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Ridership Response to Changes in Transit Services

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Evidence on ridership response to changes in transit service is presented. Mean values and standard deviations of transit-service elasticities are presented for changes in headways, vehicle miles, in-vehicle and out-of-vehicle travel time, transfers, and seat availability. A review of the methods used in estimation of demand elasticity is presented as well as suggestions on how service elasticities can be used in joint transit-fare and service-level planning to improve revenues and ridership.

The demand for public transportation has traditionally been regarded as more responsive to changes in transit service (e.g., headways and bus miles) than to changes in transit fares. Although on the aggregate level this may be true, recent evidence shows that service elasticities vary considerably from one area to another by the time of day, type of route, service quality, and other classifications, which suggests that there may be situations in which patronage may be more responsive to fare changes than to service adjustments.

In this paper a summary of the current state of knowledge on the size of transit-service elasticities is presented compiled from demonstrations and demand models. In addition, suggestions are made about how service elasticities can be used in joint transit-fare and service-level planning to improve revenues and ridership.

APPROACHES TO ESTIMATING TRANSIT-SERVICE ELASTICITIES

Nature of Approaches to Demand Estimation

Two broad approaches to estimating service elasticities may be distinguished. These approaches include (a) monitoring service changes and demonstration studies, or those that rely on data generated either by a practical demonstration of an actual change or by monitoring an actual change in service levels, and (b) nonexperimental approaches, or those that rely on a data base either devoid of an actual change in service levels or in which actual changes are part of historical trends.

Approaches in the first category include the monitoring of transit-service demonstrations and individual service changes such as those that use monthly data series. The nonexperimental approaches generally include (a) the conventional time-series analysis of annual transit operating statistics, (b) aggregate direct-demand and modal-split models based on cross-sectional data, and (c) disaggregate behavioral mode-choice models based on cross-sectional data. All the nonexperimental approaches have in common the fact that the data base does not contain an actual service change and also that the data base is not generated with the objective of controlling for nonservice changes.

The demand-elasticity estimates presented in this paper from demonstrations and selected service-monitoring studies were calculated by using a mid-point elasticity formula (1). The demand-elasticity estimates from demand models are point elasticities.

Methodological Note on Special Problems of Cross-Sectional Models

In interpreting transit-demand elasticities, some problems are posed by overreliance on elasticity estimates developed from a cross-sectional data base that contains no service change. One cannot rely on elasticity estimates from cross-sectional studies to provide accurate estimates of annual changes in patronage in response to service changes because they reflect a different type of behavior from that implicit in time-series analysis. This difference between time-series and cross-sectional models arises because the residuals from both models cannot be assumed to belong to the same underlying population. In general, cross-sectional estimates represent behavior that, for lack of a better term, economists have labeled "long-run structural adjustments" (2), although it is possible that cross sections taken at a time of rapid growth or of cyclical change could also reflect short-run annual adjustments such as those characterized by time-series relationships. Although cross-sectional models have advantages in forecasting structural changes in demand, dynamic annual-change-type responses cannot be estimated with any degree of confidence unless supporting time-series information is available to establish a systematic relationship.

Another problem is that some recent work on disaggregate behavioral models has departed from McFadden's (3) original contribution and, as a consequence, as shown by Oum (4), some of these models (a) impose many rigid a priori conditions on the elasticities and cross elasticities of demand, (b) result in estimates of elasticities that are not invariant to the choice of the base or modal denominators, and (c) possess severely irregular and inconsistent underlying preference or utility structures. Moreover, an estimation problem arises whenever simultaneous mode choices concern more than two modes. Theil (5) and Nerlove and Press (6) argue that biased coefficients result when simultaneous choices--such as the choices that involve more than two transport modes--are estimated by using single-equation estimation techniques such as the maximum-likelihood approaches currently used by transportation mode-choice modelers.

HEADWAY ELASTICITIES

Public transportation headway elasticities vary considerably, due in part to the characteristics of the route in question, but the mean aggregate values show a remarkable similarity. The evidence shows that average bus and commuter-rail headway elasticities are equivalent and the mean value for all service hours is -0.47 ± 0.17 (16 cases). (The standard deviations presented in this paper measure the variation of the respective groups of means taken from the studies and do not represent a measure of confidence in the particular means.)

Bus Headway Elasticities

The information on bus headway elasticities summarized in Table 1 from a report by Ecosometrics, Inc. (7), from the Detroit Grand River Avenue demonstration (8), from the Chesapeake/Norfolk commuter-route demonstration (9), from the Boston bus headway demonstration (10), from the Madison circular-route demonstration (11), and from the demonstration in Stevenage, Great Britain (12) shows that, although the mean bus headway elasticity based on data from monitoring service changes is -0.47 ± 0.21 for all service hours, each elasticity value appears to depend on the route characteristics and on the level of service before headway adjustments are made. As shown in Table 1, headway elasticities depend on the previous level of service for both peak and off-peak periods. During the peak period, headway elasticities are -0.58 for low-service routes. These values exceed by more than 110 percent the elasticity values of -0.27 ± 0.14 for high-service routes. The same is true during off-peak periods in which the highest elasticities, which have a mean value of -0.71 ± 0.11, predominate among low-service routes.

With regard to differences in headway elasticities by time of day, off-peak elasticities are appreciably higher than peak-period elasticities. In the Chesapeake/Norfolk demonstration of 1965-1967 (9), the off-peak elasticities were more than 50 percent above the mean peak elasticity of -0.57. The same is true of the 1962 Detroit Grand River Avenue demonstration (8), in which off-peak elasticities were almost 100 percent above the peak-hour elasticity of -0.13. The limited evidence on weekend headway elasticities indicates that these values are similar to the off-peak weekday elasticities. However, the data from the 1975 Madison (11) and 1962 Detroit Grand River Avenue demonstration (8) show that the bus headway elasticities on Sunday were larger than those on Saturday.

Commuter-Rail Headway Elasticities

Analysis of the commuter-rail headway elasticity values [Table 2 (7,10)] shows the mean elasticity for all hours to be -0.47 ± 0.14, which is congruent with the mean headway elasticity value obtained for bus service. Furthermore, most of the generalizations made for bus headway elasticities are confirmed by similar experiences with commuter-rail elasticities. As presented in Table 2, the commuter-rail elasticities, which were estimated from the five-corridor demonstration in the Boston area in 1962-1964 (10), show an aggregate mean off-peak elasticity of -0.65 ± 0.19, approximately 82 percent above the mean peak elasticity value of -0.38 ± 0.16. The comparison of peak with off-peak elasticities for the Lowell and Reading corridors, which had approximately identical headways for both periods, reinforces the conclusion that off-peak ridership is more responsive to service improvements, since the off-peak period elasticities were 70-76 percent higher than the peak-period elasticities in these corridors.

Table 1. Bus headway elasticities by service level and time period.

Service Level[a]	Peak Hours Mean	Peak Hours SD	Peak Hours No. of Cases	Off-Peak Hours Mean	Off-Peak Hours SD	Off-Peak Hours No. of Cases	Weekends Mean	Weekends SD	Weekends No. of Cases	All Hours Mean	All Hours SD	All Hours No. of Cases	Aggregate Value Mean	Aggregate Value SD	Aggregate Value No. of Cases
High	-0.27	±0.14	2	-0.19	±0.09	3	-0.22	-	1	-0.25	-	1	-0.22	±0.10	7
Medium	NA	NA	NA	-0.49	±0.20	3	-0.43	±0.16	3	NA	NA	NA	-0.46	±0.18	6
Low	-0.58	-	1	-0.71	±0.11	3	NA	NA	NA	-0.51	±0.20	6	-0.58	±0.19	10
Aggregate value	-0.37	±0.19	3	-0.46	±0.26	9	-0.38	±0.17	4	-0.47	±0.21	7	-0.44	±0.22	23

[a]Levels of service classified as follows: high, <10-min headways; medium, 10- to 50-min headways; low, >50-min headways.

Table 2. Commuter-rail headway elasticities by service level and time period.

Service Level[a]	Peak Hours Mean	Peak Hours SD	Peak Hours No. of Cases	Off-Peak Hours Mean	Off-Peak Hours SD	Off-Peak Hours No. of Cases	All Hours Mean	All Hours SD	All Hours No. of Cases	Aggregate Value Mean	Aggregate Value SD	Aggregate Value No. of Cases
Medium	-0.38	±0.16	5	-0.46	±0.09	2	-0.41	±0.09	4	-0.41	±0.13	11
Low	NA	NA	NA	-0.78	±0.10	3	-0.69	-	1	-0.76	±0.10	4
Aggregate value	-0.38	±0.16	5	-0.65	±0.19	5	-0.47	±0.14	5	-0.50	±0.20	15

[a]Levels of service classified as in Table 1.

VEHICLE-MILE ELASTICITIES

In this section, aggregate vehicle-mile service elasticities are discussed, whether they relate to frequency, route length, route density, or service-hour changes. In fact, little is known about differences in elasticities among these components of vehicle miles.

Although most work in estimating vehicle-mile service elasticities has been developed from cross-sectional and time-series studies, two important studies that monitored the effects of individual fare and service changes were performed for the cities of San Diego and Atlanta. In San Diego, Kemp (13) and Goodman, Greene, and Beesley (14) developed vehicle-mile elasticities by using least-squares regressions of time-series data over the 40-month period, during which service expanded by approximately 80 percent. The aggregate vehicle-mile elasticity varied from +0.75 to +0.85. In Atlanta, where more service was available and where service expansion occurred over a much shorter period of time, Kemp (15) estimated a vehicle-mile elasticity of +0.30.

The results from transportation demand-modeling efforts that use nonexperimental data confirm the San Diego and Atlanta results that transit demand response is inelastic to variations in vehicle miles. The mean service elasticity for all 28 cases analyzed in Table 3 (7) is +0.61 ± 0.31, a value slightly larger than the mean elasticity obtained from studies of headway variations. As shown in Table 3, vehicle-mile elasticities during the peak period are found to be only half the value observed during off-peak hours. Again, this indicates the varying ridership responsiveness at different levels of service. The mean bus-mile elasticity of +0.64 is twice the elasticity of +0.30 observed for rapid-rail service. This observation must be tempered by the lack of cases for rapid-rail service.

TRAVEL-TIME ELASTICITIES

Perhaps the most important factor that affects public transportation ridership is travel time. Unfortunately, measuring ridership response to total travel-time changes as well as to changes in trip-time components is a difficult task. In contrast to the previous sections on service elasticities, there has been scant experimentation with travel-time variations.

In-Vehicle Travel-Time Elasticities

The only travel-time elasticities available from bus-monitoring studies are estimates of ridership response to in-vehicle travel-time improvements obtained from bus priority demonstrations in three cities--Seattle, Miami, and Boston. As shown in Table 4 (7,16-18), the aggregate elasticity from the demonstration data is -0.35 ± 0.21. However, the aggregate elasticity is dominated by peak-period elasticities, which make up 90 percent of the observations.

The results of the 1970 Seattle Blue Streak demonstration (17) can be used to analyze the differential effects of time periods on the in-vehicle time elasticities. Seattle's peak-period reverse-commute service elasticity of -0.55, although smaller than the off-peak value of -0.83, is 25 percent larger than the travel-time elasticity of -0.44 obtained in the peak direction.

The estimation of in-vehicle time elasticities from mode-choice models results in much higher estimates than those from demonstrations. The results of 12 cross-sectional models reviewed by Ecosometrics, Inc. (7) show mean elasticities of -0.70 ± 0.10 (two cases) for rapid rail and -0.68 ± 0.32 (seven cases) for bus--estimates twice the size of the values from demonstrations. Although slightly smaller than the mean, McFadden's (3) bus and rapid-rail in-vehicle travel-time elasticities (-0.46 to -0.60) are relatively similar and relatively close to the demonstration elasticities. Talvitie (19) shows a large mode-choice elasticity for bus service of -1.10; however, his elasticities greatly exceed those observed from the demonstration projects and consequently are suspect.

In 1977, Hepburn (20) analyzed the commuter-rail routes that served the London metropolitan area during the period 1966-1971. The in-vehicle travel-time elasticities he obtained were -0.49 for routes shorter than 25 miles and -0.86 for routes longer than 25 miles.

Table 3. Vehicle-mile elasticities from nonexperimental data by mode and time period.

	Peak Hours			Off-Peak Hours			All Hours			Aggregate Value		
Mode	Mean	SD	No. of Cases	Mean	SD	No. of Cases	Mean	SD	No. of Cases	Mean	SD	No. of Cases
Bus	+0.33	±0.18	3	+0.63	±0.11	3	+0.69	±0.31	17	+0.64	±0.30	23
Rapid rail	+0.10	-	1	+0.25	-	1	+0.55	-	1	+0.31	±0.19	3
Bus and rapid rail	NA	NA	NA	NA	NA	NA	+0.77	±0.27	2	+0.77	±0.27	2
Aggregate value	+0.27	±0.19	4	+0.54	±0.20	4	+0.69	±0.30	20	+0.61	±0.31	28

Table 4. In-vehicle time elasticities by time period.

	Elasticity			
Time Period	Mean	SD	No. of Cases	Bus Priority Project
Peak	-0.29	±0.13	9	Miami I-95, Seattle Blue Streak, Boston Southeast Expressway
Off-peak	-0.83	-	1	Seattle Blue Streak
Aggregate value	-0.35	±0.21	10	All the above

Out-of-Vehicle Time Elasticities

All the evidence regarding out-of-vehicle time elasticities comes from nonexperimental data estimates, mainly from mode-choice models. The mean elasticity of total out-of-vehicle time is -0.59 ± 0.15, a value in general agreement (in spite of the fact that its value is derived from only three studies) with the headway elasticity values estimated earlier. It is reasonable to expect headway and out-of-vehicle time elasticities to be similar, since wait and transfer times (the major components of out-of-vehicle time) are equal to half the headway when very frequent transit service is provided or when the schedule is unknown and passengers arrive at transit stops at random.

The evidence on component out-of-vehicle time elasticities (i.e., walk-, wait-, and transfer-time elasticities) is mixed, especially in relation to in-vehicle travel-time elasticities. The value of out-of-vehicle time has been estimated by several investigators--for example, Quarmby (21)--to be two to three times greater than the value of in-vehicle time. A mode-choice model estimated for Stockholm and other Swedish cities by Algers, Hansen, and Tegner (22) resulted in relative values of waiting times that were 3-12 times the in-vehicle travel-time values. This study also indicated that the relative waiting-time value will increase rapidly as headways are increased, a finding that corresponds to the earlier conclusion that the absolute value of headway elasticities is directly proportional to the level of service.

The walk-time elasticities estimated by Pratt and DTM, Inc. (23) for Minneapolis-St. Paul are very small, as shown in Table 5. The value for all work trips is -0.26, or half the in-vehicle time elasticity; for nonwork trips, the walk-time demand elasticity is -0.14. Passenger demand on bus routes that lead to the central business district (CBD) was estimated by Pratt to be less elastic to changes in walk time than the demand on non-CBD-oriented routes.

The study also shows that wait-time elasticities are only slightly larger than walk-time elasticities. As a rule of thumb for planning headways and route density, transit planners equalize the average wait time at a bus stop to the average walk time to the stops (24). This allocation of buses to routes suggests that wait- and walk-time elasticities are equivalent, as confirmed by the Pratt model.

As shown in Table 5, a wait-time elasticity for Montreal (25) that is twice the size of the in-vehicle time elasticity is presented; however, just the opposite is shown for San Francisco (3) and the results for Minneapolis-St. Paul (23) suggest that the difference is dependent on the trip purpose. McFadden's transfer-time elasticities for peak-hour service in San Francisco are higher than the comparable first-wait-time elasticities. Note also that although the rail transfer-time elasticity is greater than the values observed for bus service, the opposite is true for first-wait time. The inconsistencies in Table 5 point out the need for controlled demonstrations of transit service on this subject.

TRANSFERS

By using mode-choice estimation models, Algers, Hansen, and Tegner (22) discovered that the overall cash value of a transfer was 30 percent higher than the cash fare per trip and corresponded to approximately 24 min of door-to-door travel time. Thus, passengers appear to be willing to pay more than twice the base fare to avoid having to transfer. Their model showed that the value of avoiding a transfer was greater for bus than for rail, primarily because of the higher potential discomfort in transferring from buses.

In one of the few studies to focus on transit demand and the number of transfers, Pratt and DTM, Inc. (23) estimated a transfer elasticity of -0.59 in their nonwork mode-split model for Minneapolis-St. Paul. This value is much larger than the wait-time and transfer-time elasticities estimated from the same three-mode choice model (-0.24 and -0.17, respectively); this confirmed the previously mentioned studies that showed that avoidance of transferring is more important to the user than the time spent waiting for a bus.

SEAT AVAILABILITY

The importance of seat availability for transit users has been documented in several studies. For example, Algers, Hansen, and Tegner (22) attempted to quantify the value of getting a seat by introducing a dummy variable into their logit mode-choice models to test the hypothesis that those who do not get a seat value their travel time more than those who get a seat. They found that the trip value for individuals who do not have a seat was 40-75 percent higher than the travel-time value for people who have a seat.

As part of a service-improvement demonstration between Vancouver (Washington) and Portland (Oregon), sponsored by the Urban Mass Transportation Administration (UMTA) Office of Service and Methods Demonstrations, seating capacity on TRI-MET's Line 5 was increased by more than 40 percent by adding a trailer bus to six peak-period runs (26). The increase in ridership attributable to the availability of seating resulted in an elasticity of

Table 5. Comparison of in-vehicle time and component out-of-vehicle time elasticities.

Type of Elasticity	Montreal Bus and Rapid Rail	San Francisco Bus (two-mode)	San Francisco Bus (three-mode)	San Francisco Rapid Rail	Minneapolis-St. Paul Bus (work)	Minneapolis-St. Paul Bus (nonwork)
In-vehicle time	-0.27	-0.46	-0.60	-0.60	-0.52	-0.12
Out-of-vehicle time						
Walk	NA	NA	NA	NA	-0.26	-0.14
Wait	-0.54	-0.17	-0.19	-0.12	-0.32	-0.21
Transfer	NA	-0.26	-0.29	-0.66	NA	NA

+0.65. We calculated this elasticity from the data presented by Systan, Inc. (26) and assumed that the percentage of passengers seated was equal to the probability of getting a seat. This relatively high value is approximately 40 percent larger than McFadden's bus in-vehicle time elasticity.

INTERACTIONS OF TRANSIT FARES AND SERVICE LEVELS

The service elasticities presented in this paper and fare elasticities presented elsewhere (7,27,28) indicate that transit demand is inelastic to both fares and services. Consequently, independent variations of fares and services will not by themselves increase both revenues and patronage at the same time. For example, an increase in service--without a corresponding fare change--will probably not result in revenue increases large enough to cover the extra costs of the service improvement because the proportional change in patronage is less than the proportional changes in service.

Aggregate service elasticities (measured in vehicle miles), however, are twice as large as aggregate fare elasticities, which suggests that passengers are more responsive to service changes than to fare changes. On the aggregate levels, this is true. However, because both fare or service elasticities vary considerably from one area to another and by the time of day, type of route, and other classifications, this generalization is not always true. For example, by using the data presented in this paper, the mean bus headway elasticity on routes that have less than 10-min headways is -0.19 during off-peak hours. The average off-peak fare elasticity for bus service, however, may be only -0.35. Since the service elasticity is so low, a transit operator cannot hope to increase ridership and revenues substantially by further headway improvements. If headway adjustments are contemplated, then they should be reduced and the operating-cost savings should be applied either to other corridors that have relatively poor service or to the same route in the form of a fare reduction.

Patronage losses associated with attempts to increase revenue can be minimized by increasing fares only for users who exhibit small demand elasticities, such as commuters. The service saved as a result of reduced demand, albeit small during the peak period, could be applied to routes that have relatively poor service and result in further revenue increases if the patronage gained by the service adjustment is greater than the patronage lost due to the fare increase. Since the marginal cost per vehicle hour of operation during off-peak periods is at least 30-50 percent lower than that during the peak period (29,30), the cost savings due to the reduction in peak service should be applied to off-peak routes that have infrequent service, which would make possible a further gain in total ridership and revenues.

If the disaggregate fare and service elasticities are known for a particular transit market, the ridership or revenues generated by a particular action or set of actions could be improved by manipulating both the fare and the service levels. If, for analytical purposes, the revenues generated by an improvement in service are assumed equal to the additional costs of providing that service (i.e., a situation in which operating costs break even) and if the fare and service elasticities are not numerically equivalent, then transit ridership can be increased with no net effect on revenues by proper fare and service adjustments. These adjustments will in turn cause the demand elasticities to change if the elasticities are assumed variable and dependent on the respective fare and service levels. Opportunities for further ridership increases will cease when the fare and service elasticities are equal (31,32). Thus, when the service elasticity for a particular market is larger than the fare elasticity, a transit agency should raise fares and use the revenues produced to finance service improvements. Conversely, if the fare elasticity is larger than the service elasticity, then fares should be decreased and the revenue loss covered by the cost savings of a simultaneous service reduction.

As an example, Table 6 presents two fare- and service-adjustment strategies to increase total bus ridership with no change in net revenue, based on disaggregate fare and service elasticities. For convenience in analysis, the model assumes a situation in which operating costs break even, so that revenue-cost considerations can be deemphasized (32), and aggregate fare and headway elasticities are -0.35 and -0.47, respectively; adjustment factors presented by Ecosometrics, Inc., are applied (7).

The two strategies presented in Table 6, however, are not the only fare- and service-adjustment options available for increasing patronage. The peak to off-peak cross-subsidy scenario described earlier is an example of such an alternative. Whatever service-adjustment decision is made, the premise on the extent to which transit riders are willing to pay more for improved service or trade one service attribute for another must be based on the disaggregate fare and service elasticities.

In spite of the obvious need for more analysis of the interactions between fares and services, most of the demand approaches, whether from monitoring demonstrations or the more sophisticated mode-choice models, explicitly ignore the possibility of analyzing fare and service interactions by assuming constant-elasticity models (i.e., assume the interactions to be zero). These constant-elasticity models should be deemphasized in favor of variable-elasticity models that have interaction effects, such as the translog models (33).

SUMMARY

This paper has shown that transit demand is service-inelastic. Evidence of this less-than-proportional response of changes in patronage to changes in transit service is provided by the fact that all demonstration studies and modeling efforts reveal service elasticity values less than 1.0.

As we have shown elsewhere (7), service elastici-

Table 6. Example of bus-fare and service interaction strategies.

	Peak Period[a]		Off-Peak Period[a]	
Bus Headway Level	Disaggregate Service Elasticity	Strategy	Disaggregate Service Elasticity	Strategy
Frequent (<10 min)	-0.15	A	-0.26	A
Medium (10-50 min)	-0.31	B	-0.54	B
Infrequent (>50 min)	-0.39	B	-0.68	B

Note: A = finance a fare reduction with the cost savings from a service reduction; B = finance a service improvement with the revenue from a fare increase.

[a]Fare elasticities of -0.21 for peak and -0.48 for off-peak periods.

ties are generally larger than fare elasticities, which suggests that passengers are more responsive to service changes than to fare changes. However, because service elasticities vary considerably from one area to another and by the time of day (with off-peak elasticities 50-100 percent higher than those observed during the peak), type of route, service quality (with larger elasticities in low-service areas), and other classifications, this generalization is not always true. Fare elasticities, for example, may be larger than service elasticities when bus headways of less than 10 min are present. The differences in disaggregate fare and service elasticities may present transit operators with opportunities for ridership and revenue improvements.

Finally, this paper has noted a general consistency of headways, bus miles, and in-vehicle time elasticities from service demonstrations and inconsistencies in results from mode-choice models, particularly in out-of-vehicle time values such as walk-, wait-, and transfer-time elasticities.

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Early Responses to Taxi Regulatory Changes in Three Cities

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Taxi regulatory changes and preliminary responses to them in San Diego, California; Portland, Oregon; and Seattle, Washington, are discussed. The full effects of the regulatory and industry changes are being evaluated. Each city relaxed its entry restrictions in some way; all provided for increased latitude in rate setting, but the specific provisions have varied. The impetus for regulatory revision was generally similar—to transfer the responsibility for regulating entry and establishing rates from the city government to the marketplace. The regulators hope to produce a greater range of improved taxi services by increasing competition and providing for flexible rate structures. Implementation of the new regulations and the earliest responses in terms of local industry size and rate structures are the main topics here. Preliminary analysis suggests that these first responses relate to conditions in the local setting. Problem areas identified during the implementation phase are highlighted, and a number of transferable implications that suggest themselves to other regulatory entities are presented. Findings of the analyses of the effects of the regulatory changes on the supply of and demand for taxi services are anticipated soon.

This paper reports on taxi regulatory changes in San Diego, California; Portland, Oregon; and Seattle, Washington. The implementation and effects of these changes are being evaluated by De Leuw, Cather and Company under contract to the Transportation Systems Center (TSC) of the U.S. Department of Transportation as case studies under the Urban Mass Transportation Administration (UMTA) Service and Methods Demonstration program. Each city adopted its new taxi regulations during 1979, so sufficient time has elapsed to permit identification of the early responses in terms of industry and rate structures while the analysis of operating and ridership data proceeds.

The impetus for regulatory change was similar in each city. Local regulators had experienced difficulties in administering their taxi regulations. In one case, alleged misconduct in the approval of a rate increase precipitated a citywide scandal that ultimately involved the indictment of every city council member. The regulators also began to doubt that the existing code provisions offered any guarantees of a balance between supply of and demand for taxi services or between operating costs and rates of fare. Population ratios were insufficiently sensitive to demand, whereas the data required to demonstrate the need for rate increases were difficult to interpret, costly to assemble, and required the regulators to rely on documentation supplied by the regulated service providers. Concepts like percentage rate of return on invested capital and ratios of overall operating costs to revenues appeared simply to guarantee that taxi rates would go up with costs.

The regulators also doubted that the existing laws served to preserve adequate levels of service. Financial difficulties had plagued the local industries during the 1970s, but one city rate analyst had demonstrated that taxi ridership had declined with each recent rate increase and asserted that rising fares produced a net loss in revenues. Some of the existing regulations inhibited taxicabs from serving a wider transportation market by preventing shared riding, fixed-route services, or differential pricing. Limited entry was charged with contributing to monopoly values in taxi licenses and suppressing competition, which impeded the very kinds of pricing and service innovations that these regulators saw as essential to the salvation of a declining industry.

The following sections describe the regulatory revisions and industry characteristics before and after the changes in each city. The responses to date across sites as well as of some of the problems that have arisen during and since the implementation phase are both discussed. The final section summarizes some transferable implications that have been found for other regulatory entities.

Evalution is in progress of the full effects of the regulatory changes on taxi operators in terms of trips per shift or fare or lease revenues or on taxi riders in terms of taxi availability or response times. At this writing, the collection of operation and ridership data was nearing completion in San Diego and had just begun in Seattle. (The Portland case study is a lower-level monitoring effort.)

SAN DIEGO

Regulatory Changes

The taxicab regulatory revisions adopted in San Diego have two major elements: (a) effective January 1, 1979, the previous ceiling on taxi permits was removed and entry was opened at a specified rate of new permits per month to independent owner-operators as well as to companies; (b) beginning August 1, 1979, competitive pricing, by which operators could charge individual rates up to an estab-