EDITORIAL NOTE

This paper is one of two companion papers which survey price elasticities of transport demand. In addition to reviewing empirical elasticity estimates for both freight and passenger demand, this paper also deals with theoretical and empirical issues in estimating transport demand elasticities. The second survey, by Dr. Philip Goodwin, is primarily concerned with empirical estimates of demand elasticities of public transit system and automobile usage. The origins and motivations for these two papers were different, as was their coverage and sources used. The two papers complement each other so we publish the papers together, with a pooled bibliography.

CONCEPTS OF PRICE ELASTICITIES OF TRANSPORT DEMAND AND RECENT EMPIRICAL ESTIMATES

An Interpretative Survey

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1. INTRODUCTION

The past two decades have seen several refinements to the theory and empirical estimation of transport demand. Among major developments are the advancements in discrete choice modelling and the associated computational algorithms, the increasing popularity of flexible functional forms, and a better linkage between empirical demand models and the theory of consumer or firm behaviour. In recognition of these and other advances in transport demand research, this paper surveys the major empirical studies of own-price elasticities of demand for transport that emerged in the last ten years or so. In the process, various concepts of and linkages between demand elasticities are outlined. Some shortcomings of existing empirical studies are also discussed.

The literature review began with the collection of articles from economics journals in Waters (1984, 1989), supplemented by a search of most major journals in transport. With emphasis on recent studies, we concentrated on studies which appeared in the late 1970s and 1980s. Our emphasis on journal articles meant we generally excluded

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empirical studies appearing in books and technical reports. In view of the vast literature related to transport demand, some omissions are inevitable. Nonetheless, the articles reviewed should provide an adequate sample for reviewing the concepts and methods of estimating transport demand elasticities.[1]

The plan of this paper is as follows. The next section acknowledges some previous survey articles concerning the demand for transport. Section 3 discusses various concepts of elasticities used in empirical demand studies, and Section 4 reviews the results of many recent empirical studies. Our observations on common shortcomings of existing studies and priorities for future research appear in Section 5. Some concluding remarks follow in Section 6.

2. PREVIOUS SURVEYS OF TRANSPORT DEMAND

There is an extensive literature on characteristics of and factors affecting transport demand, but few reviews have concentrated on empirical estimates of transport demand elasticities. Authors of specific demand studies often discuss previous empirical estimates (for example, Frankena, 1978), but these reviews are incidental rather than the primary purpose of their papers. Wilson (1980) attempted to identify "typical" values of freight transport demand elasticities. He discussed various ways of deriving freight transport demand elasticities from the elasticities of individual commodities, and included a list of elasticity estimates of freight transport demand for 127 commodities compiled by the United States Interstate Commerce Commission.

Other recent surveys of the demand for freight transport include Winston (1983) and Zlatoper and Austrian (1989). Both these surveys place major emphasis on methodological issues. Winston provides an overview of various models of freight transport demand and discusses various applications of these models. The emphasis is on the theoretical foundations of these models, although many econometric issues are also discussed. The paper by Zlatoper and Austrian contains detailed discussion of more than a dozen econometric studies on freight transport demand published since the mid-1970s. It describes the variables, data sources and estimation procedures of these studies as well as their empirical results.

More recently, Goodwin (1991) summarises studies which report empirical estimates of elasticities of demand for car and public transport. Interestingly, there are few studies which overlap between his paper and this survey. The main reason for the difference is that Goodwin's survey includes a number of government and consulting reports, conference and working papers, as well as papers published in academic and professional journals. We concentrate on studies published in academic journals. Further, Goodwin's survey is confined to the demand for car and public transport while we include both passenger and freight, and other modes of transport. Our wide coverage made searching for unpublished studies and technical reports a time-consuming and costly venture which is beyond our resources. Goodwin's survey is a valuable complement to our review since he uses a larger sample and is able to discuss demand elasticities of car and public transport in greater detail.

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1 An earlier review of demand studies covering all modes of transport was compiled as a World Bank Working Paper (Oum, Waters and Yong, 1990). The present paper is based on a subset of those studies and includes some references not in the working paper.

This review summarises empirical results from both passenger and freight demand studies. We pay particular attention to the methodological issues behind these empirical results. We discuss theoretical considerations and review a rich array of empirical estimates of transport demand elasticities. Our reliance on refereed journals serves as a screen to help to ensure that studies are methodologically sound. Further, academic journals are also the expected outlet for methodological advances. We must, however, admit that this review is more narrowly focused than many discussions of transport demand since we concentrate solely on the *own-price* elasticities of demand for transport. In many markets, particularly for higher valued freight and passenger travel, quality variables may be more important than price. Indeed, the thriving air, motor freight and container markets are testimony to the importance of service quality relative to price. This review has not looked into these "quality elasticities", but this is in no way suggesting that they are unimportant.

3. CONCEPTS OF ELASTICITIES

A price elasticity of demand measures the responsiveness of demand to a change in price. Within this general notion are a number of different concepts which are important for understanding transport demand elasticities. These concepts are discussed below and the linkages between them are summarised at the end of this section.

Ordinary and compensated demand elasticities

The ordinary or Marshallian demand is derived by maximising a representative consumer's utility function subject to a budget constraint. Formally, the ordinary demand is

$$d(p,y,s,\varepsilon) = \underset{x}{\text{Argmax}} \; [U(x,s,\varepsilon) \text{ s.t. } x \in B(p,y)], \tag{1}$$

where x is a vector of goods and services, s is a vector of observed socio-economic characteristics of the consumer, ε is a vector of unobserved variables and $B(p,y)$ is the consumer's budget constraint, which is a function of prices (p) and income (y).[2]

The compensated or Hicksian demand, on the other hand, is derived by minimising the consumer's expenditure for achieving a given utility level. Formally, the compensated demand is

$$h(p,u,s,\varepsilon) = \underset{x}{\text{Argmin}} \; [px \text{ s.t. } U(x,s,\varepsilon) \geq u]. \tag{2}$$

The price elasticity derived from each type of demand is sometimes referred to as, respectively, the ordinary and compensated elasticity. Since utility level is held constant in the case of compensated demand, the compensated price elasticity measures only the substitution effect of a price change. In contrast, the ordinary price elasticity measures both the substitution and income effects of a price change.

In practice, however, the compensated demand function is not estimable because it is a function of utility, which is not directly observable. Hence, virtually all passenger

[2] Alternatively, applying Roy's identity to a well-behaved indirect utility function (or its reciprocal) will also yield an ordinary demand system. See Diewert (1974) for a theoretical discussion and Oum and Gillen (1983) for an application to transport demand modelling.

travel demand studies estimate an ordinary demand function and report the associated elasticities. The situation is different for the case of freight demand.

The same interpretation of demand functions and elasticities apply to the case of freight transport demand although the terminology and the units of measurement differ. Typically, a representative firm's production technology is represented by a production function $q = q(x,c,\varepsilon)$ where x is a vector of inputs, c is a vector of observed characteristics of the firm and ε is a vector of unobserved variables. The firm is assumed to maximise profit, taking both input and output prices as given. The optimal values of q and x that solve the firm's maximisation problem are, respectively, the firm's supply and input demand functions.[3] They are of the form:

$$q^* = s(p,w,c,\varepsilon), \tag{3}$$

$$x^* = z(p,w,c,\varepsilon) \tag{4}$$

where p is the output price and w is a vector of input prices. It is important to note that the firm's output does not appear as an argument in the input demand system. This is in contrast to the case where the firm is assumed to minimise cost for a given output level. In this case, the conditional input demand is[4]

$$x(q,w,c,\varepsilon) = \underset{x}{\text{Argmin}}\ [wx \text{ s.t. } q(x,c,\varepsilon) \geq q] \tag{5}$$

Since output is being held constant in (5), the associated demand elasticity measures only the substitution effect of a price change. On the other hand, the ordinary input demand elasticity associated with (4) measures the combined substitution and scale or output effects of a price change.

In measuring ordinary price elasticities of freight demand, (3) and (4) indicate that the demand system must be estimated simultaneously with the shippers' output decisions, that is, treating shippers' output as endogenous. Ignoring the endogeneity of shippers' output decisions is equivalent to assuming that changes in freight rates do not affect output levels. This, in turn, is equivalent to ignoring the scale or output effect of a change in input prices. Our survey reveals that many freight demand models do not treat the output effect properly, thus the reported elasticity values may be biased.

Furthermore, in most *ad hoc* demand specifications, it is unclear whether the resulting estimates are ordinary or conditional input demand elasticities. Nonetheless, by virtue of (4) and (5), we think the following may serve as a guide: in the case of a time-series study, if shippers' output is not included in the demand equation, it is more appropriate to regard the resulting estimates as ordinary demand elasticities. On the other hand, if shippers' output is included in the demand equation, the resulting estimates may be treated as conditional or compensated elasticities. Similar interpretation applies to cross-section studies, except it should be noted that information on shippers' output is rarely available in cross-section data. A further difficulty arises when some freight demand studies include an indicator for market size in the models. Although this may be interpreted as a proxy for the aggregate output of shippers, its accuracy is questionable.

3 Alternatively, the firm's supply and input demand functions can be derived by applying Hotelling's lemma to a well-behaved profit function.

4 It is worth noting that, mathematically, (5) is of the same form as (2). Thus, the conditional input demand can also be derived by applying Shephard's lemma to a well-behaved cost function.

Since the mid-1970s, many economists have estimated neoclassical input demand systems by deriving them from the firm's or industry's cost function, often specified as a translog or other flexible functional form. Examples are Spady and Friedlaender (1978), Oum (1979a, 1979b) and Friedlaender and Spady (1980). Most of these models are derived by minimising the input costs (including freight transport costs) for transporting a given (exogenously determined) output, which corresponds to (5). Because most of these studies use cross-section data, which typically do not contain information about shippers' output, the resulting elasticity measures are thus conditional rather than ordinary input demand elasticities. The freight demand study by Oum (1979b) is an exception in that ordinary elasticities were derived by adding the output effects to the conditional elasticities computed from the neoclassical freight demand system.

Aggregate market, mode-specific and mode-choice elasticities

The concepts of demand elasticity discussed above can be applied to the study of the aggregate demand for transport as well as the demand for individual modes of transport. The market demand refers to the demand for transport relative to other (non-transport) sectors of the economy. Under the usual aggregation condition (that is, conditions for the existence of a consistent aggregate), the linkage between mode-specific elasticities (own-price elasticity F_{ii} and cross-price elasticities F_{ij}) and the own-price elasticity for aggregate transport demand, F, is:

$$F = \sum_i S_i (\sum_j F_{ij}), \tag{6}$$

where S_i denotes the volume share of mode i. In the two-mode case, the relationship becomes $F = S_1(F_{11} + F_{12}) + S_2(F_{21} + F_{22})$. Since the cross-price elasticities generally are positive because of competition among modes, (6) indicates that the aggregate elasticity is lower, in absolute value, than the weighted average of the mode-specific own-price elasticities.

In examining mode-specific demand studies, it is important to distinguish between mode-choice (also known as mode-split and volume share) elasticities and regular demand elasticities. Mode-choice studies are studies which examine shares of a fixed volume of traffic among modes. In many early studies on mode choice, logit models were applied to aggregate route or regional market share data, which not only leads to a loss of important information about changing market size in response to a price change, but is also theoretically inconsistent, as pointed out by Oum (1979c). More recently, disaggregate discrete choice models have been used to investigate users' mode choice decisions. It is, however, important to note that not all discrete choice models produce mode-choice elasticities; this and other aspects of discrete choice models are discussed below. Aggregate mode-choice studies produce elasticities between modes but they differ from the demand elasticities discussed earlier in that they do not take into account the effect of a price change on the *aggregate volume* of traffic. It is possible to derive mode-choice elasticities from regular demand elasticities but this entails a loss of information, and thus would rarely be a useful exercise (Taplin, 1982). Since ordinary demand elasticities generally are more useful than mode-choice elasticities, it is desirable to be able to convert mode-choice elasticities to ordinary demand elasticities.

The relationship between mode-choice and ordinary demand elasticities can be summarised by the following formula (see Taplin, 1982, and Quandt, 1968).

$$F_{ij} = M_{ij} + \delta_j \qquad \text{for all } i \text{ and } j, \tag{7}$$

where F_{ij} is the price elasticity of the ordinary demand for mode i with respect to price of mode j, M_{ij} is the mode-choice elasticity of choosing mode i with respect to the price of mode j, and δ_j is the elasticity of demand for the aggregate traffic, denoted Q, with respect to the price of mode j. Because information on δ_j's is not usually available, the following formula may be useful in computing them.

$$\begin{aligned}\delta_j &= (\partial Q/\partial P_j)(P_j/Q) \\ &= F(\partial P/\partial P_j)(P_j/P) < 0,\end{aligned} \tag{8}$$

where F is the price elasticity of aggregate market demand for transport (that is, $(\partial Q/\partial P)(P/Q)$), and $(\partial P/\partial P_j)(P_j/P)$ is the elasticity of aggregate price P with respect to the price of mode j. Therefore, an explicit conversion of a mode-choice elasticity to an ordinary demand elasticity for a particular mode requires information about either the elasticity of aggregate transport demand with respect to price of each mode (δ_j) or the price elasticity of aggregate transport demand (F) and the second term in (8). Unfortunately, this information is not available in the studies reviewed here. Consequently, it is virtually impossible to draw on the extensive mode-choice literature to help establish values of ordinary demand elasticities. However, a special case of (7) for the expression of own-price elasticity, $F_{ii} = M_{ii} + \delta_i$, indicates that, in terms of absolute value, the own-price mode-choice elasticity (M_{ii}) understates the ordinary own-price elasticity (F_{ii}) because δ_i is negative. The size of the difference, $\delta_i = F_{ii} - M_{ii}$, cannot be determined without further information.[5] However, it shows that the own-price elasticities of mode-choice may serve as lower bounds for ordinary elasticities in terms of absolute values. Taplin (1982) suggests that estimates of ordinary elasticities could be constructed from mode-choice elasticities using equation (7) in conjunction with an assumed value for one ordinary demand elasticity, and various constraints on elasticity values based on theoretical considerations. Of course, the accuracy of the elasticities computed depends heavily upon the validity of the assumed value of the elasticity chosen to initiate the computation. An illustration of this can be found in Taplin (1982) (see also Oum, Waters and Yong, 1990).

Disaggregate discrete choice models

Another important development in transport demand research is the introduction of disaggregate discrete choice models. (For more general discussions of discrete choice models, see Amemiya, 1981, and Maddala, 1983, among others.) These models investigate users' travel-choice behaviour based on attributes of various modes of transport and individuals' socio-economic characteristics. Unlike conventional demand models, which assume that consumers make marginal adjustment in response to changes in the environment, discrete choice models assume that consumption is an all-

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[5] Taplin notes that the sum of these "second stage elasticities", $\Sigma_j \delta_j$, is the price elasticity of the aggregate market demand in (6).

or-nothing decision — one either takes the transit or uses the car. (A more detailed discussion of discrete choice models can be found in Domencich and McFadden, 1975, Hensher and Johnson, 1981, and Ben-Akiva and Lerman, 1985, among others.)

It is important to note that various demand elasticity measures can be computed from discrete choice models. For example, it is possible to compute an elasticity which measures the percentage change in the *probability* of a representative individual choosing to travel by bus given a change in transit fare.[6] It is important to note that this is *not* the same as the regular demand elasticity *nor* mode-choice elasticity discussed earlier. Based on their empirical experience, Domencich and McFadden report that the derived regular demand elasticity is likely to be one-half to three-quarters lower than the corresponding representative individual elasticity of choice probability. In order to derive the regular demand elasticity, it is necessary to aggregate across individuals in the *population*. Conceptually, a consistent and unbiased estimate of the *fraction* of population choosing a particular mode is the expected value of the sample probability. In practice, various aggregation procedures are used to approximate the population demand. A comprehensive review of various aggregation procedures can be found in Ben-Akiva and Lerman (1985), chapter 6. Many studies use the sample aggregate as an approximation. The accuracy of this approach clearly depends on the sampling procedure used. Obviously, different procedures will be likely to produce numerically different elasticity estimates. It is therefore important for researchers to state explicitly the aggregation procedure used to derive the aggregate demand and associated elasticities.

Some discrete choice models are concerned solely with users' mode-choice decisions given a fixed volume of traffic. Many studies of urban work trips fall into this category. The demand elasticities computed from these models are more appropriately interpreted as mode-choice elasticities rather than regular demand elasticities since the effect of a price change on *aggregate traffic* is not taken into account. This is illustrated in the lower right of Figure 1. Clearly, discrete choice models that produce regular demand elasticities must include in the users' choice set the option of not making the trip. This will require socio-economic characteristics and other data on non-travellers. Therefore, an easy way to identify the types of demand elasticities reported by a discrete choice study is to examine whether the sample contains non-travellers. Although some authors recognise the importance of data on non-travellers, none of the studies reviewed here collects such data. This is rather unsatisfactory, particularly for long-run policy planning, since the planner not only needs to know how existing travellers will respond but also how overall traffic will grow given a change in transport policy.

Firm-specific demand elasticities

In addition to mode-choice and market demand elasticities, one could focus on demand elasticities of individual firms. Firm-specific elasticities vary considerably depending upon the extent and nature of competition between firms. For example, firms operating in a competitive environment will in general face very different demand elasticities than

[6] In most cases, the representative individual is the one with characteristic variables equal to the sample means (see, for example, Richards and Ben-Akiva, 1975). Its accuracy as an approximation to the aggregate elasticity is questioned by Dunne (1984).

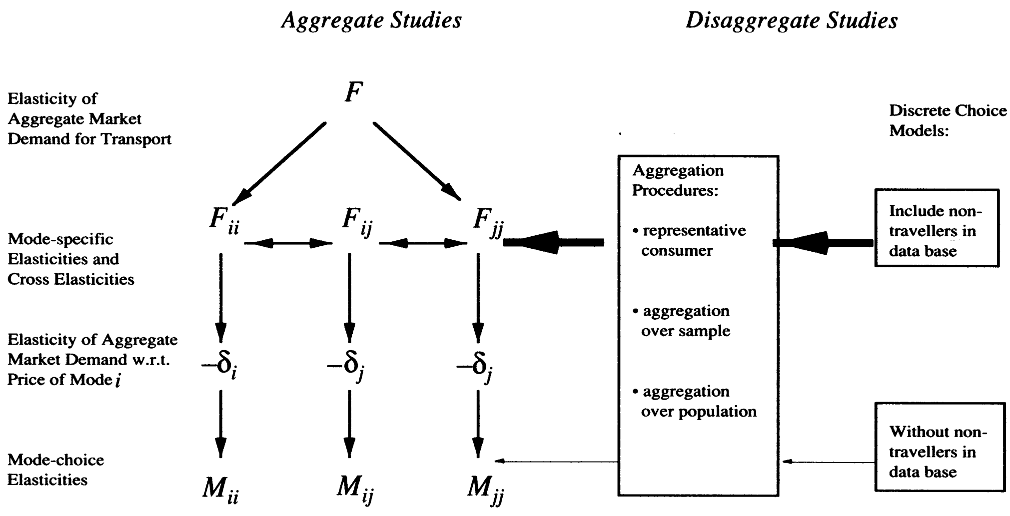

FIGURE 1
A Schematic of Concepts and Empirical Approaches to Estimation of Transport Demand Elasticities

those in a collusive oligopoly market. Not surprisingly, demand elasticities of firms in an oligopolistic market depend greatly on the nature of competition, for example Cournot quantity competition, Bertrand price competition, and so on. A growing number of economists have examined the price sensitivity of demand facing a firm within the framework of conjectural variations (see, for examples, Appelbaum, 1982, and Slade, 1984). As far as we are aware, the only application in transport pricing is Brander and Zhang (1990), which is a study of inter-firm competition between duopoly airlines in the United States. Empirical estimates of transport demand rarely focus on demand elasticities facing individual firms, hence we do not consider them further in this review.

Short-run and long-run elasticities

There is also an important distinction between short-run and long-run elasticities of demand. In the long run, consumers or firms are better able to adjust to price signals than in the short run. Hence long-run demand tends to be more elastic than short-run demand. Unfortunately, few studies are explicit about the time horizon of their elasticity estimates.

Theoretically, consumers and firms are able to vary their location choice and asset holding (for example, vehicle ownership) in the long run, whereas in the short run these are not possible. Viewed in this light, a long-run demand model should ideally model consumers' or firms' location choice and asset ownership together with their transport demand. These are particularly important for long-run policy planning since major changes in transport policy are likely to affect consumers' and firms' asset ownership and location choice. These decisions, in turn, will have significant impacts on transport demand. However, because of the enormous data requirement and the complexity involved in explicitly modelling transport decisions, asset ownership and location choice jointly, estimation of a full long-run model is, to the best of our knowledge, non-existent. Examples of studies which model households' vehicle ownership together with transport demand are Thobani (1984), and Mannering and Winston (1985). However, we are not aware of any transport demand model that includes both location choice and asset ownership. Goodwin's survey (1991) is probably the best attempt thus far to compile short- and long-run transport demand elasticities. However, he is often forced to rely on the original authors' interpretation of their results, rather than compiling elasticity estimates from studies which explicitly model short- and long-run effects.

It is common to use distributed lag models with time-series data in practice in an attempt to capture the long-run effect of price changes. In this case, the direct impact of a price change is used to compute the short-run elasticities, while the long-run elasticities are computed by allowing for the full impact of a price change (for example, Oum, 1979b). The distributed lag model is a theoretically sound and convenient procedure which, if properly executed, will capture the long-run effect of a price change. It is, however, unable to identify the different components that constitute the total effect of a price change.

Linkages between concepts of demand elasticities

Figure 1 is a schematic summary of concepts of transport demand elasticities and relationships between them. On the left side of the figure, the elasticity of aggregate market demand (denoted F) is decomposed into mode-specific demand elasticities, F_{ii}, F_{ij} and F_{jj}. The right side of Figure 1 depicts the disaggregate discrete choice models. Subject to potential sampling and aggregation errors, the aggregated elasticities derived from discrete choice models can be regarded as estimates of the corresponding aggregate elasticities. It is worth noting that a discrete choice model using trip diaries as the data base can capture the stimulation effect on total demand of a lower price if those who participated in the survey represent a true random sample of the population and the researcher incorporates the trip frequency information explicitly in the model. The resulting elasticity estimates (properly aggregated) should then approximate the regular demand elasticity. On the other hand, discrete choice studies which do not include information on non-travellers produce elasticity estimates which approximate aggregate mode-choice elasticity. In sum, although it is possible conceptually to link aggregate and disaggregate transport demand elasticities, the two approaches continue to evolve empirically with few comparisons between the two.

4. SUMMARY OF ELASTICITY ESTIMATES

The major survey results are summarised in the tables below. The results are divided into two categories: Tables 1 to 5 report the elasticity estimates of passenger travel demand whereas Tables 6 and 7 report the elasticity estimates of freight demand. The tables show the specific elasticities (or ranges) reported by authors. We do not compute

TABLE 1

Demand Elasticities of Automobile Usage
(all elasticity estimates are in negative values)

	Short Run	*Long Run*	*Unspecified*
United States	0.23	0.28	0.13–0.26, 0.15–0.45
Australia	0.09–0.24	0.22–0.31	0.22–0.52, 0.25–0.34
United Kingdom	n.a.	n.a.	0.14-0.36

Sources: From 7 single-mode studies. They are: Hensher (1985); Hensher, Milthorpe and Smith (1990); Hensher and Smith (1986c); Mannering (1986); Mannering and Winston (1985); McCarthy (1986); and White (1984).

TABLE 2

Demand Elasticities of Urban Transit
(all elasticity estimates are in negative values)

Data Types	*Elasticity Estimates*
Time Series	0.01–0.62, 0.17–0.59, 0.18–0.22, 0.23–0.25, 0.23–0.27, 0.27–0.78, 0.29–0.34, 0.36–1.32
Cross-section	0.05–0.34
Pooled data	0.06–0.44
Before/after data	0.10–0.60, 0.70

Sources: From 12 studies. They are: Anas and Lee (1982); Benham (1982); Cummings, Fairhurst, Labelle and Stuart (1989); De Rus (1990); Doi and Allen (1986); Gaudry (1980); Gilbert and Jalilian (1991); Goodwin and Williams (1985); Hamberger and Chatterjee (1987); Kyte, Stoner and Cryer (1988); Wang and Skinner (1984); and White (1981).

means or standard deviations by mode since our sample sizes are small and there is heterogeneity among studies. Our World Bank working paper presents subjective "most likely" ranges of elasticity values for various transport demand categories. The sources of these estimates are included at the end of each table.

Table 1 reports the elasticity estimates of automobile usage by countries and time horizons. We rely on the original authors' judgement to distinguish between long-run and short-run estimates. All estimates are from single-mode studies. All these studies use household survey data, except one which uses observations on ridership changes before and after a fare change. The elasticity estimates range from –0.09 to –0.52. Although long-run elasticity estimates are in general higher, the difference does not appear to be significant, although this may reflect the fact that few studies develop true long-run models which take into account changes in vehicle ownership and location choice. Despite the fact that these studies were conducted in different countries, the estimates produced are remarkably similar. All the estimates show that the demand for automobile usage is fairly inelastic. From the perspective of policymaking, the low elasticity estimates in Table 1 indicate that monetary disincentives may not be very effective in controlling automobile usage in urban cities.

TABLE 3

Demand Elasticities of Air Passenger Travel
(all elasticity estimates are in negative values)

	Time Series	*Cross-section*	*Others**
Leisure travel	0.40–1.98, 1.92	1.52	1.40–3.30, 2.20–4.60
Business travel	0.65	1.15	0.90
Mixed or unknown	0.82, 0.91, 0.36–1.81 1.12–1.28, 1.48	0.76–0.84, 1.39, 1.63 1.85, 2.83–4.51	0.53–1.00, 1.80–1.90

* Included in this column are studies with unknown data sources.
Sources: From 13 studies. They are: Abrahams (1983); Agarwal and Talley (1985); Andrikopoulos and Terovitis (1983); Doganis (1985); Fridstroöm and Thune-Larsen (1989); Haitovsky, Solomon and Silman (1987); Ippolito (1981); Oum and Gillen (1983); Oum, Gillen and Noble (1986); Straszheim (1978); Talley and Eckroade (1984); Talley and Schwarz-Miller (1988); and Taplin (1980).

Table 2 reports the elasticity estimates of the demand for urban transit by data types. Eight of the ten studies are single-mode studies. Ideally, the elasticity estimates should be classified according to peak and off-peak hours since urban travel demand is expected to differ substantially in these two periods. Unfortunately, most studies do not report their results in this manner. The range of elasticity estimates varies from –0.01 to –0.78, with most of the values falling between –0.1 to –0.6. These recent figures indicate that the demand for urban transit continues to be rather inelastic, which is consistent with other surveys of demand for public transit, such as Frankena (1978) and Goodwin (1991).

Table 3 contains estimates of demand elasticities of air passenger travel. The classification is by data types and nature of travel. The elasticity estimates range from –0.4 to –4.51, with the majority of the figures falling within –0.8 and –2.0. Unlike the demand for automobile usage and urban transit, the demand elasticities of air travel exhibits far greater variability. Results from a few studies (for example, Oum, Gillen and Noble, 1986: Straszheim, 1978) suggest that demand elasticities differ significantly among different fare classes (for example, first class, standard economy, and discount fares) and distance (for example, long haul versus short haul). This is hardly surprising because price-sensitive holiday-makers form the majority of travellers on long-distance routes whereas less price-sensitive short-distance travellers are mostly business travellers. Unfortunately, classification by fare class or distance is not possible here because most studies reviewed do not maintain these distinctions in their empirical estimates. Nonetheless, Table 3 shows that the demand for business travel is less elastic than that for leisure travel and elasticity estimates from cross-section data generally are higher than those from time-series data. However, it should be noted that data problems are likely to account for part of the differences. In particular, many researchers use regular full fare class as an approximation for business travel. This may have caused the demand elasticity of business travel to be over-estimated, since some holiday-makers travel by the regular fare class, particularly in the regulated markets (for example, in the 1970s

TABLE 4

Demand Elasticities of Intercity Rail Travel
(all elasticity estimates are in negative values)

	Time Series	*Cross-section*	*Others**
Business travel	0.67–1.00	0.70	0.15
Non-business and mixed travel	0.37–0.40, 0.74–0.90, 0.81–1.17, 0.14–1.18, 1.08–1.54	1.40	1.19–1.50, 1.00, 0.12–0.49

* Included in this column are studies with unknown data sources.
Sources: From 9 studies. They are: Glaister (1983); Goodwin and Williams (1985); Jones and Nichols (1983); Kroes and Sheldon (1985); Kroes and Sheldon (1988); McGeehan (1984); Owen and Phillips (1987); Oum and Gillen (1983); and White (1981).

in the United States). Like most transport analysts, we believe that the demand elasticity of business air travel is less than unity while that of holiday travel is greater than unity, although the empirical estimate is not unambiguous.

The elasticity estimates for intercity rail travel are presented in Table 4. Similar to the case of air travel, the classification is by data types and nature of travel. The elasticity estimates range from –0.12 to –1.54, with business travel showing elasticity estimates generally below unity while considerable variation exists in the non-business and mixed travel category. It is again difficult to generalise about the demand for intercity rail travel as a whole. However, it is likely that the presence of competing modes such as air or bus may significantly affect the elasticity values. This is likely to account for the substantial differences among elasticity estimates obtained from different cities.

Table 5 presents elasticity estimates from disaggregate discrete choice models, by mode and type of travel. With a few exceptions, these elasticity estimates are somewhat lower than those obtained from direct demand models using aggregate data. As noted earlier, discrete choice models can produce either mode-choice or regular demand elasticities, depending on the data set used. However, because all the studies reviewed here use data sets that do not contain information about non-travellers, the elasticity estimates reported probably are more appropriately interpreted as mode-choice elasticities.[7] It should be noted that some studies report the elasticity estimates of the representative individual's choice probability. These estimates are identified † in the table. As expected, these elasticity estimates are in general higher in absolute values. A more difficult problem arises when some studies do not state explicitly the types of elasticities they report. Furthermore, most studies do not outline the aggregation procedure used to derive the regular demand elasticity estimates. As a consequence, it is difficult to ensure that these estimates are comparable with each other or with the elasticity estimates reported in other tables.

7 Many discrete choice studies do allow for growth in the aggregate traffic volume among existing users in response to a price or service change. However, since they do not contain information of non-travellers in their data, the resulting elasticity estimate will be between the mode choice and regular price elasticity, as discussed above and shown on the right-hand side of Figure 1.

TABLE 5

Travel Demand Elasticities from Discrete Choice Models
(all elasticity estimates are in negative values)

	Urban Travel	*Intercity Travel*
Automobile	0.01–0.02, 0.04, 0.06–0.08, 0.16–0.62, 0.32–0.47, 0.46–2.03, 0.02–0.88†, 0.16–0.97†, 0.12–1.26†	0.08, 0.70–0.96, 0.83
Bus	0.01–0.03, 0.04, 0.06, 0.03–0.14, 0.10, 0.12–0.24, 0.37–0.56, 0.45–0.58	0.32, 0.32–0.69, 0.45–0.60
Rail	0.22–0.25, 0.57, 0.08–0.75†	0.32, 0.57–1.20, 0.86–1.14
Air	n.a.	0.18–0.38, 0.26–0.38, 0.62

† denotes elasticity of choice probability of the representative individual.
Sources: From 16 studies. They are: Anas and Moses (1984); Bajic (1984); Dunne (1984); Geltner and Barros (1984); Gillen and Cox (1979); Grayson (1981); Johnson and Hensher (1982); Madan and Groenhout (1987); Hensher and Bullock (1979); McCarthy (1982); McFadden (1974); Morrison and Winston (1983); Morrison and Winston (1985); Southworth (1981); Swait and Ben-Akiva (1987); and Thobani (1984).

TABLE 6

Demand Elasticities of Rail Freight: Selected Commodities and Functional Forms
(all elasticity estimates are in negative values)

Commodities	*Log-linear*	*Aggregate Logit*	*Translog*	*Discrete Choice Model**
Aggregate commodities	1.52	0.25–0.35, 0.83, 0.34–1.06	0.09–0.29, 0.60	n.a.
Chemicals	n.a.	0.66	0.69	2.25
Fabricated metal products	n.a.	1.57	2.16	n.a.
Food products	0.02, 1.18	1.36	2.58, 1.04	n.a.
Iron & steel products	n.a.	n.a.	2.54, 1.20	0.02
Machinery	n.a.	0.16–1.73	2.27–3.50	0.61
Paper, plastic & rubber products	0.67	0.87	1.85	0.17–1.09
Petroleum products	n.a.	n.a.	0.99	0.53
Stone, clay & glass products	n.a.	0.69	1.68	0.82
Textiles	n.a.	2.03	n.a.	0.56
Transport equipment	n.a.	n.a.	0.92–1.08	2.68
Wood & wood products	0.05	0.76	1.97, 0.58	0.08

* The estimates in this column are mode-choice elasticities.
Sources: From 11 studies. They are: Babcock and German (1983); Boyer (1977); Friedlaender and Spady (1980); Guria (1988); Levin (1978); Lewis and Widup (1982); Oum (1979a); Oum (1979b); Oum (1989); Wilson, Wilson and Koo (1988); and Winston (1981).

TABLE 7

Demand Elasticities of Truck Freight: Selected Commodities and Functional Forms
(all elasticity estimates are in negative values)

Commodities	*Log-linear*	*Aggregate Logit*	*Translog*	*Discrete Choice Model**
Aggregate commodities	1.34	0.93	0.69	n.a.
Chemicals	n.a.	n.a.	0.98	2.31
Fabricated metal products	n.a.	n.a.	1.36	0.18
Food products	1.18, 1.54	0.97	0.52, 0.65, 1.00	0.99
Machinery	n.a.	n.a.	1.08–1.23	0.78
Paper, plastic & rubber products	n.a.	n.a.	1.05	0.29
Petroleum products	n.a.	n.a.	0.52	0.66
Stone, clay & glass products	n.a.	n.a.	1.03	2.04
Transport equipment	n.a.	n.a.	0.52–0.67	2.96
Wood & wood products	n.a.	n.a.	0.56, 1.55	0.14

* The estimates in this column are mode-choice elasticities.
Sources: From 6 studies. They are: Friedlaender and Spady (1980); Lewis and Widup (1982); Oum (1979b); Oum (1989); Wilson, Wilson and Koo (1988); and Winston (1981).

Tables 6 and 7 report, respectively, elasticity estimates of demand for rail and truck freight by commodity groups and functional forms. A notable feature of these elasticity estimates is the wide range of values, not only across different commodity groups, but also for the same group of commodities estimated using different functional forms.

In summary, our survey results show that only the demand for automobile usage and urban transit are unambiguously inelastic; less can be said about intercity rail and air travel, and still less about freight transport. We believe that many factors may have contributed to the diversity of these empirical results. The following section identifies a number of the important factors, together with some priority areas for future research.

5. PITFALLS AND SUGGESTED PRIORITIES FOR FUTURE RESEARCH

After reviewing over sixty empirical studies of transport demand, we identify a number of issues which warrant attention in existing studies. In addition, we also identify some areas where future research is needed.

1. *The presence or absence of intermodal competition.*
   Some studies do not take into account the presence of intermodal competition. As a result, the own-price elasticity estimates reflect in part the intensity of intermodal competition. In particular, the own-price elasticity may be under-estimated if the prices of competing modes have changed in the same direction as that of the mode

under study. Therefore, it is important to include in a mode's demand specification the prices and service quality variables of competing modes.

2. *The use of different functional forms.*
Different functional forms can result in widely different elasticity estimates, even with the same set of data. This point is demonstrated by Oum (1989) and is evident from Tables 6 and 7. The problem is long neglected by researchers and transport practitioners. Typically, an *ad hoc* demand specification is used and little attention is directed towards testing the specification against an alternative. With the advances in econometric theory and computing technology, we think that specification testing should become an integral part of empirical transport demand research in the future.

3. *Differences in time horizons and locations.*
It is well known that demand becomes more elastic in the long run because users are better able to adjust to price changes. The distinction between long-run and short-run, however, is quite arbitrary in most transport demand studies. More carefully structured long-run studies are needed to integrate location choice and asset ownership decisions with transport demand. In addition to long-run and short-run distinctions, data drawn from different cities or countries often show markedly different elasticity estimates. This may be due, in part, to specification problems and different degrees of competition between modes in different cities or countries.

4. *The degree of aggregation.*
As more disaggregated markets are investigated, the range of elasticity estimates tends to widen because each estimate reflects unique market conditions. For example, suppose the freight demand elasticity of steel is –0.5 and that of fresh fruits is –1.2. The aggregated elasticity will lie somewhere between –0.5 and –1.2. Aggregation "averages out" some of the underlying variabilities of price sensitivity in different markets. The appropriate degree of aggregation is important if elasticity estimates are to be of practical use to decision makers.

5. *The identification problem in empirical estimation.*
In practice, the data observed by researchers are the result of interactions between forces of demand and supply. It is well known in econometrics that the parameter estimates will be biased if such interactions are not recognised. This was not a serious problem in the past because prices and service conditions were tightly controlled by regulatory agencies in many transport industries. Supply decisions were made in response to regulated price and service conditions, thus variations in observed data primarily reflect changes in demand. However, the situation has changed drastically since the early 1980s, when many countries deregulated their transport industries. Now, firms have discretion over price and service conditions and it is more difficult to sort out supply and demand effects in the data. Unfortunately, most empirical studies of transport demand have failed to take this into consideration. Greater effort needs to be directed towards modelling the interactive forces of demand and supply in future studies.

6. *The problem of aggregation in discrete choice models.*
As noted earlier, it is necessary to aggregate across individuals in order to derive the regular demand elasticity estimates from discrete choice models. This will, however, widen the confidence intervals of the resulting elasticity estimates since, in addition to the standard errors associated with the parameter estimates, there is also an error of aggregation. More importantly, the statistical distribution of the demand elasticity estimates will be difficult, if not impossible to determine, since there are two sources of errors. This problem clearly deserves further investigation in future studies.

6. CONCLUDING REMARKS

In the preparation of this paper, we surveyed over sixty studies from academic journals which report estimates of own-price elasticities of transport demand. They include both passenger and freight demand studies, using different data bases and covering many countries and cities. We have attempted to clarify the different concepts of demand elasticities used in these studies. In addition, various problems in interpreting the empirical estimates are discussed. While some generalisations, particularly on demand elasticities of automobile usage and public transit are possible, across-the-board generalisations about transport demand are impossible. This is in contrast to "conventional wisdom", which states that the demand for transport is inelastic because it is a derived demand. This is particularly the case in freight demand, which is believed to be inelastic because freight charges generally are only a fraction of the prices of commodities transported, which usually have inelastic demand themselves. In reality, competition between modes, routes or firms gives rise to a wide range of price elasticities, generally much more elastic than conventional wisdom would suggest. Furthermore, factors such as the time horizon, the degree of aggregation, the functional specification, and so on, have a significant bearing on the elasticity estimates. This also suggests that there is no short-cut to obtaining reliable demand estimates for a specific transport market without a detailed study of that market.

Date of receipt of final typescript: September 1991