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Trucking Industry Demand for Information Technology: A Multivariate Discrete Choice Model

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ABSTRACT

The objective of this research is to understand the demand for information technology among trucking companies. Of interest is the use of information technologies in both private and for-hire carrier fleet operations. A multivariate discrete technology demand model is developed using data from a large-scale survey of the trucking industry in California. In addition to offering technology providers insight into the market for current and future information technologies the model can inform decisions made by policy analysts about public sector technology implementation aimed at congestion mitigation. The impact of congestion on trucking companies' profitability and ability to provide timely and reliable service to customers is significant. Successful public sector technology implementation aimed at commercial vehicle operators will be complementary to investments made by companies themselves.

BACKGROUND

Freight transportation plays a vital role in the economy of the most countries, including the United States, and the State of California in particular. The value of total freight shipments originating in California in 1997 is estimated at $638.5 billion, 10.6 percent of all US shipments by value (BTS, 1997b). This represented 706.5 million tons of freight, or 7.2 percent of the freight moved nationally, by weight. By value and weight, respectively, 67.4 and 73.7 percent of this freight, 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 (BTS,1998c). It is estimated trucking employs one out of twelve workers in California (CTA, 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. This study examines the use of advanced information technologies in trucking operations.

Related Studies

There have been several recent studies of carriers use and propensity to use advanced technologies. These are described in detail in Regan and Golob (1999). We briefly mention these here. Scapinakis and Garrison (1993) conducted a small survey regarding carriers' perceptions of a 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.

DATA

The 1998 California Private and For-Hire Trucking Company Survey

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 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.

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%. Of the 1177 responses received, forty-one of these were not useable in this study because of missing data related to technology adoption. Hence the model described in this paper is based on a set of 1136 responses.

Non-response analyses were conducted for each of the three strata from which the sample was drawn. Golob and Regan (1998) 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.

For the private sector, the median fleet size for the 410 companies included in the survey was 28 power units, while the median fleet size for the 2,367 remaining companies was 78. 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, 1998). 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 and 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.

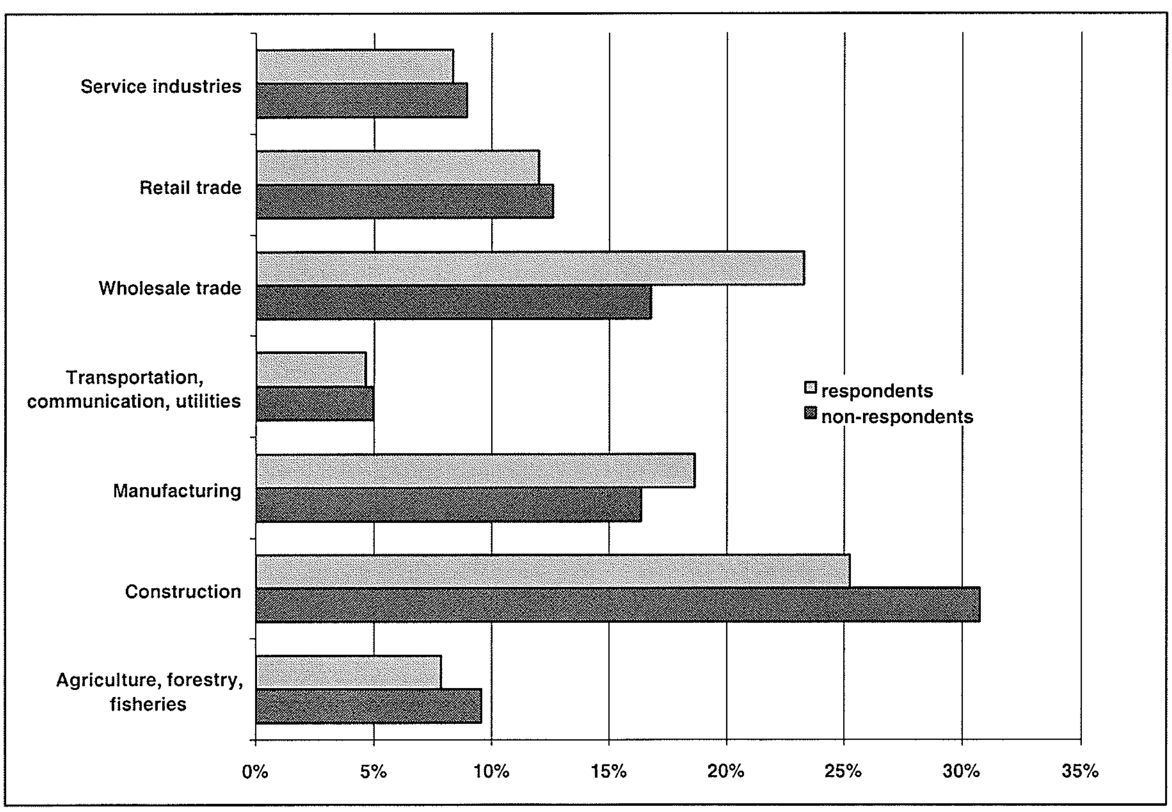

Figure 1: Distributions of Standard Industrial Classifications of Survey Respondents and Non-respondents for the Private-company Sub-sample

Approximately 69 thousand vehicles were represented by companies in the survey sample, 51.6 thousand of these in for-hire fleets and 17.4 thousand in private fleets. The U.S. Bureau of Transportation Statistics estimated that there were 295 thousand trucks and 758 thousand tractor-trailer combinations owned by and operated by commercial carriers (non private fleets) nationally, in 1995 (BTS, 1997). Assuming an increase of about 5% per year over the past three years, we estimate that there are around 1,219 thousand vehicles operated by commercial carriers nationally. The survey represents 5.7% of these, and, 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.

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 (1999a).

Traffic Congestion

This section included questions about carriers' perceptions about the impact of traffic congestion on their operations, followed by questions about the effectiveness of possible means of reducing congestion. Analyses of these data are presented by Golob and Regan (1998).

Use of Technologies

Questions were used to elicit information about carriers' current use of technologies including mobile communication devices, EDI, AVL, 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.

Use of and satisfaction with intermodal facilities in California

Carriers uses of maritime, rail and air intermodal facilities was investigated. 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, 1999b).

Operating characteristics

The remaining questions 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.

THE DATA

Penetration of Information Technology

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 two-way communication (TWC) 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 -25%	26 –75%	76 -100%
Mobile communication devices	27%	11%	61%
PrePass (AVI) transponders	87%	3%	7%
Automatic vehicle location devices	76%	4%	18%

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. 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 percent of for-hire and private vehicles represented by the this survey that are technology equipped.

To better understand the demand for technologies in carrier fleet operations we need to be able to match distinguishing company characteristics with technology use at a level greater than private, for-hire and large or small. The methods employed in this analysis provide an elegant and efficient way of identifying relevant characteristics and matching these to technology use.

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%

Seven technology variables were identified as significant in initial analysis of survey responses. These serve as the endogenous variables in this analysis. They are: (1) CB radios, (2) satellite or radio based communication, (3) automatic vehicle location technologies (AVL), (4) automatic vehicle identification systems (e.g., PrePass transponders, or AVI), (5) electronic data interchange (EDI), (6) vehicle maintenance software, and (7) routing and scheduling software. The aggregate market penetrations of these technologies in our sample of 1136 trucking companies with complete survey information are as follows. (1) CB radio: 14.7%; (2) satellite of radio communication links: 40.2%; (3) AVL: 24.8%; (4) AVI: 16.6%; (5) EDI: 31.2%; (6) vehicle maintenance software: 50.4%; and (7) routing and scheduling software = 51.5%.

Operating Characteristics

The exogenous variables in this analysis are operating characteristics which are likely to affect technology use. Characteristics such as fleet size, services offered, average length of haul, etc. all effect 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 only nineteen exogenous variables defining freight operations to be effective in explaining differences in technology use. These characteristics are listed in Table 3. Because all exogenous variables are dummy variables, the mean value of each variable represents the proportion of the sample that is endowed with that characteristic.

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

Variable	Label	Mean	Std. dev.
Engages in less than truckload operations	LTL operator	0.429	0.495
Operates primarily as a private fleet	Private fleet	0.349	0.477
Operates primarily as a common carrier	Common carrier	0.517	0.500
Primary service is general truckload	General truckloads	0.374	0.484
Primary service is household goods movement	Mover	0.064	0.245
Primary service is tank loads	Tanker	0.054	0.226
Specialized services include refrigerated units	Refrigerated loads	0.223	0.416
Specialized services include high value goods	High value loads	0.129	0.335
Specialized services include hazardous materials	HAZMAT loads	0.195	0.396
Number of power units typically operated in CA < 5	<5 power units	0.194	0.395
Number of power units typically operated in CA = 5 - 9	5-9 power units	0.132	0.339
Number of power units typically operated in CA ≥ 100	100+ power units	0.098	0.297
Picks up at or delivers to rail terminals in CA	Inter-modal rail	0.135	0.342
Picks up at or delivers to airports in CA	Inter-modal air	0.188	0.390
Picks up at or delivers to maritime ports in CA	Inter-modal port	0.373	0.484
Average loaded movements less than 25 miles	Short hauler	0.070	0.256
Average loaded movements 500 miles or more	Long hauler	0.339	0.474
100% of loads known less than 4 hrs. before pick-up	Just in time	0.062	0.241
Less than truckload operator with > 2 terminals in CA	LTL > 2 terminals	0.099	0.299

While it is possible to analyze the use of each of the seven technologies for each of the operational characteristics in Table 3, the examination of 133 cross-tabulations lends little insight into the overall patterns of technology use. This is particularly true because a single company may posses several of the operational characteristics identified as statistically significant and companies providing the same services may share some but not all of the same characteristics. An effective way to analyze factors contributing to technology use is to identify a multivariate demand model which avoids miscounting the effects of redundant operational characteristics (multicolinear independent variables).

METHODOLOGY

Specification of A Multivariate Discrete Choice Model System

Each freight operator in our sample has chosen whether or not to adopt each of the seven information technologies. Taken in isolation, we could model the demand for any one of the technologies by using a binomial (binary or dichotomous) probabilistic choice model, such as the logit or probit model. The choice of any one technology from a set of available technologies could be modeled using a multinomial logit (MNL) or multinomial probit (MNP) model. However, here we have a choice of any combination of seven technologies, rather than choice of a single technology from among seven alternatives. Our approach is to model this as seven integrated choices. Alternatively, a multinomial choice model could be designed with all combinations of the seven technologies as alternatives, but this will result in an extremely large number of alternatives, would probably require sampling of alternatives for estimation, and it would be extremely difficult to interpret the results.

Our model specifies the choices of the seven information technologies as a multivariate discrete choice system. Such a system facilitates simultaneous estimation of the effects of the exogenous variable on all choices while allowing the errors terms of each of the seven equations to be freely correlated. Details are provided in the remainder of this Section.

The *first stage* in the estimation of the multivariate discrete choice system is to convert the seven observed discrete choices to normal variates by estimating separate univariate probit models. For each of the seven information technologies, a threshold on the normal-distribution is estimated simultaneously with regression parameters for the eighteen exogenous variables using the standard probit log-likelihood method (Maddala, 1983).

The *second stage* in the procedure involves estimating the tetrachoric correlations between each pair of normal variables. The information available for each correlation is the cross-tabulation of the two observed dichotomous variables, plus the univariate thresholds and conditional probabilities estimated for each variable in the first step of the procedure. The problem is one of finding the unknown correlation coefficient of the multivariate normal distribution that maximizes the likelihood of observing the cross-tabulation frequencies. A limited-information maximum likelihood method for estimating these correlation coefficients, which are known as a tetrachoric correlation coefficients, was developed by Kirk (1973), extended and simplified by Olsson (1979) and reviewed by Jöreskog (1994).

The third and final step is to estimate the free parameters of the Γ and Ψ matrices of equation system (5) using variance analysis (method of moments). The multivariate demand system is captured in the simplified structural equation system

$$y^{*} = \Gamma x + \xi, \tag{1}$$

where y is a (7 by 1) column vector of , and x is the same (18 by 1) column vector of continuous exogenous variables. The variance-covariance matrix of ξ, the (7 by 1) vector of error terms is defined as $\Psi = E(\xi\xi')$.

We expect that the error-term correlations, represented by the off-diagonal elements of Ψ, will be significantly different from zero, because in general, what we cannot explain about the choice of one technology will be correlated with what we cannot explain about any other technology. The goal in the estimation of this system is to determine the structural parameters that best explain the discrete choice probabilities, where the choice probabilities have freely correlated error terms. Variance analysis by arbitrary distribution function weighted least squares (ADF-WLS) is an appropriate estimation method for such a problem (Browne, 1974, 1984; Muthén, 1983).

Variance analysis methods are based on making the model-replicated variance-covariance matrix as close as possible to the sample variance-covariance matrix. For our multivariate discrete choice system, the correlation matrix of the combined set of endogenous and exogenous variables is (partitioned with the endogenous variables first):

$$R = \begin{bmatrix} R_{yy} & R_{yx} \\ R'_{yx} & R_{xx} \end{bmatrix}, \tag{2}$$

where $\mathbf{R}_{yy}$ denotes the matrix of estimated tetrachoric correlations between pairs of the latent probit endogenous variables, $\mathbf{R}_{yx}$ denotes the matrix of conditional correlations between the endogenous latent variables and the exogenous variables, and $\mathbf{R}_{xx}$ denotes the correlation matrix of the exogenous variables, which is of course taken as given. It can be easily shown using matrix algebra that the corresponding variance-covariance matrix replicated by model system (5) is

$$\Sigma = \left[\begin{array}{c|c} (\Gamma \Phi \Gamma' + \Psi) & \Gamma R_{xx} \\ \hline R_{xx} \Gamma' & R_{xx} \end{array}\right] \tag{3}$$

The fitting function for ADF-WLS method used to determine the free parameters in the Γ and Ψ matrices is

$$F = [r - \sigma(\gamma,\varphi)]' W^{-1} [r - \sigma(\gamma,\varphi)], \tag{4}$$

where the corresponding elements of R (2) and those of Σ (3) are strung out in the vectors r and σ respectively, and W is a positive-definite weight matrix made up of the asymptotic estimates of the variances of the observed correlations. The ADF-WLS estimation method is analogous to weighted least squares regression, but here the observed and predicted values are correlations rather than raw observations.

Browne (1982, 1984) demonstrated that minimizing (4) will yield consistent estimates which are asymptotically efficient with asymptotically correct covariances (leading to asymptotically correct parameter z-statistics). Moreover, the Chi-square statistic, computed as the fitting function (8) multiplied by (N-1), will produce a correct test of overall model fit. The estimation can be implemented using modern versions of LISREL (Jöreskog and Sörbom, 1993) or other structural equations software that has an ADF-WLS estimation option.

RESULTS

Model Fit

If the mutivariate demand model (1) is specified to have structural zeros (no free parameters) in some of the cells of the Γ or Ψ parameter matrices, the ADF-WLS fitting function (4) will be non-zero, and the overall fit of the simplified model can be tested using various criteria, including the chi-square statistic computed from the fitting function. If all elements of the Γ or Ψ matrices are specified as free parameters, the model is saturated and the fit will be perfect. (With 7 endogenous variables and 19 exogenous variables, the Γ matrix has 133 regression effect cells, and the Ψ matrix has 7 variances and 21 covariances among the 7 endogenous variables, a total of 161 possible 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 parameters in the Γ matrix of regression effects 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. The concept of a multivariate discrete choice system requires that all parameters in the Ψ matrix of error-term variances and covariances be freely estimated.

There are 127 parameters in the final optimal model, with 99 (74%) of the possible 133 regression effects being significant. The chi-square value for the model estimated using the ADF-WLS method was 53.49 with 34 degrees of freedom. This corresponds to a probability value of $p = .018$, which means that the fitted model cannot be rejected at the $p = .01$ level (Bollen, 1989). All structural parameters are significant at the $p = .05$ level (one-tailed test). All but four of the error-term variances and covariances are also significant.

As a test of the importance of the free error-term covariances, we also estimated a model with structural zeros for the off-diagonal elements in the Ψ matrix (and with a saturated structural Γ matrix). The chi-square value for the model with no error-term covariances was 906.35 with 21 degrees of freedom. This corresponds to a probability value of $p < .001$, which means that the fitted model *can* be rejected at any reasonable confidence level. The error-term covariances are vital to the fit of this model.

Error Terms and Percent Variance Accounted For

It is instructive to look first at the estimates of the error-term variance-covariances. The significant covariances in all but the first columns of Table 4 indicate that the unique components of choice of the information technologies, with the exception of CB radio, are positively correlated. Unexplained choice of CB radio as an information link is generally not related to unexplained choice of other technologies, except that it is negatively correlated with choice of a satellite or radio based communication system.

Table 4: Error term Variances and Covariances (z-statistics in parentheses)

Endogenous demand variable	Endogenous demand variable						
	CB radio	Sat/Radio Com	AVL	AVI	EDI	Vehicle maint.	Routing & sched.
CB radio	0.800 (17.70)						
Satellite or radio-based comm. links	-.137 (-2.15)	0.925 (21.29)					
AVLS	0.026 (0.57)	0.613 (26.40)	0.789 (17.20)				
AVI	-.007 (-.15)	0.249 (5.93)	0.366 (11.33)	0.915 (21.20)			
EDI	0.090 (1.97)	0.425 (11.48)	0.524 (17.91)	0.295 (7.83)	0.777 (16.62)		
Vehicle maintenance software	0.062 (1.14)	0.239 (4.09)	0.199 (3.80)	0.205 (4.26)	0.255 (4.90)	0.855 (18.71)	
Routing and scheduling software	0.027 (0.49)	0.256 (4.65)	0.343 (7.76)	0.207 (4.28)	0.352 (7.61)	0.454 (10.12)	0.744 (14.71)

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 the final model and the saturated model[1]. As expected, the final model is comparable to the saturated model in terms of explanatory power. Demand for routing and scheduling software is most readily explained in terms of characteristics of the freight operators, followed by demand for EDI and AVLS, then CB radio. In contrast, demand for satellite or radio based communication links is less well explained in the model.

Table 5: Percent Endogenous Variable Variance Accounted for by the Factors

Endogenous variable	R^2	
	Final model	Saturated model
CB radio	0.200	0.200
Satellite/Radio communication systems	0.075	0.074
Automatic Vehicle Location systems (AVL)	0.211	0.257
Automatic vehicle identification systems (AVI)	0.085	0.110
Electronic data interchange (EDI)	0.223	0.245
Vehicle maintenance software	0.145	0.177
Routing and scheduling software	0.256	0.305

Effects of the Operating Characteristics

The estimated regression coefficients of the multivariate discrete choice model system are listed in Table 6. These can be considered similar to coefficients of standard

[1] The overall fit of a saturated model will always be better than that of a non-saturated model, but it is possible that an R^2 value will be slightly lower for the saturated model. The estimation involves all elements simultaneously, and a few variance residuals (differences between the model-replicated value and the observed value) can be greater for the saturated model, even though its overall fit is better.

univariate probit models, except that they apply to seven simultaneously estimated probit discrete choice models with free error-term correlations. The joint decisions of each freight operator are considered together in a multivariate structure.

Table 6: Standardized Effects of the Operating Characteristics (z-statistics in parentheses)

Exogenous variable	Endogenous demand variable						
	CB radio	Sat/Radio Com	AVL	AVI	EDI	Vehicle maint.	Routing & sched.
LTL operator		-.137 (-7.32)	-.075 (-4.96)	-.092 (-6.73)	-.061 (-3.73)	-.105 (-5.84)	-.126 (-7.06)
Private fleet		-.080 (-4.36)	-.224 (-13.25)	-.150 (-11.60)	-.235 (-16.13)	-.123 (-5.78)	-.141 (-7.32)
Common carrier			-.055 (-3.78)			0.096 (4.82)	0.079 (4.35)
General truckloads	-.044 (-4.27)	-.067 (-4.57)	0.024 (2.05)	0.070 (6.47)	0.113 (8.79)	0.052 (3.68)	0.083 (6.29)
Household mover	-.048 (-5.86)	-.076 (-6.55)	0.053 (4.52)		0.024 (2.16)		
Tank carrier	-.046 (-5.06)	-.036 (-3.14)		0.074 (6.92)		0.072 (5.91)	
Refrigerated loads	-.086 (-6.37)		0.126 (10.96)	0.068 (4.81)	0.108 (7.60)	0.048 (2.73)	0.146 (8.75)
High value loads	-.085 (-7.14)	-.049 (-3.83)	0.028 (2.68)			-.129 (-8.33)	-.065 (-4.59)
HAZMAT loads			0.110 (10.12)	0.023 (1.81)	0.112 (8.94)	0.102 (6.70)	0.073 (5.28)
<5 power units in CA	-.049 (-5.06)	-.029 (-2.13)	0.042 (3.62)		0.110 (8.74)	-.186 (-14.14)	0.127 (10.68)
5-9 power units in CA		0.043 (3.57)		-.017 (-2.41)	0.050 (5.14)		0.032 (2.96)
100+ power units in CA	-.017 (-1.70)	0.038 (2.78)	0.059 (4.80)	0.041 (3.42)	0.122 (9.65)	0.073 (5.88)	
Inter-modal rail	-.091 (-7.78)		-.098 (-8.69)		-.083 (-6.23)	-.082 (-5.34)	-.107 (-7.05)
Inter-modal air		0.045 (2.57)	0.122 (7.70)	0.058 (4.13)	0.098 (6.17)	0.114 (6.84)	0.137 (8.00)
Inter-modal port		0.114 (6.29)	0.137 (8.63)	0.093 (6.58)	0.170 (10.41)	0.100 (5.47)	0.142 (7.94)
Short hauler	0.077 (6.90)	0.128 (9.69)	-.063 (-9.55)		0.048 (4.88)	0.029 (2.26)	0.044 (3.74)
Long hauler	-.337 (-29.99)	-.078 (-5.16)	0.080 (6.23)	-.026 (-1.95)			0.139 (8.92)
Just in time	0.053 (4.38)	0.044 (3.71)	0.069 (7.54)	0.026 (2.73)			-.020 (-1.81)
LTL > 2 terminals			-.064 (-6.54)	0.089 (8.08)	0.037 (2.98)	0.071 (5.00)	0.077 (5.66)

INTERPRETATION OF MODEL RESULTS

The results of the mutivariate demand model are next explored in two ways. First, salient relationships between individual company characteristics and demand for the seven technologies are identified by examining the coefficients of the multivariate discrete choice model (Table 6). These coefficients are standardized, facilitating direct comparison of the relative effects. Second, the model is exercised by forecasting technology demand for hypothetical specific types of companies.

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 versus for-hire fleets. This is not surprising, and the model shows that private fleets have substantially lower levels of demand for all of the technologies with the exception of CB radio. 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 EDI and AVL technologies.

Consistently lower technology demands are also exhibited by companies with LTL operations. But model results show that larger LTL carriers, those with more that two terminals in California, are more likely than smaller LTL operators to employ electronic pre-clearance, EDI, vehicle maintenance software and routing and scheduling software. However, demands for AVL technologies are lower for LTL operators of all sizes, and size of the LTL carrier is not important in explaining demand for satellite or radio-based communication technologies.

Another instructive result of the model is that, *ceteris paribus,* carriers providing intermodal service to rail terminals are much less likely to adopt many of the technologies, while those serving ports and airports are very likely to use these same technologies. The information technologies with opposing demands by intermodal maritime and air versus intermodal rail are AVL, EDI, vehicle maintenance software, and routing and scheduling software. Similar contrasts in demand are shown by short versus long average moves. Demands by short-haul operators are in opposition to demand by long-haul operators on all technologies except for routing and scheduling software, where both types of operators have similar positive demands.

Another outcome that emerges from this study is that some operating characteristics affect demand for information technology in similar ways. For example, the characteristics of providing refrigerated service and those moving hazardous materials appear to predict technology equally. Where both model values are significant (three of the seven technologies) their values match in sign and are relatively close in magnitude. 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 three hundred carriers in our study providing one type of service or the other. Likewise, we have seen that maritime and air intermodal services explain technology demand similarly.

Influences of trucking attributes on demands for each of the individual seven information technologies are explored in the remainder of this Section.

Demand for CB Radio

The characteristic that is most strongly related to demand for CB radio is long average loaded movements; long-haul companies are less likely to rely on CB radio communication. Companies serving rail terminals, and those providing refrigerated or high-value services are also less likely to use CB radio communication, *ceteris paribus*. The only characteristics that are positive predictors of CB radio use are service to airports and exclusive just-in-time delivery.

Satellite or Radio-based Communication

Short average loaded moves and intermodal maritime operations are strong predictors of use of satellite or radio based communication technologies. On the other hand, LTL operators, household movers, companies with long average moves and private fleets are less likely to use such systems.

Automatic Vehicle Location Systems

Many characteristics are strong predictors, both positive and negative, of carriers'use of AVL technologies. Intermodal service to maritime ports and airports and refrigerated or hazardous materials transport are the strongest positive predictors. Private fleets are very much less likely to use AVL, *ceteris paribus*, while LTL operations and intermodal rail service are also strong negative predictors of AVL demand.

Automatic Vehicle Identification

Propensity to use AVI transponders is predicted by provision of intermodal service to maritime ports and airports, size of operation (LTL service with 2 or more terminals in California, or having 100 or more power units in CA), and provision of refrigerated or hazardous materials services and general truckload service. As in the case of AVL demand, private fleets exhibit lower AVI demand.

Electronic Data Interchange

Use of EDI is also predicted by service to maritime ports and airports. In addition, refrigerated or hazardous materials transport and general truckload service are positive predictors of EDI demand. The influence of size of fleet is highly nonlinear; both large fleets (100+ power units) and small fleets (<5 and 5-9 power units) are heavier users of EDI. Once again, private fleets have the lowest demand, and EDI use is also negatively predicted by LTL operations and intermodal rail service.

Vehicle Maintenance Software

While many characteristics are significant predictors of the use of vehicle maintenance software, the most outstanding indicator is the effect of very small fleet size; companies with less than five vehicles are much less likely to use such software. Companies providing high value services and intermodal rail operations, private fleets, and LTL operators and are lower users of vehicle routing and scheduling software. On the positive side, use of such software is higher among companies providing intermodal air and maritime services, HAZMAT and tanker services, as well as common carriers and large LTL carriers.

Vehicle Routing and Scheduling Software

Demand for routing and scheduling software is greatest among companies providing refrigerated services, intermodal air and maritime services, and long haul operators. Demand is also high for small operators, *ceteris paribus.* Demand for routing and scheduling software is lower for private fleets, LTL operators, and companies providing intermodal rail and high-value services.

Forecasting Technology Demands

The coefficients in Table 6 represent the estimated parameters of the Γ matrix of Equation 1, shown transposed, for standardized exogenous variables. 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 6 for characteristic i for technology j, μ_l and σ_l are the mean and standard deviation of characteristic i (given in Table 3), 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 7 for five hypothetical companies. These are just a handful of the thousands of possible combinations of characteristics.

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.

Table 7: Combined Exogenous Effects for Five Hypothetical Companies

Hypothetical company	Endogenous demand variable						
	CB radio	Sat/Radio Com	AVL	AVI	EDI	Vehicle maint.	Routing & sched.
(1) Private tank carrier with10-99 power units	0.2047	-0.1658	-0.5511	-0.0412	-0.7591	-0.0050	-0.6581
(2) Private with 5-9 power units and average length of haul less 25 miles	0.7091	0.6204	-0.7972	-0.4188	-0.4241	-0.2103	-0.3918
(3) Private fleet with less than 5 power units	0.2842	-0.0799	-0.4447	-0.3686	-0.4806	-0.7945	-0.3366
(4) LTL Household mover with greater than 100 power units	0.1551	-0.2978	0.1820	-0.1020	0.1191	-0.0321	-0.6171
(5) For-hire general truckload carrier with more than 100 power units, maritime and rail Intermodal services	-0.0059	0.3863	0.0533	0.4207	0.4864	0.4463	-0.0525

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 threshold values are: $\tau_1 = 1.049$ (CB radio); $\tau_2 = 0.247$ (satellite of radio communication links); $\tau_3 = 0.680$ (AVL); $\tau_4 = 0.969$ (AVI); $\tau_5 = 0.489$ (EDI); $\tau_6 = -0.011$ (vehicle maintenance software); and finally $\tau_j = -0.038$ (routing and scheduling software). 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 8 and graphed in Figure 1. As a point of comparison, the last row in table 8 presents the overall market penetration for each technology.

Table 8: Forecast Demand Probabilities for Five Hypothetical Companies

Hypothetical company	Endogenous demand variable						
	CB radio	Sat/Radio Com	AVL	AVI	EDI	Vehicle maint.	Routing & sched.
(1) Private tank carrier with10-99 power units	0.173	0.334	0.084	0.146	0.079	0.502	0.238
(2) Private with 5-9 power units and average length of haul less 25 miles	0.352	0.651	0.048	0.074	0.151	0.415	0.342
(3) Private fleet with less than 5 power units	0.197	0.367	0.103	0.081	0.136	0.199	0.365
(4) LTL Household mover with greater than 100 power units	0.159	0.286	0.288	0.132	0.339	0.491	0.253
(5) For-hire general truckload carrier with more than 100 power units, maritime and rail Intermodal services	0.119	0.557	0.240	0.284	0.501	0.689	0.493
Aggregate market penetration	0.147	0.402	0.248	0.166	0.312	0.504	0.515

Significant variability may be observed. For example, a large for-hire truckload carrier that provides intermodal services is likely to adopt satellite or radio based communication technology, use EDI and use both vehicle maintenance and routing and scheduling software. A medium sized private tank carrier 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.

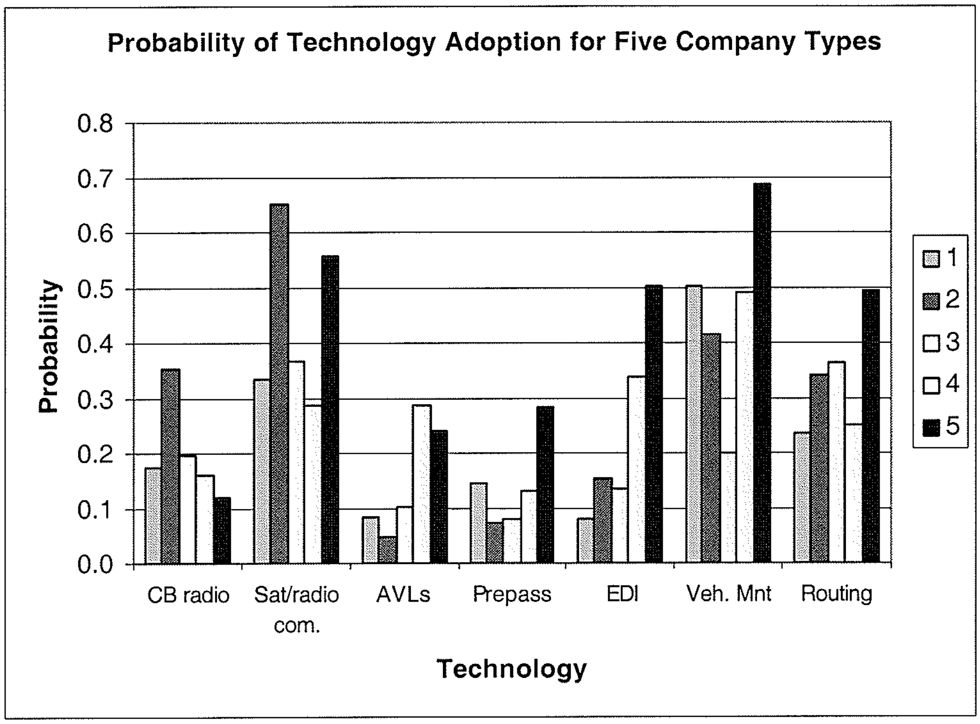

Figure 1 Predicted probabilities of technology adoption for five hypothetical companies (company types defined in Tables 7 and 8)

CONCLUSIONS

This paper presents a multivariate discrete choice model of demand for information technologies in trucking operations. Data for the model were drawn from a survey of nearly 1200 trucking companies operating in California. The mutivariate discrete choice model is an elegant way to analyze the 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. Nineteen operating characteristics were found to be significant exogenous variables. We show how to use the model 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 allow an interested reader to generate the probability of adoption for any combinations of characteristics.

In addition to offering technology providers insight into the market for current and future information technologies, this model can provide policy analysts with an understanding of private sector technology adoption. This is important because successful public sector technology implementation aimed at commercial vehicle operators will be complementary to investments made by companies themselves. Such implementation will be a key to mitigating sometimes crippling congestion in areas with heavy commercial vehicle traffic.

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