A certain degree of safety is also provided through the use of radio equipment. In cases of breakdown, accident, or other emergency, the driver is able to get aid through the local terminal or from other company vehicles in the area, if mobile-to-mobile capabilities exist. Less reliance on outside help results in greater security for driver and cargo. Communications can reduce the danger of hijacking.

POTENTIAL MARKET FOR NEW TECHNOLOGY

A market for new technology in the trucking industry will depend on one of the following three abilities of a cellular or multichannel system:

1. The ability to decrease congestion and hence transmission delays,
2. The ability to provide dispatching service at a lower cost than present mobile equipment, and
3. Capabilities not now present in dispatch and communications equipment that would aid trucking firms.

Radio users interviewed for this study did not view radio congestion as a major problem. Yet in metropolitan areas, where radio channels are shared by a number of users, congestion of the airwaves can mean inefficiency in the trucking industry as in any other type of dispatch service.

HIJACKING AND MOBILE COMMUNICATIONS

The U.S. Department of Transportation noted that the total cost of cargo theft and pilferage exceeds $1 billion/year—with the trucking industry experiencing the largest percentage of that total. Theft usually occurs during loading and unloading, in the terminal minal yard (about 85 percent of stolen cargo goes out the front gates of transportation facilities during normal operating hours and in the possession of persons and in vehicles authorized to be on premises for legitimate reasons), or in transit between terminals.

Hijacking has recently become more prevalent. Increased terminal security has reduced the first two types of loss, but the problem has moved to the road.

CONCLUSIONS

This paper has attempted to identify the significant role that mobile communications plays in the operation of pickup and delivery and over-the-road service in the trucking industry. A number of specific instances of operational and safety improvements due to the use of communications devices have been identified. Very little doubt remains that improved mobile communications technologies, such as the ones briefly described in this paper, and a more widespread adoption of available and future devices will further increase the performance of the trucking industry.

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Estimating Service-Differentiated Transport Demand Functions

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This paper develops a methodology for estimating the demand for freight transport based on a model of the shipper's decision-making process. Conditions of optimality are used to specify a choice model—subject to some assumptions about the shipper's response to the risks incurred by using the transport system. This model is expanded to allow for testing for imperfection in the goods markets. If such imperfection exists, a technique is proposed that involves generating a posterior on shipment size, conditioned on alternative choice from a prior on shipment size and the estimated choice model. The resulting expectation of the posterior, when used in combination with industry supply functions, produces demand equations. Finally, market equilibria—where demand equals supply—are computed.

Estimating the demand for freight transportation has been a favorite pastime of many transport economists (1-12). Approaches have varied from gravity models to logit analysis (13). A major advantage of a gravity model is that it actually predicts flows. Its major disadvantage is that it is not based on any economic theory and thus is generally not sensitive to microeconomic parameters such as market prices, transport rates, and service levels. An advantage of a choice model, such as probit and logit analysis, has been its responsiveness to microeconomic parameters, although its estimation has usually been performed without regard to microeconomic theory (5); notable exceptions to this are found in Allen (1) and Beuthe (3). The estimated choice probabilities are then used to separate some given total quantity to obtain estimates of shipment size for each alternative. This method is clearly limited because the total amount shipped depends on the firm's decisions regarding alternatives and shipment size.

This paper develops a consistent methodology for estimating demand equations by starting from a microeconomic model of a shipping firm, estimating a choice model dependent on both alternative and shipment size, and then producing demand equations that reflect choice of market and mode, prices at the market, transport rates for the different modes, and service characteristics of the modes. This paper also presents a theoretical analysis of the shipping firm, develops the basic approach for deriving transport demand, estimates logit models for market-mode choice, and reports the results of the demand estimation and the estimated market equilibria.

FIRM TRANSPORT DEMAND AND ANALYSIS

Theory

Consider a typical shipper who can sell a product in various markets and can use several alternative transport modes. Assume that the firm is competitive in the sense that it takes market prices and transport rates as given; the firm's location is fixed in space.

In the following analysis this notation is used:

P_j = price of the product in market j, j=1,...,J
t_{jm} = transport rate to market j by mode m, j=1,...,J and m=1,...,M
q_{jm} = quantity shipped to market j by mode m by the firm
$H_{jm}(q_{jm})$ = service-induced transport cost of shipping q_{jm}
$C(q)$ = cost to firm of producing $q = \sum\sum_{jm} q_{jm}$

Notice that the alternative of not selling in any market and merely holding inventories can be included by identifying one of the market-mode pairs with not selling and not shipping.

Modes are differentiated by their service attributes such as speed and reliability. These attributes induce certain costs that are central to the theory of transport demand as a derived demand. Induced costs and how they relate to service attributes include the following:

1. Equipment availability costs. Uncertainty as to the availability of transport equipment when it is needed induces costs. For example, inventory costs are incurred when a shipment must be placed in a holding position while waiting for the arrival of transport equipment. Penalty costs may be levied on a shipper who cannot make delivery as scheduled. To the extent that late arrival of equipment exacerbates on-time delivery, these penalty costs can be associated with equipment availability. The opportunity costs that are incurred when a shipment is tied up because equipment is not readily available is another category of availability costs. Thus, availability is a service attribute that imposes costs on the shipper.

2. Transit costs. Interest and inventory carrying costs are incurred on the value of a shipment during transit. Furthermore, variance in scheduled transit time increases the risk of incurring penalties due to late delivery of goods and loss of goodwill. Thus, transit time on each mode is a service attribute that induces costs of using a particular mode.

3. Loading and handling costs. These costs will vary by mode when different combinations of labor and capital inputs are required. For example, special facilities may be needed to load rail cars vis-à-vis trucks.

An important aspect of transport service is reliability. In the case of physical reliability, there are risks associated with loss and damage. In the case of schedule reliability, there are risks associated with the ability of the shipper to deliver a shipment on a promised date. These risks are attributable in part to uncertainty in equipment availability and transit time variance. Thus, reliability introduces the notion of risk into the shipper's decision as to where to ship and by what mode.

In Daughety and Inaba (14) the selection of market and mode was treated as a portfolio problem of investment in risky assets. Under the assumption of risk-aversion the service-induced cost function $H_{jm}(q_{jm})$ can be expected to be strictly convex in q_{jm}. Now, consider the firm's profit function:

$$\Pi(q_{11}, \ldots, q_{JM}) = \sum_j \sum_m [P_j q_{jm} - t_{jm} q_{jm} - H_{jm}(q_{jm})] - C(q)$$

The shipper chooses nonnegative q_{jm}'s so as to maximize $\Pi(q_{11},\ldots,q_{JM})$. The resulting q_{jm}'s are functions of prices P_j, rates t_{jm}, and the parameters for the functions $H_{jm}(\cdot)$ and $C(\cdot)$. These constitute the firm's derived demand for transportation. The first-order conditions are

$$P_j - t_{jm} - H'_{jm}(q_{jm}) - C'(q) = 0$$

$$q = \sum_j \sum_m q_{jm} \quad (1)$$

To clarify the relationships among the modal demand functions, the conditional (inverse) demand function for alternative η (i.e., mode m and market j; η = j,m) is defined as

$$r_\eta(q_\eta) = P_j - C'(q_\eta) - H'_\eta(q_\eta)$$

(The range of η is 1 to JM. In the sequel, lower-case Greek letters, such as ν, τ, etc., are used to represent market-mode alternatives.) Note that this is simply the left side (without t_η) of Equation 1 evaluated for $q = q_\eta$. Thus, if the only alternative available to the shipper were η (ship to j by m), then $r_\eta(q_\eta)$ is the maximum per unit rate that the shipper would be willing to pay to ship q_η on mode m to market j. Thus, it is a demand price for service. It is not the demand function for alternative η service since it is conditioned on being the only available alternative. It will be shown later that choice models give rise to $r_\eta(q_\eta)$, while regression models give rise to direct estimation of the demand function implicit in Equation 1.

If $r_\eta(q_\eta)$ is inverted, $r_\eta^{-1}(t_\eta)$ results. Summing over all firms produces $R_\eta^{-1}(t_\eta)$, the maximum price shippers would be willing to pay to ship a total of Q on alternative η, given that alternative η is the only alternative used by all shippers.

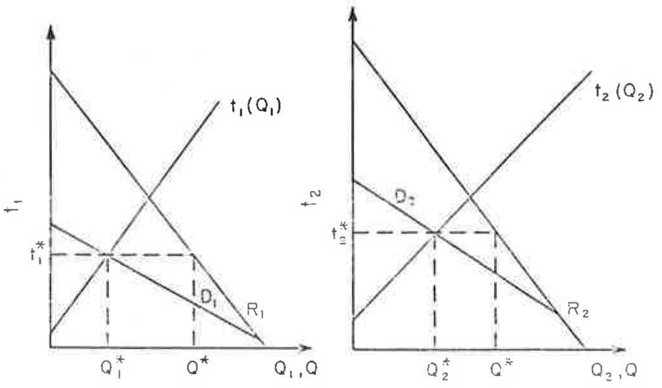
Let Q_η be the amount of service provided in alternative η. Thus, an inverse supply function $t_\eta(Q_\eta)$ is assumed, which represents rates as a function of quantities shipped. The demand for alternative η service is the set of ordered pairs (p_η, Q_η) that belong to

$$D_\eta = \left\{(p_\eta, Q_\eta)\epsilon R_+^2 \mid p_\eta \equiv R_\eta\left(\sum_\nu Q_\nu\right), t_\tau(Q_\tau) = R_\tau\left(\sum_\nu Q_\nu\right) \tau \neq \eta\right\}$$

In other words, demand for alternative η service is the set of nonnegative demand prices (p_η) and demand quantities (Q_η) so that Q_η is the residual demand left over after accounting for all other alternatives, based on a total flow $Q = \sum_\nu Q_\nu$ on all alternatives. For given Q, the $R_\nu(Q)$ is computed for each alternative. This calls forth Q_ν service $[=t_\nu^{-1}(R_\nu(Q))]$. Thus, $Q_\eta = \max(0, Q - \sum_{\nu\neq\eta} Q_\nu)$ is the residual demand quantity, and $p_\eta = R_\eta(Q)$ is the demand price. Varying Q results in tracing out the demand curve for alternative η. This is shown for a two-alternative case in Figure 1. Where unconditional demand (D_η) equals supply (t_η), the equilibrium for the transport market, which equilibrates the goods markets, exists.

The above analysis shows how demand for transport arises from a basic model of the shipper and that, in order to find demand, goods market characteristics

Figure 1. Market equilibrium using residual demand curves.



and service characteristics must be included as well as rates for service. It should be obvious that changes in, for example, service characteristics of one mode affect [via the $R_\eta(\cdot)$ function] the demand for alternative modes and, in this case, market selection as well.

Developing Estimation Models

The use of the first-order conditions does not stop with the theoretical analysis of demand. This section will show that not only can conditions of optimality be used to specify the form of the model to be estimated, but also that they provide a set of conditions indicating the applicability of various techniques (i.e., regression versus quantal choice) to the estimation problem itself.

As mentioned earlier, it can be shown that, under the assumption of risk-aversion on the part of the shipper, the service-induced cost functions $H_\eta(\cdot)$ will be strictly convex and monotonic. Consider the functions:

$$V_\eta(\cdot) \equiv P_j - t_\eta - H_\eta'(\cdot)$$

These functions reflect the marginal value of distribution of the good by alternative η. A restatement of Equation 1 is

$$V_\eta(q_\eta) = C'(\sum_\nu q_\nu) \quad \forall \tag{2}$$

Since the service-induced cost functions are strictly convex and monotonic, the $V_\eta(\cdot)$ functions are downward sloping. Figure 2 illustrates the optimal solution, assuming four alternatives. As can be seen, the optimal solution is to use more than one alternative, in other words, to pick a portfolio of alternatives. Thus, except under special conditions, the shipper will not choose just one alternative; rather, the shipper will choose a mix. Thus, quantal choice models, wherein only one alternative is chosen, are not appropriate. Again, this is due to the risk-aversion of the shipper—a very reasonable assumption. In this case, the appropriate approach is regression analysis on a system of equations. This is unfortunate; because both $C(\cdot)$ and $H_\eta(\cdot)$ are unknown, this approach will be very data intensive.

H_η is strictly convex in general. However, for firms such as those being examined here (country elevators), a linear approximation to the risk function is not too inaccurate (4) because elevators typically ship only a fraction of their holdings at a time. Thus, in terms of wealth put at risk, these firms are relatively (compared to terminal elevators) close to the origin of the risk function and, thus, a linear approximation to the unknown function is appropriate. This is not necessarily true for very large shippers with a multilevel, coordinated decision-making process such as terminal operators.

If we now approximate $H_\eta(\cdot)$ by a linear function, then $V_\eta(\cdot)$ is a constant since $H_\eta'(\cdot)$ will be a constant. The result is shown in Figure 3. The optimal solution is to pick the maximum V_η and use only that alternative. Now, rather than using regression techniques on a system of equations, we instead should use quantal choice. For if we take the total marginal return to be the sum of a measured, nonstochastic term (V_η) and a random variable (ϵ_η), then we pose the choice problem as picking the alternative with highest marginal return, i.e., we want to pick alternative η if

$$V_\eta + \epsilon_\eta > V_\nu + \epsilon_\nu \qquad \nu \neq \eta$$

Define the choice variable y that takes the value y=n, if the shipper chooses the η-th alternative. Here the alternatives are defined as market-mode pairs. Let x_η be a vector of observable characteristics of the shipper and let w be a vector of unobservable variables. Assume that the shipper's decision depends on the x_η's, z, and w. Thus, probability distribution of y is determined by the vector $x = (x_\eta)$, z, and the unknown parameters that characterize the distribution of w. Then the most general choice model [see (15)] can be mathematically represented by

$$\text{Prob}\{y = \eta \mid x,z\} = \exp F_\eta(x,z,w) / \sum_\eta \exp F_\eta(x,z,w) \tag{3}$$

Figure 2. Assuming four alternatives, shipper will choose a mix as is shown by downward-sloping curves. Risk here is strictly convex.

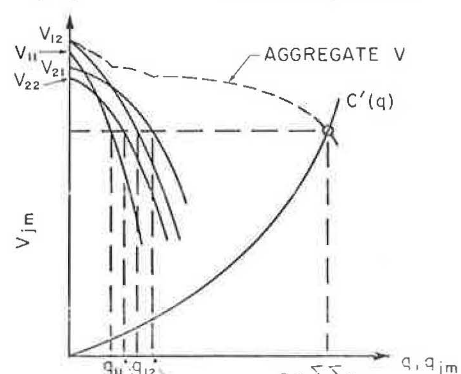
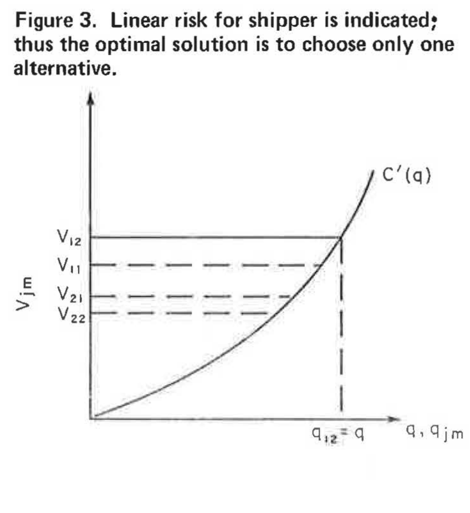


Figure 3. Linear risk for shipper is indicated; thus the optimal solution is to choose only one alternative.



where F_η is some function. Considerable effort has been expended on Equation 3 in recent years by Amemiya (15), Domencich and McFadden (16,17), and Nerlove and Press (18). McFadden has shown that if the ϵ_η's are independent with distribution $[-\exp(-\epsilon_\eta - \alpha_\eta)]$ where α_η is a parameter, then, letting F_ν (x,z,w) = $V_\nu - a_\nu$, we have

$$PR\{V_\eta + \alpha_\eta > V_\nu + \alpha_\nu\ \nu \neq \eta\} = Pr\{y = \eta \mid x,z\}$$
$$= \exp(V_\eta - \alpha_\eta) / \sum_\nu \exp(V_\nu - \alpha_\nu)$$

Therefore, if we approximate H_η with a linear function, which reflects the fact that country elevators typically make small shipments (relative to their total wealth), then a choice model can be used. We have chosen to use a logit representation of the choice problem both because of the McFadden results and computational ease as well as its closeness to alternative choice models (16,17). The models used were

$$Pr\{y = \eta \mid V\} = Prob\{V_\nu + \epsilon_\nu < V_\nu + \epsilon_\nu\ \forall_{\nu \neq \eta}\} \quad (4)$$

and

$$Pr\{y = \eta \mid q,V\} = Prob\{V_\nu q + \epsilon_\nu < V_\eta q + \epsilon_\eta\ \forall_{\nu \neq \eta}\} \quad (5)$$

where unsubscripted V stands for the vector (x,z). The reason for the second model is that, if it outperforms Equation 4, there is an indication of imperfection in the goods market. As one might expect, this is what occurred.

ESTIMATING THE CHOICE MODEL

This section deals with modeling a specific type of shipper—a country elevator that ships corn to various markets. In general, such characteristics as loss and damage and schedule reliability are not critical to such shippers, although other service characteristics are important. Specifically, we include a measure of equipment delay, i.e., availability (4). The measure that enters the shipper's profit function provides an approximate cost associated with using a mode. After estimating the two choice models, we will then show how demand functions can be derived. The analysis was performed in customary units rather than SI units.

Measuring Availability

Shippers form expectations about various service parameters. Miklius and Casavant (19) found that such expectations may not reflect reality. Nevertheless, shippers act on their expectations. In this case, grain elevator operators evaluate the availability of transport equipment, i.e., how much equipment delay they expect to experience in ordering and obtaining transportation vehicles (trucks, rail cars, barges) to fulfill commitments. Delays are often expected during the harvest period when transportation use is at its peak and resources are scarce. Then the availability of a piece of equipment can be critical. A number of different types of contracts with various provisions for delivery times exist and are used (20). In all cases, however, elevator operators require a high degree of confidence in the availability of equipment to make deliveries. Thus, opportunities may be foregone or responses to bids altered due to expectations about the availability of transport equipment.

Daughety and Inaba (4) showed how data collected by questionnaire could be used to construct an availability measure. The authors defined the α-expected delay to be n days where n is the value so that $Pr\{T \leq n\} = \alpha$ with T the number of days' delay in equipment arrival. The following table shows the 0.95-expected delay times and costs for two groups of shippers: SCR shippers (those who used only truck or single-car rail) and MCR shippers (those who used truck and single- and multiple-car rail).

Shipper	Days	Cost per Bushel ($)
Small (Truck, SCR)	7.8	0.0042
Large (Truck, SCR, MCR)	13.5	0.0072

The costs are found by evaluating the delays at the average inventory holding of 1.6¢/bushel/month. This table will not be discussed further other than to note that bigger shippers get poorer service in part because the railroads are unable to adjust their rates (4).

Specification of Model for Estimation

The behavioral model of the country elevator takes risk as linear and thus only one market and one mode are chosen to maximize the elevator's choice function (i.e., net price or net profits). Therefore, the logit technique is appropriate.

The observable part of the choice index consists of three types of exogenous variables or attributes: market variables, market-mode variables, and shipper-mode variables. Let P(n), t(n), A(n) be the vectors of exogenous variables observed by the n-th shipper where

$P_j(n)$ = the price at the j-th market,
$t_{jm}(n)$ = the transport rate of shipping to the j-th market by the m-th mode, and
$A_m(n)$ = the perceived availability cost per bushel of shipping by the m-th mode.

Following the theoretical considerations presented earlier in this paper, the choice index of the country elevator can be either net price or profits = net price x quantity. Therefore, the logit models used in this study are

1. The net-price model

$$Pr\{y = (j,m) \mid P(n), t(n), A(n)\} = \exp[\alpha_{j1} P_j(n) + \alpha_{jm2} t_{jm}(n) + \alpha_{m3} A_m(n)] / \sum_\ell \sum_k \exp[\alpha_{\ell 1} P_\ell(n) + \alpha_{\ell k2} t_{\ell k}(n) + \alpha_{k3} A_k(n)] \quad (6)$$

2. The net-profit model

$$Pr\{y = \eta \mid q(n), P(n), t(n), A(n)\} = \exp[\alpha_{j1} P_j(n) q(n) + \alpha_{jm2} t_{jm}(n) q(n) + \alpha_{m3} A_m(n) q(n)] / \sum_\ell \sum_k \exp[\alpha_{\ell 1} P_\ell(n) q(n) + \alpha_{\ell k2} t_{\ell k}(n) q(n) + \alpha_{k3} A_k(n) q(n)] \quad (7)$$

For SCR shippers, the availability cost for rail is \$0.0042/bushel, whereas for MCR shippers, this variable has the value \$0.0072/bushel. Since trucks are generally readily available (4), the availability cost is zero for all shippers in the sample.

Data and Estimated Choice Probabilities

In 1976, a survey was circulated to elevator firms in Indiana, Illinois, and Iowa. The survey asked for firm-level information (ownership structure, capacity, modes used, markets traded with, monthly storage charge, and accessibility to transport system), subjective assessments (the distribution of delay times in receiving equipment of various modes), and randomly selected shipment examples for specified times of the year and for specified crops. The individual shipment records contained information on quantity shipped, mode, contract price, transit time, transport rate, who paid the transport, destination, expected travel time, date of contract commitment, and shipment due date. For this study, only price, quantity, transport rate, whether the shipper paid the transport rate, destination, mode, and the distribution of delay times were used. Generally, no records are kept that indicate forgone opportunities. Thus, it was necessary to construct alternatives for each shipper.

Two major market areas were specified: river and local. River covers midwest and mideast destination points on the Missouri, Mississippi, Illinois, and Ohio rivers, as well as Chicago. All other midwest and mideast traffic is typically local. Shipments to the coasts were excluded. Obviously, such labels are somewhat arbitrary. The aggregation of the destinations into market areas was made on the basis of the type of activity associated with the area as well as the relative distance of a specific location to the alternative areas.

Two modes were examined: truck and single-car rail. All data were gathered for the week of October 19, 1975. This week is well into the harvest season for corn, the selected crop. Answers from those elevator firms that only used trucks to make shipments were used only to compute some average values. Since these elevator firms had eliminated other modes from their choice set, we could not include them in the overall choice analysis. An examination of why such firms choose not to even consider other modes will not be considered here.

As is well known, prices at the different markets reflect, to some extent, the commodity futures trading activity in the crop. Corn is traded at the Chicago Board of Trade. Prices did not vary greatly (σ = 0.234). Thus it was felt that the average regional prices from the data base would provide reasonable surrogates for the actual prices at the alternative markets. The regional prices per bushel were \$2.663 (river) and \$2.605 (local).

Actual transport rates were not obtained for alternatives not chosen. Rates were predicted from data collected on shipment sizes, rate paid, and distance shipped. Finally, availability costs per bushel were zero for truck, \$0.0042 for single-car rail when used by shippers who only use single-car rail at most, and \$0.0072 for single-car rail when used by shippers who also can use multiple-car rail.

Table 1 displays the estimated values of the coefficients for both of our logit models. Two models (truck and single-car rail) and two markets (river and local) result in four alternatives: truck to the river (TR), truck-local (TL), single-car to the river (SR), and single-car local (SL).

Table 1. Net-price and net-profit probability models.

	Model			
	Net-Price		Net-Profit	
Factor	River	Local	River	Local
Price	2.626 (1.046)	3.176 (1.193)	0.0014 (3.412)	0.0013 (2.945)
Truck	-33.21 (-3.889)	-64.63 (-4.491)	-0.0096 (-3.925)	-0.0128 (-3.297)
Rail	-16.74 (-3.547)	-25.29 (-3.410)	-0.0048 (-3.635)	0.0016 (-3.060)
Availability	-457.5 (-2.394)		-0.0669 (-1.951)	

Note: Asymptotic t-values for coefficients are shown in parentheses.

The first model predicted the correct choice 90 percent of the time and had a likelihood ratio index of 0.865, while the values for the second model were 82 percent and 0.4028 respectively. The likelihood ratio index gives a weak measure of the explanatory power of the model and is defined as one minus the ratio of the log-likelihood at zero, [For a discussion of this measure and its relationship to other goodness-of-fit measures, see Domencich and McFadden (16).] Asymptotic t-values for the coefficients are shown in parentheses. It is interesting to note that the first model has better summary statistics, whereas the price variables are not very significant. The theory expressed earlier suggests that, if elevators are competitive and have approximately linear service-induced transport cost functions, then the net-price model should be a good representation of market-mode choice. However, as Table 1 shows, a comparison of the t-values on the price variables suggests this is not true. The fact that market prices in the net-price model are insignificant is inconsistent with the theory, the remarks made by elevator operators, and the fact that organized futures markets exist to amplify and communicate information on market prices. On the other hand, when net price is multiplied by quantity, the market price variables in the net-profit model become significant.

Discussions with country elevator operators clarified the matter. In general, elevators face two types of buyers. One type—generally the larger buyers—accepts virtually any shipment size in response to its posted bids. These buyers reflect a perfectly elastic demand for grain. The second type of buyers poses downward-sloping demand curves. They issue a bid for grain and, as with the first type of buyer, the country elevator operator responds with an amount to ship. This is then negotiated, along with the bid price itself, either until a mutually satisfactory bid price and quantity are found or until negotiations break down. Clearly, the buyers are seeking points on their demand curve, while the elevators are attempting to stay on their supply (marginal cost) curve. The result is either a cobwebbing-in to a negotiated solution (intersection) or divergence (no contract).

The existence of such transactions is easily confirmed; their extent in the market, however, is unknown. A test for their effect on shipper choice is the estimation of Equation 7, the net-profit model. The t-values on revenues (price times quantity) are very significant, indicating that market imperfection in terms of bid negotiation is extensive and invalidates the use of Equation 6, the net-price model. The analysis in the rest of the paper is based on Equation 7.

Demand Functions and Choice Probabilities

Two ways to predict demand have already been noted. The first was through aggregating individual demand functions. If we had been able to use regression, we could now do this. It is also impossible to directly find the demand function using quantal techniques. An individual demand function would be represented as

$$E(Q_\eta \mid V) = \int_{-\infty}^{\infty} q \, dPr\{y = \eta, q \leq Q \mid V\}$$

where V is a vector of observed parameter values. By varying t_η, for example, we could trace out the demand for transportation for alternative η. Unfortunately, we do not have an estimate of $PR\{y=\eta, q \leq Q \mid V\}$. This can be seen by the following:

$$\Pr\{y = \eta, q \leq Q \mid V\} = \Pr\{q \leq Q \mid y = \eta, V\} \cdot \Pr\{y = \eta \mid V\} \quad (8)$$

$$\Pr\{y = \eta, q \leq Q \mid V\} = \int_{-\infty}^{Q} \Pr\{y = \eta \mid q \epsilon d\bar{Q}, V\} \cdot \Pr\{q \epsilon d\bar{Q} \mid V\} \quad (9)$$

Equation 8 cannot be estimated because it requires the net-price model, the applicability of which is precluded by market imperfections. Moreover, Equation 9 requires additional estimates of the firm's choice behavior, i.e., $\Pr\{q \leq Q | V\}$.

However, aggregate demand functions for each market-mode pair can be estimated from the net-profit model by using the method presented in the section on firm and transport demand theory. Let $h(q|\eta,V)$ be the posterior density on shipment size given that the firm chooses alternative η and observes the vector V of parameter values. Let f(q) be the prior density on shipment size. Then by Bayes' theorem

$$h(q \mid \eta, V) = [\Pr\{y = \eta \mid q, V\} \cdot f(q)] \Big/ \int_{-\infty}^{\infty} [\Pr\{y = \eta \mid q, V\} \cdot f(q) dq]$$

where $\Pr\{y=\eta|q,V\}$ is, of course, the selection probability of the net-profit model. Then

$$E(Q \mid \eta, V) = \int_{-\infty}^{\infty} q h(q \mid \eta, V) dq$$

gives the expected quantity shipped given η and V. Notice that if we only alter t_η (in V) and trace out the expected shipments, we will trace out $r_\eta^{-1}(t_\eta)$, the conditional demand for alternative η service discussed earlier. Using the procedure outlined, we can thus estimate $R_\eta(Q)$ functions and, given supply functions, we can estimate demand functions for each market-mode pair.

DEMAND FUNCTION ESTIMATION RESULTS

Prior Density on Shipment Size

The prior on shipment size, f(q), was taken to be normally distributed, based on an elementary central limit theorem argument. Two priors were used, i.e., one for small shippers and one for large shippers. The means and standard deviations for the priors are shown in the following table:

Shipper Size	Mean	Standard Deviation
Small	4 075	5 912
Large	11 835	23 484

Individual $r_\eta(q_\eta)$ and Market Level $R_\eta(Q)$

Using the priors shown above, $E(Q|\eta,V)$ was computed for both types of shipper, for all four alternatives, and for various values of t_η. Table 2 displays coefficients for linear regressions that were fitted to the computed values.

The regressions in Table 2 represent inverses of $r_\eta(q_\eta)$. As can be observed, all are downward sloping except small shippers, alternative (SL), which is constant. The computed shipments were then aggregated and scaled upward to represent the region (2500 elevators). Table 3 displays the inverses of $R_\eta(Q)$.

Table 2. Regression of $E(Q|\eta,V)$ on t_η.

Alternative	t_η	Constant	R^2
Small shipper:			
TR	-72 875 (16.3)	13 988 (25.5)	0.97
TL	-51 072 (-7.2)	7 748 (10.5)	0.86
SR	-32 468 (-16.9)	10 682 (25.2)	0.97
SL	51.6 (0.2)	7 757 (145.8)	-
Large shipper:			
TR	-314 030 (-5.0)	55 439 (7.2)	0.75
TL	-241 000 (-3.2)	30 515 (3.9)	0.53
SR	-44 697 (-9.2)	13 359 (12.4)	0.91
SL	-197 440 (-28.6)	62 839 (41.1)	0.99

Notes: TR = truck-to-river; TL = truck-local; SR = single-car to river; SL = single-car local.
Asymptotic t-values for coefficients are shown in parentheses.

Table 3. Inverses of $R_\eta(Q)$.

Alternative	t_η	Constant	R^2
TR	$-6.2116 \cdot 10^8$ (-5.4)	$1.1042 \cdot 10^8$ (7.8)	0.78
TL	$-4.734 \cdot 10^8$ (-3.3)	$6.0812 \cdot 10^7$ (4.1)	0.56
SR	$-1.0348 \cdot 10^8$ (-10.2)	$3.1579 \cdot 10^7$ (14.1)	0.93
SL	$-3.5937 \cdot 10^8$ (-28.7)	$1.1966 \cdot 10^8$ (43.1)	0.99

Notes: TR = truck-to-river; TL = truck-local; SR = single-car to river; SL = single-car local.
Asymptotic t-values for coefficients are shown in parentheses.

Supply

Demand for modal service is a residual demand, and supply functions must be estimated before demand curves are derived. In this study, rate functions are used as surrogates for supply curves. These approximations had to be used because supply functions for truck and rail for the region do not exist in the literature, and limitations of cost data precluded estimation of supply curves in the traditional manner.

Rate functions were estimated for the four market-mode alternatives by regressing rates on the amounts shipped by alternative. Assuming that the sample rates and quantities shipped are representative of the typical transport firm, an estimate of the aggregate amount shipped on an alternative mode was obtained by multiplying the sample quantities by an estimate of the number of typical firms providing the service. The procedure to estimate the number of typical firms providing service to each market-mode alternative is described here.

Assume that a typical firm is represented by the amount of service supplied during the period svq, where s is the number of shipments per vehicle during the period, v is the number of vehicles per firm, and q is the load per vehicle. Then the amount that a typical firm can carry on one shipment is Q = vq. If N is the number of firms providing service on an alternative, the quantity of service provided during the period must be T = Nsvq = NsQ.

Estimates of T,s,q, and Q yield estimates of N, the number of typical firms, and v, the number of vehicles per firm. To estimate the T's, the sample totals of the quantity shipped on each alternative were scaled up to the projected total shipments by alternative for the region. Estimates of s were obtained from the data on actual transit times reported in the survey. The average shipment sizes were used as estimates of the Q's. Finally, average load capacities for truck and rail hopper cars were used to approximate the q's. Our procedure yielded these estimates: the number of typical firms providing truck service to the river and local was 427 and 128 respectively; the number of typical firms providing rail service to the river and local was 416 and 416 respectively; the number of vehicles per firm was 6 and 11 trucks, 1 and 3 rail cars respectively.

Clearly, our procedure suffers from the fact that vehicles are switched and reallocated among markets on a daily basis. Consequently, our definition of a typical firm as a grouping of transport vehicles providing service sufficient to carry the average load departs considerably from the actual. However, within this constraint, the implied industry supply functions as approximated by rate functions are shown in the following table:

Alternative	Prediction Equation	R^2
TR	$t_1 = 0.189\,065q^{-0.031\,893}$	0.69
TL	$t_2 = 3.284 \cdot 10^{-8}q + 0.0531$	0.27
SR	$t_3 = 1.0474 \cdot 10^{-8}q + 0.2087$	0.39
SL	$t_4 = 1.0474 \cdot 10^{-8}q + 0.1828$	0.39

These were found by estimating individual rate functions and then scaling up to reflect the implied size of each alternative "industry."

As shown, all functions are linear except for the first alternative, which was log-linear. Rates are predicted as a function of shipment size (in bushels $\times 10^{-7}$). Again, the reader is cautioned that these are not aggregate marginal cost functions. They are simply observed relationships between rates and shipment size, scaled up by estimated number of firms.

In general, alternative one reflects an essentially horizontal supply function, while the second alternative is upward sloping. This probably reflects the fact that local movements entail search costs for the next load; movements to the river provide lower search costs due to higher concentrations of firms. The fact that the rail-rate functions slope upward does not conflict with the regulation of rails. Rates are regulated on a point-to-point basis, while the rate functions are aggregations over a three-state region.

Demand Functions and Resulting Equilibria

Elements of D_η ($=1,\ldots,4$) were computed and then fit with a linear equation to summarize their trend. These equations are displayed below:

Alternative	t_η	Constant	R^2
TR	$-7.0341 \cdot 10^8$	$1.1477 \cdot 10^8$	0.99
TL	$-5.4795 \cdot 10^8$	$5.8201 \cdot 10^7$	0.98
SR	$-1.3673 \cdot 10^8$	$2.526 \cdot 10^7$	0.99
SL	$-3.3604 \cdot 10^8$	$1.1122 \cdot 10^8$	0.93

Caution is again suggested in using these results. The high linearity is simply due to the use of linear functions to derive the demand curves. Future work must rely on more sophisticated statistical and numerical techniques. Nevertheless, the following approximate equilibria were computed:

Alternative	t_η (\$)	q (bushels)
TR	0.108	38 500 000
TL	0.103	1 500 000
SR	-	-
SL	0.289	14 000 000

For the third alternative, demand was slightly below supply and thus the model predicts no market for services. This corresponds reasonably well with the observation that, for the movements used to estimate the logit function (78 elevators), single-car-to-the-river accounted for only 6 percent of the total quantity moved. Statistical and numerical error probably account for the result indicated in the preceding table.

The estimates for the first and fourth alternatives seem slightly high (it was generally expected that total flows would be in the neighborhood of 25 to 35 million bushels). This is also reflected in the fact that total shipments ($\sum_\eta q_\eta$) do not equal implied total shipments from $R_\eta^{-1}(t_\eta)$. This is clearly a result of the heavy reliance on the estimated linear relationships among the variables and the size of the sample used. However, relative magnitudes are generally reflective of the data observed.

SUMMARY

In this paper we have developed a technique for estimating demand for transport service that is sensitive to transport rates, market prices, and service levels. We estimated own-demand functions; clearly a variety of cross-demand functions could similarly be derived as well as demand functions parameterized on perceived service level.

The approach was based on a model of a shipper's decision-making process. Conditions of optimality were used to specify a choice model subject to some assumptions about the shipper's response to the risks incurred by using the transport system. This model was expanded to allow for testing for imperfection in the goods markets. In the presence of such imperfection we proposed a technique that required generating a posterior on shipment size, conditioned on alternative choice from a prior on shipment size and the estimated choice model. The resulting expectation of the posterior, when used in combination with industry supply functions, produced demand equations. Finally, market equilibria—where demand was equal to supply—were computed.

Improvements must occur in at least two areas. First, industry supply curves based on cost analysis must be used rather than the rate functions used herein. Second, a larger sample of elevator firms is called for. Both of these problems are presently under development.

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Effect of Increased Motor-Carrier Sizes and Weights on Railroad Revenues

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Railroad net revenue is directly related to motor-carrier rates and costs on all traffic for which motor carriage can be substituted easily for rail service. Increases in maximum lawful truck sizes and weights will lead to lower motor-carrier costs. Competition and regulatory pressure will translate these lower costs into lower rates. Railroads will have to either match the lower rates or lose traffic to the competing mode. In either instance, railroad revenue will decline as a result of the increased truck sizes and weights. The amount of loss depends on the reduction in motor-carrier costs and rates brought about by the increase in capacity, and by the proportion of existing rail traffic that will move by motor carrier if the relative rates of the two modes change. If motor-carrier capacity increases from 33 249 kg to 40 834 kg (from 73 280 lb to 90 000 lb), costs of operation and rates are estimated to decline by 16.8 percent. Potential for diversion from rail to truck was estimated by examining market shares of each commodity in each distance grouping. Available market share data suggest that railroads compete with motor carriers for traffic accounting for approximately 75 percent of rail revenue. Thus, a 16.8 percent decline in motor-carrier costs and rates would force railroads to make competitive adjustments that would cost the industry up to $2 billion.

An increase in motor-carrier size and weight limits will lower the cost of carrying goods by motor carrier, thus increasing the attractiveness of motor carriage over rail carriage. Lower motor-carrier costs would permit for-hire motor carriers to reduce rates to attract traffic from railroads and would lower the costs of private carriage. Where shippers view railroads and motor carriers as alternative means of shipping goods, a change in the cost of moving by one mode rather than another will encourage substantial diversion of traffic to the mode offering service at reduced cost. The mode affected by the diversion can either lose the traffic or lower rates to maintain its share of market. The amount of diversion that will result from a given change in relative prices is a function of the elasticity of substitution between the two modes, i.e., the degree to which shippers will change modes in response to a change in price. Elasticity of substitution will vary among commodities and over different distances for the movement of a single commodity.

The 1972 Census of Transportation (1) provides information about the share of market by mode for each 3-digit commodity code by distance block. Thus, one can infer the susceptibility of each commodity to diversion