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Summary:

Short- and long-run demand effects in transport: A literature survey

Background

Demand elasticities are of vital importance to everyone who is involved in public transport planning and management. Being a measure of the demand effects of changes in for example fares or service levels, the elasticities provide planners with an efficient tool for assessment of many policy measures.

There is increasing evidence that the short-run demand response is only a fraction of the total (i.e. long-run) demand effects. In the short run most passengers have few alternatives to the services they currently depend on. In the longer run, passengers are able to respond more fully to such changes by e.g. changing location of job or dwelling, or changing their car ownership status. Several studies indicate that long-run effects are in the region of 1.5 to 3 times the effects within a year. There is also some evidence suggesting that the effects of positive and negative changes may not be symmetrical. This effect may be more pronounced in the long term as people adapt to the changes and change behaviour.

However, planners are not always aware of this important distinction between short-run and long-run effects. The most widely used "rule-of-thumb" elasticities are typically short-run elasticities. This fact means that there is a risk that the negative effects of fare increases or service withdrawals are substantially underestimated in current planning practice.

A better understanding of the dynamics of public transport demand will give rise to better evaluation of proposed public transport measures, improved precision of forecasts, better long term planning; in sum improved planning and policy-making.

This report investigates and documents the growing literature on differences in short- and long-run demand effects in public transport. It is comprised of two parts. The first part looks at the methodological issues related to the concept of long-run elasticities, and explains different estimation methods and practices. The second part summarises important recent empirical findings in the literature. Finally, the paper draws conclusions for policy making and for public transport planning in general.

Elasticities

The term elasticity is used intensively in the field of economics in general and in the transport sector in particular. Often it is considered a simple and comprehensible quantitative measure of the responsiveness of one variable to another.

The general formula for elasticity, E, is often written as:

E = percent change in x / percent change in y

One reason for the popularity of elasticity measures is that they are independent of the units of measurement of demand and other variables.

As we will get back to, this is the basic definition of the term. When used with caution, this also proves to be a good and effective way to express the responsiveness of one variable from changes in another variable.

An elasticity predicts the demand effect of a change in price or service level (X) by putting it in to this formula:

$$\left(\frac{X_{after}}{X_{before}}\right)^{E}$$

If you consider a plan to increase public transport fares by 5 percent (for simplicity, from 1 to 1.05) and you know that the fares elasticity is -0.4, then the demand effect will be:

$$\left(\frac{X_{after}}{X_{before}}\right)^{E} = \left(\frac{1.05}{1}\right)^{-0.4} = 0.981$$

that is, a passenger loss of 1.9 percent.

Different concepts and types of elasticity

Very often we consider the changes in demand for a good from changes in the price of the same good. When the changes and effects we consider are related to the same good, we are working with *own elasticities*.

When we consider the effects on one good from changes in another good, we are considering *cross-elasticities*. This can be the change in demand for public transport when the costs of car use increase. When the cross elasticity of fares is positive, such as when increased cost of car use increases the demand for public transport, we have *competing goods*. In the opposite case, we have *complementary* goods.

In some situations we consider the effect of similar changes for different goods. In that case we deal with *conditional elasticities*. For instance, we consider the changes in demand for metro from a symmetric change in the fares for all public transport modes (bus, metro, tram, train). In general, the sign of this will be the same as for the cross elasticity, but the magnitude will be much smaller.

Estimating measures for elasticity

Point elasticity
Elasticities are defined for *marginal changes only*. This is why the basic term often is labelled *point elasticity*. It is evident that an estimate based on the simple percentage change formula doesn't take the functional shape of the relationship between the variables into account. Without full knowledge of the functional form, estimates will not be transferable to other levels of demand without some assumptions such as constant elasticity. When we consider these problems, the *point elasticity* can be expressed as:

$$e_x^{point} = \left(\frac{\frac{\Delta y}{y}}{\frac{\Delta x}{x}} \right) = \left(\frac{\frac{\partial y}{y}}{\frac{\partial x}{x}} \right) = \frac{\partial y}{\partial x}\frac{x}{y}$$

In general, changes observed in the variables will not be infinitely small. Thus, caution must be made when considering larger changes in variables. At the same time we will most likely not know the exact relationship (functional form) between the variables, thus the point elasticity will generally not be valid for other values then the estimate has been made on. Thus, generalisations from observed point elasticities should be made with caution.

To cope with the problems of estimating elasticities along a functional shape that is unknown when we only have two pairs of observations, several formulas have been proposed. Some of them are presented in the following.

Arc and Line Elasticity
Arc elasticity is often used to overcome some of the problems of point elasticities. This relates both to the problem of larger changes (not marginal) and the problem of an unknown functional form. Arc elasticities are convenient when there exist only a few observations of for example demand and fares. The definition of arc elasticity is:

$$e_x^{arc} = \left(\frac{\ln y_2 - \ln y_1}{\ln x_2 - \ln x_1} \right),$$

where y_1 and y_2 express the demand before and after changes in fares from x_1 to x_2. This estimate gives us the average elasticity over the interval $<x_1, x_2>$ in the sense that this average corresponds to a constant elasticity that will produce the same observed change. The estimate requires two observations, one before and one after a change has occurred.

The definition of *line elasticity* with the same explanation as the arc elasticity, is:

$$e_x^{line} = \left(\frac{\frac{y_2 - y_1}{\frac{1}{2}(y_2 + y_1)}}{\frac{x_2 - x_1}{\frac{1}{2}(x_2 + x_2)}} \right) = \frac{(y_2 - y_1)(x_2 + x_1)}{(y_2 + y_1)(x_2 - x_1)}$$

This estimate uses in other words the midpoints of the before and after observations as the base for calculation of relative changes. In the same way as the arc elasticity, the line elasticity is better suited for larger changes compared to the point elasticity. It is a useful alternative to the acc elasticity when there is a 0 observation (e.g. zero fare) because ln(0) is not defined.

Methods to estimate long term effects

One major challenge when estimating long term effects is to identify and isolate the effects back in time. For instance, the effect from fare changes in year t is probably not as important for the demand in year t+5 as changes in other variables such as labour market, demography, quality of supply and others. In principle, all relevant explanatory variables should be included in the analysis in order to isolate the different effects. This is practically impossible and the literature is very much focusing on a number of "standard" variables such as fuel prices, fares, income level and service frequency/supply. (An exception is disaggregate data, where far more information is normally collected.)

Time series analyses

Estimates of elasticities based on static aggregate time series are not easily interpreted as neither short nor long term effects. Only when all data are non-stationary and cointegrated or when the total effect is immediate, estimates based on time series can be interpreted as long term effects. Except from these special cases, models that overlook the dynamics will be misspecified and as result provide skewed estimates (Dargay and Goodwin 1995).

Dynamic time series analysis is specified such that that previous year's endogenous variables (Y_{t-1}) or exogenous (X_{t-i}, i=1,2,..) variables explain variations in the observed endogenous variable (Y_t). This way, a lagged structure is introduced.

Lagged exogenous variable
A simple and intuitive way to use time series to estimate long-run elasticities is to use lagged exogenous variables. In the case of a price elasticity, this is simply done by making the demand in year t, Y_t, a function of the current fare P_t and the fares in previous years, P_{t-1}, P_{t-2} etc. In this way:

$$Y_t = \beta_0 P_t + \beta_1 P_{t-1} + \ldots + \beta_n P_{t-n} + \varepsilon_t = \sum_{i=0}^{n} \beta_i P_{t-1} + \varepsilon_t$$

With this model specification, the long term effect is:

$$\beta_0 + \beta_1 + \beta_2 + \ldots + \beta_n = \sum_0^n \beta_i .$$

If the data are log-transformed, this will express the long-run elasticity.

Unfortunately, such models are hard to estimate by the ordinary least squares (OLS) regression (Greene 2000). First, the lagged variables will consume substantial degrees of freedom. This may create problems if the time series are short. Second, the residuals will most likely be serially correlated. Third, we will most likely have a serious multicollinearity problem. Further, it may not be obvious how many lags to include in the model.

Lagged endogenous variable

It is not unreasonable to expect the level of Y_{t-1} to be an important determinant of Y_t. A partial adjustment model describes the desired level of consumption in period t, Y^*_t (Greene 2000) in the following way:

$Y^*_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \varepsilon_t$,

and a partial adjustment equation: $Y_t - Y_{t-1} = (1 - \lambda)(Y^*_t - Y_{t-1})$

Where:

X are exogenous variables

β are parameters

ε is error term

When solving the last equation for Y_{t-1} by inserting the first, we get:

$$Y_t = \beta_0' + \beta_1' X_{1t} + \beta_2' X_2 t + \beta_3 Y_{t-1} + \varepsilon'_t, \quad (1)$$

The model takes into account the inertia of the adjustment. At the same time we find that the Y variable for any year given is a result of changes in all previous years.

This is a robust model that can easily be estimated by OLS. If the data are log-transformed, we can interpret β_1 and β_2 as the short-run elasticities, and $\beta_1/(1-\beta_3)$ and $\beta_2/(1-\beta_3)$ as long-run elasticities of permanent changes in X_1 and/or X_2.

We may want a model specification where the elasticities depend on, for instance, the fare level (X_1). This can be done by keeping all other variables log-transformed, whereas the fare variable (X_1) is included at its real value (level). The short-run elasticity will be $\beta_1 X_1$ and the long term elasticity like $\beta_1 X_1/(1-\beta_3)$. Such an approach is described in Dargay and Hanley (2001)

The partial adjustment modelling approach can be used to estimate effects of a change over time. Following Hamilton (1994) equation 1 can be simplified as:

$Y_t = \beta_3 Y_{t-1} + W_t$,

where $W_t = \beta_0' + \beta_1' X_{1t} + \beta_2' X_2 t + \varepsilon'_t$,

The effect of W_t on Y_{t+j} is given by:

$$\frac{\partial Y_{t+j}}{\partial W_t} = \beta_3^j, \quad (2)$$

This dynamic multiplier (2) only depends on j, the time lag between changes in W_t and the observed effect on Y_{t+j}, and not on t, which is the date of observation. If we want to test the effect in Y two years after a change in X_1, we solve the following (and assume that X_{1t+1} and X_{1t+2} are independent of changes in X_{1t}):

$$\frac{\partial Y_{t+2}}{\partial X_{1t}} = \frac{\partial Y_{t+2}}{\partial W_t}\frac{\partial W_t}{\partial X_{1t}} = \beta_3^2 \beta_1$$

Assuming that $0<\beta_3<1$, the multiplier will converge towards 0 over time and the long term effect will tend towards a stable level. The closer β_3 is to 1, the longer it takes for the full adjustment to take place. When $\beta_3 \rightarrow 0$, all effects will occur in the same period as the fare changes.

Numerical example

Let Y be public transport (PT) trips per capita, X_1 the fare level and X_2 the service frequency. All numbers are annual data and log-transformed (which means that parameter estimates are interpreted as elasticities). We define the following model:

$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 Y_{t-1} + \varepsilon_t$,

and estimate the following parameters:

$Y_t = 1.134 - 0.35X_1 + 0.40X_2 + 0.55Y_{t-1}$

The immediate effect of a 1 per cent change in fares is a passenger decline of 0.35 per cent the first year. The total long term effect will be $\beta_1/(1-\beta_3) = -0.35/(1-0.55) = -0.78$, in other words a passenger decline of 0.78 per cent.

Similar calculations can estimate changes in frequency. The short and long term service elasticities are 0.4 and 0.89 per cent, respectively.

Four years after the change, we can estimate the yearly effect of the initial change to be:

$$\frac{\partial Y_{t+3}}{\partial X_{1t}} = \frac{\partial Y_{t+3}}{\partial W_t} \frac{\partial W_t}{\partial X_{1t}} = \beta_3^4 \beta_1 = 0{,}55^4 \times (-0{,}35) = -0{,}03$$

In other words, the demand is reduced by 0,03 per cent in year t+4 as a result of the initial 1 per cent change in fare in year 0. The first year after the change (t+1), the effect will be a $0.55^1 * (-0.35) = 0.19$ % decline.

Figure 1 illustrates the estimated effect in each of the 10 first years after a fare increase of 1 percent. The cumulative effect –0.78, as estimated above. We see that little additional effect of the fare increase is traceable after about 5 years.

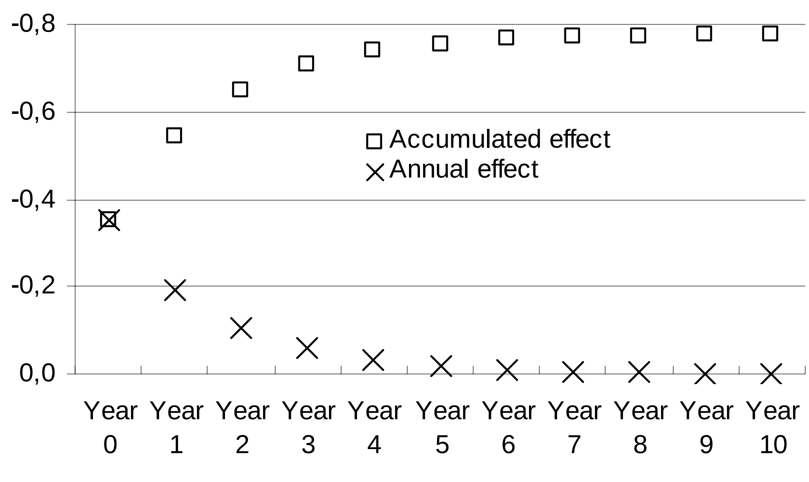

Figure 1: Example of annual and accumulated demand effect in the next 10 periods after a 1 per cent fare increase in year 0. Based on the numerical example above. Percentages.
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Aggregate cross-section analysis

Aggregate cross-section analysis (for instance different urban areas or countries) will in principle express long-run effects. This is because we can assume the different observations to be equilibrium situations of different fare levels, frequency levels, etc. An example might highlight this: Let us assume that fares in a county increase by 20%. If we only analyse the effects within the current year, we will find the short-run effect. However, if we look at two counties, where the fare level in the second traditionally lies 20% higher than the first, we can assume that the differences in demand are more than a short-run effect. The adjustments in the different counties have occurred over time and in response to local changes, so that the adjustment can be interpreted as a long-run effect.

There are, however, important problems with the interpretation of aggregate cross-section data. First, there is usually a lack of variation in the different variables between the areas. For instance the fuel price of different cities in Norway does not differ much. International cross-section data sets provide more variation, but will have the weakness that local differences will play an important role. Such differences can be attitudes towards public transport, income levels, land use, organisational issues, unemployment etc. Public transport data sets often have a more local aspect and variation compared to other data sets. Thus cross-section analysis of such data should express long term effects with a larger probability than, e.g. time series on fuel prices. The challenge is to obtain a sufficient number of observations (areas) in order to calibrate a good model.

A second problem is to interpret cross-section data, since long-term adjustments observations must be in a state of equilibrium. With important parameters such as income, domicile, fares and so on changing continuously, Dargay and Goodwin (1995) argued that we most likely will not find such equilibria. It could be more correct, as Webster and Bly argue, to interpret travel data as "a constant state of disequilibrium".

Finally, cross-section analysis will not give insight to the speed of adjustment or the relation between short-run and long-run effects, i.e. the dynamics.

It is common to merge time series for different areas. The result is a pooled cross-section/time series data set. This provides the benefits of time series as well as the variations by cross-section data sets. The disadvantage is the implicit assumption that for some explanatory variables the same demand relations and elasticities exist in all areas, only adjusted by area specific constant dummies in the models (Dargay and Hanley 2001).

Disaggregate data

The ideal data for long- and short-run elasticity estimates are observations of individuals over several periods. Disaggregate data of this type and of sufficient quality are, however, costly to collect, demand large samples and require the same persons to respond several times (panel). Such data are therefore rare. National travel surveys do, however, provide a good basis for analyses of long term adjustments on the individual (micro) level.

Micro level data is in principle also cross-section data. But unlike aggregate cross-section data, individual data provide sufficient variation in the relevant variables. Petrol cost and in many cases also public transport fares will for example vary with trip length. Further, the price of public transport relative to the price of other transport means will vary between individuals such that mode choices can be regarded as long term adjustments. Simultaneous logit models of mode choice and destination choice therefore give long term elasticity estimates.

An feature of logit models is that the elasticity estimate for a transport mode is affected by its market share – i.e. similar to what we observe in the real world. The higher market share the lower the elasticity estimate, ceteris paribus, because the elasticity is calculated as $(1-P_i)*X_i*\alpha_s$, where P_i is the probability of choosing mode i, or in other words the market share (Johansen 2001, p. 8).

Structural equation modelling (SEM)

SEM is a simultaneous equation estimation technique and is possibly a useful tool for estimation of long term effects. SEM models estimate direct, indirect and total effects. Figure 2.1 illustrates this.

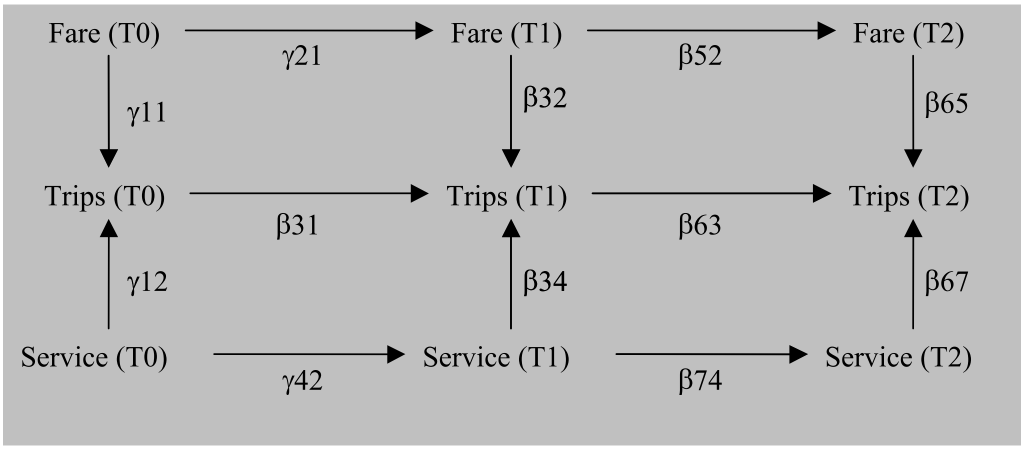

Figure 2: Illustration of construction of SEM model.
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We wish to identify the effect of Fare (T0) on Trips (T0, T1 and T2). The direct and total effect of Fare (T1) on Trips (T0) is γ11. This is the short term effect. The long term indirect and total effect of Fare (T0) on Trips (T2) is the sum of γ21×β52×β65 plus γ21×β32×β63 plus γ11×β31×β63. There are no restrictions on the number of such time lags entered into the model. SEM models are, however, generally very data intensive.

Empirical evidence

This section summarises several surveys of demand elasticities. The elasticities are both from both primary and secondary sources. Thus there are both general surveys of elasticities and surveys with their own estimates. Overviews from the early 1990s were limited in their analytical approach, more or less presenting the findings from different surveys without looking behind them and placing them in their relevant context. More recent surveys have taken the context into account and analysed the variation in the estimates with respect to choice of method, year, geographical coverage etc (Wardman and Shires, 2004; Nijkamp and Pepping, 2001). Such meta-analysis can contribute new insight and more reliable recommendations because they correct for variations in external conditions.

All estimates of elasticities are dependent on the context. Wardman and Shires (2004) found significant effects from a wide range of contextual issues. Estimated demand elasticities were influenced by trip characteristics (purpose, age and discounts), method of aggregation, method of data collection, and method of estimation. Further, Nijkamp and Pepping (2001) found that the number of competing modes of transport included in the survey affected the results. Based on this, it is of little use to make any general conclusions on the correct estimates of elasticities. Some recommendations can be made, however, when taking the context into account.

Demand elasticities in public transport

Table 1 summarises some of the most important demand elasticity estimates for public transport found in the literature survey. The dependent variables are either number of public transport trips or trips per capita. The findings are discussed below.

There is considerable variation between the elasticities of the different sources. This should come as a surprise given the varying context of the different surveys. Furthermore, some of the elasticities are based on local analysis of supply, demand and fares, whereas other ones are averages from various analyses.

The elasticity of demand for local public transport with respect to the supply (frequency/vehicle kms) ranges from 0.2 to 0.7 in the short run and from 0.4 to 1.1 in the long term. In general, the long term effect from the surveys is almost twice the short term effect.

The elasticity of demand for local public transport with respect to the fares ranges from –0.2 to –1.3 in the short term. This is a large spread that can be traced to one calculation made by Oxera. In their report, Oxera (2004) actually argues for the use of a smaller elasticities than the ones they estimate. Keeping this in mind, the picture seems pretty clear. Short time elasticities are generally less than –0.5. In the long-run, elasticities range from –0.4 to –1.3. On average, the long term elasticity is twice the short-run elasticity.

Demand for rail is often considered more price sensitive than local public transport. Our survey supports this. In general, the average values for railroad elasticities are higher than the elasticities for local public transport. The findings are quite consistent with a long term effect 1.6 times the short-run effect.

Table 1: Summary of reported elasticities.

	Area	Short-run elasticity	Long-run elasticity	LR/SR[1]
Frequency/vehicle kilometres, local public transport:				
Dargay and Hanley 1999*	UK all regions	0,43	0,81	1,88
Dargay and Hanley 1999*	UK counties	0,48	1,04	2,17
Dargay et al. in Litman 2004*	UK	0,57	0,77	1,35
Dargay et al. in Litman 2004*	France	0,29	0,57	1,97
Litman 2004^	All trips	0,50/0,70	0,70/1,10	1,50
Vibe et al. 2005*	Norway	0,20	0,43	2,15
Average		*0,43*	*0,75*	*1,84*
Fares, local public transport:				
Dargay and Hanley 1999*	UK	-0,33/-0,52	-0,62/-1,08	2,00
Dargay and Hanley 1999*	UK met. areas	-0,24/-0,57	-0,45/-0,76	1,49
Dargay and Hanley 1999*	UK counties	-0,33	-0,71	2,15
Goodwin 1992^	Europe/n.a.	-0,21/-0,28	-0,55/-0,65	2,45
Gilbert and Jalilian in Goodwin 1992*	London	-0,80	-1,20/-1,30	1,56
Dargay et al. in Litman 2004*	UK	-0,51	-0,69	1,35
Dargay et al. in Litman 2004*	France	-0,32	-0,61	1,91
Litman 2004^	All trips	-0,20/-0,50	-0,60/-0,90	2,14
Litman 2004^	Peak	-0,15/-0,30	-0,40/-0,60	2,22
Litman 2004^	Non-peak	-0,30/-0,60	-0,80/-1,00	2,00
Oxera 2004*	Scotland	-0,85/-1,34	-1,06/-1,19	1,03
Oxera 2004^	Scotland	-0,35/-0,50	-1,00	2,35
Vibe et al. 2005*	Norway	-0,23	-0,51	2,22
Wardman and Shires 2003^	UK	-0,30	-0,59	1,95
Average		*-0,44*	*-0,76*	*1,92*
Fares, train and metro:				
Owen and Philip in Goodwin 1992*	UK	-0,69	-1,08	1,57
Wardman and Shires 2003^	UK	-0,50	-0,74	1,47
Oxera 2004*	Scotland	-0,63/-0,66	-1,18/-1,25	1,88
Oxera 2004^	Scotland	-0,50/-0,70	-0,75/-1,00	1,46
Average		*-0,61*	*-0,98*	*1,59*
Average all surveys				**1,84**

[1] For simplicity, the calculation is based on mean values where high/low estimates are given
* Primary study
^ Recommendation, summary of several findings or meta-analysis
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If we assume that local public transport and rail demand adjust equally fast to changes in the factors we have studies here (fares, supply), the average of all elasticities may be a good measure of the ratio between long- and short-run elasticities. Our total average long-run effect is 1.84 times the short-run effect. This is in the lower range of the existing presumptions. For instance, Litman (2004) suggests a ratio between 2 and 3, while Dargay and Hanley (1999) found factors ranging from 1.5 to 3.

The dynamics of public transport demand

How long is the long term? And how quickly do passengers adapt to changes in fares and service levels? The question is important, particularly for operators who need to know how fast ticket revenues will change in response to a change in service or fare levels. Even planners performing cost-benefit analyses are in need of such information.

The dynamic multiplier can give an answer to much of this. As we have shown, the effect of W_t on Y_{t+j} is given by the multiplier

$$\frac{\partial Y_{t+j}}{\partial W_t} = \beta_3^j .$$

j is the time period between the change in the explanatory factor W_t and the effect Y_{t+j}. The smaller β_3 is, the longer it takes for the adjustment to be achieved.

In Figure 3, below, we have estimated the dynamics of passengers' adjustments to fare increases in a selection of studies. We have calculated the effect of a 1 percent fare increase in year 0. The figure shows that the entire effect has more or less materialised within 3-7 years. In all examples at least 90 percent of the total effect is reached after 3 years and at least 97 percent after 5 years.

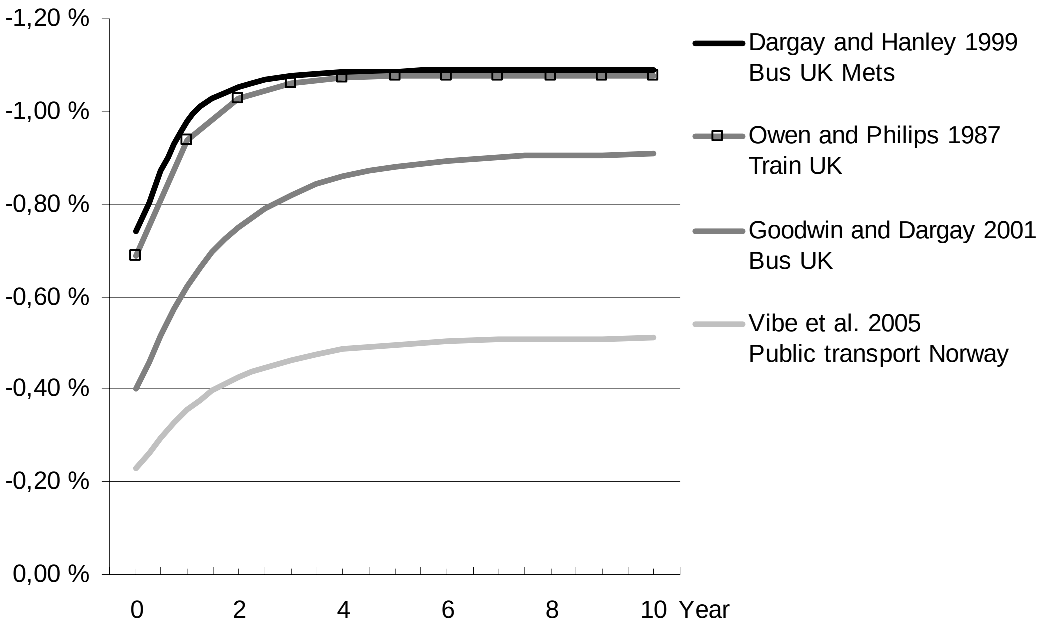

Figure 3: Dynamics of passengers' adjustments to 1 percent fare increases in year 0. Calculations based on reported coefficients in a selection of studies.

Balcombe et al (2004) provide a rule of thumb distinction between the short, medium and long term. (However, they do not stick to this distinction throughout their report.) Their *summary of findings* uses of the following distinction:

Short run: 1-2 years

Medium run: 5-7 years

Long run: 12-15 or even 20 years

Their recommended time horizons may be correct (and of interest) when *all* changes in land use, job and dwelling location and similar "slow" changes are to be included. However, for estimation or forecast purposes we do not regard it likely that demand adjustments can be detected nearly a generation after changes in service levels or fares take place. Such a definition of "long-run" is not operational. Further, the diagram above shows that there are rarely any further effects 5 years after the fare increase.

Although there may – in theory – be effects that materialise more than 10 years after a change, there are good reasons to ignore them for most practical purposes. Several other explanatory factors, which are impossible to include in an analysis, will inevitably have changed over such a long period. Such factors could e.g. be changes in quality and comfort of public transport relative to alternative transport modes, changes in lifestyles, and so on.

Conclusions and policy implications

Elasticity measures are widely used by planners and operators. The distinction between demand elasticities in the short and in the long run is rarely addressed, although there is a growing literature on the subject, and the methodology and tools for estimation of long term effects are becoming more and more accessible.

We have presented some different estimation techniques for short and long term elasticities. The point elasticity is the only true elasticity measure. However, if we have observations of two states (e.g. year 1 and year 2), but the demand function is unknown, there are several ways around the problem which may yield credible estimates. These include the arc and line elasticities.

Regarding the estimation of long-run elasticities, we have shown that different kinds of data require different estimation procedures and give rise to quite different statistical problems.

Table 2 summarises the overall findings of a literature survey of short- and long-run demand elasticities.

Table 2: A survey of empirical evidence provides the following average demand elasticities.

	Short-run elasticity	Long-run elasticity	Long-run / Short-run
Service level, local public transport	0,43	0,75	1,84
Fare level, local public transport	-0,44	-0,76	1,92
Fare level, train/metro	-0,61	-0,98	1,59
Average ratio long-run / short-run			1,84

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Finally we have argued that it makes little sense to try to estimate effects that materialise 10 or more years after a change in fare/service takes place. Too many other factors will have changed during the same period, which are impossible to include in a demand analysis. Typically, nearly 100 percent of the adjustments in demand will have materialised within 5-7 years after a change.