Bus demand theory and the factors affecting demand

2. 1 Introduction

This chapter reviews the literature on bus fare, income, service and cross price elasticities based on studies prior to and after 1990s. Major studies reviewed have concentrated on the difference between short- and long-term elasticities; variation of fare elasticities across areas, by city size and for different trip purposes; and, on the difference in fare elasticities for small and large price changes. Research work on the dynamics of response to fare and other price changes in the field of bus demand have been scrutinized. It has to be noted that the literature review exposed here have placed emphasis on studies which are partly analogous in nature to the project in hand. This chapter is organised as follows: a review of theories underlying bus demand and elasticities is conducted in Section 2. 2 followed by an overview of the empirical evidence in Section 2. 3.

2. 2 Theory

A brief overview of bus demand theory and the main factors affecting demand are discussed in Section 2. 2. 1. After that, different notions of elasticity and the factors affecting their estimations are presented in Section 2. 2. 2.

2. 2. 1 Bus Demand Theory and Factors determining Bus Demand

Demand is defined as the quantity of good or service that consumers are willing to buy at a given price in a given time period. In our context, the service is bus and the price is fare. Demand for bus transport or public transport in general is said to be a derived demand i. e. it is rarely in demand for its own characteristics, hence derived from other function. For example, an individual leaving away from Port-Louis who desires to eat and shop at " Le Caudan Waterfront" would see bus transport as a means to get there to satisfy his desire. So the more people are attracted to shop and eat in Port-Louis, the higher the demand for transport facilities there.

Some factors determining the demand for bus services are outlined below:

Price: the lower the price, the more people are likely to demand the service offered.

Relative prices charged by different modes/operators: e. g. the lower the price of taxi fares, the more people will shift from bus to taxi travel.

Passenger income: as income rises, so the amount of travelling for both leisure and business trips will increase.

Quality of service: the more comfortable, safe, reliable and faster it is, the more people are encouraged to use bus travel.

2. 2. 2 Elasticity Concept and Factors affecting Transit Elasticities

Fare is a backbone in the functioning of public transport as it generates revenue to operators. The effects of fare changes on bus patronage, ridership or simply bus demand, can be measured in terms of elasticities. Economists define elasticities as a measurement of price sensitivity of the percentage change in consumption of a good caused by a 1 % change in its price or other characteristics.

Unit elasticity refers to elasticity with an absolute value of 1. 0: price changes cause proportional consumption change. Elasticity values less than 1. 0 in absolute value are called inelastic: prices cause less than proportional change in consumption. They are elastic if they are greater than one in absolute value: prices cause more than proportional changes in consumption.

In our context, the value of the fares elasticity is the ratio of the proportional change in patronage to the proportional change in fares. Generally, a bus fare increase brings to a fall in bus patronage i. e. they are inversely related. A zero to -1 value implies that a fare increase will lead to increased revenue. A more than -1 value suggests that a fare increase will be characterized by a decline in revenue.

There exist several methods for the calculation of elasticities (Pratt, 2003. The shrinkage ratio or factor, which is not an elasticity measure, explains the change in demand relative to original demand divided by the change in price relative to the original price.

The effect of the costs of alternative modes on bus patronage can be interpreted by making use of cross-price elasticities. These assess the percentage change in quantity demanded for, say bus travel, in response to a percentage change in the price of another service, such as motoring costs. For substitutable goods and services, the cross-price elasticity is positive while for complementary ones, it is negative. If the two goods/services are independents, it would be zero.

The income elasticity, which measures the percentage change in quantity demanded with respect to a 1 % change in income, ceteris paribus, is one way to analyse the effect of income on public transport demand. A less than one income elasticity is attributed to a necessity/normal good. A greater than one income elasticity reflects the characteristic of a luxury/superior good while a negative elasticity is associated with inferior goods implying that a rise in income brings to a fall in the consumption of a good. A zero income elasticity occurs when an increase in demand has no effect on the demand for a good.

Service elasticity indicates how transit ridership is affected by transit service quality factors such as availability, convenience, speed and comfort based on transit vehicle mileage, hours and frequency (Kittleson & Associates, 1999; Phillips, Karachephone and Landis, 2001). It is defined as the percentage change in transit ridership resulting from each 1% change in transit service. A negative sign indicates that the effect operates in the opposite direction from the cause (an increase in price causes a reduction in travel).

Taylor and Fink (2003) classified the factors influencing transit elasticity analysis into external and internal. External factors such as gasoline prices, cannot be controlled by transit systems while internal ones like fare levels are controllable. These are summarized below:

User type

Transit dependent travellers and discretionary or “ choice” travellers (people who may use an alternative mode for that trip) response differently to a fare change. Because of this difference, we say that there is a kink in the demand curve (Clements, 1977), as illustrated in Figure 1. Generally, basic transit that serves transit dependent users is the less elastic portion of the demand curve, while service that attracts discretionary transit users is the more elastic portion of the curve. Non-drivers and college students are examples of dependent transit riders while drivers are considered as independent transit users.

Figure 1: A Kink in the Demand Curve

Price

Ridership

Source: Todd Litman (2007)

Time period

Fare elasticities are dynamic in nature i. e. they vary considerably with time as a result of fare changes. It is important to distinguish between short-run (SR), medium-run (MR) and long-run (LR). Explanations on SR, MR and LR elasticities can vary among authors. Most authors define SR to be 1 or 2 years; MR to be around 5 to 7 years while LR to be 12 to 15 years, or even more.

Geography

Residents of large cities are much more dependent on public transport than those in smaller cities for the simply reason that the more populated a city is, the greater the demand for bus services.

On the other hand, people in rural areas with low population density are likely to rely more on cars and less on public transport than urban residents as they have the option to switch to car if fare rises. So, fare elasticities may differ by area type.

Trip purpose

Peak journeys usually involve work and education journeys and are likely to be fixed in time and space while off-peak journeys which include leisure, shopping and personal business trips, are more flexible in terms of destination and time. So, off-peak elasticities will differ to peak ones.

Type of price change

Fare elasticity is also affected by the current level of the fare. In other words, people will response differently to high and low fares imposed.

Increase in fuel prices is the main cause of rising bus fares. If fuel prices rise up, bus fares will increase and reduce, in its turn, bus travel as less people will tend to travel. This effect can be evaluated through the measurement of elasticities for bus patronage with respect to fuel costs.

Trip generation

Fare elasticities for concessionary fares may not be the same as for full fares. Offering concessionary fares to certain groups of passengers will bring to additional trips. Concessionary fares are those fares provided to students, elderly and disabled people who are provided with a free bus pass entitling the holder to fares half the standard adult fares, lower or even free depending on the trip purpose.

2. 3 Empirical Evidence

This section summarizes the main findings of studies related to bus fare elasticities and underpins some of the theories discussed in the previous section. Most authors have used time-series analysis to study the impact of fare changes in European and American countries. The major issues considered are roughly the effect of fare changes for different areas and trip purposes; by city size; at different time periods and fare levels, and also the influence of income, car ownership, service level, employment and motoring costs on bus demand. It would be noticed that some evidences are not fully detailed because they have been re-examined from literature reviews which do not provide information on the methodologies used.

2. 3. 1 Effect of Empirical Elasticity Estimates

Curtin (1968) developed a simple measure to analyse the impact of fare changes on transit ridership known as the Simpson-Curtin formula. The formula is derived from a regression analysis of before-and-after results of 77 surface transit (bus and street car) fare changes. It is calculated as follows:

$Y = 0.80 + 0.30X$,

Where:

Y= Percent loss in ridership as compared to prior (before) ridership

X= Percent increase in fare as compared to the prior (before) fare

He found an average fare elasticity of -0. 33; i. e. a 10 % increase in fare would result into a 3. 3 % loss in patronage. However, the Simpson-Curtin formula has proved to be inaccurate today and too simplistic as it does not consider fare impacts between peak and off-peak hours or between large and small cities.

Webster and Bly’s (1980) review of public transport elasticities suggested a reasonable rule of thumb of fare elasticity of -0. 3, which was acceptable in the 1980s but started to look as if there was a drift upwards in the fare elasticity to somewhere in the range -0. 3 to -0. 4 or more, in the 1990s.

Effect of fares by city size

Unlike the Simpson-Curtin formula, Pham and Linsalata (1991) evaluated fare elasticities of a sample of 52 US transit systems for the North America and categorized the elasticities of seven systems into peak and off-peak hours in the 1980s by employing an ARIMA model. On the basis of before-and-after time-series data and with log of passenger trips as the regressand and log of deflated average fare among the explanatory variables, the model was estimated using OLS. Transit systems of different sizes in large and small cities are represented.

Table 1 summarizes the resulting fare elasticity estimates. All-hour fare elasticity for all system averaged at -0. 40: a 10 % increase in bus fares, on average, would lead to a 4 % decline in ridership in small and large cities, which is higher than the Simpson-Curtin formula.

Table 1: Bus Fare Elasticities (Pham and Linsalata, 1991)

Large Cities (More than One Million Population)

Small Cities

(Less than One Million Population)

Average for All hours

-0. 36

-0. 43

Peak Hour

-0. 18

-0. 27

Off-Peak

-0. 39

-0. 46

Off-Peak Average

-0. 42

Peak Hour Average

-0. 23

Source: American Public Transit Association, 1991

Pham and Linsata (1991) found that residents of small cities response more to fare changes than those leaving in large cities, with average fare elasticities of -0. 36 and -0. 43 respectively. Average peak hour elasticity is estimated at -0. 23 while off-peak hour elasticity is -0. 42 implying that peak-hour passengers are more price sensitive to fare variations than those travelling during off-peak hours. Alternatively, a 10 % increase in fares, on average, would lead to a double loss of off-peak passengers as compared to peak ones: 4 % against 2 % respectively.

Similarly, the ISOTOPE[1](1997) study of variation of elasticity by city size based on a sample of 89 European cities, postulated that bus fare elasticities are greater in small cities (a population of less than one million) than in large cities (a population of more than one million): -0. 50 compared to -0. 34 correspondingly. According to ISOTOPE:

“ the lower fare elasticity in large cities reflects the greater degree of captivity to public transport due to longer journey distances (making walking less attractive), a greater congestion and parking problems (making car less attractive).”

Webster and Bly (1980)’s study for North American cities disproved this statement by showing the contrary, i. e. fare elasticities for larger cities are higher than for smaller ones. Dargay and Hanly (1999) argued that this is because European cities are physically small and more congested than North American cities.

Effect of fares by time period

Goodwin (1992) conducted a review of 50 demand elasticities for bus use, derived from studies for the UK and elsewhere, and calculated a non-weighted average of -0. 41. Table 2 summarises the elasticity values categorized by type of study and time period covered by the studies (either explicitly or implicitly).

Table 2: Bus fare elasticities related to time period

Type of study

Time period

Average elasticity

Standard deviation

No. in sample

Before and after

around 6 months

-0. 21

0. 12

3

Explicit short

0-6 months

-0. 28

0. 13

8

Unlagged time series

0-12 months

-0. 37

0. 18

24

Explicit long

4+ years

-0. 55

0. 20

8

Equilibrium models

5-30

-0. 65

0. 18

7

Source: Goodwin, 1992

He brought about that the static elasticity figure of -0. 3 (Webster and Bly 1980), estimated from unlagged time-series data, is tenable for the effects within the first year (SR), and that the effect after four years or MR, would be -0. 55, rising to -0. 65 over a period of about a decade. Some studies have found higher values (up to -0. 98) and others lower (down to -0. 45).

By assuming prices of all other modes to be held constant and using complex econometric models, Gilbert and Jalilian (1991) estimated bus fare elasticities in London of -0. 8 in the SR and -1. 2 to -1. 3 in the LR: a considerably higher absolute level compared to those of other studies reviewed in Goodwin (1992) and Fowkes et al (1992). The LR value of greater than unity implies that revenue would decrease when fares were increased.

2. 3. 1. 1 Effect of other exogenous variables

Kain (1997) examined the effects of other exogenous variables on bus ridership for the US as a whole for the interval 1972-1974 to 1981-1983 and used a dummy for 1980 to reflect the impact of higher fuel prices in 1980. He applied OLS method to an econometric model relating annual transit trips to real average fares (-0. 29); service miles (0. 56); vehicle size (0. 45); real fuel prices (0. 05); employment (0. 41); a trend (-0. 02) and a dummy (0. 05). All explanatory variables except the dummy and the trend were expressed in natural logarithms. On average, any 10 % rise in service level, employment and fuel prices will be accompanied by upsurges of 5. 6, 4 and 0. 5 %, respectively, on ridership.

De Rus (1990) derived elasticity estimates for fare ad service level for eleven Spanish transport operators between 1980/88. . He employed both static and dynamic double log linear demand models using OLS estimation with passenger trips per month as the regressand and the deflated price of an ordinary ticket and vehicle kilometres per month as the regressors. These are reported in Table 3.

Table 3: Dynamic versus Static elasticity estimates

Fare

Service

Static

-0. 16 to -0. 41

0. 34 to 1. 26

Dynamic SR

LR

-0. 06 to -0. 39

-0. 09 to -0. 49

0. 26 to 1. 54

0. 64 to 1. 88

Source: Author

Both specifications quite give similar results. However, the static fare elasticities seems to converge to the SR ones, as Goodwin (1982) stated previously. Bus demand is found to be ‘ service’ elastic while ‘ fare’ inelastic in both SR and LR. Thus, changes in the quality of service will tend to cause greater changes in patronage than variations in fare prices.

Effects of other exogenous variables by area type

In order to investigate differences in fare elasticities between urban and less urban areas, Dargay and Hanly (1999) estimated separate partial adjustment models associating bus journeys per capita to bus fares (real average revenue per journey); real disposable income and service level (bus kilometres), for the Shire counties and the Metropolitan areas in UK, based on pooled data between 1986-1996. The estimated elasticities are illustrated in Table 4. OLS methods were run on double log specifications.

Table 4: Estimated elasticities based on pooled data for English Shire counties

and Metropolitan areas. Partial Adjustment Model.

Fare

Income

Service

SR LR

SR LR

SR LR

Shire counties

-0. 51 -0. 70

-0. 64 -0. 87

0. 64 0. 87

Metropolitan areas

-0. 21 -0. 43

-1. 02 -2. 08

0. 35 0. 71

Source: Dargay and Hanly, 1999

They found that travellers from less urban areas are more sensitive to fare changes than those from urban ones. This is because people have the option of travelling by car in rural areas (due to higher car ownership, less road congestion). White (2002) argued that short-run elasticities may be highest in suburban areas due to existing wider modal choices. Further, LR income elasticties for urban areas are two times the elasticities for less-urban areas. Quality of service turns up to impact more positively in less urban areas. The coefficients of adjustment (1-Î¸) for the urban and less-urban areas amounted to 0. 49 and 0. 74, respectively. To sum up, less urban people tend to adjust quicker to internal and external changes.

Effects of fares and other exogenous variables at different fare level

Dargay and Hanly (2002), still using partial adjustment approaches, specified two different models: a constant fare elasticity model/log-log specification and a variable fare elasticity model/semi log specification where only the fare variable is expressed in level term, allowing the fare elasticity to vary at different fare levels. The model estimates are summarized in Table 5.

They noticed that high fares (â‚¤ 1 in 1995 prices) were associated with higher fare elasticities than with low fares (27p in 1995 prices) in UK. For instance, when the starting point of a fare increase is relatively high, the loss in ridership would be six times higher than with the low fare increase in the LR: -0. 26 against -1. 54 respectively.

Table 5: Constant versus Variable Fare Elasticities

Fare

Income

Service

Motoring costs

% Pensioners

Specification

SR LR

SR LR

SR LR

SR LR

SR LR

Constant

-0. 33 -0. 7

-0. 39 -0. 81

0. 49 1. 02

0. 32 0. 67

(-0. 08) (-0. 17)

Variable

Minimum = 17p

Average = 56p

Maximum = â,¤ 1

-0. 13 -0. 26

-0. 41 -0. 86

-0. 74 -1. 54

-0. 39 -0. 81

0. 47 1. 0

0. 35 0. 73

(-0. 01) (-0. 02)

Source: Dargay and Hanly, 1999

Note: elasticities in parentheses are not statistically different from zero.

The other estimates from the constant model are practically the same as those derived from the semi log specification. Motoring costs (car purchase and running costs) show a positive influence on demand in both SR and LR, indicating the modal substitution effect from car to bus travel. Although insignificant in values, the effect of pensioners is negative on patronage. The coefficient of adjustment estimated at 0. 48 in both specifications, indicating that adjustments in UK bus patronage with respect to changes in controlled and uncontrolled factors, are quite low. This explains the large discrepancies between the SR and LR elasticities.

Romilly (2000) and Oxera (2003) employed error correction models for the estimation of bus demand elasticities for the British Industry. Romilly based his study on annual data for the British bus industry outside London 1953-1997 while OXERA had used data for the Government office regions (excluding London and Northern Ireland) between 1985/6 and 1999/2000. The resulting estimates are illustrated in Table 6.

Table 6: Error correction model estimates of bus demand elasticities: Passenger Journeys

Bus Fare

Bus Service

Income

Car-price

Study

SR LR

SR LR

SR LR

SR LR

Romilly (2001)

-0. 38 -1. 03

0. 11 0. 30

0. 23 0. 61

0. 17 0. 45

OXERA (2003)

-0. 63 -1. 08

0. 38 0. 37

0. 60 -0. 56

Source: TRL Report 593, 2004

While Oxera did not report the feedback parameter (Î¸-1), in Romilly model it was estimated at -0. 37, implying that passenger journeys adjust in a given time period by 37 %. Since Romilly excluded motoring costs in his model, the estimated elasticities seem slightly higher. Demand for local bus came up to be ‘ fare’ elastic in the LR.

In line with previous studies reviewed, OXERA found negative LR income elasticities whereas Romilly revealed positive ones. This is because he included a time trend among the explanatory variables.

Clark (1997) reported car ownership elasticities of -1. 04 (SR) and -1. 43 (LR) for Great Britain as a whole by using a lagged dependent dummy variable regression. Separate elasticities were also derived for London (-0. 70), the Metropolitan areas (-1. 04), Wales (-2. 01) and Scotland (-1. 35) by running simple separate regressions. On the whole, a person in a car owning household is likely to make significant fewer bus trips in both SR and LR. On the other hand, Dargay and Hanly (1999) found negligible effect of car ownership on patronage in the SR by using a structural approach. The LR elasticity amounted to -0. 73. The dynamics were represented by an error correction model and weighted 3-stage least squares for the estimation.

Meta-analysis of fare elasticities

Meta-analysis is a statistical procedure for pooling together the research findings from different empirical studies based on similar facts and developing a quantitative model explaining variations in results across studies.

Holmgren (2007) used meta-regression to elaborate on the differences of elasticity estimates obtained in previous studies. He estimated short-run U. S elasticities with respect to fare price (-0. 59), level of service (1. 05), income (-0. 62), price of petrol (0. 4) and car ownership (-1. 48).

2. 4 Conclusion

A most noticeable feature of the reviews is the difference in the elasticities obtained for the different studies. This is mainly due to the dissimilarities in data, methodology used and situations analyzed. We found that fare elasticities differ in terms of trip purpose, time of the day, time period, fare levels and by areas and city size, in the developed countries. Despite these variations, some general conclusions regarding the elasticities can be drawn on the basis of some “ likely” values and ranges.

Elasticity values were found to vary at different time perspectives. The evidence suggests that LR elasticities are from 1. 5 to over 10 times the SR elasticities. The SR fare elasticities range from -0. 06 to -0. 6 while the LR values diverge from -0. 09 to -1. 08. Therefore, changes in fare would bring to more than proportional changes in bus patronage in the LR rather than the SR. There is evidence that bus demand is more responsive at higher fare levels in both SR and LR than at low fare levels in the UK.

Peak travel is found to be less price-sensitive than off-peak travel. Peak hour elasticity is likely to be around -0. 2 while off-peak one is -0. 4 for the US. Both peak and off-peak travels are inelastic. The empirical evidence also suggests that all SR and LR elasticities are higher in rural than in non-rural areas.

Fare elasticities for smaller cities (less than one million populations) are found to be greater than for large cities (more than one million population. In the US, the elasticities for small and large cities are around -0. 4 and -0. 3 respectively.

There is a high degree of uncertainty about the expected signs on income elasticities. As a result of the different methodologies used, the income elasticities appear to be either positive or negative in both SR and LR. The SR elasticities range from 0. 2 to -1. 0 while in the LR they vary from 0. 6 to -2. 1. The negative estimates reflect the impact of income through its positive effect on car use and their negative effects on bus patronage. The evidence recommends that the negative sign will become positive as car ownership reaches saturation. Therefore, the demand for public bus service is likely to be income elastic in both SR and LR. Car ownership elasticities range from 0 to -1. 5 in the SR while the LR estimates diverge from -0. 7 to -1. 4. Hence, car ownership is likely to have no influence on patronage in the SR.

Motoring costs have a positive impact on bus use, thus indicating the price-substitution between bus and car use. The evidence show that LR car-price elasticities are 2 to over 3 times the SR values. The SR estimates lie between 0. 2 and 0. 4 while in longer periods they range between 0. 5 to 0. 7.

Service and employment levels are found to affect positively bus demand. In the SR, the service elasticities range between 0. 1 and 1. 3 while in longer periods they range from 0. 3 to 1. 9.

The evidence from the UK countries was unable to detect any impact of the percentage of pensioners on bus demand, although the relevant elasticities were found negative.