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Information technology and efficiency in trucking

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# DISCUSSION PAPER

# Information Technology and Efficiency in Trucking

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## Abstract

In this paper, we develop an econometric model to estimate the impacts of Electronic Vehicle Management Systems (*EVMS*) on the load factor (*LF*) of heavy trucks using data at the operational level. This technology is supposed to improve capacity utilization by reducing coordination costs between demand and supply. The model is estimated on a subsample of the 1999 *National Roadside Survey*, covering heavy trucks travelling in the province of Quebec. The *LF* is explained as a function of truck, trip and carrier characteristics. We show that the use of *EVMS* results in a 16 percentage points increase of *LF* on backhaul trips. However, we also find that the *LF* of equipped trucks is reduced by about 7.6 percentage points on fronthaul movements. This last effect could be explained by a rebound effect: higher expected *LF* on the returns lead carriers to accept shipments with lower fronthaul *LF*. Overall, we find that this technology has increased the tonne-kilometers transported of equipped trucks by 6.3% and their fuel efficiency by 5%.

**Key words**: Information and Communication Technology, Efficiency, Load factor, Trucking, Energy Efficiency

JEL codes: O33, Q55, R40

# Information Technology and Efficiency in Trucking

## 1. Introduction

The impact of Information and Communication Technologies (ICTs) on efficiency and productivity has been a central issue in economics for several decades. Early studies undertaken in the seventies and eighties, have found very little impact of ICTs on productivity using aggregate data leading to the so-called productivity paradox (for a review of these early studies see Brynjolsson and Shinku, 1996). More recent studies have used data at the industry or firm level and have yielded more encouraging results (see Pilat, 2004 for a review). In many cases ICTs appear to have a positive impact on productivity but the importance of the effect varies according to firm, market and economy characteristics. In this paper, we contribute to this literature by empirically assessing the impact of ICTs on the trucking industry using data disaggregated at the operational level.

Specifically, we measure the impact of new electronic vehicle management systems (*EVMS*) on capacity utilisation. The trucking industry is facing a complex matching problem between demand and capacity. A carrier needs to have the right truck at the right time and place in order to respond to a shipper demand. This matching problem necessarily leads to some capacity under-utilization with trucks travelling empty or less than fully loaded. According to the CCMTA (2002), about one out of three heavy trucks travelling on Canada's major highways are empty and more than half of those with a charge are not 100% full. EVMS feature two functionalities that may lower coordination costs between capacity and demand: i) they provide real-time transmission of the exact positioning of each truck of a carrier's fleet using GPS technology and ii) they enable dispatchers to initiate real-time communication with drivers via onboard computer. With EVMS, dispatchers may therefore be able to coordinate vehicle activities in a more efficient manner, thereby increasing the trucks load factor (*LF*). In fact, providers of this technology insist in their promotional material on the opportunities offered by EVMS to reduce empty backhauls. We test the impact of this technology on the *LF* of heavy trucks using data colleted by the *1999 National*

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*Roadside Survey* (NRS99). The survey involved more than 65,000 drivers interviewed randomly at 238 roadside sites throughout the 25,200 kilometres of Canada's main road network. We use a sub-sample of NRS99 covering trucks that have travelled at least in part in the province of Quebec. Beside the adoption of EVMS, our econometric model explaining *LF* includes variables characterizing the truck, trip and carrier.

Our analysis is related to a recent study by Hubbard (2003), examining the impact of *EVMS* on the US trucking industry. According to Hubbard, *EVMS* would have increased capacity utilization rates of equipped trucks by 13% leading to a 3% increase in the industry's overall efficiency in 1997. Besides focusing on the Canadian industry, our analysis diverges from Hubbard by using data disaggregatd at the operational level. We observe the *LF* of trucks travelling on specific trips whereas Hubbard uses measures of capacity utilization at the truck level and aggregated over a one year period (*i.e.* loaded miles and the number of weeks the truck is in use). Therefore, our data allows us to gain a better understanding of how *EVMS* affect *LF* depending upon the trip characteristics. We test separately the effect of EVMS on "fronthaul" (*F*) and "backhaul" (*B*) trips. Interestingly, we find that if *EVMS* increase *LF* on *B* trips by about 16 percentage points, this technology is also associated with a 7.6 percentage points reduction in *F* trips *LF*. These results suggest that *EVMS* creates a sort of "rebound effect". By increasing the likelihood of finding a backhaul, the *EVMS* lower the unit cost of a delivery - fixed costs associated with the entire trip being spread over a larger total load – thereby promoting acceptance by the carrier of lighter *F* loads, or trips that require a longer initial empty runs (to go pick up the load). Overall, our results suggest that this technology increases capacity utilization: we evaluate that tonne-kilometres (TKMs) transported would have increased by 6.5% for trucks equipped with this technology. Taking into account the (low) adoption rate, this implies an industry-wide increase in TKM in the order of 0.83%. Other significant factors positively affecting the *LF* on both types of trips include the truck size, the trip distance, the trailer versatility and the intensity of the economic relationship between the origin and destination. On *B* trips, for-hire carriers and owner-operator appear to do better than private truckers. Our main results are confirmed when *EVMS* is allowed to be endogenous.

These results are also important in the debate over the development of a durable transportation system. Indeed, trucking activities are a significant source of environmental degradation. They contribute to urban smog, noise pollution and greenhouse gas (GHG) emissions. For example in Canada, while total GHG emissions have increased by 24% from 1990 to 2003, medium and heavy trucks emissions have jumped by 68.8% during the same period and now account for close to 6% of total emissions (see Environment Canada, 2005 and Natural Resources Canada, 2006). Trucking does, however, also contribute positively to economic growth. It is estimated that this industry generated in 2003 close to 50-billions in revenues and employed some 320,000 full-time workers in Canada (see Transport Canada, 2003). More importantly, trucks are a vital input for most of the industries insuring the delivering of goods. It is therefore important for public policy to promote the development of a trucking industry that is both efficient and sustainable. Improvements in the load factor of trucks could provide a mean for achieving both objectives – a "win-win" solution à la Porter (see Porter and van der Linde, 1995). Based on our results, it appears that EVMS have improved the energy efficiency of adopting trucks by about 5%.

The rest of this paper is organized as follows. In section 2, we provide a general overview of the functioning of the trucking industry and the challenges associated with matching capacities and demands. We also develop a simple theoretical model highlighting the potential effects of *EVMS* depending on the type of trips. In section 3, we describe the data, the empirical specification and the estimation techniques. Results are presented and discussed in section 4. We conclude in section 5.

## 2. Capacity management in the trucking industry

The trucking industry is composed of two main segments: i) for-hire companies which transport the freight of others for compensation and ii) private trucking that involves carrying the company's goods. In dollar terms, it is estimated that private trucking accounts for about one half of the Canadian industry (Nix, 2003). Besides these two segments, there are also owner-operators who own and drive their trucks and work on contract either for-hire or private activities.

The productive capacity of a carrier depends upon its fleet size and structure. Each truck offers a capacity that can be constrained either by the shipment weight or volume. Moreover, some shipments require specialized trailers such as tanks for carrying liquids. The rate of capacity utilization is determined by the portion of time trucks that are on the road (*i.e.* in use) and their *LF*. Our analysis specifically focuses on the latter aspect. Considering only the weight constraint, *LF* can be defined as:

$$LF\,(\%) = \frac{CW}{MCW}\,x\,100 \qquad\qquad [1]$$

with *CW* the cargo weight and *MCW* the maximal cargo weight a truck can carry. It is easy to understand that *LF* is a key determinant of a carrier's competitiveness. Indeed, the cost per tonne carried clearly declines with *LF*, as several cost components are either fixed (for example the driver salary) or vary less than proportionally with *LF* (e.g. fuel costs).

It is also a key determinant of a carrier's energy efficiency. The energy efficiency associated with carrying a shipment weighting *CW*, over a distance *D*, using a truck with capacity *MCW* can be defined as:

$$Energy\ Effiency = \frac{TKM}{Energy} = \frac{CW\,x\,D}{Energy} = \frac{MCW\,x\,(LF/100)\,x\,D}{Energy} \qquad [2].$$

It is the ratio of the output measured by the tonne-kilometres carried (*TKM*) and the energy consumed. By definition, *TKM* is the product of the cargo weight and the distance over which it is shipped. Using [1], we immediately obtain that the level of production is directly proportional to *LF*. By contrast, the level of energy required to carry a shipment over distance *D* increases much less than proportionally. Indeed, it is estimated that a truck fully loaded only consumes about 20% more fuel than if it is empty (see Bridgestone/Firestone, 2006).

However, optimizing *LF* is made complicated by the fact that both demand and capacity are time, location and equipment specific. This complex matching problem necessarily leads to some under-utilization of capacity, taking the form of either empty-runs or less than fully loaded trips. Carriers can reduce these inefficiencies by trying to find complementary demands.

To illustrate these matching activities, let's consider the following simple example: a carrier located in *A* is contacted to transport a load from *A* to *B* (see figure 1). To optimize its *LF* on the whole journey (*ABA*), the carrier may engage in costly search for complementary demands.[1] First, the shipment initiating the fronthaul trip from *A* to *B* – which we will refer as the *F* trip - may not fully load a truck, in which case the carrier may want to "group" various shipments. Second, as the demand from a client is rarely bi-directional, the carrier needs to find a returning load if it wants to avoid an empty backhaul trip from *B* to *A* (from now on referred as *B* trip). Another source of inefficiency exists when the truck base is not close to the shipment origin requiring an initial empty run. Similarly, on return, a truck may be deviated in order to pick up a backload. Various market intermediaries (brokers, web load matching sites) play a role in coordinating demands with capacities. At a carrier level, dispatchers are in charge of optimizing capacity utilization (see Hubbard, 2003 for a description of the dispatcher role). Obviously, their work involves trading off search costs with the opportunity cost associated with a less than full load trip.

In the above example, the truck journey is initiated by the fronthaul shipment. In reality, there may be cases where the journey is initiated by a shipment to be carried from *B* to *A*, in which case the *AB* trip is the joint product for which the carrier needs to find a complementary demand. Ideally, we would like to know which trip (*F* or *B*) has initiated the journey and which one is the joint product. Unfortunately, the data does not allow us to distinguish between these two cases. However, *B* trips (*BA* in our example) are certainly more likely to be joint products. Indeed, carriers most often initiate trips in response to local demands. For example, carriers located in *A* are more likely to be contacted by shippers in *A* than in *B*. Indeed, shippers located in *A* probably have better information on carriers located in *A* than in *B*. Moreover, dealing with carriers located in *A* may involve longer delivery delay as trucks should first be sent from *A* to *B* before being able to pick the load. Obviously, this is not to say that this type of situations does not occur, but simply that it is less likely and will usually involved specialized equipments.

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[1] Search costs not only include the cost associated with identifying complementary demands but also the cost of having a truck unused during the search process.

The level of effort for finding complementary demands and probability of success will depend upon the truck, load, carrier, trip and market characteristics. As mentioned above, it is certainly much more difficult to find complementary demands for a load that requires very specialized equipments. Since for-hire companies are specializing in transportation activities, they may have lower search costs and thus could be more successful in avoiding empty or less-than full runs. Moreover, private companies face legal and insurance constraints that may limit their ability to serve external demands. The size of companies may also positively affect their abilities to find complementary demands. The distance between *A* and *B* is certainly a significant factor affecting the level of effort a company will invest for finding a load on the return trip. Indeed, the opportunity costs associated with returning empty is certainly increasing with distance. The demand for transport also depends upon the intensity of the social and economic relationships that exist between both of the trip extremities.

New satellite-based communication and localization technologies may also help increase the *LF* by reducing coordination costs between demands and supplies. As described by Hubbard (2003), traditionally carriers have relied on a system of "check-and-call", where drivers periodically phone their dispatcher in order to provide information on their localization. Cell phones now also allow dispatchers to initiate the communication. However, since the late eighties, *EVMS* are combining GPS technologies with on-board computers. These systems therefore allow precise real-time localization of all a carrier's vehicles as well as direct communication with the drivers. Moreover, the information provided by *EVMS* may feed software that support dispatching decisions (e.g. rerouting trucks). Manufacturers of these technologies argue that they are particularly useful to reduce empty backhauls.[2] For *F* movements, the impact of *EVMS* is less obvious. First, it is rare that trucks partially loaded are re-directed in *F* movements, unless this has been decided in advance (see Hubbard, 2003).[3] Second, by increasing the

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[2] For example, the web site of Shaw tracking reports the following customer testimonial: "Shaw Tracking allows us to reduce our empty miles considerably."
(http://www.cancomtracking.ca/pages/about_testimonial_details.asp?TestimonialID=1)
[3] Various shipments should indeed be loaded in the truck in a specific order taking into account their respective destination as well as the weight distribution.

probability of finding a backhaul load, *EVMS* may generate a sort of "rebound effect" as illustrated by the simple model below.[4]

Let's suppose that a carrier receives orders for shipments from *A* to *B*. Each order is characterized by a weight (or volume) that leads to a specific load factor $LF^{AB}$. To keep the analysis simple, we assume that $LF^{AB}$ is uniformly distributed on [0,1]. On the returning trip *BA*, potential shipments are also distributed so that the resulting load factor $LF^{BA}$ is uniformly distributed on [0,1]. However, as argued above, finding an adequate backhaul load may not be automatic or may require some waiting time. We therefore assume that the probability of getting an order on the return trip is $v < 1$. We further suppose that the price of a shipment depends upon its weight (or load factor) and that the carrier is a price taker. Specifically, we assume that the carrier receives $\alpha\ LF$ per shipments. When receiving a new order from *A* to *B*, the carrier has to decide whether to accept or refuse it depending upon the whole journey expected profit ($\pi$). Assuming risk neutrality, it will accept if:

$$E[\pi] = \alpha LF^{AB} - c - d + v(\alpha E[LF^{BA} \mid LF^{BA} \geq LF_m^{BA}] - c) \geq 0 \qquad [3]$$

with $E[\ ]$ representing the expectation, $c$ the costs directly associated with a shipment (*i.e.* the loading and unloading costs, the extra fuel cost required to carry the load, etc.) and $d$ the fixed cost generated by the round trip journey (*i.e.* the trucker's wage, the fuel needed for moving the empty truck, etc.) and $LF_m^{BA}$ is the minimal returning *LF* that is accepted by the carrier. In fact, on the *B* trip, the carrier will accept any load such that $\alpha LF^{BA} - c \geq 0$ so that $LF_m^{BA} = \dfrac{c}{\alpha}$. This implies that

$$E[LF^{BA} \mid LF^{BA} \geq LF_m^{BA}] = \frac{\alpha + c}{2\alpha} \qquad [4].$$

Replacing [4] in [3] determines the minimum acceptable load factor on the *F* trip:

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[4] This effect is indeed analogous to the well known rebound effect in the energy efficiency literature (see Greening *et al.*, 2000). For example, improvements in the fuel efficiency of cars lower operating costs which in turn stimulate driving. This effect partially counteracts the fuel consumption reduction associated with better fuel rating.

$$LF_m^{AB} = \frac{c+d}{\alpha} - \frac{v(\alpha - c)}{2\alpha} \qquad [5].$$

To be acceptable, the fronthaul shipment revenues should cover the fixed roundtrip costs, plus the *F* segment costs minus the expected net revenues generated by the *B* segment. The expected load factor on *AB* is therefore going to be:

$$E[LF^{AB} \mid LF^{AB} \geq LF_m^{AB}] = \frac{1 + LF_m^{AB}}{2} \qquad [6].$$

It is immediate from [5] and [6] that the expected load factor observed on *F* trips is declining with $v$. If EVMS do increase $v$, we could therefore very well observe that equipped trucks have lower average *LF* on *F* trips. Interestingly, our data set offers a unique opportunity to test for this possibility.[5]

## 3. The Empirical Analysis

### 3.1 The Data

Our empirical analysis uses data collected during the *1999 National Roadside Survey* coordinated by the Canadian Council of Motor Transport Administrators. The main objective of this survey was to draw a picture of heavy trucks activities in Canada. More than 65 000 truck drivers were randomly selected and interviewed at 238 survey roadside sites throughout the 25,200 kilometres (km) of Canada's main road network. Data was collected during representative weeks in the summer and fall of 1999. The questionnaire included two parts; one compulsory and the other optional. About 88% of the drivers accepted to respond to both parts of the survey.

In this study, we exploit a sub-sample of the NRS99 covering heavy trucks surveyed at one of the 51 roadside checkpoints in the province of Quebec, along with trucks surveyed elsewhere in Canada, but having travelled part of their trip in Quebec.[6] The sample is restricted to long distance trips as defined as

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[5] Note that the backhaul average load factor which is $vE[LF^{BA} \mid LF^{BA} \geq LF_m^{BA}]$ should increase with *EVMS* if this technology does indeed help coordinate demand and supply.

[6] Administrative and confidentially policies prevented us to get access to the whole data set.

trips of at least 80 km or those connecting two different "regions".[7] The *Quebec Ministry of Transport* granted us access to this sub-sample. The main advantage of using this sub-sample is that it underwent extensive consistency checks by the Ministry (see Ministère des Transports du Québec, 2003).

Each observation corresponds to a truck on a specific trip and contains a rich set of information on the truck, its load and the type of company for which the truck operates. One significant shortcoming is that it does not contain any information on the carrier size. We are therefore unable to control for this factor. This could create spurious correlation between *LF* and *EVMS* if, for example, larger carriers are more likely to adopt this technology and are also more efficient. We tackle this issue in section 4.3 where *EVMS* is allowed to be endogenous. Beside the information collected during the interviews, a traffic count was realized at each site in order to obtain a representative picture of the whole population. Trucks were classified according to their type (straight truck, tractor-trailers etc.) and the day and time of their passing through the survey sites. Based on these counts, expansion factors (*i.e.* the inverse of the sampling weights) were associated to all observations.

A trip, as defined by the NRS99, is 'a continuous move by a truck to haul cargo. The trip starts when the first cargo shipment on-board is picked-up and ends when the last cargo shipment on-board is delivered….An empty truck is also on a trip, and that trip lasts as long as the truck is empty'. It is therefore important to underline that we do not observe the truck complete roundtrip itinerary. The observed segment may also not fully represent a complete *F* or *B* trip. Indeed, suppose a carrier sends its truck from its base in Montreal to pick up a load in Ottawa to be delivered in Vancouver. While conceptually this could be viewed as one *F* trip with two segments, the NRS99 reports two different trips depending upon where the truck is intercepted between Montreal and Ottawa, or between Ottawa and Vancouver (the loading condition changes in Ottawa). Despite these limitations, the data base still offers an opportunity to distinguish between *F* and *B* segments.

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[7] For Quebec, a "region" corresponds to an administrative region or a metropolitan census region. For the rest of Canada and the U.S., a region is either a province or a state.

From the Quebec Ministry of Transport's data set, we have applied several additional criteria to construct our own sample. For example, we eliminated observations for which information on the analysis variables was missing, or corresponding to truck configurations not specifically designed for transportation activities (*e.g.* garbage trucks, tractor without trailer). The detailed description of the exclusion criteria are described in appendix 1. Our final sample includes 9091 observations (4,532 *F* trips and 4,559 *B* trips) down from an initial 20,101 sample size. These observations correspond to a total of 87,702 trips when taking into account the expansion factors. Next, we describe the empirical specification.

### 3.2 The Empirical specification

The general structure of our empirical model is as follows:

$$LF_{u,i} = f(U, I, C) \qquad [7]$$

$LF_{u,i}$ is the load factor of truck $u$ on trip $i$. It is explained as a function of variables characterizing the truck ($U$), trip ($I$) and carrier ($C$). The selected explanatory variables are expected to affect a carrier's ability or its level of effort for finding complementary demands. We estimate model [7] separately on the sub-samples of observations corresponding to $F$ and $B$ segments. As explained above, the issue of finding complementary demands is likely to be more acute on $B$ trips. To classify an observation as $F$ or $B$, we compare the relative position of the truck's base with the trip origin and destination. If the distance between the truck's base and the trip origin is less than half the distance between the base and the trip destination, we classify the observation as a $F$ segment – the truck is indeed clearly moving away from its base. Correspondingly, $B$ segments are those for which the distance base-destination is less than half the distance base-origin (*i.e.* the truck is getting closer to its base). We eliminate observations for which the two distances are not very different, since it is much more perilous to classify those as either a $F$ or $B$ segment.

### 3.2.1 The Load Factor

We use as dependent variable the evaluation of *LF* provided by the driver during the interview. Five responses are possible, namely: 0%, 25%, 50%, 75% and 100%. Moreover, if the response is 100%, a follow up question asks if the truck is full in weight or volume. This measure of *LF* has therefore the advantage of taking into account both capacity constraints. Obviously, this measure is an approximation of the true *LF*, that we denote $LF^*$ to mean that it is unobserved (latent).

### 3.2.2 The explanatory variables

Table 1 briefly describes the explanatory variables included in our analysis. As already mentioned, we are particularly interested in the impact of *EVMS* – a dummy variable set to one if the truck has an on-board computer and a satellite dish. If these systems reduce coordination costs, we would expect the variable *EVMS* to have a positive effect on *LF* on backhaul. In fronthaul segments, the effect could be somewhat different as already explained.

The truck size is captured by the number of axles (*AXLES*). Since it is likely that the opportunity cost associated with driving empty increases with the truck size, we would expect this variable to have a positive impact on *LF*. We also control for the truck base localization, distinguishing truck based in the province of Quebec, the rest of Canada (*ROC*) and the US. Given that the structure of our sample only includes trucks having travelled in Quebec, it is possible that Quebec carriers dispose of an advantage in terms of market knowledge. Also, US trucks are very likely to carry goods between the US and Canada and should therefore be affected by the trade imbalance that exists between the two countries.

The type of trailers has an impact on the nature of the cargo that can be transported. The possibilities for pooling several shipments, as well as the probability of finding complementary return loads, are more limited for specialized equipment. Table 1 presents the classification we use in this study, and that is partially based on Hubbard (2003).

We also control for the nature of the carrier operations (for-hire versus private trucking), as well as if the driver is an owner-operator. Once again, for-hire carrier and owner-operator may have more

incentive and flexibility for finding complementary demands than private carriers for which transport activities are only an input in their production process. However, it is worth mentioning that owner-operators usually operate small companies (on average seven employees, see Nix, 2003) and therefore may have less capabilities for finding complementary demands.

As the opportunity cost of driving empty increases with *DISTANCE*, we expect *LF* to be positively correlated with this variable. We also include in our model two variables measuring the importance of economic relationships between the regions of origin and destination of the trip. The variable *POPULATION* represents, using a gravitational formulation, the potential interaction force between the populations at the origin and destination. For Canada, the population data are collected at the level of the census division and in the US at the county level. The variable *INCOME* corresponds to the average of the median household income at the origin and destination.[8]

### 3.2.3 The estimation method

By definition, *LF* is bounded between 0% and 100% and takes discrete values that are naturally ordered. For these reasons, we estimate a multinomial ordered probit (MNOP) model (see for example Wooldridge, 2001). The latent response $LF_i^*$ for observation *i* is determined according to:

$$LF_i^* = x_i' \beta + \theta \, EVMS_i + u_i \qquad [8]$$

with $x_i'$ representing the vector of the control variables, $\beta$ being a parameter vector, and $\theta$ the parameter associated with the *EVMS* indicator. The observed responses are linked to the latent variable by the following threshold model:

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$$LF_i = \begin{cases} 0 & \text{if} \quad -\infty < LF_i^* \leq \alpha_1 \\ 0.25 & \text{if} \quad \alpha_1 < LF_i^* \leq \alpha_2 \\ 0.5 & \text{if} \quad \alpha_2 < LF_i^* \leq \alpha_3 \\ 0.75 & \text{if} \quad \alpha_3 < LF_i^* \leq \alpha_4 \\ 1 & \text{if} \quad \alpha_4 < LF_i^* < \infty \end{cases} \qquad [9]$$

with $\alpha_1$ to $\alpha_4$ being threshold parameters to be estimated jointly with $\beta$ and $\theta$.

We assume that the error terms $u_i$ are independently normally distributed. The sampling structure is taken into account by weighting each observation by the inverse of the expansion factor when constructing the log-likelihood function (see Wooldridge 1999 and 2001).[9] Another econometric concern is the potential correlation between the error term and *EVMS*, which would bias our results. Unobservable factors (such as the carrier size) could indeed affect both *LF* and the adoption of *EVMS*. Trucks with this technology could also be assigned to roads where it is more difficult to find a backload. We address this issue in section 4.3.

## 4. The Empirical Results

### 4.1 Preliminary evidence

Before presenting the econometric results, it is useful to examine some basic descriptive statistics. Table 2 reports the means and standard deviations for the variables computed over our sample. Clearly, the average *LF* is higher on *F* trips than on *B* trips, thereby supporting our hypothesis that trucks movements are most often initiated by local demands. In fact, the difference in the percentage of empty trucks explains that this difference for the average *LF* of loaded trucks is very similar on both type of trips at about 90%. The adoption rates of *EVMS* are quite limited, but recall that the data dates back to 1999. The

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[9] If the sampling structure is exogenous, the unweighted results are consistent and generally more efficient than the weighted results. However, if the sampling structure is endogenous, the unweighted results are not consistent while the weighted results are. In our setting, trucks were randomly chosen at each data collecting site. However, the localisation of these sites was dictated by several considerations (representation of each province, site convenience, importance of the traffic flow etc.) which may lead to an endogenous sampling structure.

intercepted trucks are mostly based in Quebec which is hardly surprising given our sample structure. Vans dominate in terms of truck trailer type. Only about 20% of the observations relates to private trucking. This can be explained by the fact that the survey targets long distance trips, while private trucking mostly specializes in local freight transportation. The average trip distance is about 450 km.

Table 3 illustrates the relationship between *LF*, the adoption rate of *EVMS* and some key explanatory factors. Higher *LF*s are associated with *EVMS*, larger trucks, for-hire operations, owner-operators and distance traveled. Moreover, Quebec-based trucks and US trucks would have lower *LF*s than trucks from the ROC. *EVMS* appears to be mostly installed on for-hire van-type trucks travelling on long distances. US and ROC based trucks are also more likely to use this technology. Looking more closely at the impact of *EVMS* by trip distance classes, Table 4 suggests that this technology is associated with improved capacity utilization on *B* trips. On *F* segments, however, the relationship is less obvious, as it appears that equipped trucks have slightly lower *LF*s and are less likely to be fully loaded on longer roads. This result is consistent with a rebound effect. Obviously, it is dangerous to conclude from these partial correlations. We therefore turn next to the econometric results.

### 4.2 The econometric results

Table 5 presents the econometric results associated with the *F* and *B* trips. We report the results obtained by simple OLS and by MNOP. Since the impacts of the explanatory variables may vary with the type of trucks, we also report the results obtained using only observations pertaining to van tractor-trailer (MNOP Van). From these results, we can assess which factors have a significant positive or negative impact on *LF*. In order to evaluate the magnitude of the effects, we also present in figure 2, the result of a simulation

based on the MNOP results.[10] This figure illustrates the change in the *LF* resulting from changes in the various explanatory with respect to a reference case.[11]

From these tables and figures, we can draw the following conclusions. *EMVS* is indeed associated with a reduction of *LF* on *F* trips in the order of 7.6 percentage point. On *B*-trips, *EMVS* has a positive and significant effect on *LF*. Our simulation indicates that trucks equipped with *EVMS* would have *LF* about 16 percentage points higher than non-equipped trucks. Thus, if this technology actually increases *LF*s on *B* trips, it also seems to incite carriers to accept lower *LF* on *F* trips. The impact appears somewhat more pronounced when estimating the model with the van subsample. In this case, the technology increase backhaul *LF* by 22.5 percentage points and reduces fronthaul *LF* by 14.4 percentage points.

As expected, the *LF* is positively affected by the truck size, particularly on *F* trips. For example, a truck with seven axles has on average a 15.7 percentage point higher *LF* than a five axles truck. While trucks from the *ROC* do not appear to have very different *LF* than Quebec trucks, US trucks have lower *LF*s on *F* trips. Trade imbalance between the US and Canada may explain this result. As expected, more specialized trailers have lower *LF*s. Private carriers have *LF*s that are about 5% lower on average than for-hire truckers in *B* trips. Interestingly, owner-operators have somewhat higher backhaul *LF*. As expected, distance is a major factor affecting *LF*s on both types of segments. A 1000 km (resp. 2000 km) trip has on average a load factor higher by 14 (25) percentage points compared to a truck travelling on a 450 km journey. *INCOME* has a positive impact on *F* trips while *POPULATION* positively affects backhaul *LF*.

In order to better assess the overall impact of *EVMS*, we simulate the change in the TKMs transported associated with this technology. To that end, we estimate the TKMs for each of the

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[10] Except for the OLS model, the magnitude of the effects cannot be directly inferred from the value of the estimated coefficients.

[11] The reference case corresponds to an "average" trip of 450 km, between two areas of 226,000 habitants each with median income of 45,000$. The reference truck has five axles, no *EVMS*, is a van based in Quebec and is operated by a for-hire carrier.

observations in our sample using the results of our econometric model, and then re-compute the TKMs that would have been carried if no truck was equipped with *EVMS*.[12] We find that this technology has allowed adopting trucks to increase their output by 6.3%, holding constant the supplied capacity. This implies an overall increase in the industry capacity utilization of about 0.83%. Our results are somewhat smaller than those reported by Hubbard (2003). Indeed, recall that Hubbard finds that adopting trucks increase their output by 13%, which translates into a 3% industry-wide capacity utilization improvement. The larger overall impact is obviously partially explained by the higher adoption rate in the US (25% of equipped trucks in Hubbard data versus 10% in ours). A higher adoption rate may also lead to higher benefits if there are learning and network effects. In fact, Hubbard's analysis suggests that benefits in the US were larger in 1997 than in 1992 when the adoption rate was lower. Finally, we can translate our results in terms of energy efficiency gains; *EVMS* would have increased fuel efficiency of adopters by close to 5% and by 0.66% at the industry level.[13] The importance of this effect should, however, be contrasted with the 40% improvement in energy efficiency that the Canadian trucking industry has experienced since 1990 (see Natural Resources Canada, 2006).

Several alternative specifications were tested, leading to results that were very much in line with those reported in table 4.[14] First, the model was estimated with a measure of *LF* based on the cargo weight and the maximum loading capacity of the truck rather than the driver estimate. Besides not taking into account the volume constraint, this variable is also an approximation since the maximal loading capacity of the truck is not directly measured, but rather it is inferred based on the truck characteristics.[15] In any case, the correlation between both measures of *LF* is close to 0.8 and the econometric results lead to similar conclusions. Second, the model was estimated without accounting for the sampling weights. While the estimated coefficients are statistically different (thereby suggesting that the unweighted results

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[12] See the numerator of [2] for the formulation used to compute TKM.
[13] We assume that a 1% increase in LF leads to a 0.2% increase in fuel consumption.
[14] All results are available from the corresponding author upon request.
[15] It is computed as the difference between the weight of the truck full and empty. The former is evaluated as the number of axles times 8 500 kg (*i.e.* the maximal weight per axles authorized by the Canadian regulation), the latter is based on the weight of empty trucks in the current survey and in the similar survey realized in 1995.

are not consistent), the sign and statistical significance of the variables of interest are similar. Third, the model was re-estimated using only trips with a distance superior to 450 km. Once again, our main conclusions remain unchanged and the estimated coefficient on *EVMS* is very similar. Fourth, we introduced for each "commercial axis" fixed effects to make sure that our variables are not capturing the impact of unobservable factors.[16] The estimated coefficients for *EVMS* are very similar in both specifications.[17] Fifth, the effects are comparable when estimating a model, explaining the probability of a truck being full or having a load (*i.e.* estimating a probit model with *FULL* or *LOADED* as dependant variables). Finally, *EVMS* may be endogenous. We tackle this concern in the next sub-section.

### 4.3 Endogeneity of EVMS adoption

*EVMS* could be correlated with the error term, thereby biasing in our results. This correlation could result from missing variables that are affecting both *LF* and *EVMS* such as for example the carrier size. It may also be that carriers assign their equipped trucks to roads depending *LF*. Dealing with this issue is made difficult by the fact that the adoption rate is low (it is more difficult to predict a rare event). Moreover, both *LF* and *EVMS* are discrete variables which require estimating an endogenous switching model. In fact, we add to the latent *LF* response model [8] and [9], the following latent model for explaining *EVMS* adoption:

$$EVMS_i^* = z_i'\gamma + \upsilon_i \qquad [10]$$

$$EVMS_i = \begin{cases} 0 & if \ EVMS_i^* \geq 0 \\ 1 & otherwise \end{cases} \qquad [11]$$

---

[16] Ideally, we would want to define these axes as precisely as possible, however, for statistical reasons, we need to have enough observations per axis. For this reason, we define a commercial axis based on the region of origin and destination. The regions are defined as follows: i) the province of Quebec is divided in four sectors using a division defined in the NRS99; ii) the rest of Canada is divided in three parts: the province of Ontario (*i.e.* Quebec's main economic partner in Canada), the West (British Columbia, Alberta, Saskatchewan, Manitoba and the North Western Territories) and the Atlantic provinces iii) the US is divided in two: the North-East is separated from the rest of the US.

[17] Obviously, as expected, the estimated coefficients associated with variables that vary little across commercial axes were affected by the introduction of the fixed effects.

with $z_i^{'}$ the vector of explanatory variables.  Furthermore, it is assumed that a shared random effect induces dependence between the error terms in [8] and [10]:

$$u_i = \lambda \varepsilon_i + \tau_i$$
$$\upsilon_i = \varepsilon_i + \zeta_i$$

where $\varepsilon_i$, $\tau_i$ and $\zeta_i$ are independently normally distributed with mean 0 and variance 1 and $\lambda$ is a free parameter.  In this model, the correlation between the two latent equation error terms is given by:

$$\rho = \frac{\lambda}{\sqrt{2(\lambda^2 + 1)}} \; .$$

*EVMS* is exogenous if $\rho = 0$.[18]   If the model can be estimated without any instruments it is, however, recommended to specify some exclusion restrictions (*i.e.* variables affecting *EVMS* but not *LF*).  We propose using as instruments variables indicating if the truck is equipped with: i) an electronic drive log that automatically records the hours of operation (*LOG*); ii) an electronic vehicle identification tag that can be read by equipment located in the roadway (*TAG*); iii) a tripmaster providing information about the best route (*TRIPMASTER*).  These electronic equipments are not designed to have an impact on *LF* but they are likely to be positively correlated with the adoption of *EVMS*.  We also use a variable indicating if the truck has anti-lock brakes (*ANTI*).  Indeed, this variable should provide an indication of the truck age.[19] Newer trucks are certainly more likely to be equipped with new up-to-date technologies such as *EVMS*. Finally, we also use a binary variable set to one if the driver has received at least a one day training course on the usage of electronic equipments in the last three years (*TRAINING*).

The results are reported in Table 6.  For both *F* and *B* trips, we cannot reject the hypothesis that $\rho = 0$ at any significance level.  The estimated coefficients are fairly close to those estimated in Table 5, except, however, for the coefficient associated with *EVMS*.  For *F* trips, the negative effect is somewhat larger but becomes statistically not significant.  For *B* trips, it is positive significant and much larger than

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[18] The model is estimated by maximum likelihood using the *ssm* "wrapper" program in Stata created by Miranda and Rabe-Hesketh (2006).
[19] In the US antilock brakes become mandatory on heavy trucks in 1997.

in table 5 (1.16 versus 0.421).  Note, however, that the *EVMS* model has difficulty to correctly predict adoption.  Indeed, the model only predicts a probability of adoption higher than 0.5 for 63 *B* observations while there are 467 equipped trucks.  In fact, the average predicted probability of adoption computed over the sample of equipped trucks on *B* trips is only 0.24.  Thus the average impact of *EVMS* in this model is likely to be best evaluated by considering a change in the predicted *LF* for *EVMS* increasing from 0 to 0.24 (rather than from 0 to 1).  In this case, the impact is relatively comparable to the one measured in Table 5.

Looking at the adoption results, we find that the probability of having an *EVMS* is positively and statistically linked to all our instruments.  It also increases with the trip distance.  Private carriers and owner-operators are less likely to adopt this technology.  The probability of adoption is also lower for specialized trailers.  These results are in line with Hubbard (2000).  Trucks from the *ROC* are more likely to have this technology than Quebec trucks.  For *US* trucks, the evidence is less clear: on *F* trips they have a much higher probability, while on *B* trips it seems to be the opposite.

## 5. Conclusion

Using data disaggregated at the operational level, we have shown that ICT improves capacity utilization in the trucking industry.  While the overall impact is relatively limited due to a low adoption rate, the effect on adopters is not negligible.  Since it is possible that benefits are increasing over time with learning and diffusion, it would be interesting to reevaluate the effect of *EVMS* using more recent data.  Our results also illustrate, once again, the difficulty in measuring the impact of ICT on aggregate productivity measures. Indeed, we have found evidence that while the technology improves capacity utilization on backhaul, it also leads carriers to accept fronthaul shipments that may not have been accepted without this technology. This could be viewed as an improvement in the quality of the services offered.  Obviously, this "rebound effect" limits the positive environmental consequences of this technology.

In future research, it would be worthwhile to further test this rebound effect using a more structural approach, where the fronthaul load factor directly depends upon the expected load factor on the

return.  This approach would, however, require observing the complete truck journey rather than only one

segment, as in our data.  Finding a proper source of identification would also be a challenge.

**Appendix 1. Criteria used to select the observations in the sample**

From the initial data set provided by the Quebec Ministry of Transport, we eliminate observations corresponding to:

- Small trucks (*i.e.* trucks with less than five axles) which are more likely to be affected by local transportation activities. We also eliminate non standard truck configuration (*i.e.* one tractor with more than one trailer) which is likely to face different operational constraints.

- Courier and less-than-truckload services (as well as peddle run). Contrary to full truckload companies, courier and less-than-truckload (LTL) carriers are specialized in relatively small freight, and usually operate within a hub-and-spoke network: freights from various clients are first shipped into a terminal before being dispatched to other terminals and then delivered to their final destination. For these types of services, optimizing *LF* is somewhat less important than providing frequent and on-time deliveries. The impact of various explanatory variables on their activities is therefore likely to be different than on those of full truckload carriers. Moreover, since relatively few observations were related to courier and LTL operations in our dataset, it was not possible to estimate the model separately for these observations.

- Trips for which it was difficult to determine if it was a fronthaul or backhaul trip. Specifically, we eliminate trips for which the distance truck base-origin and truck base-destination were relatively similar. Indeed, it is hazardous to classify these trips as fronthaul and backhaul.

- Trips with a distance less than 80 km.

**Table 1. Variable Definition.**

| Variable | Description |
|---|---|
| LF | Load factor of the truck as evaluated by the driver. Five responses are possible: 0%, 25%, 50%, 75% and 100%. |
| FULL | Binary variable sets to 1 if $LF$=100% and 0 otherwise. |
| LOADED | Binary variable sets to 1 if $LF \neq 0$ and 0 otherwise. |
| *Truck characteristics* | |
| EVMS | Binary variable sets to 1 if the truck is equipped with an on-board computer and a satellite dish. |
| AXLES | Number of axles. |
| *Truck's base* | |
| QUEBEC | Binary variable sets to 1 if the truck is registered in the province of Quebec. |
| ROC | Binary variable sets to 1 if the truck is registered in the rest of Canada. |
| USA | Binary variable sets to 1 if the truck is registered in the U.S. |
| *Type of trailer* | |
| VAN | Binary variable sets to 1 for van type trailer. |
| CONTAINER | Binary variable sets to 1 for container type trailer. |
| REFRI | Binary variable sets to 1 for refrigerated van type trailer. |
| LOGGING | Binary variable sets to 1 for trailer designed to carry logs. |
| SPECIALIZED | Binary variable sets to 1 if the trailer is a platform, a hopper, a dump or a tank. |
| *II. Carrier's Characteristics* | |
| FOR-HIRE | Binary variable sets to 1 for-hire carrier. |
| PRIVATE | Binary variable sets to 1 if private carrier. |
| OWNER-OP | Binary variable sets to 1 the truck is driven by an owner-operator. |
| *II. Trip's Characteristics* | |
| DISTANCE | Total trip distance. It is the shorter distance ("as-the-crow-flies) between the origin and destination based on these two points' longitude and latitude. |
| POPULATION | Population in the area of origin times the population in the area of destination divided the square of the trip distance. Sources: for Canada Statcan, for the US, US Census Bureau. |
| INCOME | Average of the origin and destination household median incomes. Sources: for Canada Statcan, for the US, US Census Bureau. |

**Table 2. Sample Characteristics**

| Variables | Mean (std) (*) |
|---|---|
| *LF* (%) | |
|   *B & F* trips | 64.4 (44.0) |
|   *F* trips    75.4 (38.3) | |
|   *B* trips    54.8 (46.4) | |
| *FULL* (%) | |
|   *B & F* trips | 54.3 (49.8) |
|   *B* trips    64.0 (47.9) | |
|   *F* trips    45.9 (49.8) | |
| *LOADED* (%) | |
|   *B & F* trips | 71.7 (45.0) |
|   *B* trips    83.1 (37.4) | |
|   *F* trips    61.7 (48.5) | |
| *EVMS* (%) | 8.4 (27.7) |
| *AXLES* | 5.6 (0.81) |
| *QUEBEC* (%) | 78.9 (40.7) |
| *ROC* (%) | 17.1 (37.7) |
| *US* (%) | 3.8 (19.2) |
| *VAN* (%) | 48.0 (49.9) |
| *CONTAINER* (%) | 3.9 (19.5) |
| *REFRI* (%) | 10.3 (30.4) |
| *LOGGING* (%) | 3.5 (18.3) |
| *SPECIALIZED* (%) | 33.9 (47.3) |
| *FOR-HIRE* (%) | 78.2 (41.2) |
| *PRIVATE* (%) | 21.7 (41.2) |
| *OWNER-OP* (%) | 20.0 (40.0) |
| *DISTANCE* (km) | 442.0 (480.9) |
| *POPULATION* | $2.4 \times 10^6$ ($5.2 \times 10^6$) |
| *INCOME* (en mil. CA$) | 45.5 (9.4) |
| *NUMBER OF TRIPS* | 87 702 |

(*) : The expansion factor is used to weight each observation.

**Table 3. Average *LF* and EVMS Adoption Rate as a Function of Key Variables**

| Variables | *Average LF* (*) (%) | EVMS adoption rate (*) |
|---|---|---|
| *EVMS* | | |
|     Yes | 77.2 | -- |
|     No | 63.2 | |
| | | |
|     QUEBEC | 63.1 | 6.8 |
|     ROC | 72.0 | 15.1 |
|     US | 58.1 | 10.4 |
| *VAN* | | |
|     Yes | 70.4 | 12.6 |
|     No | 58.9 | 4.4 |
| *FOR-HIRE* | | |
|     Yes | 66.8 | 9.2 |
|     No | 55.9 | 5.5 |
| *OWNER-OP* | | |
|     Yes | 68.9 | 5.5 |
|     No | 63.3 | 9.1 |
| *DISTANCE* | | |
|     < 450 km | 54.9 | 5.2 |
|     > 450 km | 80.2 | 13.6 |

(*) : The expansion factor is used to weight each observation.


**Table 4. Impact of EVMS on Capacity Utilization**

| | *LF* | | **FULL** | | **LOADED** | |
|---|---|---|---|---|---|---|
| | *EVMS* | | *EVMS* | | *EVMS* | |
| | *No* | *Yes* | *No* | *Yes* | *No* | *Yes* |
| ***F trips*** | | | | | | |
| Distance<450 | 66.6 | 66.9 | 55.3 | 55.4 | 74.4 | 74.8 |
| Distance>450 | 88.9 | 84.4 | 77.9 | 70.8 | 95.5 | 97.5 |
| ***B trips*** | | | | | | |
| Distance<450 | 44.3 | 64.7 | 36.4 | 61.2 | 50.5 | 68.7 |
| Distance>450 | 69.9 | 84.9 | 58.4 | 75.2 | 78.2 | 91.6 |

**Table 5. Estimation results (standard error)**

| Variable | F trips | | | B trips | | |
|---|---|---|---|---|---|---|
| | OLS | MNOP | MNOP Vans | OLS | MNOP | MNOP Vans |
| EVMS | -0.040 (0.031) | -0.186* (0.108) | -0.362*** (0.133) | 0.132*** (0.02) | 0.406*** (0.09) | 0.584*** (0.124) |
| AXLES | 0.073*** (0.011) | 0.231*** (0.045) | 0.244*** (0.085) | 0.009 (0.015) | 0.029 (0.041) | 0.061 (0.062) |
| QUEBEC | Reference | Reference | Reference | Reference | Reference | Reference |
| ROC | -0.029 (0.021) | -0.113 (0.077) | 0.028 (0.106) | -0.012 (0.025) | -0.066 (0.069) | -0.018 (0.101) |
| USA | -0.145*** (0.04) | -0.467*** (0.123) | -0.687*** (0.195) | 0.059 (0.058) | 0.130 (0.150) | -0.08 (0.279) |
| VAN | Reference | Reference | -- | Reference | Reference | Reference |
| CONTAINER | -0.033 (0.050) | -0.215 (0.171) | -- | -0.068 (0.054) | -0.218 (0.149) | -- |
| REFRI | -0.081** (0.028) | -0.319*** (0.095) | -- | -0.048 (0.042) | -0.132 (0.117) | -- |
| LOGGING | -0.039 (0.073) | -0.182 (0.220) | -- | -0.020 (0.058) | -0.072 (0.160) | -- |
| SPECIALIZED | -0.09*** (0.021) | -0.381*** (0.073) | -- | -0.125*** (0.025) | -0.381*** (0.068) | -- |
| FOR-HIRE | Reference | Reference | Reference | Reference | Reference | Reference |
| PRIVATE | -0.000 (0.024) | 0.016 (0.081) | 0.058 (0.121) | -0.048* (0.027) | -0.130* (0.075) | 0.050 (0.009) |
| OWNER-OP. | -0.028 (0.025) | -0.093 (0.086) | -0.073 (0.116) | 0.050* (0.026) | 0.118* (0.071) | 0.122 (0.09) |
| Log(DISTANCE) | 0.163*** (0.016) | 0.538*** (0.048) | 0.619*** (0.074) | 0.170*** (0.015) | 0.466*** (0.043) | 0.631*** (0.062) |
| Log(POPULATION) | 0.001 (0.003) | 0.001 (0.013) | 0.030 (0.019) | 0.009** (0.004) | 0.027** (0.011) | 0.059*** (0.017) |
| Log(INCOME) | 0.09*** (0.036) | 0.351*** (0.133) | 0.07 (0.175) | 0.031 (0.049) | 0.111 (0.135) | -0.228 (0.179) |
| $\alpha_1$ | | 4.480 (0.713) | 4.25 (1.09) | | 3.12 (0.68) | 3.39 (0.92) |
| $\alpha_2$ | | 4.64 (0.711) | 4.49 (1.08) | | 3.25 (0.68) | 3.55 (0.92) |
| $\alpha_3$ | | 4.79 (0.712) | 4.65 (1.09) | | 3.34 (0.68) | 3.67 (0.92) |
| $\alpha_4$ | | 5.14 (0.711) | 4.94 (1.08) | | 3.57 (0.68) | 3.87 (0.92) |
| Log-pseudolikelihood | | -4603 | -2021 | | -5052 | -2404 |
| Wald Test | | $\chi^2(13)=241$ | $\chi^2(9)=109$ | | $\chi^2(13)=272$ | $\chi^2(9)=154$ |
| R-squared | 0.135 | | | 0.13 | | |
| Pseudo R-squared (McFadden) | | 0.063 | 0.07 | | 0.06 | 0.07 |
| Numb.. obs. | 4532 | 4532 | 2224 | 4559 | 4559 | 2239 |

\* : significant at 10%, \*\* : significant at 5%, \*\*\* : significant at 1%

In parenthesis, robust standard errors (Hubber and White estimators).

$\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$ represent the threshold parameters

**Table 6. Estimation results with endogenous EVMS adoption.**

| Variable | F trips | | B trips | |
|---|---|---|---|---|
| | LF eq. | EVMS eq. | LF eq. | EVMS eq. |
| EVMS | -0.302 | -- | 1.160*** | -- |
| | (0.531) | | (0.382) | |
| AXLES | 0.234*** | -0.148** | 0.033 | -0.08 |
| | (0.04) | (0.072) | (0.042) | (0.068) |
| QUEBEC | Reference | Reference | Reference | Reference |
| ROC | -0.09 | 0.364*** | -0.092 | 0.214*** |
| | (0.08) | (0.100) | (0.070) | (0.111) |
| USA | -0.458*** | 0.563*** | 0.118 | -0.357** |
| | (0.141) | (0.171) | (0.155) | (0.189) |
| VAN | Reference | Reference | Reference | Reference |
| CONTAINER | -0.218 | -0.482*** | -0.185 | 0.239 |
| | (0.178) | (0.250) | (0.155) | (0.241) |
| REFRI | -0.333*** | 0.049 | -0.074 | -0.640*** |
| | (0.09) | (0.172) | (0.129) | (0.126) |
| LOGGING | -0.199 | -0.211 | -0.021 | -0.633*** |
| | (0.228) | (0.443) | (0.169) | (0.225) |
| SPECIALIZED | -0.391*** | -0.464*** | -0.309*** | -0.671*** |
| | (0.082) | (0.124) | (0.087) | (0.131) |
| FOR-HIRE | Reference | Reference | Reference | Reference |
| PRIVATE | 0.018 | -0.200 | -0.117 | -0.169 |
| | (0.084) | (0.136) | (0.07) | (0.146) |
| OWNER-OP. | -0.100 | -0.156 | 0.164** | -0.490*** |
| | (0.084) | (0.113) | (0.078) | (0.120) |
| Log($DISTANCE$) | 0.549*** | 0.303*** | 0.422*** | 0.261*** |
| | (0.053) | (0.061) | (0.055) | (0.06) |
| Log($POPULATION$) | 0.001 | 0.046** | 0.025** | -0.001 |
| | (0.014) | (0.018) | (0.011) | (0.01) |
| Log($INCOME$) | 0.363*** | 0.245 | 0.105 | 0.08 |
| | (0.139) | (0.191) | (0.140) | (0.193) |
| LOG | -- | 0.692*** | -- | 0.575*** |
| | | (0.146) | | (0.134) |
| TAG | -- | 0.241 | -- | 0.378*** |
| | | (0.164) | | (0.134) |
| TRIPMASTER | -- | 1.13*** | -- | 0.505*** |
| | | (0.236) | | (0.223) |
| ANTI | -- | 0.331*** | -- | 0.528*** |
| | | (0.110) | | (0.102) |
| TRAINING | -- | 0.669*** | -- | 0.657*** |
| | | (0.146) | | (0.090) |
| CONST. | -- | -4.45*** | -- | -3.15*** |
| | | (1.02) | | (0.949) |
| $\alpha_1$ | 4.58*** | | 2.96*** | |
| | (0.75) | | (0.71) | |
| $\alpha_2$ | 4.75*** | | 3.08*** | |
| | (0.75) | | (0.71) | |
| $\alpha_3$ | 5.89*** | | 3.17*** | |
| | (0.75) | | (0.71) | |
| $\alpha_4$ | 5.25*** | | 3.39*** | |
| | (0.75) | | (0.71) | |
| Log-pseudolikelihood | -47510 | | -59227 | |
| Wald chi2 (30) | 588 | | 658 | |

**Table 6. Estimation results with endogenous EVMS adoption (cont.).**

| | | |
|---|---|---|
| $\rho$ | 0.06 | -0.45 |
| LHR test for $\rho = 0$ | $\chi^2(1) = 0$ | $\chi^2(1) = 0$ |

Standard deviation in parenthesis. * : significant at 10%, ** : significant at 5%, *** : significant at 1%

**Figure 1.**



F (Fronthaul) trip
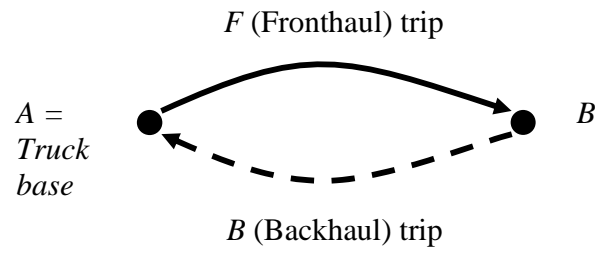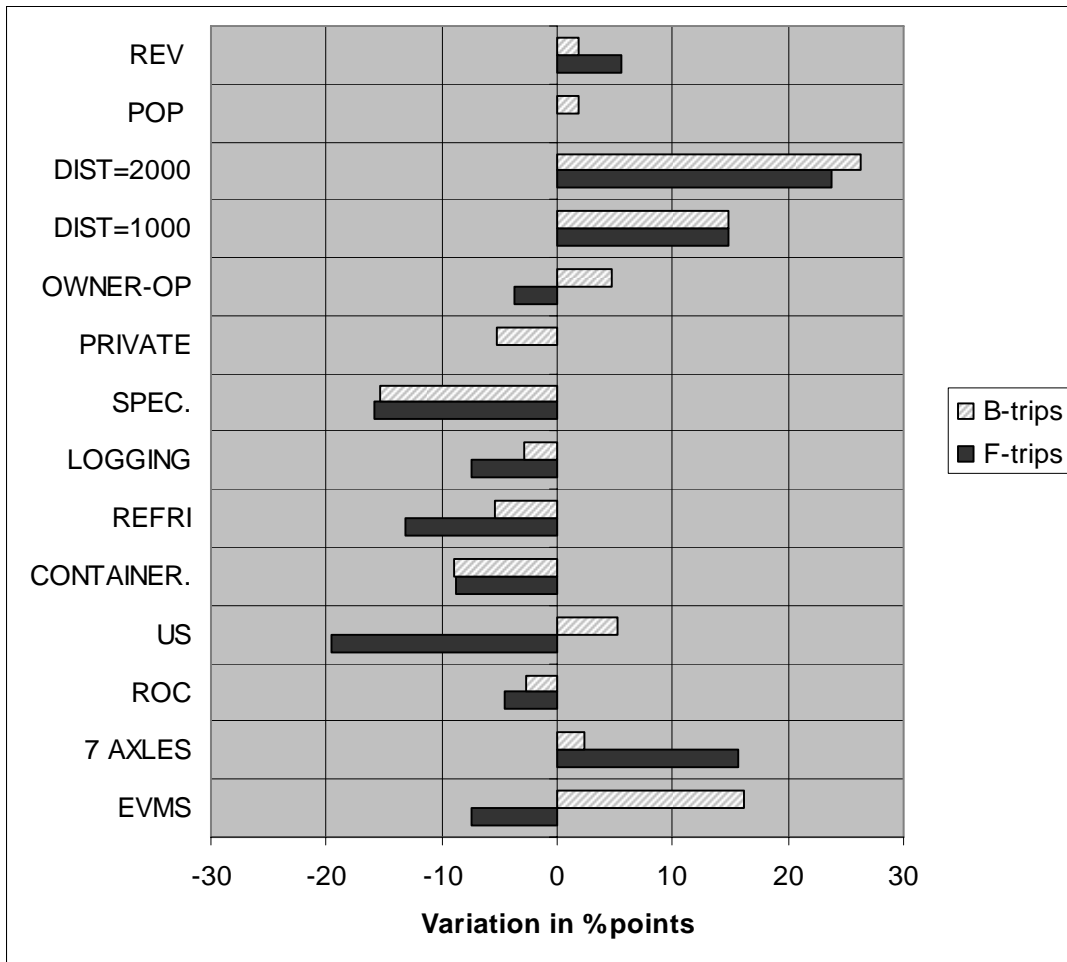
A =
Truck
base

B

B (Backhaul) trip

**Figure 2. Simulation results using column (2) estimates from Tables 4.**



The impacts are computed with respect to an "average" reference trip of 450 km, between two area of 226,000 habitants each with median income of 45,000$. The reference truck has five axles, no EVMS, is a van registered in Quebec and is operated by a for-hire carrier.

# References

Brynjolsson E. and Y. Shinku (1996), 'Information Technology and Productivity: A Review of the Literature', in Marvin Zelkowitz, ed., *Advances in computers*, Vol. 43, New York: Academic Press.

Bridestone/Firestone Commercial Truck Tires (2006), *Truck Tires.com*, available online http://www.trucktires.com/us_eng/technical/bftechnical/fuel_economoy_b.asp , February 2006.

CCMTA (Canadian Council of Motor Transport Administrators) (2002*), 1999 National Roadside Study, Truck Traffic Estimate Software Package*, Canada.

Environnement Canada (2005), 'Inventaire canadien des gaz à effet de serre 1990-2003', available on line http://www.ec.gc.ca/pdb/ghg/inventory_report/2003_report/toc_f.cfm.

Greening L., D. Greene and C. Difiglio (2000), 'Energy efficiency and consumption – the rebound effect – a survey', *Energy Policy* 28, p. 389-401.

Hubbard, T. N. (2005), 'The Demand for Monitoring Technologies: The Case of Trucking', *The Quarterly Journal of Economics*, Vol. 115 No. 2, p. 533-560.

Hubbard, T. N. (2003), 'Information, Decision, and Productivity: On-Board Computer and Capacity Utilization in Trucking', *The American Economic Review*, Volume 93, Issue 4, pages 1328 – 1353.

Pilat D. (2004), 'The ICT productivity paradox: Insights from micro data', OECD Economic Studies 38, p. 37-65.

Porter, M. E. and C. van der Linde (1995), 'Towards a New Conception of the Environmental-Competitiveness Relationship', *Journal of Economic Perspectives,* 9, 97-118.

Ministère des Transports du Québec (2003), *Les déplacements interurbains de véhicules lourds au Québec*, *Enquête sur le camionnage de 1999*, April, 147 pages.

Miranda A. and S. Rabe-Hesketh (2006), 'Maximum likelihood estimation of endogenous switching and sample selection models for binary, ordinal, and count variables', *Stata Journal*, StataCorp LP, vol. 6(3), p. 285-308.

Nix F. P. (2003), 'Truck Activity in Canada – A profile', prepared for Motor Carrier Policy Branch,

Transport Canada.

Natural Resources Canada (2006), *Energy Efficiency Trends in Canada*, Ottawa.

Transport Canada (2003). *Les transports au Canada,  Rapport Annuel 2003 et 2004*, available on line,

http://www.tc.gc.ca/pol/fr/rapport/anre2004/toc_f.htm.

Wooldridge, J. M. (1999), 'Asymptotic Properties of Weighted M-Estimators for Variable Probability

Samples', *Econometrica*, Vol. 67, No. 6, p. 1385-1406.

Wooldridge J.M. (2001), *Econometric Analysis of Cross Section and Panel Data*, The MIT Press, Cambridge,

Massachusetts, 2001, 752 pages.