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# Understanding the determinants of demand for public transport: evidence from suburban rail operations in five divisions of Indian Railways

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## Abstract

This paper analyses suburban rail fare elasticity and compares the results across five suburban divisional operations of the Indian Railways in three cities viz., Chennai, Kolkata and Mumbai. The three cities chosen have a highly varying modal share of public transport trips and thus offer interesting insights into the attitudes of trip makers towards the changes in operational variables such as fares, service levels. This paper contributes towards understanding of the determinants of demand for public transport in a developing country and applies econometric methods involving static and dynamic modelling methodologies. This research addresses the question of smaller sample sizes which constrain the use of standard regression approaches and applies a bootstrapping method which substitutes for traditional assumptions on distributions and asymptotic results. It was found that the suburban rail demand is inelastic to fare which indicates that the revenue would increase with an increase in fare. Finally, the paper illustrates the use of computed elasticities by estimating the demand for suburban rail in Kolkata.

Key words: fare elasticity, demand for public transport; suburban rail operations in India; static/dynamic modelling; bootstrapping.

## 1. Introduction

Since Transport Research Laboratory (TRL) published their report on Demand for Public Transport edited by Webster and Bly (1980), there has been an extensive research activity to understand the determinants of demand for public transport including the effect of fares, quality of service, income levels, car ownership rate, vehicle-kilometers. It is noted that the analysis of demand with respect to various factors largely remained in focus within a small group of countries having well-developed transport systems e.g. Australia, Finland, France, Netherlands, Norway, UK, USA (Bresson et al 2003, Paulley et al 2006). However, in the developing countries there is hardly any evidence of such research work in the past barring a few recent attempts. Currently, a number of cities in developing countries e.g. Mumbai, Delhi, Hyderabad, Benguluru (India), Manila (Philippines), Dhaka (Bangladesh) and Jakarta (Indonesia) have all initiated metro rail systems which are in different stages of planning/execution. Notably, some of these metro rail projects involve agencies other than the governments under the public/private partnerships. Whosoever builds/owns/operates the infrastructure it will be essential to ensure the economic viability of the project but if it involves private investment it will be necessary to estimate the financial viability too, either

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way require a good understanding of the determinants of demand. Aside from the regulatory structure, design of the new infrastructure will also depend on the estimates of demand while arriving at a suitable specification for the system being planned.

The aim of this paper is to understand the passengers' response to fare changes in suburban railway systems with the ultimate objective of improving fare policies and managing the suburban transport system better. The main hypothesis is that the demand is related to and is explained by operational variables such as fares and service frequencies. While the demand is represented in terms of pass-km, fares are represented as yield i.e. revenue /pass-km and the frequency of operations is represented by vehicle-km as a proxy. The paper hypothesises further that the demand is also related to socio-economic variables such as population and per- capita income levels besides the availability of alternative modes e.g. personal vehicles and their operating costs. Following from the literature, the paper investigates linearised relationships between the explained variable i.e. the demand and the explanatory variables including operational and socio-economic variables. The method relies on historic data obtained from Indian Railways, but as the data sets are limited to a 30- year period, this paper uses bootstrapping method to overcome the limitation of fewer degrees of freedom associated with the estimation.

The paper is set out in six sections including the introduction. Section 2 reviews the elasticities of public transport demand. Section 3 specifies the methods used in estimating elasticity. Section 4 describes the case of suburban rail operations in India in Chennai, Kolkata(E), Kolkata(SE), Mumbai(C) and Mumbai(W). Section 5 discusses the computed estimates of elasticity and considers their policy implications. Section 6 concludes the paper.

## 2. Review of public transport elasticities

Elasticity is defined as 'responsiveness of demand to changes in the factors of demand' (Balcombe et al., 2004). The first comprehensive review of elasticities of public transport was done by Webster and Bly (1980) whose rule of thumb of -0.3 was widely acknowledged and used until the end of 1980's. The second major review by Goodwin (1992) looked at 50-odd demand elasticities for bus journeys mainly in the UK and found that the average elasticity was -0.4. Goodwin also found that the bigger cities had greater elasticities an assertion that is widely rejected now. Oum et al., (1992), estimated a range of public transport elasticities from -0.01 to -0.78, with most of the values falling between -0.1 and -0.6 and concluded that the demand for public transit is rather inelastic. Preston (1998) analysed data from 89 European cities and found the elasticity to vary by the size of the city. His finding that larger cities have smaller elasticities and that the smaller cities (less than 0.5 million population) have bigger elasticities, have been largely substantiated by theories and empirical evidences. He suggested an elasticity value of -0.5 for smaller cities and -0.34 for bigger cities. Nijkamp and Pepping (1998) analysed 12 studies on public transport elasticities from European countries and they also found a wide range of values from -0.15 in the UK to -0.8 in the Netherlands. The other studies refined the methodologies and used highly disaggregated data to estimate elasticities. Massot (1994) used survey data of 2750 individuals over 12 years and 35 cities in France. He has highlighted the importance of understanding the sensitivity towards travel time which was found to be twice as important as fares. Hensher (1998) studied direct and cross fare elasticities in Sydney Metropolitan Area based on stated, revealed preference data sets and made a distinction between elasticity for different modes and different types of tickets.

### 2.1 Studies on rail demand elasticity

Besides public transport, there have been specific studies on rail demand elasticity. Owen and Phillips (1987) studied intercity rail demand elasticity in the UK. Oum et al. (1992) studied intra-city rail elasticity and found peak fare elasticity between -0.20 and -0.40, off-peak fare elasticity of less than -1.0 and all day elasticity between -0.1 and -0.70. Dargay and Hanly (2002) studied suburban rail elasticity in the UK and outside of the UK (short run UK -0.50 to -0.09 and -0.37 to -0.09 outside UK). Hague Consulting Group undertook a major study of rail demand elasticity in Sydney which besides estimating the fare elasticity of rail demand, estimated service level and service quality elasticities (Douglas and Karpouzis, 2009). Wardman (2006) studied the influence of external factors and estimated fare, income, and Gross Domestic Product (GDP) elasticity. Paulley et al. (2006) note a short run suburban rail fare elasticity of -0.5. Worsley (2012) compiled estimates of fare elasticities from several studies based on flows that had seen significant increases in fares and found a range of fare elasticities from -5.0 (London Travel Card) to -1.2 (Leisure trips from the rest of the country to London).

### 2.2 Elasticities of public transport in developing countries

In contrast to the experience noted from the developed world, there are far fewer studies estimating elasticities of public transport in developing countries and more so on railways. De Grange et al. (2013) studied integrated fare elasticity in Tran-Santiago, Chile, using discrete choice modelling in which they employed Multinomial Logit, Hierarchical Logit and Mixed Logit models. Elasticities estimated by them are presented in Table 1.

**Table 1: Elasticities in Tran-Santiago, Chile**

| Travel Alternative | Multinomial Logit | Hierarchical Logit | Mixed Logit |
|---|---|---|---|
| Metro off-peak (own) | -0.193 | -0.233 | -0.186 |
| Metro peak (own) | -0.588 | -0.557 | -0.579 |
| Bus off-peak (own) | -0.340 | -0.349 | -0.354 |
| Bus peak (own) | -0.284 | -0.268 | -0.309 |
| Metro off-peak & peak (cross) | 0.159 | 0.141 | 0.211 |

| | | | |
|---|---|---|---|
| Metro and Bus off-peak (cross) | 0.114 | 0.134 | 0.137 |
| Metro & Bus peak (cross) | 0.250 | 0.236 | 0.218 |

Source: De Grange et al. (2013)

In a doctoral thesis on public bus transport elasticities in India Deb (2008) mentions no evidence of any earlier study on elasticity either in developing countries or in India. Deb's work may be considered as one of the few existing evidences, which is based on a 10-year intercity bus transport data from 22 states of India. He found the elasticity value to vary between -0.354 and -0.523 for public bus transport (Table 2).

**Table 2: Price and income elasticity in Indian public bus transport system**

| | Fixed Effects | Random Effects | PCSE* | Corrected LSDV** | |
|---|---|---|---|---|---|
| | | | | Short run | Long run |
| Price | -0.460*** | -0.354*** | -0.359*** | -0.374*** | -0.523*** |
| Income | -0.020 | -0.065 | 0.061 | -0.027 | -0.038 |
| Service quality | 0.834*** | 0.818*** | 0.754*** | 0.676*** | 0.957*** |

*Panel Corrected Standard Errors; ** Least Squares Dummy Variables; *** Significant at 99.9% confidence level

Source: Deb (2008)

A White Paper on Indian Railways (IR 2009), however, mentions an aggregate GDP elasticity of 0.79, which is a simple arithmetic calculation of change in GDP over change in Indian Railway's earnings. There are many problems with this value. Firstly it is an aggregate value for the entire railway including earnings from freight operations. Secondly, it is a GDP elasticity and not a fare elasticity, and thirdly it is not about suburban transport systems. Then there are a few others e.g. Bharill and Rangaraj (2008) who have analysed the elasticity of rail fares in India but they have focussed solely on specific intercity rail operations. There is thus a substantial gap between the developed and developing world with regard to studies on elasticity which is summarised as in the following. The studies in developing countries - (i) were aggregate of the public transport system including bus and rail operations; (ii) did not consider passenger railway operations exclusively in their studies; and (iii) never took up the subject of suburban railways on their own. Our paper thus focuses on the suburban rail operations from five divisions of the Indian Railways.

## 3. Methods of estimating elasticity

Three different estimation methods have been used: static time series, dynamic time series (Partial Adjustment Model and Error Correction Model) and Panel Data estimation. But to facilitate understanding of the estimation methods used, we firstly need to introduce the demand models. Various functional forms of demand models have been used in the past but the two most popular model forms are: the power function and the negative exponential function (Goodwin and Williams, 1985). The power function conveniently lends itself to log transformation and therefore it is easier to estimate the elasticity because the coefficient of the variable itself is equal to the short run constant elasticity. It is also a typical constant elasticity model as described by Wardman et al., (2007). Thus in our research we specify the demand model as:

$$PKM = c(F^{\alpha})(SDP^{\beta})(PP^{\gamma})(Pop^{\delta})(VehPop^{\theta})(VKM^{\mu}) \quad (1)$$

(PKM= Passenger Kilometre (demand); F=Fare; SDP=Per Capita Net State Domestic Product; PP=Petrol Price; Pop=Population of the city area; VehPop= Road Vehicle Population; VKM=(Rail)*Vehicle Kilometre, c=constant and,* $\alpha,\beta,\gamma,\delta,\theta$ and $\mu$ are parameters to be estimated).

Taking natural log of the two sides (making it thus a log-log or double-log model), the econometric model is obtained:

$$lnPKM = c + \alpha lnF + \beta lnSDP + \gamma lnPP + \delta lnPop + \theta lnVehPop + \mu lnVKM + \varsigma \quad (2)$$

($\varsigma$ *is a random disturbance term*)

Differentiating both sides with respect to the variable of interest (say Fare):

$$\frac{1}{PKM} * \frac{\partial PKM}{\partial F} = \alpha * \frac{1}{F} * \frac{\partial F}{\partial F} \quad (3)$$

The required elasticity with respect to fare can be written as:

$$\epsilon_{PKM,F} = \frac{\partial PKM}{\partial F} * \frac{F}{PKM} = \alpha \quad (4)$$

## 3.1 Method 1: Static time series estimation

Most of the studies on demand elasticity are based on time-series data and rely on variations over time for their informational content (Wardman et al., 2007).They provide unique insights into the behavioural adjustments and time trends. A static time series model is of the type shown in equation (2) in which the coefficients reflect short run demand elasticity as noted earlier. However, it may not be possible to understand the long run effects from static models as the adjustments over time are not clear. Therefore, we propose to use a dynamic time series method which is introduced in the next section.

### 3.2 Method 2: Dynamic time series estimation

Dynamic models effectively show the time lagged effects of a change (e.g. fare) on demand. Application of dynamic modelling techniques makes it easier to compute short-run and long-run elasticities and accounts for speed of adjustment and the length of long run period. Dynamic models with short-run and long-run demand responsiveness are of three types: Partial Adjustment Models (PAM), Error Correction Models (ECM) and Auto-Distributed Lag (ADL) models (Wardman, 2014). ADL models are theoretically sound and convenient methods but are known to fail to identify the components that constitute the total effect of a price change (Oum et al. 1992). Moreover, ADL and ECM have often been found to give similar results. For these reasons ADL models have not been used in this study and hence not been described further.

#### 3.2.1 PAM

In PAM the dependent variable is lagged and used as one of the explanatory variables in the regression. Following Bresson et al., (2003), PAM can be specified as:

$$lnPKM_t = c + \alpha lnF_t + \beta lnSDP_t + \gamma lnPP_t + \delta lnPop_t + \theta lnVehPop_t + \mu lnVKM_t + \Omega lnPKM_{t-1} + \omega_t \qquad (5)$$

(w*here subscript 't' indicates time period and* $\omega_t$ is the random disturbance term)

In this kind of formulation the coefficients are short run elasticities and any coefficient over (1- Ω*)* is the long run elasticity. For example, short run fare elasticity would be ***α*,** and long run fare elasticity would be ***α / (1- Ω)***.

PAM suffers from some shortcomings, such as, inter-temporal correlation and it constrains the effects to be the same for all the variables (Chen, 2007). It could also have the problems of non-stationarity of variables and of spurious regressions. It does not give the error correction indicators. Largely, these problems are addressed by the ECMs.

#### 3.2.2 ECM

In these models independent variables as well as the dependent variable are lagged. The main purpose of using ECM is that besides giving short-run and long-run dynamics it also gives long-run equilibrium. Generally it is specified as:

$$\Delta Y_t = \alpha + \beta_0 \Delta X_t + \beta_1 X_{t-1} + \theta Y_{t-1} + \gamma u_{t-1} + \varepsilon_t \qquad (6)$$

($Where\ \Delta Y_t = Y_t / Y_{t-1}$ and $\Delta X_t = X_t / X_{t-1}$)

It may be noted that an error correction term, $u_t$ has been added to the equation and the dependent variable is also lagged along with the independent variable where $u_t = Y_t - \beta X_t$, assuming that $Y_t\ and\ X_t$ are co-integrated. Coefficient $\gamma$ is the error-correction coefficient, which shows the percent correction or the extent of equilibrium achieved in the first period. This coefficient should always be negative and significant because $Y_{t-1}$is often above its equilibrium and the negative sign of $\gamma$ will allow it to fall in the next period towards the equilibrium. $\beta_0$ is the short run elasticity and $-\beta_1/\theta$ is the long run elasticity. This model is consistent with that of Douglas and Karpouzis (2009) and eliminates the endogeneity that occurs due to the use of lags in the explained variable which can be correlated with error lags.

This model has the limitation of spurious regression due to the relationship between $\Delta Y_t$ and $Y_{t-1}$. Another limitation is that it cannot be applied to a model if non-stationary variables are integrated but are not of the same order (Chen, 2007). J*ohansen's* test of co-integration has been applied to each city's data to ascertain that the variables are co-integrated and are of first order before running ECM. As each model has some strengths and weaknesses, this study uses each one to compare various aspects of elasticity. PAM is used to estimate the long-run elasticities while the ECM is mainly used to estimate the error correction coefficients. We also have tested the data for stationarity of variables by using Dickey-Fuller test before running ECM.

### 3.3 Method 3: Panel data estimation

Panel data is a combination of time-series and cross sectional data. Several studies have pooled data into a panel set to estimate elasticity (See Batley et al. 2011). The pooling of cross-section and time periods gives the benefit of having more data than pure time series or cross-section and allows for more variation which in turn enhances the precision of estimated parameters. Now the dependent variable is explained through two channels – (i) through variations in the independent variables; and (ii) through persistent unobserved factors over time (unobserved heterogeneity). Another benefit of panel data is that it allows flexibility in modelling the heterogeneity in individual behaviours. Basic panel regression model is of the form

$$Y_{it} = \beta x_{it} + \alpha z_i + \varepsilon_{it} \tag{7}$$

In order to capture the unobserved heterogeneity $\varepsilon_{it}$ is split into two: Time invariant unobserved heterogeneity ($u_i$) and random noise ($v_{it}$) as shown in equation (8).

$$\varepsilon_{it} = u_i + v_{it} \tag{8}$$

(where $x_{it}$ contains k regressors, not including the constant term, and $\alpha z_i$ is the heterogeneity where $z_i$ contains constant and individual specific variables, observed or unobserved, and all being constant over time).

There is a range of panel data models available but Random Effects and Fixed Effects are the two commonly used ones by far. The main distinction between the Random Effects and the Fixed Effects is that the former assumes the unobserved individual heterogeneity as uncorrelated to the regressors while in the latter it is assumed to be correlated. In our case study we used Hausman test statistic which rejected the null hypothesis that the unobserved effects are correlated with the regressors. Hence Fixed effects model has not been described further.

**Random Effects**

In Random Effects models the unobserved heterogeneity is considered as a random variable which is formulated as

$$Y_{it} = \beta x_{it} + \alpha z_i + u_i + v_{it} \tag{9}$$

($u_i$ is a group specific random (unobserved) element that is identical in each period and is not correlated with the regressors)

There are mainly four assumptions that should hold for Random Effects:

a. $u_i$ *and* $v_{it}$ are not correlated with each other
b. $u_i$ are not correlated with $x_{it}$
c. $v_{it}$ are not correlated with $x_{it}$
d. $u_i$ *and* $v_{it}$ have a mean of zero and constant variance

## 3.4 Bootstrapping regression estimates

Bootstrapping is a nonparametric approach to statistical inference that substitutes for traditional distributional assumptions and asymptotic results (Effron 1979). In particular bootstrapping is very useful when the sample size is small. In our research, the historical data spread over 30 years together with up to seven explanatory variables does not offer significant degrees of freedom. Hence the bootstrapping regression method has been applied. Bootstrapping involves generating samples (called bootstrapped samples) from the original sample by replacement. Bootstrapped regression models can be generated by treating the regressors as random or by treating the regressors as fixed. In the former case, bootstrap samples are selected directly from the observed samples but in the latter case they are resampled from the residuals of the fitted regression model. However, the latter case i.e. the fixed regressor approach implicitly assumes that the regression model fitted to the data is correct and that the errors are identically distributed. For this reason, in our research we have followed the first approach by treating the regressors as random and generated 1000 bootstrap samples each per division of suburban rail operation. In this paper, we report the results of the bootstrapped regression models which produced significantly better quality results compared to the standard regression models (not reported in the paper).

## 3.5 Model specification

### 3.5.1 Dependent variable

In a travel demand model total volume of travel is the variable that is measured. There are different ways of expressing the total travel variable e.g. number of trips, distance travelled and time spent in travelling. This research uses the total number of suburban train journeys made per annum combined with the distance travelled expressed as passenger kilometre (PKM). Dargay and Hanly (1999) have also used PKM as dependent variable in their aggregate study of travel demand.

### 3.5.2 Independent variables

Fares have consistently been found to be highly significant determinant of the public transport demand (Owen and Phillips, 1987). In this work average yield (revenue per pass-km as a proxy for fare) has been used as the first explanatory variable. However, the change in individual ticket prices may actually affect the demand. Moreover, short distance off-peak fare rise may evoke a different response to that caused by a rise in long distance peak fare. Averaging of fares over a year may adversely affect estimation of short-term responses. Analysing fare changes in different periods over different distances would be interesting but the fare structures in Indian Railways have not been historically segregated for peak and off-peak periods. Therefore, in this paper we use the average yield as a proxy for fare.

The second independent variable, number of road vehicles, is one of the socio-economic attributes and is used as a proxy for the car ownership. Income and car-ownership are two strong determinants of demand for public transport in general and the rail in particular. Car-ownership data was not available for the three cities, hence an indirect measure of total vehicle population (private cars, taxis, two-wheelers and buses) was used as a proxy.

SDP of the states has been used to account for the economic (income) variable. SDP has come to be recognised as an important determinant of demand for rail journey. Other socio-economic attributes such as employment status are not included in the model because they are also subsumed in the income variable as they tend to be positively correlated.

Petrol price is included as an independent variable to account for the substitutes such as bus, car, shared taxi, toll prices, etc. As the list of substitutes is long and as there are aggregation problems, the petrol price has been assumed to reflect the characteristics of substitutes and the demand for rail is expected to be positively related to them.

Population directly affects the demand for public transport as a land-use factor. There are two land-use attributes which may have considerable effects on total distance travelled - size of the metropolitan/residential area and the urban density. Urban density is not included in this study due to lack of historical data. Therefore, to account for land-use factors in the model only population of the metropolitan area has been included.

The supply side and level of service have been accounted for by Vehicle kilometres (VKM). This measure takes into account the length of the trains which could significantly vary from city to city making the data set inconsistent. VKM operated could be taken as a crude measure of service frequency and network size. It is important to point out that as well as influencing the demand, VKM may also be influenced by the demand. If that is the case the estimates may be a little inflated (Douglas and Karpouzis 2009).

We now set out to describe the case of Indian Railways in the next section.

## 4. The case of Indian Railway’s suburban rail operations

Indian Railways carry about 22.5 million passengers every day (IR, 2012) of whom 12 million (53%) are suburban passengers. The three cities viz., Chennai, Kolkata and Mumbai put together account for almost all of the railway's suburban traffic. A profile of the suburban rail operations in each city is shown in Table 3.

Full reference to the published version: Rahman, S.A. and **Balijepalli N.C.** (2016) Understanding the determinants of demand for public transport: evidence from suburban rail operations in five divisions of Indian Railways, Transport Policy, 48, 13-22 http://dx.doi.org/10.1016/j.tranpol.2016.02.006

**Table 3: A profile of suburban rail operations**

| City | Population (Million) | RKM | Daily Passengers (million) | Avg. Lead (KM) | Services Per Day | Peak Headway (mins) | VKM (million) | PKM (billion) | No. of stations | Road Vehicles (million) | Rail share of commuting pass (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Chennai | 9 | 169 | 1.05 | 24.6 | 580 | 5-7 | 81.4 | 9.15 | 73 | 3.5 | 7 |
| Kolkata | 17 | 1344 | 3.05 | 35.6 (27.9) | 1130 | 2-5 | 261 | 38.7 | 390 | 2.3 | 16 |
| Mumbai | 19 | 381 | 7.45 | 30.4 (34.6) | 2130 | 1.8-2 | 394 | 85 | 98 | 3.4 | 51.8 |

Note: Figures are for 2011-12. VKM=Vehicle Kilometer; PKM= Passenger Kilometer; RKM=Route Kilometer). The figures are for the whole metropolitan area except average leads which are for Kolkata (E) and Mumbai (C) and separately mentioned for Kolkata (SE) and Mumbai (W) in brackets.

Chennai's suburban railway has a share of 7% in the total daily commuting trips. It has relatively smaller route length and runs fewer trains than Kolkata and Mumbai. Most of the trains are composed of 9 cars or 12 cars. Kolkata and Mumbai have two railway systems each independently operated by different zonal railways; therefore, four separate estimations viz., Kolkata Eastern, Kolkata South Eastern, Mumbai Central and Mumbai Western have been done for these two cities thus making up a total of five divisional operations when Chennai is included.

Although the importance of suburban services cannot be overemphasised, the decisions on fare for these services need not always be based on an economic rationale. These decisions are based on the recommendations of a periodic committee called Railway Fares and Freight Committee (RFFC). The last report of RFFC submitted in 1993 recommended distance-based fares which has since been the norm mutadis-mutandis (Nanjundappa et al., 1993, p. 454).

Increasing population in Indian cities together with the need for integrating city and transport planning and the ever widening gap between revenue and expenditure are exerting constant pressure on Indian Railways. Demand assessment and a suitable fare policy would be essential to show a clear road map for attracting financial investments in transport projects.

### 4.1 Data sets

Historical data for 30 years on Passenger Kilometre (PKM), Vehicle Kilometre (VKM) and average yield per passenger kilometre (Fare) from 1984 to 2013 were obtained from the Indian Railway's annual statistical statements. Data on the number of vehicles, population and price of petroleum were collected from secondary sources (Reddy and Balachandra, 2012; Pucher et al., 2005 and Verma, 2010).

Trends in core data sets e.g. real rail fare (i.e. ex-inflation), PKM and VKM are shown in Figures 1-5. The figures clearly show a declining trend in the real fares and an increasing trend in PKM.

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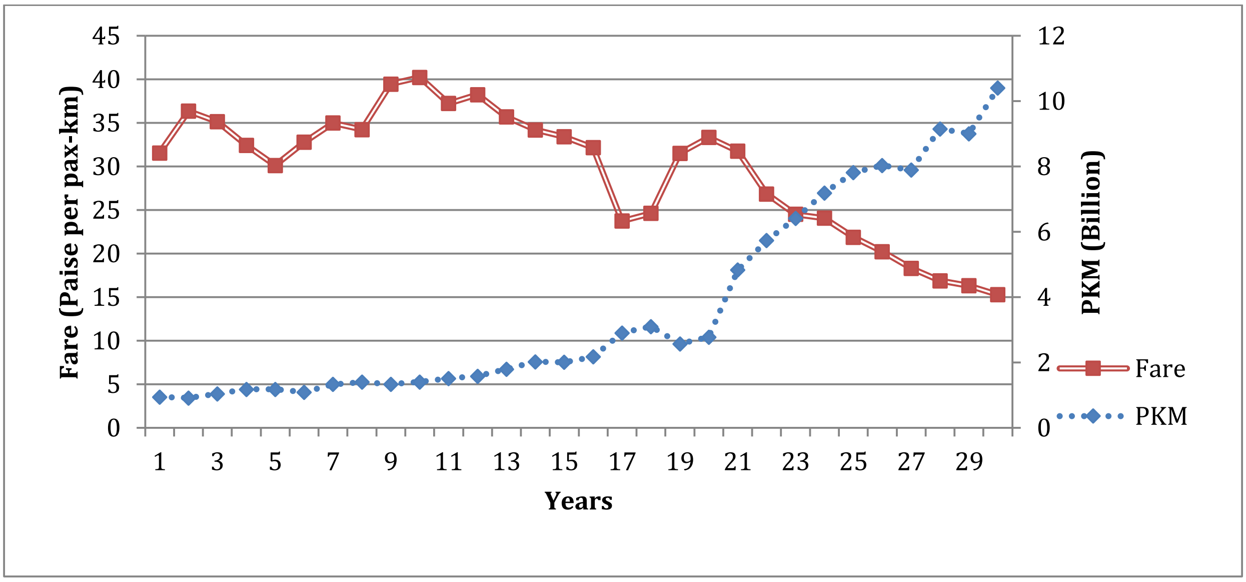


Figure 1 – Fare and Passenger Demand trends in Chennai

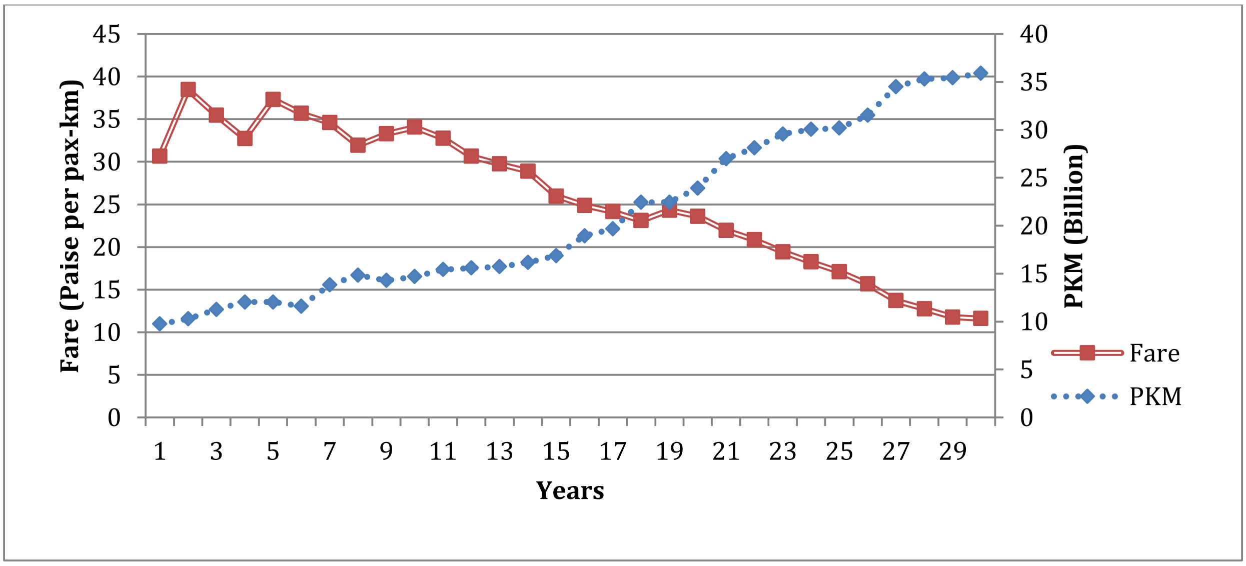


Figure 2 – Fare and Passenger Demand trends in Kolkata (E)

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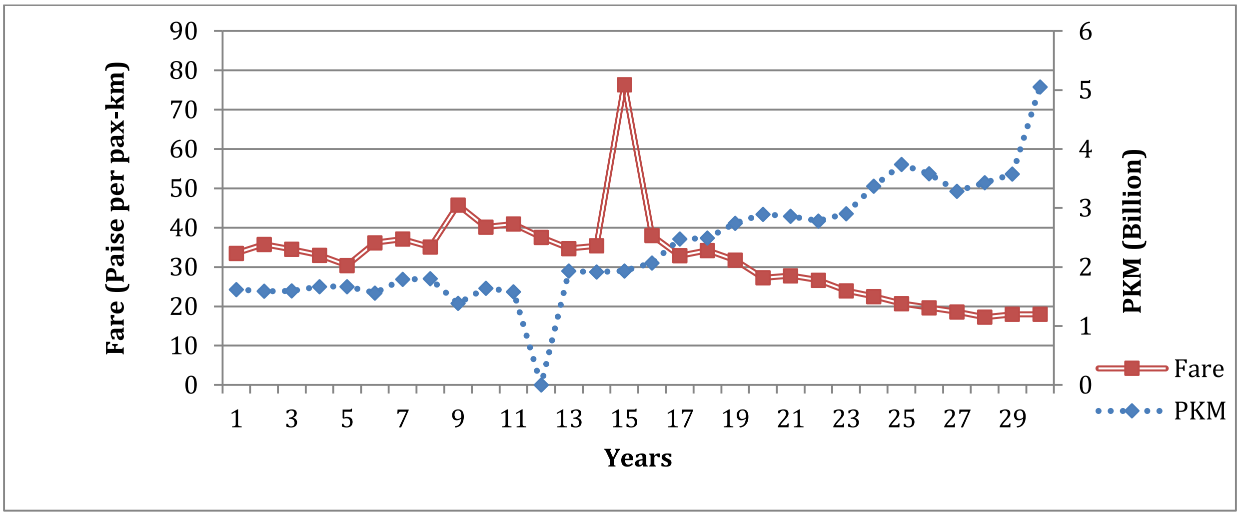


Figure 3 – Fare and Passenger Demand trends in Kolkata (SE)

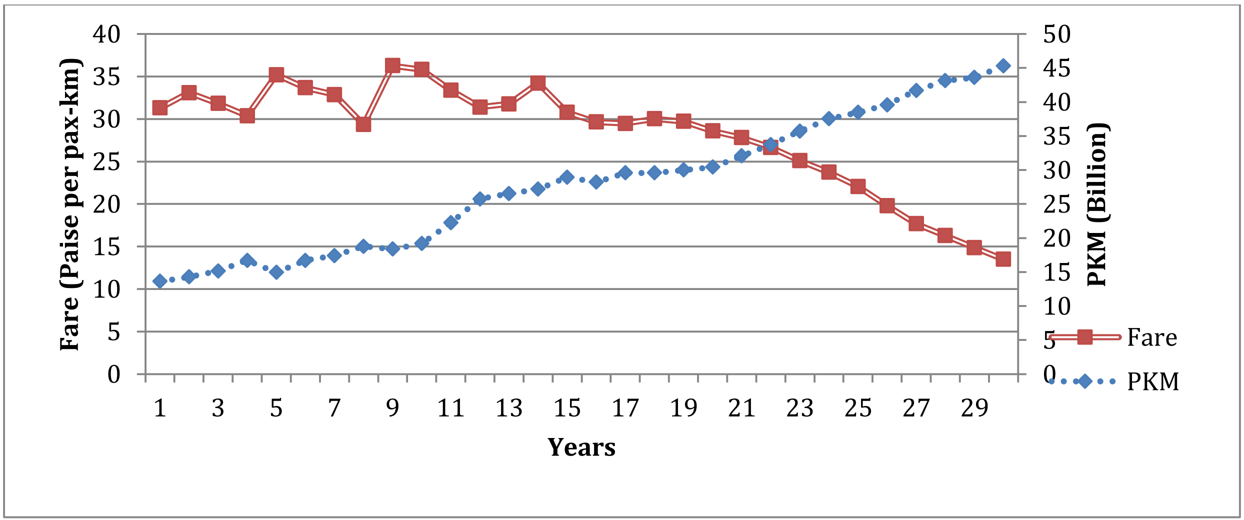


Figure 4 – Fare and Passenger Demand trends in Mumbai (C)

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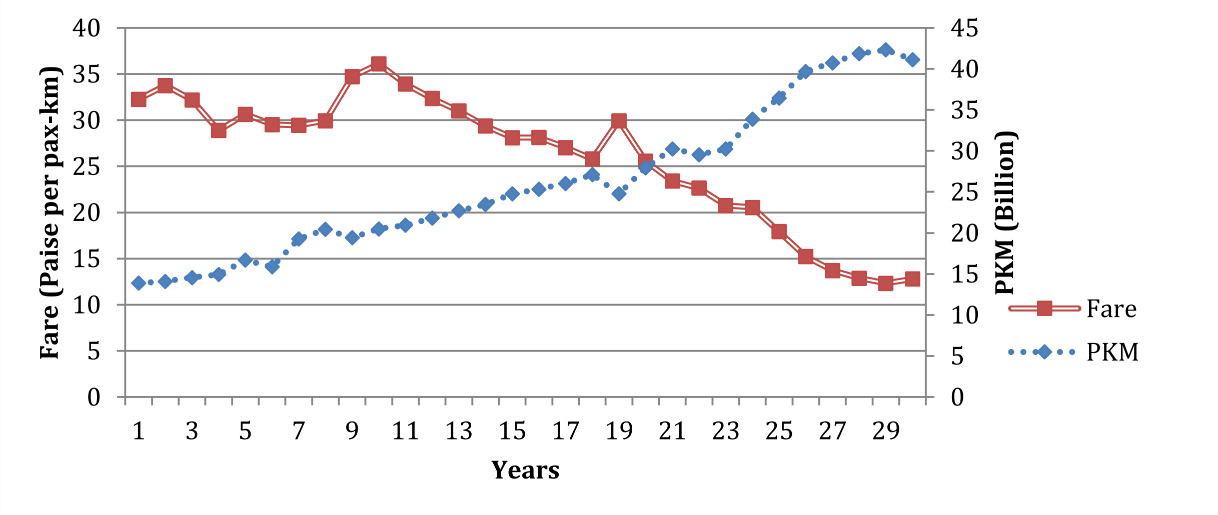


Figure 5 – Fare and Passenger Demand trends in Mumbai (W)

Real fares and petrol prices for each city were adjusted for inflation. The inflation trends for India were obtained from World Inflation Data (WID 2014). The index numbers used to compute the actual fares and fuel prices in each year were sourced from the official data published by the Labour Ministry of India (GoI, 2014). Using a simple adjustment method as described in Gavin (2009) all prices were adjusted to the common year of 2013.

The vehicle population includes all vehicles used for transportation: buses, cars, taxis and 2-wheelers. Population is for the metropolitan area and not for the whole of suburban catchment area has been used, which could potentially insignify the variable and/or to have wrong signs in the estimation.

Trends in suburban rail's Vehicle Kilometre (VKM) and number of road vehicles in three cities over the same period show an increasing trend across all the cities accounting for natural growth in traffic due to population and other demographic factors such as rural-urban migration. Real petrol prices though largely remained stable.

## 5. Estimation results

### 5.1 Estimates of elasticity from bootstrapped regression models

Table 4 shows the computed elasticity values and their statistical significances which would be at the core of all the subsequent analyses and the discussion on policy implications. Column 2 of the table describes the models used, e.g. short-run (SR) and long-run (LR) estimated from Partial Adjustment Model (PAM) and Error Correction Model (ECM). Long-run elasticities have been computed using the formulae explained in Method 2 of Section 3. Columns 3 to the end show the estimated elasticity values.

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## Table 4: Estimated elasticities by bootstrapped time-series models

| City | Model type | Fare elasticity | Petrol Price | GDP | Population | Vehicle KM | Number of Road Vehicle |
|---|---|---|---|---|---|---|---|
| Chennai | SR (static) | -0.5745* | 0.1199* | 0.0354* | -4.5807* | 0.8631* | 1.1917* |
| | SR (PAM) | -0.5745* | 0.1201* | 0.0354* | -4.5497* | 0.8639* | 1.1842* |
| | LR (PAM) | -0.5733* | 0.1197* | 0.0353* | -4.5709* | 0.8612* | 1.1891* |
| | SR (ECM) | -0.6388* | 0.1477* | 0.0393* | -3.9292* | 0.8550* | 1.0171* |
| | LR (ECM) | -2.4864* | 0.1895~ | 0.5049~ | -5.0427~ | 0.9723~ | 1.3054~ |
| Kolkata (E) | SR (static) | -0.0023~ | 0.0980* | 0.0069~ | 0.7904* | 0.5383* | 0.2882* |
| | SR (PAM) | -0.0045~ | 0.0993* | 0.0071~ | 0.7921* | 0.5437* | 0.2820* |
| | LR (PAM) | -0.0023~ | 0.0978* | 0.0069~ | 0.7888* | 0.5372* | 0.2876* |
| | SR (ECM) | -0.1199* | 0.0790* | 0.0069* | 0.5906* | 0.5182* | 0.2823* |
| | LR (ECM) | -3.1375* | 0.3401~ | 0.0295~ | 2.5416~ | 2.2299~ | 1.2149~ |
| Kolkata (SE) | SR (static) | -0.2879* | 0.0894* | 0.0513* | 1.7711* | -0.1292* | -0.3689* |
| | SR (PAM) | -0.2862* | 0.0888* | 0.0504* | 1.7840* | -0.1315* | -0.3703* |
| | LR (PAM) | -0.2903* | 0.0900* | 0.0511* | 1.8093* | -0.1334* | -0.3756* |
| | SR (ECM) | -0.3776* | 0.0803* | 0.0409* | 1.5220* | -0.1059* | -0.3211* |
| | LR (ECM) | -0.8885* | 0.2791~ | 0.1422~ | 5.2919~ | -0.3681~ | -1.1163~ |
| Mumbai (C) | SR (static) | -0.0229~ | 0.2941* | 0.1699* | -0.1502~ | 0.1171* | 0.3527* |
| | SR (PAM) | -0.0232# | 0.2937* | 0.1698* | -0.1514~ | 0.1168* | 0.3539* |
| | LR (PAM) | -0.0232# | 0.2940* | 0.1699* | -0.1516~ | 0.1170* | 0.3543* |
| | SR (ECM) | -0.0486* | 0.2875* | 0.1638* | -0.03668~ | 0.1151* | 0.2925* |
| | LR (ECM) | -1.2747* | 5.4151~ | 3.0853~ | -0.6909~ | 2.1673~ | 5.5094~ |
| Mumbai (W) | SR (static) | -0.0600* | -0.0155~ | -0.0338* | 1.0755* | -0.0577~ | 0.3324* |
| | SR (PAM) | -0.0604* | -0.0155~ | -0.0338* | 1.0764* | -0.0583~ | 0.3321* |
| | LR (PAM) | -0.0603* | -0.0154~ | -0.0337* | 1.0741* | -0.0582~ | 0.3313* |
| | SR (ECM) | -0.1129* | -0.0039~ | -0.0294* | 1.0313* | -0.1154* | 0.3377* |
| | LR (ECM) | -0.8555* | -0.0454~ | -0.3440~ | 1.2077~ | -1.3511~ | 3.9552~ |

SR= Short-run elasticity; LR= Long-run elasticity

Note: * significant at 95%; # significant at 90%;~ not significant;

### 5.1.1 General comments on signs and size of the estimates

SR fare elasticities by static models are significant and are within reasonable range for Chennai and Kolkata (SE). They are insignificant for Kolkata (E) and Mumbai (C) but at the same time are too low anyway. SR from PAM is significant for Chennai and Kolkata (SE) at 95% significance level. LR calculated from PAM is reasonable and significant only for Chennai and Kolkata (SE) at 95%. LR elasticity was calculated using estimates from ECM for fare and it was found significant for Chennai and Mumbai (C).

Petrol price elasticity is significant in all divisions except for Mumbai (W) and has a positive sign all through. The GDP elasticity is generally significant and positive except in Mumbai (W). The population elasticity is generally significant except in Mumbai (C). VKM, expectedly, is significant except for Mumbai (W) with correct signs. Finally, vehicle population is significant and generally it is positively related to the demand indicating that the road transport networks are over congested with too many vehicles.

### 5.1.2 Bootstrapped confidence intervals of estimated elasticities

Bootstrapped confidence intervals of significant estimates (SR) with error correction as an additional variable has been computed. Table 5 presents confidence intervals of elasticity value (95% significance) estimated from ECM.

**Table 5: Bootstrapped confidence-intervals of important elasticities (short-run)**

| City | Fare | | | Petrol Price | | | VKM | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Low | High | Coefficient | Low | High | Coefficient | Low | High |
| Chennai | -0.6388 | -0.6663 | -0.6027 | 0.1477 | 0.1101 | 0.1697 | 0.8631 | 0.8064 | 0.9197 |
| Kolkata (E) | -0.1199 | -0.1426 | -0.0826 | 0.0980 | 0.0579 | 0.1381 | 0.5383 | 0.4546 | 0.6220 |
| Kolkata (SE) | -0.3776 | -0.4025 | -0.3527 | 0.0803 | 0.0409 | 0.1196 | -0.1059 | -0.1355 | -0.0762 |
| Mumbai (C) | -0.0486 | -0.0704 | -0.0267 | 0.2875 | 0.2699 | 0.3052 | 0.1151 | 0.0905 | 0.1396 |
| Mumbai (W) | -0.1129 | -0.1537 | -0.0863 | -0.0155 | -0.0495 | 0.0185 | -0.0577 | -0.1378 | 0.0223 |

### 5.1.3 General comments on results from Panel data

Table 6 summarises the estimates of elasticity from Panel data by the Random Effects model. The estimates of important variables for this study are significant. Adjusted $R^2$ and F-stat for random effect are also high and significant. Confidence intervals for the estimates were also computed which are presented in Table 7. The results are largely consistent with previous studies although the fare elasticities are slightly on the lower side. It is, however, expected to be low in the developing countries due to combined effects of fare across the cities. Petrol price elasticity is very reasonable and significant too. The VKM elasticity is on the higher side but it does point to the fact that an increase in train services could be the most important determinant of an increase in passenger demand.

**Table 6: Results of Random Effect Panel estimation**

| Variable | Elasticity | Statistical significance (p-value) |
|---|---|---|
| Fare | -0.235 | 0.0003 |
| Petrol Price | 0.151 | 0.162 |
| GDP | 0.085 | -0.023 |
| Population | -0.377 | 0.065 |
| VKM | 0.814 | 0.00 |
| Number of Vehicle | 0.277 | 0.0015 |
| Adjusted R-squared – 0.9445; Prob F-stat – 0; D-W stat – 0.520 | | |

**Table 7: Confidence interval of elasticities from Random Effect**

| Fare | | | Petrol Price | | | VKM | | |
|---|---|---|---|---|---|---|---|---|
| Coefficient | Low | High | Coefficient | Low | High | Coefficient | Low | High |
| -0.235 | -0.36 | -0.11 | 0.151 | -0.062 | 0.364 | 0.814 | 0.583 | 1.045 |

## 5.2 Discussion on the estimated elasticities

Following the general comments in Section 5.1, we set out to discuss the fare elasticities for each city more in detail in this section.

### 5.2.1 Fare elasticity in Chennai

Values specific to Chennai suggest that the city has the highest fare elasticity meaning that the commuters of Chennai are more sensitive to fare changes. Elasticity values of Chennai are significant for all the models. The difference between short-run and long-run fare elasticity is very low (PAM). Its implication is that the reaction to fare change is immediate in Chennai and that long-term behavioural changes are minimal. Changes in residential or office location are unlikely to happen due to the changes in fare as commuters generally do not come from high income band and hence have less discretion in deciding where to work or live. The most important reason for small long-run elasticity however could be the small value of transport cost which is not strong enough to induce long-term changes.

### 5.2.2 Fare elasticity in Kolkata (E) and Kolkata (SE)

Fare elasticity of Kolkata (SE) is of the expected magnitude and sign. The difference in elasticity values between Kolkata (E) and Kolkata (SE) is interesting to note though. Kolkata (E) appears to be relatively inelastic and the elasticity values are insignificant which could be due to its demographic and urban structure. Suburban railway in Kolkata (E) serves densely populated areas and the suburban spread is more in Kolkata (E) than in Kolkata (SE). According to the Comprehensive Mobility Plan submitted to Kolkata Metropolitan Authority (KMA 2008), the population of Kolkata (mainly the areas in the East) increased by more than eight times from 0.6 million in 1947 to 5.1 million in 1951 after the Independence. The city has not yet recovered from this unplanned demographic explosion and has been grappling with consistent increase since then. Another wave came in 1971 during Bangladesh war when a substantial population was added to the city. Notably the geographical area of the city has increased by 30 times since 1947. It is known that transit services in dense areas where the demand is generally higher tend to be less elastic due to relatively higher dependence on them. Wardman (2014) found lower price elasticity in Passenger Transport Executive (PTE) areas and London (London-Rail) where the density of population is high as compared to non-PTE/non-suburban areas. Low elasticity of Kolkata (E) can also be due to less competition from other modes. The reaction is less obvious in the short run but appears to be quite important in the long-run situation. In Kolkata (E) share of travel for work and education is more (77%), which again tends to be inelastic.

### 5.2.3 Fare elasticity in Mumbai (C) and Mumbai (W)

For Mumbai (W) it is noted that most of the elasticity values were found significant but substantially low. Hence fare changes may not significantly alter the demand. Mumbai (C) on the other hand has very low and insignificant elasticity, which means that commuters in Mumbai (C) are relatively less sensitive to fare changes, which could be due to their dependence on commuter trains, which is to a large extent true. Commuter trains in Mumbai are essential goods, the demand for which tends to be inelastic. Mumbai (W) GDP elasticity is negative indicating the higher degree affluence who tend to use private modes (car) more than that in Mumbai (C). As Mumbai is heavily dependent upon suburban services, fare is expected to be an insignificant factor. Lower sensitivity to rail services may also stem from higher market share of suburban rail, which is the case in Mumbai (~52%).

Long-run elasticities are significant for Mumbai (W), albeit less pronounced, but not for Mumbai (C). This means that rail fare is not seen as an important factor in determining people's choice of housing or work place. This is again due to the reason that the majority of rail commuters happen to be of low-income group (more so on Mumbai (C) than in Mumbai (W)) and finally in Mumbai trip lengths are comparatively higher due to its linear structure and hence they have fewer options.

### 5.2.4 Discussion on fare elasticity from Panel data

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Elasticity value from panel data estimation is lower than that from time series but still within the acceptable bounds. The value is low because of its cross-sectional effect. Normally the values are expected to be low in developing countries due to the low-income level of users. This view is contrary to general economic understanding that people in higher income brackets tend to be less price-sensitive (Balcombe et al, 2004). Another reason for lower elasticity could be the degree of intermodal competition which is generally much less intense in developing countries making transport demands more inelastic.

### 5.2.5 Comparing the estimates of fare elasticity

A comparison between the fare elasticities from this study (only significant ones) and those from other similar studies is drawn in Table 8. Transit elasticity values from Litman (2012) were taken which were based on a survey of previous studies and is the latest of all the available surveys as of now.

**Table 8: Comparison of fare elasticity with the average available values**

| City | SR static | SR ECM | SR PAM | LR PAM | Panel data | SR* | LR* |
|---|---|---|---|---|---|---|---|
| Chennai | -0.574 | -0.639 | -0.574 | -0.573 | | | |
| Kolkata (E) | | -0.12 | | | | | |
| Kolkata (SE) | -0.288 | -0.38 | -0.286 | -0.29 | -0.235 | | |
| Mumbai (C) | - | -0.049 | | | | -0.3 to | -0.8 to |
| Mumbai (W) | -0.06 | -0.113 | -0.06 | -0.06 | | -0.6 | -1.0 |

*Litman (2012). Note: Only the significant values have been reported

Fare elasticities are less than 1 for all the cities in consideration meaning that passenger demand is fairly inelastic which is not surprising because the transport as a whole and public transport in particular tend to be inelastic. This observation is consistent with that of the findings by others, for example, Oum et al.(1992). Only discretionary travel tends to be elastic and suburban services are seldom discretionary as they tend to be often work related. Fare elasticities are within the range of values noted by Litman (Table 8). But there are substantial variations in the elasticity values across the cities because of market and other situations which vary from one another affecting the estimation as noted in Sections 5.2.1-5.2.3.

## 5.3 Policy implications

Price elasticities have several applications in transportation planning. The three most important applications are discussed here.

### 5.3.1 Demand forecasting and management

One of the basic objectives of planning for transport facilities is to forecast as to what extent those facilities will be used. In order to have a sound understanding of the future demand an efficient estimation of users' sensitivity to changes in price (e.g. fare, toll, fuel costs) and in other service attributes would be necessarily needed. Elasticities provide an efficient indication of the users' sensitivity to changes in those attributes. For example, a fare elasticity of -0.64 for Chennai would mean that for a 1 % change in fare 0.64 % of people would stop or start using the services depending on whether it is an increase or decrease in the fare. These indicators can be used to predict the demand in future under assumptions of changes in transport provisions and services. Lack of accurate forecast of demand has been one of the most important concerns of many transport projects as the entire economic viability and financial sustainability of those projects relies on it. Pervasive errors in demand forecasts suggest that forecasting error could be a major source of risk for projects. For example, in a study of forecasting (in)accuracy of different projects, Welde (2011) found that a large number of projects (40%) had inaccuracy of more than ± 20% . They recommended placing special emphasis on users' reaction to changes in costs and how these reactions can be incorporated in the demand forecasting models. Thus the elasticity of fares has a key impact in demand forecasting.

With a view to illustrating the principles we project the demand for suburban rail in Kolkata (E). Table 9 projects the demand considering 2009-10 as the base year and uses the demand model in equation (2). For the sake of simplicity constants have been assumed to be equal to 1, fare elasticity (short-run) shown in Table 4 is used and VKM and PP elasticities (short-run) from Table 8 have been used to compute the changes in demand. Percentage change in demand is projected by assuming 10% increase in fare in 2009-10 while all other factors are held constant. Table 9 predicts that the demand would reduce by 1.3% (=1-0.987). The projected values also suggest that there is insignificant long-run impact of fare changes as indicated by the adjustment parameters earlier.

**Table 9 Demand forecast for Kolkata (E) using fare elasticity**

| Year | Demand | Constant | Fare | Fare elasticity | VKM | PP | $D_{t-1}$ | Demand in t-1 |
|---|---|---|---|---|---|---|---|---|
| 2009-10 | 0.988 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 1 |
| 2010-11 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.989 |
| 2011-12 | 0.98773 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.988 |
| 2012-13 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |
| 2013-14 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |
| 2014-15 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.98 |
| 2015-16 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |
| 2016-17 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |
| 2017-18 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2018-19 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |
| 2019-20 | 0.987 | 1 | 1.1 | -0.12 | 1 | 1 | 0.096 | 0.987 |

Table 10 presents the changes in the demand for an alternative scenario i.e., a 10% increase in vehicle kilometre and petrol price respectively while all other factors are held constant. It clearly shows an increase of demand by 7 % in passengers in Kolkata (E), which would translate to around 1.73 million passengers in 2019-20.

**Table 10: Demand forecast for Kolkata (E) using Fare VKM and PP elasticity**

| Year | Demand | Constant | Fare | VKM | VKM elasticity | PP | PP Elasticity | $D_{t-1}$ | Demand in t-1 |
|---|---|---|---|---|---|---|---|---|---|
| 2009-10 | 1.063 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1 |
| 2010-11 | 1.069 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.06 |
| 2011-12 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2012-13 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2013-14 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2014-15 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2015-16 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2016-17 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2017-18 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2018-19 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |
| 2019-20 | 1.070 | 1 | 1 | 1.1 | 0.54 | 1.1 | 0.098 | 0.096 | 1.07 |

### 5.3.2 Pricing and revenue

Rational pricing of services is always an important managerial and regulatory objective. Multi-part tariff or price discrimination is based on the elasticity value of different groups of users and the prices are marked up or down in inverse proportion to the elasticity. If revenue maximisation were the main objective of Indian Railways, inelasticity of demand (elasticity value <|1|) would mean that increase in prices would always lead to an increase in revenue despite the reduction in ridership. Hence pricing can be a good way of earning revenue or of recovering costs at least. If Indian Railways were to have some sort of price differentials between the cities it would clearly price the suburban services lower in Chennai and Kolkata (SE), while it can increase the fare in Kolkata (E), Mumbai (C) and Mumbai (W). In order to achieve a finer level of discrimination price elasticity among different user groups (First class and ordinary class) or users in different times of the day (peak or off-peak) could be used to set different fares within the same city.

#### 5.3.3 Promoting sustainable transport and reducing congestion

Local/federal authorities aim at providing economically efficient, environmentally sustainable and socially equitable transport system. Promotion of public transport, among other things, tends to meet these objectives. Indian cities already have high share of public transport in daily travel by the commuters. It is however, more due to low income and necessity than being driven by any policy initiatives as seen in other cities. Rising car-ownership and premature road congestion with increase in income in Indian cities is a pointer to this. Therefore there is a need to keep the share of public transport high by having an integrated approach to transport policy. Integrated policy that takes into account the land use factors, fuel pricing, infrastructure planning, accessibility considerations and interactions between different modes of public and private transport can make public transport more sustainable.

By developing dense residential and employment areas along the suburban networks use of suburban railways can be maximised. It is seen that the cities that are densely populated (Kolkata (E) and Mumbai (C) and Mumbai (W)) have lower price elasticity indicating more dependence on railways in those cities/areas. This gives a clue for developing transit-oriented cities that are more dependent on public transport. In the cities with higher fare elasticity, fare reduction can play a substantial role in promoting public transport and discouraging private cars.

## 6. Concluding remarks

This paper studied suburban rail passengers' sensitivity to changes in fare using econometric demand models. The models were based on a time series data of 30 years of demand and fare of suburban rail services in three major cities of India: Chennai, Kolkata and Mumbai. Direct demand model was used to estimate the elasticities. Three methods were applied: static time-series, dynamic time series and panel data. In the dynamic time series Partial Adjustment Model and Error Correction Model were separately estimated. In the panel estimation method Random Effects were estimated although the preliminary consideration included the Fixed Effects. The results from these estimations reveal the following:

- Overall, the demand for suburban services in Indian cities is inelastic, i.e., the absolute value of elasticity is between 1 and 0. This result is consistent with all previous studies and also with the theoretical stand point on demand elasticity of public transport.
- The difference between long-run and short-run elasticity is not as high as theoretically expected.

- Kolkata (E) and Mumbai (C) have the lowest fare elasticity.
- Chennai and Kolkata (SE) have high fare elasticity.
- Fare elasticity from panel data is low which appears to be realistic given the low fare elasticity of public transport in general in developing countries.
- Demand elasticity with respect to petrol price was found significant in all the cities except Mumbai (W).
- Vehicle kilometre was found significant in all the cities except Mumbai (W).
- The adjustment/equilibrium factors were found to be in general very high in all the cities suggesting that the demands adjust very quickly after any change in fare or other factors.
- Demand forecasts that are not based on passengers' sensitivity to important attributes of public transport tend to be generally over-estimated (have optimism bias).

Policy implications of these findings are immense and far-reaching. If elasticity values of all the important attributes of public transport were available for each user group and for different periods, an effective control and management of public transport would be possible. Specific policies can be tested by estimating the demand for a new project or simply for a new service.

Although the results of the estimation are statistically significant and consistent with theoretical expectations there are areas where significant improvements can be made. For example:

a. Cross-elasticities with respect to other modes;
b. Elasticity with respect to time and day (peak and off-peak elasticity);
c. Further disaggregation by passenger type (adults, elderly and children), fare level, different journey lengths (e.g. disaggregated by 0.5 miles), comfort level, transit time, number of interchanges involved, waiting and walking time to the station and purpose of journey;
d. Developing a model that includes other variables (Local GDP of the city, employment rate, population density, etc.).

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