Aggregate and Disaggregate Analysis of Fuel Price and Interest Rate Impacts on Public Transport Demand

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1 Introduction

Rising auto fuel prices continue to be a major concern in terms of the affordability of transport to lower income families as well as the impacts this may have in increasing overloading on public transport. In 2006 the authors undertook a study to measure the impacts of fuel price on public transport patronage (Currie and Phung 2006). This study established statistically reliable measures of the cross elasticity of public transport demand to fuel prices in Melbourne. While this research disaggregated fuel price impacts on patronage by transit mode (rail and bus) it was hoped that future research would expand the scope of the research to examine influences by individual service groups as well as considering the effects in other cities. In this way, the dynamics, causal factors and impacts of these might be better understood.

New research has suggested that home loan interest rates may also be an important influence on both patronage of public transport and also on the vulnerability of low income families on the fringes of cities (Dodson and Sipe 2006). This research has suggested that interest rates as well as fuel prices might be worth investigating in terms of influence on public transport patronage.

This paper summarises a research project aimed at establishing statistically reliable measures of the impacts of both auto fuel price increases and home loan interest rates on public transport demand. The project covers public transport in Melbourne, Brisbane and Adelaide and also disaggregates the results by individual mode and service groups. A central aim of the work is to disaggregate patronage into groups so as to compare fuel price impacts between modes, service groups and types of trips. In this way fuel price impact may be better understood.

Section 2 of this paper presents a research background to the project. Section 3 describes the methodology applied to measure fuel price and interest rate impacts including a summary of the data inputs used. Section 4 presents the results of the aggregate city wide analysis for Melbourne, Brisbane and Adelaide. This includes some disaggregate analysis by mode and time period plus service groups in Brisbane and Adelaide. Section 5 summarises the findings of the disaggregate results by rail service group in Melbourne while Section 6 summarises the disaggregate results by bus service group in Melbourne. Section 7 concludes the papers including a discussion of the key findings and some suggestions as to the major factors driving the impacts found.

2 Research Context

The impact of auto fuel price on public transport demand has most commonly been measured in terms of the cross elasticity of demand (*e*). A meta study of auto fuel price cross elasticities was undertaken by the authors in Australia (Currie and Phung 2006) and also more recently in North America (Currie and Phung 2007). This research found that:

- A longer term value of *e* in an Australian context would be around 0.15 with a range of between 0.07 and 0.30 (based on Wallis and Schmidt 2003). In simple terms a value of *e* of 0.15 implies that a 10% increase in fuel price will increase public transport patronage by about 1.5%.
- There is some evidence that peak period values of *e* might be two to three times larger than off peak values of *e*. This may suggest that fuel prices might be a cause of recent peak period overloading on public transport occurring in Australian cities.
- Values of *e* tend to be higher where public transport patronage is a lower share of travel

The Melbourne based research (Currie and Phung 2006) established system wide (rail and bus excluding tram) aggregate value of *e* of 0.22 which is at the higher end of previous research evidence. Heavy rail values at 0.48 were established. Values for bus were found to be statistically indifferent from zero. Tram analysis was not pursued because ticket validations were shown to be a poor representation of tram patronage.

Recent research has suggested that auto fuel prices in combination with home loan interest rates might be a major driver of poverty in urban fringe Australia (Dodson and Sipe 2006). In addition to highlighting the impacts of rising fuel prices this research also highlights the knock on effects these can have on inflation and also subsequently, through National economic management measures, higher home loan interest rates. The combination of fuel prices and home loan interest rate increases is thought to cause financial stress to Australian families:

> *"Australian households are currently highly indebted largely via mortgages for house purchase. Many of these mortgages have been obtained during a marked period of house price inflation ….. The high prices paid for recent house purchases and the level of gearing to which some households are now exposed raises questions about the impact of future increases in petrol prices or interest rates."* (Dodson and Sipe 2006)

This research created a spatial index of 'vulnerability' to both fuel price rises and home loan interest rate rises. Termed the 'VAMPIRE' index its application to several major Australian cities demonstrated that fringe urban Australia is most at risk to these influences.

3 Methodology

3.1 Overview

The approach adopted examined the direct impacts of fuel price and interest rates on transit usage. The raw data examined was monthly data which required that the modelling include some allowance for seasonality impacts on transit patronage. The approach used simplifies the real world influences on transit demand. In practice the level of fares, changes in service levels and other factors such as traffic congestion affect transit usage. The simplified approach assumes these other factors are negligible and that auto fuel price and interest rates are the major driver of transit demand. This approach also omits consideration of feedback issues such as any raising of fares associated with higher fuel costs and any follow on impacts which this may have on demand. Overall these issues were considered minor issues since fare changes are generally tied to CPI increases and there are limited service level changes on the networks examined during the analysis period. Nevertheless the omission of these influences could act to affect the values for cross elasticities obtained. The approach included consideration of population growth effects and also inflationary effects over the periods analysed (using CPI adjustments to raw fuel prices).

3.2 Analytical Approach

The general approach used was to assemble data on fuel prices, interest rates and patronage on a monthly basis and to build a regression model which includes an allowance for seasonality on patronage.

Arc elasticities were calculated as follows:

$$e = \frac{\partial Q}{\partial P} \times \frac{P}{Q} = \frac{\partial \ln(Q)}{\partial \ln(P)} \qquad \textbf{[Formula 1]}$$

Where:

- e = elasticity
- P = real auto fuel price
- Q = per capita validations

A regression elasticity model was developed with the following form:

$$\ln(Q_t) = \alpha + e_{FP} \ln(P_t) + e_{IR} IR_t + \sum_{i=1}^{11} \beta_i M_i + \varepsilon_t \qquad \textbf{[Formula 2]}$$

Where:

- α = Intercept parameter – estimated in the model
- e_{FP} = Fuel price elasticity
- e_{IR} = Interest rates elasticity
- IR = Interest rates
- β = Parameter for each monthly dummy variable
- M = Monthly dummies, takes a value of 1 in the corresponding month and 0 otherwise. Base month is December, where it takes values of 0 for all dummies.
- ε = Error term
- i = Month index – 1 to 11, December is excluded as it is the base month i.e. all monthly estimates are relative to December.
- t = Time index

The monthly dummy variables enable seasonality to be modelled. The estimation method follows that of a stepwise approach, beginning with all the variables in the regression model (formula 2), then removing any insignificant regressors and repeating the regression. Note that as a result of the high correlation between interest rates and fuel prices, caution was taken when interpreting the individual p-values (see below on an a brief explanation of multicollinearity and methods of detecting and rectifying the problem).

The following tests/measures were used to check model validity and parameter significance. All statistical tests were performed at the 5% level of significance:

- Logic test : this checked whether the estimated coefficients were consistent with expectations i.e. positive or negative values
- Coefficient of Determination (R^2): This measures the percentage of variation in the response (dependent) variable by the group of explanatory (independent) variables. Models with R^2 closer to 1.0 represent a better fit. When comparing models with a different number of parameters, the adjusted R^2 is used instead, as it takes into account the number of parameters.
- Significance – F: reports the probability that the effect of the regressors on the dependent variable as a whole is statistically not different from 0. The usual cut-off mark is 0.05, i.e. a sig-F value greater than 0.05 would conclude that the regressors as a whole have no effect on the dependent variable.
- Individual p-values: reports the probability that the estimated coefficient is not different from 0. Cut-off mark is again 0.05.

Autocorrelation was ignored as it was considered to have a negligible effect; the majority of the variation was explained by seasonality.

Since interest rates and fuel prices are highly correlated, this causes issues of multicollinearity [MC], however it should be noted that MC's effect is lessened as the sample size increases (Gujariti 2003). Therefore, interest rates were included only for the rail analysis with special caution taken in determining the significance individual parameters.

A further indirect effect caused by the inclusion of interest rates in the analysis is related to the fact that interest rates and CPI are by definition related. Interest rates are a macro economic means of addressing inflation which is measured by CPI. CPI is used to adjust fuel prices in this analysis to create 'real' changes in fuel prices adjusting for inflation. By including interest rates as well as 'real' fuel prices into the analysis there is a possible theoretical problem whereby wider interest rates effects are impacting on more than one explanatory variable. After some consideration no direct adjustments have been made to the approach to adjust for these effects other than careful assessment of the significance of parameters to consider multicollinearity effects. To some extent any analysis of interest rates must accept wider knock on economic influences.

Issues brought on by MC include conflicting T and F statistics that is, parameters may fail the T-test for individual significance but as a group they have superior F-statistics, i.e. the group affect is not 0. Therefore, T-statistics and individual p-values may not be reliable in the presence of MC. Note that MC does not affect F-tests; they only affect T-tests. Therefore a range of techniques to test for individual significance were used including:

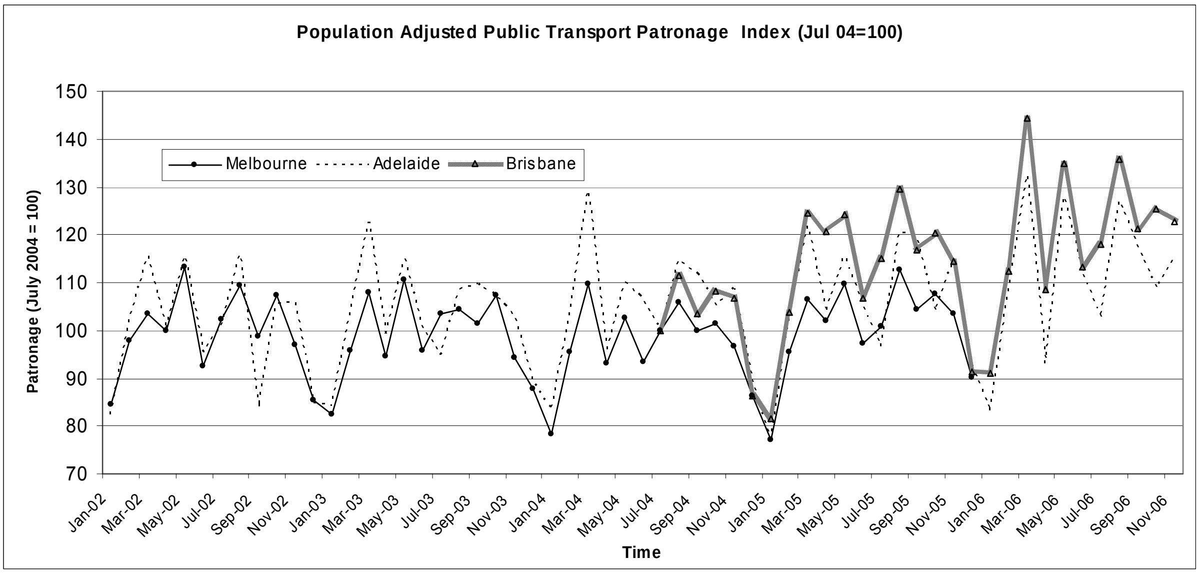
- Joint significance F-test: an F-test was utilised when both regressors had individual p-values greater than 0.05. If the joint significance of both regressors failed the F-test then it was concluded that both regressors did not affect patronage levels. However, rejecting the null hypothesis that the joint significance is 0, this would suggest that at least one of the regressors does have an affect.
- Remove regressors one-by-one: Following from the joint significance test, we would remove each regressor individually to observe the effect it has on the other regressor and the adjusted R^2. If the regressor was indeed insignificant then, removing it will not have much affect of the adjusted R^2, and the remaining regressor's coefficient will not vary significantly. If, however, upon removal of the regressor causes great changes to the adjusted R^2 and the other regressor, then that would suggest it was significant but as a result of MC, the p-value was unreliable.

The time period for the regression analysis is 3 years (Melbourne) 3.5 years (Adelaide) and 2.5 years (Brisbane) (see next section). The approach adopted is to measure impacts throughout this period i.e. to measure elasticities for the whole of the period. This tends to imply that elasticity estimates fit into a medium run set of values in 'conventional' economic elasticity analysis period terms. For example Wallis and Schmidt (2003) differentiate between short run elasticity measures (6-12 months), medium run (2 to 7 years) and long run (8 plus years). The approach adopted provides values which are at the short end of the medium run elasticity term.

3.3 Source Data

The aggregate city based analysis used raw patronage data for Melbourne (Jan02 – Dec05), Brisbane (July04 – Nov06) and Adelaide (Jan02 – Nov06). This data was obtained from Metlink (Melbourne), Translink (Brisbane) and The South Australian Government (Adelaide). Data in both the aggregate (city wide) and disaggregate (mode and route catchments) analysis were adjusted for population change effects of the respective cities. Population data was obtained from Australian Bureau of Statistics (ABS (Australian Bureau of Statistics) 2006b). Figure 1 illustrates the trends in population adjusted patronage by city during these periods.
Nominal fuel price data was obtained from the Australian Automobile Association and were adjusted for inflation effects utilising CPI data for the relevant cities, the CPI data was also obtained from the ABS(ABS (Australian Bureau of Statistics) 2006a). Interest rate data was

obtained from the Reserve Bank of Australia. A plot of the real fuel prices in the respective cities are shown in Figure 1.



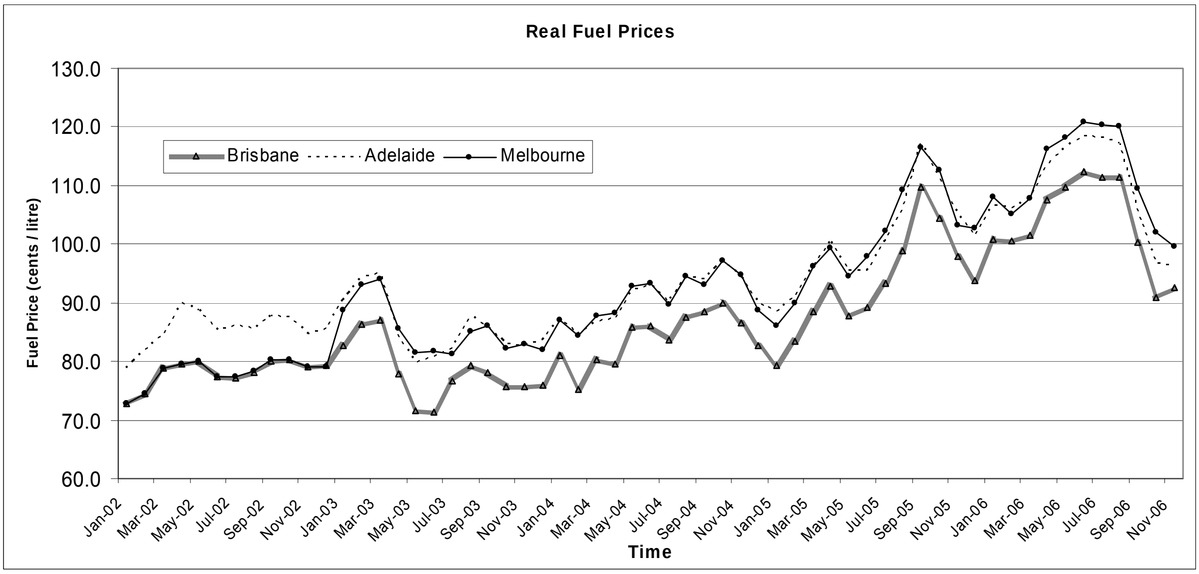


Figure 1: Population Adjusted Patronage and Real Fuel Prices – Melbourne, Brisbane and Adelaide

This shows that:

- Between January 2003 and January 2006 real fuel prices have increased by around 25% in Melbourne and Adelaide. The increase is less in Brisbane although this size of change depends much on the start and end months when changes are to be calculated
- Fuel prices in Brisbane are between 5% and 12% cheaper than in Adelaide and Melbourne due to differing state Government approaches to taxation on fuel.
- Between January 2003 and December 2005 population adjusted patronage increased by 9% in Melbourne and 10% in Brisbane. The Brisbane data shows a 23% increase in patronage between July 2004 and November 2006. Clearly seasonality dominates the patronage data but a general trend towards population adjusted growth is apparent.

4 City Based Results

4.1 Aggregate Citywide Results

Table 1 shows the aggregate city based results for total system modelling of fuel price and interest rate impacts on patronage. Values of *e* in the fuel prices and interest rates column show the cross elasticity estimate, the statistical parameter 'p-value' in parenthesis and the 95% confidence limits in brackets. Where confidence limits are not provided; this is due to the presence of multicollinearity which is also indicated with an [MC] indicator.

Table 1: Aggregate Elasticity Results – Melbourne, Brisbane and Adelaide

City	Interest Rates	Fuel Prices	Modelling Parameters	Explanatory Parameters	Statistics ($\bar{R}^2$) [sig-F]
Melbourne	-	0.22 (0.000) [0.10, 0.33]	Intercept + Seasonality	Fuel prices	(0.933) [0.000]
Adelaide	-	0.22 (0.000) [0.12, 0.32]	Intercept + Seasonality	Fuel prices	(0.815) [0.000]
Brisbane	0.14 (0.001) [0.07, 0.21]	0.14 (0.137) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.869) [0.000]

This indicates that:

- Melbourne and Adelaide analysis found fuel price elasticities of 0.22. Interest rate impacts were not statistically significant for these cities.
- Brisbane however has values for both fuel (0.14) and interest rates (0.14) although multicollinearity problems were found. This means fuel and interest rates were correlated and hence it was unclear which factors were driving patronage growth. The p-values for Brisbane fuel prices were greater than the 5% significance level; however, as a result of multicollinearity, this is expected. Individual p-values are often over-inflated in the presence of multicollinearity and therefore are unreliable, a combination of the adjusted R^2 and F-tests are used to determine the significance of an individual parameter instead.
- All other computed values were significant at the 5% significance levels.

4.2 Transit Mode Disaggregation - Citywide Results

Table 2 shows the result of the transit mode analysis for each of the cities studied. These results indicated that:

- For Melbourne only fuel price was significant. Rail values of *e* for fuel at 0.48 were established. This was consistent with previous study findings (Currie and Phung 2006)
- Interest rates were a far more significant influence in Brisbane. On the South East busway interest rates were the only significant factor (*e* interest rates =0.34) while fuel price was not significant. For other Brisbane transit modes, fuel price was a greater influence than interest rates.
- Rail vs bus results contrast between Melbourne and Brisbane/Adelaide. In Melbourne rail has a higher fuel price *e* than bus, which is not significant i.e. zero. While in Brisbane/Adelaide fuel price values for *e* for rail was less than (or zero) while bus values were high. [Note that rail values in Adelaide had multicollinearity issues].

Table 2: Mode Disaggregate Elasticity Results – Melbourne, Brisbane and Adelaide

Mode	Interest Rates	Fuel Prices	Modelling Parameters	Explanatory Parameters	Statistics ($\bar{R}^2$) [sig-F]
Melbourne (Jan. 2002 to Dec. 2005)					
Rail	0.00	0.48 (0.000) [0.34, 0.61]	Intercept + Seasonality	Fuel prices	(0.866) [0.000]
Bus	0.00	0.00	Intercept + Seasonality	None	(0.954) [0.000]
Total Public Transport	0.00	0.22 (0.000) [0.10, 0.33]	Intercept + Seasonality	Fuel prices	(0.933) [0.000]
Adelaide (Jan. 2002 to Nov. 2006)					
Rail	0.04 (0.128) [MC]	0.09 (0.267) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.759) [0.000]
North East Busway	-0.07 (0.025) [-0.12, -0.01]	0.28 (0.003) [0.10, 0.46]	Intercept + Seasonality	Interest rates + Fuel prices	(0.816) [0.000]
Other Bus	0.00	0.23 (0.000) [0.11, 0.35]	Intercept + Seasonality	Fuel prices	(0.794) [0.000]
Total Bus	0.00	0.21 (0.000) [0.10, 0.31]	Intercept + Seasonality	Fuel prices	(0.825) [0.000]
Total Public Transport	0.00	0.22 (0.000) [0.12, 0.32]	Intercept + Seasonality	Fuel prices	(0.815) [0.000]
Brisbane (July. 2004 to Nov. 2006)					
South Eastern Busway	0.34 (0.000) [0.28, 0.41]	0.00	Intercept + Seasonality	Interest rates	(0.914) [0.000]
Brisbane Transport	0.15 (0.001) [0.07, 0.23]	0.26 (0.019) [0.05, 0.47]	Intercept + Seasonality	Interest rates + Fuel prices	(0.905) [0.000]
Private Bus	0.07 (0.189) [MC]	0.31 (0.044) [0.01, 0.61]	Intercept + Seasonality	Interest rates + Fuel prices	(0.854) [0.000]
Total Bus	0.17 (0.000) [0.09, 0.25]	0.25 (0.026) [0.03, 0.46]	Intercept + Seasonality	Interest rates + Fuel prices	(0.903) [0.000]
Ferry	0.23 (0.000) [0.12, 0.34]	0.24 (0.093) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.780) [0.000]
Rail	0.00	0.00	Intercept + Seasonality	Interest rates + Fuel prices	(0.866) [0.000]
Total Public Transport	0.14 (0.001) [0.07, 0.21]	0.14 (0.137) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.869) [0.000]

4.3 Time Period Disaggregation – Brisbane Results

Patronage data provided by Brisbane authorities included a separate indication of monthly patronage by weekday peak and off peak periods. This enabled a separate computation of elasticities for peak and off peak. Table 3 shows the result of this analysis.

Table 3: Disaggregate Time Period Elasticity Results – Brisbane

Weekday Time Period	Interest Rates	Fuel Prices	Modelling Parameters	Explanatory Parameters	Statistics ($\bar{R}^2$) [sig-F]
Brisbane - All Public Transport Modes (July. 2004 to Nov. 2006)					
Peak	0.00	0.00	Intercept + Seasonality	None	(0.681) [0.000]
Off-Peak	0.12 (0.020) [0.02, 0.22]	0.19 (0.137) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.871) [0.000]
South East Busway					
Peak	0.35 (0.000) [0.27, 0.43]	0.00	Intercept + Seasonality	Interest rates	(0.898) [0.000]
Off-Peak	0.29 (0.000) [0.23, 0.35]	0.00	Intercept + Seasonality	Interest rates	(0.901) [0.000]
Brisbane Transport					
Peak	0.23 (0.014) [0.05, 0.40]	0.38 (0.103) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.622) [0.003]
Off-Peak	0.10 (0.016) [0.02, 0.18]	0.16 (0.130) [MC]	Intercept + Seasonality	Interest rates + Fuel prices	(0.889) [0.000]
Private Bus					
Peak	0.33 (0.001) [0.16, 0.50]	0.00	Intercept + Seasonality	Interest rates	(0.640) [0.002]
Off-Peak	0.00	0.33 (0.009) [0.09, 0.56]	Intercept + Seasonality	Fuel prices	(0.835) [0.000]
Ferry					
Peak	0.24 (0.011) [0.06, 0.41]	0.00	Intercept + Seasonality	Interest rates	(0.542) [0.008]
Off-Peak	0.26 (0.000) [0.15, 0.37]	0.00	Intercept + Seasonality	Interest rates	(0.696) [0.000]
Rail					
Peak	0.00	0.00	Intercept + Seasonality	None	(0.703) [0.000]
Off-Peak	0.00	0.00	Intercept + Seasonality	None	(0.919) [0.000]

Table 3 suggests that:

- Overall, fuel price and interest rate impacts are only influential at off peak times. Peak elasticity values were zero for both factors.
- For the Bus operator Brisbane Transport (BT), peak fuel price values of *e* were twice off peak values. Interest rates, which were also an influence on BT patronage were also higher in the peak, however there are multicollinearity effects here.
- For Private Buses fuel prices were only influential with off-peak ridership while interest rates were only influential in the peak.
- For the South East Busway, only interest rates were significant. Impacts were higher in the peak than the off peak.
- A similar pattern was found for Ferry while for rail no significant relationships were established.

5 Disaggregate Melbourne Rail Results

A separate disaggregate analysis of Melbourne rail services was undertaken using ticket validation data obtained from Metlink for a period of four years from January 2002 to February 2006. Three separate analysis are reported including:

- An analysis by rail service groups (using ticket validations at selected rail stations)
- An analysis for stations where park and ride to rail was significantly high.
- An analysis by travel distance (using validation data for separate ticket types)

5.1 Rail Corridor Group Analysis

Table 4 shows the results of the analysis undertaken by grouping rail station validations into line group corridors.

Table 4: Disaggregate Rail Group Results – Melbourne

Line/Group	Interest Rates	Fuel Prices	Modelling Parameters	Explanatory Parameters	Statistics ($\bar{R}^2$) [sig-F]
Aggregate	0.00	0.48 (0.000) [0.34, 0.61]	Intercept + Seasonality	Fuel prices	(0.866) [0.000]
Flagstaff – Jolimont	0.00	0.76 (0.000) [0.52, 0.99]	Intercept + Seasonality	Fuel prices	(0.795) [0.000]
Spencer Street – Richmond	0.17 (0.000) [0.10, 0.24]	0.55 (0.002) [0.21, 0.89]	Intercept + Seasonality	Interest rates + Fuel prices	(0.751) [0.000]
East Camberwell – Belgrave / Lilydale	-0.19 (0.000) [-0.29, -0.09]	0.80 (0.002) [0.32, 1.28]	Intercept + Seasonality	Interest rates + Fuel prices	(0.607) [0.000]
East Richmond – Glen Waverley / Alamein	-0.12 (0.001) [-0.19, -0.05]	0.59 (0.001) [0.27, 0.91]	Intercept + Seasonality	Interest rates + Fuel prices	(0.814) [0.000]
Hawksburn – Pakenham / Cranbourne	0.04 (0.018) [0.01, 0.08]	0.50 (0.000) [0.33, 0.68]	Intercept + Seasonality	Interest rates + Fuel prices	(0.898) [0.000]
Glen Huntly – Frankston	0.00	0.50 (0.000) [0.31, 0.68]	Intercept + Seasonality	Fuel prices	(0.661) [0.000]
South Yarra – Sandringham	0.00	0.24 (0.003) [0.09, 0.40]	Intercept + Seasonality	Fuel prices	(0.760) [0.000]
South Kensington – St. Albans / Williamstown / Werribee	0.00	0.55 (0.000) [0.42, 0.68]	Intercept + Seasonality	Fuel prices	(0.850) [0.000]
Kensington – Broadmeadows	0.00	0.39 (0.000) [0.20, 0.57]	Intercept + Seasonality	Fuel prices	(0.707) [0.000]
North Melbourne – Upfield	0.07 (0.006) [0.02, 0.11]	0.37 (0.002) [0.14, 0.59]	Intercept + Seasonality	Interest rates + Fuel prices	(0.795) [0.000]
West Richmond – Epping	0.00	0.57 (0.000) [0.40, 0.73]	Intercept + Seasonality	Fuel prices	(0.782) [0.000]
Westgarth – Hurstbridge	0.00	0.41 (0.000) [0.26, 0.56]	Intercept + Seasonality	Fuel prices	(0.831) [0.000]

This indicates that:

- In general fuel prices were significant while interest rate results were either insignificant or of a minor influence

- The Belgrave/Lilydale line had the highest fuel based value of *e* at 0.80 while the smallest (but still significant) effects were on the Sandringham line (fuel price *e*= 0.24).
- CBD stations, which are commonly associated with commuter travel had above average values for fuel price (*e* = 0.76 and 0.55).
- Other lines with above average values were (in order) the Glen Waverley, Alamein lines, Epping, Werribee/Williamstown, Pakenham, Cranbourne and Frankston lines.

5.2 Park and Ride Station Analysis

Table 5 shows the results of the analysis undertaken on rail stations known to have a high volume of park and ride users.

Table 5: Disaggregate Park and Ride Station Results – Melbourne

Line/Group	Interest Rates	Fuel Prices	Modelling Parameters	Explanatory Parameters	Statistics ($\bar{R}^2$) [sig-F]
Aggregate Rail Including All Stations	0.00	0.48 (0.000) [0.34, 0.61]	Intercept + Seasonality	Fuel prices	(0.866) [0.000]
Park and Ride Stations	-0.08 (0.004) [-0.14, -0.03]	0.55 (0.000) [0.29, 0.81]	Intercept + Seasonality	Interest rates + Fuel prices	(0.838) [0.000]

In general park and ride stations had a slightly higher fuel price values for *e* (0.55 compared to 0.48 overall). A small negative interest rate impact was also found for park and ride stations in aggregate.

5.3 Short/Long Distance Rail Ticket Analysis

Patronage data for Melbourne rail services included ticket type information. Some ticket types e.g. zone 2 or zone 3 only tickets plus the short distance trip tickets were in general associated with shorter distance travel (from around 1-2kms to about 8kms in length). Other tickets e.g., the ‘zone 1+zone 2+zone 3’ ticket were much longer distance trips (generally about 20-30 kms in length). Table 6 shows the result of the analysis undertaken on shorter and longer distance rail ticket types.

Table 6: Disaggregate Short vs Long Distance Ticket Type Results – Melbourne

Line/Group	Interest Rates	Fuel Prices	Modelling Parameters	Explanatory Parameters	Statistics ($\bar{R}^2$) [sig-F]
Aggregate Rail Including All Stations	0.00	0.48 (0.000) [0.34, 0.61]	Intercept + Seasonality	Fuel prices	(0.866) [0.000]
Aggregate Short Distance Trips	-0.11 (0.000) [-0.17, -0.05]	0.27 (0.045) [0.01, 0.54]	Intercept + Seasonality	Interest rates + Fuel prices	(0.769) [0.000]
Aggregate Long Distance Trips	0.00	0.74 (0.000) [0.52, 0.97]	Intercept + Seasonality	Fuel prices	(0.642) [0.000]

Fuel price effects are more almost three times as large for longer distance trips than short distance trip tickets (0.74 to 0.27). The shorter distance trips had a small significant interest rate impact however this was negative i.e. interest rate increases would decrease rail patronage.

6 Disaggregate Melbourne Bus Results

A separate disaggregate analysis of Melbourne bus services was undertaken using ticket validation data obtained from Metlink for a period of two years from July 2004 to July 2006. The aggregate bus analysis had established that interest rates were not influencing bus services in Melbourne (see earlier). Hence the regression analysis examined only fuel price effects. Table 7 shows the results of this analysis which was disaggregated into spatial groups of routes and also for shorter and longer distance services. These spatial groups included 'fringe feeder' routes which are long distance bus routes operating from outlying rural/urban fringe Melbourne providing connections into the urban areas (e.g. the Melton to Sunshine bus route).

Table 7: Disaggregate Bus Route Group Results – Melbourne

Group	Fuel Price *e*	P-value	R^2	Lower 95%	Upper 95%
City to Doncaster	0.19	0.011	0.963	0.05	0.33
Bayside to Sunshine	*0.01*	*0.833*	0.948	Statistically indifferent from 0 at 5% significance level	
Altona to City	*-0.17*	*0.106*	0.813	Statistically indifferent from 0 at 5% significance level	
Port Melbourne to City	0.56	0.000	0.903	0.36	0.76
City to Latrobe	0.34	0.005	0.973	0.13	0.55
Gardenvale to City	0.30	0.051	0.747	0.00	0.60
City Routes (aggregate)	**0.13**	**0.024**	**0.960**	**0.02**	**0.24**
Fringe Northwest	*-0.01*	0.854	0.919	Statistically indifferent from 0 at 5% significance level	
Fringe Outer Eastern Region	0.23	0.010	0.902	0.07	0.39
Mornington Peninsula	0.20	0.017	0.768	0.04	0.36
Fringe Feeders (aggregate)	**0.16**	**0.005**	**0.891**	**0.06**	**0.27**
SmartBus	**0.21**	**0.003**	**0.963**	**0.08**	**0.33**
NightRider	***0.21***	***0.670***	**0.462**	**Statistically indifferent from 0 at 5% significance level**	
Metro Short (western)	0.19	0.010	0.935	0.05	0.32
Metro Short (northern)	*0.04*	*0.597*	0.955	Statistically indifferent from 0 at 5% significance level	
Metro Short (eastern)	*-0.53*	*0.079*	0.706	Statistically indifferent from 0 at 5% significance level	
Metro Short (outer eastern)	*-0.07*	*0.271*	0.966	Statistically indifferent from 0 at 5% significance level	
Metro Short (southeastern)	*-0.10*	*0.386*	0.852	Statistically indifferent from 0 at 5% significance level	
Metro Short Routes (<7km)	***0.07***	***0.215***	**0.960**	**Statistically indifferent from 0 at 5% significance level**	
Metro Long (northern)	0.25	0.000	0.940	0.13	0.37
Metro Long (eastern)	0.61	0.000	0.956	0.45	0.78
Metro Long (southeastern)	-0.14	0.040	0.966	-0.28	-0.01
Metro Long Routes (>25km)	**0.32**	**0.000**	**0.967**	**0.20**	**0.44**
Other Metro Routes	*0.10*	*0.069*	0.948	Statistically indifferent from 0 at 5% significance level	
Commuter Aggregate	**0.13**	**0.020**	**0.948**	**0.02**	**0.23**
School Routes	*-0.49*	*0.313*	0.867	Statistically indifferent from 0 at 5% significance level	
Bus Aggregate	**0.16**	**0.037**	**0.959**	**0.01**	**0.30**

This indicates that:

- In aggregate, bus values of fuel price for *e* was 0.16 although the p-values for certain estimates were of a concern, this may have been due to the small sample size.
- The highest bus values for *e* were for longer distance metropolitan bus routes (0.32), aggregate fringe feeders (0.16) in particular the outer eastern suburbs (0.23) and also for Smart Bus routes (0.21). Smart bus routes are 'higher quality' route bus services

which are adopting bus rapid transit system principles to on road bus services. In general these routes are also long distance routes (over 25 kms in length).

- The Eastern long distance bus routes had particularly high (and significant) values for *e* (at 0.61)
- A number of city bus routes had significant values for *e*; Port Melbourne to City (0.56), Latrobe to City (0.34) and Gardenvale to City (0.30)
- Other bus route groups which had above average values for *e* were:
  - City to Doncaster routes, Melbourne's largest single CBD commuter bus route group, with a value for *e* at 0.19
  - City to Latrobe (0.34) and Gardenvale to City (0.30)
  - Metro Long Distance routes (Northern)
- In aggregate city bus routes and the majority of shorter distance bus routes had below average values for *e*.
- School bus routes had no statistically significant values.

7 Discussion

This section theorises about the causal factors which are creating the impacts found in the research. It is structured around the major finding areas.

7.1 Aggregate City Impacts of Interest Rates and Fuel Prices

Public transport ridership in Brisbane has been found to be influenced by both interest rates and fuel prices. However in Melbourne and Adelaide, only fuel prices have a significant influence. Also the research has established higher values of fuel price elasticities in Melbourne and Adelaide compared to Brisbane.

The fact that Brisbane has lower fuel prices than those in Melbourne/Adelaide (about 5-13% less in Figure 1) explains why fuel price cross elasticities are lower in Brisbane.

Discussions with Queensland authorities suggested home loan affordability might explain the greater impact of interest rates in Brisbane. To investigate this data on median house prices and annualised incomes in each state were identified (Table 8). A ratio of house price to income is computed.

Table 8: Relative Home Affordability – Melbourne, Brisbane and Adelaide

	Brisbane	Melbourne	Adelaide
Median House Price ($000)	316.09	323.35	271.35
Average Annual Income (State) ($000)	36.98	39.95	35.56
Ratio of Income to Price	8.55	8.09	7.63

Source: ABS 6302.0 Average Weekly Earnings, Australia, 6416.0 House Price Indexes: Eight Capital Cities Feb 2002 to Nov 2006

This indicates that Brisbane has a higher ratio of income to house price than either Melbourne or Adelaide. It suggests that housing affordability might well explain why Brisbane public transport patronage is more affected by home loan interest rates. This combined with lower fuel prices could be generating the effects measured.

The aggregate city results found elasticities in Melbourne and Adelaide which were the same (fuel price elasticity = 0.22). What is interesting about this finding is that these cities are quite dissimilar. Melbourne has a share of journey to work travel (2001) which is higher than that for Adelaide; 13.2% and 9.2% respectively. The research literature suggests that elasticities can be higher in cities where mode share is low (Wallis and Schmidt, 2003). However this view was not supported by a review of fuel price cross elasticities (Currie and Phung, 2006). It is also not supported by these equivalent findings in cities of different scale. Brisbane has a journey to work (2001) share which is higher than Melbourne (13.6%) however it total all purpose mode share is thought to be lower (3.7% compared to 7.1% for 1995/6, Kenworthy and Laube, 2001). It is not possible to see a particular relationship between mode share and estimated elasticities in these results.

7.2 Disaggregate Mode Impacts by City

The analysis (Table 2) established that Melbourne rail had high fuel price impacts (e=0.48) while Melbourne bus impacts were small and statistically insignificant. This contrasts strongly with Brisbane and Adelaide results where rail impacts were small or insignificant and bus impacts were high. In Adelaide and Brisbane the effects were particularly high on the busway corridors.

One theory that might explain these contrasts is that bus and rail services in Melbourne are very different to services in Brisbane/ Adelaide. Melbourne bus services operate in mainly middle and outer suburban areas and act as feeder services to rail (and tram). Melbourne has one of the largest tram systems in the world (Currie and Shalaby 2007) and this acts to provide the principle CBD feeder function from middle and outer suburbs. Melbourne bus services, apart from a minor share of routes, do not perform a CBD access function. As a result much bus ridership in Melbourne does not involve commuting ; only 9% of bus trips in Melbourne are home based work trips compared to 49% for rail and 39% for tram (Department of Infrastructure 2005). In contrast the bus systems in Brisbane and Adelaide perform the CBD access function which tram systems do in Melbourne.

A related theory also explains why the Adelaide and Brisbane busways may have Melbourne rail like fuel elasticities. The busways represent what are increasingly being termed ‘Bus Rapid Transit’ systems internationally (Levinson et al. 2003). In short these systems are designed using buses to provide qualities which replicate the qualities of railway based technologies. Research has established rail like patronage and passenger behaviour similarities of these busways (Currie 2006). It is possible that fuel price elasticity similarities between these busways and Melbourne rail is a result of the similarities which these system provide in terms of technology and design.

This theory does not explain why Brisbane rail and Adelaide rail do not have significant fuel price effects yet Melbourne rail does. The Adelaide rail system is quite small compared to Melbourne using older non-electric rail cars and less developed infrastructure and lower service levels. This might explain why the Adelaide rail system is less affected by fuel prices. However Brisbane’s rail system shares many similarities with Melbourne’s railway in terms of scale, service levels, technologies and quality of design. In discussing these findings with Queensland Rail (QR) it has been suggested that the lack of significant Brisbane rail results might be due to the high share of periodical ticketing used on the railway. QR have suggested that patronage is not well monitored on a monthly basis because total rail trips are estimated from a survey of periodical ticket users and these surveys are not updated on a monthly basis. This is at least a plausible answer although it is not definitive.

Another question emerging from the disaggregate mode data for Brisbane is why is interest rates are such an important factor for bus, particularly the South East Busway. One suggestion made by Translink in Brisbane was that the busway feeds a developing housing growth sector and hence penetrates the ‘mortgage belt’ of Brisbane.

7.3 Disaggregate Time Period Results – Brisbane

Table 3 found that overall interest rate and fuel price impacts affected the off peak with no influence on the peak. However bus results were quite different with Brisbane Transport and South East Busway peak effects being higher than the off peak. Ferry and Private Bus findings by time period were broadly similar.

The aggregate Brisbane findings are clearly biased by the zero impact results for rail in Brisbane. This in term might be explained by the rail season ticket patronage estimation problem suggested earlier.

In general previous research has suggested that peak period elasticities are two to three times higher than off peak values (see section 2). The bus results for Brisbane are generally consistent with this and hence what might be as expected based on previous evidence.

7.4 Disaggregate Rail Corridor Analysis - Melbourne

Table 4 shows the results of this analysis which identified selected longer distance lines and CBD stations as having higher than average fuel price values for *e*. Shorter lines including the Sandringham line had lower than average values.

These findings might be explained by the length of the lines involved and the share of commuters using them. CBD stations in particular have a high share of commuter based travel and there is much evidence that these passengers are more sensitive to fuel price increases. Much of the research evidence provided in this paper also demonstrates that longer distance travel is more likely to have higher values for fuel price cross elasticities than short distance travel (see later).

The Sandringham line is a shorter distance line which might explain its low values for fuel based *e*, however the line also services catchments which comprise some of Australia's highest income groups. It might well be that higher fuel prices are less of an issue for higher income groups.

7.5 Disaggregate Park and Ride Station Corridor Analysis - Melbourne

Table 5 shows the results of this analysis which suggests slightly higher values of fuel price impacts at railway stations where park and ride is provided. This finding suggests a link between car access to rail and auto fuel prices. However the scale of the relative park and ride impact is small. Also a separate station by station and line by line analysis showed a wide range of results with many park and ride stations demonstrating no significant fuel price (or interest rate effects). It is plausible that any impacts are restricted by parking capacity at stations which is known to be under pressure throughout the rail system.

7.6 Disaggregate Short/Long Distance Rail Ticket Analysis - Melbourne

Table 6 showed long distance ticket based values for fuel price based *e* which were almost three times higher than short distance rail tickets. A number of factors might explain this:

- Firstly longer distance travel is by definition more expensive for car drivers. Hence auto fuel price increases will have a larger absolute impact on longer distance travellers than those travelling over short distances. Mode shift from long distance car drivers to rail might be explain the higher long distance fuel price elasticity.
- Secondly it is likely that longer distance rail travellers in Melbourne are more likely to be commuters than shorter distance travellers. Rail in particular (and the 'zone 1+2+3' ticket in particular) provides the access mode from the outer suburbs to the CBD. However tram services tend to provide for inner and middle suburban CBD access (i.e. the short distance trips). Since commuter (and peak travel) is known to be related to higher fuel

price cross-elasticities, this may act to explain why longer distance travel has higher values for fuel based *e*.

- A third explanation might relate to the rail capacity problems which Melbourne's rail system is currently facing. Overloading occurs on morning peak trains as they enter the inner suburbs towards Melbourne CBD. It is plausible that as a result of this, short distance travellers sourced from inner and middle suburbs avoid rail due to overloading problems and/or cannot get onto trains due to overloading. Longer distance travellers however (and again 'zone 1+2+3' ticket holders in particular) board a.m. peak trains in the outer suburbs where they can get access to a seat. This might explain why they are over represented in rail and in peak and commuter trains in particular.
- A fourth and final theory relates to the characteristics of zone 3 ticket holders. The longer distance tickets used in this analysis (the 'zone 1+2+3' ticket) will by definition be used mostly by zone 3 residents. These passengers live in outer urban Melbourne. Much research evidence indicates that lower income dwellers and transport disadvantaged groups tend to live in outer urban areas (Travers Morgan 1992; Currie 2004; Dodson and Sipe 2006; Currie and Senbergs 2007). It is plausible that fuel price cross elasticities are higher for zone 3 residents because these are the passengers who are most vulnerable to fuel prices and interest rates as the Dodson and Sipe work suggests.

7.7 Disaggregate Bus Analysis - Melbourne

Table 7 suggested that longer distance bus routes and the largest CBD bus route corridor group (the City to Doncaster services) had higher than average values of fuel price cross elasticities. These findings are consistent with the CBD access, commuter based and long distance trip influences on travel demand discussed earlier.

8 Conclusions

This paper has explored the relative influences of auto fuel prices and home loan interest rates on aggregate and disaggregate public transport patronage in Melbourne, Brisbane and Adelaide. A series of findings have been established. Discussion has suggested that the major factors driving these results include:

- Differences in fuel prices and home affordability between Brisbane and Melbourne/Adelaide which explain why Brisbane ridership is more significantly affected by home loan interest rates than fuel prices and also why Brisbane fuel price effects are less than those in Melbourne/Adelaide
- The contrast in bus cross elasticities between Melbourne and Brisbane/Adelaide may be explained by the more suburban focus of Melbourne bus services and the strong commuter and CBD access functions of the Brisbane and Adelaide bus networks.
- The Melbourne rail like cross elasticities demonstrated for the Adelaide and Brisbane Busways might be explained by the comparative CBD access, commuter and rail design similarities which busways share with rail.
- High Melbourne rail fuel price cross elasticities compared to Adelaide rail might be explained by the relative quality of rail services under offer.
- The insignificant impacts of either fuel prices or interest rates on Brisbane rail might be explained by inexact monthly season ticket ridership monitoring
- Higher peak cross elasticities are related to commuters and for Melbourne rail, potentially longer distance travellers
- In general much of the evidence supports a view that fuel price cross elasticities are larger for longer rather than shorter distance trips. A range of theories have been suggested which would explain these results including a suggestion that what Dodson and Sipe term the 'vulnerable' fringe urban households are driving at least some of the longer distance patronage growth being experienced.

This research has suggested some plausible reasons for the findings described however clearly each are worthy of further investigation. A major research need is to identify passengers who are making additional public transport trips because of fuel price and interest rate impacts so as to better understand the behavioural drivers and their implications for service planning. This research has demonstrates plausible links with the Dodson and Sipe work on fringe urban households vulnerable to fuel price and interest rate impacts. A priority for future research is to better understand the vulnerabilities suggested and their impacts on the economic well being of these communities as well their implications for travel and transport.

A number of improvements to the approach adopted may improve the accuracy of the methodology in future research:

- We believe it would be appropriate to adjust the interest rates examined into inflation adjusted terms. Certainly future research should consider a sensitivity test of this to examine the impacts on elasticity outcomes.
- The research has adopted a national value for interest rate changes but state based values for fuel prices. Future research should investigate state based approaches to both interest rates and home loan mortgages. It may be that there are state based variations in these which may have an influence on the results.

Acknowledgement

The authors would like to thank Jessica Ross, Peter O'Loughlin, Andrew Homburg, Bernie Carolan and Andrew Hudson plus Metlink, Translink and the Government of South Australia for access to the data used in this analysis. We would also like to thank Dr Jago Dodson and Dr Neil Sipe for their excellent research which has influenced our research in this field. Also to Zed Senbergs at ITS for useful background research supporting this work. Any errors are the responsibility of the authors.

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