DETERMINANTS OF PASSENGER RAIL DEMAND IN PERTH, AUSTRALIA: A TIME SERIES ANALYSIS

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Abstract: Annual data from 1983-2008, together with modern time series econometrics methods, is used to examine the factors potentially contributing to growth in passenger rail demand in Perth, Australia. A cointegration approach is used to estimate long-run passenger rail elasticities and an error correction model to estimate short-run elasticities. The study finds that a 10-percent cut in the fare increases boardings by about 8 percent in the long run and 7.6 percent in the short run, while population exerts a significantly positive impact on demand. Rail kilometres operated and commuter perceptions are the other two most significant variables.

JEL Classification: F31
Keywords: Rail Demand Elasticity, Australia, Cointegration Method

1. Introduction

Several major cities in Australia have recently experienced an unexpected growth in passenger rail demand. For example, Melbourne experienced urban rail patronage growth of 47% between 2004/05 and 2008/09 (Gaymer 2010), Sydney experienced an increase of 5.1 million annual rail passenger journeys from the year 2001/02 to 2006/07 (Brooker & Moore 2008), while Perth, from the data collected, has experienced a passenger boarding increase from 35.7 million in 2007 to 42.6 million in 2008—roughly a 15 percent increase within a year. While an increase in urban rail demand might appear welcome, the ability to predict passenger demand more accurately represents a significant challenge. This is because it is difficult to accommodate that demand within the existing capacity and infrastructure constraints of a rail network. Urban rail services in Australia have traditionally been provided by state governments, either directly by state-owned rail operators, or through a contracting mechanism, as occurs in Melbourne, where a franchise system is in place (Department of Infrastructure 2005).

State governments are also being asked to do more with less, particularly with a move to smaller government and a reduced ability to produce revenues (Aragão et al. 2006). The ability to fund urban rail projects where they are most needed, and provide more services as required, is therefore of critical importance. This is particularly the case because governments must choose to invest, to varying degrees, in a variety of transport options, including urban rail. By the same token, providing over capacity in an urban rail network is not an attractive outcome, since funds directed to this infrastructure provision or augmentation could have been better directed to other

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projects. Hence, a clear understanding of the factors affecting passenger rail demand is crucial for infrastructure planning and service delivery. The transport industry has often used the sequential four-step model comprising (i) trip generation, (ii) trip distribution, (iii) modal choice, and (iv) route assignment for urban transport planning (Goulias et al. 1990; Wardman 1997). This kind of trip generation model was first used in the United States in the 1950s. Other countries subsequently adopted it as the main tool for urban transport planning, especially in an era of burgeoning private vehicle use driven by inexpensive automobiles, low access pricing, and cheap fuel (Mees 2000). The model has proved somewhat deficient, however, with respect to predicting the urban rail demand spikes experienced in Australian capital cities in recent years, while a failure to predict these increases has resulted in considerable pressure on existing infrastructure (Gaymer 2010).

Given the seeming inadequacies of existing demand estimation methods, it will be useful to ascertain which factors have contributed to the rise in the rail patronage from other approaches. A model worthy of investigation is a demand model estimated by employing time series data. This does not mean dispensing entirely with the traditional techniques; rather, other methods, such as time series modelling, can be used to supplement or check the more commonly used forecasting methods. In particular, it is necessary to investigate the utility of modelling techniques that may have a higher probability of providing accurate demand forecasting for urban rail passenger demand, rather than transport demand in general. Since the time series method is among those particular techniques regularly used for forecasting in finance and economics fields, it will be worthwhile to investigate its functionality, as a pilot study, in the context of the passenger demand of one Australian capital city, namely Perth.

The time series literature on passenger rail demand is not new, although the approach has not been widely used in Australian studies. Given that Australia has a long passenger rail history, the number of time series studies pertaining to its passenger rail sector, and urban rail in particular, is hardly impressive. There are only three time series studies based on Australian data, and these have been confined to Sydney and Melbourne. Our study of the passenger rail demand function for Perth therefore represents an addition to the handful of existing Australian studies, more so given that Perth, as a result of Western Australia’s mining boom, has experienced high level of growth, with concomitant changes in its urban form, whereas Sydney and Melbourne have a much more mature urban form, with an emphasis on encouraging greater density.

Modern time series techniques will be used to examine the relationship between passenger rail demand and its explanatory variables. Existing studies have not utilised these techniques fully in the estimation of passenger rail demand. For instance, it is now well known that most time series data is non-stationary. If this is not taken into account, spurious results and invalid inferences may occur (Granger and Newbold 1974). From the preliminary literature review, it emerged that there was no time series study on urban passenger rail demand in Australia that tested for stationarity—an integral part of modern time series studies. Our study therefore represents an important addition to the existing handful of studies on passenger rail demand in Australia. Another novelty is the use of modern econometric models such as cointegration and
error correction models to separate long-run and short-run elasticities. A few existing time series studies have, in fact, estimated both the long-run and short-run elasticities (Owen & Philips 1987; Smart, 2008). The method adopted in these studies, however, is not entirely secure. Owen and Philips, as well as Smart, separated the two types of elasticities by including a lagged endogenous variable in the estimation. As shown in the econometrics literature (e.g., Gujarati, 2010), the presence of lagged endogenous variable could lead to inefficient results and even biased estimators if autocorrelation is present. Correctly estimated elasticities are essential to plan adequately for infrastructure, rolling stock, and general service augmentation. Elasticities can also be useful in cost-benefit analyses (CBA) in large-scale transport capital investments.

This article is divided into five main parts. Section 2 provides a brief synoptic discussion of the relevant theoretical and pertinent empirical literature on the topic. Section 3 considers data definitions, data sources and the methodology. Section 4 examines the short-run and long-run passenger rail elasticities obtained from the estimation. The article concludes with some brief remarks in Section 5.

2. Previous studies on passenger rail demand
Before turning to the study itself, it is necessary to review previous attempts to employ a time series approach to estimate rail passenger demand. Note that some of the following studies estimate the demand for inter-city or inter-regional services, rather than urban rail services per se.

International Studies
The first published time series study on passenger rail demand was undertaken by Jones and Nichols (1983). They used four-weekly UK data from the beginning of 1969 to the middle of 1977 and applied an ordinary least squares method to estimate the passenger rail demand function for seventeen London-based routes. An important feature is the use of a single equation framework to estimate the demand function. The authors justified using this framework rather than a seemingly more appropriate simultaneous model by the fact that the price is determined by rail managers and does not change frequently enough for it to be considered an endogenous variable. A double log specification was used, so that the estimated coefficients could directly be interpreted as elasticities. The study found that the mean price elasticity was \(-0.64\), an outcome which suggests that, on average, a 10 percent increase in rail fare decreases rail patronage by 6.4 percent, thereby demonstrating that passenger rail demand is inelastic.

Although the Jones and Nichols study has its own merits, their results suffer from some serious statistical problems. As Fowkes and Nash (1991) showed, the Durbin Watson statistics reported by Jones and Nichols are significantly low, which may indicate the presence of serial correlation and potential statistical problems associated with the findings. As shown in the econometrics literature (e.g. Gujarati & Porter 2010; Brooks 2008), if error terms are autocorrelated, the ordinary least squares estimator is no longer efficient. An unbiased estimator different from the OLS estimator has a smaller variance and more reliability. Jones and Nichols’ findings should therefore be interpreted with caution. Indeed, the paper ignores possible short-run responses from the model. As a result of short-term commitments, passengers may
not be able to respond instantaneously to changes in explanatory variables, so it may take several months before a complete effect is felt on service demand.

Several time series and panel studies have followed. For instance, McGeehan (1984) estimated the rail demand function for inter-urban railway travel in the Republic of Ireland. This study utilised quarterly data from the beginning of 1970 to the end of 1982. McGeehan also used the ordinary least squares method and specified the model in a single equation setting. However, instead of using ticket sales data, he used the passenger miles run during the estimation period to represent demand. His choice of explanatory variables is also different. For instance, McGeehan argued that the revenue per passenger mile travelled is not a good proxy for the rail fare because most railways apply strong distance tapers, which means that the fare charged per mile falls with the more distance travelled. This means those making shorter trips effectively cross-subsidise those making longer ones. A clear implication is that, if passengers switch from long journeys to short ones, the revenue per passenger mile increases, although no actual change occurred in the rail fare. McGeehan constructed a weighted average fare using a certain formula. To control for the passenger income variable, he used the Index of Industrial Earnings. A rise in disposable income increases the demand for travel including rail travel, but it increases competition from other modes, particularly private vehicles. The model includes other important explanatory variables such as car ownership and three seasonal dummies. The results of the estimated model confirm the inelastic nature of passenger rail demand. Overall, McGeehan found that the price elasticity is $-0.4$, which suggests that a 10 percent increase in rail fare decreases rail patronage by 4 percent.

The next important study was undertaken by Fowkes et al. (1985). They used annual data (1972 to 1981) between ten major routes to construct a pooled data sample consisting of time series and cross-sectional data. The explanatory variables in their study included rail fare per journey, car ownership, employment, and dummy variables to capture the introduction of high speed rail (HSR). The authors found that the rail fare exerts a significantly negative effect and is inelastic, which means that that an increase in price should increase revenue. This is consistent with Jones and Nichols, as well as McGeehan. One issue, however, is the combination of data from ten different areas into a pooled data set. It is possible that different flows exist between different areas on account of route specific variables. The authors admit the potential problem associated with this course of action and take first differences of observations to overcome this issue. As shown by Stock and Watson (2001), although the use of first differences may solve some statistical problems, such as variable mean and non-constant variance, it also leads to the loss of some useful information, particularly relating to long-run relationships. Hence, an evaluation of the findings of Fowkes et al. should be based on whether we look for long- or short-run relationships. Another limitation is the assumption of no change in ticket coverage data over time between routes.

Doi and Allen (1986) analysed two time series regression models, one in linear form and the other logarithmic, to estimate the monthly ridership of a single urban rail rapid transit line using US ridership data. They regressed the passenger variable on fare, petrol price, road toll, and seasonal characteristics, and selected dummy variables. Elasticities of monthly ridership were found to be $-0.233$ (by linear model) or $-0.245$
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(by logarithmic model) with respect to the real fare. Elasticities are smaller compared to those studies using UK data, but the fare elasticity of demand is still inelastic. With respect to cross-elasticities, Doi and Allen found that alternative modes are substitutes, so that positive elasticities were seen for real petrol price in both the linear model (0.113) and the logarithmic one (0.112). The results show that an increase in real bridge tolls would therefore increase the demand for passenger rail.

Beginning with Jones and Nichols, the earlier studies considered contemporaneous relationships only, so no lag terms were included in the model specification. Later studies observed that this instantaneous adjustment assumption is too restrictive and claimed that such an assumption oversimplifies the actual response of rail users. Owen and Phillips (1987), for example, developed a dynamic rail model for analysing the effect of various economic factors on the demand for inter-city rail patronage in the United Kingdom. They demonstrated that demand responses are not instantaneous and that the long-run responses are considerably different to those of the short run. To illustrate, they observed that the short-run elasticity of −0.69 and the long-run elasticity of −1.08 means that the long-run responses to price changes could be higher. This suggests that there is a potential for an increase in revenue in the short run, but that this policy might not be successful in the long-run because consumers can change their behaviour as a result of price changes over time.

Wardman (1997) noted that the literature existing at the time of his observation permitted only a very limited degree of elasticity variation. He questioned the constant elasticity specification assumed by previous researchers and introduced a range of functional forms to the demand model. His base model was the constant elasticity model. This was extended to three other functional forms, these being: (i) a constant elasticity competition model, (ii) an exponential model, and (iii) an exponential competition model. The purpose of these amendments was to allow for the elasticities to vary with the competitive position. Wardman’s estimation method is not purely time series because annual data was available for only the 1985/86 to 1990/91 period, so the analysis was based on a pooled data set of 764 observations of changes of demand on 160 non-London flows. With the exception of the constant elasticity model, all the other three models were estimated by non-linear least squares. The study’s results confirm that the initial conjecture was correct and that elasticities do vary significantly, so the constant elasticity assumption may not be accurate in certain cases.

Voith (1991) used US data on commuter rail ridership at community level to estimate the passenger rail demand function. The data cover 118 of 165 stations on the Southeastern Pennsylvania Transportation Authority (SEPTA) commuter system on an annual basis from 1978 through to 1991. Voith found that the impact of changes in fares and service levels occurs with a lag and that the long-run effects are roughly twice the short-run effects. Furthermore, a significant variation in results was observed across stations. Voith concluded that the demographic variables explain very little of the station-specific residual. His study implies that the primary measurable determinants of ridership are related to transportation policy rather than to the ancillary effects of changing demographics.

Finally, Chen (2007) used annual data from 1995–2002 to study the demand function from 46 origin stations to London. As a result of the shorter time period explored, the paper uses panel data model specifications to estimate the rail demand
function and elasticities. The specified demand equation consisted of three main explanatory variables: (i) average revenue per journey, (ii) central London employment, and (iii) regional gross value added per head. Fare elasticity was found to be \(-0.767\), which is very close to that of Jones and Nichols (1983). The employment elasticity is positive and indicates that the demand for rail will increase if central London employment increases. Overall, the study suggests that employment in central London is the main factor affecting demand.

### Australian Studies

The first Australian time-series study is found in a report prepared by CRA international. Conducted by Smart (2008), the full details of the study have not been published. From what can be ascertained, the study employed 30 years of data (1977–2006) to estimate the passenger rail demand function for Sydney. The dependent variable was the number of passenger journeys, while explanatory variables included the fare, unemployment rate, the number of rail stations, and Sydney’s population. A number of dummy variables were also used. According to the study, rail fare, unemployment and stations variables are statistically significant; that said, the low value of the Durbin-Watson statistics would appear to indicate that the statistical significance may be misleading.

Douglas and Karpouzis (2009) used 38 years of rail patronage data from 1969 to 2008 to estimate the passenger rail demand for Sydney’s metropolitan rail. Rail demand is regressed on four variables: (i) average real fare per trip, (ii) train kilometres run, (iii) metropolitan office employment, and (iv) real gross state product of NSW per capita. Dummy variables were included to capture any major incident such as train accidents, the Sydney Olympics in 2000, and the introduction of automatic fare collection in 1989. Compared to international time series studies, the model’s overall goodness of fit is not particularly satisfactory. For example, the coefficient of determination is only 0.35, which means that only 35 percent of the variation in passenger trip rates is explained by the estimated model. In addition, none of the parameters is significant at 5 percent level of significance, although all of them have the expected signs. Only the constant term is significant, thereby suggesting that the model might have been specified incorrectly. It also seems to suffer from omitted variable bias. Previous studies, mainly in the UK context, have found that many other variables, including seasonality and petrol price, exert an impact on demand. It is also unclear whether Douglas and Karpouzis tested for unit roots in the variables.

Odgers and Schijndel (2011) estimated and analysed passenger rail demand in the Melbourne metropolitan area over a twenty-seven year period, i.e. 1983-84 to 2009-10. The dependent variable is the annual passenger boardings per year on Melbourne’s trains. The models initially include six explanatory variables; however, among the reported multivariate specifications, three of them contain three independent variables, while two of them contain only two independent variables. Another significant aspect is that different forecasts based on different specifications are provided. For instance, the first regression model forecasts that the demand for rail in Melbourne will continue to grow, with an average annual growth of 7.7% per year forecast over the next three years. One issue is that the variables are expressed in original form, so the estimated coefficients cannot be interpreted directly as elasticities. Although elasticities can be calculated using mean values of relevant variables, the
paper does not provide mean values for all the variables chosen. This omission makes it difficult to compare the rail fare elasticities obtained in other studies. Another issue is that the authors made no attempt to identify non-linear effects—the international studies examined used double log transformations, something which at least enabled the researchers to capture some of the non-linear effects.

3. The model employed
This study aims to estimate passenger rail demand in Perth using annual data from 1983-2008 inclusive. Modern time series methods are used in the estimation. In particular, a cointegration approach is employed to estimate the long-run passenger rail elasticities, while an error correction model is used to estimate the short-run elasticities. There are two main cointegration methods in the modern time series literature: (i) single equation methods, and (ii) and system based methods. We use the single equation method. As explained in the literature review, a passenger rail demand model can be estimated by a single equation because price can be regarded as an exogenous rather than endogenous variable. The most popular among the single equation models is the two-step procedure proposed by Engle and Granger (1987).

The Engle and Granger method concentrated on variables that are integrated of order one. Hence, the first step of the method is to check for unit roots in each series before estimating the model. If a unit root exists in levels but not in the first differences, that particular series is considered non-stationary and is integrated of order one, I(1). Non-stationary data may lead to spurious results; hence, they either need to be transformed or tested further for a possible cointegration relationship. If they are cointegrated, the model can be estimated in levels, with statistical inferences based on these results. There are several unit root tests available, such as the Augmented Dickey Fuller (ADF) Test, the Philips Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. All three tests were conducted, but we have opted to report only the ADF test results to preserve space, and because all three methods led to the same conclusion. There are three variations of the ADF test specification: (i) without intercept or trend, (ii) with intercept but without trends, and (iii) with both the intercept and trend. The second specification is used because it seems more consistent with the data-generating process. The results are shown in Table 1 below. The results suggest that all seven variables are non-stationary in levels, but stationary in first differences.

<table>
<thead>
<tr>
<th>TABLE 1. Augmented Dickey-Fuller unit root test results</th>
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<tbody>
<tr>
<td>Variable</td>
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<tr>
<td></td>
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<tr>
<td>Lboarding</td>
</tr>
<tr>
<td>Lfare</td>
</tr>
<tr>
<td>Lfatality</td>
</tr>
<tr>
<td>Ifuel</td>
</tr>
<tr>
<td>Lkmrun</td>
</tr>
<tr>
<td>Lpci</td>
</tr>
<tr>
<td>Lpopulation</td>
</tr>
</tbody>
</table>

Once the unit root is conducted and the order of integration is established, the Engle and Granger cointegration method (1987) involves two main steps. The first is to estimate the best possible linear model and save the residuals of the estimated model. Following the literature (e.g. Jones & Nichols 1983; Chen 2007), we assume that the functional form given in equation (1) represents the relationship between the passenger rail demand ($Y_t$) and its factors ($X_i$).

$$Y_t = \beta_0 X_{t1}^{\beta_1} X_{t2}^{\beta_2} \ldots X_{tn}^{\beta_n} \epsilon_t$$  \hspace{1cm} (1)

Many studies have converted this non-linear function into a linear in parameters form using a double-log transformation. An advantage is that the estimated coefficients can directly be interpreted as elasticities. The estimable function is given in equation (2).

$$\log Y_t = \log \beta_0 + \beta_1 \log X_{t1} + \beta_2 \log X_{t2} + \ldots + \beta_n \log X_{tn} + \epsilon_t$$  \hspace{1cm} (2)

In this particular case, $Y$ is the number of boarding passengers at time $t$. There are six explanatory variables. The rail FARE is the control variable for the price in the demand function. A seemingly appropriate variable for price is the ticket price, but this turns out to be a very complex variable. There are many different ticket groups, and there are serious complications with respect to aggregating them into one value. Jones and Nichols (1983) used revenue per kilometre run as the fare variable. We use the same variable, with FARE being the label applied to it in the model. The coefficient of FARE is the own-price elasticity and is expected to be negative as per the law of demand.

The second explanatory variable is PCI, or the per capita income. This is to control for the income variable of the demand function. If it is assumed that the passenger rail service is a normal good, we should have a positive coefficient. The coefficient of CPI is the income elasticity of the rail demand function. Australian per capita income is used as a proxy for the per capita income of Perth.

The third variable is FUEL, which will be a control variable for the prices of other goods of the demand function. This is ascertained from the fuel price index over the period being studied. Car travel, in most cases, represents a substitute mode for rail. This means that, as the price of petrol increases, the demand for rail should rise, thereby resulting in a positive coefficient on FUEL. The coefficient on FUEL measures the cross-price elasticity.

The fourth variable is Perth’s POPULATION. The higher the population, the larger the demand should be. Hence, a positive coefficient is expected on POPULATION, although it is possible that the population and per capita income are linearly related, which may lead to statistically insignificant coefficients. Dropping a theoretically relevant variable, however, is not recommended in the econometrics literature because it may lead to more serious statistical problems (Gujarati & Porter 2010).

The fifth variable is the KMRUN, i.e., the number of kilometres run annually. A change in the number of kilometres run may occur due to an increase in the frequency run or an increase in the number of stations served. A positive relationship between the passenger rail demand and the KMRUN is expected. As detailed in Smart (2008), the directional relationship is particularly clear when the new stations were constructed and a new line serving an area that was previously not served by rail.
The last explanatory variable, FATALITY, is used to control for the passengers’ perception of rail’s overall quality. FATALITY is number of accidental deaths relating to the Australian rail sector. This, admittedly, may not be the best variable to represent this perception, but other variables, such as service quality, were not available for the entire sample investigated. FATALITY is therefore only a remote proxy for passenger perception of the service, as per Litman (2010).

Several sources provided the data. Boarding and revenue data were collected by the researchers as part of a funded project, population and fuel index data were obtained from the Australian Bureau of Statistics website, and the rest were sourced from the Bureau of Infrastructure, Transport and Regional Economics (BITRE). The exact model used to estimate the passenger rail demand is given in equation (3).

\[
\log \text{BOARDING}_t = \beta_0 + \beta_1 \log \text{FARE}_t + \beta_2 \log \text{PCI}_t + \beta_3 \log \text{FUEL}_t + \beta_4 \log \text{POPULATION}_t + \beta_5 \log \text{KMRUN}_t + \beta_6 \log \text{FATALITY}_t + \epsilon_t
\]  

(3)

Results of ADF unit root test carried out on the residuals from the above best linear equation indicated that the residuals series are stationary. This means that the passenger rail demand and its six explanatory variables are cointegrated, or share a long-run equilibrium relationship. Results are given in Table 2 below.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>−20.478</td>
<td>6.490</td>
<td>−3.155</td>
<td>0.005</td>
</tr>
<tr>
<td>LOG(FARE)</td>
<td>−0.808</td>
<td>0.109</td>
<td>−7.438</td>
<td>0.000</td>
</tr>
<tr>
<td>LOG(PCI)</td>
<td>0.060</td>
<td>0.142</td>
<td>0.422</td>
<td>0.678</td>
</tr>
<tr>
<td>LOG(Population)</td>
<td>1.704</td>
<td>0.570</td>
<td>2.991</td>
<td>0.008</td>
</tr>
<tr>
<td>LOG(FUEL)</td>
<td>−0.008</td>
<td>0.197</td>
<td>−0.043</td>
<td>0.966</td>
</tr>
<tr>
<td>LOG(KMRUN)</td>
<td>0.893</td>
<td>0.076</td>
<td>11.743</td>
<td>0.000</td>
</tr>
<tr>
<td>LOG(FATALITY)</td>
<td>−0.072</td>
<td>0.097</td>
<td>−0.739</td>
<td>0.469</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.985</td>
<td>Durbin-Watson stat</td>
<td>1.587</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.075</td>
<td>F-statistic</td>
<td>274.453</td>
<td></td>
</tr>
</tbody>
</table>

After estimating the long-run elasticities, an error correction model (ECM) was employed to obtain short-run elasticities and to validate the cointegration results reported in Table 2. ECM models are useful because they show both the short-run responses and the adjustment to the long-run equilibrium in a single specification (Enders, 2004). This structure is particularly important in rail demand modelling because travellers cannot change their behaviour instantaneously, while lags do occur in their decisions. Goodwin (1976) attributes this to habit persistence. Indeed, commuters are not very willing to alter their established routine, although ingrained habits may be eroded over time (Chen 2007). There are several methods to estimate the
ECM, and we use the Engle-Granger approach because the error correction term can easily be constructed using the already estimated long-run results.

Granger representation theorem states that, if variable X and Y are generated by error correction models, they are cointegrated. The dependent variable (BOARDING), together with its explanatory variables (FARE, CPI, POPULATION, FUEL, KMRUN, FATALITY) are I(1), while the first difference of these variables (ΔBOARDING, ΔFARE, ΔCPI, ΔPOPULATION, ΔFUEL, ΔKMRUN, ΔFATALITY) is I(0). The error correction model in terms of I(0) variables is given in equation (4). ECM contains variables in first differences and an error correction term (ECT). The ECT is the one period lag residuals obtained from the cointegrating model.

\[
\Delta \log \text{BORADING}_t = \alpha_0 + \alpha_1 \Delta \log \text{FARE}_t + \alpha_2 \Delta \log \text{PCI}_t + \alpha_3 \Delta \log \text{FUEL}_t + \alpha_4 \Delta \log \text{POPULATION}_t + \alpha_5 \Delta \log \text{KMRUN}_t + \alpha_6 \Delta \log \text{FATALITY} + \lambda \text{ECT} + \epsilon_t
\] (4)

Here, the parameter \( \alpha_1 \) is the short-run elasticity of passenger rail demand with respect to FARE, \( \alpha_2 \) is the short-run income elasticity of demand, and \( \alpha_3 \) is the short-run cross-price elasticity of demand. Other parameters can be interpreted similarly. After the own-price, income and cross-price elasticity, the most important other parameter is \( \lambda \), which represents the disequilibrium error. If the cointegrating relationship is correct, the estimate on the parameter \( \lambda \) has to be negative and statistically significant (Gujarati & Porter 2010). The parameter \( \lambda \) is called the adjustment parameter because it shows how much of the disequilibrium is corrected within one period. The results of the ECM are given in Table 3 below.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.073</td>
<td>0.042</td>
<td>-1.761</td>
<td>0.096</td>
</tr>
<tr>
<td>D(LFARE)</td>
<td>-0.768</td>
<td>0.095</td>
<td>-8.081</td>
<td>0.000</td>
</tr>
<tr>
<td>D(LPCI)</td>
<td>0.032</td>
<td>0.131</td>
<td>0.241</td>
<td>0.812</td>
</tr>
<tr>
<td>D(POPULATION)</td>
<td>6.571</td>
<td>2.004</td>
<td>3.278</td>
<td>0.004</td>
</tr>
<tr>
<td>D(LFUEL)</td>
<td>-0.185</td>
<td>0.156</td>
<td>-1.190</td>
<td>0.250</td>
</tr>
<tr>
<td>D(KMRUN)</td>
<td>0.639</td>
<td>0.098</td>
<td>6.530</td>
<td>0.000</td>
</tr>
<tr>
<td>D(FATALITY)</td>
<td>-0.120</td>
<td>0.059</td>
<td>-2.054</td>
<td>0.056</td>
</tr>
<tr>
<td>ECT</td>
<td>-1.000</td>
<td>0.220</td>
<td>-4.544</td>
<td>0.000</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.835</td>
<td></td>
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</tr>
<tr>
<td>S.E. of regression</td>
<td>0.057</td>
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4. Results

The cointegration results suggest that the fare exerts a negative and statistically significant effect on passenger rail demand. In specific terms, if the fare decreases by 10 percent, the demand will increase by 8 percent. This is an inelastic demand, so a price cut will not lead to an increase in the total revenue because the percentage decrease in price is greater than the percentage increase in demand. By the same logic, however, a price increase could potentially raise the total revenue. Our finding of an inelastic demand is consistent with existing studies on passenger rail demand, with the exception of Owen and Phillips (1987), who reported a slightly elastic (1.08) rail
demand. McGeehan (1984) confirmed the inelastic nature of passenger rail demand and reported that the price elasticity is \(-0.4\), which is smaller than that put forward by Jones and Nichols \((-0.64\). Doi and Allen (1986), using US data, observed that the price elasticity is \(-0.245\), a smaller elasticity compared to UK studies. Our Perth results suggest that Australian rail passengers are generally more responsive to price changes.

Among the other explanatory variables, two variables, the population and the number of kilometres run, are statistically significant at 5 percent. They both have produced the expected positive sign, so an increase in population should lead to a higher passenger rail demand. Since Perth’s population has been expanding, the rail industry looks set to experience rising demand levels. As expected, the higher the number of kilometres runs, the larger the demand for an urban rail service. It follows that expanding the network or else increasing service frequency could lead to an increase in passenger rail demand.

Among the other explanatory variables, the income of the prospective passengers has the expected positive impact on demand, though the coefficient is not statistically significant at conventional levels of significance. The statistical insignificance might be due to a possible linear relationship between the population variable and the per capita income variable. The safety and reliability indicator also has the expected negative sign, but is not statistically significant. This could be attributed to the fact that there is no safer alternative to passenger rail, even if it suffers from an unlikely rise in safety issues. The estimate on the fuel coefficient is neither statistically significant, nor has the expected sign.

Now, we are in a position to investigate the short-run elasticities of passenger rail demand and compare them with the long-run elasticities discussed above. Short-run elasticities are shown in Table 3 above. The fare elasticity of demand has the expected sign and is statistically significant at 1% level of significance. A 10 percent cut in the price leads to a 7.68% increase in the demand for passenger rail. This is lower than what we have seen for the long-run estimation. The results, however, are not utterly dissimilar, a common outcome in time series studies when annual or low-frequency data is used. Indeed, if higher-frequency data had been used, the difference between the short and long run could have been more substantial. This caveat aside, the overall finding is consistent with the theory, in addition to the results published in other empirical studies.

In the short run, consumers might be confined to certain contracts or obligations, so complete response to a price change will not be realised until the long run. So, in general, long-run price elasticities are larger than short-run elasticities. This outcome is supported by Fearnley and Bekken (2005), who suggest that the short-run demand response is only a fraction of the total long-run demand response. The reason for this is that, in the short run, passengers have fewer options compared to the long run, where passengers are able to respond more comprehensively by changing their job or dwelling location, or their vehicle ownership status. In addition, Owen and Phillips (1987) developed a dynamic rail model for analysing the demand for inter-city rail patronage in the UK. They observed that the short-run elasticity of \(-0.69\) and the long-run elasticity of \(-1.08\) means that the long-run responses to price changes could be higher. Among the other estimates, the estimate for the adjustment parameter was found to be negative and statistically significant. This confirms the long-run
relationship obtained via the Engle-Granger two-step approach. The magnitude of the estimate is particularly interesting, for it suggests that any disequilibrium is corrected within a year.

5. Conclusions
The Engle and Granger Two-Step method was used to estimate the long-run elasticities and an error correction model was employed to estimate the short-run elasticities of Perth’s passenger rail demand. The findings suggest that passenger rail demand is price inelastic, an outcome which supports earlier findings. If one assumes that all other variables remain constant, a decrease in the fare would not lead to a rise in total revenue. On the contrary, an increase in the fare leads to a rise in the total revenue. Although a price cut would not lead to a rise in the total revenue, it does lead to a rise in the rail patronage. To illustrate this point, a 10 percent fare price reduction, according to our findings, would increase the number of boardings by 8 percent in the long run, and 7.68 percent in the short run—though the total revenue would decrease. Hence, the choice should be made according to what is more important: (i) an increase in the total revenue (via improved fare-box recovery), or (ii) an increase in the patronage.

City population is the most significant and influential of the explanatory variables examined. On the surface, this is encouraging news for passenger rail in Perth, because the population is steadily rising, despite a recent slowing in growth (ABS 2011). This means that the demand for urban passenger rail services will increase in the coming years. Yet the short-run elasticities are smaller than the long-run elasticities, an observation which suggests that passengers have fewer options in the short run, while, in the long run, passengers are able to respond more comprehensively to changes in fare price and service quality by changing their personal circumstances. It must be acknowledged, however, that the results for the two types of elasticities are not dissimilar. Furthermore, the cross-price elasticity of the passenger rail demand is not statistically significant, which means that the study does not present statistical evidence to support the proposition that the passenger rail service and private car travel are substitutes. Likewise, it presents no statistical support to suggest that higher incomes lead to more passenger boardings.

Finally, passenger perception emerges as a potentially important factor in selecting the travel mode. As a result of the lack of a suitable variable to represent this factor, we had to rely on the remote proxy variable of fatality. Given that other studies suggest that the perception of the transport mode is a critical factor in determining the demand for any particular transport mode (e.g. Henry & Litman 2006; Litman 2008; Scheurer & Kroen 2005), it is hoped that a better perception variable will be available for use in future studies.

References
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