Information, Decisions, and Productivity

On-Board Computers and Capacity Utilization in Trucking

Thomas N. Hubbard

University of Chicago and NBER

Productivity reflects not only how efficiently inputs are transformed into outputs, but also how well information is brought to bear on resource allocation decisions. This paper examines this empirically by looking at how on-board computer (OBC) adoption has affected capacity utilization in the trucking industry. Estimates using 1997 data indicate that capacity utilization has increased by an average of 11% among trucks for which advanced OBCs have been adopted. The average benefits to adopters are higher in 1997 than 1992, suggesting lags to the returns to adoption, and are highly skewed across hauls. The 1997 estimates imply that OBC-enabled improvements in communications and resource allocation decisions have led to a 3% increase in capacity utilization in the industry, which translates to billions of dollars of annual benefits. The commercialization of other wireless networking applications has the potential to generate analogous benefits in other contexts.

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1. Introduction

Theoretical links between economic performance and the use of information, such as those in Hayek's (1945) famous analysis of economic organization, are at the core of a recurring theme in the productivity literature: the premise that information technology (IT) offers opportunities for large productivity gains. Empirical evidence showing links between IT diffusion and productivity has been scarce until recently, however.[1] Researchers in the field refer to this as "the productivity paradox." The difficulty of finding relationships between IT use and productivity using aggregate data is well-summarized by Solow's oft-cited observation: "You can see the computer age everywhere except in the productivity statistics."

This paper examines micro-level empirical relationships between IT use and productivity in the trucking industry in the 1990s. Productivity in this industry, as elsewhere in the economy, depends critically on how well information is brought to bear on resource allocation decisions.[2] Supply and demand conditions change constantly; forecasting exactly when and where trucks will be available and exactly when and where shippers will demand service is difficult more than a few hours in advance. Information about trucks' availability and value in different uses is highly dispersed, and communication costs create situations where the individuals deciding how individual trucks should be used – usually, dispatchers – do not have good information about trucks' availability. Trucks are not always allocated to their most valuable use as a consequence. Poor matches between capacity and demands lead to underutilization in the form of idle trucks and partially-full or empty trailers.

In particular, I examine how on-board computer (OBC) use has affected capacity utilization. OBCs help managers at trucking firms or divisions monitor trucks and drivers. Low-end devices – trip recorders – make truck drivers' activities more contractible and help mechanics diagnose engine

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[1] Athey and Stern (2000), Brynjolffson and Hitt (1996), Lehr and Lichtenberg (1998), Lichtenberg (1995), Oliner and Sichel (2000). See Brynjolffson and Hitt (2000) and Brynjolffson and Yang (1996) for surveys of the evidence.

[2] That firms pay thousands of dollars for supply chain management software that provides managers up-to-date information about the status of production processes and inventories testifies that information about capacity is valuable and costly to obtain in other contexts.

problems. High-end devices – electronic vehicle management systems (EVMS) – also provide dispatchers real-time information about trucks' location and an efficient means of communicating with distant drivers. These additional capabilities let dispatchers make and implement better resource allocation decisions: they can allocate trucks across existing orders and market excess capacity better than they otherwise could. This, in turn, can lead to better matches between truck capacity and demands within and across firms. Better matches boost capacity utilization and productivity in the industry.

I find that OBC use has increased capacity utilization significantly in the industry. Estimates using 1997 data indicate average increases in capacity utilization of 11% among adopters of advanced OBCs. These increases appear to be almost entirely due to EVMS' advanced features, which lower communication costs and improve resource allocation decisions. There is little evidence of truck utilization increases due to incentive improvements. The average benefits to adopters are higher in 1997 than 1992, suggesting lags to the returns to adoption, and are highly skewed across hauls. In particular, they tend to be highest on trucks used for long hauls that do not require specialized trailers. The 1997 estimates imply that OBC-enabled improvements in decision-making have led to 3% higher capacity utilization in the industry, which translates to about $15 billion in annual benefits. These benefits are likely to increase as complementary economic institutions such as centralized markets develop in the industry and as diffusion becomes more widespread.

This study stands at the intersection of the productivity, economics of technology, and economics of organizations literatures, and is important for several reasons. First, it provides strong evidence of productivity gains from IT adoption. There is no "productivity paradox" in trucking. This study adds to a growing set of studies that document relationships between productivity and IT use, some of which are cited above. Second, as the Hayek cite indicates, understanding relationships between informational and resource allocation improvements is central for understanding the performance of economic organizations and how decreases in information costs lead to increases in welfare. This is one of the first empirical studies to examine these relationships in detail. An advantage of this paper's micro-level industry study approach (shared by Athey and Stern (2000)) is that one can understand exactly how and why IT use leads to productivity gains. Third, truck-tracking is one of the first commercially-important wireless networking applications. Wireless networking applications are expected to diffuse more broadly in the economy in the near future; this study helps researchers understand their economic implications. The conclusion that OBCs have generated large benefits in trucking suggests that new networking applications have the potential to generate large welfare gains elsewhere.[3] Last, few individual applications have the potential for as significant a macroeconomic effect as OBC-enabled truck-tracking. OBCs fundamentally changed how resource allocation decisions were made in an industry that interacts with most sectors of the economy and amounts to about 6% of GDP (including the value-added produced by private fleets). OBC diffusion and related logistical improvements were non-trivial contributors to economic growth in the U.S. during the 1990s.

An outline of the rest of the paper follows. The next section describes the institutional setting and depicts how OBCs improve resource allocation decisions in trucking. Section 3 presents the data and the basic empirical patterns. Section 4 outlines the empirical framework. Section 5 discusses the estimation results. Section 6 concludes.

2. Information and Capacity Utilization in Trucking

The physical part of the production process in trucking is simple. Cargo is loaded onto a truck, or a truck's trailer. An individual – a driver – drives the truck to its destination, where the cargo is unloaded. The output of the production process is the movement of cargo.

All else equal, costs per unit of output fall with capacity utilization. The per-unit cost of moving cargo on a truck increases less than proportionately with the weight of the cargo, and firms bear opportunity costs when trucks are idle, especially when idle trucks imply idle drivers. Truck capacity is lumpy and location- and time-specific. Capacity utilization is high when trucks haul a series of full loads, each of which starts close to and soon after the previous one finished.

Achieving high levels of capacity utilization is easy in some circumstances, but hard in others. When shippers have consistent demands to transport full loads of cargo back and forth between two points, high utilization rates can be achieved by dedicating trucks and drivers to a

[3]See Gordon (2000) for a skeptic's view.

shipper and route. Most situations are not like this, however. Individual shippers usually do not have demand for both legs of a round trip and shipments often do not fill trailers. In such situations, high capacity utilization requires trucks to haul different shippers' cargo on the same run.

Capacity utilization thus depends largely on how well individuals can identify and agglomerate complementary demands onto individual trucks. Higher quality matches increase capacity utilization by keeping trucks on the road and loaded more, and therefore raise truck drivers' productivity.[4]

It follows that understanding the link between information and capacity utilization requires some understanding of the institutions that facilitate matching, individuals' role within these institutions, and how informational improvements lead to better matches both directly and through organizational changes. This is the topic of the next subsection.

Institutions and Market Clearing

Market clearing in trucking is unlike that in textbook economics models. It does not take place in centralized markets in which participants simply observe prices and decide how much capacity to sell to or buy from the market. Centralized markets have traditionally been unimportant in trucking, in large part because capacity and demands are highly differentiated in terms of time, location, and equipment characteristics. Organizing centralized markets that are so narrowly-defined is costly relative to the benefits such markets would generate.[5] Instead, capacity and demand are matched in a highly decentralized manner in which buyers, sellers, and intermediaries engage in costly search. These parties identify trading opportunities by contacting each other directly rather than through markets.

One way complementary demands are identified is that shippers themselves search for other shippers with complementary demands. For example, a shipper with one-way demands between Chicago and St. Louis will search for a shipper with one-way demands between St. Louis and

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[4]Links between productivity and the efficiency of the market clearing process exist in many markets, particularly those like trucking in which supply and demand are highly differentiated. Labor markets are good examples.

[5]Narrowly-defined markets tend to be illiquid, and matches in such markets may not improve much upon those achieved through decentralized matching.

Chicago. However, much of the time complementary demands are identified by intermediaries, who add value by lowering search costs.

There are two main classes of intermediaries in trucking: for-hire carriers and brokers. They differ in whether they own trucks; for-hire carriers control truck fleets but brokers do not. As explained in Baker and Hubbard (2000b), truck ownership enhances intermediaries' incentives to find complementary hauls because it allows them to appropriate a greater share of the surplus. Most intermediaries in the industry are for-hire carriers. Shippers tend to use for-hire carriers when identifying complementary demands is important, such as for long or less-than-truckload hauls, and private fleets when it is not.

Shippers and carriers sometimes contract ahead for service. These contracts usually cover a series of recurring hauls. Arrangements of this sort reduce search costs by eliminating the need to search for trading partners recurrently, but tend to lower the short-term efficiency of the match between trucks and hauls.[6] Hubbard (2001) shows that contracting becomes more prevalent relative to simple spot arrangements as local markets become thinner, particularly for long hauls. Shippers and carriers tend to rely on short term arrangements when they use non-specialized equipment for hauls on thick shipping lanes, but longer-term arrangements when they use specialized equipment or operate on thin shipping lanes. Capacity and demands tend to be matched over longer horizons for hauls involving specialized equipment than non-specialized equipment.

Both the presence of intermediaries and the fact that most intermediaries own trucks thus can be interpreted as institutional responses to the matching problem. The presence of intermediaries lowers search costs; truck ownership provides intermediaries strong incentives to find good matches. These institutional features increase capacity utilization and thus raise truck drivers' productivity.

Dispatch and Information

Operationally, the people most directly involved in matching capacity to demand are dispatchers. Dispatchers assign trucks and drivers to hauls. Dispatchers who manage shippers' private fleets primarily assign trucks to their internal customer's hauls. Those who manage for-hire

[6]They may also serve to lower hold-up risks, by protecting relationship-specific informational investments. See Hubbard (2001).

carriers' fleets assign trucks to external customers' (shippers') hauls. Dispatchers sometimes actively search for additional hauls when doing so would increase capacity utilization, contacting shippers either directly or through brokers.[7] For example, they try to find good "backhauls" (return trips) or, when trucks are partly empty, identify other hauls along the same route that would fill trucks. Such activities are more common for dispatchers managing for-hire than private fleets. But they are not unusual within private fleets, particularly in cases where shippers use private fleets for long hauls.

Dispatchers work in a highly dynamic environment. Assignments and schedules are not set far in advance, in large part because it is often hard to forecast exactly when individual shippers will demand service and exactly when particular trucks will come free. In practice, dispatchers assign trucks and drivers to a series of hauls at the beginning of the day or a shift. This is often a provisional schedule. They then update schedules throughout the day as situations warrant, rearranging assignments in response to unexpected delays and new service orders (some of which they may have actively solicited to fill capacity). Dispatchers who do this well increase the productivity of the trucks and drivers they manage.

Information is a critical input to dispatchers' decisions. In particular, knowing where trucks are and how full their trailers are lets dispatchers forecast better the time and location capacity will become available. Better forecasts, in turn, allow them to allocate trucks across existing orders and market spare capacity more efficiently. They also can provide customers better information about arrival times.

Information processing and communication capabilities are important as well, because they help dispatchers make good decisions and redirect drivers. Most dispatchers use route-planning software packages to help develop schedules. Many of these packages are relatively inexpensive and PC-based. Dispatchers commonly use the software to draft schedules, which they then revise to account for factors not accounted for by the software.

Communicating with drivers has traditionally been difficult when trucks operate outside radio

[7]At larger firms, different individuals assign trucks to hauls and solicit business. I will abstract from the fact that individuals specialize, assuming that they work closely enough together so that they can be considered one decision-making unit.

range (about 25 miles). Dispatchers and drivers relied on a "check and call" system in which drivers stopped and called in every three to four hours. During the 1990s, declines in the price of long-distance cellular communication have led many dispatchers and drivers to abandon this system and communicate with cellular phones. This has significant advantages over the previous system because it allows dispatchers to initiate contact with distant drivers just like they do with those close by. Dispatchers no longer have wait until drivers call in to give them instructions, and drivers do not have to find a pay phone just to provide status reports and ask if there are schedule changes. Using cell phones alone has drawbacks, however. In particular, there remain significant coverage gaps, and information about trucks' location takes time to collect and is neither verifiable nor in electronically-processable form.

On-Board Computers

Two classes of OBCs began to diffuse in the trucking industry in the late 1980s: trip recorders and electronic vehicle management systems (EVMS).

Trip recorders are devices that monitor how drivers operate trucks. They record when trucks were turned on and off, trucks' speed over time, and incidents of hard braking. Trip recorders collect data onto a storage device. Dispatchers upload these data once drivers return to their base. The data trip recorders collect provide dispatchers verifiable information regarding drivers' activities, including whether they were speeding or took unauthorized breaks. Trip recorders also track how trucks' engines perform; for example, they track fault codes that result when engines work improperly. This information is useful to mechanics because it helps them diagnose engine problems better.

Trip recorders are thus useful for improving drivers' incentives and mechanics' maintenance decisions. They are not particularly useful for improving dispatchers' resource allocation decisions because they do not provide dispatchers information in a timely enough fashion.

EVMS are more advanced than trip recorders. They contain all trip recorders' capabilities. In addition, they record trucks' geographic location (for example, using satellite tracking) and provide a close-to-real time data connection between the dispatcher and the truck. These additional capabilities help dispatchers make better scheduling decisions and communicate them quickly to drivers. Knowing exactly where trucks are helps dispatchers allocate trucks across existing service orders and market excess capacity better. The communication link helps them notify drivers of schedule changes quickly and effectively.

There is an important economic distinction between trip recorders and EVMS. Both classes of devices are useful for improving incentives and maintenance decisions. EVMS, however, is also useful for improving resource allocation decisions ("coordination").

This paper focuses primarily on the impact of OBCs' coordination-improving capabilities on capacity utilization.[8] There are two reasons for this.

First, evidence from the trade press and plant visits indicates that OBCs' primarily affect capacity utilization though better dispatch, not through improvements in drivers' incentives or maintenance decisions. One exception to this is when drivers' jobs involve cargo handling as well as driving; some firms attribute productivity gains to the ability to track how long drivers spend at stops. Trucks can be utilized more intensively when drivers load and unload cargo faster. (See Baker and Hubbard (2000b).) OBC adoption also may have led some firms to provide drivers stronger fuel economy-based incentives, and this may have led to productivity gains, but there is little indication that these increases are substantial.

Second, it is difficult to isolate the impact of OBCs' incentive-improving capabilities, because all OBCs have both incentive- and maintenance-improving capabilities.

3. Data

The data are from the Bureau of the Census' 1992 and 1997 Truck Inventory and Use Surveys (TIUS).[9] The TIUS is a mail-out survey taken every five years as part of the Census of Transportation. The Census takes a random sample of trucks from vehicle registration records, and sends their owners a questionnaire that asks them about the characteristics and use of their trucks. For example, questions ask respondents their trucks' make and model. Importantly for this study, the Survey asks whether trucks have trip recorders or EVMS installed. It also asks many questions

[8]Other papers (Baker and Hubbard (2000a, 2000b)) have examined the organizational implications of OBCs' incentive-improving capabilities.

[9]The 1997 Survey is actually called the Vehicle Inventory and Use Survey. See Bureau of the Census (1995, 2000) and Hubbard (2000) for more details about these Surveys.

about how trucks were used during the previous year, including such things as whether it was owned by its driver, whether it operated within a private or for-hire fleet, how far from home it generally operated, what kind of trailer was attached, what classes of products it carried, and the state in which it was based. Although the TIUS contains observations of a wide variety of truck types, all of the analysis in this paper uses only observations of truck-tractors, the front halves of tractor-trailer combinations.

The Survey also asks several questions that elicit information regarding how intensively individual trucks were utilized. Answers to these questions provide the variables used to evaluate productivity. One question asks how many miles the truck was driven during the previous year. Other questions ask what fraction of miles the truck was driven without a trailer, and what fraction of miles it was driven empty. Combined with the number of miles the truck was driven, answers to these questions indicate the number of miles the truck was driven with cargo ("loaded miles"). The Survey also asks the weight of the truck when empty and the average weight of the truck plus cargo during a typical haul in the previous year. The difference between these figures is the average weight of the cargo the truck hauled ("cargo weight"). Multiplying loaded miles by cargo weight and dividing by 2000 gives an estimate of the truck's output during the previous year in ton-miles. Finally, these Surveys ask owners how many weeks out of the year trucks were in use. This is an important control variable. Its absence from previous Surveys is the reason I use only the 1992 and 1997 Surveys.

Responses to these questions likely overstate trucks' output and capacity utilization somewhat, although probably in a similar fashion from year to year. Cargo weight is probably overstated because respondents likely report cargo weight when trucks leave terminals, which is not the average amount of cargo in trucks' trailers while loaded when trucks deliver to multiple points. Respondents likely understate empty miles, particularly when trucks haul trailers for which backhauls are unlikely such as auto trailers. This is because respondents who do not try to find backhauls may not include backhaul capacity in the denominator of this fraction. But this bias works against finding relationships between OBC adoption and productivity increases if adoption leads firms to reconsider what they think of as unused capacity: for example, if it leads them to newly consider empty backhauls as empty miles.

The Survey therefore provides detailed information about production at the individual truck level. This level of disaggregation is rare, and provides a significant advantage in studying technology adoption, organizational structure, and productivity issues.[10] The Survey does not, however, allow one to identify trucks' owners. It is therefore impossible to determine the for-hire or private fleet in which individual trucks operated. Although one can aggregate up to the industry or industry segment level, the data cannot be used to investigate productivity at the firm level.

The following subsection summarizes some basic patterns in the data.

Simple Patterns

Table 1 presents simple trends in several output measures. The top panel indicates that capacity utilization increased between 1992 and 1997. On average, ton-miles per truck increased by 12.5%. This reflects an increase both in loaded miles and in average cargo weight: loaded miles per truck increased by 10.1% and the average weight increased by 2.7%. Overall, these figures indicate that trucks were driven more and trailers were fuller in 1997 than 1992, and that most of the increase in ton-miles per truck was due to increases in loaded miles rather than increases in cargo weight.

The bottom panel reports similar figures, averaging only over trucks that were in use at least 48 weeks out of the year. Comparing trends in these figures to those in the top panel indicates the extent to which increases in capacity utilization were due to increases in the number of weeks in service rather than increases in how intensively trucks were used conditional on being in service. The table indicates that ton-miles per truck actually increased slightly *more* within this subsample than among trucks at large. Loaded miles increased by 8.3% – somewhat less than the 10.1% increase within the full sample, but still a large increase. These figures do not suggest that increases in capacity utilization during this period were entirely due to the fact that economic growth led trucks to be in service more weeks out of the year in 1997 than 1992. Capacity utilization increased during this time even among the most-intensively-used trucks.

Figure 1 provides further evidence. This plots average weeks in use, by truck age, for the 1992 and 1997 samples. If overall capacity utilization increases reflect increases in the utilization

[10]The manufacturing equivalent perhaps would be to have data at the level of the production line rather than the establishment or firm.

of infrequently-used trucks, utilization of older trucks should be higher in 1997 than 1992. Figure 1 indicates that while weeks in use declines steadily with truck age in both years, the plots track each other very closely.[11] There is no evidence that older trucks were used more weeks per year in 1997 than 1992.

Figure 2 relates loaded miles per week to net EVMS adoption. The lines plot loaded miles per week as a function of age; the bars report net EVMS adoption between 1992 and 1997. There are three important facts. First, old trucks are used less intensively than new ones, even conditional on weeks in use. Second, the gap between 1997 and 1992 trucks is greater when comparing new trucks than old trucks. Once again the greatest increase in capacity utilization is for the trucks that are already utilized intensively. Third, the gap between the 1997 and 1992 trucks is widest where net adoption is highest – for one to five year old trucks. 1992-1996 model year trucks had much higher EVMS use rates in 1997 than 1987-1991 model year trucks did in 1992. Capacity utilization rates also appear to increase more for trucks in this range than younger or older trucks.

Table 2 provides further evidence based on truck characteristics other than age. This table uses cohorts rather than trucks as observations. Cohorts here are at the level of state-trailer: an example of an observation is "refrigerated trucks based in Iowa." I compute cohort-level averages for each capacity utilization measure and OBC adoption for each cohort in both years. Comparing cohort-level trends allows me to net out state- and trailer-specific effects that may affect both OBC adoption and capacity utilization. Table 2 reports averages using only cohorts with at least ten observations in each year.

The left panel of this table contains average changes in the capacity utilization measures. The top line, which uses trucks attached to all trailer types, generally tracks the patterns in Table 1. The lines below break things out by trailer type. The greatest increases in ton-miles were for trucks attached to dry vans, refrigerated vans, and tank trucks. The right panel reports net adoption rates for trip recorders and EVMS. From the top line, net trip recorder adoption was approximately zero between 1992 and 1997. New adoption of trip recorders was almost exactly offset by upgrading from trip recorders to EVMS. The average increase in EVMS adoption was about 14 percentage

[11] The low figure for brand-new trucks reflects that many were put into service in the middle of the survey year.

points. EVMS adoption was greatest for trucks attached to dry vans, refrigerated vans, and tank trucks – exactly the trailer categories for which capacity utilization measures increased the most.

Combined, these tables provide evidence consistent with the hypothesis that EVMS adoption contributed to increases in capacity utilization. Capacity utilization increased the most for already-intensively-used trucks, and trucks for which EVMS tended to be adopted most had the greatest increases in capacity utilization.

Furthermore, additional evidence indicates that capacity utilization increases during this time also represent increases in labor productivity. Increases in loaded miles per truck would *not* reflect increases in labor productivity if the ratio between drivers and trucks changed, as would be the case if firms were using trucks (but not drivers) for double shifts more in 1997 than 1992. However, data from the October CPS indicates that the number of truck drivers increased by 26.8% between 1992 and 1997; the 1997 VIUS indicates that the number of heavy duty trucks increased by 25.7%. The change in the driver-truck ratio was negligible during this time.

4. Empirical Framework

The empirical framework focuses on how OBCs have affected loaded miles per week of individual trucks. One simple specification is:

$$y_{it} = x_{it}\beta + d_{it}\delta + \varepsilon_{it} \tag{1}$$

where i indexes the truck, t indexes time, y_{it} is loaded miles per week, x_{it} is a vector of controls that indicate the hauls for which the truck is used, and d_{it} is a vector of dummies that indicate whether and what kind of OBC is installed on the truck. The vector δ reflects relationships between OBC use and loaded miles per week. This vector contains the coefficients of interest. For the moment, I restrict these relationships to be the same across trucks; simple extensions allow them to vary with elements of x_{it}. Below I relax this restriction, and allow for unobserved heterogeneity in OBCs' effect on loaded miles per week. The residual term ϵ_{it} reflects the effect of omitted variables on trucks' intensity of use.

If $E(\epsilon_{it}d_{it}) = 0$, estimates of δ from OLS regressions of y_{it} on x_{it} and d_{it} produce unbiased estimates of OBCs' effect on the average truck's loaded miles per week. A priori, this orthogonality condition is unlikely to hold; there are several reasons why there may be omitted factors that are correlated with both loaded miles per week and technology use. I discuss these below.

One problem is that trucks are not always used as intensively as possible. Capacity utilization fluctuates with demand. Some trucks are idled when demand is low. Some are used for multiple shifts when demand is high.[12] Trucks with OBCs may be less likely to be idled than trucks without them when capacity exceeds demand. In general, the coefficient δ may reflect variation in trucks' base usage rates as well as OBCs' effect on capacity utilization.

The data provide for a straightforward way of addressing this problem. If dispatchers' decisions lead the base rate of trucks with OBCs to be higher than the base rate of trucks without them, trucks with OBCs should both operate more weeks per year and more miles per week. Consider the multivariate specification:

$$\begin{aligned} \ln y_{it}^1 &= W_{it}\alpha + Z_{it}\gamma + d_{it}\delta^1 + \varepsilon_{it}^1 \\ \ln y_{it}^2 &= X_{it}\beta + d_{it}\delta^2 + \lambda(Z_{it}\gamma + d_{it}\delta^1) + \varepsilon_{it}^2 \end{aligned} \tag{2}$$

where y_{it}^1 and y_{it}^2 represent number of weeks and loaded miles per week of truck i in year t, respectively.[13] Z_{it} is a vector of variables that affect dispatchers' choice of trucks, but do not directly affect how intensively trucks can be used. In this paper, Z_{it} is a vector of model year dummies: dispatchers choose to use younger trucks more intensively than older trucks, but the age of the truck should not directly affect how intensively it can be used conditional on being in service. γ is therefore identified by relationships between truck age and weeks in use, and λ is identified by the ratio of the relationship between truck age and loaded miles per week and that between truck age and weeks in use. If $\lambda=1$, then truck age affects weeks in use and loaded miles per week proportionately. δ^1 captures the correlation between OBC use and weeks in use. $(\delta^2 + \lambda\delta^1)$ reflects the overall relationship between OBC use and loaded miles per week. $\lambda\delta^1$ is the part that reflects differences

[12]This particular problem is of minimal importance in circumstances where it is unlikely that multiple drivers utilize the same truck – such for long hauls and for owner-operated trucks. Utilization of these trucks is usually limited by regulatory restrictions on the number of hours particular drivers can drive. (Some drivers, of course, do not always heed these restrictions.)

[13]I permit the error terms to be correlated; this lets omitted factors affecting number of weeks also affect loaded miles per week.

in trucks' base rates and δ^2 is the part that reflects OBCs' effect on capacity utilization.

The intuition behind the identification strategy is in the following example. Suppose there are two truck vintages: young and old. Suppose young trucks are used 10% more weeks, but have 20% more loaded miles per week, than old ones. Suppose that trucks with OBCs are used 10% more weeks than those without them. The identifying assumptions then imply that trucks with OBCs should have a 20% higher base rate than trucks without them. If trucks with OBCs have 25% more loaded miles per week than those without them, the estimate of δ^2 will indicate that OBCs caused capacity utilization to increase by 5%.

A second problem is that base usage rates may differ systematically with shippers' characteristics. Some trucks deliver to sites with sophisticated cargo handling practices – such as those employed within "just-in-time" inventory systems. Trucks that do so may have higher base rates than other trucks because they are loaded or unloaded more quickly. Suppose these shippers place a high value on using carriers with OBC-equipped fleets. Then cross-sectional correlations between OBC use and loaded miles per week may reflect this omitted factor – shipper sophistication – rather than a causal relationship. Unlike the class of problems described above, this omitted factor is unlikely to affect number of weeks so the correction procedure above does not apply.

One can examine this factor's relevance in a simple manner. Shippers' organizational sophistication likely differs across products – it tends to be higher for goods delivered to manufacturing or warehouse facilities than for those delivered to raw input processors or retail outlets. If this is true, the OBC coefficients should decrease when including a set of dummy variables indicating the product trucks haul. If the OBC coefficients are similar with and without this additional vector of controls, this is evidence against the relevance of this alternative hypothesis.

An alternative way of accounting for the prospect that the coefficients from cross-sectional regressions reflect omitted variables correlated with both OBC use and trucks' base usage rate is to exploit the time series dimension of the data. As noted above, I have multiple cross-sections of data, and can examine relationships between changes in loaded miles per week and changes in OBC use through a cohort-based strategy. However, this would require restricting OBCs' effect on capacity utilization to be the same across years. The cross-sectional results presented below strongly suggests that such a restriction would be inappropriate. I therefore rely on identification strategies that exploit cross-sectional rather than time variation in the data.[14]

As noted above, the base specification assumes away unobserved heterogeneity in OBCs' impact on capacity utilization. A more general specification is:

$$\begin{aligned} \ln y_{it}^2 &= X_{it}\beta + d_{it}\delta_{it} + \varepsilon_{it} \\ &= X_{it}\beta + d_{it}(\delta + \psi_{it}) + \varepsilon_{it} \end{aligned} \tag{3}$$

Here the marginal impact of OBCs on capacity utilization varies with omitted factors. Standard selection issues arise. OLS estimates of δ, OBCs' average effect on capacity utilization across the entire sample, are biased.

$$\hat{\delta}_{ols} = \delta + E(\psi_{it} \mid d_{it} = 1) \tag{4}$$

This equation illuminates the information contained in the OLS estimate of δ. The OLS estimate overstates the average effect of OBCs across the entire sample (assuming a positive correlation between OBC use and ψ_{it}). But it captures the average effect of OBCs among adopters – the average effect of treatment on the treated. In an environment where selection of this sort is a problem, positive estimates of the OBC coefficients do provide evidence that OBCs increase capacity utilization for adopters – and are thus evidence of relationships between IT adoption and productivity increases.

The goal of the empirical work is to estimate OBCs' realized impact on capacity utilization, rather than what its impact would be if OBCs were installed on all trucks. Thus, the results section emphasizes estimates of the effect of the treatment on the treated rather than trucks in general. The estimates will indicate considerable heterogeneity in the returns to adoption among adopters; thus, while this is not this paper's focus, it is likely that the average returns to adopters reported below exceed those non-adopters would receive if they too adopted.

5. Results

[14]Furthermore, using a cohort-based strategy has the drawback of sharply reducing the number of observations in the data from the number of trucks to the number of cohorts. I have estimated cohort-based specifications of the basic model, and have found the coefficient estimates to be very noisy.

Simple Cross-Sectional Regressions

Table 3 presents results from simple cross-sectional regressions that take the form of equation (1).[15] The dependent variable is loaded miles per week. In each, the vector X_{it} contains a set of dummy variables that indicate how far from home the truck operated, a set of dummies that indicate what class of trailer was commonly attached to the truck, and dummies that indicate whether trucks were part of private fleets, used for contract carriage, were driven by owner-operators (and if so whether they were operating under long-term arrangements with larger trucking firms), and whether trucks were used to haul "less-than-truckload" shipments. The coefficients of interest are those on OBC and EVMS. OBC is a dummy that equals one if the truck has either a trip recorder or EVMS installed and zero otherwise; EVMS equals one if the truck has EVMS installed and zero otherwise. The coefficient on OBC reflects the correlation between trip recorder use and loaded miles per week; that on EVMS reflects the difference in loaded miles per week for trucks with EVMS and trucks with trip recorders. If these coefficients reflect causal relationships, the coefficient on OBC picks up the effect of OBCs' incentive- and maintenance-improving capabilities and that on EVMS picks up the effect of OBCs' coordination-improving capabilities.

The upper panel contains results using the 1992 data. The first two columns use the entire sample; the first includes no controls, while the second includes the full set of controls. From the first column, trucks with trip recorders had 159 more loaded miles per week than those without any IT. Trucks with EVMS had about 450 more than those with trip recorders. These estimates decrease sharply when including the controls, and the r-squared increases from 0.08 to 0.38. The coefficient on OBC is positive, but is small and not statistically significant. That on EVMS is positive and statistically significant, and indicates that on average, trucks with EVMS had about 100 more loaded miles per week than trucks with trip recorders. This is about 7% of the sample mean. The other two columns report analogous estimates, splitting the sample between trucks commonly attached to dry or refrigerated vans and trucks commonly attached to other, more specialized trailers. The coefficient on OBC is negative and statistically significant for vans and positive and significant for non-vans. The EVMS coefficient is positive and significant in the van subsample, but not the non-

[15]The sample size is lower here than in the previous tables because some observations have missing values for weeks in use.

van one. Considering trucks attached to vans, those with EVMS had about 182 more loaded miles per week than those with trip recorders, 12% of the sample mean.

The lower panel reports analogous estimates using the 1997 data. The general patterns are similar to the 1992 data, although most of the coefficient estimates are larger. In particular, the EVMS coefficients increase in all of the specifications with the controls. In 1997, trucks with EVMS had about 190 loaded miles per week more than those with trip recorders, about 13% of the sample mean. The EVMS coefficient is now positive and significant in both subsamples and is significantly larger in the van subsample.

The fact that the coefficients are generally larger in 1997 than 1992 is interesting because it suggests that there exist lags in the returns to technology adoption – a phenomenon some believe to be common (David (1990)). OBC adoption increased between 1992 and 1997 in large part because of falling EVMS prices. If the returns to adoption were instantaneous, one would expect the average benefits, conditional on adoption, to decrease over time as one moves down the demand curve. But this does not happen, suggesting that the benefits from OBCs to existing adopters have increased over time.

Multivariate Regressions

Tables 4 and 5 present estimates from multivariate regressions that take the form of equations (2). In each, X_{it} is the same as above. Z_{it} includes a full set of truck vintage dummies: if newer trucks are used more weeks per year than older trucks, this reflects dispatchers' (or the market's) choice of which trucks to use when demand is low. W_{it} includes other variables that correlate with the cyclicality of individual trucks' use: private carriage, contract carriage, and owner-operator dummies, trailer type dummies, and a less-than-truckload dummy. I also include dummies that indicate whether the truck was primarily used to haul fresh farm products and live animals. Trucks used to haul these goods are used far fewer weeks per year than other goods.[16]

[16]Preliminary regressions indicated that these variables were correlated with number of weeks in use. The fact that these variables have explanatory power at all is interesting, considering that the unit of observation is a truck-tractor, and truck-tractors are highly mobile and are not specific to firms, trailers, or products outside of the short run. That haul characteristics are significant is evidence of frictions in shifting trucks across uses when demand is low for what they generally haul.

Table 4 contains results from 1997. OBC1 and EVMS1 are estimates of δ^1, and reflect relationships between OBC use and ln(weeks in use). The point estimates indicate that, holding constant truck vintage and a series of controls for how they are used, trucks with trip recorders are used 3.3% more weeks than trucks without OBCs and 3.6% more weeks than trucks with EVMS. One interpretation of this is that trip recorders tend to be used for hauls with regular schedules, and these hauls tend not to be cyclical. The sum of OBC1 and EVMS1 is very close to zero, implying that trucks with EVMS are used almost exactly the same number of weeks on the average as trucks without OBCs. While base usage rates appear high for trucks with trip recorders, they are not for trucks with EVMS. The correction procedure therefore mostly adjusts for differences in base usage rates between trucks with trip recorders and the other categories, not between trucks without OBCs and with EVMS.

The middle part of the table contains the main results. The coefficients on OBC2 are not statistically significantly different from zero, although the 0.078 point estimate in the no van subsample hints at a relationship between trip recorder use and capacity utilization for these trucks. The coefficient on EVMS2 is positive and statistically significant in the first two columns. The point estimate in the first column indicates that, controlling for differences in trucks' base rates, trucks with EVMS have 11.1% greater loaded miles per week than those with trip recorders. The second column indicates that this number is 18.1% within the van subsample. In contrast, there is no evidence of relationships between EVMS use and capacity utilization in the no van subsample.

The bottom of the table reports estimates of OBC2 and EVMS2 from univariate regressions that do not use information from the weeks in use regression. Comparing these results to those in the multivariate specifications allows one to observe the effect of the correction. The coefficients on OBC2 are all much higher and statistically significant; those on EVMS2 are lower. Ignoring the fact that the base usage rate of trucks with trip recorders tends to be high leads one to overstate OBCs' incentive benefits and understate their coordination benefits.

Table 5 contains analogous results using the 1992 data. The estimates of OBC1 and EVMS1 show patterns similar to those in Table 4, but are greater in absolute value. Trucks with trip recorders are used 8.1% more weeks than those without OBCs and 5.5% more than those with EVMS. Looking at the results from the main equation, there is no evidence that OBCs' incentive-improving capabilities lead to increases in capacity utilization, and there is only evidence that their coordination-improving capabilities do so for trucks attached to vans. The coefficient on OBC2 is negative and significant. The coefficient on EVMS2 is only positive and significant for the van subsample: among these trucks, trucks with EVMS had about 13% higher loaded miles per week than trucks with trip recorders. As in Table 4, the estimates at the bottom of the table indicate that, as in 1992, ignoring differences in base usage rates leads one to overstate relationships between trip recorder use and loaded miles per week, and thus understate OBCs' coordination-related effect on capacity utilization.[17]

In specifications not reported here, I have reestimated these specifications including a full set of product dummies in X_{it}. Although some of the product dummies have explanatory value, the estimates of OBC2 and EVMS2 are almost exactly the same as in these tables. While there is evidence that base usage rates vary with the products trucks haul, there is no evidence that such cross-product differences drive relationships between OBC use and loaded miles per week.

Together, these regressions suggest that EVMS adoption has increased capacity utilization in trucking. Taking the coefficients as point estimates of the benefits to adopters, EVMS increased capacity utilization of trucks attached to vans by about 13% in 1992 and 18% in 1997. Using the means for vans in Table 3, this translates to 203 and 308 more loaded miles per week, respectively: about one more medium-distance haul per week. Alternatively, one can think of this as 5.0 and 7.2 fewer hours per 40-hour week of empty or idle time. The estimates provide no evidence that EVMS increased capacity utilization of other trucks. Furthermore, there no evidence that trip recorders increase capacity utilization. The results also indicate that not accounting for correlations between trucks' base rate and OBC use leads one to overestimate relationships between trip recorder use and capacity utilization.

In general, the estimates strongly suggest that OBCs' coordination-improving capabilities have enabled adopters to achieve higher capacity utilization through better resource allocation decisions. The productivity improvements among adopters are large for trucks attached to the least specialized trailers. Furthermore, the average improvement increases over time. This is inconsistent

[17]See Table A1 in the Appendix for the full set of coefficients from the specifications reported in the first columns of Tables 4 and 5.

with the simple "moving down the demand curve" diffusion story where the highest return adopters adopt first and appropriate the benefits instantaneously, but consistent with interpretations where the benefits of adoption come with a lag.

In contrast, there is little evidence that OBCs' incentive- and maintenance-improving capabilities have enabled adopters to achieve higher capacity utilization. Trucks with trip recorders do have higher loaded miles per week than those without them, but this appears to be due mainly to differences in their base usage rates – possibly due to the regularity of the hauls – rather than the effects of technology.

The fact that the estimated benefits differ between the van and no van subsamples suggests heterogeneity in the returns to adoption. The following subsection explores this further.

Heterogeneity in the Returns to Adoption

Table 6 reports 1997 estimates from specifications that allow the OBC and EVMS coefficients to vary across twelve cells. These cells are distance/trailer/contractual form permutations; each coefficient therefore reflects a three-way interaction. Short haul trucks include those that generally operate less than 50 miles from their base; long hauls trucks are those that generally operate more than 50 miles from home.[18] These estimates provide evidence regarding whether the returns to adopters vary in the sample according to variables I observe. The left panel reports a specification where I estimate all of the model's coefficients; the right panel reports results when I restrict all of the OBC2 coefficients to zero.

The table shows two general patterns. First, with the possible exception of the common/not van/long cell, there is little evidence that OBCs' incentive-improving capabilities lead to increases in capacity utilization in any of the cells. None of the OBC2 coefficients in the left panel are significantly different from zero. Furthermore, one can reject the null that the coefficients are jointly equal to zero using a likelihood ratio test of size 0.05.

Second, the estimates indicate considerable heterogeneity in the extent to which OBCs' coordination-improving capabilities increase capacity utilization. The EVMS2 coefficients vary considerably across cells, indicating heterogeneity in the average returns to adopters. In the right

[18] I have estimated the models dividing the long haul cells more finely. The results are similar to those below.

panel, the coefficient on EVMS2 is positive and significant for all of the common carriage cells except for the short/not van one. The coefficient in the common/van/long cell indicates that, controlling for differences in trucks' base use rates, the average adopter in this cell has 21.3% greater capacity utilization than the average non-adopter. The point estimate for the average return to adopters is even higher in the common/van/short cell (39.0%), and lower in the common/not van/medium/long cell (11.6%)[19], though the differences are not statistically significant. The cross-cell patterns are similar when considering the private carriage cells, and one cannot reject the null hypothesis that the coefficients in the private carriage cells are the same as their counterparts in the common carriage cells. This suggests that the adopters in these different governance forms face similar short-run problems in utilizing their fleets' capacity.[20] In contrast, there is less evidence of capacity utilization increases in the contract carriage cells. This is unsurprising; contract carriage arrangements tend to be used when shippers have demands for a series of regularly-scheduled hauls. Backhauls can be arranged far in advance for the bulk of these hauls, and knowing where trucks are in real time may not improve matches much. Adoption takes place in these cells, but its benefits likely come in ways other than truck utilization; for example, it may enable shippers' customers to allocate resources better by helping them track and anticipate deliveries.

Table 7 explores the distribution of EVMS-related capacity utilization increases. The first row reports the EVMS coefficient from the first column in Table 4 (0.117), followed by several calculations. Reading across, the "all trucks" cell is 100% of the industry, EVMS adoption in this cell is 25.6%, and adopters in this cell make up 25.6% of the industry. Taking 11.7% as the average capacity utilization increase among adopters in the industry, these imply that EVMS use by adopters

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[19]One should attribute this latter result to coordination-related gains with caution, since the OBC2 coefficient in the left panel is nearly statistically significant for this cell. This is the cell in which there is the strongest evidence that capacity utilization increases reflect incentive improvements.

[20]The fact that the average returns to private fleet adopters are similar to those of "common carriage" adopters does not imply anything about the relative returns to non-adopters. The returns to adoption non-adopting private fleets may be lower than non-adopting for-hire ones, as would be the case if non-adopting private fleets tend to be those that are restricted to serve only internal customers.

in this (universal) cell increased capacity utilization by 3.0% in the industry. This is an estimate of OBCs' effect on capacity utilization in the industry as of 1997.

The rest of the rows use the estimates from the right panel of Table 6 to investigate how the 3.0% capacity utilization increase splits across trailer/distance/contractual form cells. For example, the EVMS coefficient in the private/van/short cell is 0.390. This cell made up 2.7% of the industry and adoption was 15.1% in this cell. Thus adopters in this cell made up 0.4% of the industry and on the average increased capacity utilization by 39.0%. Adoption within this cell increased capacity utilization in the industry by 0.16% (0.39*0.004), which is about 5% of the industry total. Although the average returns to adopters are high within this cell, there are so few adopters in this cell that it contributes a small amount to the overall capacity utilization increase.

The main result from this table is that the distribution of IT-related productivity increases appears highly skewed. Only 5.5% of the trucks in the industry – adopters in the common/van/long cell – account for about 36% of the capacity utilization increase.[21] Approximately another 35% comes from the other two long haul van cells. Thus, about 15% of the U.S. fleet account for about 70% of the benefit. More than half of the rest come from adopters in the long haul non-van cells.

How Much of the Increase in Capacity Utilization Between 1992 and 1997 Was EVMS-Related?

Above I report that EVMS' coordination-improving features led to increases in capacity utilization of the U.S. tractor-trailer fleet of 3.0% in 1997. Some of these increases had been achieved by 1992. Table 5 reports average returns to adopters of 13.4% among trucks attached to vans at this time, but no evidence of returns to adopters among trucks attached to other trailers. Van adopters made up 7.7% of the fleet in 1992. Combined, these figures imply that EVMS' coordination-improving features led to a 1.0% (.077*.134) increase in capacity utilization as of 1992.[22] Thus, about one-third of the benefits measured in 1997 had been achieved between 1987

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[21]For all rows save the first, column 6 equals column 5 divided by 3.27, which is the sum of the column 5 entries from the cells. This differs from 3.00, the estimate of industry capacity utilization gains from Table 4, because the coefficient estimates in column 1 are from a different specification.

[22]Unlike for 1997, breaking things down by narrower cells does not shed much additional light. Table A2 shows 1992 results for a specification analogous to Table 6. The table shows that all of the returns to van adopters were for long hauls, and there are no significant differences

and 1992, and two-thirds between 1992 and 1997.

Table 3 reported that average loaded miles per week increased by from 1398 to 1507 between 1992 and 1997, or 7.8%. The point estimates in this paper suggest that about one-fourth of this increase ((3.0%-1.0%)/7.8%) was related to the growing use of on-board computers to achieve better matches between trucks and hauls. A substantial part of the rest is likely due to the expansion of the economy during this time.

What Are the IT-Enabled Increases in Capacity Utilization Worth?

Trucking makes up a significant part of economy; thus, even small proportional increases in productivity would imply large benefits in absolute terms. The American Trucking Associations estimates that trucking (including private fleets) was a $486 billion industry in 1998, or 6.1% of GDP.[23] Operating margins are small in trucking; therefore, this is a rough approximation of costs. Multiplying $486 billion by 3.0% gives a back-of-the-envelope estimate of the value of OBC-related increases in capacity utilization: $14.6 billion per year. This rough estimate does not account for any additional costs incurred in using trucks more intensively: for example, because of faster truck depreciation or any additional labor. Some of these additional costs are probably quite small, however: running trucks loaded rather than empty causes little extra depreciation, and does not require drivers to drive more. On the other hand, this estimate does not account for productivity benefits other than in truck utilization, such as any benefits that accrue to shippers and receivers from being better able to anticipate trucks' arrivals. $15 billion in annual benefits therefore may well be a conservative estimate for the general productivity gains associated with OBC diffusion as of 1997.

6. Conclusion

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in the returns to adopters across governance types for long hauls. The coefficients are all about 0.15. Long haul van adopters were 7.6% of the sample. Using these figures leads to an estimate of a 1.1% (.076*.15) rather than 1.0%.

[23]American Trucking Associations (2000). I quote the estimate for 1998 because methodological changes and new data led this and other publications to substantially increase their estimate of the size of the industry, starting first with estimates for 1998. These methodological changes account for the fact, for example, that much of "rail" and "air" freight travels by truck for all or part of the way.

Technologies that collect and disseminate information play a unique role in the economy. As Hayek stated more than fifty years ago, such technologies increase productivity by improving *decisions*, in particular resource allocation decisions. This paper examines the impact of one such technology – on-board computers – on capacity utilization in the trucking industry. Preliminary evidence indicates that on-board computer use has increased capacity utilization significantly: in 1997, EVMS increased capacity utilization by 11% on adopting trucks. This increase appears to be entirely due to advanced capabilities that let dispatchers determine trucks' position in real time, and allow dispatchers and drivers to communicate while drivers are in their truck. These capabilities enable dispatchers and drivers to keep trucks on the road and loaded more.

On-board computers in trucking are among the first commercially-important applications of wireless networking technologies. Many other such applications are likely to follow in the near future, as companies are currently attempting to develop and commercialize wireless applications that work off a diverse set of hardware platforms, including cellular phones and handheld computers. The economic value of these applications is based on the same principle as OBCs: information improves decisions; communication enables decisions to be executed. This allows dispersed individuals to identify and avail themselves of economic opportunities. The estimates in this paper indicate that the welfare gains from such applications can be quite large.

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Table 1
Truck Utilization – 1992, 1997

		Miles	Loaded Miles	Fraction w/Load	Cargo Weight	Ton-Miles	N
All Trucks							
	1992	65451	58559	0.882	38190	1178	36082
	1997	70351	64500	0.904	39223	1325	23183
	Change	7.5%	10.1%	2.5%	2.7%	12.5%	
Trucks in use > 48 weeks							
	1992	77764	69993	0.893	37890	1399	18683
	1997	82488	75836	0.915	39602	1592	11376
	Change	6.1%	8.3%	2.5%	4.5%	13.8%	

Figure 1

Average Weeks In Use

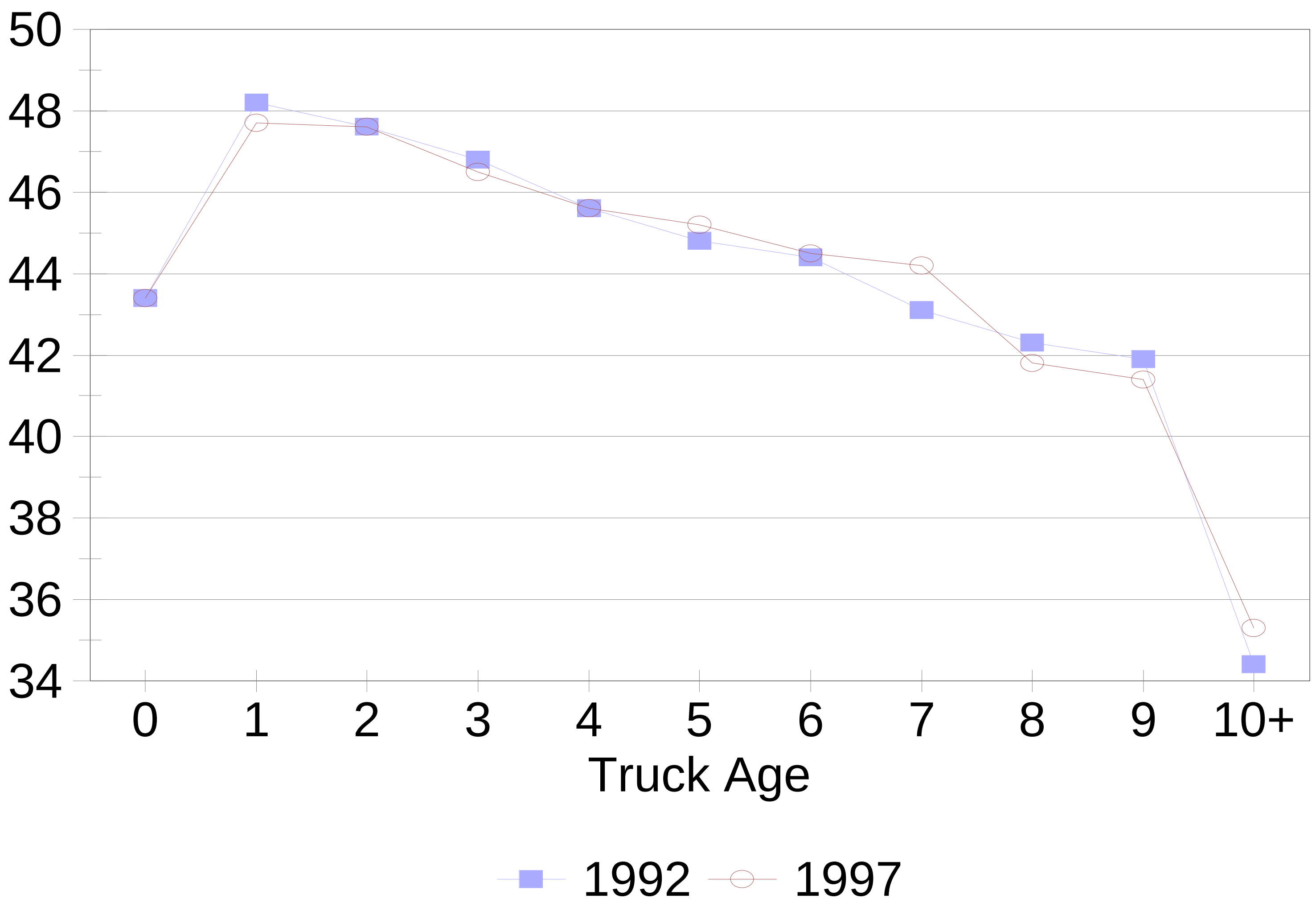

Figure 2

Loaded Miles/Week, Net EVMS Adoption

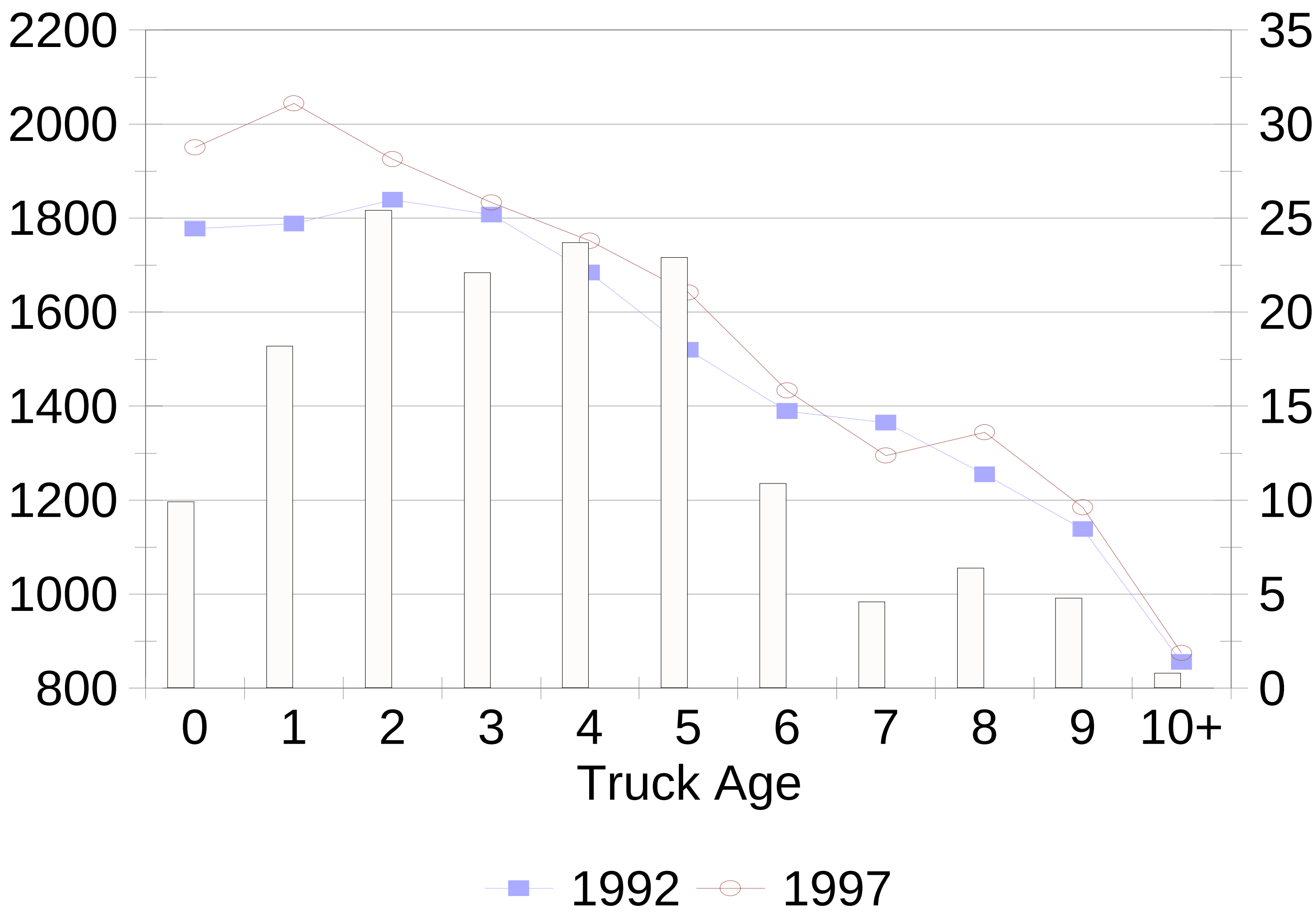

Table 2

Changes in Truck Utilization, OBC Use – 1992 to 1997

by Trailer Type

	Miles	Loaded Miles	Fraction w/Load	Cargo Weight	Ton-Miles	Trip Recorder	EVMS
All	3022	3876	0.016	1673	127	-0.6%	14.2%
Non-Refrigerated Vans	4390	5930	0.022	3092	222	-2.0%	17.3%
Tank Trucks (Liquid)	1603	3587	0.028	1426	128	-4.5%	19.2%
Refrigerated Vans	4244	4008	0.011	1194	145	1.0%	15.9%
Plaforms	184	335	0.005	94	-13	0.2%	10.4%
Low Boys	3447	3872	0.018	1331	76	0.4%	5.7%
Grain Bodies	-6658	-7074	-0.004	133	-180	-0.2%	5.0%
Dump Trailers	2944	3359	0.013	86	92	1.3%	9.6%

Includes state-trailer cohorts with at least 10 observations in 1992 and 1997.

Table 3
Cross-Sectional Regressions

Dependent Variable: Loaded Miles Per Week

	All Trucks		Trailer Type: Vans Only	Trailer Type: All Others
1992 Sample				
OBC	**158.80**	18.45	**-66.68**	**135.55**
	(19.79)	(16.71)	**(24.19)**	**(23.50)**
EVMS	**453.17**	**101.58**	**182.39**	-47.30
	(24.69)	**(20.83)**	**(28.78)**	(31.93)
Controls?	N	Y	Y	Y
R-squared	0.080	0.379	0.350	0.316
Mean of DV	1398	1398	1564	1309
N	35766	35766	15303	20463
1997 Sample				
OBC	**413.42**	**56.65**	-35.54	**118.37**
	(24.66)	**(21.13)**	(38.42)	**(25.13)**
EVMS	**268.49**	**189.86**	**306.97**	**109.29**
	(26.80)	**(22.37)**	**(39.07)**	**(27.48)**
Controls?	N	Y	Y	Y
R-squared	0.034	0.359	0.360	0.265
Mean of DV	1507	1507	1715	1378
N	22206	22206	9858	12348

Controls include distance dummies, trailer dummies, private carriage, contract carriage, independent owner-operator, subcontracted owner-operator, LTL, and LTL*short haul dummies.

Table 4
Cross-Sectional Regressions – 1997

	All Trucks	Trailer Type: Vans Only	Trailer Type: All Others
Dependent Variable: ln(weeks in use)			
OBC1	**0.033**	0.023	**0.051**
	(0.013)	(0.013)	**(0.022)**
EVMS1	**-0.036**	**-0.035**	-0.024
	(0.013)	**(0.013)**	(0.024)
Dependent Variable: ln(loaded miles per week)			
OBC2	0.003	-0.061	0.078
	(0.025)	(0.035)	(0.041)
EVMS2	**0.110**	**0.181**	0.015
	(0.027)	**(0.035)**	(0.044)
Lambda	**1.297**	**1.842**	**1.110**
	(0.054)	**(0.147)**	**(0.062)**
Dependent Variable: ln(loaded miles per week)			
OBC2	**0.126**	0.040	**0.236**
	(0.018)	(0.022)	**(0.030)**
EVMS2	**0.102**	**0.136**	0.058
	(0.019)	**(0.023)**	(0.033)
N	22206	9858	12348

ln(loaded miles per week) equation includes distance dummies, trailer dummies, private, contract indy, indysub, ltl, and ltl*short haul as controls.
ln(weeks in use) equation includes vintage dummies, private, contract, indy, indysub, trailer, LTL, LTL*short haul, and farm and animal product dummies as controls.

Bold indicates rejection of a two-tailed t-test of size 0.05 of H0: beta=0.

Table 5
Cross-Sectional Regressions – 1992

	All Trucks	Trailer Type Vans Only	 All Others
Dependent Variable: ln(weeks in use)			
OBC1	**0.081**	**0.058**	**0.101**
	(0.011)	**(0.014)**	**(0.014)**
EVMS1	**-0.055**	**-0.040**	**-0.053**
	(0.013)	**(0.016)**	**(0.018)**
Dependent Variable: ln(loaded miles per week)			
OBC2	**-0.046**	-0.034	**-0.062**
	(0.021)	(0.034)	**(0.027)**
EVMS2	0.036	**0.134**	-0.057
	(0.026)	**(0.039)**	(0.034)
Lambda	**1.213**	**1.474**	**1.146**
	(0.038)	**(0.094)**	**(0.040)**
Dependent Variable: ln(loaded miles per week)			
OBC2	**0.099**	**0.069**	**0.120**
	(0.016)	**(0.024)**	**(0.019)**
EVMS2	-0.030	**0.084**	**-0.110**
	(0.019)	**(0.028)**	**(0.025)**
N	35766	11039	24727

ln(loaded miles per week) equation includes distance dummies, trailer dummies, private, contract indy, indysub, ltl, and ltl*short haul as controls.
ln(weeks in use) equation includes vintage dummies, private, contract, indy, indysub, trailer, LTL, LTL*short haul, and farm and animal product dummies as controls.

Bold indicates rejection of a two-tailed t-test of size 0.05 of H0: beta=0.

Table 6
Cross-Sectional Interactions – 1997

		Unrestricted Specification		*OBC2 = 0*	
		Length of Haul		Length of Haul	
OBC2		Short	Long	Short	Long
	Private, Van	-0.015	0.042		
		(0.150)	(0.057)		
	Private, Not Van	0.044	-0.078		
		(0.127)	(0.067)		
	Contract, Van	-0.174	-0.002		
		(0.436)	(0.070)		
	Contract, Not Van	0.009	0.100		
		(0.327)	(0.074)		
	Common, Van	0.597	-0.103		
		(0.411)	(0.059)		
	Common, Not Van	-0.467	0.168		
		(0.277)	(0.096)		
EVMS2					
	Private, Van	**0.405**	**0.121**	**0.390**	**0.155**
		(0.179)	**(0.061)**	**(0.119)**	**(0.040)**
	Private, Not Van	-0.015	**0.167**	0.020	**0.093**
		(0.147)	**(0.075)**	(0.085)	**(0.046)**
	Contract, Van	0.364	0.090	0.190	**0.088**
		(0.490)	(0.070)	(0.251)	**(0.039)**
	Contract, Not Van	0.405	-0.089	0.409	-0.011
		(0.377)	(0.079)	(0.232)	(0.053)
	Common, Van	-0.225	**0.296**	**0.357**	**0.213**
		(0.428)	**(0.061)**	**(0.147)**	**(0.037)**
	Common, Not Van	0.575	-0.036	0.123	**0.116**
		(0.323)	(0.103)	(0.186)	**(0.054)**
	Log of likelihood fn.	-40120.9		-40128.5	

Specifications are analogous to those in Table 5.
Bold indicates rejection of a two-tailed t-test of size 0.05 of H0: beta=0.

Table 7
Distribution of EVMS-Related Capacity Utilization Increases, 1997

Column	(1)	(2)	(3)	(4)	(5)	(6)
Label	EVMS2 Coefficient	Share of Industry	EVMS Adoption	Industry Share of of Adopters in Cell	Industry CU Gains from Cell	Share of CU Gains
Formula				(2)*(3)	(1)*(2)*(3)	
All Trucks	**0.117**	100.0%	25.6%	25.6%	3.00%	100.0%
Private, Van, Short	**0.390**	2.7%	15.1%	0.4%	0.16%	4.9%
Private, Not Van, Short	0.020	11.8%	7.0%	0.8%	0.02%	0.5%
Contract, Van, Short	0.190	0.9%	10.0%	0.1%	0.02%	0.5%
Contract, Not Van, Short	0.409	0.7%	15.8%	0.1%	0.05%	1.4%
Common, Van, Short	**0.357**	1.9%	14.6%	0.3%	0.10%	3.1%
Common, Not Van, Short	0.123	1.7%	9.4%	0.2%	0.02%	0.6%
Private, Van, Med/Long	**0.155**	14.6%	31.0%	4.5%	0.70%	21.4%
Private, Not Van, Med/Long	**0.093**	18.2%	16.6%	3.0%	0.28%	8.6%
Contract, Van, Med/Long	**0.088**	13.5%	44.4%	6.0%	0.53%	16.1%
Contract, Not Van, Med/Long	-0.011	8.6%	29.4%	2.5%	-0.03%	-0.8%
Common, Van, Med/Long	**0.213**	16.1%	34.3%	5.5%	1.17%	35.9%
Common, Not Van, Med/Long	**0.116**	9.4%	23.7%	2.2%	0.26%	7.9%

Cell EVMS2 coefficients are from the right panel of Table 6.

Table A1
Cross-Sectional Regressions – All Coefficients

	1997		1992	
Dependent Variable: ln(loaded miles per week)				
C	**6.379**	**0.022**	**6.376**	**0.017**
OBC	0.003	0.025	-0.039	0.021
EVMS	**0.110**	**0.026**	0.034	0.026
Area: 50-100 Miles	**0.478**	**0.016**	**0.470**	**0.013**
Area: 100-200 Miles	**0.770**	**0.018**	**0.748**	**0.014**
Area: 200-500 Miles	**1.034**	**0.017**	**0.970**	**0.014**
Area: >500 Miles	**1.221**	**0.018**	**1.136**	**0.014**
Private Carriage	**-0.131**	**0.017**	**-0.149**	**0.012**
Contract Carriage	**0.072**	**0.017**	0.070	0.014
Owner-Operator: Independent	**0.171**	**0.029**	**0.121**	**0.024**
Owner-Operator: Subcontractor	**0.199**	**0.026**	**0.198**	**0.021**
Trailer: Lowboy	-0.076	0.030	-0.074	0.024
Trailer: Platform	-0.004	0.018	-0.011	0.015
Trailer: Logging	**0.362**	**0.044**	**0.202**	**0.034**
Trailer: Grain Body	**0.640**	**0.033**	**0.636**	**0.029**
Trailer: Dump	**0.342**	**0.027**	**0.337**	**0.021**
Trailer: Tank	0.024	0.021	0.005	0.016
Trailer: Other	**-0.147**	**0.016**	**-0.218**	**0.013**
LTL	**-0.132**	**0.021**	**-0.126**	**0.019**
LTL*(Area < 50)	**0.112**	**0.047**	**-0.221**	**0.035**
Lambda	**1.297**	**0.054**	**1.213**	**0.038**
Dependent Variable: ln(weeks in use)				
C	**3.810**	**0.011**	**3.748**	**0.009**
OBC	**0.033**	**0.013**	**0.080**	**0.011**
EVMS	**-0.036**	**0.013**	**-0.055**	**0.013**
Private Carriage	**-0.083**	**0.009**	**-0.105**	**0.007**
Contract Carriage	-0.008	-0.009	**-0.022**	**-0.008**
Owner-Operator: Independent	**-0.112**	**0.016**	**-0.048**	**0.013**
Owner-Operator: Subcontractor	**-0.085**	**0.014**	**-0.064**	**0.012**
Trailer: Lowboy	**-0.241**	**0.016**	**-0.308**	**0.012**
Trailer: Platform	**-0.062**	**0.009**	**-0.071**	**0.008**
Trailer: Logging	**-0.094**	**0.024**	-0.027	0.018
Trailer: Grain Body	**-0.460**	**0.019**	**-0.407**	**0.016**
Trailer: Dump	**-0.081**	**0.014**	**-0.117**	**0.011**
LTL	**0.026**	**0.011**	0.007	0.010
LTL*(Area < 50)	**0.090**	**0.025**	**0.093**	**0.018**
Farm Products	**-0.130**	**0.011**	**-0.118**	**0.008**
Live Animals	**-0.147**	**0.017**	**-0.065**	**0.017**
Gamma vector: coefficients appearing in both equations				
MY96	**0.101**	**0.010**	**0.170**	**0.010**
MY95	**0.092**	**0.010**	**0.186**	**0.010**
MY94	**0.070**	**0.010**	**0.152**	**0.010**
MY93	**0.054**	**0.011**	**0.130**	**0.010**
MY92	**0.055**	**0.013**	**0.109**	**0.010**
MY91	0.019	0.013	**0.068**	**0.010**
MY90	**-0.024**	**0.012**	**0.044**	**0.010**
MY89	**-0.028**	**0.013**	**0.020**	**0.010**
MY88	**-0.075**	**0.013**	0.002	0.013
MY87	**-0.279**	**0.010**	**-0.240**	**0.009**

Bold indicates rejection of a two-tailed t-test of size 0.05 of H0: beta=0.

Table A2
Cross-Sectional Interactions – 1992

Unrestricted Specification

		Length of Haul	
OBC2		Short	Long
	Private, Van	**0.653**	**-0.160**
		(0.133)	**(0.041)**
	Private, Not Van	-0.021	0.006
		(0.084)	(0.052)
	Contract, Van	0.016	-0.107
		(0.327)	(0.066)
	Contract, Not Van	-0.367	-0.137
		(0.233)	(0.073)
	Common, Van	0.409	-0.120
		(0.234)	(0.066)
	Common, Not Van	-0.284	**0.288**
		(0.175)	**(0.069)**
EVMS2			
	Private, Van	**-0.617**	**0.181**
		(0.223)	**(0.057)**
	Private, Not Van	**-0.377**	0.134
		(0.129)	(0.078)
	Contract, Van	-0.290	0.128
		(0.646)	(0.075)
	Contract, Not Van	0.436	-0.049
		(0.435)	(0.091)
	Common, Van	-0.112	**0.168**
		(0.363)	**(0.069)**
	Common, Not Van	0.256	**-0.500**
		(0.280)	**(0.086)**
	Log of likelihood fn.	-68438	

Specifications are analogous to those in Table 4.
Bold indicates rejection of a two-tailed t-test of size 0.05 of H0: beta=0.