Title

Traffic Congestion and Trucking Managers' Use of Automated Routing and Scheduling

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Abstract

Using data from a 2001 survey of managers of 700 trucking companies operating in California, we tested competing hypotheses about the relationship between managers' perceptions of the impact of traffic congestion on their operations and their companies' adoption of routing and scheduling software. Demand for automated routing and scheduling was found to be influenced directly by the need to re-route drivers, and indirectly by the need, generated by customers' schedules, to operate during congested periods. We were also able to identify which types of trucking companies are most affected by congestion and which types are more likely to adopt such software.

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1 Introduction

Researchers in operations research, transportation engineering and computer science have taken a keen interest in the development of optimization techniques for routing and scheduling (R/S) of commercial vehicle operations. A recent library search of a single database (INSPEC) turned up over 1300 English language journal articles with key words "traveling salesman problem" and over 500 journal articles with key words "vehicle routing" published since 1995. (The traveling salesman problem is the sub-problem upon which most vehicle R/S algorithms are based.) Nonetheless, despite this considerable interest among academics, companies have been slow to adopt R/S tools. There are several reasons for their reluctance to invest. Companies may feel that their operations are too unique to be adequately served by off-the-shelf commercial software. While such software is relatively inexpensive, custom-made software can be prohibitively expensive. In addition, companies that can afford to invest in the development of custom-made software typically do not want to subsidize the development of products that could then be sold to their competitors. Another reason for lack of adoption is that trucking companies may feel that the stochastic nature of their operations renders static solutions sub-optimal. Finally, some R/S problems are small enough that human dispatchers can provide good solutions, while other problems require so much dispatcher knowledge (which presumably could not be easily expressed to an optimization package) that they can only be solved by human dispatchers. One of the aspects of this study is to investigate how demand for Use of R/S software is related to the operating characteristics of a wide variety of trucking companies.

The second aspect of our research concerns the effects of traffic congestion on trucking operations. On-road traffic congestion is a growing problem for trucking companies operating in urban areas, and we would like to know the extent to which managers' perceptions of the overall problem of congestion are related to the degree to which schedules are missed and drivers are re-routed due to congestion. We also wish to explore the degree to which managers' perceive that they are forced by customer time-windows for pickup and delivery to work in congested conditions when they would otherwise wait for less congested times. As in the case of R/S software, we attempt to explain how each of these components of the congestion problem is related to the operating characteristics of trucking companies.

Both aspects of this research converge when we examine how adoption of R/S software is related to perceptions about the impacts of traffic congestion. We would like to know how uncertainty and the need to re-route drivers due to congestion affects the tendency to adopt R/S software. Does a higher level of perceived congestion increase the use of R/S software as a tool in coping with the problem, or does it decrease the use of R/S software, because stochastic effects adversely affect planned routes and schedules? Answers to such questions will guide the development of R/S software to better serve the evolving needs of trucking companies.

Using data from a survey of logistics or operations managers of 700 trucking companies operating in California, we developed structural equations models linking company characteristics, with five different endogenous variables: four different impressions about congestion problems, and the choice of whether the company uses R/S software. By testing alternative hypotheses concerning causal relations among these five endogenous variables, we are able to establish the most probable links between aspects of congestion and we can exhibit the degrees to which the data support alternative links between perceived congestion and demand for R/S software.

2 Related Studies

The adoption of Information technology (IT) by commercial vehicle operators has been studied since the early 1990s. Scapinakis and Garrison (1991) reported results from a survey of a small group of carriers regarding their perceptions of the use of communications and positioning systems, and Kavalaris and Sinha (1995) documented a survey of trucking companies that had as its focus attitudes towards ITS technologies. Ng *et al.* (1995) studied acceptance of ATIS technologies, including route guidance, navigation, road and traffic information, roadside services and personal communication, based on two nationwide surveys of dispatchers and commercial vehicle operators. Regan, *et al.* (1995) surveyed approximately 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) 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, while 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. Forster and Regan (2001) examined IT adoption and its impacts in the air cargo sector. Golob and Regan (2002a) present a multivariate discrete choice model of trucking industry adoption of communication and information technologies, and Golob and Regan (2002b) examine perceptions of the usefulness of a variety of different traffic information sources. To our knowledge, the specific issue of the adoption of R/S software has not been examined in the literature.

3 Data

3.1 2001 Survey of Trucking Companies Operating in California

Logistics managers of more than 700 trucking companies operating in California were surveyed in spring 2001. The main focus of the survey was the use and impacts of information technologies in their operations. Of particular interest was the use of Advanced Traveler Information Systems (ATIS). Other parts of the survey dealt with the perceived effects of traffic congestion on trucking operations, communication between dispatchers and drivers, company use of the Internet, and relationships to third-party logistics providers (3PLs). Extensive questions about the operations of each company provided independent variables for our models.

The survey was conducted as a computer aided telephone interview (CATI). The interviews lasted an average of 17 minutes. The three-part sample was comprised of: (1) large national carriers with operations in the state of California, (2) California based carriers of all sizes, and (3) private fleets corporately located in the state. The contact list for the survey was obtained from a company that maintains extensive contact information for U.S. trucking companies.

Survey responses are tabulated in Table 1. Managers of 3438 companies were contacted, and 86% of these qualified by having operations in California. Of the 2972 companies with California operations, 75% (2218) initially agreed to participate in the survey. For these companies, 712 interviews were completed with the person in charge of California operations. The large number of unresolved contacts reflects the difficulty of tracking down persons responsible and the need to schedule call-backs when people have available time. The 712 completed interviews represent a 49% response rate of all resolved contacts, and a 24% response rate of all qualified companies.

Table 1. Survey Response Rates

Contacts attempted	5085
Bad contact information (e.g., wrong number, disconnected, fax machine)	-794
Potentially valid respondent	4263
Unable to contact (e.g., repeated busy signal, no answer, automated response)	-825
Contacted	3438
No business in California (does not qualify)	-466
Valid contact	2972
Refused	-754
Agreed to participate	2218
Unresolved (survey closed before call backs were completed)	-1506
Completed	712
Completed as % of all valid contacts	24.0%
Completed as % of all resolved contacts	48.6%

3.2 Descriptive Statistics

The specific survey questions that provide data for the present analysis are listed in Table 2, which lists the aggregate response frequencies for the complete sample of 712. Regarding the effects of traffic congestion on schedules, thirty percent of all trucking managers said that schedules are often or very often missed due to traffic congestion. The majority of managers (56%) reported that congestion sometimes caused missed schedules. Only fifteen percent reported no effects of congestion on schedules. Contingency table analyses of this variable versus company operating characteristics reveal that managers of large carriers, carriers operating in the Greater Los Angeles and San Francisco Bay Areas, and carriers providing flat bed and container operations are more likely to indicate that they have a scheduling problem due to congestion. Small carriers and private fleets are less likely to have such a problem.

Table 2. Responses to Questions Concerning Traffic Congestion and Routing and Scheduling

Question	Responses (percentage of sample, N = 712)			
	Never	Sometimes	Often	Very often
How often are your schedules missed because of congestion?	14.9%	55.8%	20.6%	8.7%
How often are drivers re-routed because of road congestion?	19.9%	57.2%	16.4%	6.55%
Do customer time-windows for pickup and delivery force your drivers to work in congested conditions?	22.1%	33.1%	36.4%	8.4%
	Not serious	Somewhat serious	Very serious	Critically serious
Overall, how serious of a problem is congestion for your business?	18.7%	45.8%	26.5%	9.0%
	Fixed routes & schedules	Manual assignment	R/S software	
What is the primary method used in your company to develop driver assignments?	14.6%	62.6%	22.8%	

Responses are similar to the question concerning how often drivers are re-routed due to congestion. Eighty percent said that their drivers were re-routed at least sometimes, while a minority of managers, here twenty percent, report no problems with re-routing drivers. Managers of all types of for-hire (common) carriers, especially flatbed and container operators, are more likely to report re-routing of drivers, while less re-routing is reported by managers of private fleets, providers of tanker services, and carriers with short loaded movements (less than 75 miles).

A somewhat different pattern emerges with regard to how often managers reported that their drivers were forced, due to customer time windows to work in very congested traffic conditions. The "sometimes" response is less prevalent, as forty-four percent said that this happened often or very often. However there is once again a minority, here twenty-two percent, that report no such problems. Forced schedules are perceived to be greater among managers with long-haul operations, for-hire carriers and all types of carriers with large fleets, companies that provide air cargo and intermodal rail services, companies that operate in the Los Angeles and San Francisco Bay Areas, and those that provide either flatbed/container or hazardous waste services.

With respect to perception of the overall problem of traffic congestion, thirty-six percent of the managers surveyed said that congestion was a serious or critically serious problem for their businesses. Nineteen percent of the managers perceived that the problem was not a serious one, while the remaining forty-six percent perceived that it was a somewhat serious problem. The problem is perceived to be more serious by managers of larger fleets, for-hire carriers, carriers with maritime and air intermodal operations, and for carriers operating in the Los Angeles and San Francisco Bay Areas.

Just over twenty-six percent of the companies in our survey without fixed schedules use R/S software to route and re-route drivers. Use of R/S software is positively related to the size of the fleet and the average length of a company's loaded movements. For-hire (common) carriers tend to use R/S software more than private fleets or contract carriers, and R/S software is less prevalent among bulk and flatbed/container operators.

In our models, we treat these five variables that measure the impacts of congestion and the use of R/S software as being endogenous functions of company operational characteristics as well as potential functions of one another. These variables are denoted as (y_1) "missed schedules," (y_2) "drivers re-routed," (y_3) "forced schedules," (y_4) "overall problem," and (y_5) "(demand for) R/S software." The twenty exogenous variables listed in Table 3 represent operating characteristics deemed important in related studies, and they include all characteristics found to be significantly related to at least one of our endogenous variables. Our objective is to determine how the fve endogenous variables are interrelated, conditional upon the effects of the twenty exogenous variables. The sample size for the modeling is 561, derived from a total survey sample size of 712, excluding the 104 companies with fixed routes and schedules, and excluding an additional 47 companies which had missing data on one or more of the exogenous variables.

4 Methodology

Structural equation modeling (SEM) is used to test relationships among the endogenous variables – perceptions of congestion and the demand for R/S software – while simultaneously capturing the effects of operating characteristics on these endogenous variables. Our models can be viewed as a simultaneous model with two interrelated parts: a demand model for R/S software and a model of how congestion is perceived to affect trucking operations. The independent variables are the characteristics of trucking operations.

Table 3. Descriptive Statistics of the Exogenous Variables (N = 561)

Variable	Distribution (%) No (= 0)	Distribution (%) Yes (= 1)
Operates as a for-hire carrier[a]	48.5%	51.5%
Operates as a private fleet[a]	68.3%	31.7%
Small fleet (< 4 power units in CA)	91.6%	8.4%
Natural log of number of power units typically operated in CA	(mean = 2.97; std.dev. = 1.32)	
Engages in less-than-truckload (LTL) operations	73.6%	26.4%
Engages in tank operations	92.0%	8.0%
Engages in flatbed or container operations	81.1%	18.9%
Engages in refrigerated operations	90.0%	10.0%
Engages in construction operations	90.2%	9.8%
Engages in Bulk operations	93.2%	6.8%
High value goods operations	93.6%	6.4%
Hazardous materials operations	90.7%	9.3%
Maritime intermodal operations	61.5%	38.5%
Air intermodal operations	70.9%	29.1%
Rail intermodal operations	75.0%	25.0%
Ave. loaded move < 75 mi.	70.8%	29.2%
Ave. loaded move 75-149 mi.	84.0%	16.0%
Ave. loaded move > 500 mi.	74.9%	25.1%
Operates in Los Angeles Area	19.4%	80.6%
Operates in San Francisco Bay Area	35.5%	64.5%

[a] Response categories were: (1) for hire, (2) private, (3) contract carrier, (4) both for-hire and contract

SEM is described in a transportation research context in Golob (in press): "[SEM] is a modeling technique that can handle a large number of endogenous and exogenous variables, as well as latent (unobserved) variables specified as linear combinations (weighted averages) of the observed variables. Regression, simultaneous equations (with and without error-term correlations), path analysis, and variations of factor analysis and canonical correlation analysis are all special cases of SEM. It is a confirmatory, rather than exploratory method, because the modeler is required to construct a model in terms of a system of unidirectional effects of one variable on another. Each direct effect corresponds to an arrow in a path (flow) diagram. In SEM one can also separate errors in measurement from errors in equations, and one can correlate error terms within all types of errors. SEM is a relatively new method, having its roots in the 1970s. Most applications have been in psychology, sociology, the biological sciences, educational research, political science, and market research."

A SEM with observed variables corresponds to a simple simultaneous equation system expressed in terms of matrices of direct effects between variables:

$$y = \mathrm{B}y + \Gamma x + \zeta \tag{1}$$

where y is column vector of (m) endogenous variables, x is a column vector of (n) exogenous variables, ζ is a vector of error terms for the m endogenous variables with a (m by m, symmetric) variance-covariance matrix $\Psi = E[\zeta'\zeta]$, B is an (m by m) matrix of direct effects of one endogenous variable upon another, and Γ is an (m by n) matrix of direct (regression) effects of the exogenous variables on the endogenous variables.

The parameters in SEM (1) involve the elements of the B, Γ and Ψ matrices. There are m·(m-1) possible non-zero parameters in the m matrix (the main diagonal of B must always contain zeros), m·n possible parameters in the Γ matrix, and m·(m+1)/2 possible parameters in the Ψ matrix. Restrictions on identification limit the number of possible combinations of free parameters. A necessary and sufficient condition for identification is that the rank of the matrix $[(I - \mathrm{B})| - \Gamma]$ be equal to m-1. Assuming that the model is identified and $(I - \mathrm{B})$ is nonsingular, the reduced form equations, expressing the endogenous variables solely in terms of exogenous variables, are given by

$$y = (I - \mathrm{B})^{-1}(\Gamma x + \zeta) \tag{2}$$

In our application m = 4 endogenous variables in the first set of models (described Section 3.1) and m = 5 endogenous variables in the second set of models (Section 3.2). In all cases n = 20 exogenous variables, which are listed in Table 3. All of our models can be shown to be identified.

All SEM are estimated using covariance analysis (method of moments), in which parameters are found that make the model-replicated variance-covariance matrix of the observed variables as close as possible to the observed sample values. There are several estimation methods available to accomplish this, the most common being normal-theory maximum likelihood estimation. Goodness-of-fit tests are used to determine if a model specified by the researcher is consistent with the pattern of variance-covariances in the data. Alternative SEM specifications can be tested against one another, and several criteria are available that allow the modeler to determine an optimal model out of a set of competing models (Golob, in press). However, because the first four of our endogenous variables are ordered discrete (ordinal scaled), and the fifth is a discrete dichotomous variable, the standard errors of parameter estimates and the goodness of fit of an estimated model can be inaccurate using maximum likelihood estimation. Maximum likelihood estimates can be corrected to account for the most important biases introduced by limited endogenous variables (e.g., Satorra and Bentler, 1988), but we choose instead to use an estimation method specifically designed to handle ordered discrete endogenous variables. Known as asymptotically distribution-free weighted least squares (ADF-WLS), the method was apparently first applied to SEM by Muthén (1983)(1984). ADF-WLS estimation treats the endogenous variables as being generated by ordered-response or binomial probit models.

The ADF-WLS method, which is described in texts such as Bollen (1989), yields asymptotically correct parameter standard errors and overall chi-square goodness of fit statistics provided that the sample size is sufficient (Browne, 1984). Here the sample size meets the criteria of having at least ten times more observations than free parameters (Hoogland and Boomstra, 1998, reproduced in Shipley, 2000), although it falls short of the recommendation of 1,000 observations. Golob and Hensher (1998) and Golob and Regan (2001) describe the ADF-WLS estimation method in SEM applications with ordinal scale and discrete choice variables similar to those in the present data.

The following structural equations model results for the five endogenous variables under study. To aid in interpreting results, Table 4 identifies all of the possible direct effects between pairs of endogenous variables, each direct effect being an element of parameter matrix B in equation (1). For example, specification of β_{13} as a free parameter means that the model will include the direct effect of forced schedules (y_3) on missed schedules (y_1). That is, missed schedules will be a function of forced schedules, as well as any other variables that can effect missed schedules directly, or indirectly. Other direct effects can come from other endogenous variables, as revealed by other free parameters in the first row of the Table 4 matrix, as well any effects from the exogenous variables (parameters of the first row of the Γ matrix of equation (1)). Indirect effects will be from variables that are linked to y_1 through a chain of effects involving intermediate endogenous variables.

Table 4. Parametric Designation of Possible Direct Effects Between the Five Endogenous Variables

To	From				
	Missed schedules	Drivers re-routed	Forced schedules	Overall problem	R/S software
Missed schedules	-	β_{12}	β_{13}	β_{14}	β_{15}
Drivers re-routed	β_{21}	-	β_{23}	β_{24}	β_{25}
Forced schedules	β_{31}	β_{32}	-	β_{34}	β_{35}
Overall problem	β_{41}	β_{42}	β_{43}	-	β_{45}
R/S software	β_{51}	β_{52}	β_{53}	β_{54}	-

5 Model Results

5.1 A Model of Perceived Effects of Traffic Congestion

The first step is to find the optimal SEM for the first four endogenous variables listed in Table 4, all of which involve perceptions of the impacts of traffic congestion. We begin by establishing a base model that contains all statistically significant exogenous regression effects. There are 33 significant effects for the n = 20 exogenous variables, resulting in a model with 53 degrees of freedom (df). The chi-square (X^2) for this model is 135.01 with 53 df, corresponding to a probability (p) < 0.001. Since this X^2 value is significant, the sample and model-replicated moment matrices are different and the model can be rejected. Also, compared to an independence model with only fixed exogenous covariances (C^2 = 841.78 with 90 df), the Comparative Fit Index (CFI, Bentler, 1990), which measures the proportional reduction in the expected value of the non-centrality parameter of the non-central chi-square distribution, is 0.891. This CFI value, which is one measure of the degree of model misspecification, is well below the threshold value 0.95 used as a rule of thumb for an acceptable model. All of these results clearly indicate that, as expected, the four endogenous variables measuring different aspects of the perceived effects of congestion on trucking operations are strongly related, which means that an endogenous causal structure is needed to fit an SEM containing these variables.

The next steps involved determining the optimal structure of the relationships among the four endogenous variables. The exogenous structure was held constant in all models tested. In selecting the optimal model we postulated that forced schedules (y_3) will likely cause problems for truckers but will not itself be a function of any of the other endogenous variables. Comparative evaluation of the models was conducted by using three different Bayesian criteria and designed to identify the best model from a set of candidate models based on the goodness of fit and the dimensionality of each model. The first criterion, proposed by Akaike (1974)(1987), is commonly known as the Akaike Bayesian Information Criterion (variously abbreviated as ABIC, BIC or AIC). A modification of the ABIC, proposed by Bozdogen (1987) takes into account the sample size as well as the model's X^2 statistic and number of free parameters, and is commonly known as the Consistent Akaike Information Criterion (CAIC). Finally, a similar derivation of the ABIC was developed by Schwarz (1978) and is commonly known as the Schwarz Bayesian Criterion (SBC). These three criteria are defined in the footnotes to Table 5. For each criterion, the model that yields the smallest value is considered to be the best. Discussions of the role of parsimony in model evaluation and the effects of sample size and model complexity on criteria such as the three used here are provided by Bentler (1990), Bentler and Bonett (1980), McDonald and Marsh (1990), and Mulaik, *et al.* (1989).

Seven models were evaluated in addition to three baseline models. Six of these models were developed by sequentially adding a single direct effect (represented by an additional free parameter in the beta matrix (B) of equation (1)), the additional parameter in each case being the one which maximally improves the model fit. The seventh model involves freeing all 12 possible B parameters. The three baseline models are an independence model with no free B, Γ or Ψ parameters, the previously described model with exogenous effects only, and a fully saturated model which, by definition, fits the data perfectly. The estimation results for these ten models are listed in order of increasing dimensionality (complexity) in Table 5. Additional models (not shown) were also attempted, but none of these performed as well as the models listed in Table 5. For each level of dimensionality (number of direct effects in the B matrix structure), the models listed in Table 5 out-preformed all other possible models.

Table 5. Goodness of Fit Criterion for Models Tested with Four Endogenous Variables and Twenty Exogenous Variables

	Model Structure	C^2	*df*[a]	C^2/df	ABIC[b]	CAIC[c]	SBC[d]
1	Independence model (fixed x)	841.78	90	9.353	1261.8	2381.0	2171.0
2	Exogenous effects only	135.01	53	2.547	629.0	1945.5	1698.5
3	+ β_{12}	104.58	52	2.011	600.6	1922.3	1674.3
4	+ β_{12} + β_{13}	98.17	51	1.925	596.2	1923.3	1674.3
5	+ β_{12} + β_{13} + β_{41}	84.38	50	1.688	584.4	1916.8	1666.8
6	+ β_{12} + β_{13} + β_{41}+ β_{42}	80.05	49	1.634	582.0	1919.8	1668.8
7	+ β_{12} + β_{13} + β_{41}+ β_{42}+ β_{43}	72.43	48	1.509	576.4	1919.5	1667.5
8	**+ b_{12} + b_{13} + b_{41} + b_{42} + b_{43}+ b_{23}**	**27.52**	**47**	**0.585**	**533.5**	**1881.9**	**1628.9**
9	Saturated endogenous effects[e]	21.45	41	0.523	539.4	1919.8	1660.8
10	Fully saturated	0	0	--	600.0	2198.9	1898.9

[a] *df* = degrees of freedom

[b] AIC = Akaike Baysian Information Criterion = $X^2 + 2\delta$ (where δ = number of free parameters)

[c] CAIC = Consistent AIC = X^2 + [ln(N)+1]t

[d] Schwarz Baysian Criterion = X^2 + ln(N)t

[e] All 12 parameters in matrix of endogenous effects freely estimated

All three of the criteria, based on information theory for selecting model dimensionality, identify the same model as being optimal. This optimal model, Model 8 in Table 5, involves a fully recursive structure with six B parameters. According to a hypothesis test of nested models, the fully recursive model represents a statistically significant improvement over the model with no effects among the four endogenous variables (ΔX^2 = (135.01 - 27.52) = 107.49 with (53 - 47) = 6 df, corresponding to $p < .001$).

The flow diagram for this fully recursive model is shown in Figure 1. The model implies that the degree to which operators are forced by customers' schedules to work during congested periods causes drivers to be rerouted. These two factors combine to cause schedules to be missed. Finally, all three effects of congestion contribute to managers' feelings about the overall problem of congestion. All effects are significant at $p < .01$ as measured by z-statistics (the ratio of a coefficient to its standard error being asymptotically normally distributed with this estimation method). Because the parameter estimates are standardized, we can also directly compare the strengths of the effects. The strongest effect is that of forced schedules on re-routing of drivers. The remaining five direct effects are weaker and similar in magnitude.

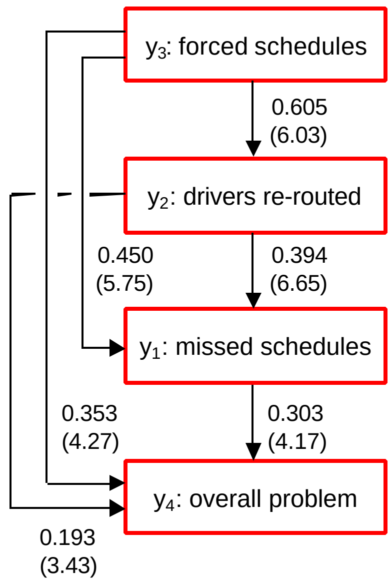

Figure 1. Flow Diagram with Estimated Direct Effects (z-statistics in parenthesis) for the Fully Recursive Model of the Perceived Effects of Traffic Congestion on Trucking Operations

5.2 *A Joint Model of Demand for Routing and Scheduling Software and the Perceived Effects of Congestion*

The final step was to introduce the fifth endogenous variable, demand for R/S software (y_5), and determine how demand for R/S software is related to the complex of four congestion variables. The hypotheses tested are as follows. Each of these hypotheses is represented by a single link in Figure 2 between demand for R/S software and one of the other endogenous variables. Any combination of hypotheses is also possible. The hypotheses are:

1. Demand for R/S software is influenced by the necessity to operate during congested periods, because of customers' schedules, (link β_{53}).
2. Demand for R/S software is influenced by the need to re-route drivers (link β_{52}); by consequence of the structure among the first four endogenous variables, this

link also implies that demand for R/S software is indirectly influenced by forced schedules.

3. The re-routing of drivers is influenced by the availability of R/S software (β_{25}).

4. Demand for R/S software is influenced by the occurrence of missed schedules (β_{51}), which is indirectly affected by forced schedules and the need for re-routing.

5. The incidence of missed schedules is influenced by the availability of R/S software (link β_{51}, possibly negative).

6. Finally, managers' perception of the overall problem of congestion directly influences demand for R/S software (β_{54}); indirectly demand for R/S software is influenced by all of the other variables as well.

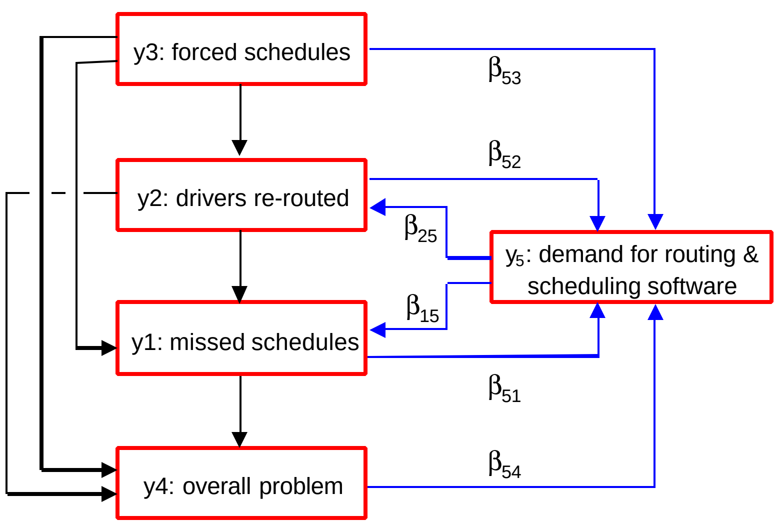

Figure 2. Flow Diagram Indicating the Links Tested (shown as dashed arrows with labels referring to the corresponding parameter in the Beta matrix of equation system (1)) Between Congestion Variables and Demand for Routing and Scheduling Software.

Each of the hypotheses and meaningful combinations of them were tested in a manner described in the previous section, using the three criteria based on Bayesian Information Theory, as well as standard chi-square difference tests of nested models. Results are listed in Table 6. All criteria once again unambiguously identify an optimal model, Model 3 in Table 6: demand for R/S software is positively influenced directly by the need to re-route drivers, and indirectly by the need, generated by customers' schedules, to operate during congested periods. The optimal model is depicted in the flow (path) diagram of Figure 3. All direct effects in this model from the endogenous variables are significant at $p < .01$.

Table 6. Goodness of Fit Criterion for Models Tested with Five Endogenous Variables and Twenty Exogenous Variables

	Model structure	X^2	df[a]	X^2/df	ABIC[b]	CAIC[c]	SBC[d]
1	Base model [e]	47.63	60	0.794	577.6	1990.0	1725.0
2	Base + β_{51}	45.91	59	0.778	577.9	1995.6	1729.6
3	**Base +** $\mathbf{b_{52}}$	**38.05**	**59**	**0.645**	**570.1**	**1987.8**	**1721.7**
4	Base + β_{53}	47.61	59	0.807	579.6	1997.3	1731.3
5	Base + β_{54}	46.36	59	0.786	578.4	1996.1	1730.1
6	Base + β_{15}	47.56	59	0.806	579.6	1997.3	1731.3
7	Base + β_{25}	42.98	59	0.728	575.0	1992.7	1726.7
8	Base + β_{52} + β_{25}	37.57	58	0.648	571.6	1994.6	1727.6
9	Base + β_{52} + β_{25} + β_{53}	37.40	57	0.656	573.4	2001.8	1733.8
10	Base + β_{51}+β_{52}+β_{53}+β_{54}+β_{15}+β_{25}	36.11	54	0.669	578.1	2022.5	1751.5
11	Fully saturated	0	0	--	650.0	2382.2	2057.2

[a] df = degrees of freedom

b ABIC = Akaike Baysian Information Criterion = $X^2 + 2t$ (where t = number of free parameters)

[c] CAIC = Consistent AIC = $X^2 + [\ln(N)+1]t$

d Schwarz Baysian Criterion = $X^2 + \ln(N)t$

e The Base Model consists of the fully recursive effects among the four perceived effects of traffic congestion, plus 44 exogenous regression effects that are consistently free parameters in all the models tested

Parameter β_{52} is the only single addition to the base model which leads to a statistically significant improvement at the $p = .05$ level (ΔX^2 = (47.63 - 38.05) = 9.58 with 1 *df*, corresponding to $p < .001$). Once this link is in the model, according to all criteria, no additional link involving demand for R/S software leads to any significant model improvement. In particular, the eighth model consists of reciprocal links in both directions between y_2 and y_5. The z-statistic for the β_{52} link in Model 8 is 2.39, while the z-statistic for link in the opposite direction, β_{52}, is –0.68. This is clear evidence that, controlling for all other effects, the causality is from the incidence of re-routing to demand for R/S software, and not in the opposite direction. In order to determine whether this result was brought about in part by the indirect effect of forced schedules on demand, Model 9 was estimated with the reciprocal links β_{52} and β_{52} and a direct link from forced schedules to software demand, β_{53}. The results were similar, in that the coefficient for β_{52} was significant at the $p = .05$ level, while the other two coefficients were small and insignificant. Other models, not shown, were also tested, to determine whether or not the above results were dependent upon the specific (fully recursive) structure among the first four (congestion) variables. Results show that the chosen model is superior to all others, regardless of whether or not the models contain the fully recursive structure among the first four endogenous variables.

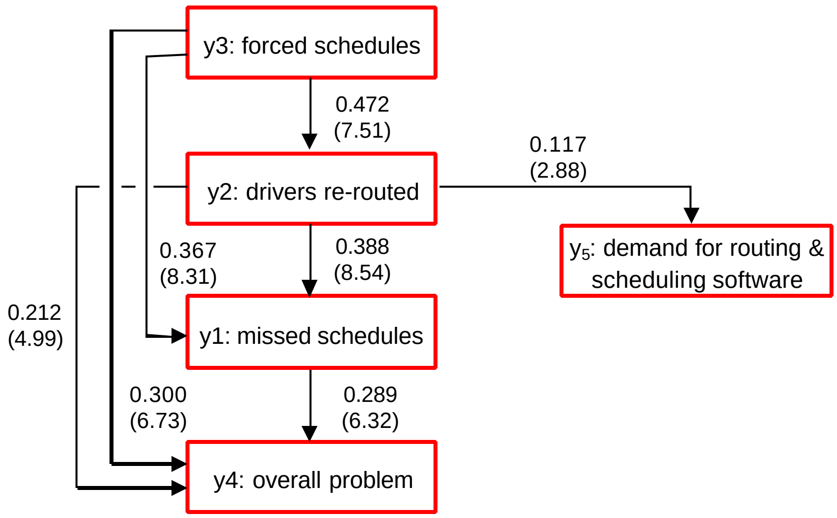

Figure 3. Flow Diagram with Estimated Direct Effects (z-statistics in parenthesis) for the Final Structural Equations Model

The estimated total effects of the company characteristics on the five endogenous variables, ordered according to the recursive structure of Figure 3, are listed in Table 7. The statistically significant results in Table 7 can be interpreted as follows.

1. Managers of large carriers, and managers of carriers with LTL or construction operations, as well as carriers that operate in the Los Angeles Metropolitan Area, are more likely to perceive that they are forced to work in congested conditions because of customer time-windows for pickup and delivery. Managers of private fleets are less likely to perceive that they are forced to operate in such a manner.

2. Re-routing of drivers due to traffic congestion is more likely to be experienced by for-hire carriers, larger carriers of all types, LTL carriers, carriers providing flatbed or container and construction services, and carriers that operate in the Greater Los Angeles Metropolitan Area. Conversely, re-routing is less likely to be applied by private fleets, tank operators, carriers that serve maritime ports, short-haul and long-haul carriers, and carriers operating in the San Francisco Bay Area. The constraints imposed by bridges in the Bay Area might contribute to the inability to re-route drivers there.

Table 7. Total Effects of the Exogenous Variables (z-statistics in parentheses)

Exogenous variable	Influenced endogenous variable: y_3 Forced schedules	y_2 Drivers re-routed	y_5 R/S software	y_1 Missed schedules	y_4 Overall problem
For-hire carrier		0.073 (2.22)	0.092 (4.51)	0.130 (3.76)	0.132 (3.72)
Private fleet	-.222 (-5.53)	-.105 (-4.97)	-.012 (-2.18)	0.008 (0.20)	0.007 (0.17)
Small fleet (< 4 power units in CA)			0.186 (9.59)		
Log of number of power units in CA	0.137 (3.60)	0.065 (3.21)	0.217 (8.47)	0.076 (3.33)	0.077 (3.30)
LTL operations	0.102 (2.93)	0.048 (2.62)	0.006 (1.67)	-.020 (-.66)	0.035 (1.57)
Tank operations		-.117 (-6.15)	-.014 (-2.68)	-.045 (-5.03)	-.038 (-4.64)
Flatbed or container operations	0.078 (1.71)	0.105 (2.55)	-.070 (-2.96)	0.069 (2.23)	0.114 (2.80)
Refrigerated operations					-.044 (-3.32)
Construction operations	0.117 (2.92)	0.104 (3.20)	0.012 (2.29)	0.087 (3.26)	0.081 (3.25)
Bulk operations			-.144 (-18.31)	-.032 (-2.41)	-.009 (-2.27)
High value goods operations			-.044 (-4.86)	-.057 (-5.51)	-.016 (-3.80)
Hazardous materials operations			0.103 (7.39)		-.048 (-3.12)
Maritime intermodal operations		-.060 (-2.17)	-.007 (-1.70)	0.042 (1.42)	0.065 (2.26)
Air intermodal operations		0.035 (1.27)	0.004 (1.28)	0.014 (1.28)	0.011 (1.30)
Rail intermodal operations			-.052 (-3.23)		
Ave. loaded move < 75 mi.		-.063 (-2.34)	-.140 (-8.91)	0.016 (0.60)	0.052 (1.84)
Ave. loaded move 75-149 mi.			0.125 (7.00)		
Ave. loaded move > 500 mi.		-.113 (-4.41)	0.170 (3.86)	-.044 (-4.10)	-.037 (-3.85)
Operates in Los Angeles Area	0.106 (2.58)	0.138 (3.37)	0.016 (2.15)	0.167 (4.10)	0.236 (5.86)
Operates in San Francisco Bay Area		-0.119 (-3.98)	-.014 (-2.32)	0.031 (0.96)	-.016 (-1.08)

3. R/S software is more likely to be used by for-hire carriers, by carriers providing construction or hazardous materials services, by long-haul carriers and those with average loaded movements of 75-149 miles, and by carriers operating in the Los Angeles Area. Long-haul carriers are more likely to use R/S in spite of the fact that these companies are less likely to miss schedules or re-route drivers due to congestion. Private fleets, short-haul carriers, carriers serving rail terminals, and carriers with, bulk, high-value, or flat bed/container operations are less likely to use R/S software. The relationship between propensity to use R/S software and fleet size is positive, with the exception that R/S software is also more likely to be used by the very smallest fleets. This somewhat surprising result for small fleets is confirmed by descriptive statistics for all non-fixed route fleets, which reveal that 32.1% of carriers with less than four power units use R/S software, compared to an overall average of 26.6% for all fleets and 11.8% for fleets with six to ten power units.
4. Missed schedules due to congestion are more likely to be experienced by for-hire carriers, larger carriers of all types, carriers providing flatbed or container and construction services, and carriers that operate in the Los Angeles Metropolitan Area. Conversely, missed schedules are less likely to be experienced by long-haul carriers and carriers with tank, bulk and high-value operations.
5. Finally, the overall problem of traffic congestion is perceived to be greater by managers of for-hire companies, companies with large fleets, and those with flatbed or container, construction and maritime intermodal services. Traffic congestion in general is judged to be less of a problem for long-haul carriers and carriers with tank, refrigerated, bulk and hazardous materials operations.

6 Conclusions

This research examines several hypotheses about the relationship between trucking operations managers' perceptions of the impact of traffic congestion on their operations and their use of R/S software. The evidence suggests that the demand for R/S software is positively influenced directly by the need to re-route drivers, and indirectly by the need, generated by customers' schedules, to operate during congested periods. This is potentially an important finding since it reveals that uncertainty does not itself prevent companies from adopting R/S systems. Our model forecasts that increased congestion will lead to increased demand for R/S software. This also implies that R/S can be improved by using advanced traveler information systems (ATIS) to input real-time information on traffic congestion to R/S software. ATIS are typically touted in terms of the value of direct information for drivers, but operations managers can take advantage of ATIS for dynamic R/S of multiple vehicles.

Companies with larger fleets are forced by customer time-windows for pickup and delivery to work in more congested conditions as are companies with operations in the Los Angeles Metropolitan Area and those providing construction services. These types of companies, as well as for-hire carriers in general, are more likely to re-route drivers due to congestion, and are more likely to use R/S software. On the negative side, private fleets, short-haul carriers, companies providing tanker services, and companies operating in the San Francisco Bay Area are less likely to re-route drivers and also less likely to use R/S software. Other types of companies exhibit unique patterns of congestion affects and R/S software use. Long-haul carriers are less affected by congestion, but nevertheless these carriers are more likely to use R/S software. Also, very small fleets (with less than four power units) and companies with hazardous goods operations are also more likely to use R/S software. Lower propensity of R/S software use is indicated by the provision of intermodal rail, high value, or bulk hauling services.

The empirical results suggest that those trucking companies most concerned about the problem of traffic congestion on freeways and surface streets include for-hire carriers in general, and companies providing flatbed and container services, those serving maritime ports, and those operating in the Los Angeles Area. Less concern about traffic congestion is expressed by managers of long-haul carriers and companies providing specialized services such as tanker, refrigerated, bulk, high value and hazardous goods movement. These results emphasize the heterogeneous nature of the trucking industry in terms of the effects of traffic congestion and the demand for R/S software.

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References

Akaike, H. 1974. A new look at the statistical identification model. *IEEE transactions on Automatic Control* **19** 716-723.

Akaike, H. 1974. Factor analysis and AIC. *Psychometrika* **52** 317-332.

Bentler, P.M. 1990. Comparative fit indexes in structural models. *Psychometrika* **107** 238-246.

Bentler, P.M. and Bonett, D.G. 1980. Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin* **88** 558-606.

Bollen, K.A. 1989. *Structural Equations With Latent Variables.* Wiley, New York.

Bozdogan, H. 1987. Model selection and Akaike's Information Criterion (AIC): the general theory and its analytical extensions. *Psychometrika* **52** 345-370.

Browne, M.W. 1984. Asymptotic distribution free methods in analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology* **37** 62-83.

Crum, M. R., D.A. Johnson and B.F. Allen. 1998. A longitudinal assessment of EDI use in the U.S. Motor Carrier Industry. *Transportation Journal* **38** 15-28.

Forster, P. and A.C. Regan. 2001. Information Technology in Air Cargo: Interorganizational Systems and On-Time Performance, *Transportation Journal. Transportation Journal* **40** 46-61.

Golob, T.F. (in press). Structural equation modeling for travel behavior research. *Transportation Research, Part B: Methodological*, in press.

Golob, T.F. and D.A. Hensher. 1998. Greenhouse gas emissions and Australian commuters' attitudes and behaviour concerning abatement policies and personal involvement. *Transportation Research, Part D* **3** 1-18.

Golob, T.F. and A.C. Regan. 2001. Impacts of highway congestion on freight operations: perceptions of trucking industry managers. *Transportation Research, Part A* **35** 577-599.

Golob, T.F. and A. C. Regan. 2002a. Trucking Industry Adoption of Information Technology: A Structural Multivariate Probit Model*, Transportation Research, Part C* **10** pp. 205-228.

Golob, T.F. and A. C. Regan. 2002b. CVO Perspectives on the Usefulness of Various Sources of Traffic Information, *Transportation Research Part E* **38** 96-116.

Hall, R.W. and C. Intihar. 1997. Commercial vehicle operations: government interfaces and intelligent transportation systems. California PATH Research Report UCB-ITS-PRR-97-12, Institute of Transportation Studies, University of California, Berkeley.

Holguin-Veras, J, and C.M. Walton. 1996. State of the practice of information technology at marine container ports. *Transportation Research Record* **1522** 87-93.

Hoogland, J.J. and A. Boomstra. 1998. Robustness studies in covariance structure models: An overview and a meta-analysis. *Sociological Methods and Research*, **26** 239-367.

Kavalaris, J.G. and K.C. Sinha. 1995. Intelligent vehicle highway system commercial vehicle operations: Perceptions, needs and concerns of Indiana-based motor carriers. *Transportation Research Record No. 1511* 34-41.

McDonald, R.P. and H.W. Marsh. 1990. Choosing a multivariate model: Noncentrality and goodness of fit. *Psychological Bulletin* **107** 247-255.

Mulaik, S.A., L.R. James, J. van Alstine, N. Bennett, S. Lind and C.D. Stilwell. 1989. Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin* **105** 430-445.

Muthén, B. 1983. Latent variable structural equation modeling with categorical data. *Journal of Econometrics* **22** 43-65.

Muthén, B. 1984. A general structural equation model with dichotomous, ordered categorical and continuous latent variable indicators. *Psychometrika* **49** 115-132.

Ng, L., R.L. Wessels, D. Do, F. Mannering and W. Barfield. 1995. Statistical analysis of commercial driver and dispatcher requirements for advanced traveler information systems. *Transportation Research, Part C* **3** 353-369.

Regan, A.C., H.S. Mahmassani and P. Jaillet. 1995. Improving efficiency of commercial vehicle operations using real-time information: potential uses and assignment strategies. *Transportation Research Record* **1493** 188-198.

Satorra, A. and P.M. Bentler, 1988. Scaling corrections for chi-squared statistics in covariance structure analysis. In *Proceedings of the American Statistical Association*, 308-313. American Statistical Association, Alexandria, VA.

Scapinakis, D.A., and W.L. Garrison. 1991. Communications and Positioning Systems in the Motor Carrier Industry, PATH Research Report UCB-ITS-PRR-91-10, Institute of Transportation Studies, University of California, Berkeley.

Schwarz, G. 1978. Estimating the dimension of a model. *Annals of Statistics* **6** 461-464.

Shipley, B. 2000. *Cause and Correlation in Biology: A Users Guide to Path Analysis, Structural Equations and Causal Inference.* Cambridge University Press.