pared for U.S. Department of Transportation, Federal Highway Administration, Jan. 1972.
31. COMSIS Corporation. Traffic Assignment. U.S. Department of Transportation, Federal Highway Administration, Aug. 1973.
32. R. J. Paquette, N. Ashford, and P. H. Wright. Transportation Engineering: Planning and Design. Ronald Press, New York, 1972.
33. R. H. Pratt and Associates. A Method for Distributing Traffic Volumes Across Cutlines. Kensington, MD, 1976.
34. Gruen Associates. Land Use and Arterial Spacing in Suburban Areas. Prepared for U.S. Department of Transportation, Federal Highway Administration, May 1977.
35. R. B. Dial. A Probabilistic Multipath Traffic Assignment Model Which Obviates Path Enumeration. Prepared for U.S. Department of Transportation, Federal Highway Administration, May 1970.
36. H. McInerney and S. Peterson. Intersection Capacity Measurement Through Critical Movement Summations: A Planning Tool. Traffic Engineering, Vol. 41, No. 1, Jan. 1971.
37. Highway Capacity Manual. HRB, Special Rept. 87, 1965.
38. R. Creighton and others. Estimating Efficient Spacing for Arterials and Expressways. HRB, Bulletin 253, 1960.
39. A. Haikalis and H. Joseph. Economic Evaluation of Traffic Networks. HRB, Bulletin 306, 1961.
40. System Considerations for Urban Freeways. ITE, Washington, D.C., Informational Rept., Oct. 1967.
41. J. E. Baerwald, ed. Transportation and Traffic Engineering Handbook. Prentice-Hall, Englewood Cliffs, NJ, 1976.
42. Nationwide Personal Transportation Study. U.S. Department of Transportation, Federal Highway Administration, Repts. 1 and 8, Apr. 1972.

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Tabulating Demand Elasticities for Urban Travel Forecasting

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This paper presents a compendium of demand elasticities in a tabulated form in order to facilitate urban travel forecasting. A number of elasticity estimates have been reported for a variety of cities over the past decade, but the scenarios or base conditions differ from one site to another. In order to systematically tabulate these disparate estimates, demand elasticities were pooled into four cells according to urban size (large versus medium) and urban structure (core-concentrated versus multinucleated). Such a classification has been verified to stratify cities into groups sharing common socioeconomic and travel patterns. Demand elasticities can be divided into two categories: empirical elasticities and calibrated elasticities. The former were measured in the field before and after notable incidents such as a fare increase in the transit system, while the latter were derived from demand models. The elasticities can be further identified as either aggregate or disaggregate depending on whether they are calculated from areawide or subarea data. All these result in a collection of elasticities that have rather different values. This paper tries to explain some of these differences to gain insights into the general characteristics of elasticities for urban areas of different sizes and structures. The elasticity tabulation and the general properties of the elasticities provide both practitioners and researchers with factual information for estimating urban travel demand simply and systematically.

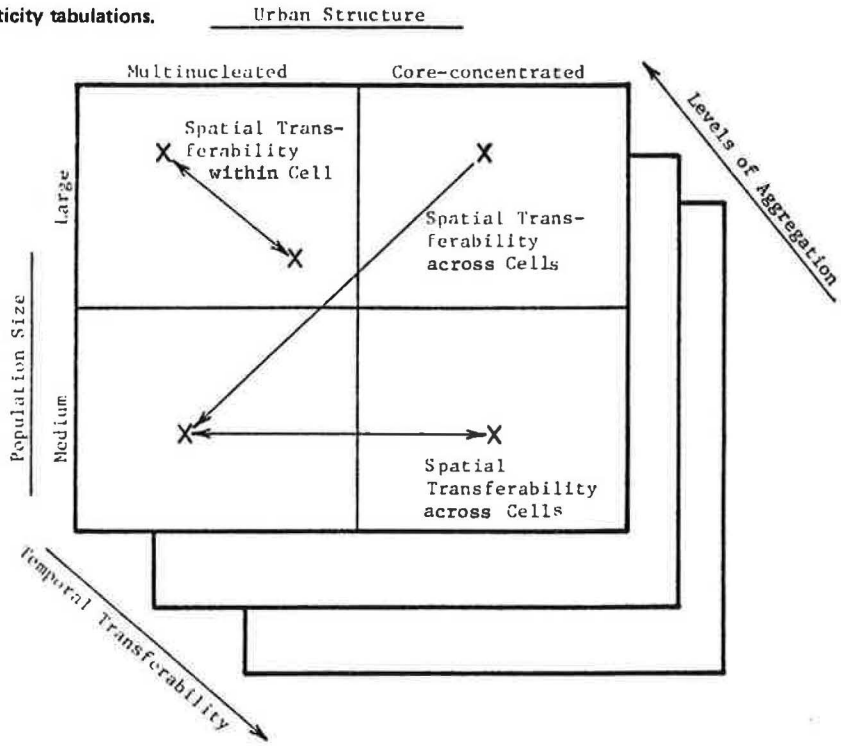
Demand elasticities are often used in conjunction with urban travel forecasting. They have been applied frequently, however, under circumstances that are inconsistent with the assumptions under which they were derived. The purpose of this paper is to resolve some of these inconsistencies and to provide some guidelines—including a systematic tabulation of the available elasticities—for their consistent application in demand estimation.

There are three areas where inconsistencies may be introduced. First, elasticities are often applied in a scenario very different from the base conditions from which they were empirically developed. For example, a fare elasticity of -0.13 measured during the New York subway fare increase of January 1970 refers specifically to the base conditions that existed at that time, including the patronage and fare level. To apply the elasticity indiscriminately for other fare and patronage levels is a futile exercise at best. Unfortunately we found many cases where elasticities are cited out of context and, hence, erroneous inferences are drawn.

Demand elasticities found in a large metropolis such as New York City provide little information on other cities either smaller or of similar size, since they may have drastically different urban structures. Very limited research has been performed in relating elasticities to cities classified according to size and other urban characteristics. Until a better understanding of such a relationship is gained, our knowledge about elasticities in specific sites cannot help us in demand forecasting in other cities.

The measurement of elasticities was performed by using methods ranging from areawide empirical tabulations to disaggregate demand modeling. These various levels of aggregation can often lead to very different estimates of demand elasticities for the same study area. A case study in Chicago, for example, shows that the difference between areawide and household elasticities can be as high as 40 percent, depending on the homogeneity of travel behavior among households in the area (1, Appendix 8). Citing an elasticity without specifying the level of aggregation can therefore result in estimates significantly out of kilter with reality. All these conditions point to the fact that guidelines for applying demand elasticities need to be found. The way the elasticities

Figure 1. Conditions in elasticity tabulations.



are compiled and categorized in this paper is, in our judgment, a step in this direction (Figure 1).

TRANSFERABILITY OF ELASTICITIES

Since elasticity measures are defined for a particular base condition, they cannot be directly applied to a scenario with a different base condition unless steps are taken to guarantee their transferability. In order to apply elasticities to travel forecasting, a group of elasticities must be compiled for cities that share common socioeconomic and travel characteristics. Such a stratification may explain some of the variations in elasticities among areas.

Spatial Transferability

A stratification scheme according to city size is intuitively appealing, since the travel patterns are found to be different among large, medium, and small cities. Travel demand is also found to be affected by the urban structure. For example, the number of trips is probably greater when employment and shopping centers are dispersed than when they are concentrated (which results in a major flow of traffic to and from the city center). A stratification of cities into multinucleated versus core-concentrated categories is therefore advisable when explaining the variations in travel demand.

We set up a hypothesis to group the U.S. cities with at least 50 000 population into four cells: (a) large core-concentrated, (b) large multinucleated, (c) medium core-concentrated, and (d) medium multinucleated.

Several experiments conducted (1) to verify or improve such a hypothesis have utilized techniques such as cluster analysis, factor analysis, regressions, and linear goal programming. The results indicate that such a classification scheme, for the data assembled from 55 percent of the U.S. cities, is statistically significant in explaining the variations in the base travel conditions among the cities within the same cell. When 800 000 population is used as a demarkation between large and medium cities, cities in the same cell of the classification are found to share common relationships on a key urban travel parameter: person-trip hours of travel (PHT). This finding is rather gratifying, since PHT, aside from being a measurement of travel intensity, is the product of travel volume and trip impedance that captures the base conditions for which an elasticity is defined. [Demand elasticity, or the percentage of change in travel in response to 1 percent change in such travel impedance as trip time or cost, is defined as (Δ volume/base volume)/(Δ impedance/base impedance).] Such a result leads us to believe that the travel responses, or elasticities, are similar among the city groups under the taxonomy scheme. In the following sections, then, we shall discuss the outcomes of classifying elasticities according to city size and urban structure as defined in our city stratification scheme.

Temporal Transferability

The four-cell stratification may guarantee spatial transferability of elasticities among cities in the same cell, enabling the elasticities from one city to be applied in another city (belonging to the same group). However, there is still another major consideration before a table of elasticities can be used in a meaningful way, and that is the problem of temporal transferability (Figure 1), which we explain below.

The use of tabulated elasticities as a measurement of demand changes, with respect to changes in travel time and travel cost, is predicated on the hypothesis that these elasticities are stable over time. If we define η_b as the demand elasticity of base year b, and η_f for the forecast year f, the assumption of temporal transferability amounts to equating η_b with η_f. Obviously such an assumption needs to be verified.

As pointed out earlier, demand elasticities are derived for a specified volume of demand and trip impedance (or level of service), which are collectively re-

ferred to as the base travel conditions. Kannel and Heathington (2) examined the form of household travel relations to determine the stability of these relations over time. The results indicate that the trip-making volumes estimated from the 1964 data could successfully predict household travel in 1971.

A study by Voorhees (3) indicates that travel impedances such as trip time can be estimated from city population as a temporally stable relationship. Examinations by Chan of the time series data collected from 1956 through 1976 for 55 percent of the U.S. cities show reasonable temporal stability among both travel volume and travel impedance as represented by trip time (1).

An intuitive explanation of these stability properties can also be offered. Recent investigations into travel decisions and time budgets suggest that an individual spends a relatively constant percentage of his normal day on travel, which implies that the PHT (frequency and duration of trip making) are relatively stable.

Aside from the base conditions, temporal transferability is also reported for demand elasticities. McFadden (4) and Train (5), in their works with the San Francisco Bay Area Rapid Transit (BART), calibrated modal choice models before the implementation of the rapid transit system in order to forecast BART ridership. All the predicted shares turned out to be within one standard error of the corresponding observed shares after the implementation of BART. The forecasting error in total BART patronage amounts to only 2.3 percent. The research by Atherton and Ben-Akiva (6) provides more evidence of temporal transferability in the time span from 1963 to 1968. While the details of the findings may vary, however, we feel that there is enough evidence of temporal and spatial transferability of elasticities using the proposed urban size and structure stratification to warrant more detailed investigation.

ELASTICITY TABULATIONS

Having established a way to group cities, let us tabulate the elasticities reported in the literature. These can be classified into two major categories: empirical elasticities and calibrated elasticities. Empirical elasticities are obtained from field measurements before and after a notable incident such as a fare increase. Calibrated elasticities, on the other hand, are derived from various types of demand models.

According to the methodology and data used for the computation, elasticities can also be divided into two categories: aggregate versus disaggregate, where the latter approach is founded on more detailed data (such as an individual or household unit of analysis), while the former approach is based on coarser data (such as the areawide geographic unit). Empirical elasticities, measured typically on a corridor or areawide basis, are therefore more aggregate than calibrated elasticities, often on a zone or household level basis.

According to the above taxonomy, elasticities can be classified as (a) those calibrated by aggregate data using aggregate methodology (η_{AA}) and (b) those calibrated by disaggregate data using a disaggregate methodology (η_{DD}).

It is hypothesized that η_{DD} tends to overestimate the magnitude of demand response, while η_{AA} will underestimate demand elasticities, on the average. The relationship can be expressed by the following inequality:

$$|\eta_{DD}| > |\eta_{real}| > |\eta_{AA}| \qquad (1)$$

The reason for the above relationship is that observation errors tend to impart downward bias to aggregate parameters, while the elasticity obtained by aggregating over η_{DD} is likely to yield higher values (7). Without further empirical studies one cannot know precisely the quantitative nature of the inequality. It is one of the objectives of this paper to address this issue by reporting on some preliminary findings on a limited set of empirical (areawide) and calibrated (subareal) elasticities.

In the following tabulations, both aggregate and disaggregate demand elasticities will be further stratified by trip purpose (whether it be working, shopping, social and recreational, or others) and a variety of impedance or level-of-service attributes such as time and cost. For example, an excess time elasticity may be defined for work trips, while a fare elasticity may be defined for nonwork travel.

Empirical Elasticities

An empirically derived set of elasticities is compiled for the transit ridership experiences of 19 cities in the United States. For each city, the elasticities over the years corresponding to the various fare increases (such as in New York City) are recorded. Some of the measurements are performed during the peak hours and some during off-peak hours (such as in St. Louis), but most of the numbers are reported for overall trips without stratification into trip purposes.

The variation in these empirical measurements ranges from -0.07 to -3.80, although all of them are transit demand elasticities with respect to the levels of service. An arrangement of these elasticities according to the four-cell stratification scheme is shown in Tables 1 and 2 (8, 9, 10, 11, 12, 13, 14, 15). After the site and level-of-service attributes are specified, the largest variation in each of the entries is from -0.63 to -3.8, which is the range recorded for the excess time elasticities in large core-concentrated cities. This represents a substantial improvement over the -0.07 to -3.80 range found in the original data before classification. We view this as a partial illustration of the effectiveness of the stratification scheme for our elasticity tabulation.

Calibrated Elasticities

Two groups of calibrated elasticities will be compiled: those calibrated using zone data models and those calibrated using household data models. Shown in Table 3 (16) and Table 4 (6, 17, 18, 19, 20, 21, 22, 23, 24) are the value ranges of the calibrated elasticities obtained by using zone direct-demand models and household modal-split models. It should be noted that among all trip purposes, only the most complete data set, work elasticities, is reported here for conciseness. Elasticities for other trip purposes are reported elsewhere (1) and will not be reproduced here.

The usefulness of Tables 3 and 4 (and for that matter Tables 1 and 2) can be illustrated via a simple example. The linehaul time elasticity for bus patronage, for instance, ranges from -0.78 to -0.30 for a large core-concentrated city, which may be interpreted to say that, in general, the ridership goes down by about -0.54 percent (the average of the two extremes) in response to a one percent rise of the linehaul travel time.

The reader is reminded that some of these rather wide ranges of the elasticity values as shown in Tables 1-4 can be attributed to several factors. First, they are obtained from different cities with disparate base levels of service and travel volumes. Second, they are obtained from both areawide and subarea (zone or household) estimations that may yield rather different elasticities even for the same study area. Thus far, we have had some success in explaining the variations among cities by using the city classification scheme. The variations due to the level of aggregation, however, remain to be explained.

Comparison Between Calibrated and Empirical Elasticities

The ad hoc manner in which empirical elasticities were compiled and the severe limitations of the data base make a rigorous comparison with the calibrated values difficult. The fact that these two sets of elasticities are generally compiled for different trip purposes (overall versus work, respectively) further complicates the matter. Finally, the different data base (before and after versus cross-sectional, areawide versus subarea) constitutes the last straw. However, a discussion is still useful as a check as long as we keep in mind that work demand elasticities are more inelastic by nature than elasticities for overall trip purposes.

Amid these complications an experimental relationship between the empirical (areawide) elasticity η_{AA} and the calibrated (subarea) elasticity η_{DD} was discerned. It is encouraging to find that the magnitude of the corresponding numbers in Tables 1-4 confirms our initial conjecture (Equation 1) that elasticities estimated from a set of more disaggregate data are higher in value than those estimates from a more aggregate set, as can be explained below.

In Figure 2, the same elasticities estimated from empirical versus model calibrations are put on the same plot. It appears that the calibrated elasticities show up consistently higher in value than the empirical ones. While there may be several factors that contribute to this, the level of aggregation could be the dominant factor. The reason is that preliminary analysis shows that the ratios of work to overall elasticity range from 1.0 to 1.3, with the average of the two extremes being 1.15. The slope of regression line is 1.97 in Figure 2. The difference between 1.97 and 1.15 has to be attributed to the level of data aggregation.

Table 1. Range of empirical transit demand elasticities for overall trips for medium cities.

	Medium Multinucleated Cities Transit[a]			Medium Core-Concentrated Cities Transit[b]		
Item	Total	Bus	Rail	Total	Bus	Rail
Total						
Linehaul time	NA	NA	NA	NA	NA	NA
Excess time	NA	NA	NA	NA	NA	NA
Cost	NA	NA	NA	NA	NA	NA
Bus						
Linehaul time	NA	NA	NA	NA	NA	NA
Excess time	NA	NA	NA	NA	-0.83	NA
Cost	NA	-0.12 ~ -0.34	NA	NA	-0.25 ~ -0.65	NA
Rail						
Linehaul time	NA	NA	NA	NA	NA	NA
Excess time	NA	NA	NA	NA	NA	NA
Cost	NA	NA	NA	NA	NA	NA

[a]Salt Lake City and Springfield, Massachusetts.
[b]Chesapeake, Virginia; Portland, Maine; Tulsa; and York, Pennsylvania.

GENERAL CHARACTERISTICS OF ELASTICITIES

When one regards urban transportation as a service to the consumer, one can assign a generalized price to purchasing such a service in terms of cost and time. Since demand elasticity is a measure of the percentage of responsiveness of travel demand to 1 percent change in the level of service, it evaluates the marginal demand contributions of a change in cost or time. It is found in our tabulations that, while individual travel demand elasticities in a class of urban areas often share some common characteristics, the elasticities among groups of cities are disparate. The difference between demand elasticities among different groups of urban areas can be explained below.

Saturation of Demand

According to the theory of demand, the marginal utility of additional trips tends to diminish when demanded trips approach served trips. This explains why, in the larger urban areas where served trips often fall short of demanded trips, demand is highly sensitive to change in level of service. The results of three case studies in Boston (17), Chicago (18), and Louisville (16) strongly support this theory. Bus demand elasticities with respect to linehaul time, excess time, and cost are -1.10, -1.84, and -0.51, respectively, for a large city such as Chicago and -0.19, -0.38, and -0.40, respectively, for a smaller city such as Louisville. The comparison of auto demand elasticity with respect to its own linehaul time and cost between a large city and a medium city also shows this tendency. For instance, auto linehaul time and cost elasticities for Boston are -0.82 and -0.494, while for Louisville they are -0.39 and -0.12.

Level-of-Service Attributes

According to consumer behavior, when the price of a commodity or a service is high, the response of demand to a change in price is more elastic. This leads to a corollary that states that elasticities are lower in value where level of service is high. In smaller cities where

Table 2. Range of empirical transit demand elasticities for overall trips for large cities.

	Large Multinucleated Cities Transit[a]			Large Core-Concentrated Cities Transit[b]		
Item	Total	Bus	Rail	Total	Bus	Rail
Total						
Linehaul time	NA	NA	NA		NA	NA
Excess time	NA	NA	-0.90(10)		NA	NA
Cost	-0.30(5)	NA	NA		NA	NA
Bus						
Linehaul time	NA	}-0.55	NA		NA	NA
Excess time	NA	-0.20 ~ -0.60	NA		-0.63 ~ -3.8	NA
Cost	NA	-0.11 ~ -0.64	NA		-0.08 ~ -0.60	NA
Rail						
Linehaul time	NA	NA	NA		NA	NA
Excess time	NA	NA	NA		NA	-0.24
Cost	NA	NA	NA		NA	-0.07 ~ -0.19

[a]Atlanta, Boston, Detroit, Philadelphia, San Diego, and San Francisco.
[b]Baltimore, Cincinnati, Milwaukee, New York, and St. Louis.

Table 3. Range of calibrated work-trip elasticities for medium cities.

Transportation System Variable	Medium Multinucleated City[a]					Medium Core-Concentrated City[b]				
	Para-transit	Transit			Auto	Para-transit	Transit			Auto
		Total	Bus	Rail			Total	Bus	Rail	
Paratransit										
Linehaul time			NA		NA	-0.315		0.194		0.194
Excess time			NA		NA	-0.189		0.117		0.117
Cost			NA		NA	-0.057		0.035		0.035
Total										
Linehaul time			NA		NA	NA		NA		NA
Excess time			NA		NA	NA		NA		NA
Cost			NA		NA	NA		NA		NA
Bus										
Linehaul time			}-2.80 (Total time)		}1.11	0.022		-0.19 ~ -0.373		0.022
Excess time			NA		NA	0.092		-0.38 ~ -1.55		0.092
Cost			-0.51		0.06	0.05		-0.40 ~ -0.852		0.05 ~ 0.15
Rail										
Linehaul time			NA		NA	NA		NA		NA
Excess time			NA		NA	NA		NA		NA
Cost			NA		NA	NA		NA		NA
Auto										
Linehaul time			}2.81 (Total time)		}-1.11	0.173		0.173		-0.138 ~ -0.39
Excess time			NA		NA	0.173		0.173		-0.138
Cost			1.39		-0.55	0.115		0.115		-0.092 ~ -0.12

[a]Richmond, Virginia. [b]Louisville, Kentucky.

Table 4. Range of calibrated work-trip elasticities for large cities.

Transportation System Variable	Large Multinucleated Cities[a]					Large Core-Concentrated City[b]				
	Para-transit	Transit			Auto	Para-transit	Transit			Auto
		Total	Bus	Rail			Total	Bus	Rail	
Paratransit										
Linehaul time	-0.02 ~ -0.664	NA	-0.27	NA	NA	-0.59		0.22	NA	NA
Excess time	-0.122	NA	NA	NA	NA	-0.28		0.10		NA
Cost	-0.01 ~ -0.092	NA	-0.06	NA	NA	-0.10		0.04		NA
Total										
Linehaul time	NA	-0.20 ~ -0.39	NA	NA	NA	NA		NA		NA
Excess time	NA	-0.69 ~ -0.709	NA	NA	NA	NA		NA		NA
Cost	NA	-0.09 ~ -0.58	NA	NA	NA	NA		NA		NA
Bus										
Linehaul time	0.04	NA	-0.46 ~ -1.10	0.23	0.04 ~ 0.14	NA		-0.30 ~ -0.78		0.25
Excess time	0.10	NA	-0.17 ~ -2.28	0 ~ 0.06	0.05 ~ 0.373	NA		-0.94		0.30
Cost	0.03	NA	-0.1 ~ -0.58	0 ~ 0.28	0.02 ~ 0.138	NA		-0.12 ~ -0.20		0.06
Rail										
Linehaul time	NA	NA	0.13 ~ 1.02	-0.60 ~ -0.80	0.10	NA		NA		NA
Excess time	NA	NA	0.03 ~ 1.15	-0.12 ~ -2.06	0.02	NA		NA		NA
Cost	NA	NA	0 ~ 0.25	-0.86 ~ -1.80	0.13	NA		NA		NA
Auto										
Linehaul time	NA	0 ~ 0.37	0.36 ~ 0.39	0.27 ~ 0.41	-0.02 ~ -0.82	NA		0.17 ~0.53	NA	-0.18
Excess time	NA	0	NA	NA	-0.027 ~ -1.437	NA		0.33	NA	-0.35
Cost	NA	0 ~ 0.80	0.06 ~ 0.97	0.06 ~ 0.97	-0.01 ~ -0.494	NA		0.15	NA	-0.16

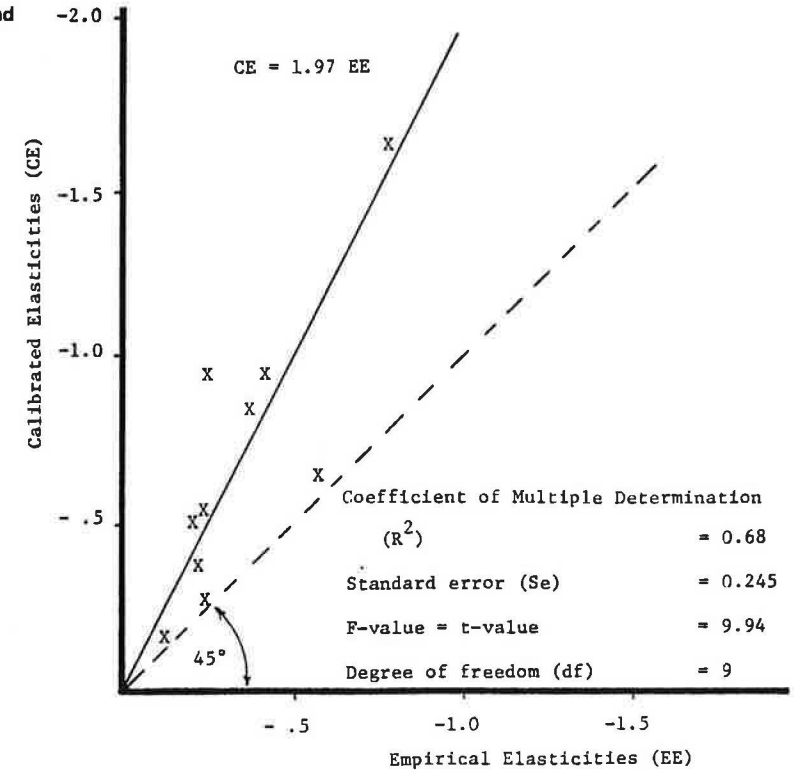
[a]Boston, Chicago, San Francisco, Los Angeles, San Diego, Minneapolis-St. Paul. [b]Washington, D.C.

the level of service is generally higher (meaning that the travel time is shorter and the travel cost is lower), demands are therefore less elastic. However, for headway elasticities where the headway is longer (hence the level of service lower) for smaller cities the reverse is true.

The examples used in explaining the saturation of demand support this assertion. Additional evidence can be found in the case studies on bus demand elasticities in New Bedford, Massachusetts; San Francisco; Washington, D.C.; and Los Angeles (1, 22), where the bus ridership in large cities is more sensitive to changes in travel time.

Another example of transit schedule frequency can be

Figure 2. Comparison of mean values and empirical and calibrated elasticities.



cited. Large cities generally have higher levels of service in terms of schedule frequency. The headway change of buses from 5 to 10 min has less impact on ridership compared to the same percentage of change in medium cities from 15 to 30 min. This is shown in the empirical findings of Chesapeake, Virginia, a medium-sized city, and several large cities such as Boston, New York, and Detroit (but not Milwaukee). The headway elasticity for the former is -0.83, and the headway elasticities for the latter are -0.60, -0.20, and -0.63. This reasoning is further supported by empirical findings in New York, where ridership impacts corresponding to changes in the schedule frequencies of buses and subways were measured (Tables 1 and 2). The bus (with lower level of service) has an elasticity of -0.63, while the subway (with higher level of service) has an elasticity of -0.24.

New Mode

Based on modal choice theory, the demand elasticities are more elastic if the trip maker has more than one choice of mode. This is shown in two sets of observations. In the BART study (22), the bus demand elasticities for linehaul time, excess time, and cost are -0.46, -0.17, and -0.45 respectively for pre-BART, and -0.60, -0.19, and -0.58 for post-BART, while the auto demand elasticities with respect to changes in linehaul time and cost are -0.13, -0.32, and -0.22, -0.47 corresponding to two different points in time.

Summary

Due to the difference of social and economic backgrounds, different areas have different levels of saturation of demand, levels of service, mode choices, and other variables. These lead to the variation of demand elasticities among areas. To some extent, the city classification scheme employed in our analysis accounts for a number of these factors and helps to explain some of the elasticity variations. The size of the city is used to group cities into different levels of demand saturation and level of service. The urban structure, on the other hand, separates core-concentrated cities (where there are generally more choices of mode) from multinucleated cities (where there are fewer mode choices).

If one examines the elasticities in each of the four groups of cities, he or she will notice that, generally speaking, the numerical values are larger in large cities and sites with a core-concentrated urban structure. This constitutes a verification of the two-way classification scheme.

CONCLUSIONS

The main purpose of this paper is to translate all of the reported demand elasticities into a consistent form that will be useful in demand forecasting. Of special concern are the spatial and temporal transferabilities of these elasticities, in which the former means that parameters calibrated in one area can be applied to other areas, while the latter implies that parameters are stable over time.

We emphasize that demand elasticity alone, being a point estimate, cannot be used to forecast effectively. This is because elasticity is defined only for a particular base condition, which is often characterized by a particular level of service and traffic volume. In order to apply the elasticities obtained in one city to another, one should group cities according to similar socioeconomic and travel patterns. The patterns are collectively referred to as the base conditions.

An analysis was performed to uncover some of the base conditions under which the elasticities were derived, and a city classification scheme was found for grouping cities into generic cells within which elasticities may be transferable. Elasticities were then tabulated for the respective cells according to the stratification of modes and level-of-service attributes. It was found that a good deal of the variations among the time and cost elasticities

can be explained by the city classification scheme, which groups cities according to their level of demand saturation, level of service, and choice of modes.

At the same time, the variations among the values obtained for the same elasticity may be attributed to the different level of data aggregation. Empirical elasticities, which are measured from areawide or corridor data, provide the lower bound estimate, while calibrated elasticities, which are obtained from zone or household data, give the upper bound estimate. The true value of elasticities lies somewhere in between the two extremes.

Like many other studies of this nature, this research can be refined by expanding the data base and continuing the methodological investigations. In the interim, there are some very positive contributions reported in this paper. For the practitioners, it provides a handbook of elasticities, thus reducing the replication of demand forecasting model calibration efforts, and serves as a tool to perform travel estimation in a fast and consistent manner using the available elasticity tabulations. For the researchers, it offers some insights into the general properties of elasticity measurement in American cities of different urban size and urban structure.

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REFERENCES

1. Y. Chan, F. L. Ou, J. Perl, and E. Regan. Review and Compilation of Demand Forecasting Experiences: An Aggregation of Estimation Procedures. Pennsylvania Transportation Institute, Pennsylvania State Univ., University Park, Final Rept., PTI 7708, 1977.
2. E. J. Kannel and K. W. Heathington. Temporal Stability of Trip Generation Relations. HRB, Highway Research Record 472, 1973, pp. 17-27.
3. Alan M. Voorhees and Associates. Factors and Trends in Trip Length. NCHRP, Rept. 48, 1968.
4. D. McFadden. The Theory and Practice of Disaggregate Demand Forecasting for Various Modes of Urban Transportation. Paper presented at the Seminar on Emerging Transportation Planning Methods, Daytona Beach, FL, 1976.
5. K. Train. A Post-BART Model of Mode Choice: Some Specification Tests. Urban Travel Demand Forecasting Project, Institute of Transportation Studies, Univ. of California, Berkeley, Working Paper 7620, 1976.
6. T. J. Atherton and M. Ben-Akiva. Transferability and Updating of Disaggregate Travel Demand Model. Paper presented at the 55th Annual Meeting, TRB, 1976.
7. D. McFadden and F. Reid. Aggregate Travel Demand Forecasting From Disaggregated Behavioral Models. TRB, Transportation Research Record 534, 1975, pp. 24-37.
8. J. F. Curtain. Effect of Fares on Transit Riding. HRB, Highway Research Record 213, 1968, pp. 8-20.
9. D. K. Holland. A Review of Reports Relating to the Effects of Fare and Service Changes in Metropolitan Public Transportation Systems. U.S. Department of Transportation, Federal Highway Administration, 1974.
10. M. A. Kemp. Some Evidence of Transit Demand Elasticities. Transportation, Vol. 2, 1973, pp. 25-52.
11. W. Lassow. Effect of the Fare Increase of July 1966 on the Number of Passengers Carried on the New York City Transit System. HRB, Highway Research Record 213, 1968, pp. 1-7.
12. J. I. Scheiner and G. Starling. The Political Economy of Free-Fare Transit. Urban Affairs Quarterly, Vol. 2, No. 10, 1974, pp. 170-184.
13. A. B. Sosslau, K. E. Heanue, and A. J. Balek. Evaluation of a New Modal Split Procedure. HRB, Highway Research Record 88, 1965, pp. 44-63.
14. Tri-State Regional Planning Commission. Urban Densities for Public Transportation. Prepared for the Urban Mass Transportation Administration, 1976.
15. R. H. Pratt and Associates. Traveler Responses to Transportation System Changes: A Handbook for Transportation Planners. U.S. Department of Transportation, 1977.
16. F. C. Kavak and M. J. Demetsky. Behavioral Modeling of Express Bus-Fringe Parking Decision. TRB, Transportation Research Record 534, 1975, pp. 10-23.
17. T. A. Domencich, G. Kraft, and J. P. Vallette. Estimation of Urban Passenger Travel Behavior: An Economic Demand Model. HRB, Highway Research Record 238, 1968, pp. 64-78.
18. A. Talvitie. A Direct Demand Model for Downtown Work Trips. Transportation, Vol. 2, 1975, pp. 121-152.
19. L. A. Lave. Modal Choice in Urban Transportation: A Behavioral Approach. Department of Economics, Stanford Univ., Ph.D. thesis, 1968.
20. S. L. Warner. Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice. Northwestern Univ. Press, Chicago, 1962.
21. T. E. Lisco. The Value of Commuters' Travel Time: A Study in Urban Transportation. Department of Economics, Univ. of Chicago, Ph.D. thesis, 1967.
22. D. McFadden. The Measurement of Urban Travel Demand. Journal of Public Economics, Vol. 3, 1974, pp. 303-328.
23. R. G. McGillivray. Binary Choice of Transport Mode in the San Francisco Bay Area. Univ. of California, Berkeley, Ph.D. thesis, 1969.
24. Peat, Marwick, Mitchell and Co. Implementation of the n-Dimensional Logit Model. Comprehensive Planning Organization, San Diego County, Final Rept., 1972.
25. Development and Calibration of Mode Choice Models for the Twin Cities Area. R. H. Pratt and Associates and DTM, Minneapolis, MN, 1976.

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