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Abstract

The objective of this research is to understand the demand for information technology among trucking companies. A multivariate discrete choice model is estimated on data from a large-scale survey of the trucking industry in California. This model is designed to identify the influences of each of twenty operational characteristics on the propensity to adopt each of seven different information technologies, while simultaneously allowing the seven error terms to be freely correlated. Results showed that the distinction between for-hire and private fleets is paramount, as is size of the fleet and the provision of intermodal maritime and air services.

Key words: Information Technology, Commercial Vehicle Operations, Freight Transportation, Trucking Operations, Intermodal operations, Intelligent Transportation Systems, Discrete Choice Models, Multivariate Probit

1. BACKGROUND

1.1. Motivation

Freight transportation plays a vital role in the economy of the most countries, including the United States, and the State of California in particular. According to the latest available data, over $183 billion is spent annually on trucking in the US. Shipments originating in California accounted for 10.6 percent and 7.2 percent of total US shipments, by value and weight respectively. The vast majority, 67.4 percent by value and 73.7 percent by weight, moved by truck. An additional 15.4 and 2.4 percent (by value and weight) of the freight originating in California moved over more than one mode, most likely spending part of its journey over the road (Bureau of Transportation Statistics (BTS), 1999, 1997b, 1997c). While estimates of the size of the trucking related work force range from one in thirty to one in twelve persons in the state of California, all sources agree that trucking and warehousing employs a large fraction of the workforce (BTS, 1999, California Trucking Association, 1996).

Much of California's transportation network in heavily congested; the impact of congestion on trucking companies' profitability and ability to provide timely and reliable service to customers in some areas is significant. The recent past has brought with it myriad technologies and applications of information technologies to traffic network management in general and in particular to commercial vehicle operations. Those developments pale in comparison with the literal explosion of technologies coming on-line today. Information technologies are poised to transform whole industries and segments of society. Business to business e-commerce including the use of internet based electronic data interchange will impact goods movement in many different ways. The increase in time-sensitive shipments attributable to just-in-time manufacturing and distribution systems may look small relative to the further increases caused by vendor-managed inventory and “seamless” supply chains. Information technology adoption across the supply chain will likely lead to a noticeable reduction in average shipment sizes, particularly in urban areas. How soon these changes will occur and how well their impacts will be managed will both be impacted by technology adoption.

Because our study was performed using data from a 1998 survey, its results should be interpreted as identifying early adopters of technologies. We suspect that many of the industry sectors that were not early adopters of technology must be using them today, or preparing for near term adoption. Characteristics of companies that were early adopters of technologies and the technologies selected for early adoption are of interest. We examine these issues through the development of a multivariate discrete choice model which is relatively new in transportation research.

1.2. Related Studies

There have been several recent studies of carriers' use and propensity to use advanced technologies. These are described in detail in Golob and Regan (2001a) and Regan and Golob (1999). Scapinakis and Garrison (1993) conducted a small survey regarding carriers' perceptions of use of communications and positioning systems, and Kavalaris and Sinha (1994) surveyed trucking companies with a focus on their awareness of and attitudes towards ITS technologies. Ng *et al.*(1996) reported results from two nationwide surveys of dispatchers and commercial vehicle operators to determine characteristics that would determine likely acceptance of Advanced Traveler Information Systems (ATIS) technologies, including route guidance, navigation, road and traffic information, roadside services and personal communication. Regan *et al.* (1995) surveyed 300 companies to determine carriers' propensity to use new technologies, particularly two-way communication and automatic vehicle location/identification technologies. Holguin-Veras and Walton (1996) and Holguin-Veras (1999) also investigated the use of IT in port operations through interviews with port operators and a small survey of carriers. Crum *et al.* (1998) studied the use of electronic data interchange (EDI) technology, and Hall and Intihar (1997) studied IT adaptation through a series of interviews with trucking terminal managers, focus group meetings with representatives of the trucking industry, and telephone interviews with technology providers.

2. DATA SOURCE: 1998 ITS TRUCKING INDUSTRY SURVEY

2.1. Protocol and sample

During the Spring of 1998, a survey of California based for-hire trucking companies, California based private trucking fleets and large national carriers with operations in California was carried out by a private survey research company for the Institute of Transportation Studies (ITS) at the University of California, Irvine. The survey was implemented as a computer aided telephone interview (CATI) directed to the logistics or operations manager in charge of operations in California. A total of 1177 trucking companies were surveyed, with an average telephone interview time of just over 18 minutes.

The sample was drawn randomly from a set of 5,258 freight operators, broken down into: (1) 804 California based for-hire trucking companies with annual revenues of over $1 million, (2) 2129 California based private fleets of at least 10 vehicles (power units) and (3) 2,325 for-hire large national carriers (not based in California) with annual revenues of over $6 million. The lists of companies and individual contact information was drawn from a database of over 21,000 for-hire carrier and 25,000 private fleets maintained by Transportation Technical Services Inc. An overall response rate of

22.4% was obtained, with many of the national carriers excluded on the basis of insufficient operations in the state of California. Eliminating the contacts with no operations in California and invalid telephone numbers, the effective response rate was approximately 35%.

Non-response analyses were conducted for each of the three strata from which the sample was drawn. Golob and Regan (1999) report that there are no statistically significant differences between respondents and non-respondents on any of three criteria available in the database from which the sample was drawn: revenue, overall size of fleet, and number of years in business. For the for-hire sector (California-based companies and large national companies combined), the median fleet size for the 767 companies included in the survey was 81 power units, while the median fleet size for the 2,367 companies not in the survey was 78.

The median fleet size for the 410 private fleets included in the survey was 28 power units, while the median fleet size for the 1,718 fleets not surveyed was 29 power units. The database from which the sample of private fleets was drawn also contained the standard industrial classification (SIC) codes of the companies. A comparison of the SIC code distributions for our sample of private trucking companies and their complement of non-sampled companies is provided in Figure 1 (Golob and Regan, 1999). Our sample slightly over-represents trucking operations from the wholesale trade sector, and under-represents those from the construction sector (p = 038 for chi-square = 13.37 with 6 degrees of freedom). Because there is no evidence that the sample is biased in terms of fleet size, and because the overall deviation in terms of the distribution of SIC codes is not significant at the p = .01 level, we judge that the private fleet component of the sample is a good representation of private trucking companies operating in California in 1998.

Approximately 69,000 vehicles were represented by companies in the survey sample, approximately 52,000 of these in for-hire fleets and 17,000 in private fleets. The U.S. Bureau of Transportation Statistics estimated that there were 295,000 trucks and 758,000 tractor-trailer combinations owned by and operated by commercial carriers (non private fleets) nationally, in 1995 (BTS, 1997a). Assuming an increase of about 5% per year over the past three years, we estimate that there are around 1,219,000 vehicles operated by commercial carriers nationally. The survey represents 5.7% of these. Assuming that 7-10% of the vehicles operating nationally are in California at one time, this 5.7% represents between forty and fifty-seven percent of the for-hire vehicles operating in California.

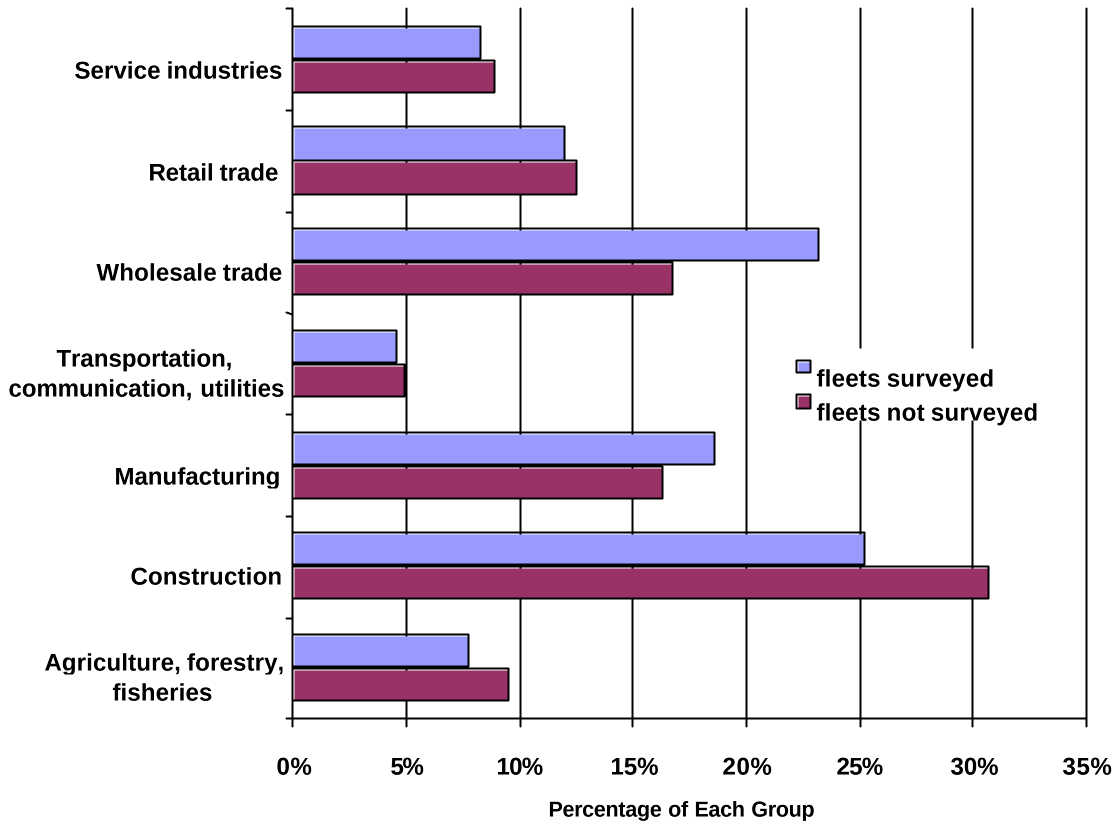

Figure 1.
Distributions of Standard Industrial Classifications of Survey Respondents and Non-respondents for the Private-company Sub-sample

2.2. Survey Content

The survey was conducted as a computer-aided telephone interview (CATI), with an average interview time of 18 minutes. The survey dealt with four main topics: (1) traffic congestion, (2) use and usefulness of information technologies, (3) use and efficiency of intermodal terminals in California, and (4) operational characteristics. Each section is briefly described below. An overview of survey results is presented in Regan and Golob (1999).

First, a section on traffic congestion included questions about carriers' perceptions about the impact of traffic congestion on their operations. Golob and Regan (2001b) use these data in a model to determine how five aspects of the congestion problem differ across sectors of the trucking industry. The five aspects were slow average speeds, unreliable travel times, increased driver frustration and morale, higher fuel and maintenance costs, and higher costs of accidents and insurance. The model also simultaneously estimates how these five aspects combine to predict the perceived overall magnitude of the problem. Questions were also asked about the effectiveness of possible means of reducing congestion. Analyses of these data are presented by Golob and Regan (1999), where a factor-analytic model is developed to summarize how trucking company managers' perceive potential solutions, as a function of the operating characteristics of the companies.

Second, a technology usage section contained questions about carriers' current use of technologies including mobile communication devices, EDI, AVLS (automatic vehicle location systems), an electronic clearance system (PrePass™), as well as publicly available traffic information updates. Some questions asked the respondents to rate the usefulness of various technologies and information sources. Data from this section of the survey are analyzed in the research presented here.

Usage of and satisfaction with maritime, rail and air intermodal facilities in California was investigated in the third section of the questionnaire. Questions were asked about typical delays and the predictability of the time required for picking up and delivering loads to these facilities. Respondents were also invited to describe the types of problems they faced in operating at intermodal facilities. Results from analyses of problems associated with intermodal maritime truck operations are documented in Regan and Golob (2000).

Finally, the last section focused on the operational characteristics of the companies. Of interest were the types of services offered, the average length of haul, time sensitivity of the operations, the locations of the main terminals and the fleet size. These characteristics serve as exogenous variables in models aimed at explaining technology adoption and the perceptions of trucking company managers.

3. DATA DESCRIPTION

3.1. Penetration of Information Technology

The sample size for this analysis is 1136, as 41 of the 1177 companies in the 1998 Trucking Industry Survey could not answer all of the relevant technology questions. While technology implementation is increasing, it appears that it has not kept pace with the rapid decrease in the cost of such technologies. Most vehicles are equipped with mobile communication devices but not with automatic vehicle location (AVL) devices or automatic vehicle identification (AVI) devices. Table 1 shows the frequency of responses to questions regarding the percent of the fleet equipped with these devices.

Table 1.
Percent of fleets equipped with certain information technology devices

Technology	Percentage of California fleet equipped with the technology					
	0%	1-25%	26-50%	51-75%	76-99%	100%
Mobile communication devices	20%	8%	6%	5%	10%	52%
PrePass transponders	84%	6%	2%	2%	1%	6%
Automatic vehicle location devices	74%	3%	2%	2%	3%	16%

It was believed that larger companies would be much more likely to have technology equipped operations and that these raw responses may under-represent the true likelihood that vehicles are equipped. For that reason, an estimate of the fraction of the vehicles represented in the survey that are equipped was also computed by multiplying the reported estimate of the fraction of the fleets equipped by the number of vehicles in each companies' fleet. It was further supposed that carriers might be equipped with AVI devices other than PrePass. However, a negligible number of operators reported to be using other AVI transponders. As expected, for-hire fleets use these technologies more than private fleets and large fleets use technologies more than small ones. Table 2 shows the estimated percentages of for-hire and private vehicles that are technology equipped.

Table 2.
Comparison of technology use: private and for-hire fleets

Type of freight operation	Estimated percentage of vehicles with technology		
	Mobile communication devices	PrePass (AVI) transponders	Automatic vehicle location devices
Private fleets	64%	6%	11%
For-hire fleets	72%	10%	25%
Overall	70%	9%	21%

To better understand the demand for technologies in carrier fleet operations we need to be able to match company characteristics with technology use. The methods employed in this analysis provide an efficient way of doing that.

We focus on adoption of seven different components of technology in this analysis. They are: (1) satellite or radio based communication (abbreviated S/RC), (2) automatic vehicle location technologies (AVL), (3) automatic vehicle identification systems (AVI, including PrePass transponders), (4) electronic data interchange (EDI), (5) vehicle maintenance software (VMS), (6) routing and scheduling software (R/SS), and (7) CB radio (CBR). This last variable is not usually regarded as a component of information technology, but it can be considered to be a competing alternative to certain of the other technology components, particularly the communications devices. The aggregate penetrations of these technologies in our sample of 1136 trucking companies with complete survey information are as follows.; (1) satellite- or radio-based communication links (S/RC): 40.2%; (2) AVLS: 24.8%; (3) AVI: 16.6%; (4) EDI: 31.3%; (5) vehicle maintenance software (VMS): 50.4%; (6) routing and scheduling software (R/SS): 51.5%; and (7) CB radio (CBR): 14.7%.

3.2. Operating Characteristics

The exogenous variables in this analysis represent some of the operating characteristics likely to affect technology use. Characteristics such as basic carrier type (private fleet, for-hire fleet, or contract carrier), primary service, specialized services offered, average length of haul, size of fleet, and extent of intermodal operations all affect the use and usefulness of information technologies in trucking operations. While many variables can be defined to characterize the freight operations of each respondent’s company, we found the twenty exogenous variables listed in Table 3 to be most effective in explaining differences in technology use. All of these exogenous variables are dummy variables, and they are organized according to five groups: (1) carrier type in terms of two mutually exclusive variables (the excluded category being companies that operate primarily as contract carriers), (2) primary service, in terms of the three mutually exclusive variables found to be most related to technology adoption, (3) load types, in terms of eight non-mutually exclusive variables capturing important specialized services and average lengths of loaded movements, (4) size, in terms of three mutually exclusive categories for the number of power units typically operated in California, and (5) intermodal services, with all three non-mutually exclusive modes (sea, air, and rail) and a fourth interaction term measuring joint provision of air and maritime services. The four variables comprising the fifth group, intermodal services, are aggregates of the following combinations of service provision: 49.6% of the 1136 companies provided no intermodal services, 20.5% provided maritime only, 8.0% air only, 4.2% rail only, 8.0% air plus maritime but no rail, 6.4% rail plus maritime but no air, 0.6% rail plus air but no maritime, and 2.6% of the companies provided all three intermodal services. Only the interaction term representing joint air and maritime services had sufficiently even split (89.4%/10.6%) to avoid collinearity problems.

Many other combinations of operating characteristics are possible, but, through trial and error, these were found to be the most effective in explaining adoption of the technologies in question. The addition of more exogenous variables is prevented by collinearity problems and by sample size considerations related to the chosen methodology, as discussed in Section 4.3.

Table 3.
Relevant Operating Characteristics Used as Exogenous Variables
(All dummy variables coded 0 = no / 1 = yes; N = 1136)

Variable	Label	mean	N: yes
Carrier Type			
Operates primarily as a private fleet	Private fleet	0.349	397
Operates primarily as a common carrier	For-hire carrier	0.521	592
Primary Service			
Primary service is general truckload	Truckload carrier	0.374	425
Less-than-truckload with > 2 terminals in CA	Large LTL carrier	0.102	116
Primary service is household goods movement	Mover	0.064	73
Size			
Number of power units operated in CA < 10	<10 power units	0.277	315
Number of power units operated in CA = 10 – 24	10-24 power units	0.268	305
Number of power units operated in CA ≥ 100	100+ power units	0.123	140
Load Types			
Engages in less-than-truckload operations	LTL operations	0.429	474
100% of loads known < 4 hrs. before pick-up	Just-in-time carrier	0.063	71
Average loaded movements less than 25 miles	Short hauler	0.070	79
Average loaded movements 500 miles or more	Long hauler	0.344	391
Specialized Services Provided			
Specialized services include tank loads	Tanker ops.	0.094	107
Specialized services include refrigerated units	Refrigerated ops.	0.223	253
Specialized services include hazardous materials	HAZMAT ops.	0.195	221
Specialized services include high value goods	High value ops.	0.129	146
Intermodal Services			
Picks up at or delivers to maritime ports in CA	Intermodal sea	0.376	427
Picks up at or delivers to airports in CA	Intermodal air	0.193	219
Picks up at or delivers to both air- and seaports	Air and Sea ops.	0.107	121
Picks up at or delivers to rail terminals in CA	Intermodal rail	0.139	158

4. METHODOLOGY

4.1. Application of a Multivariate Discrete Choice Model

Adoption of the seven technologies is here modeled using a structural multivariate probit model, which is one form of a multivariate discrete choice model. Using such a model, the exogenous influences on demand for the seven technologies are estimated simultaneously, while the unexplained portions of demand (error terms) are allowed to be freely correlated. Recent developments in multivariate discrete choice methods are reviewed in Section 4.2, and in Section 4.3 we focus on the pros and cons of the structural multivariate probit model which we use.

Instead of a multivariate model, it is possible to adopt a much simpler approach and estimate independent discrete choice models for each of the seven technologies as functions of the twenty operating characteristics listed in Table 3. However, such independent estimations will fail to take into account relationships between demand for different technologies. Some combinations of technologies might be viewed by trucking industry decision makers as being complementary, while other combinations might be viewed as being competing. Also, some companies might view their operations as not requiring any technology or they might wish to minimize costs by refraining from adopting information technology in general. Other companies might feel that many types of information technology are needed because of the complexity of their operations or in order for them to maintain competitive advantage. Each of these scenarios will result in managers viewing the separate components of information technology in bundles, rather than in isolation. Independently estimated choice models will not capture the relationships between adoption of the different technology components.

As an alternative to a complicated multivariate model with seven endogenous discrete choice variables, one could employ a multinomial discrete choice model, in which the choice set is made up of all combinations of technology components, or $2^7 = 128$ alternatives. (Of these 128 available alternatives, 97 were actually chosen by at least one company in our sample of 1136 companies.) Estimation of a multinomial logit (MNL) is certainly possible with a problem of this size (128 alternatives and 20 exogenous variables), but it would be difficult to interpret the influences of the exogenous variables on choices of each of the original seven separate technologies. Independence of irrelevant alternatives (IIA) properties also limit the usefulness of MNL in such a scheme. Multinomial probit (MNP) and "mixed" or random-coefficients multinomial logit are more appropriate in such a situation, and parameter estimation of large MNP and mixed logit models is now possible using simulation methods, both Bayesian and non-Bayesian, estimation (reviewed in Brownstone, 2000). However, all multinomial replications of a multivariate choice system are still burdened with the problem of interpreting of exogenous effects, and the simulation estimation methods available now are usually computationally burdensome and are plagued with certain other problems common to simulation estimation methods for multivariate models discussed in the next Section.

4.2. Multivariate Probit and Logit Models

Until recently, joint estimation of three or more equations with dichotomous dependent variables was computationally infeasible. However, in the last twenty years, and especially in the last decade, several methods for estimating multivariate probit models (MPM), multivariate logit models (MLM), and other types of correlated binary response regression models have been developed. These developments have been motivated by applications in three broad fields: (1) econometrics and marketing science, where the problem is usually in terms of a multivariate discrete choice model, (2) biometrics and biostatistics, where models are needed to analyze multiple correlated binary physiological responses and (3) other social sciences and education (particularly psychometrics and sociometrics), which deal with related sets of dichotomous item scores and human responses. An informative, but somewhat dated overview of alternative methods for multivariate analysis of dichotomous variables (binary response data) can be found in Joe (1997).

The multinomial probit model (MPM) has received the most attention because it is based on the multivariate normal distribution. The first MPM can be traced to Ashford and Sowden (1970), in which an exact maximum likelihood (ML) solution was developed for the bivariate case. This first application was in the field of epidemiology. Evaluation of the likelihood function for higher numbers of endogenous variables is analytically difficult except under simplifying assumptions (Chib and Greenberg, 1998). It is further noted by Keane and Moffitt (1998) that imposing an MPM utility structure results in a choice problem with an intractable solution, because the region of the error space within which different choice combinations are optimal, is too complex to derive.

Muthén (1979) proposed a general MPM based on latent variables and structural equations. However, the ML solution was found to exhibit “too heavy complications in the general case” (Muthén, 1979, p. 810). Muthén (1983) then turned to a limited-information generalized least-squares (GLS) approach to estimating a MPM with latent variables and that avoids the computational problems associated with full-information ML. The Muthén (1983) GLS method, a precursor to the structural MPM method which we used in the present research, is supported by the findings of Amemiya (1978) (the Muthén work being applied to psychometric and sociometric data, the Amemiya work to econometric data).

Muthén (1994) refined the GLS approach, and included structural MPM within a procedure that can accommodate structural equations with a mixture of dichotomous, ordered categorical and continuous endogenous variables. We employ a later version of this method in estimating our structural MPM. The method, known as ADF-WLS, which stands for arbitrary distribution function (or, asymptotically distribution free) weighted least squares, is described in detail and contrasted to alternative approaches for structural MPM in van Wissen and Golob (1990). Briefly, the first stage of the estimation procedure is to estimate separate reduced-form univariate probit models for each of the endogenous dichotomous variables, using the standard ML method (Maddala, 1983). In the second stage of the procedure, the unknown (tetrachoric) correlation coefficient of the multivariate normal distribution are estimated for each pair of endogenous variables, using the limited-information maximum likelihood method developed by Kirk (1973) and extended by Olsson (1979). The information available for each tetrachoric correlation consists only of the cross-tabulation of the two dichotomous variables plus the thresholds from the two univariate probit models. The third and final stage of the procedure then uses variance analysis (method of moments) to estimate the exogenous regression effects of the exogenous variables and the error-term variances and covariances. The variance analysis method applied at this stage is analogous to weighted least squares regression, but in this case the observed and predicted values are correlations rather than raw observations. Browne (1982, 1984) demonstrated that the fitting function is well-behaved, the method will yield consistent estimates which are asymptotically efficient with asymptotically correct covariances, and the Chi-square statistic computed from the fitting function will produce an asymptotically correct test of overall model fit.

Biometricians and statisticians have also developed several variance analysis methods for MPM that have many properties in common with the ADF-WLS method. Among these are the method of general estimation equations (GEE) (Liang, Zeger and Qaqish, 1992, Prentice, 1988, Zhao and Prentice, 1990), and the mean and covariance structure analysis (MECOSA) approach (Schepers, Arminger and Küsters, 1991). Spiess and Hamerle (1995) compared these approaches to ML using simulated data and concluded that GEE performed well compared to ML, while MECOSA estimates were less efficient and biased in the case of tetrachoric correlations. The efficiency gain of ML over both methods increases with the true value of the correlations of the endogenous variables.

Most recently, MPM is being estimated using simulation. In such methods, choice probabilities are simulated using Monte Carlo methods, rather than evaluated using conventional numerical methods, thus avoiding evaluation of multiple integrals. The primary simulation approaches, which have been applied to both multivariate and multinomial choice models, stem from simulated maximum likelihood (SML) (Lerman and Manski, 1981) and the method of simulated moments (MSM) (McFadden, 1989, Pakes and Pollard, 1989, and McFadden and Ruud, 1994). Keane and Moffitt (1998) compared the performance of SML and MSM for joint estimation of MPM. They found MSM to be more computationally burdensome than MSL, and developed a two-stage modified MSM estimation technique that was simpler but gave similar estimates. It is not known whether the Keane and Moffitt (1998) method, used by Gibbons and Lavigne (1998), can be used with a problem as big as ours (seven endogenous variables and twenty exogenous variables). Many of the simulation estimation procedures use the highly accurate GHK probability simulator (described in Geweke, Keane and Runkle, 1994) originally applied to the MNP model.

A promising direction in simulation estimation of MPM is the use of Bayesian methods. Brownstone (2000) reviews Bayesian simulation approaches for estimating multinomial discrete choice models, particularly MNP. Many of these same techniques are being applied to MPM as well. Most of the Bayesian approaches use MCMC (Markov Chain Monte Carlo) methods (Gelfand and Smith, 1990, Tierney, 1994). Using MCMC and extending results from earlier analyses of binomial probit models (Albert and Chib, 1995), Chib and Greenberg (1998) developed a method of simulated maximum likelihood for MPM in which estimates are obtained using a Monte Carlo version of the E-M algorithm (Wei and Tanner, 1990).

Finally, multivariate logit models (MLM) have also been advanced (Glonek and McCullagh, 1995), but these efforts require substantial approximations due to the lack of a multivariate logistic distribution. As extensions to the general log-linear model, MLM has been estimated using methods similar to those applied to MPM, in particular, GEE (Zhao and Prentice, 1990, and Carey, Zeger and Diggle, 1993) and simulation estimation (Dey, Ghosh and Mallick, 2000). In general, however, advanced estimation methods for correlated binary response data have are been centered on the MPM.

4.3. Advantages and Limitations of the Structural Multivariate Probit Model

When comparing our structural MPM estimated using ADF-WLS to full-information maximum likelihood (simulation) methods, there are advantages and disadvantages to each. The structural MPM uses a well-established estimation method that has been widely applied in the behavioral, social, biological, and educational sciences to model relationships involving multiple dichotomous and ordinal endogenous variables (see, *e.g*., Bollen, 1989, Hoyle, 1995, Mueller, 1996). Thus, there is extensive documented knowledge about data requirements, assessing goodness-of-fit, and robustness of the estimates under violations of assumptions. The solution algorithm is well behaved and its performance under a variety of model specifications has been extensively studied. However, it is well known that MPM full-information simulation estimation methods, at their current state of development, are subject to numerous computational difficulties in finding an optimal solution for all but the simplest models. The performance of these algorithms will undoubtedly improve with experience and with attention from a growing body of developers and users.

A second point is access to software. Structural equations software that includes ADF-WLS estimation is readily available. This includes modern versions of LISREL (Jöreskog and Sörbom, 1993, utilizing Muthén, 1997) and EQS (Bentler, 1989), or the estimation method can be easily programmed in matrix languages such as GUASS and MATLAB. Until just recently, simulation estimation has been available only to a limited number of developers and specialists in discrete choice modeling. However, this is changing as simulation estimation programs for MPM are just becoming widely available (e.g., ESI, 2000).

Third, no specialized knowledge is required to set up a structural MPM and to test hypotheses concerning alternative model structures. Structural equations methods are designed for efficient testing of alternative causal structures, and the diagnostics provided by most structural equations software is very useful in detecting an optimal model when there are many choices available. In the present case, the choices involved selection of an optimal set of parameters in a seven-by-twenty matrix of exogenous effects of operating characteristics on technology adoption probabilities.

A fourth point of contrast concerns sample sizes. Required sample size can be a disadvantage for the structural MPM. The desirable properties of the estimators are predicated on asymptotic theory, which requires sufficient sample size vis-à-vis problem size. The variance-covariance matrix of the correlations contains [k(k-1)/2][k(k-1)/2+1]/2 elements, where k is the total number of (endogenous plus exogenous) variables. A rule of thumb is that the number of observations should be greater than 1.5k(k+1) (Jöreskog and Sörbom, 1993). With 1136 companies and 7 endogenous variables, this limits the maximum number of exogenous variables to twenty. The asymptotic variance-covariance matrix is unlikely to be positive definite if the sample sizes are smaller than the number given by the rule of thumb. Other estimation methods might accommodate lesser sample sizes. However, both SML and structural methods rely on asymptotic theory, and it is not well known how either set of asymptotic assumptions holds up with realistic sample sizes. Sample size problems are likely to be manifested in biased inference due to poor estimates of parameter variance-covariances.

Another limitation of the structural MPM is one which plagues all simultaneous equations systems with a relatively large number of variables, particularly systems comprised mostly of dichotomous variables. Collinearity, which manifests itself in non-positive definite moment matrices, is difficult to foresee. In addition to being constrained by sample size to no more that twenty exogenous variables, we were constrained to finding exogenous variables that did not lead to singularity when combined together with the endogenous variables. In the present application, this limited the number of fleet size categories and the number of specialized service categories we were able to use. Collinearity also prevented us from testing interaction terms between fleet size categories and other operating characteristics. It is possible to test whether some of these new variables are significantly related to technology adoption, but to do so, we would have to eliminate some other important variables from the model. Presentation of numerous alternative model specifications is beyond the scope of this paper.

Fortunately, the limited empirical studies that have compared full-information maximum likelihood and limited-information GLS methods have shown that the two methods yield similar estimates. ADF-WLS estimates and their variance-covariances have been shown to be consistent and asymptotically efficient under broad conditions (Bentler, 1983, Browne, 1982, 1984, Muthén, 1983, 1984). However, we have a finite sample size, and the use of binomial probit models in the limited-information sequence in the first two stages the ADF-WLS estimation method beg the question of whether estimates can be improved in some way by iterating and looping back through the first stages conditional on the structural estimates from the third stage of the method. In spite of these potential differences, Bock and Gibbons (1996, p. 1187) compared maximum likelihood results with those of GLS (ADF-WLS) and concluded that “all results agreed to second and third decimal places except for a few of the correlations and their standard errors." It was observed that the correlation estimates should be more accurate in the full-information solution, but the same may not be true of the standard errors of the correlations, which are approximations in many full-information methods. They concluded that the GLS procedure is quite satisfactory in many applications. Clearly, a fruitful task for further research is to compare our results with those of a full-information MPM simulation estimation on the same data set. In general, Monte Carlo studies are needed to establish the extent of the efficiency loss for ADF-WLS and to assess the relative asymptotic performance of the two sets of methods.

5. RESULTS

5.1. Thresholds and Tetrachoric Correlations

The first stage of the structural MPM procedure described in Section 4.2 is to estimate thresholds for the seven probit latent variables. These thresholds are estimated jointly with regression coefficients for the twenty exogenous variables for each of the seven endogenous variables. The estimated thresholds are: (1) S/RC: 0.247 (2) AVLS: 0.680; (3) AVI: 0.969; (4) EDI: 0.489; (5) VMS: -0.011; (6) R/SS: -0.038; and (7) CBR: 1.049.

The tetrachoric correlations estimated in the second stage of the estimation procedure are listed in Table 4 together with their asymptotic z-statistics. These are maximum likelihood estimates of the correlations between two normally distributed latent variables. As such, they are directly comparable measures of association between the adoption probabilities for pairs of technology components. The values listed in Table 4 show a high degree of association between all of the technology components with the exception of CBR. In particular, one bundle of components is comprised of (1) AVLS, (2) S/RC, and (3) EDI. The consistently high correlations for each pair of these technology components indicate that if a company has one of the components, it typically has all three of them. Another bundle is comprised of (1) R/SS, (2) VMS, and (3) EDI, with the link between VMS and EDI being the weakest. In addition, there is a strong correlation between the adoption probabilities of R/SS and AVLS. The overlapping nature of these groups of related technologies reveals how all of the correlations involving the first six components are significantly different from zero.

5.2. Overall Model Fit

If the mutivariate demand model (1) is over identified (specified to have structural zeros for some regression effects), the ADF-WLS fitting function (4) will be non-zero. Therefore, the overall fit of the simplified model can be tested using the chi-square statistic computed from the fitting function. If all regression effects are specified as free parameters, the model is saturated and the fit will be perfect. With 7 endogenous variables and 20 exogenous variables, the saturated model has 140 regression effects, and the error-term variance-covariance matrix has 7 variances and 21 covariances, for a total of 168 free parameters. However, saturated models are difficult to interpret, because statistically significant effects can be diminished due to multicolinearity with insignificant effects. Our approach was to first estimate a saturated model and then to sequentially eliminate structural regression parameters until all remaining regression parameters were significant at the 95% confidence level. Sensitivity analyses were conducted to make sure that the fit of the final model was the best that could be obtained under the constraint that all exogenous variable effect are statistically significant. We further specified all error-term variances and covariances to be free parameters, in the expectation that the technology choices would be highly related. If any pairs of choices are truly independent, then the appropriate error-term covariance should be only randomly different from zero.

Table 4.
Estimated Tetrachoric Correlations (z-statistics in parentheses)

	S/RC	AVLS	AVI	EDI	VMS	R/SS
AVLS	0.611 (27.06)					
AVI	0.230 (5.55)	0.434 (15.95)				
EDI	0.423 (11.82)	0.695 (40.81)	0.372 (11.76)			
Vehicle maintenance software (VMS)	0.212 (3.83)	0.269 (5.91)	0.245 (5.68)	0.350 (8.18)		
Routing/scheduling software (R/SS)	0.219 (3.97)	0.507 (16.63)	0.264 (6.26)	0.527 (16.83)	0.572 (17.57)	
CB Radio (CBR)	-0.184 (-2.94)	-0.174 (-3.15)	-0.128 (-2.60)	-0.091 (-1.68)	-0.069 (-1.50)	-0.210 (-3.04)

There are 127 parameters in the final optimal model. The chi-square value for the structural model estimated using the ADF-WLS method was 40.74 with 46 degrees of freedom. This corresponds to a probability value of p = .692, which means that the fitted model cannot be rejected at the p = .05 level (Bollen, 1989). All structural parameters are also significant at the p = .05 level.

As a test of the importance of the free error-term covariances, we also estimated a model with structural zeros for the error-term covariances (and with saturated regression effects). The chi-square value for the model with no error-term covariances was 906.70 with 21 degrees of freedom. This corresponds to a probability value of $p <$ .0001, which means that the fitted model *can* be rejected at any reasonable confidence level. The non-zero error-term covariances are vital to the fit of this model, implying that the adoptions of the technology components are indeed interrelated.

5.3. Error Terms

The error-term variances, the parameters of the diagonal elements of Ψ, provide estimates of R^2 values for the latent variables, because the variances of the latent endogenous variables are unity by definition (i.e., variances are not separately identifiable in probit models). These R^2 estimates are listed in Table 5 for both three different sets of models: (1) the final model, (2) the saturated model, and (3) the seven separate univariate probit models estimated in the first step of the estimation method. The univariate models are directly comparable to the saturated multivariate model in that they include all exogenous variables. The differences in R^2 values between the saturated and final models describe the reduction in explanatory power that comes from eliminating all exogenous variable effects that are not statistically significant at the p = .05 level. Both the saturated model and the more parsimonious final model perform considerably better than the univariate model for each of the endogenous variables. Adoption of EDI is most effectively explained in the multivariate models, followed by AVLS, R/SS, and VMS. In contrast, demand for S/RC and AVLS is less well explained by the models.

Table 5.
Percent Variance Accounted For by Different Models

Endogenous variable	Estimated R^2		
	Final model	Saturated model	Univariate models
Satellite- or radio-based communication systems	0.082	0.087	0.054
Automatic Vehicle Location Systems (AVLS)	0.165	0.190	0.104
Automatic Vehicle identification systems (AVI)	0.095	0.113	0.052
Electronic Data Interchange (EDI)	0.181	0.213	0.126
Vehicle maintenance software	0.142	0.161	0.102
Routing and scheduling software	0.159	0.201	0.128
CB radio	0.115	0.116	0.048

It is also instructive to look at the estimates of the error-term variance-covariances. All but five of the error-term variances and covariances are significant at the p = .05 level. The significant covariances in all but the last row of Table 6 indicate that the error terms for all of technology components, with the exception of CBR, are positively correlated. The unexplained component of choice of CBR is generally not related to unexplained choices of other technologies, except that it is negatively correlated with choice of S/RC. Comparing these error covariances with the tetrachoric correlations (Table 4), it can be seen that the model explains a substantial proportion of the relationship between choices of (a) EDI and (b) R/SS, as well as the relationship between choices of (a) EDI and (b) AVLS. The model does a relatively poor job of explaining the relationships between choices of (a) S/RC and (b) EDI, and choices of (a) S/RC and (b) AVLS. The common role of EDI technology is more easily explained than the common role of S/RC technology.

Table 6.
Estimated Error-term Variances and Covariances (z-statistics in parentheses)

	S/RC	AVLS	AVI	EDI	VMS	R/SS	CBR
Satellite or radio communication (S/RC)	0.918 (29.17)						
AVLS	0.588 (23.54)	0.835 (24.90)					
AVI	0.222 (5.09)	0.362 (11.03)	0.905 (28.83)				
EDI	0.436 (12.03)	0.564 (20.92)	0.313 (8.50)	0.819 (23.65)			
Vehicle maint. software (VMS)	0.210 (3.61)	0.214 (4.13)	0.206 (4.30)	0.285 (5.70)	0.858 (24.96)		
Routing/scheduling Software (R/SS)	0.264 (4.86)	0.405 (10.05)	0.235 (5.07)	0.426 (10.34)	0.504 (12.35)	0.841 (23.42)	
CB Radio (CBR)	-0.133 (-2.14)	-0.016 (-0.32)	-0.027 (-0.59)	0.072 (1.55)	0.034 (0.60)	-0.032 (-0.528)	0.885 (27.92)

5.4. Effects of the Operating Characteristics

The estimated structural coefficients of the multivariate discrete choice model system are listed in Table 7. Ninety-four (67%) of the possible 140 regression effects were found to be significant at the p = .05 level, and the vast majority of these are significant at p < .01. These can be considered similar to coefficients of standard univariate probit models, except that they apply to seven simultaneously estimated probit discrete choice models with free error-term correlations. The coefficients are standardized because estimation was performed on the correlation matrix, thus allowing direct comparison of relative effects. These results are interpreted in two ways in the next Section.

Table 7.
Estimated Effects of the Operating Characteristics (z-statistics in parentheses)

Exogenous variable	Endogenous variable						
	S/RC	AVLS	AVI	EDI	VMS	R/SS	CBR
Private fleet		-0.204 (-13.85)	-0.100 (-7.09)	-0.229 (-13.73)	-0.148 (-7.56)	-0.205 (-10.13)	0.173 (10.79)
For-hire carrier					0.089 (6.56)		
Truckload carrier	-0.118 (-8.80)		0.035 (3.15)	0.083 (6.99)		0.072 (5.47)	-0.115 (-9.37)
Large LTL carrier	0.064 (4.82)	0.069 (6.02)	0.065 (5.82)				-0.029 (-2.57)
Mover	-0.073 (-6.14)	0.052 (4.84)		0.039 (3.56)			-0.051 (-5.58)
<10 power units	-0.170 (-10.71)	-0.083 (-7.26)	-0.151 (-13.46)		-0.157 (-10.01)		-0.102 (-11.19)
10-24 power units	-0.071 (-4.74)	-0.040 (-3.30)	-0.068 (-5.78)	-0.046 (-4.07)	-0.110 (-7.25)		
100+ power units	0.061 (4.19)	0.045 (3.51)	0.054 (4.74)	0.120 (9.26)	0.097 (6.81)	0.037 (2.94)	
LTL operations	-0.091 (-5.58)	-0.058 (-4.83)	-0.030 (-2.45)		-0.033 (-1.98)	-0.052 (-3.24)	0.056 (4.06)
Just-in-time carrier	0.070 (6.82)	0.069 (7.95)	0.076 (6.39)				-0.036 (-3.68)
Short hauler	-0.033 (-2.88)	-0.021 (-2.13)		-0.024 (-2.29)		0.069 (5.89)	
Long hauler	-0.059 (-4.32)		-0.042 (-3.95)		-0.076 (-5.32)		-0.103 (-7.96)
Tanker ops.		-0.034 (-3.33)	0.045 (3.73)			-0.047 (-3.96)	0.021 (1.98)
Refrigerated ops.		0.166 (13.25)	0.072 (5.13)	0.134 (9.24)	0.063 (3.45)	0.192 (10.44)	-0.136 (-9.96)
HAZMAT ops.	0.067 (3.88)	0.160 (9.97)	0.078 (5.42)	0.173 (10.45)	0.176 (9.70)	0.156 (8.53)	
High value ops.		0.083 (7.21)	0.054 (4.94)	0.046 (3.82)	-0.077 (-6.61)		-0.068 (-5.81)
Intermodal sea		0.064 (5.31)	0.041 (3.49)	0.067 (5.65)	0.050 (3.71)	0.081 (5.65)	0.078 (6.72)
Intermodal air			-.099 (-9.10)		-0.048 (-3.92)		0.145 (10.37)
Air and Sea ops.	-0.056 (-4.53)	-0.078 (-6.97)	0.048 (3.68)			-.087 (-6.37)	-0.097 (-6.30)
Intermodal rail	-0.054 (-3.84)	-0.033 (-2.69)	-0.051 (-4.44)	-0.126 (-10.53)	-0.026 (-2.00)		

6. Interpretation OF Model Results

6.1. Characteristics Important in Explaining Demand

Several overall patterns are clear in the results of the mutivariate demand model. The greatest overall explanatory power resides in distinguishing private fleets. Private fleets have substantially lower levels of demand for all of the technologies with the exception of S/RC and CBR. The more routine operations of many private fleets negate the need for advanced communications and routing and scheduling technologies. The greatest differences between private and for-hire fleets are in demand for VMS, followed by EDI, AVLS and R/SS.

Adoption of information technology is also strongly related to fleet size. Large fleets (with 100 or more power units typically operating in California) exhibit the greatest demand for each of the first six technology components, and small fleets (with less than ten power units typically operating in California) exhibit the lowest demand for all technology components with the exception of EDI. For EDI, demand is lowest for mid-sized fleets.

Consistently lower probabilities of technology adoption are also exhibited by companies with LTL operations, unless the company is a large LTL operator with more than two terminals in California. These larger LTL carriers are more likely than smaller LTL operators to employ all of the technology components with the exception of EDI and CBR. Carriers engaged in just-in-time operations exhibit higher probabilities of adopting S/RC, AVLS and AVI. Short-haul carriers are less likely to adopt satellite or radio communication links, AVLS and EDI, but are more likely to adopt R/SS. Long-haul carriers, on the other hand, are less likely to adopt S/RC, AVI and VMS.

The four specialized service variables are significantly related to adoption of most of the technology components, particularly AVLS and AVI. Two of these variables have similar patterns of influence. Provision of refrigerated services and hazardous materials services have similar effects on adoption of AVLS, AVI, and to a certain degree, EDI and R/SS. While there is some overlap of these characteristics (30% of those in our study providing reefer service also move hazardous materials while 35% of those moving hazardous materials also provide reefer service), there are also over 300 carriers in our study providing one type of service but not the other. Information technology is clearly important in operations that involve either of these specialized services.

Regarding intermodal services, carriers serving rail terminals are much less likely to adopt many of the technologies, while those serving seaports and airports are more likely to use these same technologies. The information technology components with opposing demands by intermodal maritime and air versus intermodal rail are AVLS, AVI, EDI, and VMS. This is a somewhat surprising result, because conventional wisdom generally considers intermodal maritime and rail to be the most similar pair of intermodal services. Instead, we found that, when controlling for all other operating characteristics, all three modes have unique influences on demand for information technology, and the interaction between maritime and air services is also important. When significantly different than zero, this interaction term ensures that the effect of joint provision of sea and air services is not simply equal to the sum of the two separate effects. Taking the interaction term into consideration, the most similar intermodal effects are the negative effects on adoption of S/RC by joint sea and air operators and by rail operators.

Influences of trucking attributes on demands for each of the first six components of information technologies are explored in the remainder of this Section.

6.2. Satellite or Radio-based Communication (S/RC)

Fleet size is a strong predictor of adoption of satellite or radio communication links. Small fleets in particular are less likely to use such links. Truckload carriers, household movers, small LTL carriers, and companies with either long average loaded movements are also less likely to use S/RC. To a lesser extent, adoption of S/RC is negatively related to provision of rail intermodal service and multiple air and sea intermodal services. Just-in-time carriers are likely to be equipped with S/RC.

6.3. Automatic Vehicle Location Systems (AVLS)

Sixteen of the twenty operating characteristics are strong predictors, both positive and negative, of carriers' use of AVLS technologies. Large fleets, movers, and carriers that provide refrigerated, hazardous materials (HAZMAT), high value, or just-in-time services are most likely to adopt AVLS. Private fleets are much less likely to use AVLS, *ceteris paribus*, as are carriers with small and medium-sized fleets and carriers engaged in short-haul or tanker operations. Intermodal maritime operations is a positive predictor of AVLS adoption, while intermodal rail operations is a negative predictor; air or joint sea/air operations have little affect on demand.

6.4. Automatic Vehicle Identification (AVI)

Propensity to use AVI devices in the form of PrePass transponders is predicted by size of operation (LTL service with 2 or more terminals in California, or having 100 or more power units in CA) and provision of any of the specialized services (tanker, refrigerated, HAZMAT, or high value service). General truckload and just-in-time carriers are also more likely to adopt AVI, while long-haul carriers, private fleets, and small LTL carriers are less likely to adopt AVI. As in the case of AVLS, intermodal maritime operations is a positive predictor of AVI adoption, and intermodal rail operations is a negative predictor. However, here provision of service to airports is a strong negative predictor of AVI. The sea/air interaction term cancels the two countervailing forces, so that there is a nearly neutral result for carriers that provide both air and maritime services.

6.5. Electronic Data Interchange (EDI)

Adoption of electronic data interchange is highest among truckload carriers, household goods movers, and providers of refrigerated, HAZMAT, and high value services. Use of EDI is also predicted by service to maritime ports. The influence of size of fleet is non-monotonic; probability of adoption is high for large fleets and low for mid-sized fleets, with small fleets being neutral. Once again, private fleets are least likely to adopt EDI, as are carriers engaged in short-haul or intermodal rail operations.

6.6. Vehicle Maintenance Software (VMS)

The most effective indicator of adoption of vehicle maintenance software is fleet size; companies with less than twenty-five vehicles are less likely to use VMS. As expected, companies that provide HAZMAT services are much more likely to use VMS, and refrigerated and intermodal maritime services are also a positive predictors. Private fleets, LTL operators, long-haul operators and carriers providing intermodal air or rail operations are less likely to adopt VMS.

6.7. Vehicle Routing and Scheduling Software (R/SS)

Only ten of the twenty exogenous variables are significant predictors of adoption of routing and scheduling software. First and foremost, R/SS adoption is greatest among companies providing refrigerated and HAZMAT services. R/SS adoption is also more likely for large fleets, truckload carriers, and carriers engaged in short-haul operations, *ceteris paribus*. Demand for R/SS is lower for private fleets, LTL operators, and companies providing tanker operations. Carriers that serve maritime ports are more likely to use R/SS, but rail, air or joint sea/air (taking into account the interaction term) operations have no significant affect on adoption of routing and scheduling software.

7. Forecasting Technology Demands

The linear combination of effects of the operating characteristics may be obtained for companies possessing one or more characteristics by generating the matrix $(x_i-\mu_i)\,\gamma'_{ij}\ /\ \sigma_l$ where γ'_{ij} represents the coefficient in Table 7 for characteristic i for technology j, μ_l and σ_l are the mean and standard deviation of characteristic i; and $x_i = 1$ if a company possesses characteristic i, $x_i = 0$ otherwise. The column sums of this transformed effects matrix are presented in Table 8 for five hypothetical companies. These hypothetical characteristics were simply selected as examples of the thousands of possible combinations of characteristics that could be explored.

Table 8.
Combined Exogenous Effects for Five Hypothetical Companies

Hypothetical company	Endogenous variable						
	S/RC	AVLS	AVI	EDI	VMS	R/SS	CBR
(1) Private tank carrier	0.571	0.199	-0.663	-0.126	-0.560	-0.151	-0.665
(2) Private carrier with less than 10 power units and average length of haul less than 25 miles	0.272	-0.310	-0.815	-0.617	-0.654	-0.502	-0.232
(3) Large LTL carrier (> 100 power units, 2 or more terminals in CA), air intermodal operations	0.521	0.201	-0.099	-0.217	0.285	0.266	-0.067
(4) Large contract carrier with refrigerated service	-0.190	0.385	0.417	0.267	0.607	0.601	0.500
(5) For-hire general truckload carrier with more than 100 power units, serving ports and railheads	0.060	-0.015	0.054	0.103	0.231	0.660	0.354

In order to obtain the probability that a particular type of company will select the technologies, we generate N observations (random companies with these characteristics) from a multivariate normal distribution MVN(μ,S), where μ is a vector of combined effects for the relevant exogenous variables and S is the error term variance-covariance matrix for the endogenous variables. The value of N is arbitrarily set at 1,500,000, far higher than required for convergence of the results.

The method of generating multinomial normal random variates is described in Cheng, (1998). It is typically the case in these kinds of analyses that we would calculate the probability of adoption based on the number of trials for which $\mu+\varepsilon > 0$. However, we use probit models to establish thresholds for each of the normal variates. We are interested in the observations for which $\mu_j + \varepsilon_j$ is greater than the threshold value τ_j for each of the j technologies. The estimated threshold values are listed in Section 5.1. The probability that $Z_j > \tau_j$ is exactly equal to the aggregate market penetration of the technologies in our sample of 1136 companies.

The forecast probabilities that each of the five hypothetical companies will adopt these technologies are listed in Table 9 and graphed in Figure 2. As a point of comparison, the last row in table 9 presents the overall market penetration for each technology. These forecasts are likely to be change if the MPM was estimated using estimation method (as discussed in Section 4.3).

Table 9.
Forecast Demand Probabilities for Five Hypothetical Companies

Hypothetical company	Endogenous variable						
	S/RC	AVLS	AVI	EDI	VMS	R/SS	CBR
(1) Private tank carrier	0.306	0.480	0.071	0.125	0.124	0.440	0.189
(2) Private carrier with less than 10 power units and average length of haul less than 25 miles	0.205	0.281	0.051	0.048	0.104	0.298	0.393
(3) Large LTL carrier (> 100 power units, 2 or more terminals in CA), air intermodal operations	0.288	0.481	0.197	0.106	0.412	0.617	0.485
(4) Large contract carrier with refrigerated service	0.094	0.556	0.387	0.231	0.552	0.744	0.775
(5) For-hire general truckload carrier with more than 100 power units, serving ports and railheads	0.147	0.392	0.247	0.182	0.389	0.764	0.709
Aggregate market penetration	0.147	0.402	0.248	0.166	0.312	0.504	0.515

There are substantial differences among the hypothetical companies in terms of forecasts of technology adoption. For example, the model predicts that a large for-hire truckload carrier that provides intermodal services (hypothetical company 5) is likely to adopt satellite or radio based communication technology, use EDI and use both vehicle maintenance and routing and scheduling software. A medium-size private tank carrier (company 1) is likely to use vehicle maintenance software but not routing and scheduling software (their routes are likely fixed well ahead of time) and is more likely to use a satellite or radio based communication system than CD radio.

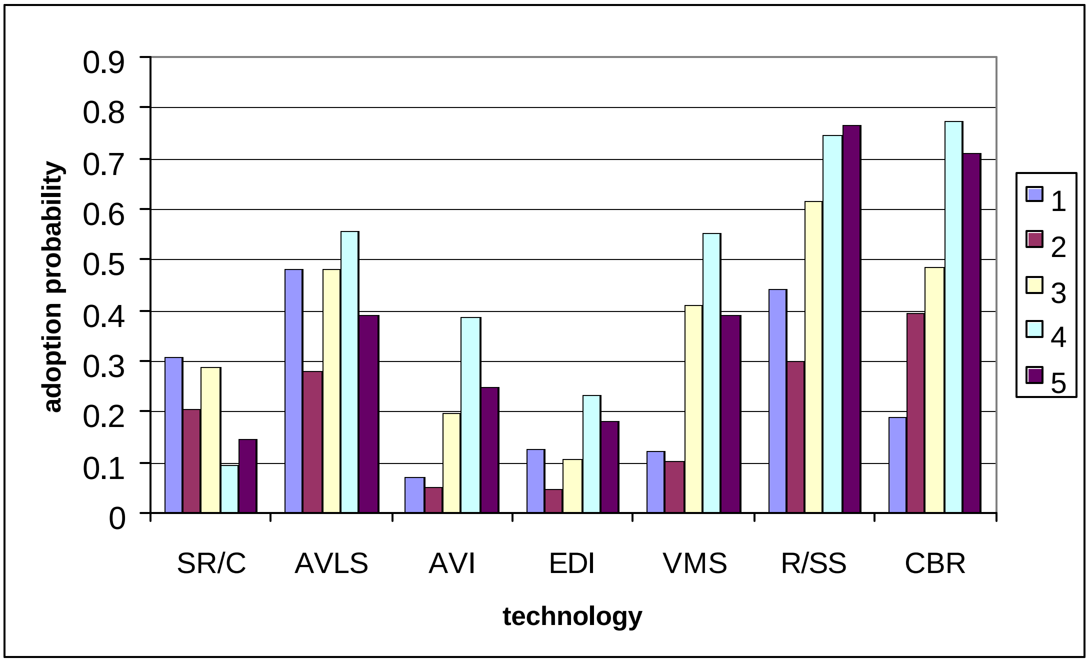

Figure 2
Predicted probabilities of technology adoption for five hypothetical companies
(Company types are defined in Tables 8 and 9)

8. Conclusions and Directions for Further Research

In this paper we present a multivariate discrete choice model of adoption of information technologies in trucking operations. Data for the model were drawn from a 1998 survey of more than 1,100 trucking companies operating in California. The mutivariate discrete choice model provides a means of analyzing demand for seven information technologies simultaneously. It can be conveniently estimated using available structural equations modeling software. The methodology is appropriate for many problems involving the choice of any combinations from a fairly large set of non-exclusion alternatives.

The model predicts which set of information technology alternatives will be selected by companies with different characteristics. Twenty operating characteristics were found to be significant exogenous variables. The model estimates were then used to forecast probabilities of technology adoption for a set of candidate companies. These results are easily replicated and extended. Information provided in the paper is sufficient to generate the probability of adoption for any combinations of characteristics. Such information could be useful to technology providers and might provide policy analysts with an understanding of trucking industry behavior. Public sector encouragement for technologies advantageous in advanced traveler information systems (ATIS) can help in mitigating congestion in areas with heavy commercial vehicle traffic.

The multivariate discrete choice model presented here is relatively new in transportation research. A useful topic for future research would be to compare this type of multivariate choice against multinomial models more familiar to transportation researchers, such as multinomial probit (MNP) and mixed logit. The present model is particularly easy to implement using readily available structural equations software packages, and It can easily handle many endogenous choices (in this case seven). MNP and mixed logit, on the other hand, take more effort to understand and use, especially when the number of choice alternatives is large (in this case $2^7 = 128$). Further research is needed to compare coefficient estimates and forecasts from the multivariate and multinomial models using identical data.

Finally, the issue of IT adoption by commercial vehicle operators is one that will remain of significant interest in the near future. Information technologies are poised to transform whole industries and segments of society. Business to business e-commerce including the use of internet based electronic data interchange will impact goods movement in many different ways. The increase in time-sensitive shipments attributable to just-in-time manufacturing and distribution systems may pale in comparison to the further increases caused by vendor-managed inventory and "seamless" supply chains. Information technology adoption across the supply chain will likely lead to a noticeable reduction in average shipment sizes, particularly in urban areas. How soon these changes will occur and how well their impacts will be managed will both be impacted by technology adoption.

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