cost leads to a gradual shift towards smaller vehicles. These seemingly contradicting 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 fuel price rise) firms prefer to use heavier vehicles. On the other hand, policies or secular changes which increase fixed costs, and hence total cost, (e.g. registration tax, permits, licenses etc.), force firms to use smaller vehicles. *(A paper based on this chapter was presented at the* ***Kuhmo-Nectar 2012, LATSIS 2012****, and* ***ETC 2012*** *conferences)*

Chapter 4 is exploratory in nature and looks at how the fuel price hikes and financial crisis of the last decade (2000s) have affected the operating characteristic of fright movement. Both had a significant impact on the structure of the trucking industry and how freight is moved. In particular, the chapter analyzes the effect of fuel price on the average length of haul and the level of capacity utilization. It proposes an empirical model which is based on central arguments that during periods of high fuel prices firms lower the average length of hauls- the average distance a tonne of fright moves, and improve capacity utilization. For analysis, a unique quarterly dataset from the Danish heavy trucks trip diary that spans 8 years is used. The data are disaggregated and allow for a simple and flexible empirical strategy that controls for vehicle, firm and haul characteristics.

The results show that average length of haul is sensitive to changes in fuel price: a DKK 1 increase in fuel prices leads to a 3 percent decrease in average length of haul in the 2004-2007 period. This implies that firms improve transport efficiency by reducing the number of kilometers needed to transport a tonne of cargo as a short run response to fuel price increases. This result, however, is not confirmed for the years following the 2008 financial crisis. It also depends on where in the distribution of the average length of haul one looks. A similar pattern is observed for the effect of diesel price on the share of loaded trips vehicles make: with a significant effect in the pre-2008 period and no significant effect afterwards. The findings of this study -exploratory as they may be- represent important stepping stones for future research. They also reveal interesting short run freight demand responses, which have not previously been studied.

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CHAPTER I

Capacity Utilisation of Vehicles for Road Freight Transport- a review *

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Abstract

This paper discusses a central aspect of freight transportation – capacity utilization with a link to empty running of commercial freight vehicles. It provides an overview of the literature on these topics and groups the contributions into two segments according to their analytical approach and origin of research. The first approach looks at utilization based on economic theories such as the firms' objective to maximize profitability and considers how various firm and haul (market) characteristics influence utilization. The second approach stems from the transport modelling literature and its main aim is analyzing vehicle movement and usage in transport demand modelling context. A strand of this second group of contributions is the modelling of trip-chain and its implication on the level of capacity utilization. A key lesson from the reviewed studies is that it is important to take into account the commercial activity that initiates vehicle movements to evaluate performance. It appears that there is room for further enrichment of the modelling exercise by incorporating information regarding the operator to give a stronger behavioural basis for the vehicle movements and utilization analysis.

*A version of this chapter is forthcoming in Freight Transport Modeling book edited by Eddy Van de Voorde, Moshe Ben-Akiva, and Hilde Meersman, which will be published by Emerald in the first half of 2013. We thank two anonymous referees for suggestions. All errors are ours.

1 Introduction

Road freight transport is vital for most industries to ensure smooth movement of goods. Moreover, the transport sector employs a large number of the labour force and contributes with a rather large share to GDP in most developed countries (Transport Canada, 2003; American Trucking Trends, 2011). Thus the level of capacity utilisation of vehicles used for freight transport is an important indicator of how well economic resources are used both from the perspective of vehicle operators and other sectors of the economy, which rely on their service. Despite its positive contributions, freight transport leads to negative externalities that need to be reduced, ideally, not at the expense of economic prosperity. If capacity utilisation can be improved then it will be possible to reduce the amount of vehicle kilometres required to satisfy the demand for goods movements and the related detrimental effects. It is, therefore, interesting to investigate the factors behind capacity utilisation and how it influences overall travel demand.

The observed level of capacity utilisation is naturally the consequence of some optimisation by the transport operators due to e.g. cost minimisation, optimal resource use etc. This optimisation is taken as given for the analysis of capacity utilisation. So the choices influencing capacity utilisation as is described here is implicitly the result of the underlying economic optimisation of the firm.

In this paper we study capacity utilisation and present literature contributions on the subject from different approaches that has followed independent paths. We will shed some light on its measurement and its determinants. In particular, we focus on how the different approaches improve current methodologies within freight transport modelling as well as within economic modelling of the vehicle operators' decisions. There are several studies ranging from the economics to the transport literature that analyse the issue of vehicle capacity utilisation. These studies usually define capacity utilisation as a function of the physical dimensions of a load such as weight and volume. Each study emphasises different and yet key aspects of utilisation from which interesting insights can be gained.

Studies from the economics literature analyse the underlying determinants of capacity utilisation giving particular weight to cost minimisation and other economic incentives as the main behavioural issues behind resource allocation decisions (Wilson and Beilock, 1994; Wilson and Dooly, 1993; Beilock and Kilmer, 1986; Winston, 1985). They show how various haul (trip), vehicle and carrier (operator) characteristics affect the level of utilisation. According to the economics literature there is a persistent challenge of matching capacity with demand as a result of two factors: freight movement imbalance between regions and market access cost differential between operators. Studies from this strand of the literature show how information technology capabilities improve utilisation by facilitating the matching process (e.g. Hubbard, 2003; Barla et al, 2010).

Studies from the transport literature mainly focus on modelling vehicle movements as part of freight demand modelling and a vehicle routing problem with the aim of predicting directional traffic. One frontier interest of these studies is the issue of 'trip chain' or 'tour' undertaken by freight vehicles in urban areas and its implication on efficiency (Holguin-Veras and Thorson, 2003; Raothanachonkun et al, 2008). Empty runs or the number of kilometres driven without a load is often taken as the main indicator of capacity utilisation in this literature. However, some studies (Figliozzi, 2007; Figliozzi et al, 2007) show that the extent of empty running is a poor proxy for efficiency of vehicle movements, unless the purpose of commercial activity which initiated the movement is taken into considerations.

The key lesson from both strands of the literature is that capacity utilisation varies depending on the specific setting in which vehicles are used. The extraordinary heterogeneity in terms of weight and volume of loads, direction and distance of movement as well as time window constraints results in varying degree of utilisation even for rather identical vehicles. Future studies should focus on micro level vehicle utilisation rather than a general level analysis. Empirical analysis showing the scope of potential gains from improved utilisation can also be an interesting addition to this important topic.

The rest of the paper is organized as follows. Section 2 gives an overview of the concept of capacity utilisation, output measure and production technology in trucking. Section 3 discusses determinants of capacity utilisation and 'Trip chain' as it is discussed in the economics and transport modelling literature followed by concluding remarks in Section 4.

2 Production Technology and Output Measures in Trucking

2.1 Production Technology

Measuring the capacity utilisation of a truck mainly involves consideration of two dimensions: spatial attributes of a truck movement and the physical attributes of a shipment (i.e. for a given capital and labour input of the firm). Both dimensions can be considered independently or they can be considered simultaneously. The location of origin-destination pairs (ODs) and the distance between them constitute the main component of the spatial dimension. As for the physical attributes, the weight and the volume (density) of a shipment essentially determine how well a truck can be used relative to its maximum carrying capacity. To characterize capacity utilisation of a truck we note that different pictures emerge depending on how the output of a freight transport service is defined. The following discussion illustrates this point.

Hubbard (2003) discusses two concepts of capacity utilisation. The first concept relates to the share of "loaded kilometres", defined as the numbers of kilometres trucks are driven with a load during the periods trucks are in operation away from their base. Seen this way, the performance of a truck can be evaluated by the share of "loaded kilometres" relative to the total kilometres the truck is driven. The second concept considers the number of times trucks are in use in a given period. For instance, trucks that are driven more weeks in a year are considered to have a higher level of capacity utilisation than those used for a fewer number of weeks due to frequent maintenance or lack of demand. It is assumed here that being away from base of operation more often implies higher level of utilisation. Such temporal consideration of truck usage is not common in the literature, but it adds an interesting perspective

Using these two concepts on Danish data from 1999 to 2009 shows developments depicted in Figure 1. As mentioned above, in many freight transport models the average load on vehicles is used as a measure of utilisation in order to calculate number of vehicles. This measure is also shown in Figure 1.

An important dimension overlooked in Hubbard's discussion is the attributes of the load carried by trucks. Failing to consider weight and/or volume of the load can be misleading since utilisation does depend also on trucks' carrying capacity that is filled with cargo or the level of the load factor. According to Hubbard's first definition, two identical trucks carrying different size of otherwise identical loads are reported to have equal level of utilisation in terms of 'loaded kilometres' performance if they travel over the same distance. Their performance in terms of the level of the load factor, however, is clearly different, which can be seen form the comparison of these different performance measures outlined in Figure 1.

An informative comparison of utilisation can be made using ton-kilometres (TKM) as an output measure. TKM is defined as the product of cargo weight carried and the distance over which it is shipped. Boyer and Burks (2009) use TKM to define capacity utilisation (productivity) at a vehicle level as the annual ton-kilometres per truck-and-driver combination. As pointed out earlier, to have higher utilisation a vehicle has to be driven over long distance and loaded to its maximum capacity. However, unless both dimensions - distance and weight - are taken into account it is difficult to fully capture utilisation. Moreover, TKM does not consider the type of transport service undertaken since the more kilometres a vehicle is running the better the capacity utilisation is. For instance, if a truck is used for a specific type of delivery service, where loading and unloading takes extended time then the truck will run only few kilometres and will not be able to have large TKM. But it may be fully loaded when it is operating. To overcome this problem, capacity utilisation can also be defined as the extent of the actual versus the maximum laden capacity of the vehicles on the trips that they have actually performed. Such a definition using TKM is also shown in Figure 1.

Another important dimension, volume of a load, is missing when one looks only at TKM performance. Light and voluminous items fill up physical space of a vehicle before its maximum laden capacity is reached. Vehicles carrying such items will appear less productive compared to those moving less voluminous and heavy item over the same distance. In relation to this, it may also be important to consider the specific type of good being carried. Some goods such as dangerous goods, and oil products require particular types of trucks and should therefore be considered specifically. The same may of course be the case for other goods although these may be carried in normal articulated trucks (e.g. food and general cargo). Ideally, one needs to consider the distance travelled by the vehicle, the specific type of good, weight and volume of the load carried to make a complete comparison of capacity utilisation of vehicles.

As indicated by Femie and McKinnon (2003), quality of service with regard to 'time utilisation' and deviation from schedule as well as fuel efficiency should also be quantified to know how a truck's hauling capacity is effectively utilised.

Finally, note that the above definitions of capacity utilisation take into account only the physical (engineering) aspect of freight transport service since their focus is on vehicles rather than firms. In general no single capacity measure can accommodate all of these 'requirements'. It is thus important to be specific about what is the objective of the measure is (for example to be usable for political decisions).

2.2 Empty Running and Capacity Utilisation

Empty running is another important indicator of the extent of capacity utilisation. It arises when carriers provide capacity to several locations (markets segments) and choose to access only some of them due to unavailability of load or vehicle routing decision. A vehicle moving in a round trip between two locations may choose to carry a load on the front-direction and run empty during backhaul or vice-versa.

For a vehicle moving in a more complex pattern, empty runs occur at several stages of its journey. An illustration of this is included in Figure 2. To make it simple, we assume that all goods going from a production (P) to a consumption (C) pass through two distribution centres (DC), where the goods are consolidated and only truck is used. In the figure we consider three 'supply chains' one going from P1 to C1, another going from P2 to P3 and a third going from P3 to C3. The chain P1C1 passes through distribution centres DC1 and DC2, the chain P2C2 passes through DC3 and DC4, while the chain P3C3 passes through DC4 and DC1.

Each leg of the supply chains is performed by a distinct vehicle. However in the figure we follow a single truck in a trip chain starting in DC1 going to DC2 (loaded), from DC2 to DC3 (un loaded), from DC3 to DC4 (loaded), from DC4 to DC5 without load, and finally from DC5 to DC1 with load. The trip chain consists of 5 individual trips determined by separate supply chains and a trip back to the origin for the trip chain.

We may also observe simpler cases where there are one to one relations between supply and trip chain. For example when a consignment is conveyed directly from P to C and where the vehicle return to its origin loaded or (more likely) empty.

The figure reveals that although vehicle trips are derived as part of the supply chain(s) they cannot describe all observed trips by trucks and they cannot always determine the actual use of vehicles. Empty trips are more likely related to the trip chain rather than the supply chains. Moreover, utilisation of vehicles is also related to the trip chain and to a large extent also to loaded and un-loaded trips. For example if a truck owner must decided between undertaking an empty trip to go to a place, where a full load can be picked up of whether he chooses to take a smaller consignment from where the truck has made its delivery. The two choices influence the probability of either a higher load/utilisation and the probability of an empty trip.

Barla et al (2010) identify three stages being part of the chains: first, at the initial stage of a journey empty runs occurs if the vehicles' base is not close to the shipment origin; Second, empty runs arise during a backhaul trip, since demand from a client is rarely bidirectional (typical feature of freight movement); and finally, empty runs occur during a return trip if a truck is diverted in order to pick up a backload. It is important to note that in some of these situations empty running is inevitable. For example, geographical imbalances in freight movement forces trucks to run empty during backhaul from a net freight importing region. It is also impractical to find a back load for specialized vehicles such as oil tankers in to which loading edible oil is impossible (McKinnon and Ge, 2006). They also indicate lack of transparency in the road freight market, short haul lengths, scheduling constraints and the incompatibility of vehicles and loads as possible causes of empty running. Seeing vehicle utilisation solely based the extent of empty runs may portray an incomplete picture since utilisation also depends on vehicle routing problem faced by the operators and the activity which initiates the movement in the first place.

Generally, empty running can be considered as a reflection of sub-optimal capacity utilisation when it arises due to a matching problem between demand and supply. From an individual operator's point of view there might be cases where running empty in specific direction is optimal and hence load is not searched (for example, to pick a load in another location). For an operator choosing to operate in this fashion, the price received for a movement of load in the accessed market reflects the cost of operating a vehicle to locations for which capacity is supplied but not utilized. From societal point of view, however, where the objective is sometimes to minimise vehicle movements due to environmental concerns, empty runs that could have been loaded are considered as underutilized capacity. In the next section, studies which analyse the underlying determinants of capacity utilisation are discussed. Finally, we note that when we compare the various truck output and utilisation measures it is evident that they each tell us something different about the level of usage, and that they cannot be interchanged for each other. This shows the importance of choosing the right capacity measure that suits the specific purpose for the analysis and that comparing capacity utilisation across different studies etc. should be done with care.

3 Determinants of Productivity in Trucking

3.1 Lessons from the Economics Literature

Studies from the economics literature aim at finding determinants of empty running and capacity utilisation of trucks giving particular emphasis to underlying behavioural issues. They give theoretical and empirical analysis for questions such as: why does a truck or a carrier to be precise, choose to access some market segments (origin-destination pairs) and not others? Why do we see empty trucks alongside fully loaded trucks starting from the same origin and going to the same destination? Answers to the first question explain the determinants of individual carrier's vehicle utilisation while answers for the second question explain carriers' market behaviour. The two common factors that determine how well trucking carriers use their capacity are distance and the respective freight movement imbalance between market segments. The effect of these two factors and regulatory environment on rate of capacity utilisation is thoroughly analysed by Wilson and Beilock (1994), Wilson and Dooly (1993) and Beilock and Kilmer (1986) for the US trucking industry. Recent studies focus more on the structure and the relative efficiency within the trucking sector arising from information technology capabilities of trucks (Barla et al, 2010 and Hubbard, 2003).

Early empirical studies mainly focus on the cost structure of carriers to explain differences in utilisation performance (see Beilock and Kilmer, 1986; Wilson and Dooly, 1993; and Wilson and Beilock, 1994). Their basic explanation is that if there is a systematic cost differential between carriers, then we see difference in capacity utilisation level between similar trucks even if they are used for the same haul and between the same origins and destinations. There are two implied assumptions in these studies, carriers incur more or less equal cost of operating empty trucks and they face equal freight rates. With regard to costs associated with accessing a particular freight market, however, some carriers may have cost advantages. Two main sources of cost advantages and their implication to trucking efficiency are discussed in the literature, namely market regulation and information technology (see Abate, 2012 for a detailed discussion).

The first source of cost advantages arises from government intervention in the trucking industry. The effect of market regulation on carriers' decision to access different freight markets is discussed by Wilson and Beilock (1994), Wilson and Dooly (1993) and Beilock and Kilmer (1986). Even if trucking activities are now free from government intervention in most countries, these studies identify an important source of variation in access cost. All argue, from different angles, that having a special license to haul a regulated commodity improves capacity utilisation (less empty runs) by lowering access cost; whereas not having such a license forces carriers to forego loading opportunities and increase their 'search cost' for finding new loads. There are also later examples where firms choose not to undertake costs to be allowed to carry special types of loads (e.g. permission to carry dangerous goods, which in addition can only happen at certain times during a day or week and thus leading to additional time where a vehicle and driver is not in operation

One important limitation of these studies is that capacity utilisation is measured solely based on whether a truck is loaded or not without considering how much of the truck's capacity is utilized during a loaded trip (i.e. the load factor).

Another source that leads to different cost structure between carriers is information technology (IT) capability of trucks. Controlling for firm, truck and haul characteristics, Barla et al. (2010) and Hubbard (2003) show that on-board IT capabilities results in higher capacity utilisation by lowering search cost and by improving the matching of vehicle capacity with the available load. The IT systems considered are not clearly defined, but they provide a better communication between operator and driver. Hence, other ITS systems involved in the operation of trucks, such as the logistic operators' software used to optimise the use of vehicles and the general positioning of the vehicles are not included in these studies, although they play important roles in the trucking industry. Chakraborty and Kazarosian (2001) also find positive impact of IT capabilities on productivity by controlling for marketing objectives such as on-time-performance vs. lower rate carrier.

For in depth review on IT capabilities and transport we refer to Banister and Stead (2004). The specific aspects of capacity utilisation considered in these studies are the level of the load factor and the number of loaded kilometres respectively. Both studies use data from the late nineties when IT adoption was relatively small in North America. Thus IT capability may not explain capacity utilisation differences in today's activities since the technology might have diffused well by now. It is likely that other attributes of trucks (size, fuel efficiency etc) or structural changes in the industry are playing important roles in determining how well a particular truck is used. For instance Boyer and Burks (2009) argue that trucking in the US has increased its proportion of traffic that is relatively cheap to handle. As a result changes in traffic composition have inflated productivity level in the transport industry. Their finding to some degree plays down the claim that real productivity gains result from systematic difference in cost structure between carriers. However, it may also be that continuously improved matching and routing software continue to induce differences across the trucking industry, but this is very difficult to verify.

Finally, note that optimal decision in a net revenue maximisation framework assumed in the studies summarized above may not be similar to other alternative objectives of firms such as fleet optimisation and/or driver optimisation. For example, drivers may have to call at their home base at a pre-specified time to pick up another load, for vehicle maintenance or to change drivers. This is forcing them to skip a loading opportunity during a backhaul. Note that the reviewed studies focus on trucks travelling in round trips between two locations (Wilson and Beilock, 1994) or only on one leg of a truck's journey (Barla et al ,2010). This is a rather simplistic depiction of a complex freight vehicle movement which involves a journey with several segments or trips. The reasons often cited for such an approach is limited data availability and analytical tractability. A realistic analysis, however, needs to consider all segments of a truck's movement.

3.2 Lessons from the Transport Modelling Literature

In the transport literature the issue of vehicle capacity utilisation and the empty running problem is discussed under freight demand modelling and a vehicle routing problem (VRP). The literature on VRP is rich. An overview of recent developments can be found in Golden et al (2008). However, most of this literature does not take the capacity utilisation of vehicles or the empty running explicitly into account. An exception is Jordan and Burns (1984 and 1987), which give interesting discussions of truck backhauling as part of a VRP.

Here, we give a short review from the freight demand modelling studies with particular emphasis on trip chain or tours in freight movements and the inclusion of empty trips. We think this is the area where there is a potential for the transport and economics literature to complement each other. Little is known about the behavioural underpinnings resulting commercial vehicle tours. What we know already is from studies based on either simulation or limited data. Starting with general discussions on freight demand modelling and how empty trips can be included, we present a short overview of some of some of these studies in this section.

3.2.1 Capacity Utilisation in Freight Demand Modelling

The literature of freight demand modelling is very rich. Some of the recent developments can be found in this volume on freight modelling, but also the earlier book on freight modelling (Ben-Akiva et al, 2008) as well as in a very early study by Winston (1983). Moreover, recent model developments focus on the logistic choices that can be used to determine the load of vehicles and further the number of vehicles needed to move the quantities determined by the OD matrices (see e.g. de Jong and Ben-Akiva, 2007). We refer to these volumes for more insights. Here we focus on the specific parts, where capacity utilisation and empty trips can be included.

There are two major freight demand modelling platforms, where capacity and empty trips can be included: commodity-based modelling and vehicle-based modelling (Holguin-Veras and Thorson, 2000; Federal Highway Administration, 2007).[1] The difference between them lies in the level of emphasis put on various dimensions such as weight, volume, number of vehicle trips, and economic value of the commodities being transported. In the case of commodity-based modelling, the weight and volume of the freight are the main units of analysis. The assumption is that by focusing on the characteristics of the commodity being transported, it is possible to capture the underlying economic activity which gives rise to vehicle movements. The limitation of commodity-based models is their inability to predict empty trips and the level of vehicle capacity utilisation. This limitation is ameliorated by vehicle-based models, which use vehicle trips to estimate freight demand. As pointed out by Holguin-Veras and Thorson (2000), vehicle-based models in turn overlook the characteristics of cargoes that play an important role in the vehicle selection, mode choice and routing process. Furthermore, these models have limited applicability to multimodal freight transport systems because of their focus on the vehicle trip which is an outcome of prior choice process (Holguin-Veras and Jara-Diaz, 1999, McFadden et al., 1986 and Abdelwahab, 1998).

There have been two different approaches to overcome the problems that arise from focusing either on commodity or vehicle movements in the context of urban freight movement. Wang and Holguin-Veras (2008) refer to them as: 'hybrid models' (which estimate commodity flows between origin-destination pairs and delivery routes) and 'tour models' (which directly estimate tours based on logistic considerations, tour-based behavioural

[1] Here, the concept of demand refers to the flow of freight or the level of freight transport demanded. See Boyer (1998) for an interesting comparison of this concept to when demand is defined as a relationship between the amount of freight transport and the price paid for it.

models, activity models or profit maximization behaviour). The common feature of these approaches is consideration of vehicle tours directly or indirectly. But they differ on the extent of treatment of underlying behavioural support for the way individual tours are generated. What is lacking in both approaches is a deeper analysis of the determinants of capacity utilisation of vehicles used for goods-transport. Improvements may be obtained by explicit inclusion of operators' objective function disparities as a result of the characteristics of the owner of the vehicle and its impact on a type of tour undertaken can make the analyses more complete.

As indicated in the second section, the level of capacity utilisation of freight vehicles depends on the distance range they are used. Interurban freight movements usually tend to be more efficient since high emphasis is put on consolidation to avoid empty running and less-than-truckload movements. In short range or urban settings, vehicles are usually used in a less efficient manner since several stops are involved. Recent studies on freight demand modelling try to characterise 'trip-chain' or 'tour' based vehicle movements involving several stops. Their main theme is incorporating empty trips and 'trip-chain' behaviour in freight demand modelling (e.g. the modelling approach used by Holguin-Veras and Thorsen, 2002). These studies are analysed from a traffic modelling point of view in which the aim is estimation of directional traffic. Other than depicting directional traffic, they do not deeply analyse underlying causes of why some vehicles run empty and others do not. However, there are interesting behavioural analyses of capacity utilisation of vehicles with regard to 'trip chain' movements. In what follows, a brief review of some of these studies is given.

3.2.2 Trip chain and capacity utilisation

'Trip chain' or 'tour' is used interchangeably in the literature to describe vehicle movement involving several stops. According to Wang and Holguin-Veras (2008) a trip is defined as an individual vehicle movement connecting an origin to a destination for a specific purpose, and an entire journey comprising two or more trips is a 'trip chain' or 'tour'. Trip-chain is a typical feature of urban freight vehicle movement. Vehicles usually serve several destinations in succession before finally returning back to their base which usually lies in peripheries of cities or near major traffic generators such as distribution centres or ports. Previous studies from Denver (Holguin-Veras and Patil, 2005), Calgary (Hunt and Stefan, 2005), and Amsterdam (Vleugel and Janic, 2004) report an average number of stops per tour of 5.6, 6 and 6.2, respectively.

Figliozzi (2007) gives a theoretical analysis of efficiency of urban commercial vehicle tours with regard to their generation of vehicle kilometres travelled (VKT) assuming a simple scenario where several destinations in an urban area are served from a single distribution centre. He argues that the efficiency of tours depends on the requirements of commercial activity, which initiates the tours and vehicle routing constraints imposed by truck capacity, frequency of service, tour length and time window length. Similarly, Holguin-Veras and Thorson (2003) depict the number of empty trips as a function of the routing choices that the commercial vehicle operators make, which in turn are based on the commodity flows in the study area. Figliozzi's (2007) findings indicate that multi-stop tours generate more VKT than direct deliveries even for equal payloads. Another interesting finding is that the percentage of empty trips has no correlation with the efficiency of the tour regarding VKT generation. According to Figliozzi (2007) looking at the share of empty trips as a measure of efficiency can be misleading. Direct delivery tours, the most efficient tours in terms of VKT since deviations are minimised, always have a 50% share of empty trips while for the less efficient multi-stop tours the share declines with the number of stops. Using data from a single truck engaged in less-than-truckload delivery tours in the city of Sydney, Figliozzi et al (2007) also shows that there is no clear relationship between tour distance, percentage of empty trips, and percentage of empty distance. It has to be noted that the context of these studies is urban transport where distance travelled is already short and as such the gain from lower VKT and efficiency is limited.

An empirical analysis using a synthetic dataset of trip chaining behaviour is given by Wang and Holguin-Veras (2008). Even though their study is entirely based on simulation, it gives interesting insights into determinants of destination choice and decision to end a tour using discrete choice models. Destination choice is modelled using a multinomial logit model where the choice set is updated at every node of the trip chain. At each node, a vehicle is faced with four alternative destinations randomly selected based on criteria set by the median distance between all nodes in the network (this is similar to a 'stratified importance sampling technique' suggested by Ben-Akiva and Lerman, 2000). Wang and Holguin-Veras (2008) report that the choice of next destination is negatively affected by the distance from the current location to the potential destination, and it is positively affected by the amount of cargo available for pickup and delivery. As for tour termination decision, the benefit derived from tour termination declines with the increase of return distance and increases with the accumulation of cargo delivered.

A detailed analysis of urban tour-based vehicle movements for the city of Calgary in Canada is given by Hunt and Stefan (2007). The analysis uses a tour-based micro-simulation to model movements made by light vehicles and heavier vehicles with single unit and multi-unit configurations operating in all sectors of the economy. The overall simulation is based on models of tour generation and subsequent sub-models, which determine vehicle and tour purpose, next stop purpose and next stop location. To determine the probability of the next stop's purpose in a tour (which includes carriage of goods, service stops, return-to-establishment and other stop categories), a logit model is used. The total number of previous stops is shown to decrease the propensity to return to vehicle terminal, indicating that tours with a large number of stops are less likely to end at a given next stop. In addition, the time elapsed in travel is shown to impact the propensity to end tours more than the total time elapsed (including both travel time and stop time). Once the purpose of the next stop is known, they use another logit model to determine the location of the next stop. Accordingly, they show that the tendency for the next stop on a tour to be near the current stop is greater than the tendency for the next stop to be near the vehicle terminal. Both models are estimated for 13 different segments of commercial movements based on combination of industry category, vehicle type and tour (stop) primary purpose. The reviewed literature in this section highlights the importance of explicit consideration of trip chaining behaviour to gain insights into commercial vehicle movements. The amount of VKT generated can be an interesting aspect to look into to evaluate efficiency. As shown, however, the share of empty trips of a tour is a poor indicator of efficiency with regard to VKT. It appears that there is a big challenge with regard to finding data as some of the studies are based on simulation and information gathered from operation of a single vehicle. To test some of the theoretical findings, future studies should be based on dataset that contain both the full movement of vehicles over several weeks or months and information on the owners of the vehicles. One such approach is outlined in Abate (2012) for interurban trips. Using detailed trip-by-trip information for about 2000 vehicles for an entire week of operation, this study econometrically estimates determinants of capacity utilisation.

4 Concluding Remarks

In this paper we looked at studies on capacity utilisation of freight vehicles. We classified the studies to general categories of either transport or economics literature, which address the issue from different perspectives. In Table 1 some of the reviewed examples of the different strands of literature are summarised. The main characteristics regarding type of utilisation measure as well as the main topic of the studies are highlighted. The list is not comprehensive, but provides an overview..

Our review shows that the strands of the literature have not fully benefited from each other. According to studies based on economic theory, vehicle capacity is underutilised as a result of constant challenge of matching capacity with demand arising from freight movement imbalances between regions and market access cost differential between operators. The problem caused by freight imbalances is considered as an external (exogenous) problem that operators can only minimise through appropriate location of their principal base of operation near major traffic generators, at least in the long run. However, operators have to make continual market access decision as part of the challenge to match specific demand with specific capacity based on net revenue considerations. Accordingly, to the extent to which there are differences in access costs which are not distance related, we see some vehicles running with a load while others running empty across similar market segments and carriers. Recent studies from this strand of literature show the effect of information technology capabilities to match capacity with demand by enabling carriers to keep their trucks on the road and loaded more often by lowering market access costs.

Our review also found that despite simple production process involved in the physical part of the transport process, measuring capacity utilisation is complex due to the extraordinary heterogeneity in terms of weight and volume of a load, direction and distance of vehicle movement. Therefore, a realistic efficiency analysis should account for such heterogeneity that may lead to productivity differences arising from the various settings in which vehicles are used.

In the transport literature, the recent focus is on the relationship between 'trip-chain' and the vehicle routing problem faced by operators in urban freight transport context where utilisation is lower compared to long haul operation. It is shown that unless the commercial activity, which initiates vehicle movements is taken into consideration, measures such as the share of empty trips (or distance) can be a poor proxy as efficiency measure when utilisation is compared with regard to generation of vehicle kilometres travelled (VKT). The trip-chain approach to analyse freight movement can improve the modelling of freight transport demand greatly. An even more interesting analysis is the potential of using the information contained in data about trip chaining in relation to the firm optimisation behaviour investigated in the economics literature. The trip chain approach also adds a spatial element to the firms' desire to match capacity with demand. The analysis of the operators' choice of optimal location of their principal base may very well be affected by the specific inclusion of trip chain information. Moreover, including trip chains and/or the relationship between loaded trips and empty trips in the analysis of the matching behaviour will increase the predictive power of such analysis.

Finally, empirical analyses of the scope of possible gains from improved capacity utilisation are limited. More studies are needed along the McKinnon and Ge (2006) study to put into perspective how much can be gained by improving empty runs. It is also interesting to know how the desire for sustainable transport can be accommodated within the objective of transport operators which is usually based on economic efficiency. The recent freight transport modelling approach, where the logistic decisions are involved to better predict vehicle movements is an obvious link between the operators' pursuit of efficiency analysed in the economics literature and the freight transport models. The determinants in the operators' decision making influence capacity utilisation and thus also the vehicles that are loaded onto the network in the assignment models. A joint estimation of firm optimising behaviour and the logistics of freight transport models will thus be a natural research objective to investigate further.

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Figure 1: Different measures of capacity utilisation on Danish freight transport each quarter from 1999 to 2009

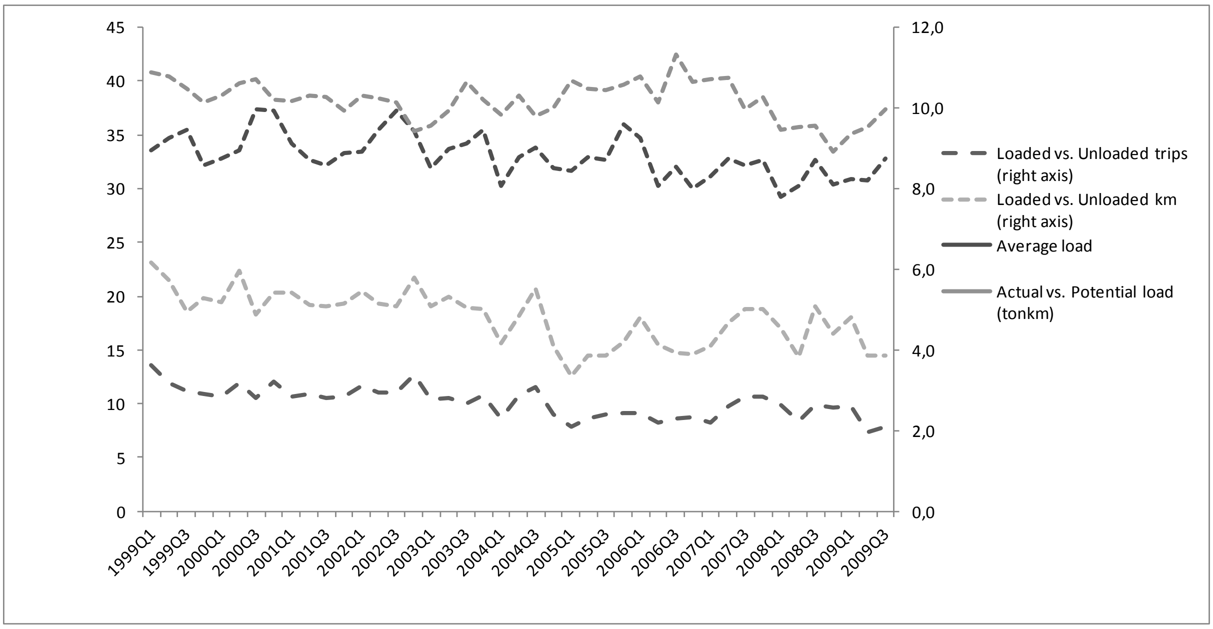

Figure 2: Complex trip chains and the related supply chains.

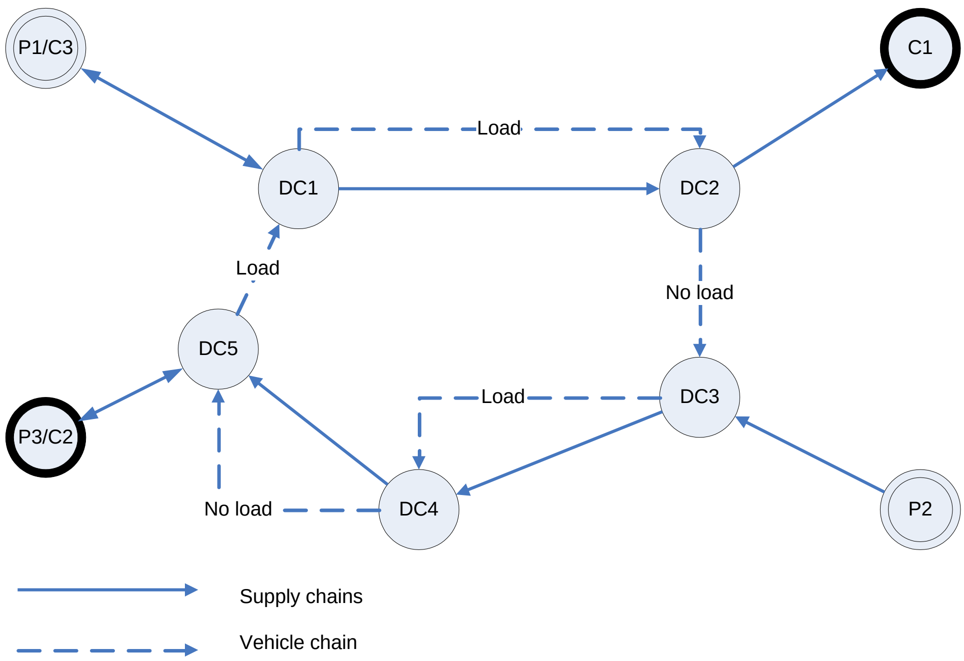

Table 1: Main studies on capacity utilisation.

	Source	Utilisation measure	Missing dimension	Remark
Economics Literature	Boyer and Burks (2009)	Ton-Miles per truck	density and value cargo; quality of service	main theme- the effect of traffic composition on trucking productivity
	Barla et al (2010)	load factor	density and value of cargo; quality of service	main theme- the impact of IT technology on capacity utilisation
	Hubbard (2003)	number of loaded miles and number of periods trucks are in use per period	weight, density and value of cargo; quality of service	main theme- the impact of IT technology on capacity utilisation
	Abate (forthcoming)	load factor and Empty running	quality of service and value of cargo; quality of service	this study uses a joint econometric model that considers both load factor and empty running
	Wilson and Beilock (1994); Wilson and Dooley (1993); Beilock and Kilmer (1986)	empty trips	weight, density and value of cargo; quality of service	Main theme- the effect of market deregulation on trucking performance
Transport Modelling Literature	Figliozzi (2007)	vehicle miles travelled (VMT)	weight, density and value of cargo; quality of service	The study analyzes urban commercial vehicles
	Holguín-Veras and Thorson, 2000	empty trips	weight, density and value of cargo; quality of service	
	Holguín-Veras et al (2011)	total travel time, Vehicle miles traveled (VMT), and pollution levels	density and value of a cargo; quality of service	The study analyzes urban delivery vehicle classes

CHAPTER II

Determinants of Capacity Utilization in Road Freight Transportation*

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Abstract

Recent performance indicators in the European road freight transport sector show that there is an excess capacity. To shed light on this phenomenon, this paper studies two aspects of capacity utilization in trucking: the extent of empty running and the load factor. Using a joint econometric modeling framework, this paper shows that they can be explained as a function of haul, carrier and truck characteristics. For estimation, a unique dataset from the Danish heavy vehicle trip diary was used. The results indicate that distance and being a for-hire carrier have positive effect on capacity utilization, whereas the effect of truck size is non-linear.

Keywords: capacity utilization; load factor; empty running; freight transportation

JEL classification: R0, L91

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1 Introduction

The capacity utilization of trucks shows how well economic resources are being used from the perspective of transport operators and the sectors reliant on road freight transport services. It is also central to the debate on sustainable transport since trucking operations are significant sources of emissions harmful to the environment. A recent report for 13 European countries reveals that on about 30 per cent of all trips made the trucks are empty, while the percentage of a truck's carrying capacity filled with a cargo (that is, the load factor) remained stable at an average of 50 per cent over the period 1990-2008 (European Environmental Agency, 2010). Although some level of empty runs and load factors below 100 per cent are inevitable due to the complexity of optimization in trucking, these performance figures suggest that there is excess capacity that could be minimized. This would ultimately reduce the total kilometers driven, and thereby ease congestion and provide economic and environmental benefits.

Various aspects of capacity utilization have been analyzed in the literature. The utilization differential between freight carriers is usually explained by differences in carrier, haul and truck characteristics. Hubbard (2003) and Barla et al. (2010) show that the information technology capability of trucks improves the number of loaded kilometers driven and the load factor. Boyer and Burks (2010) find that the relaxing of weight, length, and speed limits is the most likely explanation for the growth in productivity in the US trucking industry. Other studies (Beilock and Kilmer, 1986; Wilson and Dooley, 1993; Wilson and Beilock, 1994) give restrictive government polices as the main explanation for the prevalence of empty running.[1] Although insightful explanations for the determinants of capacity utilization are given in these studies, they analyze utilization indicators separately, and therefore may not fully explain the resource allocation process in trucking.

This paper aims to give a detailed analysis of the determinants of capacity utilization. The paper's contribution to the literature is in showing that a joint consideration of capacity utilization indicators leads to a sound empirical analysis, and provides a more appropriate picture of freight movements. In particular, this paper argues that to study determinants of the load factor, the extent of empty running also needs to be considered,

[1] Capacity utilization has also been shown to be related to the level of competition in the trucking industry. For instance, just-in-time inventory strategies on the part of shippers may prompt carriers to engage in frequency competition that results in the over-supply of capacity. Theoretical analyses by Shah and Brueckner (2011) and De Vany and Saving (1977) suggest that excess capacity can be used by carriers as a strategic tool in service quality competition.

because a carrier's decision to move a truck empty or loaded is interrelated with how much a truck carries when loaded. Accordingly, the paper employs an econometric framework based on Heckman (1979) that simultaneously estimates a market access decision (empty or loaded movement decision) and the load factor. For model estimation, a nationally representative dataset that comes from the Danish heavy trucks trip diary was used. The dataset has a one-week operational information on a trip by trip basis for 1921 trucks in 2006 and 2007. It is a unique dataset that allows for both a trip and truck level analysis. Furthermore, it is the most disaggregated data on road freight transport and allows for a detailed analysis of capacity utilization unparalleled in other studies.

The results show that trip distance, truck size, fleet size and carrier type are the main determinants of capacity utilization. In particular, trucks on longer trips tend to have higher levels of load factor, and are more likely to be loaded. But the effect of a truck's size on utilization is not straightforward; while an increase in truck size contributes to excess capacity to some extent; its overall effect appears to be positive. The analysis consistently shows that trucks owned by for-hire carriers are better utilized than those owned by own-account shippers, which suggests that specialization in haulage service helps to optimize resource use.

The findings of this study uncover important policy intervention areas by showing how capacity utilization responds to changes in trip length, carrier type, or vehicle size. It may not always be possible to affect these variables directly and change capacity utilization in such a complex activity as trucking. However, as shown by previous studies (Holguin-Veras et al, 2006), carriers do respond to policy interventions by improving productivity. Policy makers can, therefore, formulate policies that directly or indirectly affect these variables and so improve performance in trucking. The rest of the paper is organized as follows: Section 2 gives a brief background to the paper and Section 3 presents the econometric framework. Data descriptions, results, and conclusions are given in Sections 4, 5 and 6, respectively.

2 Background

The physical aspect of production in trucking involves a simple process of moving a load from one point to another by a truck and a driver.[2] Trucking production technology is a simple Leontief type technology where a single labor (driver) and capital (truck) combination is always required to produce an output (a movement of a load). As pointed out by Boyer and Burks (2009), the scope for getting more output (e.g. tonne-kilometers) per truck per period using the classic manufacturing method – that is substituting capital for labor through automation – appears to be limited. To fully optimize resources, carriers should therefore maximize capacity utilization.

Previous studies have mainly focused on the cost structure of carriers to explain differences in utilization (see Beilock and Kilmer 1986; Wilson and Dooley 1993; Wilson 1994). Their basic explanation is that if there is a systematic market access cost differential between carriers, we will see a difference in utilization level between similar trucks even if they are used for the same haul and between the same origins and destinations. There are two implied assumptions in these studies: carriers incur more or less equal costs in operating empty trucks and they face equal freight rates. With regard to costs associated with accessing a particular freight market, however, some carriers may have cost advantages. These cost advantages could come from government regulation (Wilson and Dooley, 1993; Beilock and Kilmer, 1986) and/or the information technology (IT) capabilities of trucks (Barla et al., 2010; Hubbard, 2003).[3]

In another strand of the literature, which deals with shipment size and mode choice, the issue of capacity utilization is raised indirectly and the reason why it varies between carriers is given little attention. For instance, the interaction between shippers and carriers and its implications for mode choice have been extensively studied (see McFadden et al., 1985; Abdelwahab and Sargious, 1992; Holguin-Veras et al., 2009). The main finding in these studies is that this interaction leads to simultaneous choice of mode and shipment size to ensure that freight is carried by an efficient mode of transportation. In each chosen mode, however, carriers are simply assumed to allocate their fleet efficiently across hauls. This paper is an interesting extension to the joint empirical framework of these studies to understand capacity utilization at the operational level.

[2] The overall freight moving activity, however, involves a complex interaction between carriers, shippers and logistic service providers (see Holguin-Veras et al. (2009) for an interesting discussion).

[3] See Abate and Kveiborg (forthcoming) for more discussion on the implication of cost advantages on trucking efficiency .

3 Econometric framework

This paper proposes an econometric framework in which the decision to run empty or loaded during a given trip (hereafter referred to as the market access decision) and the load factor are jointly estimated. Carriers are assumed to make continual market access decisions with an underlying objective of minimizing empty running, whereas in accessed markets (or during a loaded trip), they aim at maximizing the load factor.[4] We hypothesizes that in a competitive environment, the market access decision depends on variables pertaining to the characteristics of carrier, haul and truck. By and large the same variables determine the load factor, but there are a few that we use as exclusion restrictions which affect the probability of market access but not the load factor. The joint estimation proceeds with a Heckman (1979) type model with a structural model for the load factor and a reduced-form probit model for the market access decision.

The load factor (LF_i) is given by the following equation:

$$LF_i = B_1 X_1 + u_1 \tag{1}$$

where X_1 is a vector of explanatory variables and u_1 is a residual term. Observability of LF_i is conditional on the following market access equation:

$$L_i = \begin{cases} 1 \; if \;\; \delta_2 X_2 + v_2 \geqq 0 \\ \quad 0 \; otherwise \end{cases} \tag{2}$$

where $L_i = 1$ if a truck is loaded; X_2 contains all variables in X_1 and additional variables for identification (exclusion restrictions); and v_2 is a residual term. X_2 is always observed, regardless of L_i. The following assumptions are made for estimation (Wooldridge, 2001 p. 562):

- a. (X_2, L_i) are always observed, but LF_i is only observed when L_i =1;

  b. (u_1, v_2) is independent of X_2 with zero mean (X_2 is exogenous in the population);

  c. $u_1 \sim normal\ (0, 1)$;

[4] Note that in some situations, empty runs and sub-optimal capacity utilization are inevitable. Previous studies have shown lack of perfect information, fluctuations in shippers demand, and drivers working hour regulation may prevent full utilization of trucking resources (Powell et al, 2002). Lo and Hall (2008) also show that congestion can affect how well trucking companies perform in urban areas. Finally, incompatibility of vehicles and loads also usually result in empty backhauls for trucks which transport milk, fuel, chemical, logs etc. (McKinnon and Ge, 2006).

d. $E(u_1 \mid v_2) = \gamma_2 v_2$ (residuals may be correlated; e.g. bivariate normality).

Assumptions 'c' and 'd' imply that the covariance between the two error terms is γ_2. A specification problem arises if γ_2 is statistically different from zero suggesting that the residual in the load factor equation is correlated with the residual in the market access equation. The parameters of equations 1 and 2 will be estimated by full information maximum likelihood (FIML).

The joint estimation was selected because we are interested in the determinants of both the load factor and market access decision.[5] Modeling the load factor exclusively based on loaded trips by dropping empty trips, would introduce a sample selection problem because an empty trip does not necessarily imply that carriers were not offered a loading opportunity. They may have been offered the opportunity, but decided to run an empty truck due to higher costs than revenue (Beilock and Kilmer, 1986). Therefore, a joint estimation is needed to model the load factor to understand its determinants at a population level.

Barla et al (2010) estimate a variant of Equation 1 using a multinomial ordered probit model to find the effect of the IT capability of a truck on the load factor. In their specification, the load factor is classified into five discrete groups, and both loaded and empty trips are included in LF_i. Doing this implies that a single mechanism determines the load factor and the probability of being loaded. But, it is possible that trucks with a high probability of being loaded also tend to have a high load factor, and vice versa. The econometric specification should therefore account for and explain why some trucks have a higher load factor than others jointly with why some trucks tend to move loaded more frequently than others. The present study aims to give such an explanation by estimating a reduced-form probit model for the market access decision jointly with the load factor. Section 5.2 compares this modeling approach to other econometric techniques, namely the standard Tobit model (Amemiya, 1985) and the two-part model (Cragg, 1971), that could be used for this study. The following subsections present an outline of the relationship between the explanatory variables (X_1 and X_2) and the two dependent variables (LF_i and L_i).

[5] The methodology is usually referred to as discrete-continuous modeling in transport economics literature. It has been widely applied in many transportation problems (see Mannering and Hensher, 1987 for an excellent early review; see Heres-Del-Valle and Niemeier, 2011; Andersson et al. 2012 for recent applications).

3.1 Determinants of the load factor

The load factor can be measured in various ways. Here, it is defined as the percentage share of a truck's loading capacity that is filled with a cargo. Its level is constrained both by the weight and volume (density) of cargo. Ideally, both constraints should be taken into account when using the load factor as a capacity utilization measure. Unfortunately, our data does not contain an exact measure of volume, thus the following formula is used to calculate a weight based load factor measure:

$$LF_i(\%) = \frac{CW}{MC} \times 100 \tag{3}$$

where LF_i, CW and MC stand for the load factor, cargo weight (based on the estimation of the respondent) and the maximum legal carrying capacity of a truck, respectively. Carriers generally want to maximize the load factor for their trucks for two main reasons. First, it is conceivable that profit margins depend on how often carriers can have their truck filled to its potential. Second, the load factor is one of the key determinants of energy efficiency since a high load factor implies a higher level of tonne-kilometer (output) for a given vehicle-kilometer (input). The energy consumption, however, increases less than proportionally with the load factor over a distance. As indicated by Barla et al. (2010), a fully loaded truck consumes only about 20 % more fuel compared to an empty truck.

Given the above discussion, it is assumed that carriers generally want to maximize the load factor and its level depends on explanatory variables pertaining to characteristics of haul, truck and carrier. We control for two haul characteristics, namely the type of commodity carried and trip distance. Using dummy variables that indicate the commodity type of cargo carried, we capture the effect of density on the load factor. This reduces heterogeneity biases that may result from comparing high-density cargo with light and low-density cargo that fills up the vehicle space before the maximum carrying capacity (in terms of weight) is reached.

In addition to showing the effect of density, the commodity dummies reveal, to a reasonable degree, shipper characteristics and their effect on the load factor. To see the pure effect of density on the load factor, we include a dummy variable which indicates whether a cargo is voluminous or not based on the evaluation of drivers, and it is expected to have a negative effect on the load factor. As for the effect of trip distance, the load factor tends to be higher for trucks hauling cargo over a long distance because of the high opportunity cost of running partially filled trucks (Barla et al, 2010). Trip distance is, therefore, expected to have a positive effect on the load factor.

Truck size may affect the load factor in two opposite directions. On the one hand, carriers may find filling a smaller truck easier because it is easily maneuverable to aggregate loads from different shippers (Holguin-Veras, 2002). Carriers may also follow an optimization strategy of filling the smallest available truck with the largest available load. Smaller trucks, therefore, may tend to have a higher load factor than larger trucks (Fowkes, 2007). On the other hand, it is also possible that larger trucks are filled to their capacity more often than smaller trucks as carriers try to avoid the relatively high opportunity cost of running partially filled large trucks. This would reverse the effect of truck size on the load factor.

The likely explanation for the contradictory effects of truck size on the load factor is the non-linearity of truck size. While the range of a cargo size for shipment is more-or-less continuous, a truck's size is rather discontinuous, and trucks are classified in various vehicle classes. To uncover the two opposing effects of a truck's size on the load factor, we include two variables: size (measured by the number of axles) and the square of size. We expect a negative sign for the former reflecting that smaller trucks can easily be filled fully, and a positive sign for the latter reflecting the claim that carriers dislike operating larger trucks that are only partially filled. Finally, we expect that for-hire carriers will tend to have a higher load factor for their trucks compared to own-account shippers since they usually have more incentive and flexibility to find complementary demands than own-account shippers (Hubbard, 2003; Barla et al., 2010).

3.2 Determinants of market access

The market access decision, defined as the probability of being loaded, is captured by Equation 2. The vector X_2 include observable carrier, haul and truck characteristics such as carrier type, trip distance, and freight movement balance between regions, truck size, and age. Looking further at the effect of these variables, for-hire carriers are expected to have a better market access than own-account shippers because they have specialized staff engaged to find complementary demand (Hubbard, 2003). In contrast, own-account shippers may have a higher opportunity cost of market access because they often have prior commitments to proceed to other destinations to haul their firms' good (Wilson and Beilock, 1994). Therefore, we expect a positive sign for a dummy variable that takes a value equal to one if a truck is owned by a for-hire carrier or zero otherwise.

To capture the effect of haul characteristics on the market access decision, two variables are included: trip distance and a dummy variable that indicates the freight movement balance between regions. It is usually the case that the longer the trip distance, the higher will be the probability of market access since operating an empty truck over a long distance is costly. Between nearby locations, however, trucks may be seen running empty for repositioning or refueling purposes. It is also possible that finding complementary demand for short distance trips can be difficult, which would increase the chances of empty runs (Barla et al., 2010; Wilson and Dooley, 1993). Thus, trip distance is expected to affect the probability of being loaded positively.

The freight movement balance between regions is also an important determinant of the probability of getting a load since it affects the market access expectations of carriers. For instance, it is likely that carriers will more often get a return load from a net exporting region than from a net importing region. Conversely, the probability of empty running to a net importing region is lower since carriers usually make a loaded trip to the region because of slimmer chances of getting a return load (Beilock and Kilmer, 1986). To capture the effect of freight balance, we include a dummy variable which equals one if a trip is made toward a net importing region and zero otherwise.[6] And its effect on market access is expected to be positive.

Both the load factor and the market access decisions may also depend on fleet size. A small carrier (in terms of fleet size) may appear less efficient if it is forced to use a rather big truck for a small load compared with a larger carrier that can match its truck capacity with available load. As noted by Barla et al (2010) larger fleet size can also improve carriers' ability to find complementary demands. To test this hypothesis we include dummy variables which classify trucks according to the size of the fleet of which they are part.

The proposed joint estimation requires one or more variables that affect the market access decision but not the load factor. We use the freight balance dummy variables and the age of a truck as exclusion restrictions in the market access model (Eq. 2).We assume that a difference in freight flow between regions is more likely to affect how often a truck is

[6] The regions in our dataset are classified as net exporting and net importing regions based on the freight movement in our dataset (a physical measure) rather than a trade flow expressed in monetary unit. Since freight transport is a derived demand such a classification gives more sense to capture the underlying physical movement.

loaded, but not how intensively it is used during a loaded trip. With regard to the validity of age as an exclusion restriction, most likely a correlation between a truck's age and the load factor reflects variations in the probability of market access, but not variations in the level of capacity utilization during a loaded trip. This is a plausible assertion given the general trend that carriers tend to use their newer trucks more often to rest older trucks, especially when faced with excess capacity (Hubbard, 2003). There are two pieces of evidence in the data that support this assertion.

First, the age of a truck has a significant (at one per cent) and negative correlation with both the number of days a truck is used and the number of kilometers it is driven with a load, implying a preference for newer trucks. Second, we find a rather small but significant (at one per cent) and positive correlation between the load factor and age. This finding again implies that old trucks are loaded as full as new ones, if not more, during a loaded trip.

Finally, it should be noted that to fully capture determinants of capacity utilization more variables are required. The main focus in this study is on the variables discussed above because they explain most of the variation in the market access decision, at least in economic terms. There is also a data limitation: variables that capture market conditions that lead to trip generation are missing in our analysis. Controlling for whether a truck is tied up to serve a specific shipper (as in Beilock and Kilmer, 1986) during the survey period may explain why a carrier forgoes loading opportunities. The IT capability of trucks and additional carrier specific variables (such as membership of online load sharing arrangements) should also have been controlled for. The neglect of these variables, however, matters only in so far as they are correlated with the variables we control for. At this point we assume that there is no such a correlation and proceed with the proposed joint estimation. In Section 5.2 discusses the potential problems of this assumption and provide alternative models to address some of them.

4 Data

The main data source for the study is the Danish heavy trucks trip diary. The diary has detailed one week operational information. Statistics Denmark (DST), the statistics bureau in Denmark, has been collecting a sample of heavy trucks with a maximum legal carrying capacity of 6 tonnes and above since 1980.[7] The dataset is complied based on reports from truck owners, both for-hire and own-account shippers, across Denmark. DST granted us access to the trip diary for 2006 and 2007.

The dataset is best described as repeated cross-section because the trip diary is filled out for different trucks in every quarter. It has detailed one-week operational information on a trip by trip basis for about 3000 trucks. Since analyzing intercity truck movement is our main objective, we use a part of the data which comprises 18,176 trips made by 1921 trucks between 15 regions inside Denmark. The data contains information on vehicle type, commodity type, and cargo size and trip origins and destinations zones. All the stops a truck makes in a given day, for both loaded and empty runs, are recorded as separate trips.

The dataset contains three vehicle types of which rigid trucks constitute 28 per cent, semi-trailers 24 per cent and articulated trucks 48 per cent. The transported commodities are grouped to 28 different classes based on the standard Danish freight transport commodity classification. Three groups: food (15 per cent), construction (21 per cent) and general cargo (19 per cent) constitute the majority of the trips. Table 1 presents summary statistics of the main variables of interest.[8] One limitation of the data is that it does not have sufficient information to construct trip chains or truck tours (Section 5.2 discusses the implications of this limitation and ways to address it). But it has two unique features.

Firstly, it is the most disaggregate data on road freight transport which allows a detailed analysis of capacity utilization unparalleled in other studies. Unlike datasets used by previous studies which are relatively aggregate, our dataset is suitable for studying patterns of capacity utilization since it has a detailed (at a trip level) information for an individual truck. Although such a dataset exits in many European countries, accessing it is extremely difficult due to confidentiality reasons. Denmark is an exception on this regard; the dataset provided by the DST enabled us to undertake in-depth analysis of capacity utilization.

Secondly, similar to many small-sized countries, trucking is the dominant mode in

[7]The data covers truck operations within Denmark and contains most trucking activities with the exception of municipal waste collection and those that involve special vehicles (such as crane, trolley, snowplow, and sweeper etc) and private road. It is used for market monitoring, and as the main source of information for the Danish transport ministry and the European Commission (see Denmark Statistics, 2011 for details). The source of the fleet size variable is the MOTV register data for vehicles owned by Danish companies.

[8]The statistics are weighted only by their occurrence (i.e. trips). Applying the expansion factor given by Statistics Denmark did not result in significant difference in statistics of the main variables either on the intercity trips or the entire data.

Denmark (with 75 percent market share), and there is a limited scope for modal substitution. Improvement of capacity utilization within trucking is, therefore, very crucial for such countries (Bjørner 1999; Kamakaté and Schipper, 2009; Rich et al, 2011). The dataset presents a unique opportunity to gain insights into the performance road freight transport. Finally, the analyses and findings from this study can be a stepping stone to future studies on how to exploit similar datasets.

5 Results

5.1 Main results

Table 2 presents results from four different models based on the full information maximum likelihood (FIML) estimation.[9] All the continuous variables are in levels. We used two exclusion restrictions in the load factor equation (Eq. 1); that is in each model 'age' and the freight movement balance indicator, 'netimport', variables are included only in the market access equation (Eq. 2). In line with our expectation, these variables have significant (at one per cent) negative and positive effects on the probability of market access, respectively. The appropriateness of the joint estimation is confirmed by the significance of the correlation coefficient between the residual terms, rho, in the two equations. The result implies that the subsample of only loaded trips is not random (see Section 5.2 for more discussion).

Model 1 in Table 2, in addition to the main variables of interest, controls for the commodity class of a load to capture how the load factor differs between the various shippers served by carriers (the commodity dummies are not presented to save space but most of them are significant).[10] The commodity dummies partly reveal the effect of density on the load factor because there are differences in size and packaging requirements between commodities. To disentangle the dual effect of the commodity type, model 2 directly controls for the effect of density by using a dummy variable which indicates whether the carried cargo is voluminous or not. As expected, being a voluminous cargo has a significant

[9] A Heckit procedure, a two-step model similar to Heckman (1979), resulted in almost identical results with a significant and negative sign for the inverse Mill's ratio. But we opted for the FIML results which are proven to give more efficient estimates (Puhani, 2000).

[10] We cannot directly control for commodity type in the market access model because we are interested in the probability of being loaded or carrying a commodity. Instead, we tried to include commodity information (and thereby shipper characteristics) indirectly by using a dummy variable which indicates the typical commodity carried by each truck. But the attempt gave counter -intuitive results, probably due to an aggregation bias.

and negative effect on the load factor.

Truck size appears to have a negative effect both on the load factor and the probability of market access in Models 1 and 2. Inclusion of size-squared (size^2) in Model 3 reveals that the effect of size depends on the size of trucks, implying that size has an increasing effect on the load factor. Thus while an increase in truck size contributes to excess capacity for some range, its over-all effect appears to be positive. Figure 1 depicts the relationship between predicted load factors (based on truncated regression) and truck size. For the average truck (at the first vertical line) this relationship is negative; however, for truck with more than 6 axles it is reversed. We also note that in the third model, size does not seem to have any effect on the market access decision. Nonetheless, in line with our hypothesis the overall effect of truck size on capacity utilization appears to be non-linear.

In Model 4, fleet size, as expected, appears to have a positive effect on capacity utilization, implying that larger carriers are more efficient in using their loading capacity.[11] In all the models, distance (as expected) is shown to have a positive and significant effect (at one per cent) on both the load factor and the probability of market access. Its point estimates, however, are rather small. The co-efficient of 'for-hire' shows that being a for-hire carrier does not seem to have a significant effect on the market access decision, but it has a positive and significant (at one percent) effect on the load factor. The result confirms the hypothesis that for-hire carriers are more capable of aggregating loads for a given trip compared to own-account shippers.

The negative sign for rho may appear anomalous since most studies based on sample selection models get a positive sign for it. In our context, a positive sign might also sound more 'plausible', because the unmeasured effects that increase the chances of market access are also likely to increase the load factor. A negative correlation, however, implies that a truck that carries a load, when it is predicted to be unlikely to be loaded on the basis of the market access equation has a lower load factor than would be predicted from the load factor equation on the basis of the measured characteristics. A negative correlation is not uncommon in the literature, and we can give the following two explanations:

First, it is important to note that there is no prior reason to expect a positive relationship between the two error terms. A theoretical paper by Ermisch and Wright (1994) shows that a negative correlation can arise if the variance of the error term in the struc-

[11] But we found this effect to be sensitive to various fleet size classifications (the reported classification is based on quartiles). This is possibly due to multicollinearity. The fleet size variables may pick the effect of the carrier type dummy, because usually for-hire carriers happen to have larger fleet size.

tural equation (in our case the load factor equation) is less than the variance of the error term for the latent variable in the reduced-form probit equation (in our case the market access equation). That is, given the exogenous variables in the load factor and the market access equations, the load factor exhibits less dispersion than the latent variable. As indicated in Section 3, our estimates are based on the assumption that a higher level of load factor leads to a larger profit. In fact, implicit in the market access probit equation is an optimization process where carriers access a market if net profit is greater than or equal to zero. Therefore, it is possible that the dispersion of net profit, the latent variable, is greater than the dispersion in the load factor, resulting in a negative correlation between the two residual terms.

A second explanation for the negative correlation is related to carriers' expectations. For a truck in a backhaul trip it is usually difficult to get a return load. A carrier may, therefore, choose to carry a small load (implying a lower load factor) instead of running empty if freight rates cover market access costs (implying less empty running). A negative correlation can also occur because of carriers' tendency to have a higher level of load factor on trucks for which there is no anticipated return load than on trucks expected to be loaded in both a front-haul and backhaul directions. Similarly, carriers may forego a loading opportunity in outbound direction (Barla et al. 2010) if they anticipate a backload leading to a negative correlation between the probability of market access and the load factor.[12]

Table 3 reports elasticity estimates of the main explanatory variables. Panel A and Panel B display the percentage changes in the probability of loaded trip and the load factor for loaded trips, respectively. The estimates show that the dependent variables are rather inelastic, on average. The relative elasticities of the variables are, however, revealing. Distance has the highest impact in the probability of loaded trips. Figure 2 shows interesting patterns of the relative elasticities of the age and size of a truck for different distance bands. As seen, their elasticities greatly differ by distance. At the average trip distance (120 km), there is about 0.5 percentage point difference. Interestingly, for trips longer than 550 km both elasticities virtually reduce to zero. This finding implies that for farthest trips, we see loaded trips regardless of the characteristics of the truck.

[12] As one of the anonymous referees pointed out, there are fundamental differences between intercity versus intracity markets that are not fully captured in the data and this in turn may translate into a selectivity problem.

5.2 Robustness checks

This section presents alternative estimates to check the robustness of the main results. The first part of this section provides estimates using truck level data to test the importance of the interdependence between trips made by the same truck. The second part compares the joint model presented in Table 2 to alternative models such as the Tobit model and the two-part model.

The econometric model in Section 3 is based on the assumptions that all trips made by a truck are independent, but some of the trips might be part of a trip-chain or a tour. If so, both the market access decision and the load factor may not be determined at an individual trip level (as is assumed here); so, the interdependence between trips within a trip-chain should be controlled for. To address this problem we look at determinants of capacity utilization at a truck level. We now re-define capacity utilization as the average load factor and the number of loaded trips made by each truck per week. Despite the problems that may result from aggregation of variables from a trip to a truck level, each observation now comes from an individual truck in the sample, and independence is achieved by definition.[13]

We use most of the explanatory variables in Section 3 and maintain similar hypotheses. Following Hubbard (2003), we specify the following multivariate regression:

$$TLF_i = \alpha_1 Z_{1i} + e_{1i} \tag{4}$$

$$TLT_i = \alpha_2 Z_{2i} + e_{2i} \tag{5}$$

where TLF_i is the average load factor during loaded trips per truck i; Z_{1i} includes carrier, haul, and truck characteristics; TLT_i stands for the share of loaded trips, Z_2 contains all the variables in Z_1 and truck age. We also estimate an alternative two-equation system where TLF_i is measured based on all trips (including both empty and loaded trips), and TLT_i is redefined as the number of trips per truck per day. Such a truck level analysis adds more realism to our analysis if the main variables of interest have similar influence on the two vehicle utilization indicators (the share of loaded trips per

[13] This comes at a cost, each truck is now assumed to carry only one commodity, the one that is transported most frequently, though it may carry more. In addition, as a result of aggregation we lose some trip level information: freight movement balance between regions and volume of a cargo. The presence of other control variables in the dataset, however, makes this problem less serious.

truck and the number of trips per truck per day). Following the discussion in Section 3, an important identifying assumption is that correlations between truck age and the load factor reflect only differences in the number of periods in use, and not differences in load factor per period in use.

As with our main findings, the estimated coefficients for Model 1 in Table 3 have the signs we expect except for the coefficient of for-hire which is now negative, but not significant. Other things being equal, trucks owned by for-hire carriers have a higher load factor, and longer trips have higher predicted load factor and share of loaded trips. The coefficients on size and size squared imply that size has an increasing effect on load factor, but neither has a statistically significant effect on the share of loaded trips. More-or-less similar results hold in Model 2, where the dependent variables are the load factor defined for all trips and the number of trips per day. Understandably, the effect of distance on the number of trips made per day is negative. Older trucks are estimated to make fewer trips. In both models the errors across the two equations appear to be negatively correlated. Interestingly, this result is in line with the effect of rho in Table 2.

To test whether the decisions on the empty/loaded movement and on the load factor are determined by the same process, we can compare the fit of the Tobit model and other more flexible models, such as the two-part model (Cragg, 1971), and the Heckman model (Wooldridge,2010). Note that unlike the Tobit model these two models assume that the dependent variables are determined by separate processes. Based on the results on Table 4, the likelihood ratio test (LR test) shows that the single process assumption of the Tobit model can be rejected at the 1 per cent level against the alternative two-part model. Normality and homoskedasticity tests also showed that the Tobit model results in a poor fit. As for the choice between the two-part and the Heckman models, since the two models are not nested we cannot perform the LR test. Alternatively, as suggested by Leung and Yu (1996) a test of rho = 0 in the Heckman model can be used to test the null hypothesis that the two-part model is correct. As discussed in section 5.1, the null hypothesis (rho = 0 or the correlation between the error terms in Eq. 1 and Eq. 2 is zero) is rejected at the 5 per cent level. Given these findings, the joint model (i.e. the Heckman model) used in the paper is appropriate and supported by the data.

6 Conclusions and policy implications

This paper has analyzed the underlying determinants of two important aspects of capacity utilization in road freight transportation: the extent of empty running and the load factor. Detailed information about a truck's operation at a truck and trip level made it possible to model the empty/loaded movement decision and the load factor jointly. Trip distance is shown to have a positive effect on both the load factor and the probability of loaded trips. Furthermore, while being a for-hire carrier does not appear to have a significant effect on the probability of being loaded, it has a positive and significant effect on the load factor. This confirms the premise that for-hire carriers are more capable of aggregating loads from different shippers than own-account shippers. Interestingly, the carrying capacity of a truck appears to have a negative effect on the load factor, but a significant and positive coefficient for its squared term shows that the effect is non-linear.

Admittedly, capacity utilization in road freight transportation is complex and it cannot be fully explained by an econometric model nor easily be changed by policy levers. It is, however, possible to draw the following policy implications from this paper. First, the relationship between distance and utilization can be seen as the relationship between the variable cost of operating a truck (which is positivity correlated with distance) and utilization. Thus one implication of the present study is that, in the face of policies or exogenous shocks which raise the variable cost of trucking operation, firms will improve the utilization of their trucks.

Second, since for-hire carriers have better capacity utilization, trucking regulation could conceivably be used to change the balance between for-hire and own-account carriers in favor of the former. Third, the effect of truck size implies that while an increase in truck size contributes to excess capacity to some extent, its overall effect is probably positive. Allowing bigger trucks on the roads, therefore, does not necessarily lead to lower utilization. This analysis can be seen as a first step on the way to finding the effect of truck size on capacity utilization, but this issue needs a closer analysis, and more data to reach clearer conclusions. Finally, in future studies the findings of this paper and the proposed model can be used to quantify the effect of policy interventions, such as road pricing, on the load factor and extent of empty running.

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Table 1. Summary statistics

Variable ID	Variable discription	Avg./%	Std. dev.
LF	Load factor for loaded trips	53%	33
	Load factor for all loaded trips	36%	36
Distance	Trip dstance (km)	120	100
MC	Maximum legal carrying capacity (tonnes)	28	13
Size	Number of axles	4.8	1.5
Fleet	Fleet Size	37.6	76
CW	Cargo weight (tonnes)	14.1	19.4
Age	Age of truck (years)	3.76	3.5
L	1 if a truck is loaded	69%	0.46
For-hire	1 if a truck is owned by a for-hire carrier	86%	0.35
Net-importer	1 if a trip is made towards a net importing region	42%	0.49
Voluminous	1if a cargo is voluminous	6%	0.23

Source: The Danish Heavy Vehicles Trip Diary, 2006 and 2007 and MOTV vehicle registration data, 2006 and 2007. All the statistics are calculated at trip level. Statistics for the Cargo size variable are based on loaded trips only.

Table 2 : FIML Heckman Model estimates

Variables	Model 1	Model 2	Model 3	Model 4
Load Factor Equation (LF)				
For-hire	0.0645***	0.0654***	0.0680***	0.0680***
	(0.021)	(0.021)	(0.021)	(0.021)
Distance	0.0003***	0.0004***	0.0004***	0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.0400***	-0.0401***	-0.1238***	-0.1225***
	(0.005)	(0.005)	(0.029)	(0.030)
Voluminous		-0.1032***	-0.1021***	-0.1026***
		(0.021)	(0.021)	(0.020)
Size2			0.0096***	0.0094***
			(0.003)	(0.003)
Fleet size 5-12				0.0019
				(0.019)
Fleet size 13-33				0.0208
				(0.018)
Fleet size > 33				-0.0078
				(0.017)
Commodity fixed effects	Included	Included	Included	Included
Constant	0.6076***	0.6040***	0.7628***	0.7632***
	(0.049)	(0.049)	(0.077)	(0.077)
Rho	-0.1545**	-0.1545**	-0.1489**	-0.1568**
	(0.074)	(0.070)	(0.071)	(0.067)
Sigma	-1.2659***	-1.2706***	-1.2732***	-1.2732***
	(0.017)	(0.017)	(0.017)	(0.016)
Market Access Equation (L)				
For-hire	0.0222	0.0220	0.0222	0.0188
	(0.041)	(0.041)	(0.041)	(0.042)
Distance	0.0043***	0.0043***	0.0043***	0.0043***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.0373***	-0.0374***	-0.0471	-0.0514
	(0.011)	(0.011)	(0.071)	(0.070)
Size2			0.0011	0.0018
			(0.008)	(0.008)
Fleet size 5-12				0.0957**
				(0.046)
Fleet size 13-33				-0.0260
				(0.045)
Fleet size > 33				0.0533
				(0.043)
Age	-0.0096**	-0.0097**	-0.0099**	-0.0088*
	(0.005)	(0.005)	(0.005)	(0.005)
Net-importer	0.1418***	0.1416***	0.1406***	0.1412***
	(0.046)	(0.046)	(0.046)	(0.046)
Constant	0.1875***	0.1883***	0.2082	0.1786
	(0.068)	(0.068)	(0.146)	(0.147)
Log.Likelihood	-12371	-12365	-12306	-12279
No. Of observations	L= 18,176 , LF = 12655			

Note: Clustered standard errors, at vehicle level, in parentheses. *** p<0.01, **p<0.05,*p<0.1

Table 3: Elasticity estimates

Panel A : Marginal effects (% Δ) for P(Loaded = 1)	
For-hire	0.010
	(0.015)
Distance	0.18***
	(0.005)
Size	-0.077**
	(0.029)
Age	-0.019***
	(0.006)
Net-importer	0.071***
	(0.01)
Panel B : Marginal effects (% Δ) for (Load factor / Loaded = 1)	
Distance	0.067***
	(0.01)
Size	-0.171***
	(0.054)

Note: Standard errors, in parentheses, calculated by the Delta-method. Significance is marked *** p<0.01, ** p<0.05, and * p<0.1. The marginal effects are a 1 % increase for the continuous variables and a discrete change from the base level for dummy variables.

Figure 1: Load factor and truck size

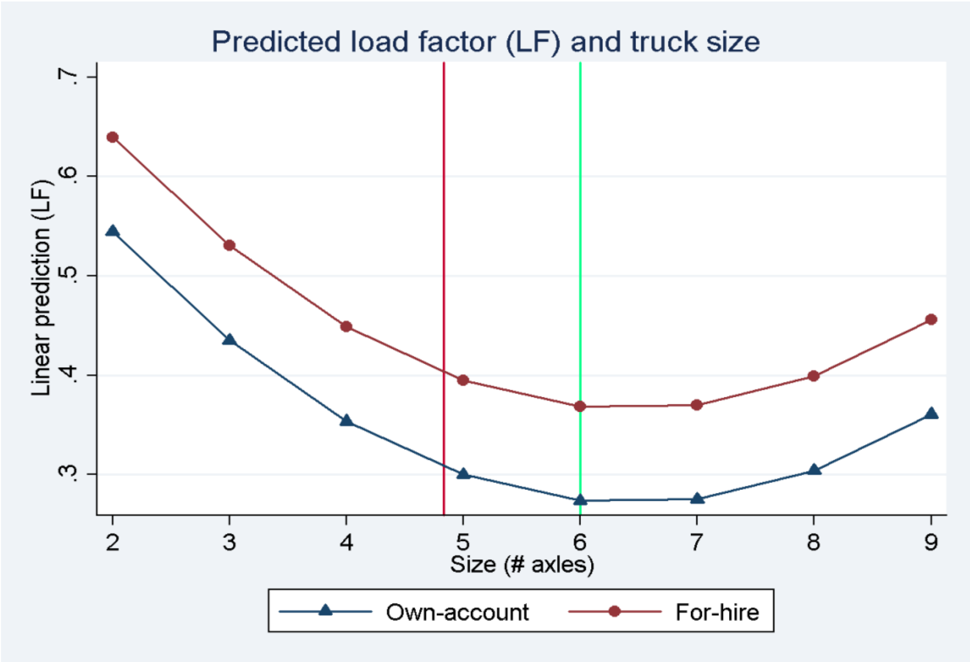

Figure 2: Marginal effects of truck characteristics and distance

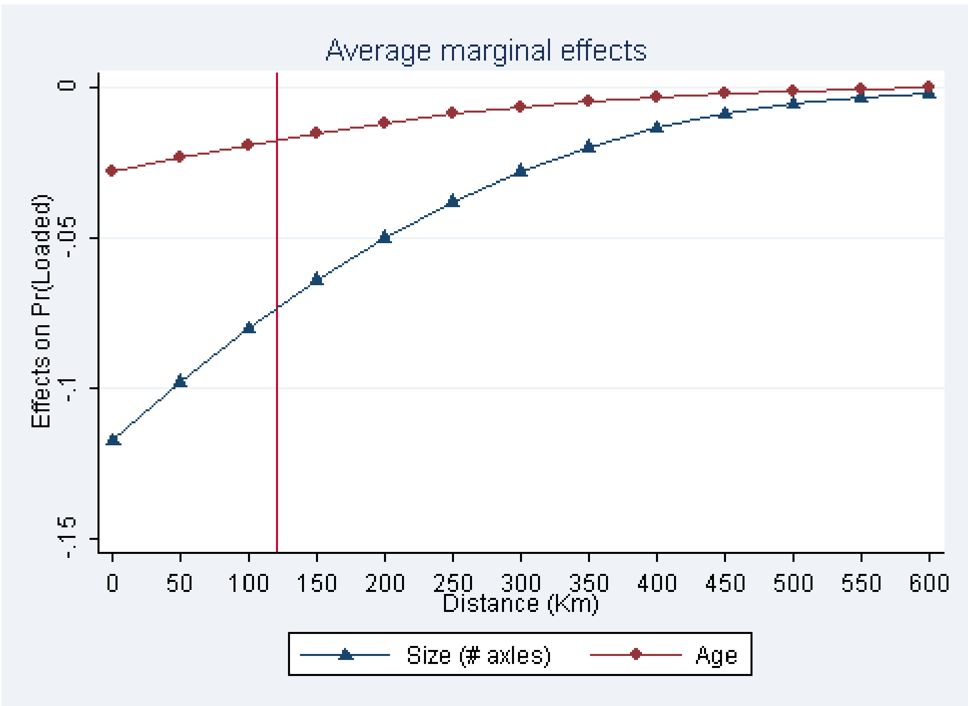

Table 4: Alternative Estimates

Variables	OLS	Tobit	Two-part	
			Pr(L=1)	E(LF|L=1)
For-hire	0.0235	0.0279	0.0203	0.056
	(0.015)	(0.019)	(0.042)	(0.037)
Distance	0.0007***	0.0011***	0.0043***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.0860***	-0.0970***	-0.0537	-0.1773***
	(0.027)	(0.033)	(0.07)	(0.051)
Size2	0.0088***	0.0096***	0.0021	0.0192***
	(0.003)	(0.004)	(0.008)	(0.006)
Fleet size 5-12	0.0012	0.011	0.0942**	-0.0348
	(0.017)	(0.029	(0.046)	(0.037)
Fleet size 13-33	-0.0087	-0.0136	-0.0247	-0.0087
	(0.016)	(0.02)	(0.045)	(0.035)
Fleet size > 33	-0.0219	-0.0181	0.0534	-0.0750**
	(0.015)	-0.018	(0.043)	(0.034)
Age	0.0030*	0.0023	-0.0096**	0.0116***
	(0.002)	(0.002)	(0.004)	(0.003)
Net-importer	0.0166	0.0315*	0.1422***	-0.0136
	(0.012)	(0.017)	(0.046)	(0.019)
Constant	0.4350***	0.3184***	0.1877*	0.666***
	(0.058)	(0.071)	(0.147)	(0.011)
R-squared	0.043			
Log.Likelihood		-13359	-12928	
Observations	18,176	18,176	18,176	12,637

Note: Clustered standard errors, at vehicle level, in parentheses. *** p<0.01, **p<0.05,*p<0.1

Table 5: Multivariate (SUR) estimates

	Variable	Model 1	Model 2
	For-hire	0.0453**	0.0297**
		(0.017)	(0.014)
	Distance	0.0004***	0.0008**
		(0.0001)	(0.0001)
	Size	-0.0813	-0.0914***
α_1 vector		(0.025)	(0.022)
	Size2	0.0047	0.0062**
		(0.003)	(0.003)
	Commodity fixed effects	Included	Included
	Constant	0.9002***	0.6304***
		(0.058)	(0.050)
	For-hire	-0.002	0.352***
		(0.013)	(0.101)
	Distance	0.0009***	-0.0062***
		(0.000)	(0.0004)
	Size	-0.0294	0.2687
		(0.019)	(0.151)
α_2 vector	Size2	0.0017	-0.0086
		(0.002)	(0.017)
	Age	-0.0021	-0.044***
		(0.001)	(0.009)
	Commodity fixed effects	Included	Included
	Constant	0.6604***	1.626***
		(0.047)	(0.362)
	Cross model correlation	-0.0410	-0.0550
	System weighted R-Square	0.2268	0.1911
	No. Observations	1921	1921

Note: Standard errors in parentheses. Significance is marked *** p<0.01, ** p<0.05, and * p<0.1.

CHAPTER III

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.

Keywords: Vehicle Choice; Shipment Size; Discrete-Continuous Models;

JEL classification : R0, L91

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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). 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 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.

[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).

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 to 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 theroectical 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 and Sections 6 summrizes 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; Holguín-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.[2] 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, Holguín-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 Holguín-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 problem that most selection models suffer from. But, unlike the above studies, 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 robustness check for the main results, the paper presents alternative estimates based on the indirect approach suggested by Holguín-Veras (2002) and Johnson and de Jong (2011).

[2] 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).

3 Conceptual framework

The determinants of vehicle/mode choice and shipment size are usually derived from shipment size optimization theory (Baumol and Vinod, 1970 and de Jong and Ben-Akiva, 2007). 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).[3] Put differently, larger shipment size for higher demand and for longer trips is due to decreasing unit transport cost.

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. 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 port or terminal-handling costs, inventory holding costs, and transport costs.[4] 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, 2001; Shirley and Winston, 2004; de Jong and Ben-Akiva, 2007; Combes, 2011).

[3] 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.

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

Below we present the basic structure of the theory based on McCann (2001)[5], followed by a discussion of the main hypotheses of the model. Assume that the per-period total logistics cost (TLC) for firm i is given by[6]:

$$TLC_i = \frac{Q_i S_i}{q_i} + \frac{I q_i (c_i + t_i d_i)}{2} + t_i d_i Q_i \tag{1}$$

where Q_i is the total per-period shipment quantity (tonne/period); S_i is terminal cost (\$/vehicle); q_i is the individual shipment size (tonne/vehicle); I is the inventory capital holding coefficient (%/period); c_i is the Free On Board (FOB) purchase price of good (\$/tonne); t_i is the transport charge (\$/tonne-kilometer); d_i is the haulage distance (kilometer). The first term on the right-hand side is the total terminal handling costs which are independent of the capacity of a vehicle. The second term is the inventory/stock holding cost that can be further split into two components: $\frac{I q_i c_i}{2}$, the average stock holding cost, and $\frac{I q_i t_i d_i}{2}$, the inventory cost during transit.[7] The final term is a transport movement cost that is incurred when goods are moved. Minimizing TLC_i with respect to q_i results in the following:

$$q_i^* = \sqrt{\frac{2 Q_i S_i}{I(c_i + t_i d_i)}} \tag{2}$$

Eq. 2 implies that the optimized shipment size q^* falls as the haulage distance d_i increases. But this is counter-intuitive given empirical evidence that shows on longer trips, larger shipment sizes and therefore larger vehicles are usually chosen (Kendall, 1972; Jansson and Shneerson, 1982). According to McCann (2001), the reason for this incongruous result is that in reality t_i will also be a function of q_i, and q_i is a function of t_i, that is there is no closed form solution for the problem. McCann shows that defining the transport cost component in Eq. 1 as a vehicle movement cost results in a shipment size solution consistent with the empirical evidence. A key insight in his analysis is that for a fixed total tonnage of goods to be shipped per time period, the per tonne-kilometer cost

[5] McCann's formulation is used because it allows a unified framework to analyze the optimal shipment size and the optimal vehicle size as part of the same optimization problem. Furthermore, it explicitly adds a spatial dimension and transport cost to the basic theory, both of which are important elements in our empirical model.

[6] This specification assumes that goods are delivered and consumed at a constant rate and there are no stock-outs (i.e. replenishments are instant). And the firm is assumed to be an own-account shipper. If factory gate pricing is assumed, the formulation can also apply to a for-hire carrier. 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.

[7] The latter represents interest cost associated with labor and fuel operating costs incurred during transit (McCann, 2001).

t_i depends on the weight of the individual batch shipment q_i. To incorporate this insight in the optimization problem, we first define vehicle movement cost as $v_i = a + bq_i$, where a and b are the intercept and slope parameter values across the range of vehicle choices available. Assuming that the logistics planner has access to multiple vehicles and can always make sure that individual shipments take place as full-load shipments, a transport rate function can now be given as[8]:

$t = \frac{a+bq}{q} = \frac{a+bq^*}{q^*} = \frac{a}{q^*} + b$

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

$$TLC_i = \frac{Q_i S_i}{q_i} + \frac{I q_i c_i}{2} + \frac{I q_i (\frac{a}{q_i} + b) d_i}{2} + (\frac{a}{q_i} + b)\ d_i Q_i \tag{3}$$

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

$$q_i^* = \sqrt{\frac{2Q_i(S_i + ad_i)}{I(c_i + bd_i)}} \tag{4}$$

Eq. 4 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 relative to the carrying capacity of a vehicle (i.e. $a > b$). 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 value of a shipment (c_i) and its inventory

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

[9] Note that the solution given in Eq. 4 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 (m^3) 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's 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

capital holding cost (I) increase, the optimal shipment size decreases.

To test the main hypotheses of the model empirically, we can take the logarithm of Eq. 4 and add a stochastic component. This is possible for estimation of the optimal shipment size, but when 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

$$q_v^* = \beta_v X + u_v \tag{5}$$

$$U_v^* = \gamma_v Z + \eta_v, \tag{6}$$

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 γ_v are parameters to be estimated, u_v and η_v are idiosyncratic terms. The conceptual framework section established that total freight demand (Q) and shipment distance (d), and various

to be taken into account to find the true effect of distance on the optimal vehicle size. In our econometeric model, we control for the effect of vehicle age.

[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).

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^* conditional on every feasible alternative. Thus conditional on X, it is observed to ship q^* by alternative v if the net-benefit of shipping by vehicle type v is greater than any type j, that is

$$U_v^* > \max(U_j^*) \tag{7}$$

Note that the two error terms, u_v and η_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. In fact, 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;

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

Bourguignon et al., 2007). Bourguignon et al. (2007) propose alternative estimators based on Dubin-McFadden (1984) but allowing for a general distribution of u_v, in particular, the normal distribution. Their Monte Carlo studies show that the alternative estimators are more robust in various data generating processes. What follows presents the basic structure of the 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 η_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 η_v is distributed extreme value type I, the probability that vehicle v is preferred is given by P_v

$$P_v = \frac{\exp(\gamma_v Z)}{\sum\limits_v \exp(\gamma_v Z)} \tag{8}$$

The selectivity correction procedure involves using the parameter estimates from the choice model to construct the selectivity correction terms, appending these to Eq. 5 to get the following

$$q_v^* \;= \beta_v X + \mu(P_1, ..., P_V) + w_1 \tag{9}$$

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.5) 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. For example, we would know if a vehicle is carrying more or less shipment when it is observed in the shipment size equation of another vehicle.

The various methods of estimating Eq. 9 differ in the kind of restrictions they impose on $\mu(P_1, ..., P_V)$. Dubin and McFadden (1984) assume an important linearity condition

$E(u_v \mid \eta_1 ... \eta_V) = \sigma \sum_{v=1..V} r_v(\eta_v - E(\eta_v))$

where, where r_v is a correlation coefficient between $u_1$and η_v, and by construction it sums to zero ($\sum_{v=1...V} r_v = 0$). They showed that OLS estimates of β_v from the following equation will be consistent:

$$q_1^* = \beta_v X_1 + \sigma \sum_{v=2 \ldots V} r_v \left(\frac{P_v \ln(P_v)}{1 - P_v} + \ln(P_1) \right) + w_1 \tag{10}$$

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 extereme 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 consider both methods in this paper.[13] Finally, it is important to note that the econometric framework presented in this section relies on the IIA assumption. Violation of this assumption could, therefore, compromise our results. To test the importance of this assumption Section 5.2 gives alternatives results based on the mixed multinomial logit model.

5 Data and empirical results

5.1 Data

The primary data source for this research was the Danish heavy trucks trip diary for 2006 and 2007. 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 (2012), respectively. Together, these datasets provide detailed operational information for modeling the joint decision of shipment size and vehicle choice. 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).

These datasets, however, do not include detailed information on the origin and destination of a trip, total shipment demand per period, or commodity price (for calculation of

[13] The STATA selmlog command developed by Bourguignon et al. (2007) was used to estimate the two D/C models.

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.[14] 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.[15] 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. 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.

[14] 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.

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

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 based on the mixed MNL model to check the robustness of the main results.

5.2.1 Main results

Table 3 presents coefficient estimates from Eq. 8, 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 $\gamma_1 = 0$ and $\beta_{12} = 0$ is imposed. The estimates for cost show that it is statistically significant at the 1% level, and, as expected, reduces the probability of choosing a vehicle.[16] 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 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)[17] 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. 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

[16] 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.

[17] The cargo density dummy indicates whether a cargo is voluminous or not based on the evaluation of truck drivers.

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 (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 elasticities for selected variables from Table 3. These elasticities are average marginal effects which show the percentage change in the probability of choosing a vehicle for a 1% change in the continuous explanatory variables or a discrete change from the base category for the dummy variable. As shown, a 1% 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 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 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.[18] 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.

Figures 2, 3 and 4 display probability plots for total and variable costs based on the

[18] 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.

MNL models presented in Tables 3 and 5, respectively. 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.

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.[19] 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.[20]

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.[21]

[19] Results from the alternative model based on Bourguignon et al. (2007) are reported on Table 8. They are more-or-less similar to the ones in Table 7, but include five correction terms, as opposed to the four in Table 7, for each alternative.

[20] 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.

[21] 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.

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

5.2.2 Robustness checks

It is instructive at this point to discuss the potential limitations of the econometric results presented above and the procedure used to get around them. The main limitation is the distributional assumption required to make the estimation of the MNL model computationally tractable: the alternative errors are independently and identically distributed (that is the IIA assumption). Violations of the IIA assumption would compromise the results. One way to fix this problem is to model the vehicle selection, Eq. 8, 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

$$U_v^* = M\theta + \phi q_v + \varepsilon_k + \eta_v \tag{11}$$

where, $v = (1, \ldots V)$ 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 $\varepsilon_k \sim N(0, \Sigma)$. This specification mimics a vehicle class/type based nested logit model which is shown in Figure 5.

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 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.[22] The second variable is a cargo-vehicle-fit variable which is defined as

$$L_v = |MC_v - q_v| \tag{12}$$

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, forthcoming; 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:

$$q_v^* = H\delta + \zeta \tag{13}$$

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

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

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 9 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, 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 5.1 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. 11. 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 supports the IIA assumption, and thus the results from the selection model in this respect can be relied upon.

6 Summary

This paper has developed a discrete-continuous model of shipment size and vehicle size class choice. Similar models have been used before in freight transport, but mainly to study the shipment size and mode choice decisions. As explanatory 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.

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. The difference in the effect of operating cost and total cost has important policy implications. For instance, in the face of policies (or exogenous shocks) which raise the variable cost of trucking operations firms prefer to use heavier vehicles. On the other hand, policies or other changes which increase fixed costs and therefore total costs make firms to use smaller vehicles. A possible extension of 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	-0.231***	-0.364***	-0.613***	-0.443***
	(0.0310)	(0.0301)	(0.0310)	(0.0299)
Age	0.0350***	-0.0392***	-0.121***	-0.185***
	(0.00813)	(0.00789)	(0.00834)	(0.00821)
Log. fleet	0.460***	0.488***	0.364***	0.450***
	(0.0347)	(0.0338)	(0.0350)	(0.0335)
Log. demand	0.156***	0.152***	0.520***	0.561***
	(0.0387)	(0.0371)	(0.0392)	(0.0375)
Voluminous	-0.415***	-0.849***	-0.136	-0.103
	(0.104)	(0.107)	(0.109)	(0.0982)
For-hire	0.587***	1.344***	2.226***	2.707***
	(0.0767)	(0.0740)	(0.0801)	(0.0773)
constant	-0.819**	0.762**	-1.325***	-2.066***
	(0.384)	(0.364)	(0.384)	(0.370)
Observations	39,420			
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 (%)
Log. cost	0.424***	0.193***	0.059***	-.189***	-0.018**
	(0.028)	(0.015)	(0.007)	(0.009)	(0.007)
Age	0.099***	0.134***	0.059***	-0.022***	-0.086***
	(0.007)	(0.004)	(0.0024)	(0.002)	(0.0025)
Log. fleet	-0.428***	0.033**	0.059***	-0.064***	0.022**
	(0.031)	(0.015)	(0.008)	(0.01)	(0.007)
Log. demand	-0.371***	-.215***	-.218***	0.15***	0.19***
	(0.034)	(0.02)	(0.011)	(0.013)	(0.10)

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 (%)
Log. distance	-0.33***	-0.18***	-0.20***	0.10***	0.19**
	(0.03)	(0.016)	(0.007)	(0.009)	(0.007)
Log. 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

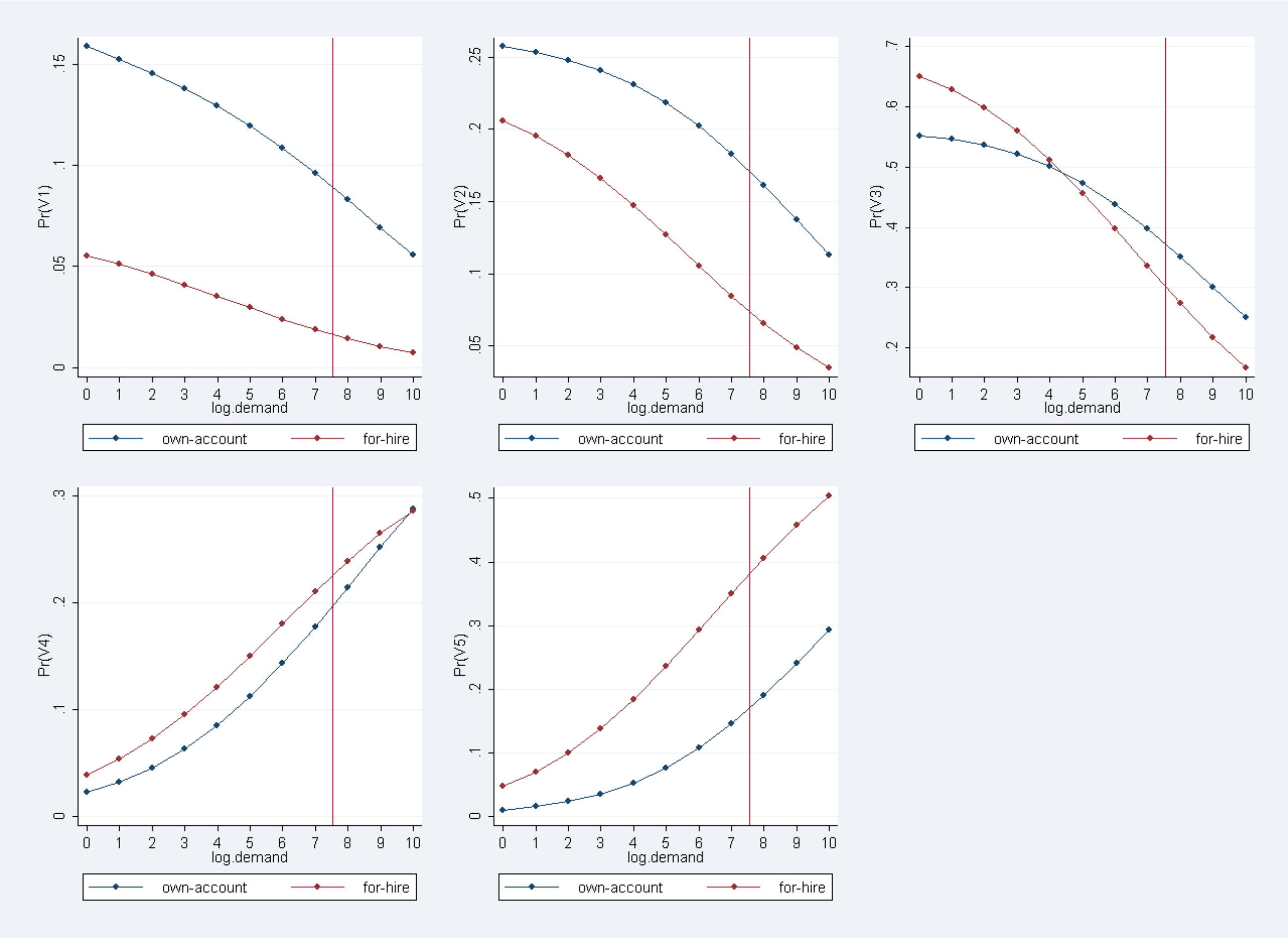

Figure 2: Probability of vehicle choice and total cost

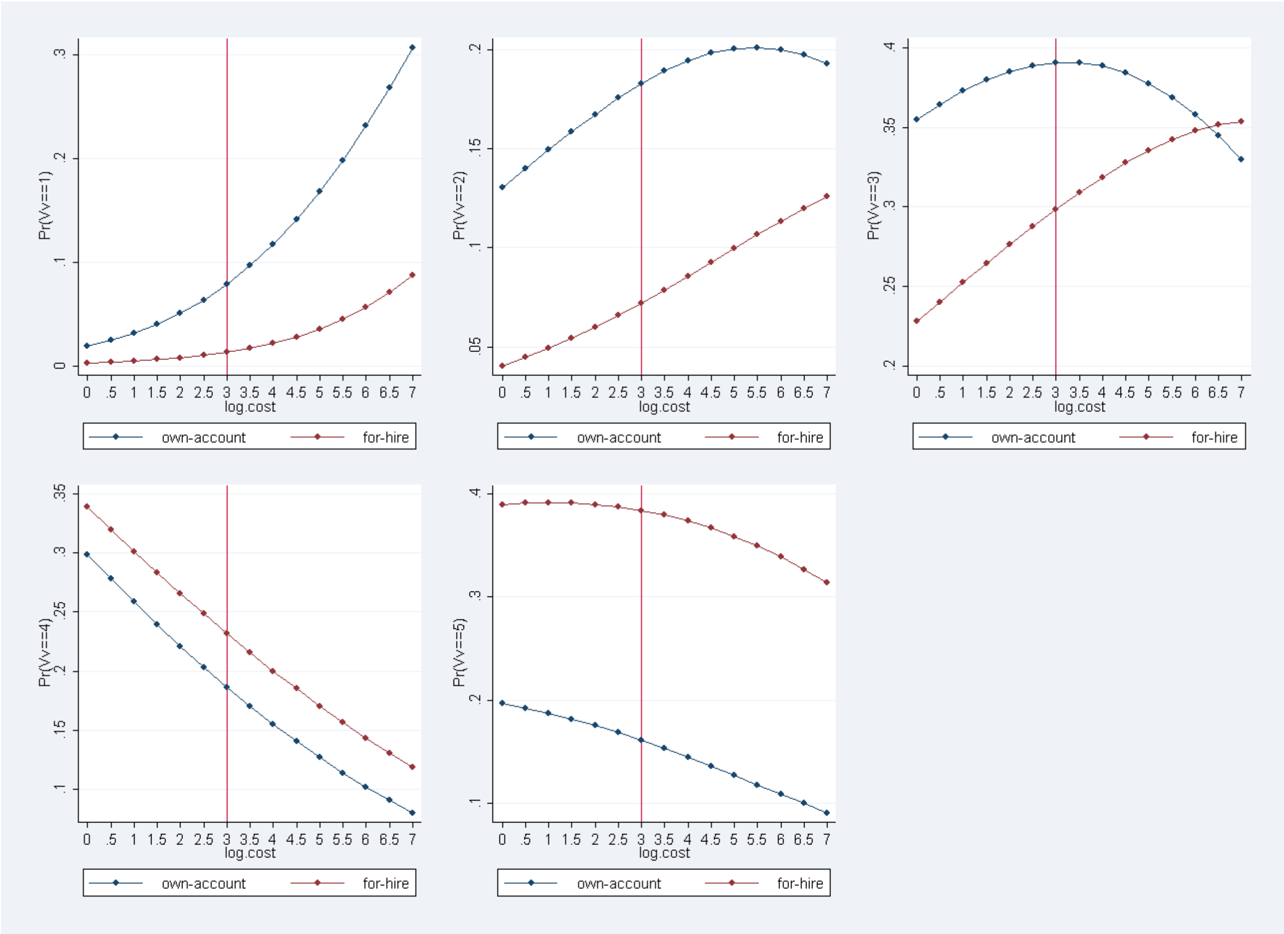

Figure 3: Probability of vehicle choice and fuel price

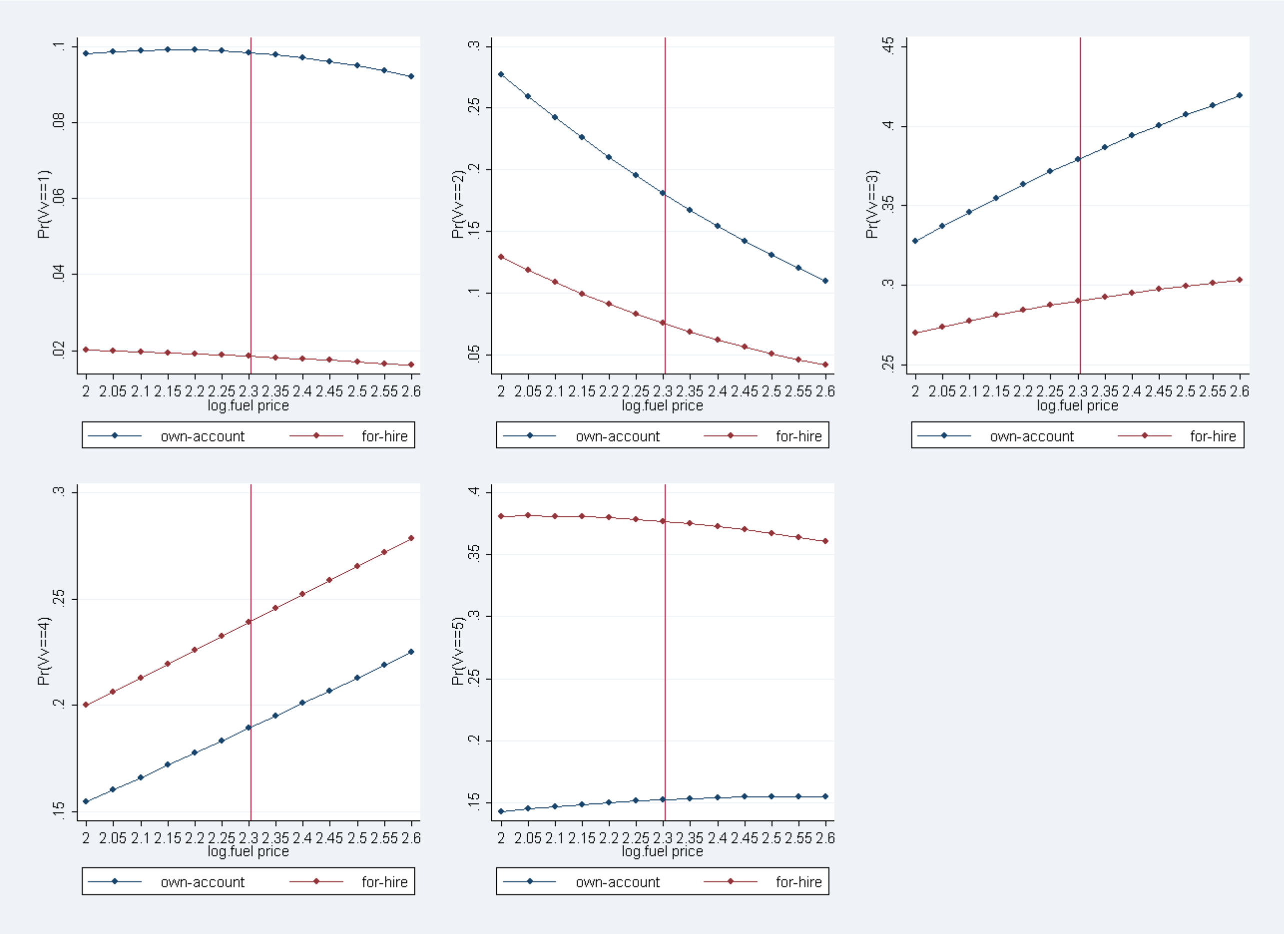

Figure 4: Probability of vehicle choice and trip distance

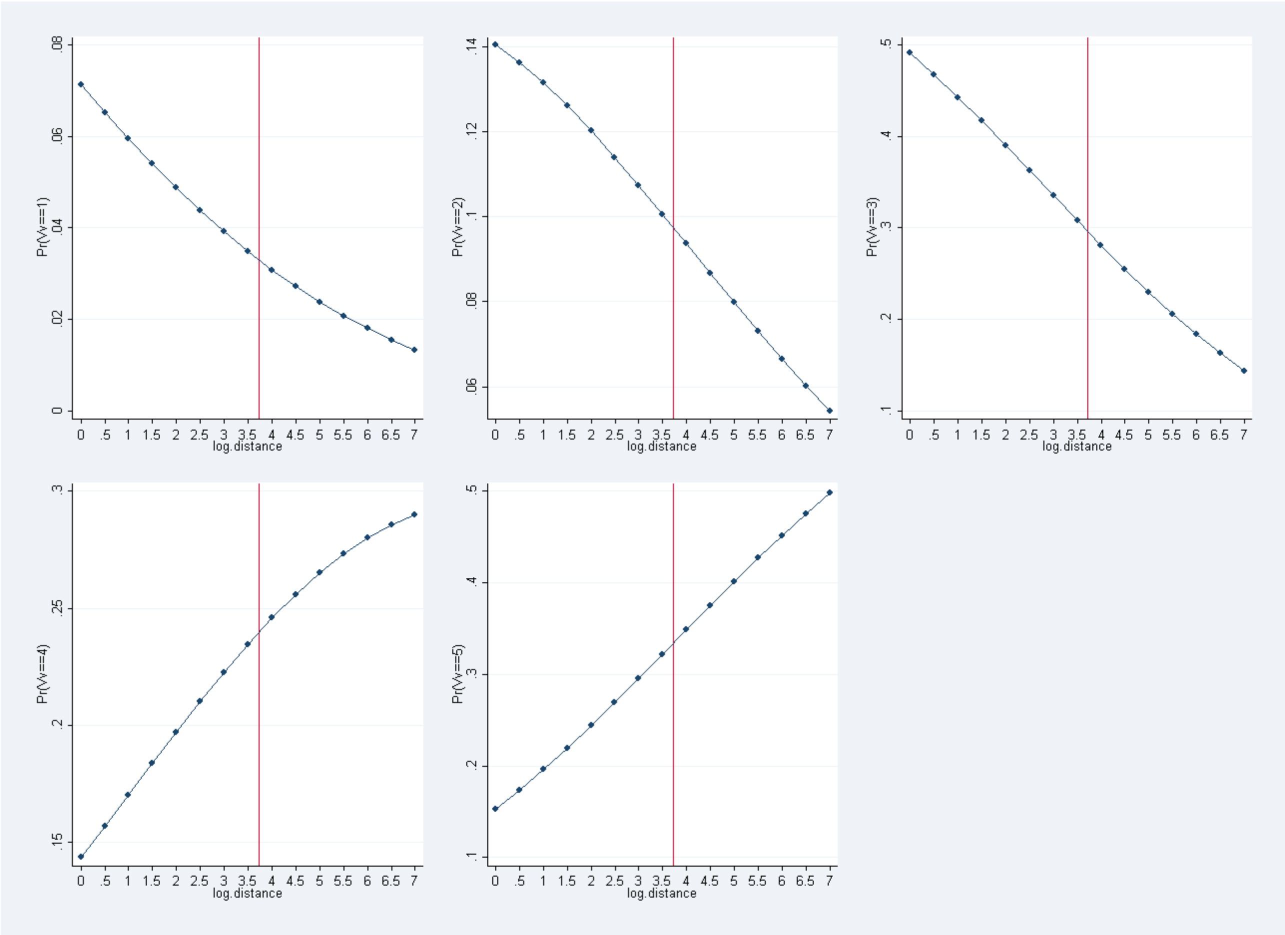

Table 7: Conditional shipment quantity model using the Dubin-McFadden Method

	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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Conditional shipment quantity model using Bourguignon et al. (2007) Method

	q1	q2	q3	q4	q5
log. Demand	0.120***	0.136***	0.0801***	0.0690***	0.115***
	(0.0369)	(0.0370)	(0.0134)	(0.0180)	(0.019)
Log. Distance	0.0719**	0.178***	0.201***	0.309***	0.321***
	(0.0361)	(0.0256)	(0.0167)	(0.0296)	(0.022)
For-hire	0.243*	0.405***	0.110**	0.0882	-0.386***
	(0.134)	(0.0900)	(0.0476)	(0.0794)	(0.042)
Voluminous	-0.0872	-0.230***	-0.431***	-0.339***	-1.758***
	(0.129)	(0.0780)	(0.0811)	(0.0548)	(0.442)
Selection V1	0.0497	-0.237	0.695**	1.339***	0.075
	(0.122)	(0.232)	(0.290)	(0.343)	(0.157)
Selection V2	0.697	-0.292***	-0.0949	0.839***	0.858***
	(0.473)	(0.0914)	(0.239)	(0.326)	(0.142)
Selection V3	-1.325***	1.020***	0.0534	1.164***	1.009***
	(0.231)	(0.306)	(0.115)	(0.0961)	(0.226)
Selection V4	-0.170	1.305***	-1.141***	0.0143	-1.237***
	(0.716)	(0.274)	(0.225)	(0.142)	(0.279)
Selection V5	1.006***	-0.466**	0.553**	1.210***	0.477***
	(0.312)	(0.194)	(0.260)	(0.232)	(0.051)
Sigma2	2.759**	2.806***	1.430***	2.973***	3.777***
	(1.236)	(0.928)	(0.256)	(0.640)	(0.757)
Constant	-1.257***	0.499	0.0566	2.397***	1.443
	(0.443)	(0.700)	(0.175)	(0.531)	(0.700)
Observations	1.233	3623	11888	9011	13235

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

Figure 5: Vehicle choice nest structure

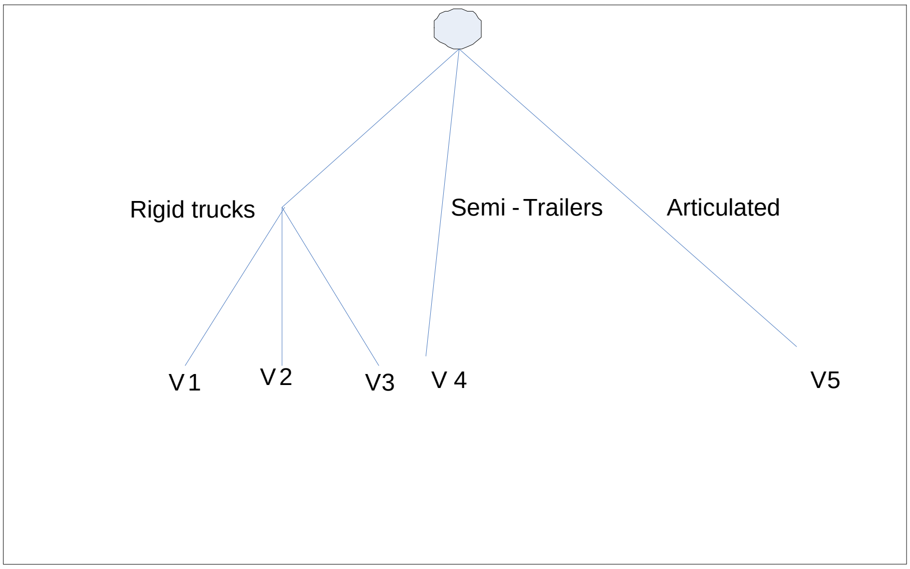

Table 9: Mixed MNL vehicle choice model

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.

CHAPTER IV

The Effect of Fuel Prices on Trucking Industry's Network Characteristics:

Exploratory assessment using Danish HGV data

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Abstract

The 2000s were dominated by rising fuel prices and economic recession. Both had an impact on the structure of the trucking industry and how freight was moved. This paper examines how fuel prices shaped trucking industry's network characteristics such as the average length of haul, average load, and capacity utilization. In particular, we show the effect of fuel price on average length of haul using 29 quarterly independent surveys from the Danish heavy goods vehicle (HGV) trip diary from 2004 to 2011. The results show that the average length of haul is sensitive to changes in fuel price: a DKK 1 increase in fuel prices leads to a 4 percent decrease in the average length of haul in the 2004-2007 period. This implies that firms improve transport efficiency by reducing the number of kilometers needed to transport a tonne of cargo as a short run response to fuel price increases. This result, however, is not confirmed for the years following the 2008 financial crisis. It also depends on where in the distribution of the average length of haul one looks.

Keywords: Fuel price; Average Length of Haul; Trucking Industry; Capacity Utilization

JEL classification : Q41, R0, L91

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1 Introduction

The sharp rise in fuel price in the 2000s reignited interest in the study of the impact of energy prices on the trucking industry's structure and performance. The industry responded to increases in fuel prices in various ways: accumulation of inventories, centralization, modal shift (Eyefortransport, 2008). Rising fuel price was also considered as the most important reason for energy efficiency improvement initiatives by freight carriers (Liimatainen et al, 2012). Early estimates suggested that road transport costs represent about 1.6 percent of sales revenue for a typical European company (Ross, 1995). This rather small share led to the conclusion that much of the strategic decision-making of firms is relatively insensitive to variation in fuel prices (McKinnon, 1999). Although transport costs remain relatively small, fuel costs for freight carriers have always been significant. Besides, fossil fuel is still the main source energy for motive power (Knittel, 2012). It is, therefore, quite reasonable to expect that firms would respond to changes in energy prices, especially during periods of rapid price rises.

Knowing the direction and magnitude of these responses gives further understanding for tackling the perennial question in transportation economics: the price sensitivity of transport activities. In freight transport, questions related to the extent of response and the mechanism of response (modal shift, improvement in capacity utilization, or logistical restructuring) to changes in transport costs are still relevant. The effects of changes in the overall transport cost (cost/tonne-kilometer or cost/vehicle-kilometer) have already been well documented in the literature (see Significance and CE (2010) for a comprehensive recent review). The fuel price sensitivity of road freight transport, however, has been less researched. In particular, the sensitivity of the network (operating) characteristics of trucking firms such as average length of haul, average load, and capacity utilization has been hardly touched.

This paper takes an important first step to showing how fuel price affects the network characteristics of the trucking industry. It estimates the effect of changes in the price of diesel on the average length of haul and the share of loaded trips (proxies for network characteristics) using a unique quarterly dataset from the Danish heavy trucks trip diary that spans 8 years. The data are disaggregated and allow for a simple and flexible empirical strategy that controls for various vehicle, firm and haul characteristics.

The central premise of this paper is that during periods of high fuel prices firms reduce the average length of hauls (the average distance a tonne of freight moves) and improve capacity utilization. The results confirm this premise to a reasonable degree. The price of diesel significantly affects the operating characteristics of freight movement. A DKK 1 ($\simeq$ \$0.17) increase in diesel price results in 4 to 7 percent decline in the average length of haul in the years 2004-2007. However, this effect disappears in the years after the financial crisis of 2008. A similar pattern is observed for the effect of diesel price on the share of loaded trips vehicles make: with a significant effect in the pre-2008 period and no significant effect afterwards.

The paper is structured as follows: Section 2 reviews the literature on the relationship between fuel prices and freight demand. Section 3 presents the econometric model and data, while Section 4 describes the estimation results. Section 5 concludes.

2 Fuel price and freight transport

Significance and CE (pp. 21, 2010) identify three potential responses from firms (carriers/shippers) to an increase in fuel price. First, they invest more in fuel-efficient vehicles or implement a more fuel efficient way of driving. Second, they improve transport efficiency or capacity utilization by reducing the number of kilometers needed to transport a tonne of cargo. Third, if cost increases due to fuel price rises are not fully contained through the first two mechanisms, shippers would ultimately be forced to reduce the number of tonne-kilometers.

These responses mainly differ in terms of the time needed for implementation. Firms can adopt more fuel-efficient driving and improve transport efficiency faster than they can invest in more fuel-efficient vehicles or reduce the need for transport (as implied under the third response).[1] In the long run, however, the reduction in distance will be lower as firms adopt more fuel-efficient vehicles. This is because of the so called "rebound effect". Using aggregate data from Denmark for 1987-2007, de Borger and Mulalic (2012) find that improvements in fuel efficiency resulted in a less than proportional reduction in fuel use. Their estimates show that a 1 percent increase in fuel efficiency led to 0.9-0.83

[1] As correctly pointed out by Green (1984) in terms of the production process, short run demand for fuel is conditional upon the vehicle stock and the technology embodied in it, both of which are essentially fixed. Thus firms need to reorganize production and distribution systems, source inputs locally and invest in routing optimization technology as possible ways of reducing the average length of haul (McKinnon, 1999).

percent reduction in fuel use depending in the time needed for adjustment.[2] Despite being disproportional, the reduction in fuel use is assumed to come from the reduced distance traveled. The following paragraphs discuss possible effects of fuel price rise on the distance traveled.

The effect of fuel price on a trucking firm's network characteristics can be inferred from its effect on the average length of haul (ALH), average load and the capacity utilization of their vehicles. The literature provides no guide on how the latter two characteristics are related to fuel price. As for ALH there are many studies that relate it to a firm's overall costs, of which fuel cost is an important part. ALH is usually taken as a measure of the average distance a unit of freight is moved in a single vehicle movement. It is estimated by dividing total tonne-km by total tonnes lifted: $ALH = \sum_m TKM / \sum_M T$ where TKM is the total tonne-kilometer for all movements (M) of a vehicle, and T is the total tonnes lifted. Both in the literature and in industry, ALH, average load and shipment size are used as proxies for network size and density.

ALH is mostly discussed in the literature in relation to a firm's cost function. In almost all of these studies, a firm's network, which includes its average length of haul, is treated as an exogenous environment in which the firm tries to minimize/maximize costs/profits.[3] Such an approach is appropriate if the firm operates in a regulated environment in which operating rights are determined by a regulator. Or it can be justified on the basis of the very nature of freight transportation activity, which depends on the spatial distribution of demand[4] (locations of shippers or receivers of goods relative to major freight generators), which changes only in the long run. Hence treating network structures as exogenous can be justified. But if firms could freely choose their network structure or if there are exogenous shocks in the economy (sharp rises in fuel price, economic recession, etc.) which change the spatial distribution of demand, etc., the optimal network size (ALH) would be endogenously determined based on cost considerations.[5] What follows is a discussion of the

[2] Kamakaté and Schipper (2009) point out that improvement in the fuel economy of individual vehicles plays a small part. They discuss that large reductions in trucking energy use and emissions will come from better logistics and driving, higher load factors, and better matching of truck capacity to load.

[3] Ying and Keeler (1991) treat commodity attributes or network characteristics as exogenous, but they point out that they are likely to be influenced by cost considerations as well.

[4] Boyer (1993) indicates that trucking is inherently spatial in nature, and that a service from point A to point B is not a perfect substitute for a service from point C to point D; he argues that the two services are "as likely to be complements as substitutes".

[5] Friedlaender and Spady (1980) indicate that although the value and density of the commodity to be shipped are exogenous to the firm, the way in which it is shipped is not; so ALH and shipment size are endogenous to the firm, and are jointly determined with transport rate. See Morrison and Winston (1985) for an interesting discussion on the effect of deregulation on the route structure of intercity transportation.

relationship between a firm's costs and its network structure when networks are exogenous, and of the conditions under which network size could be endogenously determined.

There are two contradicting findings in the literature with regard to the effect of ALH on trucking firm's cost structure. One the one hand, it has been shown (see Friedlaender and Spady, 1980; Chiang and Friedlaender 1984; Daugherty et al., 1985) that firms with larger networks reduce their costs by exploiting economies of networks because larger networks allow for better utilization of specialist equipment, and afford longer hauls which are associated with more efficient use of fuel and trucks.[6] These studies find that longer ALH results in lower costs to the firm.

On the other hand, Keeler (1989) and Gagné (1990)[7] argue that if a firm has a longer ALH, for a given output level, then it will likely have a thinner route structure which implies less than optimal utilization of capacity, which will lead to higher costs. So, the literature gives no clear conclusion on how ALH affects costs or vice-versa. Would firms increase ALH to manage their operating costs? Or would they decrease it? Neither does the literature provide answers as to whether firms would increase/decrease their ALH when faced with changing economic circumstances. This is basically an empirical question, which involves consideration of a firm's vehicle choice process, inventory management, vehicle technology choice, and the relative importance of freight transport as a factor of production in the shipper's production function. The next section presents an econometric model which analyzes a reduced-form relationship between fuel price and the average length of haul.

3 Methodology and Data

3.1 Empirical framework

Section 2 argued that increases in fuel price changes the network characteristics of freight movement. It also showed that a likely short run response to higher fuel prices from firms is that they will manage operating costs by cutting back haulage distances. It is quite reasonable, therefore, to expect lower average length of hauls and improvement in capacity utilization during periods of high fuel prices. This section presents an econometric model

[6] Ying and Keeler (1991) argue that a longer ALH reduces the cost per ton-mile of a shipment because it implies lower terminal handling expense.

[7] Gagné argues that the cost elasticity of ALH depends on whether we evaluate these effects for a given tonne-kilometer (TKM) or a given number of shipments. If it is based on TKM, longer hauls imply lower costs, but if is based on the number of shipments longer hauls lead to higher costs.

to test whether these hypotheses hold. Equation (1) below is a baseline regression model for the average length of haul, and Equation (3) is a model for capacity utilization.

$$\ln ALH_{i,t} = \alpha + \beta f_{i,t} + \gamma age_i + X\varphi + \varepsilon_{i,t} \tag{1}$$

where the dependent variable $\ln ALH_{i,t}$, is the log of the average length of haul of a vehicle i in period t; $f_{i,t}$ is the per-liter price of diesel; age_i, is the age of a vehicle; α, β, and φ are coefficients; $\varepsilon_{i,t}$ is a residual that is assumed to be orthogonal to the explanatory variables. β is the parameter of interest and is expected to be negative since higher fuel expenses directly add to firms' line-haul costs. γ is also expected to be negative as older vehicles are usually driven a lower number of kilometers.[8] Furthermore, Equation (1) contains a vector of control variables, X, such as the number of axles on the vehicle, the type of firm which owns it (own-account or for-hire), and commodity and year fixed effects.

The number of axles is a proxy for vehicle carrying capacity. It is expected to affect ALH positively because firms usually employ their larger vehicles on longer hauls where there are fewer stops. As for the effect of ownership type, for-hire carriers typically have longer network as they serve several customers which are distributed over a wide geographical area. Own-account shippers, on the other hand, tend to move most of their freight from factory to factory, factory to distributor, etc which implies usage of vehicles over a limited distance range.[9]

Interpreting β as the impact of diesel pirce on ALH requires the orthogonality condition $E(\varepsilon_{i,t}|f_{i,t}) = 0$ to hold: fuel price is independent of unobserved haul, vehicle and firm characteristics that do affect ALH. One potential violation of this condition arises because differences in ALH over vehicles may simply indicate differences in the unobserved spatial distribution of freight demand.[10] To control for this possible source of endogeneity X includes the number of days a vehicle is used per period. This variable allows one to see the effect of fuel price conditional on the number of days used and the other control

[8] It is important to note that older vehicles' lower number of kilometers is partly due to the fact that they are used fewer times per period. For a given number of usages, however, older vehicles are used as much as younger ones (Hubbard, 2003). Operating cost differential affects the number of days or periods in use rather than how efficiently a truck is used per period. So, one would expect that older vehicle would be used less frequently during times of higher fuel prices.

[9] Figure 3 shows the kernel density of the distribution of ALH by firm type. It is clear from the figure that for-hire carriers' vehicles are used on longer hauls

[10] However, it is reasonable to expect vehicles to have a comparable distance range over which they are frequently used. Hubbard (2003) argues that most trucks are used in consistent ways from period to period.

variables.

Equation (1) assumes there is no unobserved heterogeneity in impact of diesel price on ALH. However, it is possible that fuel prices affect ALH differently across vehicles of different vintage. In the connection one might ask whether increases in diesel price makes deriving older vehicles more expensive than driving younger vehicles. To test this hypothesis a more general specification is:

$$\ln ALH_{i,t} = \alpha + \rho f_{i,t} \times AG_i + X\varphi + \varepsilon_{i,t} \tag{2}$$

Here the real diesel price, $f_{i,t}$, is interacted with AG_i, a dummy variable for whether the vehicle belongs to the older vehicles category for a given period and within the same vehicle type. The age categories are: $AG_i = 1$ if age equals 1 or less, $AG_i = 2$ if age equals 2 or 3, $AG_i = 3$ if age equals 4 or 5, $AG_i = 4$if age equals 6 or 7, $AG_i = 5$ if age equals 8 or 9, and $AG_i = 6$ if age > 9.

Note that identification comes from comparing the effect of diesel price on the ALH of otherwise identical vehicles that only differ in their age. The parameter ρ is identified by the time-series variation of the price of diesel and the cross-sectional variation of the age group. This identification strategy implies that firms will use their older vehicles for shorter hauls and their younger vehicles (which are probably are more fuel efficient) for longer hauls. Such a strategy allows us to observe how fuel prices affect older vehicles compared with younger vehicles, not the effect of fuel price on the ALH of any given vehicle. This distinction is crucial because the latter effect cannot be distinguished from other factors that might affect both diesel price and ALH.

To check the robustness of the baseline regression, and to describe ALH differential in a more realistic fashion the baseline regression model is extended on several fronts. First, we classify the vehicles in our sample according to their Euro-class classification.[11] Doing so helps one to see whether firms would prefer to use vehicles in the latest Euro-class during times of high fuel prices.

Second, many empirical applications have found quantile regression analysis useful when the variables of interest potentially have varying effects at different points in the

[11] The Euro-classification is based on the classification available at the time a vehicle is observed in the sample. It is based on EU's emission standards legislation (Ref.) which has been imposed for new vehicles sold in Europe since 1992. The classification categories are: Pre-Euro (prior to 1992), Euro I (1992 – 30 September 1996), Euro II (1 October 1996 – 30 September 2001), Euro III (1 October 2001 – 30 September 2006), Euro IV (1 October 2006 – 30 September 2009), and Euro V (1 October 2009 onwards).

conditional distribution of the outcome variable. While mean regression provides a valuable summary of the impact of the covariates, it does not describe the effects on different parts of the ALH distribution. In the context of this paper, it is likely that in the short run firms are only able to cut short hauls (e.g. feeder trips), which are less fuel efficient, implying that fuel price rises may have larger effects on short hauls than on longer hauls. To test this possibility, we use quantile regression (QR), introduced by Koenker and Bassett (1978), and analyze the effect of diesel price at several points in the distribution of ALH. Third, to fully exploit the time-dimension of the data, which is a repeated-cross-section, a cohort was defined based on vehicle type, sector and firm type. Doing so made it possible to test for the presence of inertia and whether firms were responding to contemporaneous fuel price or lag fuel prices.

The lower levels of ALH during episodes of high fuel prices imply some sort of improvement in capacity utilization. This is because firms would be able to provide the same level of freight service only if they cut empty runs or increased average load during loaded trips to improve the load factor. However, distinguishing the pure effect of fuel price from other unobserved factors that affect capacity utilization is rather difficult because capacity utilization will increase for all vehicles regardless of their age or sectors they are used in. One way to check the relationship between fuel price and capacity utilization is through a regression model that relates the share of loaded trips a vehicle makes per period and fuel price. Such a model makes it possible one to see whether firms would increase the share of loaded trips if fuel prices rise so as to keep line-haul costs in check. Accordingly, the model for loaded-trip share is:

$$CU_{i,t} = \tau + \theta f_{i,t} + Z\vartheta + \omega_{i,t} \tag{3}$$

where $CU_{i,t}$ is the share of loaded trips (out of total trips) for a vehicle i, in period t, a proxy for capacity utilization; Z is a vector of vehicle, haul and firm characteristics; τ, θ, and ϑ are coefficients; $\omega_{i,t}$ is a residual that is assumed to be orthogonal to the explanatory variables. $CU_{i,t}$ may not be an ideal measure of the level of capacity utilization unless we control for the type of trips made by vehicles. As correctly pointed out by Figliozzi (2007), urban delivery vehicles usually have a higher proportion of loaded trips because it is only the last trip (usually back to terminals) that is empty. On the other hand, vehicles engaged in inter-city trips face a problem of backhauls that leads to a higher proportion of empty trips. To account for this operational difference, Equation 3 controls for the type of trip (as indicated by vehicle owners), distribution or normal trip.

All the above regressions control commodity fixed effects to account for possible differences in the supply chain and logistical structure of moving different commodities. Furthermore, the regressions contain year fixed effects to control for the average effect of the price of fuel on the ALH and capacity utilization.

3.2 Data

The main source of data for this paper is the Danish heavy vehicles trip diaries. The diaries report all the trips made by a vehicle for one week operation. They contain information on vehicle type, number of axels, type and weight of commodity carried, haulage distance, and the type of firm that owns the truck. Different trucks are sampled each quarter so the data is best described as a repeated cross-section. Diesel prices are published by the Danish Oil Industry Association (eof.dk) which has kept daily fuel prices since 1972. Much to the advantage of this research, the trip diary data contains information on the specific week in a quarter in which each truck in the sample made their trips. This made it possible to use monthly average diesel prices[12] which resulted in an extensive variation in the diesel price variable.

The trip diary is unique and provides disaggregate data on road freight transport which allows a detailed analysis of the trucking industry. Unfortunately, Statistics Denmark changed the commodity classification from NST/R to NTS2007 in 2008 which reduced the number of commodity types from 29 to 21. Due to the importance of this variable in the econometric analyses, the data is divided into two periods, 2004 -2007 and 2008-2011. Due to the economic recession in 2008, it would have been necessary to divide the data in a similar fashion anyway.

Table 1 presents summary statistics. Figure 2 shows the trends of ALH for the three vehicle types in the data. The two heaviest vehicle types, semi-trailers and articulated trucks, have visibly longer ALH while, rigid trucks are commonly used on shorter hauls. Figure 3 displays the kernel density of ALH for own-account shippers and for-hire carriers. As shown the former have slightly lower ALH.

[12] Diesel is the main fuel type used by heavy trucks, and it is the main fuel type used in Denmark (de Borger and Mulalic, 2012). Figure 1 shows the monthly average diesel price in Denmark from 1999-2012.

4 Results

4.1 Diesel price and ALH

Table 2 reports estimates that show the relationship between the ALH and fuel price for the period 2004-2007. Each column presents results for different sets of controls, age, Euro-class, and the number of days a vehicle was operated. An increase in diesel price significantly reduces the ALH of a vehicle. The point estimates for diesel price are very similar across the models, and they show that a DKK 1 increase in price results in around 4 percent decline in the average length of hauls. As for the other explanatory variables, vehicles owned by an own-account shipper exhibit lower ALH.

As expected, larger vehicles are employed in longer hauls, whereas older vehicles are used for shorter hauls. Controlling for a vehicle's Euro class instead of its age reveals similar patterns; vehicles belonging in the older vehicles classifications, Euro class 5 and 6, are used on shorter hauls. The last column shows that frequently used vehicles are also used to move freight over longer hauls. This is an expected result because the characteristics of a vehicle that make a vehicle frequently used are also correlated with how far it can be used.

Table 3 reports a similar set of estimates for the period 2008-2011. Although it is statistically insignificant, the effect of diesel price appears to have been reversed in this period. This is partly due to the economic recession in the period, which might have structurally changed the pattern of freight movement. It is also challenging to find a causal effect of fuel price in this period because both fuel price and the average length of hauls might have been affected by other factors. As for the other control variables, they appear to have had comparable effects to those in Table 2.

To allow for a more flexible functional form, diesel price is interacted with indicator variables for six vehicle age groups.[13] Figure 4 shows the coefficients on these interaction terms for each age group; the excluded group is age group 1, which corresponds to the youngest vehicles (Age $<= 1$). The negative effect of diesel price on ALH is evident as vehicles get older. However, the effects are relatively small for younger vehicles. For vehicles in groups 5 and 6, those with age > 7, a DKK 1 increase in diesel price would lead to 0.069 and 0.074 percentage point shorter haul length compared to vehicles in the first group.

[13] In unreported results, the fleet size of firms was used to explore the heterogeneity of fuel price. These results, although comparable to the ones reported here, were not robust.

One advantage of using a large sample is that it is possible to study how the effect of diesel price changes at different aggregation levels. Accordingly, the data was aggregated to form a cohort of vehicles based on three criteria: (i) the sector they are used in (agriculture, chemicals, food, mining and construction, technology, wood and paper); (ii) the type of firm which owns them (own-account shipper, for-hire carrier); and (iii) the vehicle type category they belong to (rigid truck, semi-trailers, articulated). The resulting panel data makes it possible to exploit the time dimension in the data.[14] Table 4 reports a fixed effects model on the cohort data. The contemporaneous and lagged effects of diesel price are shown under columns 1 and 2, respectively. The results show that firms respond to the existing diesel price levels, not to the levels in the previous period.

All the above estimates show the effects of the explanatory variables at a single moment, that is the mean of the ALH of vehicles. Table 4 presents results from a quantile regression that gives a richer characterization of the effect of diesel price and the control variables.[15] The estimates are for quantiles: $q = [0.1; 0.25; 0.5; 0.75; 0.9]$. The effect of diesel price differs depending on where on the distribution of the ALH one looks. As it turns out, this effect is only significant at the 10th and 25th percentiles. This is partly due to the possibility that in the short run firms are only able to cut shorter hauls in response to higher fuel prices. Figure 5 shows the variation in the effect of the explanatory variables at the different quantiles with the 95 % confidence interval. It is interesting to note that most of these effects differ in size and importance throughout the distribution of ALH.

4.2 Diesel price and capacity utilization

Table 6 shows the relationship between the share of loaded trips (proxy for capacity utilization) and diesel price. The results are mixed. Diesel price has a significant effect on the share loaded trips a vehicle makes in the 2004-2007 period. However, it has no sigfnicant effect in the 2008-2011 period. As indicated in Section 3 finding a causal relationship between fuel price and capacity utilization is rather difficult. This is because of the difficulty of distinguishing the pure effect of fuel price from other unobserved factors. As expected vehicles used in hauls in which there are several stops (distribution trips) appear to have higher share of loaded trips.

[14] All the variables were averaged at cohort level and estimation was done using a similar procedure to that suggested by the seminal work by Deaton (1985).

[15] Quantile regression on the 2008-2011 data gave no significant result.

5 Conclusions

This paper has examined the effect of fuel prices on the operating characteristics of freight movement. It proposes an empirical model which is based on central arguments that during periods of high fuel prices firms lower average length of hauls, the average distance a tonne of freight moves, and improve capacity utilization. The model was tested using a unique dataset from the Danish heavy goods vehicle (HGV) trip diary for 2004 to 2011. The results show that the average length of haul is sensitive to changes in fuel price with a decline ranging from 0.4 to 0.7 percent for every DKK 1 increase in diesel price in the period 2004-2007. This result, however, is not confirmed for the years following the 2008 financial crisis. It also depends on where in the distribution of the average length of haul one looks. In particular, fuel price rises are shown to have larger and significant effects only in the lower end of its distribution (10th and 25th percentile). As for the effect of fuel price on capacity utilization, rising diesel prices led to an improvement in the number of loaded trips vehicles make per period in use. However, this effect is significant only in the period 2004-2007.

Possible caveats should be noted regarding these results. First, the fact that there is no consistent effect of diesel price on the operating characteristics for the whole sample period might imply that the findings are driven by a single episode of energy price rises. The economic recession in the post-2008 period has also made it difficult to deduce strong causal relationships. The results should thus be interpreted with care. Second, although the relationship between the price of diesel and the operating characteristics is suggestive, it needs to be recalled that fuel costs are part -not the whole part- of the total operating cost of a vehicle. The operating characteristics would therefore have also been driven by other components of cost.

Third, firms' fuel price expectations were not considered in this paper. They might, however, play an important role because of the possibility that some firms might engage in oil futures, making them less sensitive to short run price fluctuations. It was not possible to investigate this possibility in this research due to lack of data. Regardless of these caveats, the findings of this study -exploratory as they may be- represent important stepping stones for future research. They also reveal interesting short run freight demand responses, which have not previously been studied.

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Table 1: Summary Statistics

	[2004-2011]	[2004-2007]	[2008-2011]
Diesel price	9.38	9.70	10.26
	(1.14)	(.73)	(.89)
Ln. Average length of haul	4.12	4.08	4.33
	(.913)	(.89)	(.88)
Loaded share (%)	79.46	77.01	80.00
	(21.74)	(21.48)	(22.09)
Vehicle age	4.75	5.04	4.01
	(4.08)	(4.36)	(3.54)
No. axles	4.41	4.20	4.93
	(1.58)	(1.60)	(1.46)
No. observations	24106	6659	8,238

Note: The cells report means, with standard deviations in parentheses. The statistics are based on Data from the Danish Heavy Vehicles Trip Diary (DST, 2012) and the Danish Oil Industry Association (EOF).

Table 2: Main results: Log. Average Length of Haul, 2004-2007 - Vehicle level data

	[1]	[2]	[3]
Diesel price	-0.043**	-0.044**	-0.046**
	(0.02)	(0.02)	(0.02)
No. axels	0.113***	0.115***	0.113***
	(0.007)	(0.007)	(0.007)
Own-account carrier	-0.209***	-0.211***	-0.203***
	(0.026)	(0.026)	(0.026)
Vehicle age	-0.022***		-0.020***
	(0.002)		(0.003)
Euro class 3		0.047	
		(0.056)	
Euro class 4		-0.027	
		(0.058)	
Euro class 5		-0.158**	
		(0.067)	
Euro class 6		-0.283***	
		(0.07)	
Number of days used			0.032***
			(0.009)
Commodity Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	4.240***	4.167***	4.128***
	(0.181)	(0.187)	(0.184)
N	6,659	6,659	6,659
R-squared	0.275	0.275	0.277

Note: Standard errors in parentheses. Significance is marked: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Main results: Log. Average Length of Haul 2008-2011 - Vehicle level data

	[1]	[2]
Diesel price	0.210	0.191
	(0.174)	(0.174)
No. axels	0.081***	0.083***
	(0.007)	(0.007)
Own-account carrier	-0.023***	-0.288***
	(0.003)	(0.028)
Vehicle age	-0.286***	
	(0.028)	
Euro class 2		0.023
		(0.026)
Euro class 3		-0.008
		(0.027)
Euro class 4		-0.250***
		(0.044)
Euro class 5		-0.162**
		(0.079)
Euro class 6		-0.365***
		(0.97)
Commodity fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Constant	3.430***	3.410***
	(0.419)	(0.420)
N	8,238	8,238
R-squared	0.222	0.222

Note: Standard errors in parentheses. Significance is marked: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Fixed effects regressions of Log. Average Length of Haul- Cohort data

	2004 - 2007		2008 - 2011	
	[1]	[2]	[3]	[4]
Diesel price	-0.071**	-0.071**	0.062*	0.043
	(0.028)	(0.030)	(0.036)	(0.030)
Diesel price$_{t-1}$		-0.025		0.081
		(0.034)		(0.052)
Vehicle age	-0.034**	-0.034*	-0.005	0.005
	(0.015)	(0.017)	(0.022)	(0.016)
Chemicals	-0.038	-0.055	0.003	-0.005
	(0.064)	(0.068)	(0.106)	(0.105)
Food	0.115*	0.114*	0.122	0.104
	(0.057)	(0.058)	(0.084)	(0.083)
Mining and construction	-0.410***	-0.418***	-0.459***	-0.476***
	(0.067)	(0.069)	(0.114)	(0.107)
Technology	0.142***	0.142***	-0.023	-0.063
	(0.050)	(0.051)	(0.082)	(0.084)
Semi-trailers	0.260***	0.259***	0.269***	0.228***
	(0.049)	(0.050)	(0.078)	(0.070)
Articulated	0.349***	0.340***	0.469***	0.422***
	(0.052)	(0.058)	(0.082)	(0.068)
Own-account	-0.104**	-0.113**	-0.220***	-0.257***
	(0.045)	(0.047)	(0.071)	(0.074)
Wood and paper			-0.172	-0.212**
			(0.121)	(0.098)
Year fixed effects	Yes	Yes	Yes	No
Year_2008			-0.246**	-0.244***
Constant	5.123***	5.193***	3.768***	3.182***
	(0.332)	(0.314)	(0.414)	(0.689)
Observations	464	452	439	392
R-squared	0.434	0.437	0.317	0.394

Note: Standard errors in parentheses. Significance is marked: *** p<0.01, ** p<0.05, * p<0.1. The reference category for sector type dummies is the agricultural sector.

Table 5: Quantile Regressions of Log. Average Length of Haul, 2004-2007

	q=.10	q=.25	q=.50	q=.75	q=.90
Disel price	-0.092**	-0.065*	-0.022	-0.017	-0.009
	(0.040)	(0.033)	(0.026)	(0.026)	(0.021)
No. axles	0.139***	0.141***	0.123***	0.088***	0.082***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)
Own-account carrier	-0.301***	-0.233***	-0.203***	-0.170***	-0.135***
	(0.010)	(0.010)	(0.007)	(0.007)	(0.009)
Vehicle age	-0.027***	-0.021***	-0.018***	-0.020***	-0.016***
	(0.040)	(0.034)	(0.040)	(0.029)	(0.033)
Constant	3.666***	3.893***	3.930***	4.628***	4.913***
	(0.372)	(0.279)	(0.219)	(0.232)	(0.182)
Pseudo R^2	0.16	0.18	0.17	0.15	0.12
Observations	6,659	6,659	6,659	6,659	6,659

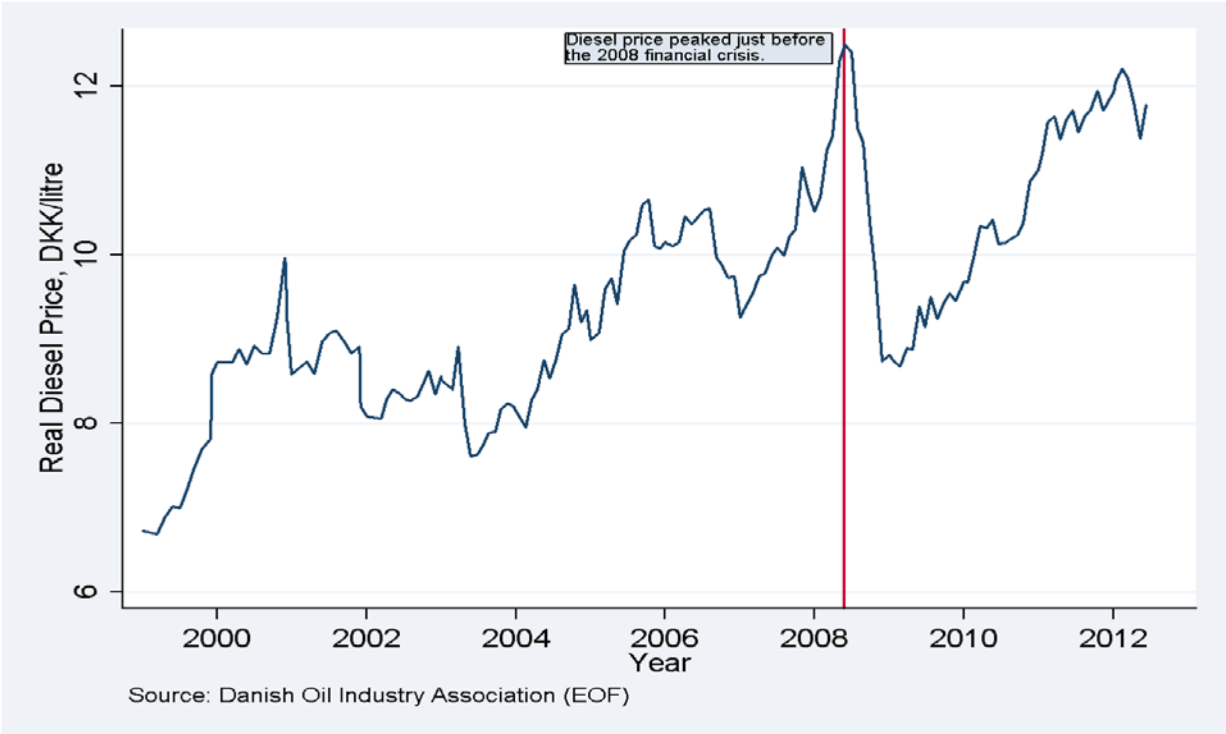
Note: Standard errors in parentheses. Significance is marked: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors were calculated through 299 bootstrap replications.

Table 6: Capacity utilization and diesel price

	2004-2007	2008-2011
Diesel price	0.016***	0.001
	(0.006)	(0.004)
Distribution trip	0.258***	0.247***
	(0.004)	(0.004)
Semi-trailers	-0.017***	-0.028***
	(0.006)	(0.007)
Articulated trucks	-0.015***	-0.021***
	(0.005)	(0.006)
Own-account shippers	0.020***	0.033***
	(0.005)	(0.006)
Constant	0.502***	0.613***
	(0.049)	(0.037)
N	6,659	8,238
R-squared	0.453	0.385

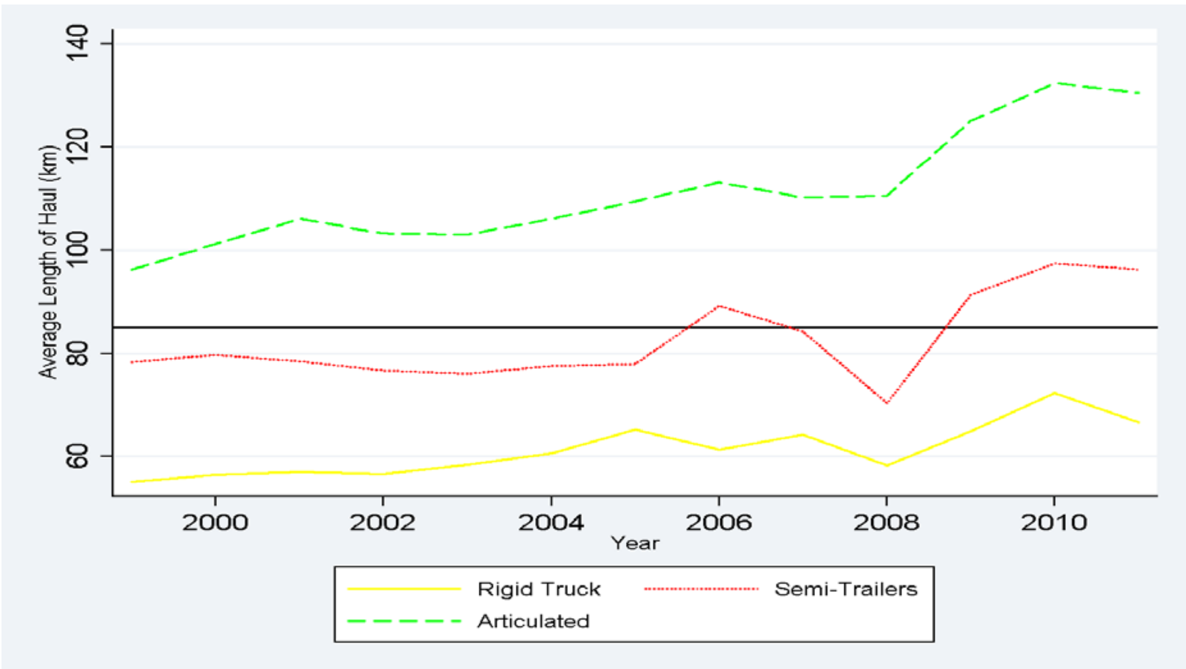
Note: The dependent variable is the share of loaded trips. Standard errors in parentheses. Significance is marked: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Inflation-adjusted price of diesel



Note: The diesel prices are monthly averages in 2010 prices.

Figure 2: Average Length of Haul by vehicle type



Note: The solid horizontal line indicates the mean of average length of haul (87 km) during the sample period.

Figure 3: Kernel density estimates by firm type

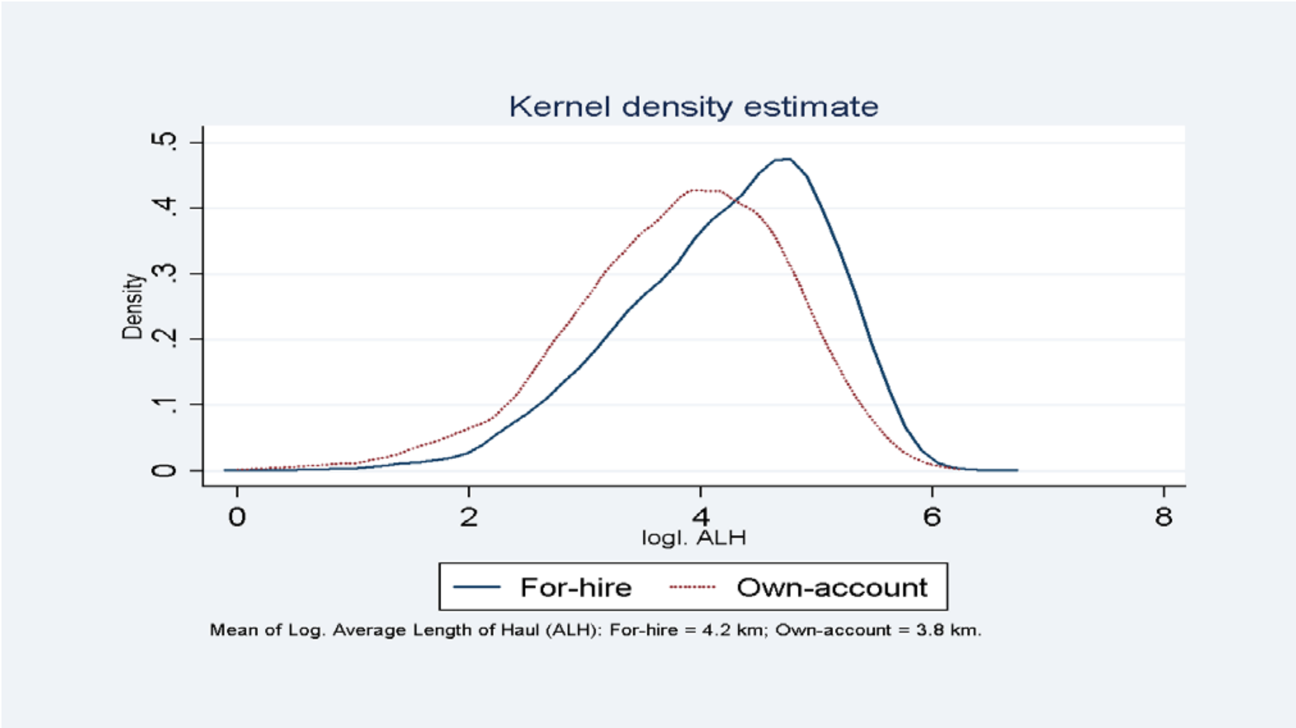
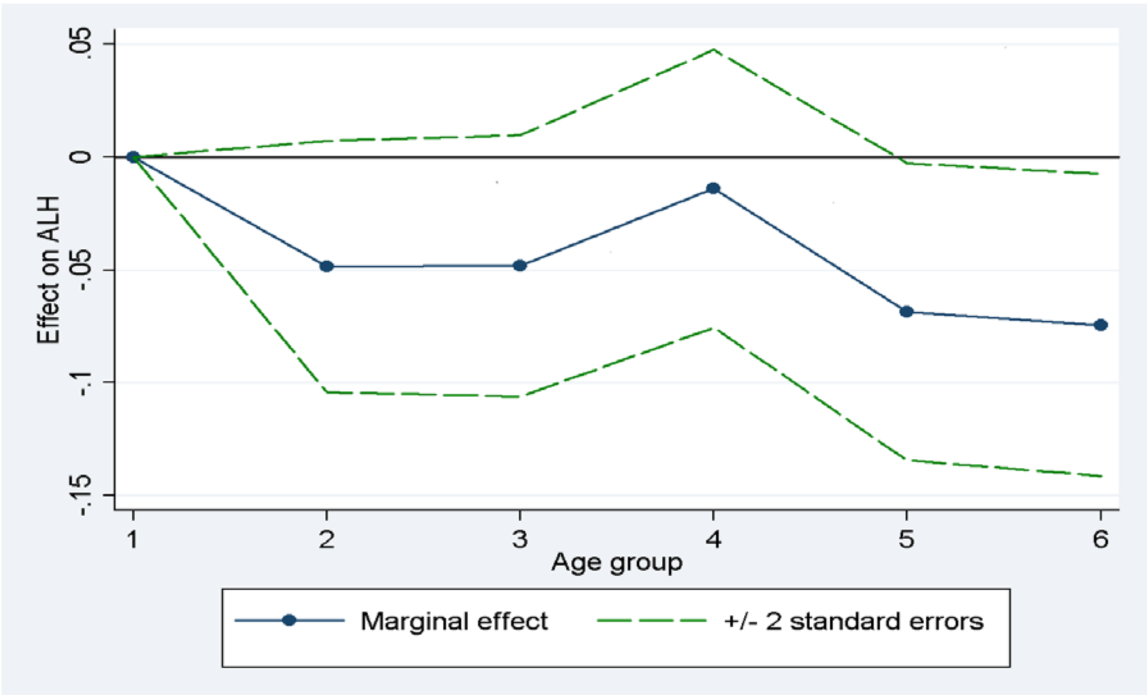
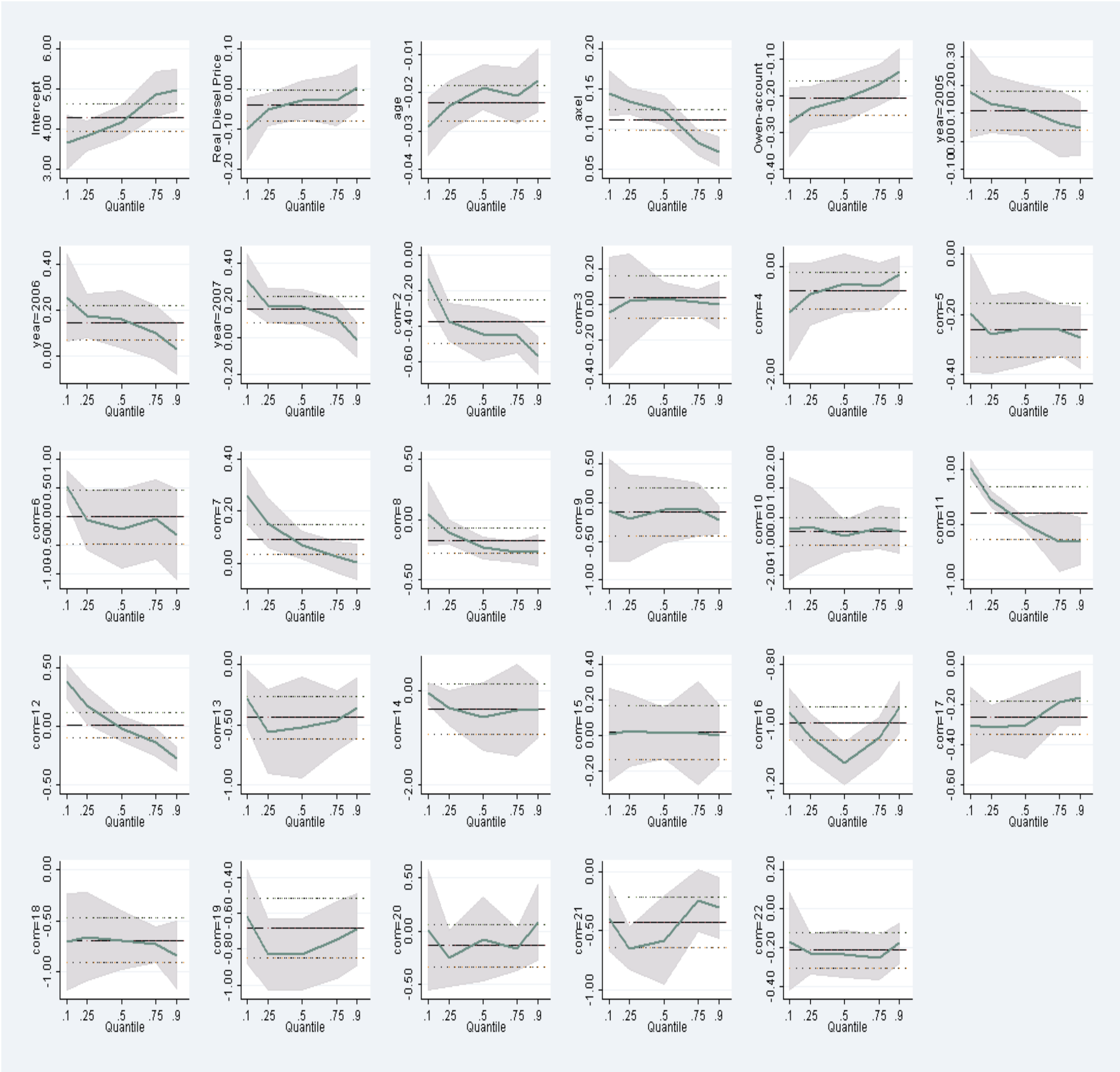


Figure 4: Effect of diesel price on average length of haul (ALH) by age group



Note: This figure shows the effect of diesel price on average length of haul by age group. The effects are relative to the youngest age group 1, which corresponds to the youngest vehicles (Age <= 1).

Figure 5: Quantile regression and OLS coefficients



Note: This figure displays quantile regression and OLS coefficients and 95-percent confidence intervals for each explanatory variable for quantiles: q = [0.1; 0.25; 0.5; 0.75; 0.9].