POLICY INSTRUMENTS FOR INCREASING DEMAND FOR PUBLIC TRANSPORT IN INDIA

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Policy Instruments for Increasing Demand for Public Transport in India

Kaushik Deb, BP,* Massimo Filippini **

* Corresponding author: kaushikdeb@gmail.com
** Department of Management, Technology and Economics, ETH Zurich

Abstract

Efficient public transport is important for meeting mobility needs in a rapidly growing economy in India. A higher share of public transport would also reduce emissions and energy demand. Hence, it is important to identify policy variables that could significantly influence public transport demand. This influence can be characterized using the demand elasticity. This research has estimated static and dynamic log linear demand functions for public transport using a panel of Indian cities over 1990-2011. Transit fare is significant and inelastic with respect to transit demand. Service quality, approximated by the density of the coverage of the transport service, is the most important policy variable that affects demand, and can be a key lever for increasing the share of public transport, even more so than bus fares. Finally, social and demographic variables highlight the complex nature of public bus transit demand in India.

Public bus transport is of great import in India. Not just is an efficient public bus system important for meeting the mobility needs in this rapidly growing economy, a higher share of bus transport would also have a positive impact on pollution, both local and global, and energy demand. That apart, an extensive public transport system is critical for ensuring access to basic services such as education and health, and integrating rural communities in the economic mainstream. To increase the share of public transport and to identify the relevant policy directions, this research identifies the factors influencing public bus transport demand and the role of monetary and non–monetary policy variables.

The empirical approach used for any estimation thus is dependent on the research objectives, and is constrained by the data available. This research uses an unbalanced aggregate panel dataset between 1990/91 and 2000/01 for 22 large states in India to assess the price and income effects on public bus transport demand. Here, direct price elasticities can be obtained after estimating an aggregate demand model and hence the choice based approach is not used in this study. In terms of estimating an aggregate demand system, a comprehensive dataset that includes information on all household expenditures on all commodities is required. Consequently, estimation of a system of equations is not possible using information only on one commodity, as is the case with the dataset available for this study. Only states with government run public transit services are included in the analysis since this is the only data available. Different static and dynamic panel data models are estimated to compare the short run and long run effects of price, income, and other changes. Demand characteristics are then reported in terms of price, income, and service quality elasticities.

1. Public transport in India

Passenger transport in India is dominated by two modes, rail and road. Over time, there has been a shift in traffic from rail to road with road meeting 80% of passenger traffic. Within the road transport sector, liberalization of the automobile industry in parallel to a rapid increase in per capita incomes has led to a shift towards personal vehicles. The share of public transport, on the other hand, has declined over time. The economy is now being constrained by the increasing number of vehicles causing congestion, and thus slower speeds on roads. Transport infrastructure is recognized as being the critical constraint here (Ramanathan and Parikh 1999). Efficient and optimal utilization of the available transport infrastructure would require meeting mobility needs through a greater share of public transport (Planning Commission 2002). For the railways, this would imply an increase in the rolling stock for passenger transport, a greater emphasis on passenger comfort, and providing services that reflect consumer preferences. More importantly, since most passenger transport in India is road based, the share of public bus transport should be increased.

Public bus transport in India is overwhelmingly provided by government owned bus companies. Even though the private sector owns more buses than the government, privately owned buses are rarely allowed to operate as public transport and are generally put to use in servicing schools and other educational institutions, tourists, etc. Thus, to increase the share of public transport, an increase in the capacity of the government owned public bus companies in India is required (Singh 2005). In addition to an increase in the capacity of public transport, improvements in service quality are also needed. These could come about through a greater sensitivity to consumer's needs in terms of network design, route planning, scheduling, and with an emphasis on comfort, travel time, and scientific traffic planning. In addition, given that access to public transport is not universal in India, an improvement in access to public transport is the most significant attribute of service quality.

Personal vehicles dominate road passenger transport in India as indicated by a rapid growth in the number of vehicles registered. The gradual liberalization of the Indian automobile industry since the mid 1980s and faster growth in per capita incomes in this period has meant that personal vehicles have become more affordable. Before 1983, the automobile sector in India was governed by regulations where imports, collaborations, and equity ventures were severely restricted by the government. Technology transfer from foreign companies was subject to government approvals. The partial liberalization of the sector in 1983 was followed by extensive liberalization in the 1990s. This has led to the entry of new small and fuel–efficient cars and a proliferation of two–wheelers, with an increase in the domestic as well as foreign investment. The consequence has been a phenomenal growth in the vehicle population. However, the growth has not been even across all categories of motor vehicles, with personal modes of transport scooters, motorcycles, and cars/jeeps dominating sales.

The share of buses in the number of vehicles has steadily fallen over this period. (Planning Commission 2002) reports that personal and privately owned vehicles currently account for 90% of passenger road traffic in the country. The remaining 10% is then provided by government owned public transport bus companies. While the private sector owns a larger number of buses compared to the government about 85% of the total number of buses), most private bus operations are based on the 'Contract Carriage permit' that allows these buses to be hired and leased out for private use, and prohibits their use as a means of public transit (Maunder, Fouracre et al. 1987). In some cities with a large commuting population such as Delhi and Kolkata, though, public transit operations by private buses are prevalent. These are exceptions, and in general, public transit is usually a government owned legal monopoly in most parts of India (Gowda 1999).

The major reasons for the decline in the share of public transport are the inability of public transport operators to keep pace with the increasing demand and the deteriorating quality of service arising out of continued losses and thus inadequate capital generation for capacity augmentation (Gowda 1999). Such a situation has arisen because of continuing inefficiency in operations and uneconomical operations to meet the universal service obligation (Maunder 1984). This has also resulted in a continuous drain on scarce budgetary resources and been compounded by the growing inability of the government to provide grants. Funding of bus transport in India by internal resources, market borrowings, and equity capital provided by the Union and state governments is proving to be inadequate. Simultaneously, the gradual liberalization of the automobile industry since the mid 1980s has increased the number of personal vehicles and hence has resulted in a shift away from public transport. This has presented another concern – any increase in tariffs can lead to further erosion of the ridership in public transport.

Thus, the sector is faced with a unique challenge. Though fare increases are considered necessary to ensure financial viability, they are constrained by two factors: meeting the universal service obligation and the threat of reduced ridership due to the shift away from public transport. The sector has to increase capacity while improving service quality in terms of access to transport, comfort, frequency, and reducing travel time. This calls for a two–pronged strategy, namely, efficiency in service provision in terms of the organization of the sector, and cost recovery based on efficient pricing.

2. Transport demand estimation

Transport demand models need to account for the peculiar characteristics of transport markets (Small and Winston 1999). Since transport is a derived demand, it encompasses several interrelated decisions of mode, destination, vehicle ownership, and location. In addition, every trip is unique in terms of temporal, origin–destination, and purpose characteristics. Finally, demand is sensitive to service quality attributes. The effect on transit demand of these factors is generally expressed in terms of elasticities. Statistically, isolating the impact of these different factors is often the key issue most research focuses on (Cervero 1990).

Recognizing this, (Berechman 1993) defines a three–phase methodological framework as a common approach to identifying factors influencing transit travel demand. First, a theoretical model of household travel decision making is defined. This is followed by an analytical specification of a travel demand function including explanatory variables. The exact specification here would depend on the preceding theoretical model. The third phase is an empirical estimation of this demand function. The results from this estimation indicate the statistical significance of the various demand determinants and their relative contribution to travel decisions. This three–phase framework reflects the complexity of modeling travel demand comprising activity location, and demographic and socioeconomic changes. The literature has been reviewed in the context of the framework suggested by (Berechman 1993) assessing the impact that different specifications and estimation approaches have on demand elasticities. A summary of some recent studies using either panel data or those estimating aggregate demand functions is presented in Table 1. Following that, a review of some issues in estimating travel demand using aggregate data, and how they have been addressed in the relevant literature, are outlined.

Table 1. Recent studies estimating demand functions

Paper	Variables	Functional Form & Estimation Method	Data	Price elasticity		Income elasticity		Service elasticity	
				Short run	Long run	Short run	Long run	Short run	Long run
(Dargay and Hanly 1999)[1]	Two models: Bus passenger kilometers per capita and bus trips per capita bus fares, disposable income, car ownership and motoring costs used only in the structural models.	Two types of models: Error Correction Models and Structural Models.	Time series of annual observations between 1970 and 1996 for the United Kingdom.	From –0.33 to –0.40 for trips. –0.18 to –0.19 for passenger kilometers	From –0.62 to –0.95 for trips. –0.43 to –0.92 for passenger kilometers	From 0.18 to 0.41 for trips. 0.05 to 0.16 for passenger kilometers	From –0.45 to –0.80 for trips. –0.15 to –0.63 for passenger kilometers		
Romilly 2001)	Bus journeys per capita. Personal disposable income, index of bus fares, index of motoring cost, service frequency measured by vehicle kilometers per person.	Log linear model, estimated as a single equation Auto Regressive Distributed Lag model after corrections for cointigrating relationships.	Time series of annual observations between 1953 and 1997 for United Kingdom excluding London.	–0.38	–1.03	0.23	0.61	0.11	0.30

[1] Only national level results reported.

Paper	Variables	Functional Form & Estimation Method	Data	Price elasticity		Income elasticity		Service elasticity	
(Dargay and Hanly 2002)	Bus journeys per capita fare, service level, per capital disposable income, pensioners in population, motoring costs.	Partial adjustment Fixed Effects, Random Effects, and Random Coefficient models. Two specifications: log linear, semi log where only fares are in levels and not logs.	Panel data between 1987 and 1996 for 46 counties in United Kingdom.	From –0.33 to –0.44	From –0.68 to –0.75	From –0.39 to –0.60	From –0.81 to –1.02	0.42 to 0.49	0.79 to 1.03
(Bresson, Dargay et al. 2003) [2]	Journeys per capita. Mean fare defined as revenue per trip, service measured by vehicle kilometers per capita, disposable income per capita	Two specifications: Semi log with only fares being in levels, and log linear. Estimated as Arellano and Bond fixed coefficients and random coefficient models	Panel data of 46 county annual observations in United Kingdom and 62 urban areas in France during 1987 and 1996.	–0.53 for England and –0.40 for France	–0.73 for England and –0.70 for France	–0.48 for England and –0.01 for France	–0.66 for England and –0.02 for France	–0.71 for England. –0.19 for France	–0.97 for England. –0.33 for France

[2] Only fixed coefficients' results reported.

2.1 Specification issues

Most travel demand models use the number of trips or passengers as the dependent variable (Hanly and Dargay 1999; Romilly 2001; Dargay and Hanly 2002). A trip, comprising a combination of an origin with a destination, can be definitely defined as a commodity, and hence can be priced. (Dargay and Hanly 1999) is the only study in the literature review undertaken that uses passenger kilometers as the measure of demand for their aggregate national analysis of travel demand. However, using only the number of trips or passengers as a measure of travel demand ignores an important characteristic of demand, the length of each trip. This is clearly an important parameter that also reflects the motivation for the supply and pricing of public transit services.

The other issue in the definition of the dependent variable is that demand is often normalized by a size measure such as population, as is reflected in Table 1. However, as (FitzRoy and Smith 1999) point out, if travel demand is not completely localized, then such normalization would not reflect the complete magnitude of operations. Data on travel demand used in this research has been obtained from all the government owned public transit firms operating in India. Several firms have a few routes that terminate outside their primary area or state of operation. However, the share of the traffic of these routes is relatively small.

In this research, the objective is to identify factors that influence public bus transit demand from the perspective of the bus transport industry. Hence, the definition of demand needs to reflect actual market transactions. Using passenger kilometers as an output measure allows transit demand to be related to a supply measure and hence can be used to analyze public transit markets, as is the objective of this research. The two measures of transit demand, the number of passengers and passenger kilometers, are very highly correlated in the dataset used in this analysis, with a correlation of over 90%. Hence, passenger kilometers are taken as the output measure. Moreover, a measure of the extent of operation, proxied by the population of the state that the firm is based in, could be suitably used as an indicator of market size.

In terms of independent variables, the studies listed in Table 1 show that the empirical estimation of a demand function is determined by monetary and non–monetary variables. Monetary variables include the price of the product, prices of available alternatives, and wealth or income levels. Non–monetary variables include non–price product attributes such as quality and other characteristics, and consumer tastes. In estimating transit demand, the non–monetary attributes include product characteristics such as access to the network, travel time, and quality of service. Consumer tastes are represented by non–income characteristics of households such as demographic or cultural attributes (Goodwin and Williams 1985). Hence, transit demand can then be described as follows (Berechman 1993)):

$$x = x\left(p, w, \mathbf{y}, \mathbf{s}, \mathbf{q}, \mathbf{p}_{\mathrm{v}}, \mathbf{L}\right)$$

where x is transit demand in units of trips or passenger trips, p is public transit fare, w is the aggregate wealth or income level, $\mathbf{y}$ is a vector of outputs such as vehicle kilometers), $\mathbf{s}$ is a vector of passenger characteristics including income, car ownership and other socioeconomic factors), $\mathbf{q}$ is a vector of service attributes frequency of service, reliability, speed of travel, period of operation and route design), $\mathbf{p}_{\mathrm{v}}$ is a vector of prices of alternative modes, $\mathbf{L}$ is a vector of land use characteristics rural or urban (Meurs, van Eyck et al. 1990)), population density. Since data on actual fares for each trip is not always available, the public transit fare is usually approximated by the revenue per trip or revenue per passenger kilometer adjusted for an inflation measure (Balcombe, Mackett et al. 2004).

The two significant and long run influences on travel demand are land use and urban structure changes, and socioeconomic characteristics (Berechman 1993). Socioeconomic characteristics include demographic factors population density, age distribution, sex ratio), economic factors per capita income, share of services in employment and output), and social factors private car ownership, female participation in the labour force, proportion of school going children (Goodwin and Williams 1985).

Income is the most important socioeconomic characteristic that affects transit demand (Berechman 1993). A higher income is associated with lower demand for public transit. This inverse relationship is due to two factors, namely, car ownership and value of time. A rise in income is correlated with a higher rate of car ownership and the value of time that trip makers perceive, hence leading to a lower demand for transit (Dargay and Hanly 1999). This effect is different from the direct income effect where a rise in income is associated with greater demand for travel. Empirical analysis can help distinguish between these two effects in terms of income and car ownership elasticities. Other socioeconomic and demographic characteristics such as occupation, lifestyle, age, and gender are also known to affect the demand for transit (Wabe 1969; Kemp 1973). (Matas 2004) uses the level of suburbanization and employment levels to explain demand changes in Madrid during 1979–2001. The empirical estimation of the effect of these variables on transit demand is not always straightforward since many of them are highly correlated with income or with other socioeconomic variables.

A public transit demand model should include some variables representing the quality of the service. Some studies use output measures such as vehicle kilometers as service quality measures (Goodwin and Williams 1985; Fitzroy and Smith 1993; Balcombe, Mackett et al. 2004). Such measures, however, result in an identification problem between the variable defining demand, and the variable defining service quality. In addition, service quality changes due to changes in capacity, such as larger buses resulting in more seat kilometers, would be ignored in such a measure (Balcombe, Mackett et al. 2004). Other aggregate service quality measures use the ratio of network length to area size or population as a proxy of access to transit services to avoid such identification issues (Romilly 2001; Dargay and Hanly 2002). (Bresson, Dargay et al. 2003) estimate a log linear specification with income, price, and network density as variables for quality. (FitzRoy and Smith 1997) argue that journey time is an important quality parameter and use average frequency and route density as proxies.

Finally, translating consumer theory into an empirically estimated demand function often requires some ad hoc assumptions that simplify the specification and functional form which can then be estimated using the datasets available (Thomas 1987). There are various functional forms that have been used in the literature to estimate aggregate transit demand, namely, linear functions, semi–log or log linear, and generalized non–linear models (de Rus 1990); (Appelbaum and Berechman 1991). The most common functional form used is the log linear (Romilly 2001). Only a handful studies have estimated a semi–log functional form where only transit price is included in levels and all other explanatory variables are in logs (Dargay and Hanly 2002; Bresson, Dargay et al. 2003). Statistically, a log linear specification significantly reduces the number of coefficients to be estimated. In terms of the estimates, the coefficients can be readily interpreted as elasticities. Finally, the log linear form also allows for non–linear interactions between demand and the various parameters, hence capturing more complex relationships than just simple linear effects (Oum 1989; Clements and Selvanathan 1994). Since the focus of this study is to estimate direct price elasticities for transit demand, a log linear specification is estimated.

2.2 Elasticities reported in literature

The studies presented in Table 1 are representative of the elasticity estimates reported in the literature. However, it is important to recognize some limitations in comparing elasticity estimates from different studies (Berechman 1993). Most elasticity measures are reported at the sample mean and are point elasticities. Hence, unless the demand function is a constant elasticity type such as a Cobb–Douglas, elasticity estimates will vary with the level of demand. There is no a priori reason for demand elasticities to be constant (Goodwin and Williams 1985). In addition, elasticities reported in the literature are regarded as long run equilibrium elasticities. As mentioned above, persistence could be an important influence on aggregate demand. Finally, depending on the functional form selected, and appropriate for the market under consideration, the observed demand changes may be influenced not just by prices and income, but also other factors. Hence, a numerical representation of elasticity may not reflect the complexity of transit demand determination.

(Nijkamp and Pepping 1998) highlight several factors that may explain the differences in elasticity estimates and may limit the application of elasticity estimates from a particular study to every context. Even after controlling for the differences in the definition of elasticity, definition of variables, and time horizon of the study, variation in the type of data, estimation methods, modes included, and heterogeneity in local conditions are important in explaining the differences in literature.

Elasticities can be differentiated as short run and long run, particularly when recognizing the importance of habit formation (Cowie and Fitzroy 1993). (McCarthy 2001) argues that optimization errors arising from incomplete information also gives rise to persistence in travel demand. Such decompositions, however, require quite large databases and estimation of dynamic demand models as described in Table 1. One common approach to capture the long run effects of price changes is to use a distributed lag model where the direct price impact yields only the short run elasticity (Oum 1979).

Fare elasticities vary with temporal, socioeconomic, and demographic factors. (Goodwin and Williams 1985) report that most transit operators in the United Kingdom use an elasticity measure of –0.3 for operational purposes. This value was also commonly used in the Unites States, though (Kemp 1973) reports the elasticity estimates in the range of –0.1 and –0.7. (Oum, Waters et al. 1992) provide a detailed survey of own price elasticities of transport demand and methodological issues therein, covering both freight and passenger transport over all modes. (Goodwin 1992) provides a similarly detailed survey focusing on public transport and automobile demand. The range of demand elasticity estimates for urban transit in the former is –0.01 to –0.78. The ranges are smaller in pooled data and cross section studies though still significant. (Goodwin 1992) reports an average bus fare elasticity of –0.41, with a range between –0.21 to –0.65, the higher end corresponding to long run elasticities. This is also similar to the elasticity estimated for 52 transit systems in the United States (Pham and Linsalata 1991). A meta analysis of European transit systems estimates price elasticities in the range of –0.4 and –0.6 (Nijkamp and Pepping 1998). Estimates for the United Kingdom are –0.4 for the short run and –0.7 for the long run in the case of rising fares (Hanly and Dargay 1999). (Hanly and Dargay 1999) report that income and price elasticities decrease with as the network size increases. The review by (Litman 2004) suggests short run price elasticities are in the range between –0.2 to –0.5, and long run elasticities are in the range –0.6 and –0.9. (Balcombe, Mackett et al. 2004) report an average short run value of –0.41 from a survey of 44 studies same as (Goodwin 1992) and (Paulley, Balcombe et al. 2006) and a long run estimate close to unity. In a review of dynamic direct aggregate demand models, (Meurs, van Eyck et al. 1990) report elasticity estimates between –0.21 and –0.28 for the short term, and –0.55 and –0.65 for the long term. These estimates also reflect the range of elasticities reported from the literature listed in Table 1.

In general, the literature reports negative elasticities for bus and rail transit travel with respect to income and car ownership. Early reviews reported a range of –0.2 to –0.8 for income, and –0.1 to –0.8 for vehicle ownership (Webster and Bly 1981). Hence, public transport is reported to be an inferior good (Fitzroy and Smith 1993). More recent studies report that a 10% rise in income will reduce the demand for transit by 3–7% (Bresson, Dargay et al. 2003; Balcombe, Mackett et al. 2004)), whereas a 10% increase in car ownership will reduce transit demand by 5–7%. (Dargay and Hanly 1999) conclude a unitary elasticity of transit demand with respect to car ownership. The negative elasticity with respect to income is thought to reflect the positive effect of income on car ownership and usage, and the resultant negative effect on bus patronage (Dargay and Hanly 1999). (Maunder 1984) reports for India that income effects are significant only for very low income levels. Once per capita income rises above a threshold, changes in income have negligible impact on public transit demand. As mentioned earlier, including vehicle ownership in the analysis can help establish if public transit is a normal or inferior good based on true income effects. Previous research in India, however, has been ambiguous about the impact of vehicle ownership and demand for transit services (Maunder 1984). Hence, it would be interesting to assess if definitive income effects are obtained in this research, and the impact of vehicle ownership on travel demand.

Estimates for service quality elasticities range from 0.2 to 1.2 with a median of about 0.7 in research studies (Webster and Bly 1981; Dargay and Hanly 2002) and 0.5 in actual operations (Goodwin and Williams 1985). Service quality measures here are defined in terms of network density or other measures for access to the service. (de Rus 1990) reports positive service elasticity estimates between 0.39 and 1.88 in a study of 11 Spanish cities. (Massot 1994) reports per capita vehicle kilometers as the most robust explanatory variable for public transit demand. Only one transit operator with a negative elasticity is reported in the literature (Goodwin and Williams 1985). In their review of 20 studies reporting service elasticities, (Lago and Mayworm 1981) report a higher elasticity between 0.75 and 0.85 if the starting level of service was low, and 0.30 with a higher starting point. They conclude that transit demand is relatively inelastic to service levels. Again, off–peak service elasticities are reported to be twice as high as peak hour elasticities. Using route kilometers per square kilometer, (FitzRoy and Smith 1995) report a service elasticity of 0.73 for rail passenger transit in a sample of European countries. (Fouracre and Maunder 1987) estimate service quality and access to be the most significant variable influencing demand in their study of three Indian cities using survey data collected between 1983 and 1985.

3. Model specification

The model specification presented in this section is based on the review of the literature presented above and the issues discussed therein. Since the study assesses public bus transit price elasticities in the context of actual market transactions, passenger kilometers have been taken as the demand measure (pkm). Several variables have been selected as explanatory variables. Public bus transit fares ($Public\ transit\ fare$) and per capita income ($Per\ capita\ income$) are the monetary variables. Service quality is characterized by the density of coverage ($Densiy\ of\ \operatorname{cov}erage$). The total population ($population$) of the state is included to isolate the effect of size of the market. The demographic and socioeconomic variables in the model are the proportion of population in the labour force ($Labor\ force\ participation$) and literacy rate ($literacy$)[3]. Unfortunately, data on the prices of substitutes and complements are not available in this study. The only significant transport service here is personal vehicle usage. The impact of changes in personal vehicle usage can be approximated using another socioeconomic variable, per capita private vehicle ownership ($Vehicles\ per\ person$).

From the studies reviewed in Table 1, the functional forms most commonly used in the literature are log linear and semi–log. Since the log linear form is easily interpretable, and simple for computing elasticities, the log linear function has been estimated[4]. The demographic variables are already in percentages. These have not been converted into logs and are included as reported. In this case, the coefficients can be readily interpreted as elasticities. Thus, the static model is the following,

$$\begin{aligned}\mathrm{Ln}pkm_{it} &= \alpha_o + \alpha_p \mathrm{Ln}\left(Public\ transit\ fare_{it}\right) + \alpha_w \mathrm{Ln}\left(Per\ capita\ income_{it}\right) + \alpha_q \mathrm{Ln}\left(Densiy\ of\ \ \mathrm{cov}\,erage_{it}\right) \\ &+ \alpha_s \mathrm{Ln}\left(Vehicles\ per\ person_{it}\right) + \alpha_{pop}\mathrm{Ln}\left(population_{it}\right) + \alpha_{work}\left(Labor\ force\ participation_{it}\right) \\ &+ \alpha_{lit}\left(literacy_{it}\right) + \varepsilon_{it}\end{aligned} \tag{1}$$

The dynamic structure of demand has been captured using a partial adjustment model. This implies that given an optimum, but unobservable, level of transit demand, pkm^*, demand only gradually converges towards the optimum level between any two periods. Hence,

$$\mathrm{Ln}pkm_{it} - \mathrm{Ln}pkm_{i,t-1} = \delta(\mathrm{Ln}pkm^* - \mathrm{Ln}pkm_{i,t-1}) + \eta_{it} \tag{2}$$

where $\left(1-\delta\right)$ is the adjustment coefficient indicating the rate of adjustment of pkm to pkm^* and ε_{it} is random disturbance ((Kmenta 1978)). Substituting pkm^* in the dynamic adjustment equation gives:

$$\begin{aligned}\mathrm{Ln}pkm_{it} &= \alpha_o' + \alpha_p' \mathrm{Ln}\left(Public\ transit\ fare_{it}\right) + \alpha_w' \mathrm{Ln}\left(Per\ capita\ income_{it}\right) + \alpha_q' \mathrm{Ln}\left(Densiy\ of\ \ \mathrm{cov}\,erage_{it}\right) \\ &+ \alpha_s' \mathrm{Ln}\left(Vehicles\ per\ person_{it}\right) + \alpha_{pop}'\mathrm{Ln}\left(population_{it}\right) + \alpha_{work}'\left(Labor\ force\ participation_{it}\right) \\ &+ \alpha_{lit}'\left(literacy_{it}\right) + (1-\delta)\mathrm{Ln}pkm_{i,t-1} + \varepsilon_{it}'\end{aligned} \tag{3}$$

where $\alpha_i' = \alpha_i\delta$ and $\varepsilon_{it}' = \delta\varepsilon_{it} + \eta_{it}$. This dynamic specification is estimated.

This is possibly one of the few studies estimating public bus transit demand in developing countries. The specification being used also attempts to capture actual market transactions to relate these with firm behaviour using passenger kilometers as a measure of demand. In addition, using density of coverage provides a proxy indicator of service quality in terms of access to the transit network, and hence avoids simultaneity with the measure of demand and output. Finally, the use of demographic

[3] The proportion of population living in urban areas and the sex ratio were also included in early specifications on the model. However, these variables did not significantly improve the goodness of fit. In addition, in terms of the elasticities obtained for the key variables of interest, these were not found to have any significant influence.

[4] The elasticities obtained from using the log linear and the semi–log functional forms were compared and found to be similar.

and social characteristics is expected to reveal the import of such non–monetary variables in the context of a developing country.

4. Data and estimation methods

An unbalanced panel of 22 states in India between 1990/91 and 2000/01 has been used in the analysis with 206 observations. The panel ranges from 21 states in 1993/94 to 16 in 1997/98. This data set is characterized by a relatively small number of cross-sectional units and a relatively long time period. Data on public bus transit demand for the entire state, including both urban and rural areas, has been taken from (CIRT Various years)[5]. Public bus transit fares have been estimated as the ratio between traffic revenue and total demand, with the information obtained from (CIRT Various years). Thus, non–traffic revenue, such as advertising revenue or interest accrued, has been excluded from the definition of public transit fares. Unfortunately, user costs and external costs are not available for this study and hence only public bus transit fares are included. Hence, the price elasticities obtained are only for public bus transit fares and not generalized transportation costs for the public bus users as in (Mohring 1970).

Density of coverage has been estimated as the ratio between vehicle kilometers reported in (CIRT Various years) and the area of each state. Demographic and social variables have been obtained from (Census of India 2001 2001). The per capita income series is based on total State Domestic Product reported in (EPWRF 2003) and population totals from (Census of India 2001 2001). Private vehicles in the analysis have been defined as cars, two–wheelers, and jeeps, with the data from (MTS Various Issues). This has been divided by the population of each state to obtain the per capita private vehicle ownership. The two monetary variables, namely public bus transit fares and per capita incomes, have both been deflated to 1989/91 prices using the Wholesale Price Index for All Commodities reported by the (Government of India 2005) to carry out the estimations in terms of real values[6].

Table 2 describes the dataset and the variables used in the analysis. Each observation of each variable, x_{it} ,has also been decomposed into two separate series of between observations $\left(\bar{x}_i = \sum_t x_{it} / T \right)$ and within observations $\left(x_{it} - \bar{x}_i + \sum_i \bar{x}_i / I \right)$ to examine the cross section and time series behaviour in terms of the Between and Within standard deviations ((STATA 2005)). For most variables, the overall variation in the dataset comes from the Between Variation. In addition, there is a large variation in the dataset for most variables as can be observed from the minimum and maximum values. Hence, it is important to include a variable that reflects the size differences between states. This size effect is captured by using the total population of each state.

Table 2. Descriptive Statistics of variables included in the analysis.

[5] For the six states with more than one operator, data has been summed across all the operators to obtain state level aggregates.

[6] The price index data in India is available in the form of a Wholesale Price Index and four Consumer Price Index series. The only aggregate price index available in India is the Wholesale Price Index since it is not possible to aggregate the four Consumer Price Indices into one composite index. However, it may be noted that tests show that the trend-level CPI lags is strongly correlated with the WPI.

Variable		Mean	Std. Dev.	Min	Max
Passenger kilometers (10^5 km)	Overall	230 194.300	324 248.600	112.570	2 236 124.000
	Between		292 371.900		
	Within		127 504.700		
Public transit fare (Rupees[#] per passenger kilometer)	Overall	0.089	0.046	0.031	0.384
	Between		0.038		
	Within		0.033		
Per capita income (Rupees per person)	Overall	6 073.593	3 430.798	164.383	19 191.890
	Between		3 398.596		
	Within		1 470.881		
Density of coverage (10^5 vehicle km per km^2)	Overall	0.257	0.778	0.0001	4.089
	Between		0.868		
	Within		0.123		
Per capita private vehicle ownership (Vehicles per person)	Overall	0.047	0.079	0.005	0.493
	Between		0.089		
	Within		0.017		
Population (number)	Overall	43 700 000.000	38 300 000.000	719 601.000	166000 000.000
	Between		38 300 000.000		
	Within		3 029 920.000		
Population the labour force (%)	Overall	38.87%	0.048	30.87%	49.24%
	Between		0.047		
	Within		0.009		
Literacy rate (%)	Overall	53.55%	0.109	30.57%	80.04%
	Between		0.106		
	Within		0.035		

With regard to the choice of econometric technique, it should be noted that in the econometric literature there are various panel data models that take into account unobserved heterogeneity across units. Moreover, we can distinguish between static and dynamic econometric approaches[7]. In this paper we estimated the static version of the demand model (1) using the two classical panel data estimators, the Fixed effects (FE) and the Random effects estimators (RE). Moreover, to account for possible endogeneity of the price and quality variables, we estimate the static models using the lag variable for price and quality[8].

In estimating the dynamic panel data model (3), FE or a RE is not appropriate because the inclusion of a lagged dependent variable in the explanatory variables violates the strict exogeneity assumption. In fact, the lagged demand variable is correlated with the error term, and thus leads to biased and inconsistent estimates of FE and RE. The commonly used technique to estimate dynamic panel data models with unobserved heterogeneity is to transform the model into first differences and then use sequential moment conditions to estimate parameters using Generalized Method of Moments. (Arellano and Bond 1991) present a Generalized Method of Moments estimator for panels with a dynamic specification that removes individual effects by carrying out estimation in differences. The

[7] For a detailed presentation of the econometric methods that have been used to analyze panel data, see Greene (2003) and Baltagi (1995).

[8] We are aware that this approach to deal with an endogeneity problem is relatively simple. However, due to limited available data and the small data set, it was not possible to use a 2SLS estimator.

prerequisite for this model is that the number of periods should be larger than the number of regressors in the model, and the number of instruments should be less than the number of cross sectional units. As an alternative to the approach suggested by (Arellano and Bond 1991), (Blundell and Bond 1998) propose a system GMM estimator, which uses lagged first differences as instruments for equations in level as well as the lag variable in first-difference equations.

(Baltagi 2002) and (Roodman 2009), in estimation of dynamic models using small samples, point out that with an increase in the number of explanatory variables, moment conditions get close to the number of observations. In such a situation, too many instruments can produce over-fitting of the instrumented variable, and the resulting estimates from GMM estimators such as those proposed by (Arellano and Bond 1991) and (Blundell and Bond 1998) are biased toward those of the OLS[9]. Another problem of these two estimators is that their properties hold for large N, so the estimation results can be biased in panel data with a small number of cross-sectional units. An alternative approach proposed by (Kiviet 1995), which is based on the correction of the bias of LSDV, has recently been used in several studies. (Kiviet 1995) and (Judson and Owen 1999) have shown in a Monte Carlo analysis that in typical aggregate dynamic small panels characterized by $T \leq 20$ and $N \leq 50$, as in our case, the Anderson-Hsiao and the Kiviet Corrected LSDV estimators are better than the GMM estimator proposed by (Arellano and Bond 1991). (Abrate, Piacenza et al. 2007) is one application of this approach to public transit demand.

5. Analysis and results

The data have been analyzed and the estimations carried out in STATA Intercooled Version 10.0. Two models each for both the static and dynamic specifications have been estimated. A comparison of the dynamic models with the static models demonstrates the importance of persistence in demand, , at least in one model, and the difference between the short run and long run equilibrium behaviour. In the static specification, the first type of models are the conventional static one way panel data models, namely, Fixed Effects and Random Effects. For the estimation of the dynamic specification, we used the Arellano–Bond and the Corrected LSDV estimators.

5.1 Comparing the models

The static and dynamic specifications cannot be directly compared in terms of statistical performance except in terms of general goodness of fit and significance of key variables. The empirical results are presented in Table 3.

Table 3. Regression results

	Fixed Effects[&]		Random Effects[&]		Arellano–Bond		Corrected–LSDV	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Ln*(Public transit fare)*	-0.289***	0.062	-0.232***	0.070	-0.428***	0.057	-0.374***	0.044

[9] From the literature it is known that in a dynamic specification the coefficient for the lagged variable obtained using OLS is biased upwards, whereas the coefficient obtained from the LSDV is biased downwards as in this case the lagged endogenous variable correlates negatively with the transformed error term. See Nickell, S. (1981). "Biases in Dynamic Models with Fixed Effects." Econometrica **49**: 1417-1426. for a discussion.

Ln*(Per capita income)*	-0.033	0.040	-0.059	0.046	-0.026	0.025	-0.027	0.024
Ln*(Density of coverage)*	0.867***	0.051	0.847***	0.043	0.717***	0.134	0.676***	0.052
Ln*(Per capita private vehicle ownership)*	0.053	0.076	-0.084	0.078	0.059	0.048	0.037	0.054
Ln*(population)*	-0.856**	0.312	0.927***	0.074	-0.893**	0.291	-0.500**	0.248
Labour force participation rate	3.615**	1.650	5.557***	1.476	3.728*	1.830	2.449**	1.085
Literacy rate	-2.423**	0.751	-3.736***	0.676	-2.057***	0.481	-1.974***	0.506
Ln(lagged demand)					0.126	0.091	0.294***	0.056
α'_o	28.440***	5.149	-2.227	1.425	26.476***	4.680		
F statistic	135.29***							
R^2	0.8949							
Sargan (p value)					0.21			
AR (1) (p value)					0.06			
AR (2) (p value)					0.82			

[&]*price* and *quality* variables in these regressions are in the first lags

*Variables significant at 95% confidence level

**Variables significant at 99% confidence level

***Variables significant at 99.9% confidence level

The estimated coefficients of the Fixed and Random Effects models can be directly compared and are relatively similar. The Hausman test comparing the coefficients on the regressors in the Fixed Effects and Random Effects rejects the null hypothesis that the Random Effects Coefficients are consistent ($\chi^2_{(7)} = 152.27$). However, as pointed out by (Cameron and Trivedi 2005), the low Within Variation for several of the regressors could result in imprecise coefficients in the Fixed Effects model since it relies on Within Variation to carry out the estimation. For this reason, we calculate the price, income and quality elasticities also using the results obtained with the Random Effects model.

Within the dynamic models, the null hypothesis in the Sargan test that the over–identifying restrictions are valid is not rejected in the Arellano–Bond model (Table 3). The p-values of the test statistics for autocorrelation show that in both models the errors exhibit no second order serial correlation. Hence, the estimates in the Arellano–Bond model are consistent.

The Corrected LSDV has been estimated with coefficients from the Arellano–Bond estimation as the starting values since these were the only consistent and statistically significant dynamic estimates available. In addition, the estimates are not very sensitive to the initial values assumed and initial values from the Blundell–Bond estimates result in coefficient values comparable to the Arellano–Bond initial values. The bootstrapped errors have been estimated based on 300 replications. In this case, the estimates are robust to the number of replications.

In comparing the static and the dynamic specifications, the parameter of interest is the coefficient on lagged demand variable, since this denotes the importance of the dynamic component in the model. Observing the estimated value in Table 3, the coefficient of adjustment is significant in the Corrected LSDV model, though it is not significant in the Arellano–Bond model. Hence, the benefits from using a dynamic specification are not completely evident. As mentioned earlier, in the estimation of dynamic models using panels data set characterized by $T \leq 20$ and $N \leq 50$, the Corrected LSDV estimators are better than the GMM estimator proposed by Arellano and Bond (1991). Therefore, in this study the short run and long run elasticity results are presented for the Corrected LSDV estimators. Thus, including the results obtained with the static model, the elasticity results are presented and discussed for FE, RE, and Corrected LSDV.

5.2 Regression results

The regression results from all the models are presented in Table 3. The coefficient of transit price has the correct sign and is significant in all the models. The coefficient of per capita income is negative but not significant in any of the models. As reported in some of the literature, the negative sign indicates that public bus transit is an inferior good. Even with the distinction between the direct income effect on demand and the indirect effect through higher per capita vehicle ownership, a negative income effect is obtained. However, since the coefficient is not significant in any of the models, a negative income effect is not definite. Related to wealth, private vehicle ownership is negatively correlated with demand and is significant. (Table 3).

Service quality, defined as the density of public transport routes, has the highest elasticity values. As expected from the literature ((Cervero 1990)), including literature from India ((Maunder 1986; Palmner, Astrop et al. 1996)), this variable is important in explaining public bus transport demand. Following (Lago and Mayworm 1981), this likely reflects the low coverage of public transit services in India. However, increasing the density of public transport routes probably lead to an increase in cost of service delivery and hence put an upward pressure on tariffs.

Literacy rate is negatively correlated with demand. Since literacy is positively correlated with income ((Stroup and Hargrove 1969; Matteo 1997)), this could indicate a negative wealth effect. A higher literacy rate could also indicate a more equitable income distribution or a lower poverty rate. The impact of a large working population is positive and significant. Thus, with a larger proportion of population in the workforce, travel demand is higher and resulting in a larger demand for public transit. In general, the significance of social variables such as the proportion of working population and literacy rates indicated the importance of non–monetary factors in determining travel demand.

5.3 Price, Income, and Service Quality Elasticities

Given the model specification as log linear in transit price, income, and service quality, the coefficients on these variables can be interpreted as elasticities. However, arising from the log linear specification, elasticity values do not vary with the level of demand. The long run elasticities have been approximated around their mean values using the Delta method ((Oehlert 1992)) to obtain significance levels as well. The estimated price and income elasticities are reported in Table 4.

Table 4. Price, Income, and Service Quality Elasticity estimates

	Fixed Effects	Random Effects	Corrected LSDV	
			Short run	Long run
Price	–0.289***	–0.232**	–0.374***	–0.523***
Income	–0.033	–0.059	–0.027	–0.038
Service quality	0.867***	0.847***	0.676***	0.957***

Significant at 99% confidence level, * Significant at 99.9% confidence level

The reported price elasticity is significant in all models and less than unity in absolute value. The estimates lie between –0.232 and –0.523 in equilibrium or the long run. In all cases, transit demand is inelastic to fare changes. Also, as predicted by (Doel van den and Kiviet 1995), the static panel models report lower price elasticity values than the long run estimates using dynamic models, though the difference is not large. The price elasticity values are very much in consonance with the literature reported in section 2. The lower long run values compared to the literature could be perhaps explained by the fact that, most demand elasticity estimates in the literature have been obtained using datasets from developed countries, while this study is based in India. The low elasticity values, therefore, may represent the state of economic development in India vis–à–vis estimates in other studies. The inelastic demand may also arise from the fact that only public transit fares are included in this analysis since estimates for user costs and external costs are not available for this study. As a result, these estimates do not reflect the elasticity of demand with respect to the generalized transportation costs for the public bus users.

The literature reports negative income elasticities and characterizes public transit as an inferior good. Even though the estimates presented about report negative income elasticity, since the coefficients are not significant, public transit cannot be characterized as an inferior good in India. These results are similar to (Maunder 1984) where again income effects are reported to be insignificant in India above a minimum threshold of income. (Dargay and Hanly 1999) report that the negative income elasticity during the period of analysis in their study of the United Kingdom between 1970 and 1998 coincided with a rapid increase in personal vehicle ownership. This may be the case in this study as well, given the rapid increase in personal vehicle population in India during the period under consideration and the significant negative coefficient obtained for personal vehicle ownership in most models.

Service quality is an important variable for influencing transit demand. Again, this is as expected since the constraining factor for most infrastructure services in India, including public bus transit, is availability ((Lago and Mayworm 1981)). (Fouracre and Maunder 1987) also report in their limited analysis of three Indian cities that a higher level of service results in a higher demand for public transit. However, as noted earlier, increasing the share of public transport through a denser network of routes would call for a cost–benefit analysis of using service quality as a policy tool to increase demand for public transport.

6. Conclusions

The estimated price elasticity is significant in all models and transit demand is inelastic to the fare level. The importance of public bus transport in meeting passenger road travel demand in India and the unavailability of close substitutes within the road public transport sector could explain the price inelastic demand observed. The literature reports a negative relationship between public bus transport demand and income. This is sometimes ascribed to the positive correlation between vehicle ownership and income, and the negative correlation between vehicle ownership and public bus transit demand. In this research, vehicle ownership was included in the specification of the demand function in addition to income, to separate the income effect from that of vehicle ownership. The income effect obtained from such estimations were not significant and were negative. As expected, vehicle ownership had a significant and negative impact on public bus transit demand. The most significant policy variable influencing demand was access to the public bus transport network, which was included as a variable describing the quality of service. Clearly, in a developing country context, access to public transport services is of great import. Access to public transport is also a more effective policy instrument for increasing the ridership of public bus transport compared to only on bus pricing. Finally, in terms of demographic variables, a larger working population implies a higher demand for public transport, while a higher literacy rate implies a lower demand. The significance of such demographic and social variables reflects the complex nature of public bus transport demand in India.

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