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BUREAU OF TRANSPORTATION STATISTICS UNITED STATES DEPARTMENT OF TRANSPORTATION

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Letter from the Director of the Bureau of Transportation Statistics

Dear Readers,

This issue of the *Journal of Transportation and Statistics* closes out the second year of publication for the U.S. Department of Transportation's (DOT's) only peer-reviewed journal. In this letter, I'd like to share my thoughts with you about the future direction of the journal. When I joined the Bureau of Transportation Statistics in November of 1998, one of my goals was to strengthen the journal's statistical component. We have instituted terms for members of the Editorial Board, and thus, in January 2000, the original Editorial Board will begin to change. Some of the board will be replaced by members from the statistical community. There will also be some changes among our DOT modal representatives.

To encourage more statistical paper submissions, we will accept LATEX files and in the near future will have a LATEX template available for authors. We will also continue to accept files in Word, WordPerfect, and Excel.

In 2000, we plan to release three issues. A special issue on motor vehicle emissions will have a guest editor—Tim Coburn from the Department of Mathematics and Computer Science at Abilene Christian University in Abilene, Texas. The other two issues will contain a broad mix of articles.

I am pleased to report that the number and quality of paper submissions has risen. I am committed to ensuring that the journal becomes a recognized source of information for the transportation community. On reviewing the original goals of the journal, I think they will continue to provide an excellent direction for authors wishing to submit papers. The goals are to:

- measure transportation activity and the performance of transportation systems,
- measure and analyze the importance of transportation and its consequences,
- measure and analyze transportation trends, and
- advance the science of acquiring, validating, managing, and disseminating transportation information.

This year we welcome David Banks of BTS as our Deputy Editor-in-Chief. David is a mathematical statistician, with a degree from Virginia Polytechnic Institute. He was a post-doctoral fellow at the University of California at Berkeley, a visiting lecturer at the University of Cambridge, and an associate Professor at Carnegie Mellon University. He comes to BTS from the National Institute of Standards and Technology. His research areas include random graphs, high-dimensional nonparametric regression, and Bayesian metrology.

In 2001, David Banks will take over from our current Editor-in-Chief, David Greene of Oak Ridge National Laboratory. Starting anything, particularly an academic journal, requires a high level of skill and dedication, and David Greene has done a wonderful job putting the journal on sound footing in only two years. I have no doubt that by the time he steps down, JTS will become a leading transportation journal.

ASHISH K. SEN

Director

Bureau of Transportation Statistics

The Structure of Public Transit Costs in the Presence of Multiple Serial Correlation

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ABSTRACT

Most studies indicate that public transit systems operate under increasing returns to capital stock utilization and are significantly overcapitalized. Existing flexible form time series analyses, however, fail to correct for serial correlation. In this paper, evidence is presented to show that ignoring multiple serial correlation can have important policy implications. Based on monthly time series data from the Indianapolis Public Transit Corporation, the results indicate that failure to correct for serial correlation significantly affects economies of capital utilization estimates and has potentially important implications for optimal size of the transit fleet.

INTRODUCTION

Since the 1960s, when most U.S. transit systems were privately owned and operated and received no public financial assistance, subsidies have increased rapidly. Government financial support for public transport has grown, while operating losses and investment needs have also been increasing. The total operating subsidy from all levels of government (local, state, and federal) rose from \$318 million in 1970 to \$9.27 billion in 1990, a

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near thirtyfold increase in 20 years (Pucher 1995). Similarly, the total capital subsidy from all levels of government rose from $200 million in 1970 to $5.56 billion in 1990, nearly 28 times higher (Pucher 1995). In spite of some evidence that subsidies have led to mild increases in ridership (Cervero 1984, Bly and Oldfield 1986), there is a general consensus that subsidies have had a degrading effect on system efficiency and productivity and have increased operating costs.[1] (Obeng 1985, Kim and Spiegel 1987, Bly and Oldfield 1986).

Several analyses have identified two related effects of continuing capital subsidies on public transit operations. First, public transit systems have an incentive to prematurely replace their capital stock (Frankena 1987). Second, by lowering the unit price of rolling stock, public transit capital subsidies provide public transit managers with an incentive to overcapitalize their systems. Although sparse, the evidence on overcapitalization in public transit is not only consistent with this hypothesis but also indicates that the extent of overcapitalization may be large. Viton (1981), for example, found that public transit systems were overcapitalized by as much as 57%. De Rus (1990) and Obeng (1984, 1985) also found that actual fleet sizes for transit systems are much larger than necessary to produce the current levels of output.

Claiming that their bus fleets are not excessive but rather needed for peak period demands, public transit managers generally argue against the empirical evidence that their systems are overcapitalized. This raises an interesting question. Do public transit agencies routinely overcapitalize their systems by as much as 50%, as existing empirical evidence suggests? Or, are existing empirical models deficient in some way that, if corrected, would produce results on the economic structure that are more consistent with observed behavior?

Of the studies that have analyzed public transit costs, all have used either panel data or time series data. However, although some authors have recognized that serial correlation may be present and could affect the study's results, none of these studies adjusted for serial correlation.[2] As is well known, the presence of serial correlation produces unbiased, consistent, but inefficient parameter estimates; further, variance estimates are biased and inconsistent, thereby invalidating hypothesis tests. The question addressed here is whether the presence of uncorrected, serially correlated errors in a flexible form cost function affects the model's implications on a public transit firm's production technology. To explore this, we developed and estimated a translog cost function model for the city of Indianapolis for a 60-month period, from January 1991 through December 1995. The next section, Methodology, identifies the model and summarizes the data used for the analysis, and the third section presents the estimation results. The final section provides concluding comments.

METHODOLOGY

Assuming one output y (vehicle-miles), three variable inputs z_i (labor, fuel, and maintenance), and one fixed input k (number of buses), equation (1) identifies a public transit firm's short-run translog cost function:

$$
\begin{aligned}
\ln VC = {} & \alpha_0 + \alpha_y \ln y + \sum_{i=1}^{3} \alpha_i \ln p_i + \\
& \alpha_k \ln k + \sum_{i=1}^{3} \gamma_{iy} \ln p_i \ln y + \sum_{i=1}^{3} \gamma_{ik} \ln p_i \ln k \\
& + \frac{1}{2} \sum_{i=1}^{3} \sum_{i=1}^{3} \gamma_{ij} \ln p_i \ln p_j + \gamma_{ky} \ln k \ln y \\
& + \frac{1}{2} \gamma_{yy} (\ln y)^2 \ln y + u
\end{aligned}
\tag{1}
$$

[1] In a cross-country comparative analysis of public transit systems and subsidies, Pucher (1995) notes "In virtually no other country have transit subsidies been as ineffective as in the United States." (p. 401)

[2] Berechman and Giuliano (1984), for example, identified second-order autocorrelation in their quarterly time series analysis of AC Transit in Alameda County, California. However, there was no attempt to correct for the problem. De Borger (1984), Berechman (1987), and Colburn and Talley (1992) also estimated time series models, but neither tested nor corrected for serial correlation. Outside of the public transit literature, Braeutigam et al. (1984) corrected for first-order serial correlation in a study on railroad costs using monthly time series data. While monthly time series data could potentially suffer from first- to twelfth-order serial correlation, the authors did not report the results of the model without correction for autocorrelation or whether they tested for higher order autocorrelation. As a result, it is not possible to assess how seriously autocorrelation affected their results.

where VC is the variable cost of production, p_i is the price of variable input factor $z_i(i = 1, 2, 3)$, u is the disturbance term, and α_0 , α_y, α_i (i = 1, 2, 3), α_k, and γ_{ij} (i, j = 1, 2, 3, y, k) are parameters to be estimated. According to equation (1), a transit firm's fleet size is fixed in the short run, implying that the level of variable inputs the firm employs at any given set of prices or output will depend on the level of rolling stock available to the system. The associated share equations (using Shephard's lemma) are:

$$s_i = \frac{p_i z_i}{VC} = \alpha_i + \sum_{j=1}^{J} \gamma_{ij} \ln p_i + \gamma_{iy} \ln y + $$

$$+ \gamma_{ik} \ln k + u_i \quad i = 1,2,3 \tag{2}$$

where s_i (i = 1, 2, 3) is the share of input i, and u_i (i = 1, 2, 3) is the error term for share equation i. Equations (1) and (2) constitute a multivariate equation system that can be written more generally as (Berndt 1991):

$$Y_t = X_t\, b + u_t \tag{3}$$

where Y_t is the ($n \times 1$) vector of dependent variables, X_t is the ($n \times m$) vector of independent variables, b is the ($m \times 1$) coefficient vector, t denotes a given time period, and u_t is an ($n \times 1$) vector of random disturbances. If u_t has a first-order stationary univariate autoregressive structure, then

$$u_t = Ru_{t-1} + \epsilon_t \qquad t = 1, \dots , T \tag{4}$$

where R is an ($n \times n$) autocovariance matrix, and ϵ_t is a vector of disturbances with mean zero and constant variance. Combining (4) and (5) results in an equation with uncorrelated disturbances:

$$Y_t = RY_{t-1} + (X_i\; RX_{t-1})b + \epsilon_t \qquad t = 1, \dots , T \tag{5}$$

The usual maximum likelihood estimation methods could be applied to equation (5). However, only J–1 equations are independent, due to the constraint that the shares at each observation sum to unity (Berndt and Savin 1975).

Because the J disturbances must sum to zero at each observation, the ($J \times J$) disturbance covariance matrices are singular, and this singularity condition imposes restrictions on the autoregressive process. Violation of these restrictions implies that the maximum likelihood estimates, and associated likelihood ratio test statistics, depend on which share equation is deleted from the system.

In order for the parameter estimates of the multivariate equation system in equation (5) to be invariant to the share equation deleted, the matrix R has to be diagonal, and all the diagonal elements must be equal (Berndt and Savin 1975). Moreover, the autoregressive multivariate system in equation (5) can be generalized to account for higher order autoregressive processes. In particular, for an Mth-order autoregressive process,

$$u_t = R_1 u_{t-1} + R_2 u_{t-2} + \;\; + R_M u_{t-M} + t \qquad t = 1, \dots , M \tag{6}$$

where each R_i (i = 1, … , M) is a diagonal matrix whose elements must all be equal for the coefficient estimates to satisfy the invariance property (Berndt and Savin 1975).

ESTIMATION RESULTS

Model Estimation

Data for the analysis come from monthly observations for the city of Indianapolis over a five-year period, January 1991 through December 1995.[3] Table 1 reports the translog estimation results for the uncorrected model and for the

[3] The Indianapolis transit system, operated as a public enterprise since 1972, is a medium-sized system that, for the period under study, served an average population of 950,000 with an average fleet of 247 buses. Although the Indianapolis Public Transportation Corporation primarily provides fixed route, fixed schedule services, the data also reflect some demand-responsive services that the city offers. Since demand-responsive services account for less than 3% of the total, their inclusion is not expected to significantly affect the results.

TABLE 1 Short-Run Translog Cost Functions[a]

Dependent Variable: Short-Run Costs (10^6)		(a) Uncorrected model		(b) Corrected model	
Variable	**Parameter**	**Estimate**[b]	**(t-statistic)**	**Estimate**[b]	**(t-statistic)**
Constant term	α_o	14.135	(1,084.80)	14.106	(280.80)
Output (vehicle-miles, units of 105)[c]	α_y	0.571	(2.78)	1.145	(5.39)
Price of labor ($/hour)[d]	α_l	0.648	(201.50)	0.574	(15.40)
Price of maintenance ($/hour)[d]	α_m	0.295	(104.30)	0.350	(11.60)
Number of buses[e]	α_k	0.380	(1.38)	0.191	(0.59)
(Price of labor) • (price of labor)	γ_{ll}	0.175	(6.76)	0.167	(8.14)
(Price of maintenance) • (price of maintenance)	γ_{mm}	0.177	(12.40)	0.189	(16.50)
(Number of buses) • (number of buses)	γ_{kk}	10.280	(1.54)	1.813	(0.63)
(Output coefficient) • (output coefficient)	γ_{yy}	–3.019	(–0.76)	–0.683	(–0.50)
(Price of labor) • (price of maintenance)	γ_{ml}	–0.157	(–8.88)	–0.161	(–11.20)
(Price of labor) • (number of buses)	γ_{lk}	–0.067	(–0.87)	0.042	(0.45)
(Price of maintenance) • (number of buses)	γ_{mk}	0.051	(0.74)	–0.054	(–0.64)
Price of labor output	γ_{ly}	0.050	(0.92)	0.355	(4.91)
Price of maintenance output	γ_{my}	–0.066	(–1.32)	–0.355	(5.67)
Number of buses output	γ_{ky}	10.326	(1.88)	2.701	(1.22)
Dummy for 1st quarter	d_{q1}	0.043	(2.76)	0.017	(2.03)
Dummy for 2nd quarter	d_{q2}	0.030	(2.71)	0.015	(2.21)
1st-order autocorrelation, cost equation	ar_{c1}	—	—	0.551	(5.06)
2nd-order autocorrelation, cost equation	ar_{c2}	—	—	0.346	3.14)
1st-order autocorrelation, share equations	ar_{sh1}	—	—	0.659	(6.74)
2nd-order autocorrelation, share equations	ar_{sh2}	—	—	0.386	(3.98)
6th-order autocorrelation, share equations	ar_{sh6}	—	—	–0.058	(–1.39)
$\tilde{R}^2$ (system R^2)		0.985		0.991	

[a] Full information maximum likelihood estimates are invariant to share equation deleted (Berndt 1991, p. 463). The estimation results presented in table 1 normalize on the price of fuel.
[b] The data were collected from the Indianapolis Public Transit Corporation accounting, maintenance, and operations reports for fiscal years 1991–1995. The system's total monthly operating cost, excluding depreciation and amortization of intangibles, measures short-run operating costs. To capture the possibility that the system faces systematic differences in its operating environment during different months, preliminary runs of the model included peak-base vehicle ratio, average speed of service, and age of fleet. In each case, we could not reject the null hypothesis of no effect. We also included a time trend in earlier model runs, but the coefficients for the first- and second-order time trends were not significant. Moreover, the model with time trend variables violated the concavity requirements at two points in the sample. As a result, we excluded the time trend in the final model specification.
[c] Total vehicle-miles provided was selected as the output measure since bus operations are the primary determinant of costs in a transit system (Savage 1997). The output measure also includes "deadhead" miles, that is, miles traveled by revenue vehicles when not in revenue service (not available for passengers). These are a small portion of the total and typically include miles traveled to and from storage and maintenance facilities as well as some training mileage.
[d] As is common in many translog cost function models for public transit, well-defined measures for the input prices do not exist. In this study, similar to methodology of others (e.g., Berechman and Giuliano 1984, Applebaum and Berechman 1993, and Talley and Colburn 1993), we allocate monthly expenses to the various input categories (i.e., labor and maintenance) and then divide the expenses by paid monthly labor hours per category. The monthly price of labor, for example, was estimated by dividing the total labor expenses (including wages, fringe benefits, and pension payments to operators and administrative employees) by the paid labor hours to operators and administrative employees. A similar procedure was followed to determine the price of maintenance. For the price of fuel, we used actual prices since these were available from the monthly reports.
[e] Bus fleet size is the number of buses the system owns and operates during a given month.
[f] In earlier model runs, a full complement of monthly dummy variables was included, but likelihood ratio tests could not reject the null hypothesis that the monthly dummy variables in a quarter were equal.

model corrected for multiple serial correlation.[4] From column (a) in table 1, the system R^2 indicates that the model fits the data well. 98.5% of the generalized variance in the dependent variable is "explained" by the variation in the explanatory variables in the system of equations.[5] Further, the estimated function satisfies the necessary neoclassical conditions that the cost function be linear, homogeneous, nondecreasing, and concave in input prices.[6] While linear homogeneity is imposed on the model's parameters (see footnote 4), the estimation results must be checked ex post facto to determine whether the function is nondecreasing and concave in input prices. At every point in the sample, the estimated cost function satisfies each of these latter two conditions.

Indianapolis' mean behavior during the five-year period reveals that the coefficients for price of labor (α_l) and price of maintenance (α_m), respectively, estimate the share of costs attributed to labor and maintenance at mean production. Although the share equation for fuel was dropped in order to estimate the model, the linear homogeneity conditions identified in footnote 4 imply that the coefficient for price of fuel is $\alpha_f = 1 - \alpha_l - \alpha_m$

The interpretation of the coefficient for output, α_y, is somewhat ambiguous. Public transit firms operate with a given amount of rolling capital (e.g., buses) and over a fixed (at least in the short run) network. With data on both rolling stock and network size, the coefficient for output would provide information on economies of traffic density. That is, the coefficient would identify the impact that an increase in output would have on the cost of using a fixed rolling stock over a given network. However, for this model, there were no data available on whether Indianapolis' network size significantly changed over the five-year period. If, in fact, there was little change in network size, then the coefficient for output in table 1 reflects economies of traffic density for a given rolling stock. On the other hand, if there were large changes to the network between 1991 and 1995, the coefficient for output would more appropriately reflect economies of capital utilization. Since in either case rolling stock is held fixed, we shall interpret α_y as a measure of economies of rolling stock utilization but bear in mind that it may also reflect economies of traffic density to the extent that Indianapolis' network underwent little change during the sample period.[7]

In general, the estimation results are consistent with expectations. First, the price coefficients are positive and strongly significant. At mean production, labor and maintenance account for 64.8% and 29.5% of costs. From the linear homogeneity conditions, fuel accounts for 5.7% of costs. Also, relative to the latter part of a year, the results indicate that the transit system experiences higher costs during the winter and spring quarters.[8]

The coefficient for output indicates that the Indianapolis mass transit system operates under

[4] To ensure homogeneity of degree one in variable input prices, given the fixed factor k and output y, the following restrictions are imposed on the parameters:

$$\sum_{i=1}^{3} \alpha_i = 1, \; \gamma_{ij} = \gamma_{ji} \; \forall i, j$$

$$\sum_{i=1}^{3} \gamma_{ij} = \sum_{j=1}^{3} \gamma_{ji} = \sum_{i=1}^{3} \gamma_{iy} = \sum_{i=1}^{3} \gamma_{ik} = 0$$

[5] The system R^2 reported in the table is computed as (Berndt 1991)

$$\tilde{R}^2 = 1 - \frac{|EE'|}{|y'y|}$$

where $|EE'|$ is the determinant of the residual cross-product matrix of the full model, and $|y'y|$ is the determinant of the residual cross-product matrix of a model in which all slope parameters are simultaneously set to zero. See Berndt (1991) for a discussion of this measure.

[6] The cost function is nondecreasing in input prices if the fitted factor shares are positive at each observation and is concave in input prices if the Hessian matrix based on the fitted factor shares is negative semidefinite.

[7] An issue of interest is whether output is endogeneously determined. That is, do increases in output cause changes in cost, or are both variables endogenously determined? To check for this, we used Granger's (1969) causality test. By running two sets of two regressions, we rejected the hypothesis that "x (output) Granger causes y (cost)" and accepted the hypothesis that "y does not Granger cause x" (both F-tests were evaluated at the five percent significance level). As a result, we can say that output "Granger causes cost." In this context, the finding that output is exogenous is not surprising since political motivations, in addition to market forces, often play a large role in the transit services actually provided.

[8] In earlier model runs, a full complement of monthly dummy variables were included, but likelihood ratio tests could not reject the null hypothesis that the monthly dummy variables in a quarter were equal.

increasing returns to rolling stock utilization at mean production level. Holding all else constant, including the size of bus fleet, a 10% increase in output increases short-run variable costs 5.7%.[9] In addition to operating under increasing returns to capital utilization, we see in column (a) of table 1 that the coefficient for number of buses is positive and significant at a 0.10 level (one tail test). A 1% increase in rolling stock raises operating costs 0.38%. As discussed more fully in the final section, this finding suggests that Indianapolis' system is overcapitalized, since a necessary condition for cost minimization is that the coefficient on capital stock be negative. [10]

Column (b) in table 1 provides parameter estimates when the model is adjusted for serial correlation, and we see that this has improved the overall fit of the model.[11] The system $\tilde{R}^2$ increases from 98.5% to 99.1%.[12] Adjusting for first- and second-order autocorrelation in the cost function and first-, second-, and sixth-order autocorrelation in the share equations provided the best model fit. It is important to recall that the autocorrelation coefficients for the share equations (ar_{sh1}, ar_{sh2}, ar_{sh6}) are restricted to being equal across share equations to satisfy the diagonality requirement of the R_i matrices. The estimated pattern of the autocorrelation coefficients indicates a positive first- and second-order correlation and a mild sixth-order correlation for the share equations.

We again see that the price variables have their expected positive signs and are strongly significant. However, there are two interesting differences between columns (a) and (b). First, whereas Indianapolis was estimated to be operating under increasing returns to capital utilization when serial correlation is ignored, we see in column (b) that, when adjusted for serial correlation, Indianapolis' transit system is estimated to be operating under mildly decreasing returns to utilization. However, at normal levels of significance we cannot reject the null hypothesis of constant returns to utilization, suggesting that Indianapolis may be an efficient short-run producer of vehicle-miles.[13]

A second difference relates to the coefficient of the fixed factor, number of buses. Although still positive, the estimated coefficient α_k is lower and, more importantly, not statistically significant at any reasonable level of significance.

Comparative Analysis of the Models

Table 2 presents test results for two restrictive production technologies, homotheticity (i.e., output changes can be met with constant input ratios), and Cobb-Douglas production technologies (homotheticity plus constant unitary elasticities of substitution between inputs) for the uncorrected model and the model adjusted for serial correlation.[14] Consistent with other studies, a Cobb-Douglas production technology is strongly rejected in each case.[15] However, when serial correlation is present but not corrected, the model accepts the null hypothesis of homotheticity, while the correct-

[9] De Borger (1984) found a similar result using annual time series data from Belgium.

[10] If the coefficient on capital stock is negative, then an increase in a transit system's rolling capital stock will generate savings in variable costs in excess of the unit bus price. A bus system is overcapitalized if the variable cost savings is either less than the unit bus price or actually increases. As noted previously, Frankena (1987) found that capital subsidies increase bus turnover. This suggests that public transit systems that overcapitalize, i.e., inefficiently invest in capital, will have an inefficiently low average fleet age and higher unit operating costs relative to optimal capital investment, which could produce a positive correlation between increased capital and operating expenses in a well-specified model. This does not appear to characterize Indianapolis' system, whose 16–18 year average age of fleet (over the five-year period) is a bit older than the industry average.

[11] To test for serial correlation, the model was initially estimated under the constraint that the R_i matrices (from equation 6) equal zero and then was re-estimated with R_i not equal to zero. The usual likelihood ratio test is based on the sample maximized log-likelihood functions obtained from the previous models (Berndt 1991). The null hypothesis of no autocorrelation was rejected at the 0.01 level.

[12] When adjusted for serial correlation, the cost function was also found to be nondecreasing and concave in input prices at each point in the sample.

[13] The t-statistic for the hypothesis that $\alpha_y = 1$ is 0.68.

[14] Testing for homotheticity is equivalent to testing the null hypothesis that $\gamma_{iy} = 0$ (i = labor, maintenance) versus the alternative hypothesis that at least one of these parameters is nonzero.

[15] A Cobb-Douglas technology characterizes the production of transit trips if we can accept the null hypothesis that $\gamma_{yy} = \gamma_{ij} = \gamma_{iy} = 0 \forall$i. Viton (1981) and Obeng (1984) reject a Cobb-Douglas technology in short-run analyses, while Williams and Hall (1981), Berechman and Giuliano (1984), and de Rus (1990) reject a Cobb-Douglas technolgoy in long-run analyses.

TABLE 2 Test Statistics for Homotheticity and Cobb-Douglas Production Technologies

Null hypothesis	$-2(lnL_R - lnL_U)$[a]	# Restrictions (n)	$\chi^2_{.01}(n)$	Result
Model with no correction for autocorrelation				
Cobb-Douglas	192.22	10	23.21	Rejected
Homotheticity	6.26	2	9.21	Not rejected
Model with correction for autocorrelation				
Cobb-Douglas	227.54	10	23.21	Rejected
Homotheticity	67.73	2	9.21	Rejected

[a] $ln\ L_U$ is the sample maximized log-likelihood value without restrictions, and lnL_R is the sample maximized log-likelihood with restrictions.

ed model rejects the hypothesis, implying that the cost function is not separable in output and that changes in a factor's price will not only affect input demand ratios but also the cost elasticity with respect to output.[16]

[16] Berechman and Giuliano (1984), de Borger (1984), Berechman (1987), and de Rus (1990) also found a non-homothetic production structure. However, and similar to the model without correction for autocorrelation, Williams and Dalal (1981), Williams and Hall (1981), and Berechman (1983) could not reject the null hypothesis of a homothetic production structure.

Table 3 presents the own price (e_{ii}) and Allen elasticities of substitution (σ_{ij}) evaluated at the sample mean and by year for both models. As expected, the own price elasticities have the correct negative sign. In both models and consistent with other studies, the elasticities are small for labor and maintenance, while fuel appears to be more elastic when the estimated model corrects for autocorrelation. It is interesting to note that while the own price elasticity of labor and maintenance has remained fairly constant over the period, the demand for fuel has demonstrated a tendency to become more inelastic with the passage of time.

TABLE 3 Short-Run Own Factor Demand Elasticities and Elasticities of Substitution

			Price elasticity[a]			
Period	e_{ll}	e_{ff}	e_{mm}	σ_{lf}[b]	σ_{lm}	σ_{mf}
Model without correction for autocorrelation						
Mean	–0.081	–0.267	–0.103	0.515	0.178	–0.224
1991	–0.074	–0.352	–0.078	0.591	0.131	–0.133
1992	–0.073	–0.291	–0.077	0.541	0.136	–0.254
1993	–0.084	–0.275	–0.098	0.514	0.173	–0.196
1994	–0.075	–0.198	–0.093	0.468	0.172	–0.382
1995	–0.091	–0.149	–0.124	0.407	0.222	–0.337
Model with correction for autocorrelation						
Mean	–0.092	–0.354	–0.053	0.854	0.141	–0.068
1991	–0.095	–0.436	–0.048	0.877	0.119	–0.046
1992	–0.087	–0.389	–0.039	0.865	0.119	–0.065
1993	–0.094	–0.373	–0.051	0.858	0.139	–0.062
1994	–0.087	–0.308	–0.051	0.844	0.144	–0.085
1995	–0.099	–0.266	–0.076	0.828	0.185	–0.084

[a] e: own price elasticity of demand, σ: Allen partial elasticity of substitution; where: l = labor, f = fuel, m = maintenance.
[b] Elasticities of substitution are symmetric.

The Allen elasticity results indicate that labor and maintenance and labor and fuel are substitutes for each other, while maintenance and fuel are complements. Further, there is a significant change in the Allen elasticity between maintenance and fuel when the model is corrected for autocorrelation, rising from –0.224 (evaluated at the mean) in the uncorrected model to –0.046 in the corrected model. The latter indicates that maintenance and fuel are weakly complementary.

DISCUSSION AND CONCLUDING COMMENTS

Although the deficiencies of models that suffer from uncorrected multiple serial correlation are recognized in the public transit cost literature, existing translog cost results have failed to account for serial correlation. Policy implications based on such models are accordingly suspect. When serial correlation is ignored, the translog cost function results for a medium-sized public transit system are consistent with existing literature. However, when corrected for the presence of serial correlation, the estimation results have significantly different implications with respect to a transit system's production technology and possibly its optimal fleet size.

This raises three questions that await further research. First, what are the sources of serial correlation? Consistent with other monthly time series data, the data for this analysis exhibit seasonal and cyclical effects that will generate autocorrelated errors. By testing for various orders of monthly related serial correlation and ultimately adjusting for first- and second-order serial correlation in the cost function and first-, second-, and sixth-order serial correlation in share equations, we find that the models presented likely capture much of the seasonally generated autocorrelation. In particular, the sixth-order correlation coincides with the seasonality of demand for bus services, which is lower during the summer and higher during the winter months (Berechman and Giuliano 1984).

An additional source of autocorrelation is missing information, that is, omitted variables that are serially correlated. The lack of data on network changes, for example, over the five-year period shows up in the error terms. If there were systematic changes in network size (e.g., continual increases) over the 60-month period of this analysis, errors that are serially correlated in the model would be generated.[17]

A final source of serially correlated errors could reflect an adaptive expectations framework in which changes in short-run costs are based on changes in the expected or desired level of the explanatory variables. This produces an empirical specification that is formally identical to a Koyck distributed lag model, which is characterized by serial correlation (Pindyck and Rubinfeld 1976).[18]

Second, we noted above that these findings may have implications for a system's optimal fleet size. Recall the findings reported in table 1 for the model that was not corrected for serial correlation. The coefficient on number of buses, the fixed factor, was positive and significant at a 0.10 level. This finding is consistent with other analyses of public transit costs and suggests that the transit system is overcapitalized. On the other hand, when corrected for serial correlation, the coefficient on number of buses was positive but with a t-statistic well below 1.0, implying that Indianapolis' system is operating efficiently. To illustrate the potential importance of correctly specifying the model, the mean fleet size for the sample period was 227 buses. When uncorrected for serial correlation, optimal fleet size was estimated as 171 buses, indicating substantial (35%) overcapitalization. However, when corrected for serial correlation, optimal fleet size increased to 214 buses, implying considerably less (6%) overcapitalization in the system.[19] The importance of this finding is its implication of

[17] To obtain desirable properties of the estimates by adjusting for serial correlation in this instance assumes that the omitted variables and included variables are uncorrelated (Maddala 1977).

[18] The authors would like to thank an anonymous referee for suggesting this.

[19] To obtain the optimal level of the fixed factor, we solved the following equation

$$\frac{\partial CV}{\partial x_F^*} = -p_F$$

where the subscript F refers to the fixed factor (optimal number of buses), CV is short-run total cost, p_F is unit price of the fixed factor, and x_F is the optimal level of the fixed factor. Unfortunately, it is impossible to find a closed form solution for x_F, since the equation yields an equation involving both x_F and its logarithm. Using the modified Nelson (1972) approach (Berechman and Giuliano 1984), we calculated a price for p_F and solved for the optimal level of rolling stock through a numerical procedure.

the need for further research to determine more accurately the extent of overcapitalization of current systems.

Last, the vehicle-miles supplied is the output measure used for this analysis and may be overly restrictive. A more general approach would entail a multiple output (e.g., passenger-miles as well as vehicle-miles) translog cost model enabling the estimation of short-run economies of scope as well as economies of capital stock utilization.

Public policy toward deregulation, privatization, and subsidization is only useful when we have accurate information on the underlying structure of transit firms' production and costs. The significant differences identified in this paper imply that ignoring statistical problems such as multiple serial correlation in translog cost function models may have important consequences for public transit policy.

REFERENCES

Applebaum, E. and J. Berechman. 1991. Demand Conditions, Regulation and the Measurement of Productivity. *Journal of Econometrics* 47:379–400.

Berechman, J. 1987. Cost Structure and Production Technology in Transit. *Regional Science and Urban Economics* 17:519–534.

Berechman, J. 1993. *Public Transit Economics and Deregulation Policy.* North-Holland, Amsterdam.

Berechman, J., and G. Giuliano. 1984. Analysis of the Cost Structure of an Urban Bus Transit Property. *Transportation Research B* 18B, no. 4/5:277–287.

Berndt, E.R. 1991. *The Practice of Econometrics:Classic and Contemporary.* Reading, MA:Addison-Wesley.

Berndt, E.R. and N.E. Savin. 1975. Estimation and Hypothesis Testing in Singular Equation Systems with Autoregressive Disturbances. *Econometrica* 43:937–958.

Bly, P.H. and R.H. Oldfield. 1986. The Effects of Public Transport Subsidies on Demand and Supply. *Transportation Research* 20A, no. 8:415–427.

Braeutigam, R.R., A.F. Daughety, and M.A. Turnquist. 1984. A Firm Specific Analysis of Economies of Density in the U.S. Railroad Industry. *The Journal of Industrial Economics* 33, no. 1:3–17.

Cervero, R. 1984. Cost and Performance Impacts of Transit Subsidy Programs. *Transportation Research A* 18A, no. 5/6:407–413.

Colburn, C. and W. Talley. 1992. A Firm Specific Analysis of Economies of Size in the U.S. Urban Multiservice Transit Industry. *Transportation Research B* 26B, no. 3:195–206.

De Borger. 1984. Cost and Productivity in Regional Bus Transportation:The Belgium Case Study. *Journal of Industrial Economics* 37:35–54.

De Rus, G. 1990. Public Transport Demand in Spain. *Journal of Transport Economics and Policy*, May:189–201.

Frankena, M. 1987. Capital-Based Subsidies, Bureaucratic Monitoring, and Bus Scrapping. *Journal of Urban Economics* 21:180–193.

Granger, C.W.J. 1969. Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica* 37:424–438.

Kim, M. and M. Spiegel. 1987. The Effects of Lump-Sum Subsidies on the Structure of Production and Productivity in Regulated Industries. *Journal of Public Economics* 34: 105–119.

Maddala, G. 1977. *Econometrics*. New York, NY:McGraw-Hill Book Co.

Nelson, G. 1972. An Econometric Model of Urban Transit Operations, Institute of Defense Analyses. Washington, DC, 863.

Obeng, K. 1984. The Economics of Bus Transit Operation. *The Logistics and Transportation Review* 20, no. 1:45–65.

____. 1985. Bus Cost, Productivity and Factor Substitution. *Journal of Transport Economics and Policy* 19, no. 2:183–203.

Pindyck, R. and D. Rubinfeld. 1976. *Econometric Models and Economic Forecasts.* New York, NY:McGraw-Hill Book Co.

Pucher, J. 1995. Urban Passenger Transport in the United States and Europe:A Comparative Analysis of Public Policies—Part 2:Public Transport, Overall Comparisons and Recommendations. *Transport Reviews* 15, no. 3:211–227, 401.

Savage. 1997. Scale Economies in United States Rail Transit Systems. *Transportation Research* 31A:459–478.

Viton, P.A. 1981. On Competition and Product Differentiation in Urban Transportation:The San Francisco Bay Area. *Bell Journal of Economics* 12:362–379.

Williams, M. and A. Dalal. 1981. Estimation of the Elasticity of Factor Substitution in Urban Bus Transportation:A Cost Function Approach. *Journal of Regional Science* 21, no. 2:263–275.

Williams, M. and C. Hall. 1981. Returns to Scale in the United States Intercity Bus Industry. *Regional Science and Urban Economics* 11:573–584.

On the Measurement and Valuation of Travel Time Variability Due to Incidents on Freeways

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ABSTRACT

Incidents on freeways frequently cause long, unanticipated delays, increasing the economic cost of travel to motorists. This paper provides a simple model for estimating the mean and variance of time lost due to incidents on freeways. It also reviews methods for assigning a monetary value to the variability that such incidents introduce into daily travel. The paper offers an easy-to-implement approach to measuring the performance of freeway incident reduction strategies, an approach that should be useful in early project selection exercises where a sketch planning process is used to identify promising actions.

INTRODUCTION

From the perspective of economic theory, avoidable time spent traveling is a nonproductive activity against which there is an opportunity cost. For example, work time may be lost due to delays in the daily commute. A common approach to placing a cost on this extra time spent in travel is to assess the value of such time in terms of the hours lost multiplied by some fraction of the gross hourly wage, including Worker's Compensation and other fringe benefits paid for by employers (Hensher

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1997). Alternatively, numerous travel behavior studies have used consumer choice models to derive the value of time spent in travel, for both work and nonwork purposes. The most popular approach has been to estimate logit models of mode or route choice. In these models, the choices made by a sample of travelers are related to the differences these individuals face in terms of in-vehicle and out-of-vehicle travel times and also in terms of the various monetary costs associated with each mode or route alternative. The ratio of the resulting parameter values assigned to the travel time versus travel cost variables in these models is then used to derive a monetary value of time savings (Hensher 1997).

Most of these time valuation studies have based their findings on estimated traveler responses to changes in averaged or, more usually, representative daily travel times. However, a number of empirical studies have demonstrated the importance of also considering travel time variability in the derivation of traveler cost functions (for example, Jackson and Jucker 1982, Polak 1987, Black and Towriss 1993, Senna 1994, Abdel-Aty et al. 1995, Noland and Small 1995, Small et al. 1995, 1997). These studies indicate that under the right circumstances, notably during congested peak period travel, reducing the variability, and hence the uncertainty, associated with trip times can offer significant traveler benefits. This is important because it is usual for travel time savings to dominate the benefits assigned to major transportation improvement projects (USDOT FHWA 1996).

Empirical evidence confirms that a major cause of day-to-day variability in trip times is the occurrence of traffic incidents, including major accidents that block traffic lanes for extended periods and many minor incidents, such as vehicle breakdowns (see Lindley 1987, Giuliano 1989, Schrank et al. 1993). In the following section, a model is described for estimating both the mean and variance in the time lost due to such traffic incidents along freeways. The model is fitted to data on a number of different incident types, for two-, three-, and four-lane freeways, and for a range of congestion levels.

In the third section of the paper, methods are reviewed for assigning a monetary value to the variability that such incidents introduce into daily travel. A high level of daily variability in the time it takes to complete a specific trip implies a less-than-reliable transportation system. Such variability is likely to result in one of two outcomes, either a) the traveler arrives late or b) the traveler makes an earlier departure than desired, with the possibility on any given day of arriving earlier than necessary. Either way, time is lost or at least used in a less than optimal fashion. If travelers attach a high value to on-time arrivals, then a high level of variability in daily travel times represents a significant disbenefit that needs to be accounted for in project assessments. Recent research, discussed below, indicates that this is the case. In particular, a number of studies were found to have used stated preference (SP) surveys to capture and quantify traveler perceptions about the day-to-day reliability of their travel options. While numerical results from these studies vary a good deal, they indicate that travelers involved in repetitive trip-making are likely to place a significant premium on consistency in day-to-day trip times. Based on this literature, two different valuation methods were selected and linked to the incident delay model described in the second section of the paper. The two methods are used to demonstrate the importance of incorporating the costs of either travel time variability or the congestion that produces it into project benefit-cost analyses.

The results of the modeling also suggest that real time incident management (IM) systems, based on rapid and accurate incident detection and clearance, are promising components of regional Intelligent Transportation System (ITS) strategies. In this context, freeway-based IM systems appear to be especially good candidates for further analysis since they deal with the redirection or control of potentially large traffic volumes. The following analysis offers an easy-to-implement approach to measuring the performance of freeway incident reduction strategies, an approach that should be useful in early project selection exercises where a sketch planning process is used to identify likely project candidates.

MEASURING TRAVEL TIME VARIABILITY: AN INCIDENT ANALYSIS PROCEDURE

In this section, a model is presented for estimating the mean and variance of delays due to freeway incidents as a function of volume-to-capacity (V/C) ratio. Results of fitting the model to data on the magnitude, frequency, and duration of incidents are also presented.

The model provides estimates of delays due to accidents, debris, and vehicle breakdowns. It does not include the effects of delays due to day-to-day variations in traffic volume, weather conditions, or roadwork. Taking these effects into account could significantly increase our estimates of day-to-day variations in travel times. However, delays due to variations in traffic volume, weather conditions, and roadwork are more easily anticipated by motorists than delays due to accidents and vehicle breakdowns. Issues regarding the valuation of different types of delays are discussed further in the third section.

The following variables are used in the model description:

- V = average volume on the freeway (in vehicles per hour). This is the rate at which vehicles arrive at the back of the queue after an incident occurs and a queue forms.
- C = the capacity (Level of Service E) of the freeway prior to the occurrence of the incident (in vehicles per hour).
- r = capacity reduction factor due to the incident. The quantity rC is the rate at which vehicles pass the incident before it is cleared. If $r = 0$, the freeway is completely blocked by the incident.
- g = average "getaway" volume from the queue after the incident is cleared, expressed as a fraction of C.
- T_i = incident duration (in hours).
- T_g = duration of the getaway period during which the queue is dissipating (in hours).
- Q = maximum queue length (in vehicles).
- D_i = total delay incurred by all vehicles during the incident (in vehicle-hours).
- D_g = total delay incurred by all vehicles during the getaway period (in vehicle-hours).
- D = total delay incurred as a result of the incident (in vehicle-hours).

The model calculates D as a function of V, C, r, g, and T_i.

An incident will cause a queue if the freeway volume V is greater than the available freeway capacity during the incident (i.e., if $V>rC$). The queue will grow in length until the incident is cleared (T_i hours after the incident occurred). The queue growth rate during the incident (in vehicles per hour) is equal to the rate at which vehicles arrive at the end of the queue (V) minus the rate at which they get past the incident (rC). The maximum queue length, which occurs at that point in time when the queue is cleared, is calculated as follows

$$Q = (V - rC)\, T_i \tag{1.1}$$

Because the queue grows from a length of zero (when the incident occurs) to a length of Q (when the incident is cleared), the average length of the queue during the incident is $Q/2$. Hence, the delay incurred by vehicles during the incident is calculated as follows:

$$D_i = (1/2)\ Q\ T_i = (1/2)(V - r\,C)\ T_i^2 \tag{1.2}$$

After the incident is cleared, the queue will gradually dissipate, at a rate dependent on the getaway capacity and the volume:

$$T_g = Q/(gC - V) \tag{1.3}$$

Hence, the delay incurred by vehicles while the queue is dissipating is calculated as follows:

$$D_g = (1/2)\ Q\ T_g = (1/2)\ Q^2/(gC - V) = (1/2)\ (V - r\,C)^2\ T_i^2\ /(gC - V) \tag{1.4}$$

Total delay due to the incident is then calculated as follows:

$$D = Di + D_g = (1/2)\ C\ T_i^2\ (V/C - r)\ (g - r)/(g - V/C) \tag{1.5}$$

An important implication of this simple model is that the total delay due to an incident varies with the *square* of incident duration. For example, if the duration of incidents is reduced by 10%, then the total delay caused by the incident is reduced by 19% ($1-0.9^2$). This is because reducing incident duration by 10% means that 10% fewer vehicles will be caught in the queue caused by the incident, and each vehicle caught in the queue will spend 10% less time in the queue.

Equation (1.5) provides an estimate of total delay to all vehicles due to an incident. To estimate the mean and variance of incident-related delays experienced by individual motorists, we make the following assumptions for each class of incident (k) to be examined:

- The occurrence of incidents on a highway section is governed by a Poisson process such that the expected number of incidents is equal to $\lambda_k VL$, where λ_k is the incident rate, V is volume, and L is section length.
- Incident durations follow a Gamma distribution[1] with mean m_k and variance s_k^2.
- Not all motorists affected by an incident experience the same amount of delay. In particular, we assumed that delays experienced by motorists during a given incident would follow a uniform distribution ranging from zero to twice the expected delay for the incident.

Using these assumptions, we can calculate the mean and variance of a motorist's delay per vehicle-mile for each class of incidents as follows:

$$\mu_{dk} = \lambda_k \,(1/2)\, C\, (m_k^2+s_k^2)\, (V/C-r_k)(g-r_k)/(g-V/C) \tag{1.6}$$

$$\sigma_{dk}^2 = (4/3)\mu_{dk}\, m_k\, (1-r_k/(V/C))(s_k^2 + m_k^2/2)/(s_k^2 + m_k^2)-\mu_{dk}^2 \tag{1.7}$$

where

- μ_{dk} is the mean delay (in hours per vehicle-mile) due to the class of incidents.
- σ_{dk}^2 is the variance of delay due to the class of incidents.
- Other variables are as defined above.

In deriving equations (1.6) and (1.7), we used the fact that the expected value of the square of any random variable is equal to the sum of its variance and the square of its mean. We also used the fact that if the probability density function of a random variable t is uniform between 0 and $2T$, then the expected value of t^2 is equal to $4T^2/3$.

A spreadsheet was developed to apply these equations to estimate the mean and variance of delays due to incidents as a function of volume-to-capacity ratio. In the spreadsheet, incidents were classified by type (abandoned vehicle, accident, debris, mechanical/electrical, stalled vehicle, flat tire, and other) and severity (shoulder, one, two, three, or four lanes blocked). For each class of incident, data from Sullivan et al. (1995) were used to estimate m_k, s_k^2, λ_k, and r_k, and runs of the traffic microsimulation model FRESIM[2] performed by Margiotta et al. (1997) were used to estimate g.

With the above equations for μ_{dk} and σ_{dk}^2, estimates of the mean and variance of delays due to each class of incident were developed for volume-to-capacity ratios ranging from 0.05 to 1.0 for freeways with 2, 3, and 4 lanes in each direction.[3] The means and variances for individual incident classes were then summed to produce the mean and variance of all delays due to incidents as a function of number of lanes and volume-to-capacity ratio.[4] The results, shown in figures 1 and 2, were a set of smooth curves to which the following equations[5] were fit.

- Freeways with two lanes in each direction:

$$\mu_d = 0.0154(V/C)^{18.7} + 0.00446(V/C)^{3.93} \tag{1.8}$$

$$\sigma_d^2 = 0.00408(V/C)^{21.2} + 0.00199(V/C)^{4.07} \tag{1.9}$$

- Freeways with three lanes in each direction:

$$\mu_d = 0.0127(V/C)^{22.3} + 0.00474(V/C)^{5.01} \tag{1.10}$$

$$\sigma_d^2 = 0.00288(V/C)^{23.2} + 0.00166(V/C)^{5.06} \tag{1.11}$$

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[1] Golob et al. (1987) and Giuliano (1989) found incident durations to fit a log-normal distribution. However, this distribution presents some analytically intractable problems. The Gamma distribution offers an approximation that is easier to work with.

[2] FRESIM is a traffic microsimulation model. Simulation runs were required to estimate the value of the parameter g. The other variables are derived directly from the data provided by Sullivan et al. (1995).

[3] In estimating the mean and variance of incident delays for a given V/C ratio, we assume that the volume of traffic does not vary over time, since our focus is on developing simple relationships for sketch planning. For more detailed applications, Sullivan et al. (1995) developed a computer program named IMPACT for estimating incident delays with time-varying traffic.

[4] Under the assumptions presented earlier in this section, delays for the different incident classes constitute a set of independent random variables. For independent random variables, the mean of their sum is equal to the sum of their means, and the variance of their sum is equal to the sum of their variances (see Drake 1967, 107–108).

[5] Equations are not applicable when $V/C > 1.0$, i.e., when demand volume exceeds capacity so that queuing occurs even if there are no incidents.

- Freeways with four or more lanes in each direction:

$$\mu_d = 0.00715(V/C)^{32.2} + 0.00653(V/C)^{7.05} \quad (1.12)$$

$$\sigma_d^2 = 0.00229(V/C)^{22.2} + 0.00124(V/C)^{5.27} \quad (1.13)$$

where

- μ_d is the average delay experienced by a motorist due to all incidents in hours per vehicle-mile.
- σ_d^2 is the variance of delay experienced by a motorist due to all incidents in hours squared per vehicle-mile.
- V is volume in vehicles per hour.
- C is capacity in vehicles per hour.

The equations presented above closely fit the results presented in figures 1 and 2. In all cases, the adjusted R-squared values exceeded 0.99.

VALUATION METHODS: BENEFITS OF MORE RELIABLE TRAVEL TIMES

In this section, two different approaches to assigning a user benefit (cost) to more (less) reliable travel times are linked to the above model of delays due to incidents. In each case the method is based on recently reported empirical analyses in which traveler cost models have been fitted to data from SP surveys designed to explore traveler responses to variability in day-to-day travel times. In the first approach, an additional cost of travel is assigned directly to a measure of trip time variability. In the second approach, an additional cost of travel is assigned instead to that part of a trip in which delays caused by congestion occur. The objective in both instances is to provide a method for quantifying the benefits associated with improved system reliability that can also make use of data that can be routinely collected with the deployment of real time regional traffic monitoring systems.

The first of these trip cost models (model 1) has the form:

$$U_c = a_1{*}T + a_2{*}V(T) + a_3{*}M \quad (2.1)$$

where U_c equals the expected cost of the daily trip (e.g., the commute), and a_1, a_2, and a_3 are parameters that reflect travelers' relative dislike of, respectively, trip time T, a measure of trip time variability $V(T)$, and a monetary travel cost, M. In recent years, a number of researchers have attempted to derive the parameters for this and more elaborate travel cost models by using SP surveys. In such surveys, a sample of travelers is asked to choose between a number of hypothetical trip-making options that offer different trade-offs between trip time, trip time variability, and trip costs (see Jackson and Jucker 1982, Black and Towriss 1993, Small et al. 1997). The resulting ratio of a_2/a_1 in equation (2.1) provides a useful

FIGURE 1 Expected Delay Due to Incidents on Two-, Three-, and Four-Lane Freeways

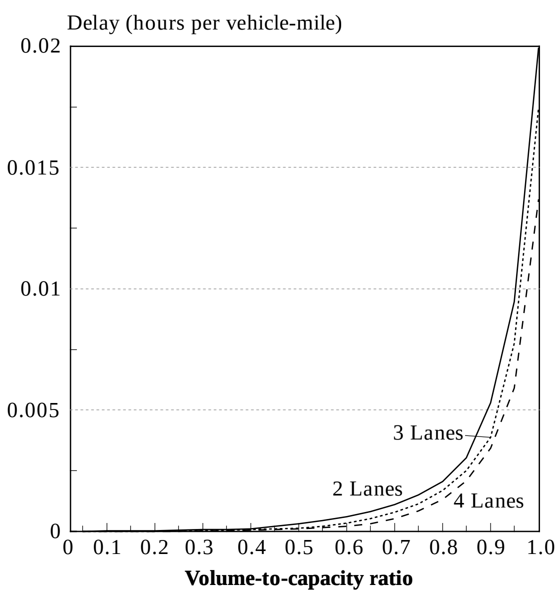
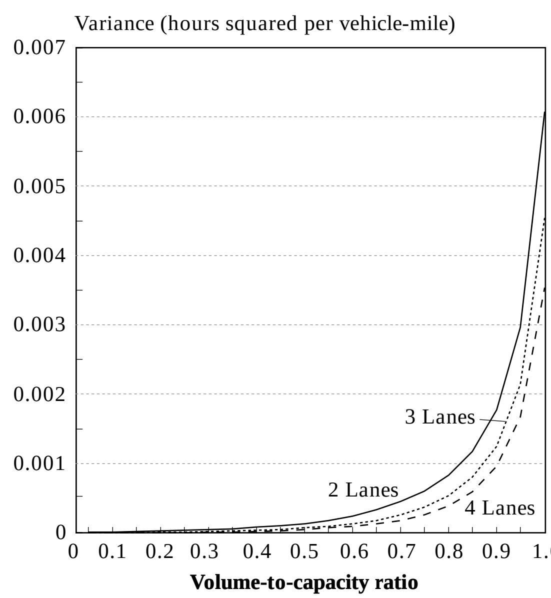


FIGURE 2 Variance of Delay Due to Incidents on Two-, Three-, and Four-Lane Freeways



measure of the relative importance of changes in travel time variability versus changes in total trip time. The ratio of a_2/a_3 also allows a monetary cost to be assigned to the importance of such variability.

In their London study of travel time reliability, Black and Towriss (1993) used such a model to obtain a value of 0.55 for the ratio of a_2/a_1 (quoted in Small et al. 1995, 54). They define *V(T)* in their model as the standard deviation of travel time. This indicates that changes in the standard deviation of trip time is significant, at a little more than half the value of an equivalent increase in trip duration itself. A similar ratio of 0.35 was obtained by the SP-based study of morning commuters route choice in Los Angeles, carried out by Abdel-Aty et al. (1995). In this case, their model leaves out the monetary costs of commuting. A more recent study by Small et al. (1997) also used a stated preference survey of morning peak period commuters in southern California. They estimated a number of different binary logit choice models, including a version of equation (2.1) above, with *V(T)* also set equal to the standard deviation of travel time. They obtained much higher values on this variability term than previous studies. In their case, an additional increase of 1 minute in the standard deviation of travel time was valued at 1.31 times that of an additional minute of total time savings per se, where this latter was taken to be 50% of the median wage rate in their sample. A similar result, with a_2/a_1 producing a ratio of 1.27, was also obtained by Small et al. (1995), using a different SP survey of Los Angeles commuters and a model that left out the monetary cost variable *M* in equation (2.1) above.

The significant differences in the values associated with variability (reliability) across these and related studies appear to result to a large degree from differences in study intent as well as survey design. However, the empirical work discussed by Senna (1994), Small et al. (1995, 1997), Noland et al. (1997), and Bates (1997) also demonstrates that we should expect some significant differences in value of time use parameters based on trip purpose (notably work-related versus commuting versus noncommuting activities), socioeconomic status (such as income and family structure), and based on differences in traveler attitudes towards schedule compliance (e.g., risk-prone versus risk-averse types). Scheduling constraints imposed by the inflexibility and importance of fixed working hours are also likely to differentially influence travelers' responses to uncertain trip times. It is also possible, though currently unclear, that the underlying level of recurrent congestion may affect such valuations. Small et al. (1995, 54) quotes a British study (MVA Consultancy 1992) as suggesting a plausible value for the ratio of a_2/a_1 between 1.1 and 2.2, but this is based on very limited empirical evidence. More work is obviously warranted on this topic, with the probable conclusion that the effects of travel time reliability ought to be evaluated on a market-sector and context-sensitive basis.

Model 1 is one of the simplest traveler cost models to incorporate travel time variability impacts. Polak (1987), Senna (1994), and Noland et al. (1997) offer others. In particular, the recent work by Small et al. (1997) provides a more direct empirical link between commuting costs, travel time variability, and travelers' valuation of early as well as late arrivals. An important finding of their work is that model 1, with *V(T)* defined as the standard deviation of travel time, appears to be a useful surrogate for their more elaborate travel (commuting) cost equations, in which the effects of scheduling delays are captured by the use of explicit early and late arrival penalties. This suggests that we can use equation (2.1) to capture most of the time-use benefits resulting for incident-induced delays, without having to go into more elaborate schedule-impact modeling, at least for the purposes of sketch planning studies.

A second approach (model 2) to assigning a valuation to system reliability is to assign a cost directly to congestion. This has the practical advantage of linking directly computable measures of the location and duration of congestion (using in-vehicle and along-the-highway sensor systems) to a suitable valuation of travelers' dissatisfaction with unexpected en route delays. There is a limited body of empirical evidence to indicate that congested travel time is assigned a comparatively high cost by travelers, although once again the values reported cover quite a wide range. The most recent empirical work on this topic is reported by Small et al. (1997), who

TABLE 1

	Model 1	Model 2
Value of travel time under uncongested conditions	V	V
Value of incident-related delay	V	2V to 6V
Value of standard deviation of trip time	0.3V to 1.3 V	—

TABLE 2

Cost components	Model 1	Model 2
Travel time under uncongested conditions	3.64	3.64
Incident-related delay	0.80	1.60 to 4.81
Standard deviation of trip time	0.47 to 2.03	—
Total	4.91 to 6.47	5.24 to 8.45

estimated binary logit travel choice models using travel cost functions of the following general form, again using data from their SP survey of southern California morning commuters in 1995:

$$U_c = a_1 * T + a_2 * f[T_c] + a_3 * M \qquad (2.2)$$

where T=total expected travel time, $f(T_c)$ = a function of the time spent in traffic congestion, M=monetary cost of travel, and a_1, a_2, a_3 are again the estimated model parameters. They use two specifications for $f(T_c)$. The first of these sets $f(T_c)$ equal to the percentage of the trip time spent in congestion, while the second model uses the number of minutes spent in congestion directly. The authors also introduce income effects into their more elaborate model formulations. As a set, their results indicate a considerable aversion to congestion among their respondents. Their results imply that, for the study's median trip length of 26 minutes, a shift from 1 minute of uncongested to congested travel time was valued at almost 3 times the value of the time itself, which in turn implies that the value of congested time is about 4 times the value of uncongested time. Their results also suggest that this ratio may vary a good deal by trip length, with values ranging from about 2 times higher for 60-minute trips to six times higher for 15-minute trips. Past literature suggests that their results are on the high side. This is probably due to the congestion focus of the study and to the high levels of congestion their respondents are used to. Again, results to date are likely to be model-formulation as well as context and market-sector sensitive.

Table 1 summarizes high and low values suggested by the literature for models 1 and 2 in relation to the value of travel time under uncongested conditions.

LINKING INCIDENT DELAY MODELS AND VALUATION METHODS

In this section, we demonstrate the implications of linking the valuation methods in the third section with the incident delay models in the second.

Our first hypothetical case for this demonstration is a 20-mile commuter trip on a 3-lane freeway with a typical volume to capacity ratio of 0.90. These circumstances are typical of those experienced by the California commuters surveyed by Small et al. We also assume that when traffic is not affected by incidents, the average speed is 55 miles per hour and the cost of travel time under uncongested conditions for commuters is $10 per vehicle-hour.

For this hypothetical case, the average delay due to incidents is:

$$(20 \text{ miles})(0.0127(0.90)^{22.3} + 0.00474 (0.90)^{5.01}) = 0.080 \text{ hours}$$

and the standard deviation of trip time is:

$$((20 \text{ miles})(0.00288(0.90)^{23.2} + 0.00166 (0.90)^{5.06}))^{0.5} = 0.156 \text{ hours}$$

Table 2 shows the results of applying models 1 and 2 with high and low values.

Our second hypothetical case for this demonstration is a 5-mile commuter trip on a 2-lane freeway with a typical volume to capacity ratio of 0.80. We also assume that when traffic is not affected by incidents, the average speed is 60 miles per hour and the cost of travel time under uncongested conditions is $10 per hour.

For this hypothetical case, the average delay due to incidents is:

$$(5 \text{ miles})(0.0154(0.80)^{18.7} + 0.00446 (0.80)^{3.93}) = 0.010 \text{ hours}$$

TABLE 3

Cost components	Model 1	Model 2
Travel time under uncongested conditions	0.83	0.83
Incident-related delay	0.10	0.21 to 0.63
Standard deviation of trip time	0.19 to 0.84	—
Total	1.12 to 1.77	1.04 to 1.46

and the standard deviation of trip time is

$$((5 \text{ miles})(0.00408(0.80)^{21.2} + 0.00199 (0.80)^{4.07}))^{0.5} = 0.065 \text{ hours}$$

Table 3 shows the results of applying models 1 and 2 with high and low values.

Model 2 produces somewhat higher costs for our hypothetical case with a 20-mile trip, and model 1 produces somewhat higher costs for our hypothetical case with a 5-mile trip. The principal reason for this difference is that model 2 is based on incident delay only, whereas model 1 is based on both incident delay and the standard deviation of trip time. Expected incident delay increases in direct proportion to trip distance. The standard deviation of trip time increases in proportion to the square root of trip distance. Hence, model 1 will produce higher costs for short trips, and model 2 will produce higher costs for long trips, other things being equal. The difference between these two models highlights the need for more research to determine the most appropriate model form for valuation of delays due to incidents.

SUMMARY

In summary, a model of traffic incident-based delays was formulated and estimated for freeways of different capacities, for a range of traffic congestion levels up to ideal roadway capacities. This yielded equations for both the mean and variance of such delays, on a per vehicle-mile basis. These results were used to demonstrate the potentially significant time-use benefits that could occur from reducing such variances. To do this, the literature on valuing travel time reliability was surveyed for appropriate models and parameter values. Two simple models were chosen to demonstrate the size of the potential time-use benefits involved. The results mirror similar conclusions reached by Wilson (1989) and by Noland and Small (1995). If the results implied by the above approach are reflective of actual traffic conditions, then policies to reduce variability in commuting times, such as rapid response incident clearance systems, may prove cost-effective, even if *average* trip times change little or not at all. Such systems may perhaps offer a cost effective alternative to relatively expensive capacity expansion projects that focus on reducing average commuting times per se. Given the limited amount of empirical work on both the valuation and nature of traveler responses to highly variable travel conditions, more work in this area is warranted in support of more accurate benefit-cost analyses.

ACKNOWLEDGMENTS

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REFERENCES

Abdel-Aty, M., R. Kitamura, and P.P. Jovanis. 1995. Investigating Effect of Travel Time Variability on Route Choice Using Repeated-Measurement Stated Preference Data. *Transportation Research Record* 1493:39–45.

Bates, J.J. 1997. Departure Time Choice—Theory and Practice, paper presented at the 8th Meeting of the International Association for Travel Behaviour Research, September 21–25, 1997. Austin, Texas.

Black, I.G. and J.G. Towriss. 1993. *Demand Effects of Travel Time Reliability.* London, England: United Kingdom Department of Transport.

Drake, A.W. 1967. *Fundamentals of Applied Probability Theory.* New York, NY: McGraw-Hill Book Company.

Giuliano, G. 1989. Incident Characteristics, Frequency, and Duration on a High Volume Urban Freeway. *Transportation Research* 23A:387–396.

Golob, T.F., W.W. Recker, and J.D. Leonard. 1987. An Analysis of the Severity and Incident Duration of Truck-Involved Freeway Accidents. *Accident Analysis and Prevention* 19:375–395.

Hensher, D.A. 1997. Behavioral Value of Time Savings in Personal and Commercial Automobile Travel. *The Full Costs and Benefits of Transportation*. Berlin, Germany: Springer-Verlag, 245–280.

Jackson, W.B. and J.V. Jucker. 1982. An Empirical Study of Travel Time Variability and Travel Choice Behavior. *Transportation Science* 16.4:460–475.

Lindley, J.A. 1987. Urban Freeway Congestion: Quantification of the Problem and Effectiveness of Potential Solutions. *Journal of the Institute of Traffic Engineers* 57.1:27–32.

Margiotta, R.A., A.K. Rathi, M. Penic, and A. Dixson. 1997. Examination of Freeway Bottleneck Traffic Parameters Using FRESIM, unpublished manuscript.

MVA Consultancy. 1992. Quality of a Journey: Final Report, prepared for the United Kingdom Department of Transport, contract no. 02/c/5274.

Noland, R. B. and K.A. Small. 1995. Travel-Time Uncertainty, Departure Time Choice, and the Cost of Morning Commutes. *Transportation Research Record* 1493:150–158.

Noland R.B., K.A. Small, P.M. Kostenoja, and X. Chu. 1997. Simulating Travel Reliability. *Regional Science and Urban Economics* (Forthcoming).

Polak, J. 1987. Travel Time Variability and Travel Departure Time Choice: A Utility Theoretic Approach, discussion paper no. 15. Polytechnic of Central London.

Schrank, D.L., S.M. Turner, and T.J. Lomax. 1993. Estimates of Urban Roadway Congestion–1990, report no. FHWA/TX-90/1131-5. Washington, DC: U.S. Department of Transportation, Federal Highway Administration.

Senna, L.A.D.S. 1994. The Influence of Travel Time Variability on the Value of Time. *Transportation* 21:203–229.

Small, K., X. Chu, and R. Noland. 1997. Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation, NCHRP 2-18(2), draft. Washington, DC: Hickling Lewis Brod Inc.

Small, K.A., R.B. Noland, and P. Koskenoja. 1995. Socio-Economic Attributes and Impacts of Travel Reliability: A Stated Preference Approach, California PATH research report UCB-ITS-PRR-95-36. University of California, Irvine, CA.

Sullivan, E., S. Taff, and J. Daly. 1995. A Methodology for Measurement and Reporting of Incidents and Prediction of Incident Impacts on Freeways, report prepared for the U.S. Department of Transportation, Federal Highway Administration. San Diego, CA: Ball Systems Engineering Division.

U.S. Department of Transportation, Federal Highway Administration (USDOT FHWA). 1996. Exploring the Application of Benefit-Cost Methodologies to Transportation Infrastructure Decision Making, report no. 16, Policy Discussion Series. Washington, DC.

Wilson, P.W. 1989. Scheduling Cost and the Value of Travel Time. *Urban Studies* 26:356–366.

California Vehicle License Fees: Incidence and Equity

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ABSTRACT

Most states tax the value of residents' motor vehicles. In recent political debates over the future of these levies, the relative effects of these taxes on different socioeconomic groups have been a prominent question. By linking data from the Nationwide Personal Transportation Survey with estimates of vehicle values from consumer vehicle pricing guides, the socioeconomic and demographic incidence of California's Vehicle License Fee is examined. After the effects of state and federal income tax deductions are taken into account, the fee is found to be as regressive as the state's sales tax.

INTRODUCTION

Value-based assessments on motor vehicles, including personal property taxes and vehicle license fees, have emerged as a key focus of state-level tax-cutting efforts nationwide. This paper examines the incidence of one such tax, California's Vehicle License Fee (VLF), which has been assessed on all privately owned, registered vehicles in the state since 1935. It is a uniform, statewide property tax that was set, until recently, at 2% of a vehicle's value, based on its most recent purchase price and

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a fixed depreciation schedule. If the VLF had remained unchanged, it would have raised approximately \$3.9 billion in the 1998–99 fiscal year (State of California 1998).

Around the nation, concerns about equity have been at the center of many of the debates surrounding these tax cuts. In California, where a budgetary surplus led legislators to reduce the VLF by 25% last year, little information was available on how the benefits of this action would be distributed across the population. Because of this gap, the Senate Office of Research asked the California Policy Research Center and the Institute of Urban and Regional Development at the University of California, Berkeley, to prepare an analysis of the incidence of the fee. This paper grew from that research effort.

The VLF and its equivalents elsewhere pose interesting questions because they are distinct from other transportation-related taxes. Unlike many other taxes, the VLF bears no relationship to costs or benefits from use of the transportation system. Some transportation-related taxes seek to recapture some external benefits by taxing actual system use (crossing a bridge or tunnel, consuming gasoline) or by taxing the wealth derived from the system (real property, since local streets confer the property with value by providing access). Other taxes are assessed in some rough proportion to the impacts that a user places on the system, simply by participating (e.g., registering a vehicle) or by imposing specific externalities (e.g., causing road damage from excessive axle weight, driving during rush hour, etc.).

The VLF does not fit any of these categories; instead, it is loosely related to individuals' ability-to-pay. But unlike other levies that rely on current expenditures to reveal ability-to-pay, such as the vehicle sales/transfer tax or the general sales tax, the VLF targets a portion of wealth that is derived from past expenditures.

Another unique characteristic is that the VLF is typically not earmarked for transportation-related expenditures. Because of its origins as a local tax on personal property, it continues to be used as a source of local general revenue. As a result, it is not easy to determine how VLF revenues are spent. For this reason, we focus more narrowly on the incidence of the tax burden imposed by the VLF.

Finally, because it is not based directly on expenditures in the marketplace or on easily observable characteristics of vehicles or travelers, the VLF is difficult to measure. As a result, the implications of this tax are not as well understood as those of other taxes, despite the tax's magnitude in many states.

METHODOLOGY

The methodology and assumptions used in this research are outlined briefly here and described in detail in the appendix. Before the 1998 tax cut, the California Department of Motor Vehicles (DMV) charged the VLF annually for each vehicle, using the following formula (equation 1) and a depreciation schedule (table 1):

$$VLF = 0.02 \times \textit{initial vehicle value (rounded to nearest \$100)} \times \textit{depreciation factor} \quad (1)$$

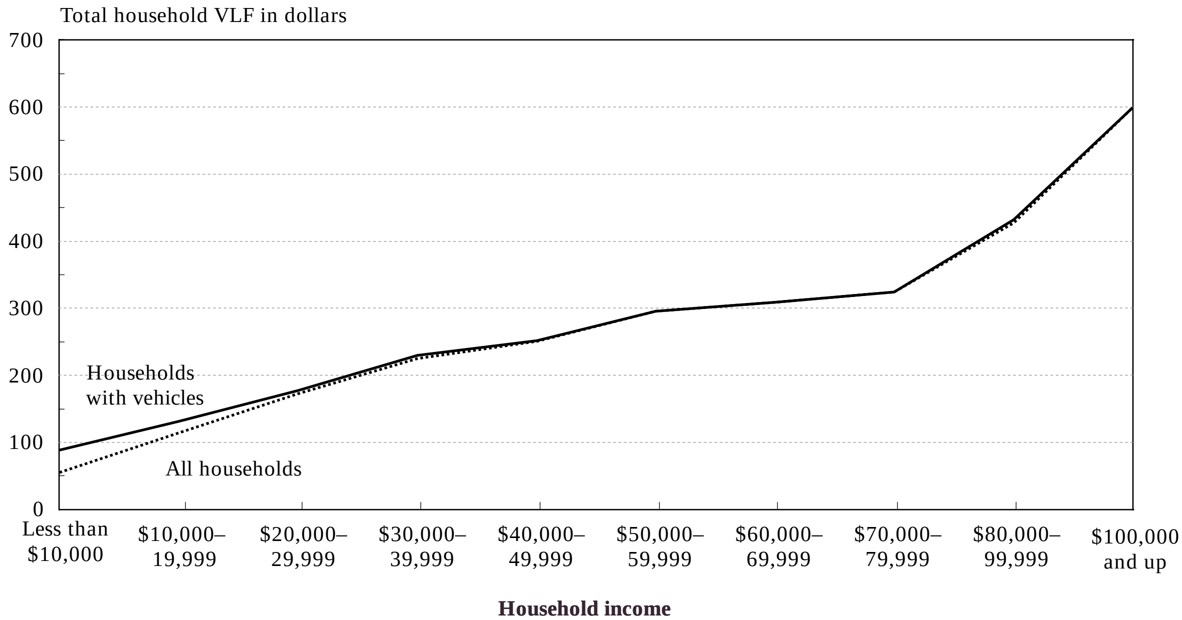
Therefore, two pieces of information on each household vehicle are needed to calculate the VLF: 1) purchase price (or reported value) of the vehicle when it was first registered by the current owner, and 2) initial year of vehicle registration by the current owner, which determines the depreciation factor. While the DMV collects the VLF, it does not gather data on household income or demographic characteristics needed for an incidence analysis. Moreover, raw DMV data on vehicle registrations were not available for this study.

Instead, we relied on an alternative source, the 1995 Nationwide Personal Transportation Survey (NPTS). The NPTS sample includes 2,262 households in California, which collectively have over

TABLE 1 VLF Depreciation Schedule

Year of registration	Depreciation factor (autos)
1	100%
2	90%
3	80%
4	70%
5	60%
6	50%
7	40%
8	30%
9	25%
10	20%
11 and later	15%

FIGURE 1 Average Total Household Vehicle License Fees



4,200 vehicles available for regular use. Using the NPTS required a number of assumptions for initial value and year of acquisition. Where the acquisition year of vehicles was not known, we assumed that: 1) new vehicles were acquired the same year as the model year and 2) used vehicles were acquired halfway between the model year and the year of the survey. Based on these estimated purchase dates, plus vehicle make and model information from the NPTS, we estimated vehicle purchase values using standard vehicle pricing guides.

FINDINGS

How Do VLF Payments Vary with Income?

In 1996, the average California household paid $247 in VLFs. Total household VLFs ranged from $55 for households with annual incomes under $10,000 to $599 for households with incomes over $100,000[1] (see figure 1). The 25% reduction in the VLF will save the households with the lowest incomes an average of $13.75. The average household will save $61.75, and households in the highest income group will save nearly $150.

Approximately 5.7% of California households do not own or lease any vehicles and, therefore, do not pay the VLF. These households will not benefit from the tax cut, unless they purchase or lease a vehicle in the future. More than one-third of households with incomes less than $10,000 do not own or lease vehicles; excluding these households, the average total VLF payment for this income group is $88 per year.

VLFs increase with income because wealthier households tend to own more vehicles, and the vehicles they own tend to be newer and more expensive (see figure 2). The average number of vehicles per household levels off at about 2.25 for the highest income households, but the value of each vehicle continues to increase.

Figure 3 shows the range of total VLF paid by different income groups. The median is the 50th percentile: half of the households pay more than that amount, and half pay less. The 90th percentile line represents the total VLF below which 90% of the households in an income category pay; 10% of the households in that income category pay more than that amount. Similarly, the 10th percentile line represents the amount of VLF below which the

[1] In figure 1, the total VLF appears to rise sharply for households in the highest two income categories. However, note that the highest two income categories ($80,000–99,999 and $100,000 and above) are broader than the other categories, which are in $10,000 increments. This difference in increment is due to the data source and makes the increase in the VLF appear sharper than it should.

FIGURE 2 Average Value and Vehicle Counts per Household

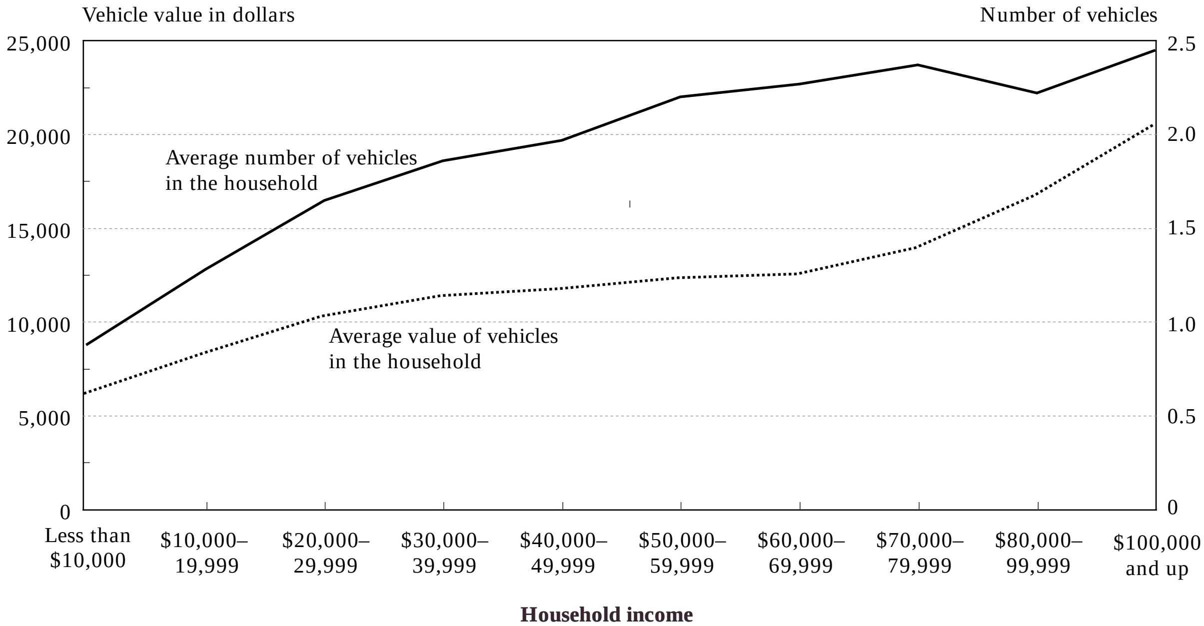
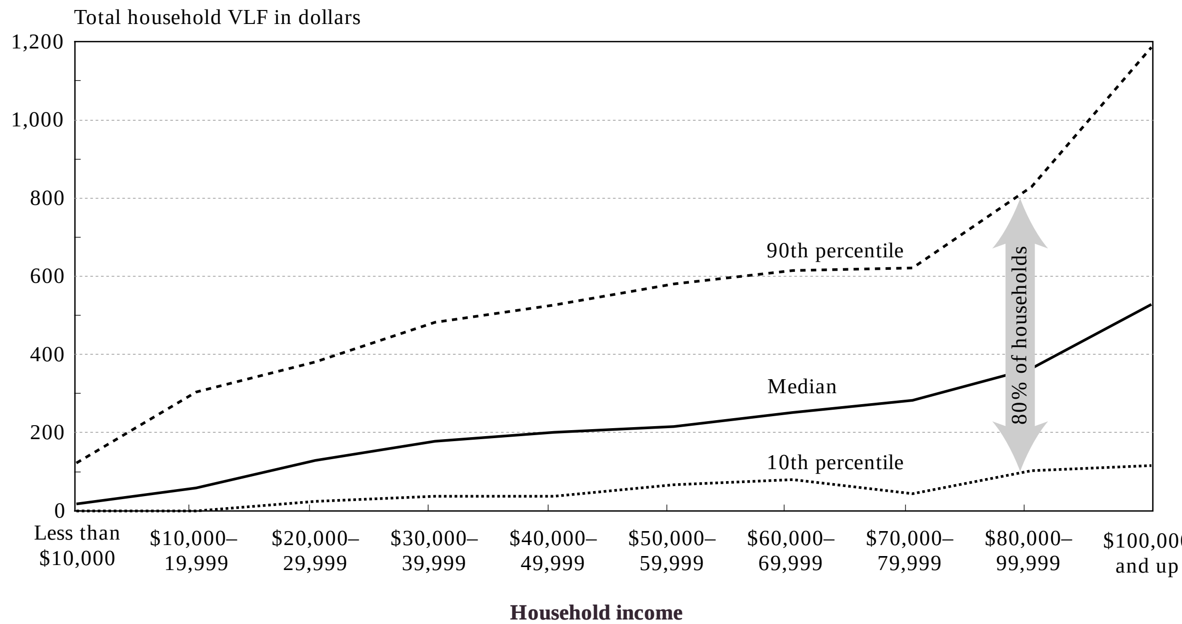


FIGURE 3 Total VLF by Income: 10th, 50th, and 90th Percentiles

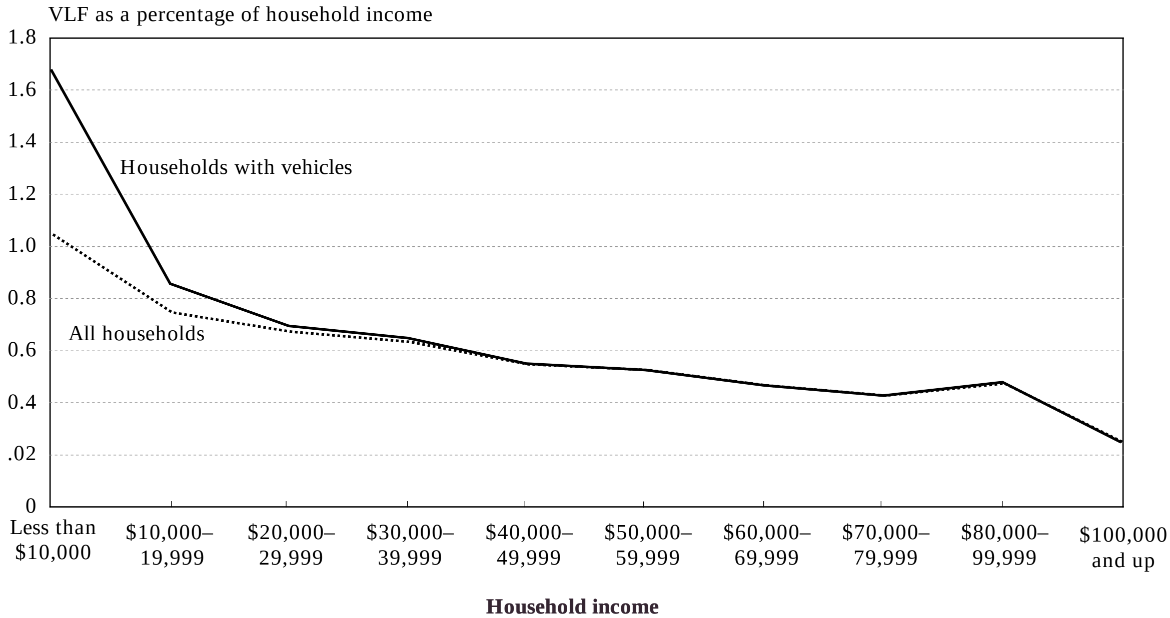


lowest 10% of households in that income group pay. Therefore, 80% of the households pay a total VLF within the range between the 10th and 90th percentile lines.

Is the VLF Equitable?

Discussions of equity in transportation finance usually focus on measures of horizontal equity (fairness across different user groups, demographic groups, or geographic areas) and/or vertical equity (fairness across different income groups). In both cases, the *net benefits* to each group are of primary importance. However, because the revenues from the VLF tend not to be targeted for transportation expenditures, it is not possible to compare the costs and benefits. We, therefore, focus exclusively on the cost side of the equation.

FIGURE 4 Total VLF as a Percentage of Household Income



On average, the California VLF consumes 0.61% of annual household income. The VLF's impact relative to household income declines as income rises (see figure 4), indicating that this is a regressive tax. Overall, the poorest households pay an average of 1.05% of their income in VLFs; this value rises to 1.68% for low-income households that own vehicles. For vehicle-owning households with incomes less than $10,000, the 25% cut in the VLF will be most noticeable: on average, it will save them nearly 0.5% of their annual incomes.

The regressivity of the VLF is heightened when interactions with other taxes are taken into account. Households can significantly reduce their net VLF payments by deducting personal property taxes (including the VLF) from their taxable income. The vast majority of the benefits of this tax rule accrue to upper income households (see figure 5). There are two reasons for this: higher income taxpayers tend to be more likely to itemize deductions, and they benefit more from doing so, since they have higher marginal tax rates. Most families (84%) do not claim a deduction for the VLF. However, including the majority who do not claim this deduction, the average household at the highest income levels wins back one-quarter of its VLF bill when it pays income taxes. The average household at the lowest income levels saves only 2% of its VLF payments through tax deductions.

A different perspective on equity can be seen by comparing the percentage of the total fee paid by a certain group with the percentage of the total population that group represents. This analysis is shown in figure 6. Households with incomes below $10,000 pay under 2% of the total VLF collected, while they represent over 7% of the households in California. The transition appears to occur near $40,000: households above this level pay 55.7% of the VLF, while representing only 39.8% of the population. Any proportional reduction in the tax rate will have a greater absolute benefit for these higher income households.

How Does the VLF Compare with Other Taxes?

As discussed earlier, license fees based on vehicle values are only one of many different taxes and fees that vehicle owners pay. Other types of assessments include registration fees, vehicle sales and transfer taxes, gasoline taxes, wheel taxes, weight taxes, title fees, emissions charges, and special interest or personalized license plate fees.

Some predictions can be made concerning the relative regressivity of various tax options. In general, taxes that target discretionary expenditures will be less regressive than those that target essen-

FIGURE 5 Household VLF, Adjusted for Income Tax Deductions

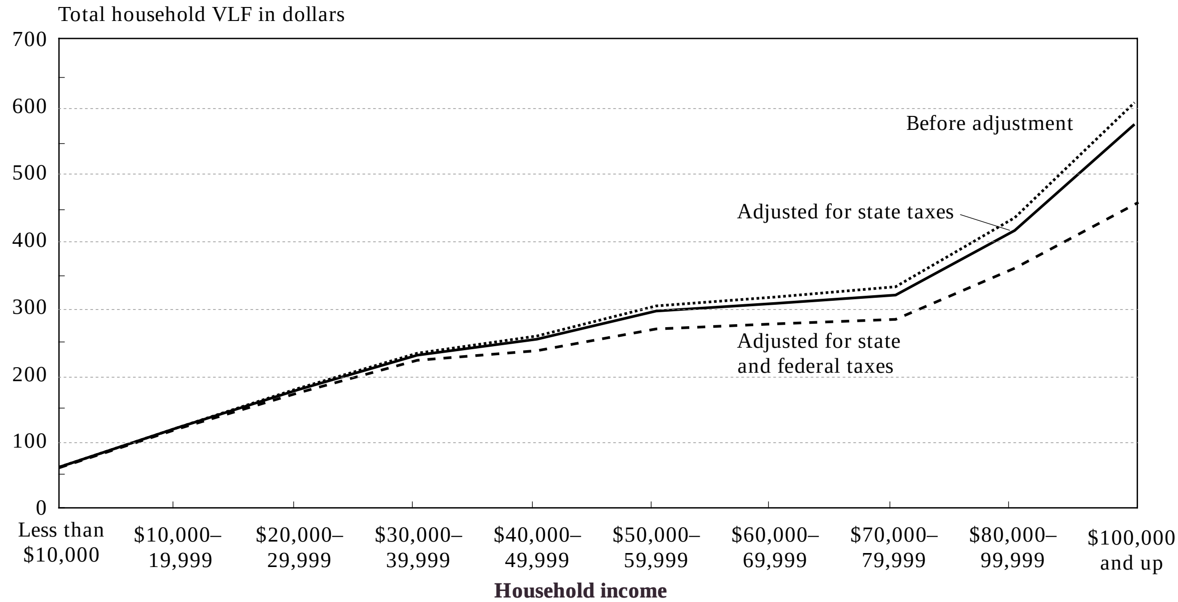
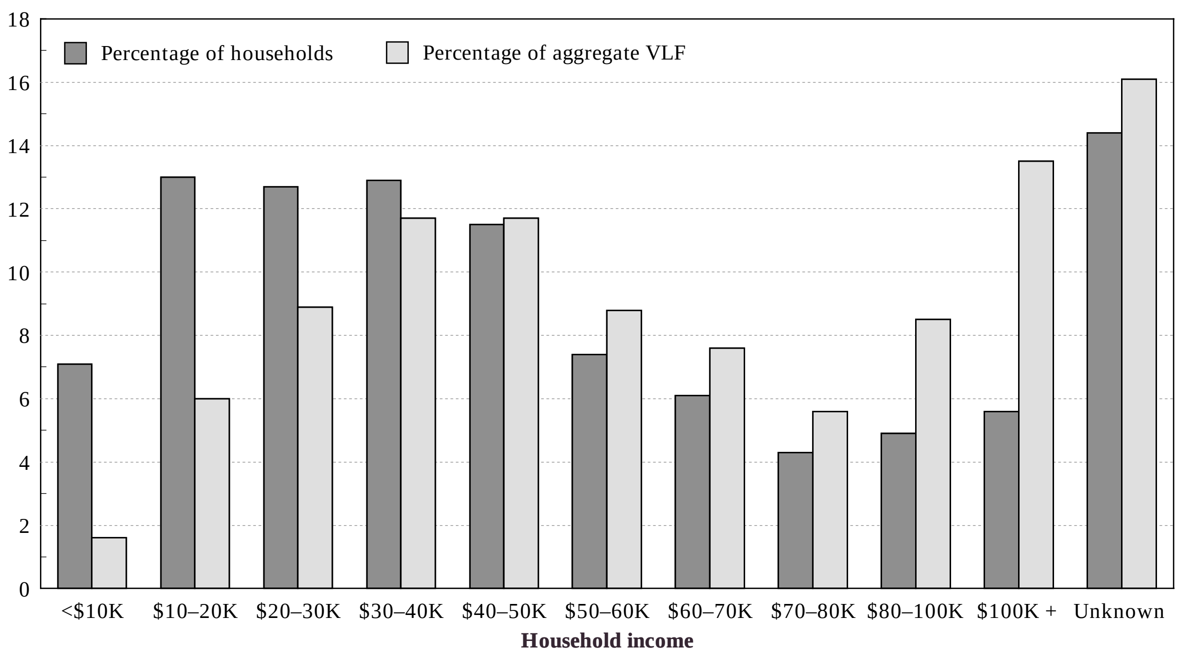


FIGURE 6 Percentage of Households and Aggregate VLF Paid



tial expenditures. In California, the regressivity of the sales tax is alleviated somewhat because the least discretionary expenditures—food, utilities, and some health-related products and services—are exempt from the tax. This is not the case for the gas tax, which remains highly regressive because a high proportion of the state's poor population is automobile dependent.

The VLF is expected to be less regressive than these other taxes. The choice of vehicle is highly discretionary: the age, value, and number of vehicles a family owns is strongly influenced by family income. However, unlike sales and gasoline taxes, the VLF is deductible from state and federal income taxes, a policy that disproportionately benefits higher income groups.

FIGURE 7 Tax Burden vs. Income in California: 1995

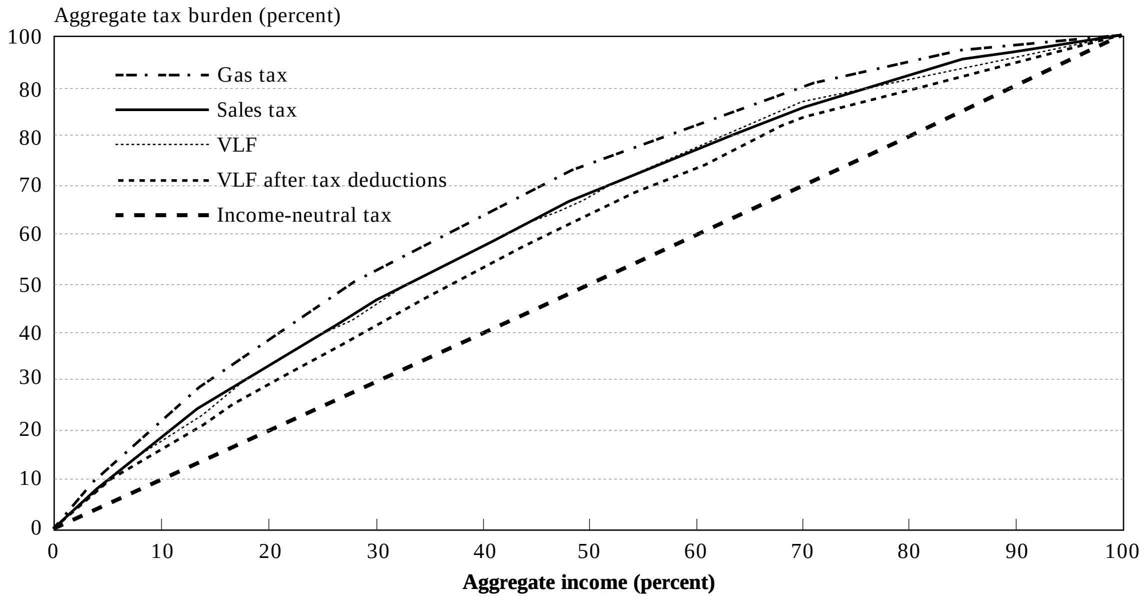
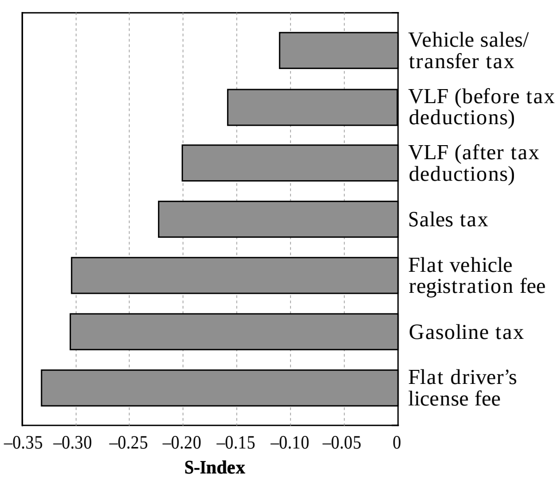


FIGURE 8 Relative Regressivity of Various Taxes and Fees



One way of comparing the relative incidence of different taxes is to plot the aggregate percentage of the tax burden against the aggregate percentage of total income. Figure 7 compares the VLF results with data on the incidence of gasoline and sales taxes (Citizens for Tax Justice 1996). The results confirm the expectations described above: the gas tax is the most regressive, followed by the sales tax, and ultimately by the VLF. After the tax deductibility of the VLF is taken into account, the VLF is extremely similar to the sales tax.

These relationships can be quantified using the S-Index (Suits 1977), which relates the area under the tax incidence curve to the area under the line representing income neutrality. The S-Index ranges from +1 (extreme progressivity) to –1 (extreme regressivity), with a value of 0 indicating a tax burden equitably distributed across incomes. The index has been applied before to the analysis of transportation taxes, based on data from the Consumer Expenditures Survey (Rock 1982, 1990). It has also been used to evaluate the incidence of vehicle emissions taxes, based on data from the NPTS (Walls and Hanson 1996).

The relative regressivity of various transportation-related taxes and fees in California is shown in figure 8.[2] Values for VLFs, before and after tax deductions, are based on data produced in this study. Values for the flat registration and driver's license fees were derived from the NPTS database by multiplying a flat fee by the number of vehicles and the number of drivers in each household, respectively. Values for the sales and gasoline taxes

[2] Household income quintiles were used to calculate the values in figure 8. Because the tax incidence curve is concave, the use of coarse income categories underestimates the area under the curve and thus understates the actual regressivity of the taxes. Although richer detail is available for each of the taxes examined here, the income ranges are not compatible across data sources, and quintiles must be used to ensure comparability.

were derived from a study that estimated the distribution of payments of these taxes in California in 1995, based on the Consumer Expenditures Survey (Citizens for Tax Justice 1996). Values for the vehicle sales/transfer tax were derived directly from 1994/95 Consumer Expenditures Survey data for the western United States (USDOL 1994–1995).

Of these tax options, the vehicle sales/transfer tax is the only one more progressive than the VLF. This is consistent with the theoretical predictions outlined above since households have greater discretion in their decisions to *purchase* vehicles than they do in their decisions to *own* vehicles. Lower income households tend to make these purchases less frequently because they hold on to their cars for longer periods of time.

How Do VLF Payments Vary with Household Location and Demographics?

The average household VLF was compared across several demographic variables, including race and ethnicity, family life cycle category, age, and location. For example, figure 9 displays the results of an analysis of how the VLF as a percentage of household income varies by family life cycle category. There are three noteworthy patterns in these results: 1) households comprised of two or more adults pay greater VLF in comparison to their incomes, 2) nonretired households without children pay more (probably because they are able to devote more of their resources to automobile purchases), and 3) households with older teens pay more (probably because their ownership of an extra car is not fully compensated by the salary that a teenager can earn). A key question is whether the VLF places a disproportionate economic burden on retirees, given their relatively low fixed incomes. Figure 9 suggests that retired families do not bear higher costs relative to their means.

Table 2 shows the total household VLF for households of different races and Hispanic ethnicity, along with factors that directly influence VLF payments: the number of vehicles per household, the initial value of the vehicle, and the number of years household vehicles were registered.[3] Asian households pay the highest average VLF, while African-American and Hispanic households pay a lower average VLF. Households in the San

[3] Household race is based on the race of the "reference person" for the survey. The reference person is the person or one of the persons who owns or rents the home.

FIGURE 9 VLF as a Percentage of Household Income, by Life Cycle Category

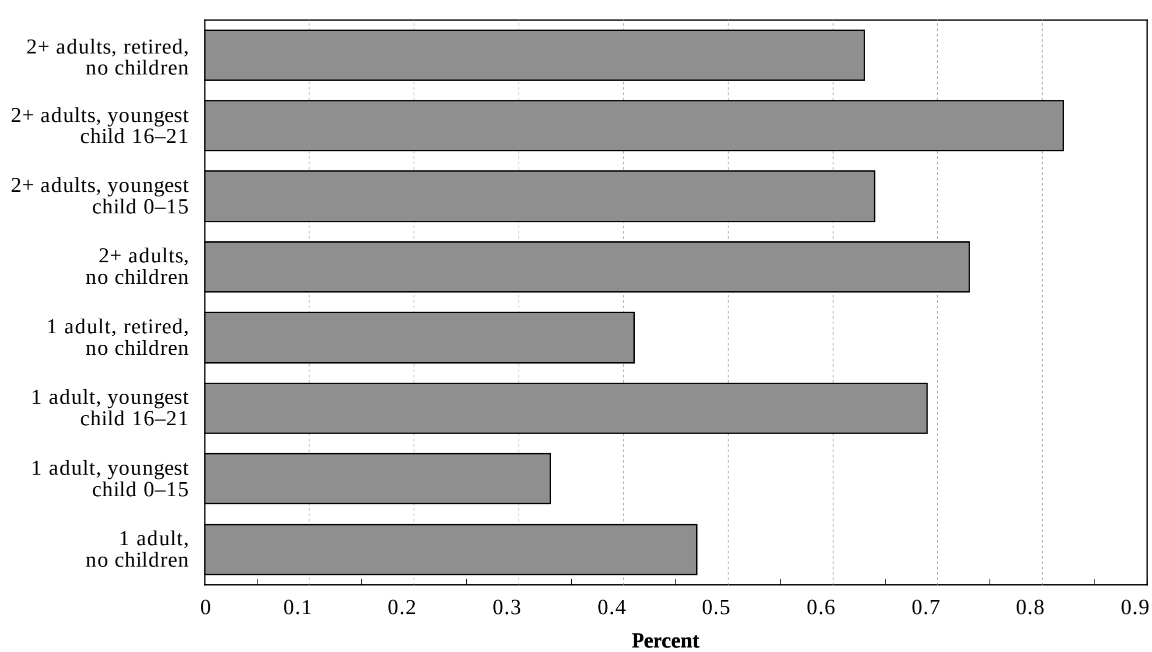


TABLE 2 VLF Payments by Race and Ethnicity

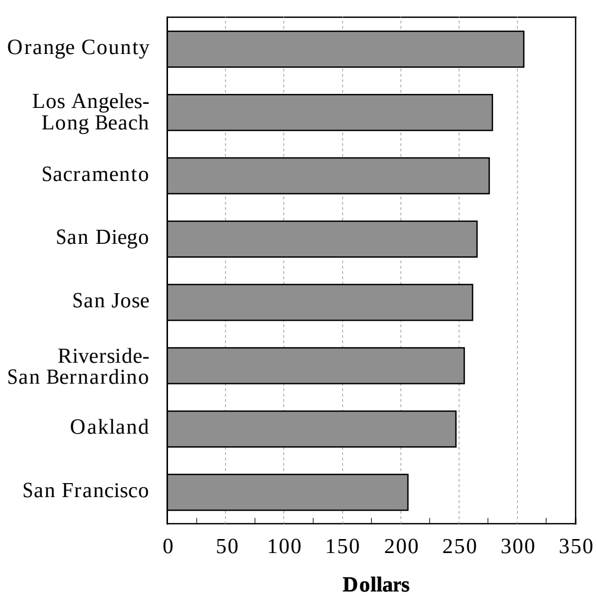
	Total VLF per household	Vehicles per household	Initial value of vehicle	Length of vehicle registration (years)
Asian	$297	2.02	$13,500	6.1
White	$252	1.85	$12,110	7.0
African-American	$210	1.46	$11,970	6.8
Other	$227	1.82	$10,290	6.4
Non-Hispanic	$257	1.85	$12,410	6.9
Hispanic	$205	1.72	$ 9,780	6.4

Francisco metropolitan statistical area (MSA) pay the lowest average VLF of the state's MSAs ($206), while Orange County MSA residents pay the highest ($306), as shown in figure 10.

The differences in VLF payments by life cycle, race, and region are of interest to political decisionmakers when evaluating tax-cut proposals. However, a regression analysis demonstrates that many of the differences in VLF payments between households disappear after controlling for income and the number of vehicles or drivers per household. Table 3 shows the results of a stepwise, least squares linear regression model with total household VLF payments as the dependent variable (model 1).

As expected, households with higher incomes and more vehicles pay greater VLFs. Additional significant variables include white households and the San Francisco and Oakland MSAs. The significance of the latter two variables suggests that urban form or the existence of a regional rail system may enable some households to defer expenditures on vehicles. However, as noted at the bottom of the table, the adjusted r^2 for a model with only income and number of vehicles as independent variables is identical to the model with the additional variables.

FIGURE 10 Mean Total Household VLF by MSA



Models 2, 3, and 4 employ three different dependent variables: the number of household vehicles, the average initial value of the household vehicles, and the average length of vehicle registration in years, respectively. As described earlier, total household VLF payments were calculated directly from the initial vehicle value and the length of registration for each household vehicle, applying equation 1. Therefore, any relationship between household characteristics and VLF payments enters through one or more of the three dependent variables shown in models 2–4.

Several factors are significant when estimating vehicle ownership (model 2). For example, senior households have fewer vehicles, as do African-American, Hispanic, and San Francisco households. However, these additional variables do little to explain vehicle ownership beyond income and the number of drivers. The adjusted r^2 for the complete model is 0.47, compared with 0.46 for a reduced model with only income and number of drivers as variables.

Model 3 shows that, even after accounting for income, some household characteristics may have an impact on the purchase price of vehicles. For example, having more children in a household correlates with lower value cars, indicating that households with children may divert income from vehicle purchases to other expenses. Asian house-

TABLE 3 Ordinary Least Squares Regression Models

	Model 1	*Model 2*	*Model 3*	*Model 4*
Dependent variable	**Total household VLF**	**Number of household vehicles**	**Average inital vehicle value**	**Average length of vehicle registration (years)**
Relationship to VLF		*Positive*	*Positive*	*Negative*
Constant	–18.82 (–1.32)	0.32*** (6.42)	9,219.16*** (33.58)	6.69*** (23.16)
Household income ($1,000)	1.55*** (16.74)	0.002*** (6.22)	49.5*** (18.02)	–0.006*** (–3.86)
Number of vehicles	116.70*** (22.42)	n.a.		0.53*** (4.24)
Number of drivers		0.84*** (33.20)		–0.65*** (–3.71)
Number of children			–377.30* (–2.53)	
Teen in household (1 = yes)		–0.16** (–2.90)		–0.52[a] (–1.78)
Senior household (average age 70)		–0.18** (–3.04)		2.58*** (7.91)
White head of household	–30.66* (–2.50)			
Asian head of household			1,418.47* (2.16)	
African-American head of household		–0.25** (–3.42)		
Hispanic head of household		–0.15** (–2.63)	–1,702.05** (–3.21)	
Urbanized area (1 = yes)		0.15** (3.26)		
San Francisco MSA	–44.10* (–2.14)	–0.14* (–2.00)		1.04** (2.74)
Oakland MSA	–53.06** (–2.96)			0.73* (2.23)
Orange County MSA			1,834.79** (3.23)	
Los Angeles-Long Beach MSA			895.76* (2.26)	
Adjusted r^2	0.38	0.47	0.18	0.07
N	1,807	1,864	1,708	1,708
Adjusted r^2 for model with only income and number of vehicles as independent variables	0.38	0.09 (Income only)	0.17	0.01
Adjusted r^2 for model with only income and number of drivers as independent variables	0.29	0.46	0.17	0.02

Key: *p < 0.05; **p < 0.01; ***p < 0.001; [a]p = 0.075.

Note: Variables excluded from all models—San Jose, Sacramento, San Diego, and Riverside-San Bernardino MSAs, and number of adults.

holds and households in Los Angeles-Long Beach and Orange County spend more on vehicles, even after controlling for income. However, as with model 2, these additional variables add little to explain the model beyond the income variable. The adjusted r^2 for the full model is 0.18, compared with 0.17 for a reduced model with only income and the number of vehicles or drivers as variables.

The average length of time a vehicle has been registered determines the depreciation factor used to calculate the VLF. The estimated coefficients (model 4) confirm expectations: a negative relationship between income and length of registration and a positive relationship between the number of vehicles in the household and length of registration. In addition, senior households hold on to their vehicles longer, as do residents of the San Francisco and Oakland MSAs. These last two variables carry through to total household VLF payments (model 1), where San Francisco and Oakland households are seen to pay lower VLFs. Overall, however, the variables in model 4 explain less than 10% of the variation in the data (adjusted $r^2 = 0.07$). In contrast to models 1–3, the income and number of drivers or vehicles variables do not account for a large portion of the explanatory power of Model 4.

APPLICABILITY TO OTHER STATES

The taxation of the value of motor vehicles is not unique to California. At the beginning of 1998, 31 states had some form of value-based vehicle license fee (Mackey and Rafool 1998). These taxes have been receiving increased political attention in recent years. Indiana started the trend, cutting its vehicle taxes by up to 50%. Soon afterwards, James Gilmore III was elected Governor of Virginia, after making elimination of the state's "car tax" a centerpiece of his campaign. His victory helped to catapult the issue into the national spotlight. By the end of 1998, at least seven other states (Arizona, California, Nebraska, Rhode Island, Utah, Virginia, and Washington) had reduced, restructured, or eliminated their VLFs, and voters in Kentucky had amended their state constitution to enable the repeal of their VLFs. In 1999, expanding state budget surpluses are continuing to fuel calls for VLF cuts.

The magnitude of these taxes varies significantly around the country: in 1998, rates ranged from 1% of vehicle value in Iowa to 7.68% of vehicle value in Rhode Island (Lopez 1998). Sixteen states set uniform rates, with taxes collected either by local governments or the state, in which case revenues are usually recycled back to local governments. Tax rates are set by local jurisdictions in 12 states, and 3 states have hybrid systems. Among the states with uniform rates, the median annual tax rate was 1.8% of assessed vehicle value (Mackey and Rafool 1998).

The method of determining the value of vehicles subject to taxation also varies significantly among the states. Four broad methods are used to establish these values (Mackey and Rafool 1998):

- *Most recent purchase price* (California and Indiana). In these states, a fixed schedule is used to determine the depreciated value of the vehicle in subsequent years.
- *Manufacturer's standard retail price* (Arizona, Colorado, Maine, Massachusetts, Michigan, Minnesota, Montana, Nebraska, Nevada, New Hampshire, Oklahoma, Washington, and Wyoming). This is also used with a fixed depreciation schedule.
- *Market value*, determined by a standard pricing guide, local assessor, or state commission (Alabama, Alaska, Arkansas, Connecticut, Georgia, Kansas, Kentucky, Mississippi, Missouri, North Carolina, Rhode Island, South Carolina, Texas, Utah, Virginia, and West Virginia). Depreciation occurs naturally according to market demand.
- *Vehicle vintage* (Alaska, Utah).[4] This is only a very rough proxy for vehicle value.

Although each state has a unique method for assessing its vehicle property taxes, the general approach outlined in this paper should be applicable elsewhere. In most states, the tax basis is simply determined by the list price and purchase year, purchase year alone, or fair market value. These can be determined from consumer pricing guides, the method most often used by the state governments. However, since most transportation surveys

[4] Local jurisdictions in Alaska may choose between assessing a property tax and a vintage-based registration tax. Utah shifted from a market value-based property tax to a vintage-based user fee in 1998.

do not provide enough information to pinpoint either list price or market value exactly, some price averaging within a model family will still be necessary.

License fees in California and Indiana are more difficult to model because they are based on actual purchase price and year, neither of which are included in the NPTS. As a result, purchase year and price had to be estimated on the basis of data that the NPTS provides. We estimated the values of vehicles purchased new from the list price. The values of vehicles purchased used were estimated from the market value in the year they were estimated to have been purchased (see the appendix for a full discussion of our methodology).

The limited size of the NPTS sample in any single state may be overcome by pooling data from several nearby states. The finding that regional differences were significant in predicting VLF payments—even after income and number of drivers were taken into account—suggests that urban form factors merit particular attention when assembling a sample.

CONCLUSIONS

Annual taxes or fees based on the value of motor vehicles are a significant source of income to state and local governments. They have recently received a great deal of public attention as states consider their financial futures and as public officials and candidates propose major changes in the ways in which these charges are levied. We found surprisingly few studies of the mechanisms by which the VLF is levied, of the uses to which the proceeds of the fees are put, or of the incidence of the fees according to spatial, demographic, or economic characteristics of the population.

This study found that VLF payments increase substantially with income because car ownership and the value of vehicles both increase with income. Although upper income citizens of California pay much more through their VLF payments than do poorer people, the VLF is a regressive tax in that it takes from households a declining proportion of income as income rises. When the income tax deductibility of the VLF is taken into consideration, regressivity increases. The analysis showed some interesting differences in VLF payments by ethnicity and area of residence, but most of this variability could be explained by differences in income and number of drivers in households.

This study examined the incidence of VLFs levied against light-duty motor vehicles held by California households. We did not look into the economic or fiscal issues related to the VLF paid by California's commercial vehicle fleet, which includes medium- and heavy-duty trucks and light-duty vehicles owned and operated by fleets, as well as rental vehicles. Since fleet vehicles tend to be newer than vehicles held by households and fees are based on vehicle value, it is reasonable to conclude that fleet vehicles are responsible for a higher proportion of VLF revenues than their simple proportion of the fleet would suggest. Examination of the incidence of fleet and commercial VLFs would be a logical extension of this study and would require a substantial investment in data collection and analysis.

APPENDIX: METHODOLOGY FOR ESTIMATING VLF INCIDENCE

The evaluation of VLF payments by households requires a database that combines household demographic characteristics (income, race, life cycle characteristics, etc.) with detailed information on household vehicles (i.e., purchase year and purchase price). We used the 1995 NPTS sample of 2,260 households in California (USDOT 1997a, 1997b). For each vehicle in a household, respondents provided information on the vehicle make (e.g., Ford), model (e.g., Taurus), model year, and whether the vehicle was acquired new or used. The survey includes all vehicles that the household owned or had available for regular use, including home-based vehicles that are actually owned by businesses.

Methodology

Two pieces of information on each vehicle owned by a household are needed to calculate the amount of VLF paid: 1) purchase price (or reported value) of the vehicle when it was first registered by the current owner and 2) initial year of vehicle registration by the current owner. Purchase price was not collected in the NPTS survey, and the date of acquisition was collected only for vehicles acquired in the most recent 12 months. Therefore, both pieces of information had to be estimated.

1. Estimate of Vehicle Purchase Year

For vehicles purchased during the previous 12 months, the exact month and year of purchase were recorded. Where this information was not recorded, the following assumptions were used to estimate the vehicle purchase year:

- *Vehicles acquired new* were assumed to have been acquired in the vehicle's model year. While some of these vehicles were purchased when new models were introduced the previous summer or fall (e.g., a 1997 car bought in late 1996) and some new models are purchased the following year (e.g., a new 1996 car bought in 1997), this simplifying assumption is adequate for this level of analysis.
- *Vehicles acquired used.* The year of acquisition was estimated as the midpoint between the model year and the survey year. That is, a respondent owning a 1975 vehicle (purchased used) in the 1995 survey year was assumed to have purchased it in 1985.

2. Estimate of Vehicle Purchase Price

Initial purchase prices were estimated using the *Kelley Blue Book 1975–95* for automobiles, vans, pickup trucks, and sport utility vehicles, and the National Automotive Dealers Association's *NADA Motorcycle Appraisal Guide 1975–95* for motorcycles. The following assumptions were used in this analysis:

- *Vehicles acquired new* were assumed to have been purchased at list price.
- *Vehicles acquired used.* The wholesale and retail prices were obtained from the January issue of the appropriate *Blue Book* or *NADA Guide* for the estimated year of acquisition. Wholesale prices are what dealerships pay to purchase vehicles; retail prices are what consumers pay to purchase vehicles from a dealership. Vehicles sold between two private parties are typically sold at a price halfway between the wholesale and retail prices. Assuming that half of all used vehicles are sold by dealerships and half are sold directly by their owners, the purchase price of used vehicles was estimated to be:

$$\tfrac{1}{2}\,(retail + \tfrac{1}{2}\,(retail + wholesale)) \qquad (2)$$

- *"Average" model prices.* The NPTS defines vehicle models more broadly than the *Blue Book*. For example, the NPTS may identify a vehicle only as a Ford Taurus, whereas the *Blue Book* provides separate prices for the Taurus GL Sedan and Wagon, SE Sedan, LX Sedan and Wagon, and SHO Sedan. In these cases, prices were estimated as the average of the high and low values for all submodels within a model family.
- *"Typical" options packages.* The *Blue Book* prices are based on standard packages of options, determined by the vehicle's class and model year. All vehicles in this analysis were assumed to have this typical package of options.

Using this methodology, we obtained initial vehicle values for over 90% of the vehicles from the NPTS California sample. Missing values were most often due to missing data, such as incomplete make or model information. In addition, we excluded recreational vehicles and medium- and heavy-duty trucks from the analysis because no price guide was available for these vehicles (there were fewer than 30 of these in the California sample). Finally, we excluded model years 1918 through 1964 because NPTS assigned all of these to model year 1955 (there were fewer than 50 of these in the California sample), preventing meaningful value estimates.

The estimated purchase prices were compared with findings published by the State of California's Legislative Analyst's Office (1998). This comparison is shown in table 4. Overall, the data from the NPTS-based estimation are consistent with the Legislative Analyst's report. The estimation based

TABLE 4 Comparison of Initial Purchase Price Estimates

Purchase price	Estimates from NPTS & *Blue Book*	Legislative Analyst's Office (1998)
Less then $5,000	23%	27%
$5,000–9,999	23%	23%
$10,000–14,999	23%	19%
$15,000–19,999	18%	15%
$20,000–24,999	8%	8%
$25,000–29,999	2%	4%
$30,000–34,999	1%	2%
$35,000 and above	2%	2%

on the NPTS data has slightly fewer vehicles valued at less than $5,000 and more vehicles valued between $10,000 and $19,999. With the estimated acquisition year and vehicle value, the 1996 VLF for each vehicle was estimated using equation (1) and the depreciation schedule in table 1.

The average VLF per automobile (including cars, pickup trucks, vans, and sport utility vehicles) estimated from the NPTS data was $136 in 1996. The average for motorcycles was $55. The Legislative Analyst's report estimated the average automobile VLF in 1997 as $171 and the average motorcycle VLF as $57 (State of California 1998). The difference in the average automobile VLF may be due to the fact that the NPTS data include only household vehicles. The DMV data used for the Legislative Analyst's estimate include vehicles owned by businesses, including rental-car and other fleets. These vehicles are likely to be newer, i.e., registered for fewer years, and would incur a higher VLF. For example, we estimated that the average VLF for rental vehicles is $349 (Dill et al. 1999).

3. Estimate of Income Tax Deductions

Although the VLF is deductible from state and federal income taxes, relatively few taxpayers claim this deduction. Nonetheless, because the tendency to itemize tax deductions varies with income, it is appropriate to estimate how this affects the actual incidence of the tax.

Data supplied by the California Franchise Tax Board (FTB) were used for this part of the analysis. Based on the FTB's weighted sample of 100,000 California tax returns, average marginal tax rates and percentage of households itemizing deductions for personal property tax payments were estimated for each income group and filing status category. This involved the following assumptions:

- *Households vs. taxpayers.* The data from the FTB are a sample of taxpayers, not households. This creates potential problems if we wish to apply statistics from this sample to the households in our sample from the NPTS. First, some households with more than one adult (e.g., nonfamily households or married couples filing separately) may be overrepresented. In addition, businesses filing tax returns are included in the sample. Small businesses may comprise a large proportion of the returns at lower income levels, since low-income families are not required to file if they do not owe taxes.
- *Filing status.* Average marginal tax rates vary with the filing status (single, married filing jointly, etc.) of the taxpayer. Because the NPTS does not provide information on tax filing status, household life cycle categories were used as a proxy. Households with two or more adults were assumed to file taxes as "married couples filing jointly;" households with one adult and no children were assumed to file as "single" taxpayers; and households with one adult and one or more children were assumed to file as "head of household" taxpayers.
- *Personal property tax deductions.* Taxpayers may deduct state "personal property taxes" on their federal tax forms. For California residents, the VLF is the most significant of these taxes. We have assumed that all California taxpayers itemizing deductions for personal property taxes (about 16% of all filers) from their federal income taxes included the VLF in the amount that they deducted.

Based on these assumptions, the estimates for average marginal tax rates and percentage of households deducting personal property taxes were applied to each household on the basis of income and family life cycle. The estimated VLF was adjusted as follows:

$$VLF_{adjusted} = VLF \times (1 - (\%\ deducting\ VLF) \times (average\ marginal\ tax\ rate)) \quad (3)$$

Potential Sources of Error

Systematic errors in our analysis may potentially originate with the data themselves or with the assumptions that we applied in using the data.

- *Vehicle purchase dates.* The assumption that used vehicles were purchased halfway between their model year and the survey year may systematically underestimate VLF charges for older vehicles. Since cars built in the early 1970s were all assumed to have been purchased more than 10 years prior to the survey date, they were all assigned to the lowest VLF fee categories (15% to 20%), whereas in reality, some of these vehicles would have been purchased more recently.
- *Used-vehicle values.* The assumption that used-vehicle values are a function of the *Kelley Blue*

Book retail and wholesale values may systematically overestimate actual reported vehicle values. This is because many used vehicles are not in the "excellent" condition that corresponds to the *Blue Book* prices and because some purchasers of used vehicles may underreport vehicle sale prices to evade the state sales tax and the VLF.

- *New-vehicle values.* The assumption that new vehicles were purchased at list price may overestimate actual new vehicle values because some dealerships may sell below list price. It also masks price variations among vehicle submodels and options packages.
- *Tax deductions.* Some taxpayers running businesses may deduct the VLF as a business expense rather than as a personal property tax. These deductions are not counted in our analysis.
- *Company vehicles.* An unknown percentage of the vehicles in the sample are owned or leased by an entity other than the household, such as an employer. In many of these cases, the household does not pay the VLF directly or indirectly. Therefore, VLF may be overestimated for higher income households that are more likely to use company-owned vehicles.

The most important net effect of these errors is expected to be the combination of assumptions about vehicle purchase dates and vehicle values. In each case, the use of "average" values is likely to mask significant underlying income effects, leading to more level (and therefore more regressive) estimates of the relationship between income and VLF than actually exist.

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REFERENCES

Citizens for Tax Justice and the Institute on Taxation and Economic Policy. 1996. *Who Pays? A Distributional Analysis of the Tax Systems in All 50 States.* Washington, DC.

Dill, J., T. Goldman, and M. Wachs. 1999. *The Incidence of the California Vehicle License Fee.* Berkeley, CA: California Policy Research Center.

Kelley Blue Book. 1975–1995. *Kelley Blue Book Used Car Guide.* Irvine, CA.

Lopez, E. 1998. *Vehicle License Fee: A Comparison Among the Most Populous Cities of Each State*, CRB-98-0008. Sacramento, CA: California Research Bureau, California State Library.

Mackey, S. and M. Rafool. 1998. *State and Local Value-Based Taxes on Motor Vehicles.* Washington, DC: National Conference of State Legislatures.

National Automotive Dealers Association. 1975–1995. *NADA Motorcycle Appraisal Guide.* McLean, VA.

Rock, S.M. 1982. Applying the S-Index to Transportation Financing Alternatives. *Transportation Research Record* 858.

____. 1990. Equity of Local Option Taxes. *Transportation Quarterly* 44:3.

State of California, Legislative Analyst's Office. 1998. *A Primer on the Vehicle License Fee.* Sacramento, CA.

Suits, D.B. 1977. Measurement of Tax Progressivity. *American Economic Review* 67:4.

U.S. Department of Labor (USDOL), Bureau of Labor Statistics. 1994–95. Consumer Expenditure Survey.

U.S. Department of Transportation, Federal Highway Administration. 1997a. *1995 NPTS Data Files (CD-ROM)*, FHWA-PL-97-034. Washington, DC.

____. 1997b. *1995 NPTS User's Guide for the Public Use Data Files.* Washington, DC.

Walls, M. and J. Hanson. 1996. *Distributional Impacts of an Environmental Tax Shift: The Case of Motor Vehicle Emissions Taxes,* Discussion Paper 96-11. Washington, DC: Resources for the Future.

Freight Demand Characteristics and Mode Choice: An Analysis of the Results of Modeling with Disaggregate Revealed Preference Data

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ABSTRACT

Considerably less research has been done on modeling freight demand with disaggregate discrete models than on modeling passenger demand. The principal reason for this imbalance is the lack of freight demand data. Freight demand characteristics are expensive to obtain and are sometimes confidential. This paper analyzes the freight demand characteristics that drive modal choice by means of a large-scale, national, disaggregate revealed preference database for shippers in France in 1988, using a nested logit. Particular attention is given to private transportation (own account transportation) and combined public and private transportation. After aggregation and validation of discrete choice models, the influence of demand characteristics on freight modal choice is analyzed. The maximum probability of choosing public road transportation takes place at approximately 700 kilometers, while that of choosing rail transportation take place at 1,300 kilometers.

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INTRODUCTION

In France, freight is increasingly transported by road, which results in a variety of negative, external effects such as congestion, pollution, and accidents. This has led public authorities to attempt to reduce its predominance. One area of interest is intercity freight modal choice and the competition between rail and road. The French Ministry of Transport, in cooperation with other French transportation research organizations, the National College of Bridge and Roads (ENPC) and the French National Research Institutes for Transport and Safety (INRETS), has for the first time developed a freight analysis system that emphasizes the modeling of freight mode choice.

These discrete-choice models permit the construction of a very general utility function incorporating many freight demand characteristics and transportation service attributes. Freight modal choice depends on transportation demand and infrastructure as well as service supply characteristics. It thus embodies a trade off between generalized transportation costs and shippers' logistical costs. On the supply side, the principal explanatory variables that have been included in previous disaggregate models are alternative-specific transportation service variables, such as transportation cost and transit time, frequency, and damage rates (Daugherty 1979, Van Es 1982, Gary 1982, Fowkes and Tweddle 1988, Widlert and Bradley 1992). However, on the demand side, few studies have attempted to systematically establish a relationship between mode choice and freight demand characteristics. The chief reason for the absence of freight demand analysis is the difficulty in collecting the necessary data, due to the great heterogeneity of firms and to questions of confidentiality and reliability of data (Ortuzar and Willumsen 1994). Thus, the influence of demand characteristics on freight mode choice has not been sufficiently understood.

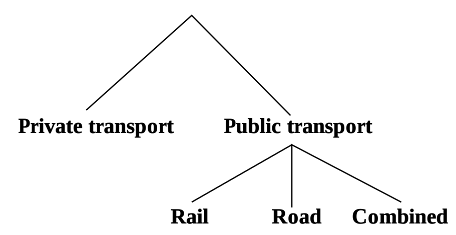
In fact, demand characteristics, such as the attributes of the shipper, the attributes of the goods to be transported, and the spatial attributes of shipments, strongly influence modal choice. Any change in these characteristics can make shippers' demands for transportation service change considerably, often leading to the choice of a new transportation mode. In order to provide a quantitative evaluation of freight demand characteristics, INRETS carried out a shippers' survey in 1988 for its freight research and development program. The survey was carried out by professional investigators who interviewed the logistics managers of industrial and commercial enterprises. The first step they took was a presurvey aimed at finding a suitable methodology for the quantification of transportation demand. The second step, the principal survey, proceeded according to a sample design that ensured representation at the national level. Selected by activities, size, and other characteristics, 1,742 industrial and commercial firms distributed in 21 regions and 20 economic sectors were requested to provide information on three shipments. The principal survey thus included 5,110 shipments. The questionnaire was comprised of three parts that dealt with 1) the characteristics of the firms, either shippers or receivers, 2) the physical characteristics of the shipment, such as type of goods, size, cost, and packaging, and 3) information about the linkages and itinerary of the shipment. The resulting database covers 51 quantitative and qualitative characteristic variables. Transportation service attributes, such as transportation time and cost, were also requested, but, unfortunately, very few shippers answered the questions for reasons of confidentiality and lack of knowledge about service attributes (Gouvernal and Hanappe 1986, Bredeloup et al. 1989). At present, the INRETS survey is the only national disaggregate revealed preference database for freight transportation in France. For this reason, this paper concentrates only on freight demand characteristics.

The purpose of this paper is to analyze how freight demand characteristics relate to and influence shippers' modal choice, using a nested logit model as an analytical tool. The contents of the paper are as follows: the second section describes the transportation mode and demand characteristic variables considered. The third section presents the results of estimating the nested logit models of modal choice. The fourth sections aggregates the results of the models, and the fifth section validates the aggregated results. The sixth section examines the marginal effects of demand characteristics and transportation services on mode choice. The final section presents our conclusions.

TRANSPORTATION MODES AND FREIGHT DEMAND CHARACTERISTICS

The various modes covered by the INRETS shippers' survey can be grouped into two transportation modes: private road transportation (i.e., own account transportation) and public (purchased) transportation. Public transportation includes rail, road, inland waterways, air transportation, maritime, pipelines, and intermodal transportation. Private transportation has long been regarded as a means of transporting goods over short distances but not as competitive with the other transportation modes over long distances. However, with the development of integrated logistic systems, public transportation modes must compete with private transportation to create added value for shippers in the movement of goods. In this new system, shippers can opt for private transportation even for long distance shipments, leading to an additional increase in road traffic. In view of the importance of the private versus public transportation choice, this paper will first deal with the modal choice between private and public transportation and then with the choice between rail, road, and combined transportation. Figure 1 represents this process.

FIGURE 1 Nested Multinominal Logit Model Structure



Two situations were considered rail transportation: when the departure or arrival point is a rail branch line and when there is road plus rail with passage through railway stations. Only the rail-road traffic through CNC or Novatrans (two combined transportation companies in France) loading yards were considered. In total, the data used include 3,473 observations, which can be broken down as follows: 1,421 observations for private transportation; 2,052 observations for public transportation, of which 1,866 observations relate to road transportation, 123 are rail transportation, and 63 are combined transportation.

We can divide available freight demand characteristics into three types: a firm's (shipper's or receiver's) characteristics, goods' physical attributes, and the spatial and flow characteristics of shipments. A firm's characteristics include the nature of the firm, such that in this category we find type of firm (for example, factories, shopping centers, or warehouses); the firm's structure (small, nationwide, or worldwide); the firm's location (for example, the accessibility to rail branch lines and highways); and the firm's size, represented by the number of employees. A firm's own transportation facilities closely relate to its transportation demand and are also an important factor in its modal choice. In addition, a firm's information system strongly influences its logistic practices and plays an increasingly important role in its transportation decisions. All of these characteristics are represented by dummy variables and are taken as long term factors for modal choice because changes in these characteristics will be made at the strategic, long term level, rather than at the day-to-day decision-making level.

The next type of demand characteristic is the attributes of the goods to be transported, such as type of product, weight, value, and packaging. The type of product includes a wide range of categories, for example, foodstuffs and fodder, machines and metal articles, transportation and agricultural materials. Packaging is generally either parcels and pallets or tanks, containers, and cases.

Finally, frequency, distance, origin, and destination of a shipment are its spatial distribution and physical flow attributes. Transportation distance was calculated from the 1988 Information System for Freight Transport (SITRAM) database of the French Ministry of Transport. Destinations include all French regions and many European countries, such as Italy, Spain, Belgium, Switzerland, Germany, and the Netherlands. Since these characteristics can change in a short time according to market demand, they are taken to be short term factors for modal choice.

The various long and short term characteristics can be summarized as follows:

- Long term factors: the firm's nature, size, location, information system, structure, and trucks owned by the firm
- Short term factors: physical attributes of goods, physical flow attributes, and the spatial distribution characteristics of shipments.

MODEL SPECIFICATION AND EMPIRICAL FINDINGS

The multinomial logit model (MNL) has often been used to model freight modal choice. However, because the unobserved attributes of road, rail, and combined transportation modes viewed as public transportation are likely to be correlated, the independent and identically distributed (IID) assumption of the multinomial logit model will likely not be satisfied if we define the choice set as private transportation, road, railway, and combined transportation. It is probably more accurate to represent the decisionmaking process of modal choice for shippers with a nested MNL model: the higher level modal choice is between private and public transportation, and the choice among road, railway, and combined transportation is within the public mode.

First Level: The Choice Between Road, Rail and Combined Transportation

$$P_n\ (y{=}road){=}\frac{\exp(V_{road})}{1+\exp(V_{road})+\exp(V_{comb})} \quad (1.1)$$

where

V_{road} and V_{comb} are utility functions for road transportation and combined transportation.

Second Level: the Choice Between Private and Public Transportation

$$P_n\ (y{=}public){=}\frac{\exp(V_{public}+V'_p * \mu_p)}{1+\exp(V_{public})+V'_p * \mu_p)} \quad (1.2)$$

where

- p represents public transportation.
- μ_p is the scale parameter for public transportation.
- V_{public} is utility function for public transportation.
- V'_p represents the log-sum variable of the nested logit model and can be written as:

$$V'_p = \ln[\exp(V_{road}) + \exp(V_{comb}) + 1]. \quad (1.3)$$

Hence, the modal choice probability for public road transportation compared with private transportation is :

$$P_n\ (y{=}road){=}\frac{\exp(V_{road})}{1+\exp(V_{road})+\exp(V_{comb})} * \frac{\exp(V_{public}+V'_p * \mu_p)}{1+\exp(V_{public})+V'_p * \mu_p)} \quad (1.4)$$

Estimation results on the first level of choice between road, rail, and combined transportation are presented in table 1, where the referenced alternative is rail transportation. The t statistics in parentheses indicate that most of the variables are statistically significant, although for the choice between road and rail, variables such as shipment size, shipment frequency, and shipment to Paris, they are less significant, and for the choice between combined transportation and railway, the variables such as warehouse and shipment in barrels-tank are less significant. The signs of variables indicate shippers' preferences for mode choice. We note that long distance transportation, shippers and receivers located on rail branch lines, large firms, shippers with their own smaller sized trucks, and shipments from Paris are favorable for rail transportation. Conversely, shippers who package in pallets and shippers with information systems prefer other modes to rail transportation. For combined transportation, there are positive effects for long distance transportation, shipments to Paris, large firms, and shippers with rail branch lines. However, for large size shipments, shipments to foreign countries, and shippers near highways, less combined transportation tends to be favored. On the other hand, for short distance transportation, shippers with information systems such as EDI, near highways, or with shipments packaged in pallets and in tanks favor road transportation. In contrast, large companies, shippers and receivers near rail branch lines, and shippers with their own small trucks tend to favor transportation by road less.

TABLE 1 Modeling Results for the First Level Choice

Explanatory variable	Road vs. rail[1]		Combined vs. rail	
Constancy for road	4.76	*(16.4)*		
Constancy for combined transport			–1.22	*(–2.4)*
Distance	–0.0017	*(–5.3)*	0.003	*(5.0)*
Shipment size	0.00000319	*(–1.2)*	0	*(–2.8)*
Shipment frequency	0.00000445	*(–1.7)*		
Number of employees	–0.0005	*(–3.6)*		
Warehouse	–1.3	*(–3.8)*	–1.26	*(–1.7)*
Shopping center	–0.832	*(–2.8)*		
Shipper with information system	1.82	*(2.8)*	1.65	*(1.9)*
Shipper near highway			–0.995	*(–2.6)*
Shipper with rail branch line	–0.52	*(–2.5)*		
Receiver with rail branch line	–1.2	*(–4.9)*	–0.977	*(–2.0)*
Package in barrels–tank	2.25	*(2.5)*	1.96	*(1.4)*
Package in tank container	1.46	*(2.7)*		
Pallets	0.799	*(2.6)*	1.14	*(2.5)*
Shipment in a circuit	2.02	*(2.0)*		
Shipment to foreign country			–4.6	*(–3.7)*
Shipment to Paris	–0.445	*(–1.6)*	0.786	*(1.9)*
Shipment from Paris	–0.842	*(–3.3)*	–0.9	*(–1.8)*
Shipper with own wagon	–0.0282	*(–2.5)*		
Shipper with own truck(<3t)	–0.945	*(–3.7)*	–0.873	*(–2.1)*
Shipper with own truck (3–6t)	–1.14	*(–4.1)*	–0.884	*(–1.8)*
Log-likelihood of complete model		*–585.99*		
Log-likelihood of restraint model		*–742.93*		
McFadden's pseudo-R2		*0.21*		
Percentage of correct prediction		*85.76*		

[1] Numbers in parentheses represent *t*-statistics

Estimation results on the second level of choice between private (in house) and public (purchased) transportation are presented in table 2 where the referenced alternative is private transportation. All of the variables are significant as indicated by their *t*-statistics. In addition, the scale parameter of the log-sum term is equal to 0.272 and is therefore between 0 and 1. This confirms that a nested logit model should be used for this case and that a simple MNL formulation would be incorrect. As for the shippers' preference for mode choice, the signs of variables indicate that for long distance transportation, high frequency shipments, both shipper and receiver located on a rail branch line, shipment in parcel, worldwide companies, manufacturing products, and metal industries public, transportation is preferred. On the other hand, for warehouse receivers, shipment in a circuit, small companies, shippers with own truck, food, and agricultural products, private transportation tends to be favored.

We further discuss the importance of demand characteristics for mode choice in a later section by analyzing the marginal effects of demand characteristics.

Aggregation of the Results

The ultimate objective of modeling is to forecast and measure the sensitivity of transportation demand to transportation policy and economic conditions. However, for purposes of government policy-making, aggregate behavior is of greater interest than the behavior of any individual firm.

TABLE 2 Modeling Results for the Second Level Choice

Variable	Public vs. private[1]	
Constancy	–1.498	*(–6.3)*
Distance	0.005	*(20.3)*
Shipment frequency	0.00000915	*(5.1)*
Receiver is a warehouse	–0.431	*(3.0)*
Shipper with rail branch line	0.533	*(4.5)*
Receiver with rail branch line	0.605	*(4.1)*
Parcel	0.761	*(7.1)*
Shipment in a circuit	–2.45	*(–12.6)*
Small firm	–0.413	*(–2.9)*
Worldwide company	0.676	*(5.1)*
Shipper with own truck (6–17t)	–1.825	*(–12.6)*
Shipper with own truck (>17t)	–1.983	*(–16.1)*
Manufacturing products	0.338	*(2.9)*
Foods	–0.295	*(–2.0)*
Metal	0.642	*(2.0)*
Agricultural products	–0.565	*(–2.0)*
V'_p	0.272	*(5.4)*
Log-likelihood	–1,363.725	
Numbers of observation for public transport (1)	1,967	
Number of observation for private transport (2)	1,317	

[1] Numbers in parentheses represent *t*-statistics

Therefore, the aggregation of disaggregate forecasts from discrete models is indispensable. The simplest method is direct aggregation or the naïve method. In this case, the average values for all explanatory variables are calculated, and then the aggregated choice probabilities are estimated with these average values. This approach is prone to aggregation bias when applied to nonlinear models. For this reason, researchers have developed approximate methods, such as the TALVITIE method and the market segmentation method, in order to find the best combination of calculation cost and precision of results (Ben-Akiva and Lerman 1985).

The TALVITIE method constructs the second order Taylor expansion of a choice probability function as an approximation of the exact choice probability. This expression is then used to compute the aggregate choice probabilities at the mean value of the explanatory variables. The result of the TALVITIE method is equivalent to the result of the naïve method, plus an error term, which depends jointly on the sample and the result of naïve method. Unfortunately, it is not clear that the TALVITIE method provides more precise results than the naïve method with an appropriate error term.

The market segmentation method is a logical extension of the naïve method. It divides the given market into several homogeneous groups so that error variance is minimized in each group and is maximized between groups. Then the direct (naïve) method is applied to each defined segment. The aggregate result is finally obtained by taking the average value of probabilities for each market segment, weighted by the market shares of each given market segment. This method reduces the aggregation bias produced by the use of average values, due to the fact that the data's characteristics in each segment are not significantly different.

Each of these methods has been used in passenger transportation modal choice analyses. For the aggregation of freight transportation demand, there have been no special methods developed, and few case studies exist. From existing empirical applications for passenger transportation, it appears that the most commonly used methods are sample enumeration and market segmentation. Other methods, such as the TALVITIE and the naïve methods, are very seldom used. Assuming that commodities' logistical families determine their transportation demand, we believe that market segmentation is a satisfactory method for the aggregation of freight forecasting results

The first stage of the market segmentation method is to select variables that can explain shippers' behavior and to determine the number of categories to be created for each selected variable in order to minimize the variability of representative utility (i.e., the bias of aggregation). Clearly, there is a trade off between the reduction of bias and the complexity of segmentation. Additionally, preference is given to segments corresponding to existing aggregate information so that the forecast results can be compared with observed data.

In France, SITRAM and the Database for Road Freight Transportation (TRM) are the government's two databases for freight transportation.

Important variables for segmenting the market include the type of goods (Nomenclature pour les Statistique de Transport (NST) classification), distance, and packaging. Using the SITRAM database, we calculated the average transportation distance and the modal share for each type of product. In general, only products transported over long distances (more than 150 kilometers) with a relatively low rail share have been thought to have the potential for shifting from road to rail in France. The following products make up 65% of total traffic:

- Foodstuffs and fodder (NST 1)
- Basic chemical products (NST 8)
- Transportation and agricultural material (NST 9A)
- Machines and metal articles (NST 9B)
- Other manufactured products (NST 9C)

THE VALIDATION OF MODELS

The logical step following model development is model validation. Model validation has been defined as the process that assures that a model describing a phenomenon does so adequately for the model's intended use (Miser 1993). Three types of validation have been distinguished: technical, operational, and dynamic (Gass 1983). Technical validation refers to the use of the correct kind of data, assumptions, and relations in the model, along with method. This is also referred to as internal validation (Taylor 1983). Operational validation concerns the assessment of the kind and the importance of errors produced by the model in comparison with reality (i.e., how the model represents reality). Finally, dynamic validation is concerned with determining how well the model predicts over different time periods. Operational and dynamic validation are also referred to as external validation (Taylor 1983).

In this paper we test the operational validity of the model. Operational validation provides information about the practicality of the model and shows the difference between reality and the results of the model. This requires a database that describes an actual situation. The database used here is SITRAM; in it the modal shares are represented by tons or tons-kilometers. But, the forecasted probabilities or modal shares obtained from our models are expressed in terms of the number of shipments. Therefore, in order to compare the forecasted results with actual results, the first step is to transform the modal shares in numbers of shipments to the modal shares in tons or ton-kilometers. To do this, we have used the following formulas:

where

$$P(i)_T = \frac{P(i)_E * W(i)}{\sum_{j=1}^{J} P(j)_E * W(j)} \tag{2.1}$$

or

$$P(i)_{TKM} = \frac{P(i)_E * W(i) * D(i)}{\sum_{j=1}^{J} P(j)_E * W(j) * W(i)} \tag{2.2}$$

- $P(i)_T$ is choice probability in tons for mode *i*.
- $P(i)_{TKM}$ is choice probability in ton-kilometers for mode *i*.
- $P(i)_E$ is choice probability expressed in percentage of shipments for mode *i*.
- $W(i)$ is average weight of shipment for mode *i*, and
- $D(i)$ is average distance for mode *i*.

The average weights and average distances are obtained from SITRAM. The aggregated shipment shares are predicted by our models. By combining them, we obtain mode share in tons and ton-kilometers for each segment, which can then be compared with actual statistics. Table 3 presents the comparison of mode share in tons. The forecast error for foodstuffs and fodder and for chemical products is the largest, most likely because there are fewer observations of these types of goods in the sample. In general, we found that the forecast results for each segment obtained this way are more precise than those derived by the direct aggregate method.

MARGINAL EFFECTS OF DEMAND CHARACTERISTICS

The marginal effects of the explanatory variables on modal choice behavior for dummy variables have means that are fractions.

The elasticities of choice probabilities between road, rail, and combined transportation with respect to explanatory variables shown in table 4 enable us to analyze the role of demand characteristics in mode choice. For the choice between road and rail transportation, transportation distance,

TABLE 3 Comparison of Forecasted and Actual Results (percent)

	Private transport			Public road		
Segments	**Estimation**	**SITRAM**	**Error**	**Estimation**	**SITRAM**	**Error**
Foodstuffs and fodder	68.17	61.73	6.44	29.18	33.51	–4.33
Chemical products	31.66	31.81	–0.15	65.16	59.30	5.86
Other manufactured products	37.27	37.44	–0.17	53.35	52.53	0.82
Agricultural and transportation material	48.03	47.12	0.91	51.11	51.59	–0.48
Machines and metal articles	33.43	34.10	–0.67	63.82	60.75	3.07
TOTAL	56.25	59.33	–3.08	38.12	34.90	3.22

company size, information system, rail branch line, use of pallets, and shippers owning trucks play the most important roles. Among these factors, only information system and pallets show preference for road transportation. For the choice of combined transportation, transportation distance, shipment size, shipment to a foreign country, shipper proximity to a highway, shipment to Paris, company size, and rail branch line are very important factors. For long distance shipments and shipments to Paris, combined transportation is especially preferred.

To analyze shippers' modal choice behavior among private transportation, road, rail, and combined transportation, the partial derivatives of probability with respect to the explanatory variables must be calculated. It can be expressed in the following formula (Liao 1994).

$$\left(\frac{\partial P_1}{\partial x}\right)P_{2/1} + \frac{\partial P_{2/1}}{\partial x} + \left(\frac{\partial P_1}{\partial x}\right)\left(\frac{\partial P_{2/1}}{\partial x}\right) \tag{3.1}$$

Using equation 3.1, we can estimate elasticities, and the results are found in table 5. Because companies generally use their own trucks for the deliveries of goods and call on public transportation for the supply of goods for production, the shipper's own large trucks play an important role for the initial choice between private and public transportation. Furthermore, companies owning trucks of more than 17 tons strongly prefer private transportation, although this tendency is diminished for long distance transportation.

We also found that transportation distance, shipment in parcel or in a circuit, and the accessibility of railways' infrastructure strongly influence the choice between private and public transportation. For example, long distance shipments or shipments packaged in parcels are more likely to be shipped by public transportation, but shipments in a circuit rely heavily on private transportation.

TABLE 4 Elasticities of the Choices Between Road, Rail, and Combined Transportation (at means)

Variable	**Road**	**Combined**	**Rail**
Distance	–0.038	1.807	0.619
Shipment size	0.004	–0.596	0.025
Shipment frequency	–0.002	0.048	0.048
Number of employees	–0.007	0.154	0.154
Warehouse	–0.002	–0.00019	0.059
Shopping center	–0.002	0.050	0.050
Shipper with information system	0.005	–0.009	–0.141
Shipper near highway	0.003	–0.293	0.003
Shipper with rail branch line	–0.006	0.146	0.146
Receiver with rail branch line	–0.007	0.028	0.181
Package in barrels–tank	0.003	–0.008	–0.079
Package in tank container	0.003	–0.074	–0.074
Pallets	0.005	0.076	–0.161
Shipment in a circuit	0.003	–0.073	–0.073
Shipment to foreign country	0.003	–0.380	0.003
Shipment to Paris	–0.004	0.194	0.068
Shipment from Paris	–0.004	–0.012	0.113
Shipper with own wagon	–0.001	0.014	0.014
Shipper with own truck(<3t)	–0.006	0.007	0.172
Shipper with own truck (3–6t)	–0.004	0.022	0.114

TABLE 5 Elasticities of the Choice of Four Modes Considered (at means)

Variable	Private	Road	Combined	Rail
Distance	–0.995	0.449	1.782	0.924
Shipment frequency	–0.068	0.030	0.079	0.079
Receiver is a warehouse	0.033	–0.016	–0.016	–0.016
Shipper with rail branch line	–0.098	0.040	0.205	0.205
Receiver with rail branch line	–0.056	0.020	0.056	0.216
Parcel	–0.243	0.116	0.116	0.116
Shipment in a circuit	0.221	–0.103	–0.159	–0.159
Small firm	0.039	–0.019	–0.019	–0.019
Worldwide company	–0.090	0.043	0.043	0.043
Shipper with own truck (6–17t)	0.169	–0.081	–0.081	–0.081
Shipper with own truck (>17t)	0.304	–0.145	–0.145	–0.145
Manufacturing products	–0.060	0.029	0.029	0.029
Foods	0.028	–0.013	–0.013	–0.013
Metal	–0.012	0.006	0.006	0.006
Agricultural products	0.013	–0.006	–0.006	–0.006

Finally, we considered the changes in choice probabilities as functions of continuous variables, such as transportation distance, shipment size, and shipment frequency. In general, an increase in transportation distance and shipment frequency tends to raise the shares for rail and combined transportation. However, with increasing shipment size, the probability of choosing combined transportation diminishes, while that of rail transportation increases.

Transportation distance is a very important factor in mode choice. Figure 2 shows the evolution of choice probability for transportation distances between 100 and 3,000 kilometers. For short distance transportation, road transportation is the dominant mode and has little competition from other modes. On the other hand, the shares of rail, road, and combined transportation depend strongly on transportation distance at distances longer than 1,000 kilometers. For example, if the distance is less than 300 kilometers, the traffic is shared between private truck transportation and public road transportation. The maximum probability of choosing public road transportation takes place at approximately 700 kilometers, but that of choosing rail transportation occurs at 1,300 kilometers. Combined transportation becomes dominant if transportation distance is more than 1,400 kilometers.

We can also examine the joint effects of transportation distance and shipment destination. Figure 3 shows the probability of choosing combined transportation versus railway with respect to transportation distance for an international or national shipment. We can see that for long dis-

FIGURE 2 The Effect of Transport Distance on Mode Choice

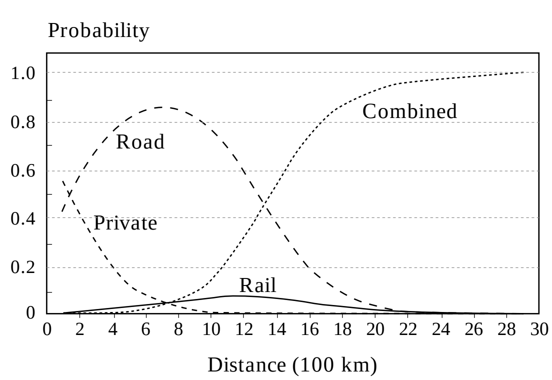
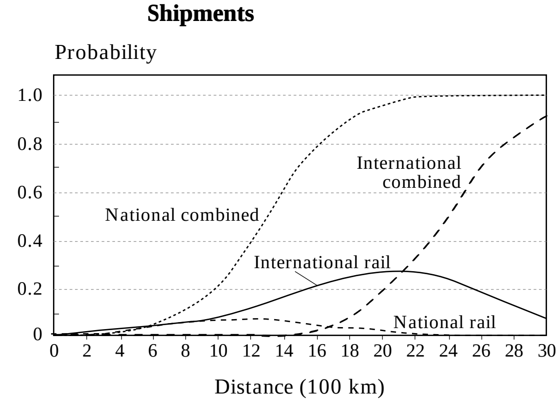


FIGURE 3 The Effect of Distance on the Mode Choice for National and International Shipments



tance international shipments, rail plays a more important role than for long distance intranational shipments. Furthermore, if the shipment distance is less than 1,500 kilometers, international shipments tend not to use combined transportation.

CONCLUSION

In this study, we used French freight demand survey data to estimate a disaggregate, discrete choice model. Using elasticities of choice probabilities, we analyzed how demand characteristics influence the choice between transportation on a shipper's own account versus purchased road, rail, and combined transportation. We found that transportation distance, the shipper's accessibility to transportation infrastructure, the shipper's own transportation facilities, and shipment packaging (pallets and parcel) are the critical determinants of the demand for rail and combined transportation. For long distance nationwide transportation, combined transportation may be an important mode, but for long distance international transportation, the existing quality of service of combined transportation apparently fails to satisfy shippers' needs, and conventional rail transportation plays a significant role.

This study's results point to the need for careful and systematic analysis of the changes in firms' logistical systems for predicting traffic mode split and for evaluation of the effects of transportation infrastructure decisions on the modal structure of freight traffic. Much greater detail is needed concerning the interactions between firms' logistical decisions, their shipment demands, and the characteristics of alternative transportation modes. We hope that this study provides a starting point for these issues and their influence on freight modal choice.

REFERENCES

Ben-Akiva, M. and S. R. Leman. 1985. *Discrete Choice Demand: Theory and Application to Travel Demand.* Cambridge, Massachusetts: MIT Press.

Bredeloup, E and G. Costa. 1988. Bilan Méthodologique de l'Enquête Auprès des Chargeurs, Rapport Provisoire de l'Inrets.

Bredeloup, E., P. Hanapp, E. Gouvernal, M. Guillbault, J.P. Hubert, and M. Mezghani. 1989. Pratique de Transport des Industries et des Commerces de Gros, Résultats de l'Analyse de 5,000 Chaînes de Transport, Rapport Inrets 99.

Daugherty, A.F. 1979. Freight Transport Demand Revised: A Microeconomic View of Multimodal Multicharacteristic Service Uncertainty and the Demand for Freight Transport. *Transportation Research* 13B:21, 81–288.

Fowkes, A.S. and D. Tweddle. 1988. A Computer Guided Stated Preference Experiment for Freight Mode Choice, paper presented at the PTRC, 16th Summer Annual Meeting.

Gary, R. 1982. Behavioural Approaches to Freight Transport Modal Choice. *Transport Reviews* 2:2, 161–184.

Gass, S.I. 1983. Decision-Aiding Models: Validation, Assessment, and Related Issues for Policy Analysis. *Operations Research* 31: 4, 603–631.

Gouvernal, E. and P. Hanappe. 1986. Enquête auprès des Chargeurs, Bilan de la pré-enquête, Rapport Inrets 13.

Liao, T.F. 1994. *Interpreting Probability Models Logit, Probit, and Other Generalized Linear Model.* California: Sage Publications.

Miser, H.J. 1993. A Foundational Concept of Science Appropriate for Validation in Operational Research. *European Journal of Operational Research* 66, 204–215.

Ortuzar, J. de D. and L.G. Willumsen. 1994. Modelling Transport. England: John Wiley & Sons.

Taylor, A.J. 1983. The Verification of Dynamic Simulation Models. *Journal of Operational Research Society* 34, 233–242.

Van Es, J.V. 1982. Transports de Marchandises—Une Evaluation. Table Ronde 58, CEMT. Paris.

Widlert, S. and M. Bradley. 1992. Preference of Freight Services in Sweden, paper presented at the Sixth World Conference in Transport Research, Lyon, France.

Research Note

Comparing International Crash Statistics

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ABSTRACT

In order to examine national developments in traffic safety, crash statistics from several of the more developed countries are compared with those of the United States. Data obtained from the Fatality Analysis Reporting System (FARS) and the International Road Traffic and Accident Database (IRTAD) are analyzed. Trend analysis results for the countries included, the United States, the European Community, Canada, Japan, New Zealand, and Australia, show that all regions have experienced decreases over time in the fatality rate per 100,000 population as well as the fatality rate per 100,000 registered vehicles. Fatality data are partitioned by age group, travel type, and roadway type. A variety of problems in collecting and analyzing international data is presented with some recommendations for further improvement.

INTRODUCTION

Traffic crashes and their attendant injuries and fatalities are a worldwide public health problem. To address national developments in the area of traffic safety more accurately, it is advantageous to view traffic crashes in an international context. As such, the German Federal Ministries of Transport, Building and Housing, and the Federal Highway Research Institute (BASt) established an International Road Traffic and Accident Database (IRTAD) in the mid-1980s. Since 1990, that database has been operated within the framework of the Road Transport Research Programme within the Organization for Economic Co-operation and Development (OECD) in Paris, France and includes aggregate data from all OECD countries, with BASt acting as the administrator of the database. The purpose of this database is to provide international comparative traffic safety statistics for its members. IRTAD is the only international database that attempts to provide historical consistency and international comparability for traffic crash data. However, IRTAD does not address risk in terms of different vehicle types or roadways.

This paper examines the safety statistics of some of the more developed nations around the world that participate in this database. The regions included in this paper are the Unites States, the European Community (Austria, Belgium, Denmark, Finland, Germany, Greece, France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom), Canada, Japan, and the Pacific Region (New Zealand and Australia).

The data used in this report came from the annual reports on traffic crashes, injuries, and fatalities issued by the respective countries and submitted, in a uniform format, to the IRTAD from 1980 to 1996. The U.S. fatality data came from the Fatality Analysis Reporting System (FARS). Meeting the exacting requirements of IRTAD, the U.S. injury crash data are the sums of counts of police-reported injury crashes collected by the individual states and submitted to the Federal Highway Administration, rather than the National Highway Traffic Safety Administration (NHTSA) General Estimates System (GES) estimates derived from a sample of

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approximately 50,000 crashes. This uniform data collection and reporting procedure is followed by each participating nation and provides the most comparable data for international analysis.

IRTAD provides the following data for all of the nations included in this paper:

1. Number of injury accidents classified by road types,
2. Fatality figures with a breakdown by vehicle type, age groups, and road type,
3. Population data, and
4. Vehicle registration data.

Two measures of traffic safety were used: the number of fatalities and the number of injury crashes by year. Data for these two variables were generally available for the countries included in this paper. The exception was the number of injury crashes for Australia, which was not available.

FATALITIES

A traffic crash-related fatality is defined by the Vienna Convention as an individual who dies at the scene of the crash or within 30 days following the crash (Pozuelo and Izarzugaza 1996). This definition is consistent with the definition used by NHTSA, with the imposition of a further restriction, that the traffic crash must occur on a roadway customarily open to the public. Although there is an international standard definition, it is not used by all OECD countries. Not all countries follow the 30-day time frame. To address the problem of comparing fatalities across international lines, the fatality data were adjusted by IRTAD to approximate the international definition. IRTAD applied the following internationally-agreed on adjustment factors to the fatality data submitted by each nation. The number in parentheses indicates each country's standard time frame for a fatality's inclusion in a crash report.

- Austria: (3 days) 1980 to 1982 +15%, 1983 to 1991 +12%
- France: (6 days) 1980 to 1992 +9%, since 1993 +5.7%
- Greece: (3 days) before 1996 +15%
- Italy: (7 days) +8%
- Japan: (24 hours) before 1993 +30%
- Portugal: (less than 24 hours) +30%
- Spain: (24 hours) before 1993 +30%

Lack of a single international definition of a traffic fatality used by all of the OECD countries is perhaps the most serious problem in the analysis of international fatality crash data. Additionally, in virtually all OECD countries, some traffic deaths are missed and not included in the national statistics. Matthijs J. Koornstra, President of the IRTAD Management Bureau of the Steering Committee for the Road Transport Research Programme of the OECD, pointed out in the forward of A. Mónica Colás Pozuelo and J. Izarzugaza's report (1996) that: "The nonregistered road fatalities and inaccurateness in the reporting of road fatalities is a problem in every country, even if this is officially denied." Hence, the fatality data within this paper must be considered best estimates with associated errors rather than actual counts.

Trends for fatalities and injury crashes are presented for 1980 to 1996. Fatality data for Greece and Luxembourg were not available for 1996; 1995 data were used as proxies. Injury crashes include fatal crashes. Tables 1 and 2 show the numbers of fatalities and injuries for each geographical area by year Figure 1 shows the yearly fatality trends for each geographical area. Figure 2 shows the percentage change in fatalities measured from 1980. The European Community and the United States dominate other geographical areas in numbers of fatalities. Although the European Community had 13,000 more fatalities than did the United States in 1980, its lead had decreased to less than 2,000 by 1996. Canada has experienced the largest percentage decrease in fatalities, over 40%, from 1980 to 1996. Japan is the only area where the fatalities have increased over time.

CRASHES

Henrik Hvoslef (1994) points out that there is a serious problem of under-reporting traffic crashes. Susanne Berns (1998, 20) states that

> The registration of injured accident victims constitutes a large problem. The under-reporting of traffic accidents depends very much on the type of accident. In general, serious injuries are more often reported to the police than slight injuries. The level of under-reporting depends on a number of factors. It can also vary from one country to another due to national factors: how accidents are defined, how serious the least reportable injury is, etc. Differences in the local

TABLE 1 Number of Fatalities by Year

Year	U.S.	E.C.	Canada	Japan	Pacific
1980	51,091	64,199	5,461	11,388	3,871
1981	49,301	61,530	5,383	11,335	3,989
1982	43,945	60,135	4,169	11,795	3,926
1983	42,589	59,698	4,216	12,376	3,399
1984	44,257	56,817	4,120	12,041	3,491
1985	43,825	52,644	4,364	12,039	3,687
1986	46,056	54,736	4,068	12,112	3,654
1987	46,390	52,705	4,286	12,151	3,571
1988	47,087	55,046	4,154	13,447	3,615
1989	45,582	55,972	4,246	14,412	3,563
1990	44,529	56,374	3,960	14,595	3,060
1991	41,462	55,960	3,691	14,436	2,763
1992	39,235	52,729	3,501	14,886	2,627
1993	40,150	48,211	3,615	13,269	2,553
1994	40,716	46,479	3,263	12,768	2,517
1995	41,798	46,047	3,347	12,670	2,598
1996	41,907	43,828	3,082	11,674	2,487

TABLE 2 Number of Reported Injury Crashes

Year	U.S.	E.C.	Canada	Japan	N.Z.
1980	2,074,257	1,400,085	184,302	476,677	10,728
1981	2,062,285	1,367,989	183,643	485,578	10,659
1982	2,007,687	1,356,587	160,376	502,261	11,256
1983	2,043,414	1,352,762	160,623	526,362	11,511
1984	2,176,716	1,333,123	168,801	518,642	12,561
1985	2,257,695	1,277,991	183,478	552,788	13,548
1986	2,294,762	1,296,881	187,563	579,190	13,465
1987	2,335,438	1,274,772	196,966	590,723	13,362
1988	2,344,629	1,331,515	193,704	614,481	12,561
1989	2,425,077	1,348,675	196,246	661,363	12,004
1990	2,540,946	1,342,844	181,960	643,097	12,818
1991	2,227,053	1,301,398	173,921	662,388	12,163
1992	2,251,173	1,291,028	172,713	695,345	11,639
1993	2,216,092	1,236,472	171,205	724,675	10,994
1994	2,128,223	1,258,191	169,622	729,457	11,876
1995	2,371,844	1,268,847	167,038	761,789	12,220
1996	2,448,145	1,250,963	167,038	771,084	10,564

tradition for reporting accidents to the police and how the recording procedure is organized are other important factors explaining differences between countries.

At the personal level, there are also several reasons for the under-reporting of crashes. Ignorance of the legal obligation, forgetting, that the injury only becomes obvious after the crash, and fear of prosecution for being engaged in unlawful or criminal activities are among the reasons given. Injury crash reporting also varies with the inclusion of crash victims treated on a hospital out-patient basis only and/or pedalcyclists injured in the crash.

The rate of reporting crashes also varies over time. Norway, though not a member of the European Community and therefore not included in this paper, provides an excellent example of how increased public awareness combined with improved reporting routines by the police resulted in an increase in reported injury crashes. The rate at which crashes are reported can also vary within a

FIGURE 1 Fatalities by Year

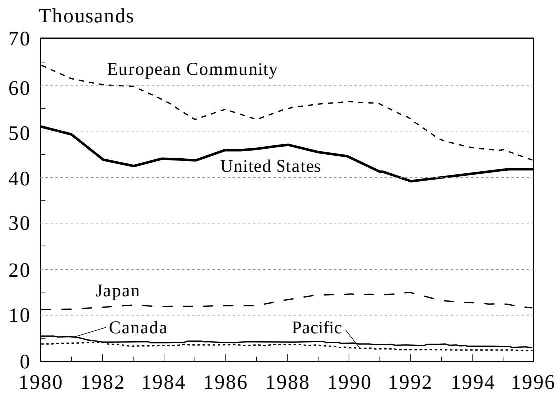
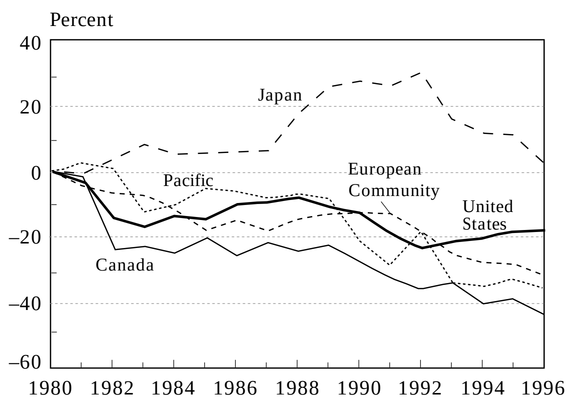


FIGURE 2 Percentage of Change in Fatalities from 1980



country or a district and between rural and urban areas. Also, the rate is often a function of the distance to the nearest hospital or emergency facility. Koornstra goes so far as to state "One at least ought to question the validity of any international comparisons on general road safety, if it is not based on fatalities only"(qtd. in Hvoslef 1994, forward). Hvoslef (1994, 4) further reports:

> It is commonly known that not all traffic accidents with personal injury are reported to the police, even if they are supposed to be so by law. Research done in several countries by matching data from hospitals with police records, both of in-patients and out-patients, reveals that the police are receiving information on about 30–60% of all the personal injury accidents they are supposed to know about.

Not only is there a problem of under-reporting, there is also a problem of under-recording. Again, Hvoslef states (1994, 5–6)

> Another problem is under-recording, a problem connected to the way the recording by police is organized, procedures for filling out forms, etc. Some casualties recorded in paper reports do not appear in the computer files, most likely due to clerical errors. In some cases, casualties treated in hospitals occurred in accidents recorded by the police as "damage-only" accidents. In many cases, this is connected to injuries being reported to the police some days after the accident, often the case for whiplash injuries. A third reason for under-recording occurs when there is a lack of detailed information about the injured person. A study in Greater Manchester (Hopkin et al. 1993) revealed that under-recording occurred in 12% of the cases treated in hospitals when an injury was diagnosed and in 20% of the casualties where information about the accident was reported to the police.

With all of the caveats listed above, table 2 and figures 3 and 4 provide the number of reported injury crashes by year, 1980–1996. Due to the problems with injury crashes identified above, the data for injury crashes are limited to these three

FIGURE 3 Injury Crashes by Year

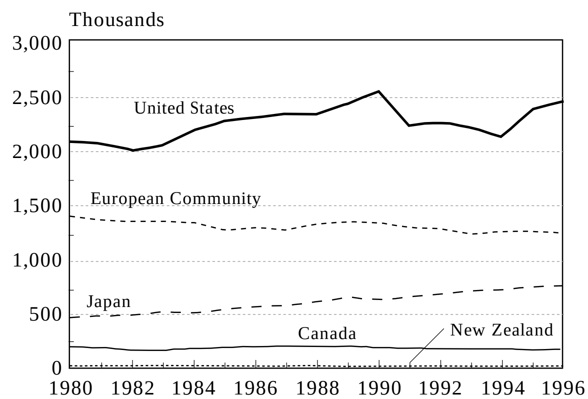
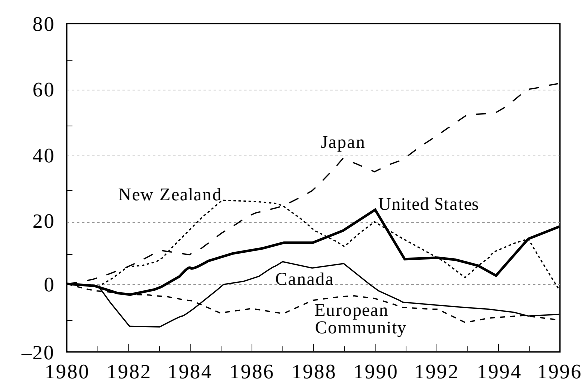


FIGURE 4 Percentage of Change in Injury Crashes from 1980



examples. Australia does not report the number of injury crashes; therefore, data are reported only for New Zealand. As noted above, the procedures for reporting injury-related crashes in the countries under study vary considerably. In table 1, we see that the number of U.S. fatalities is always less than the number of fatalities in the European Community. However, the United States reports almost twice the number of injury crashes as does the European Community.

With the large differences in reporting standards, it is inappropriate to compare total reported crashes across regions. However, we can examine the change in reported injury crashes within each geographical area. The United States, the European Community, Canada, and New Zealand are within 20% of the levels reported in 1980. The number of reported injury crashes in the United States increased approximately 18%. The European Community, Canada, and New Zealand reported decreases in injury crashes of 11%, 9%, and 2%, respectively. Japan reported that injury crashes rose 62% (see figure 4). The number of injury crashes was not available for Greece, Luxembourg, or Canada for 1996. The 1995 data were used in their place.

FATALITY RATES

Although most of the crash fatalities are reported and accepted correction factors are applied, comparisons of the absolute number of fatalities across geographical areas are not very useful. The various geographical areas have different populations, mixes of road structures, traffic compositions, and usage patterns. A better approach is to compare fatality rates adjusted for some amount of relevant exposure. The need for these exposure measures is clear. However, there are no internationally agreed on standards.

The number of vehicle-miles traveled is one of the most popular measures of exposure within the United States. The corresponding international measure of exposure, number of vehicle-kilometers traveled, is collected and reported to BASt by many of the countries within the European Community but not by all. Therefore, any attempt to report the European Community's data in this manner would be so highly flawed that all such references have intentionally been omitted.

FIGURE 5 Fatality Rates

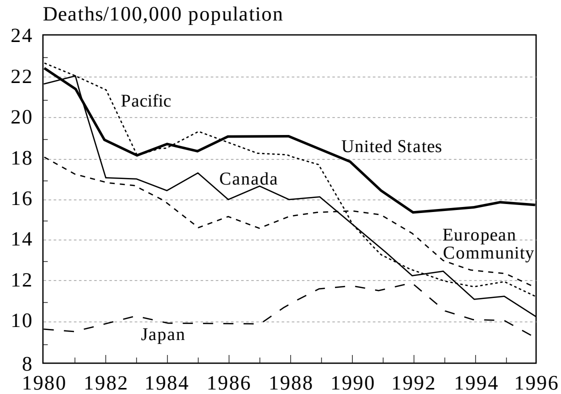
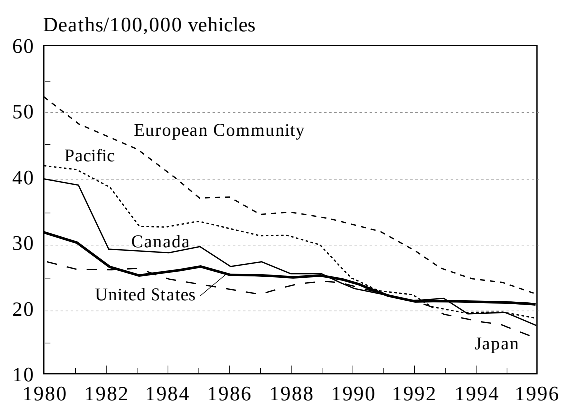


Figure 5 reports fatality rates per 100,000 population. In 1980, Canada had the highest rate of fatalities per 100,000 residents (22.71 fatalities per 100,000 residents). Canada also experienced the greatest reduction in the fatality rate per 100,000 residents between 1980 and 1996, when it had the second lowest rate of any geographical area: 10.29 fatalities per 100,000 residents in 1996. Japan reported the smallest decline in fatalities per 100,000 residents between 1980 and 1996, 5%. However, for all years of the study, Japan had the lowest fatality rates.

Figure 6 reports the fatality rates per 100,000 registered vehicles. Since 1980, all geographical areas have experienced substantial drops in the rate of fatalities per 100,000 registered vehicles. The rates have dropped by approximately 35% for the United States, 40% for Japan, and 55% for the European Community, Canada, and the Pacific Region.

FIGURE 6 Fatality Rates per Vehicle



A serious mistake can be made in interpreting these data, namely, to assume a direct cause and effect relationship between the increase in the population or number of registered vehicles and the decrease in fatality rate, adjusted by population or by the number of registered vehicles. (This same phenomenon is noticed with vehicle-kilometers traveled in the denominator). Although at first glance it appears that this relationship may exist, the actual situation is more complex. There are several other "lurking" variables that contribute to the reduction in rates.

The observed reduction in rates spans several years. The time period of interest for this paper is 1980 to 1996. Over this period, several factors have contributed to the rate reduction. A short list of these factors includes: increased use of seat belts, reductions in drinking and driving, installation of daytime running lamps, introduction of anti-lock brakes, use of center high mounted stop lamps, airbags, safety education programs, stricter alcohol/driving laws, improvements in roadway construction, improvements in emergency medical service, and improved medical care. The available data do not have the fidelity to estimate the effects of these variables, but they exist nonetheless. The point is that the reduction in the fatality rate is due to the effects of these and similar variables, not the increase in population or number of registered vehicles.

Nilsson (1997, 17) points out that "comparisons of fatality rates and injury rates must be done for homogeneous environments and road user groups, not for whole countries and all road user groups." Figures 7 to 10 attempt to address this concern. The distributions of fatalities by age group are similar for the United States, the European Community, and Canada. The Japanese have a larger portion of their fatalities in the 65 and older category, over 30%. The Pacific Region has almost 30% of their fatalities in the 15–24 year old category, higher than any other region (see figure 7). There were no 1996 data available for Greece, Canada, or Italy; data from 1995 were used for both Greece and Canada; data from 1994 were used for Italy.

Figure 8 presents information on the fatality rates by age group for the geographic areas. The

FIGURE 7 Percentage of Fatalities by Age Group

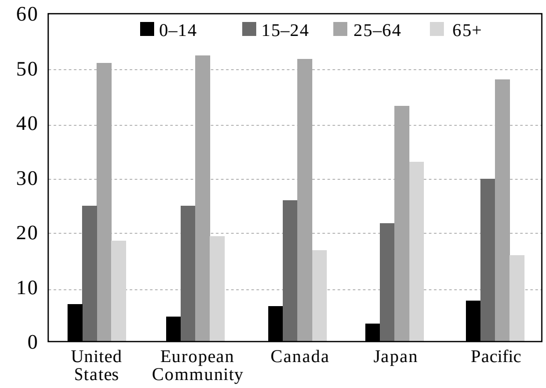
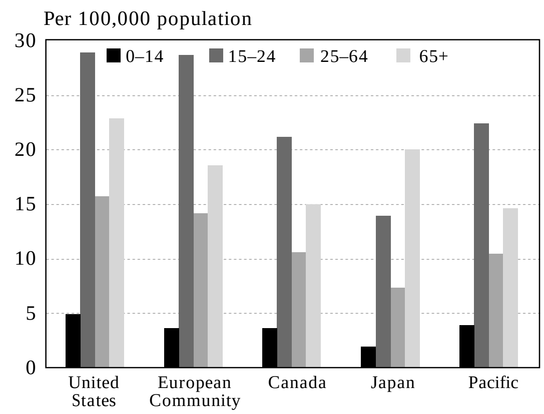


FIGURE 8 Fatalities by Age Group



United States and the European Community have similar patterns. However, the European Community's fatality rates are slightly lower than those of the United States for all age groups. Japan's fatality rates are the lowest for all age groups, with the exception of 65 and older age group. Only the United States' fatality rate for the 65 and older age group exceeds Japan's fatality rate for the same group.

Fatalities can be classified into four categories of travel type: pedestrians; bicyclists; riders of motorized two-wheel vehicles, including motorcycles and motor scooters; and occupants of passenger cars and station wagons. Light trucks, sport utility vehicles, and vans are not addressed in these data. Figure 9 shows that the United States, the European Community, Canada, and the Pacific Region have somewhat similar distributions of fatalities by travel type. Japan has a larger proportion of pedestrian and bicycle fatalities and correspondingly fewer passenger car fatalities. Canadian data for

FIGURE 9 Percentage of Fatalities by Travel Type

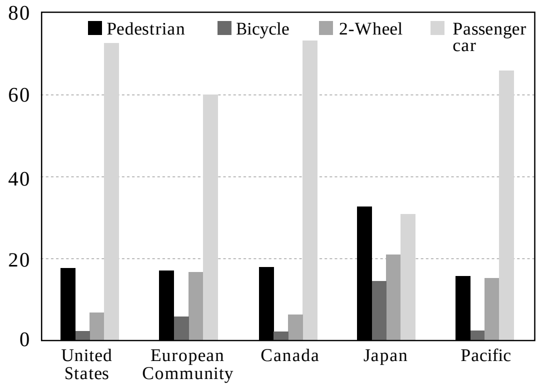
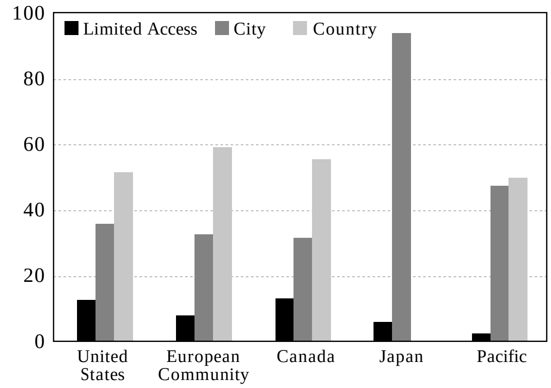


FIGURE 10 Percentage of Fatalities by Roadway Type



motorized two-wheel vehicles and passenger cars in 1996 were missing; 1995 data were used in their place. The 1996 data from Greece and Italy were also missing. Similar data from 1995 and 1994, respectively, were used as surrogate data. Data were not available from Australia for riders of motorized two-wheel vehicles and passenger cars. The data were estimated using the total fatalities for Australia and the proportions from New Zealand.

Roadway type has been divided into three categories: limited access, city, and country. Limited access roads include both urban and rural limited access roads. City roads consist of all public, urban, nonlimited access roads. Country roads are public, rural, nonlimited access roads. Japan does not provide information on country road fatalities. The United States, the European Community, and Canada have similar patterns of fatalities for roadway type (see figure 10). The Pacific countries have almost equal numbers of fatalities on both city and country roads. Data for 1996 were not available for Italy, Canada, or Australia. Data from 1995 were used for Italy and Canada, and 1992 data were used for Australia. The limited access data for Denmark were from 1995, while the country data came from 1994. Both the city and country data for Luxembourg were from 1994. Data for limited access and country roads were not available for Greece and have been set to zero. This slightly underestimates the fatalities for limited access and country roads for the European Community.

OBSERVATIONS

This paper has presented traffic crash data for some of the more developed nations around the world. Although progress has been made in improving the comparability of international safety data, much more work remains. There remain many differences in the data reported by various countries. A variety of jurisdictions, some local, others regional or national, have been involved in the collection and aggregation of the data. Each jurisdiction has applied its own set of criteria for data collection and dissemination. Although briefly mentioned within this report, ways to resolve these differences have not been thoroughly addressed and are beyond the scope of this note.

Nonetheless, areas for further improvement include:

- Standardizing definitions of crash data and the associated data collection methods and reporting thresholds so that data can be compared across international boundaries;
- Until standard collection and reporting methods have been adopted, developing a set of adjustment factors for each country to account more accurately for the number of traffic crashes at all levels;
- Creating an annual forum for the exchange of analysis techniques;
- Investigating procedures to link hospital data to crash data and implementing them where appropriate;

- Developing a uniform, verified, hierarchical database that documents crashes at the crash, vehicle/driver, and person levels. It may be possible to collect detailed data for all fatal crashes and a representative sample of injury crashes.

On the positive side, there is universal good news in the international statistics, in that every geographical region made progress in reducing fatalities over the past decade.

REFERENCES

Berns, S. 1998. Definitions and Data Availability Compilation and Evaluation of A-Level Roads and Hospitalized Victims in OECD Countries Accident and Injury Definitions, IRTAD special report. Germany: BASt. June.

Hopkin, J.M., P.A. Muray, M. Pitcher, and C.S.B. Galasko. 1993. Police and Hospital Recording of Non-Fatal Road Accident Casualties: A Study in Greater Manchester, research report 379. Crowthorne, Berkshire, United Kingdom: TRL.

Hvoslef, H. 1994. Under-Reporting of Road Traffic Accidents Recorded by the Police, at the International Level, IRTAD special report. Norway: Public Roads Administration. November.

Nilsson, G. 1997. *Methods and Necessity of Exposure Data in Relation to Accident and Injury Statistics.* Linköping, Sweden: Swedish Road & Transport Research Institute (VTI). January.

Pozuelo, A.M.C. and J. Izarzugaza. 1996. Follow-up of Traffic Victims During the 30 Day Period After the Accident, IRTAD special report. Spain: Dirección General de Tráfico. June.

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in the text: (Kargon 1974)

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in the text: (Michaelis et al. 1996)

National Academy of Sciences (NAS), Committee on National Statistics. 1985. *Sharing Research Data.* Washington, DC: National Academy Press.

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