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Assessing systematic sources of variation in public transport elasticities: Some comparative warnings

By

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ABSTRACT: There is an extensive and continually growing body of empirical evidence on the sensitivity of potential and actual users of public transport to fare and service levels. The sources of the evidence are disparate in terms of methods, data collection strategy, data paradigms, trip purpose, location, time period, and attribute definition. In this paper we draw on a data set we have been compiling since 2003 that contains over 1,100 elasticity items associated with prices and services of public transport and car modes. The focus herein is on direct elasticities associated with public transport choice and demand, and the systematic sources of influence on the variations in the mean estimates for fares, in-vehicle time, and headway obtained from 319 studies. The major influences on variations in mean estimates of public transport elasticities are the time of day (peak, all day vs. off-peak), the data paradigm (especially combined SP/RP vs. revealed preference (RP)), whether an average fare or class of tickets is included, the unit of analysis (trips vs. vkm), specific trip purposes, country, and specific-mode (i.e., bus, train) in contrast to the generic class of public transport.

KEY WORDS: ***Elasticity, public transport, meta analysis, fares, in-vehicle time, headway, influences on direct elasticities***

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DATE: January 2008

1. Introduction

The worlds of research and practice rely extensively on published estimates of price and service elasticities to develop predictions of switching behaviour towards or away from public transport. For at least 50 years we have seen an accumulation of empirical estimates of direct and cross fare and service elasticities reported in the literature. There are some classic reviews such as Goodwin (1992) and Oum *et al.* (1992)[1], which have synthesised many of the *better* studies undertaken prior to 1990.

Kremers *et al.* (2002), Nijkamp and Pepping (1998) and Holmgren (2007) have undertaken meta-analyses on samples of public transport elasticities to identify systematic sources of variation. They find, in particular, that differences in elasticities can, in part, be explained by the functional form of the model, whether the estimates reflect the short run or long run, the nature of the data structure (e.g., cross section, time series etc.), location (such as country or city size) and whether data is aggregated or disaggregated.

A particularly interesting aspect of the studies is the evidence of differences obtained using revealed preference (RP) data and that reported in stand alone stated preference (SP) or combined RP/SP data when individual choice or (aggregated) share models are being used. One of the problems we have with the comparison is that the majority of SP studies do not appear to calibrate their models to reproduce base modal shares[2] and hence the comparison is likely to reflect as much the failure to calibrate the model constants rather than any possible systematic under or over estimate of mean elasticity. This is an important point, which we will return to in the empirical analysis, since it is easy for skeptics of SP or SP/RP applications to argue that they under- or over-estimate compared to models estimated with RP data (although who says that it is the correct reference anyway?).

Unlike the meta analysis studies cited above, which studied each class of elasticity separately, we have pooled the data for fare, in-vehicle time and headway direct elasticities, to give us a sample of 319 observations. In some of the previous meta-studies (e.g., Kremers et al. 2002), price elasticities from different modes of transport are pooled, but it is the pooling of price and service elasticities that is new in this study. The advantage of our approach is that we have a significant sample size to add confidence to inference, in contrast to the earlier studies where sample sizes were often as low as 12 data points. Holmgren’s sample sizes varied from 17 to 81. In addition, the focus is on establishing sources of systematic variations in a broad class of direct elasticities, and so the assessment of candidate sources across three key attributes of public transport seems appropriate. To control for possible biases attributable to a sub-class (e.g., fares), we introduce dummy variables for each sub-class, normalizing on one sub-class for identification.

The key purpose of this paper is to suggest points of assistance for policy makers in the decision as to what extent, existing knowledge on behavioural response as captured through direct

[1] Both articles are ranked as the most cited articles from the Journal of Transport Economics and Policy between 1975 and 2006 (Morrison *et al.* 2007).

[2] An essential requirement for constructing elasticity estimates since they depend on the choice probabilities or modal shares in addition to the relevant parameter estimates and levels of attributes. This is in contrast to willingness to pay which depends only of the ratio of parameter estimates.

elasticities, might be used in another context, and what are some lessons we can learn from a meta analysis in guiding the definition of elasticity outputs obtained from new primary data.

The paper is organized as follows. We describe the data set in the next section and the approach we had adopted to establish potential sources of systematic variation. This is followed by the empirical evidence on three key direct elasticities of public transport, namely fares, in-vehicle time, headway. The paper concludes with comments on the evidence and offers three very specific warning signals when selecting elasticities from secondary sources for use in particular contexts, and when designing new studies that collect primary data.

2. The data source

The data was compiled from 40 available publications (see Appendix B), a number of which were reviews of the literature (i.e., Balcombe *et al.* 2004, Goodwin 1992, Hanly *et al.* 2002, Lago *et al.* 1981, Litman 2002 and 2005, Luk and Hepburn 1993, Bly and Webster 1981, and Oum *et al.* 1992). Tracking the details on the nature of the data structure (e.g., SP, RP, combined SP/RP; aggregate vs. disaggregate data), time period, years, elasticity formula used (e.g., point or arc), and estimation method (e.g., single cross section, time series of cross sections, panel) is not easy when one has to rely on secondary sources, and even when primary sources are available, there is often limited reporting to establish the precise approach adopted.

The studies that survived our culling are those where we have been able to identify some key crucial features of the method used. Specifically, we set as our minimum requirements, complete information on the type of elasticity (e.g. direct or cross), the applicable location, whether the data was SP, RP or SP/RP; the definition of the fare variable (e.g., an average or a specific ticket type); time of day (notably peak, off-peak or all day); geographical location (i.e., country and city), and the specific mode or mode mix (i.e. bus, train, public transport). Evidence on time period (short vs. long run), the span of years of the data, and trip purpose were, surprisingly, poorly documented. In this paper we have focused on three direct elasticities for public transport.

Having satisfied the criteria above, we then compiled the data set and undertook a check of the range of estimated elasticities within each segment of interest. On close inspection, for the subset of data of interest herein from the fuller data set including other elasticities (e.g., cross elasticties, fuel price elasticities) we found two studies representing nine data points that reported estimates substantially higher that those for the rest of the studies, namely as high as -1.825 for fares and -1.920 for in-vehicle time (See Table 1). These data points are deemed to be outliers under the rule of exceeding two standard deviations around the mean of the sample. Removal of this data reduced the sample size from 328 to 319. The final data points that have been pooled across fares, in-vehicle time and headways for public transport direct elasticities are given in Figure 1, and the first and second moments and range are summarized in Table 1. The mean estimate of -0.395 for fares is close to -0.38 reported in Holmgren (2007) and other reviews such as Goodwin (1992), Oum et al. (1992) and Litman (2002). Graphical representation of the data is given in Appendix A for a range of direct elasticities.

Table 1: Elasticity evidence from relevant sub-samples

Elasticity	Sample size	Mean	Std Dev	Minimum	Maximum
Mix of fares, in-vehicle time and headway	319	-0.408	0.275	-0.002	-1.290
Fares	241	-0.395	0.274	-0.002	-1.121
In-vehicle time	57	-0.547	0.374	-0.006	-1.290
Headway	21	-0.287	0.184	-0.076	-0.700

A further breakdown of the elasticity evidence by a number of dimensions is given in Table 2 (based on the data profile in Appendix A). A number of cells are empty or are not applicable (e.g., single fare effects for in-vehicle time and headway). Overall, we find that, on average, commuters are less sensitive to fares and in-vehicle time, but more sensitive to headways, than non-commuters. When we drill further down, we find that evidence from single cross sections (in contrast to time series and before-and-after studies) is lower (contrasted to the overall means); responsiveness to fares in the peak is similar or less than the overall fare elasticity, similar to the overall estimate for in-vehicle time, and considerably lower for headway. Single fare commuters are less fare sensitive that all commuters, which is not unexpected given that such individuals tend to be less frequent users, and would normally purchase a weekly or multiride ticket in a regular commute. The evidence for SP vs. RP is discussed below, but it suggests that RP and combined SP/RP estimates are higher than SP stand alone where data can be compared, namely in-vehicle time elasticity for commuters.

Table 2: Elasticity evidence from selective sub-samples

	Fare		**In-vehicle time**		**Headway**	
	Commuting	Non-Commuting	Commuting	Non-Commuting	Commuting	Non-Commuting
Overall	-.218 (.215) (37)	-.429 (.271) (204)	-.441 (.314) (32)	-.574 (.221) (26)	-.336 (.245) (5)	-.271 (.167) (15)
Single cross section	-.183 (.153) (3)	-.270 (.128) (4)	-.309 (.242) (4)	-	-.089 (.018) (2)	-
Peak	-.223 (.222) (34)	-.230 (.090) (27)	-.436 (.318) (31)	-.576 (.218) (9)	-.186 (.169) (3)	-.174 (.111) (5)
Single fare	-.132 (.118) (7)	-.458 (.306) (11)	N/A	N/A	N/A	N/A
SP/RP	-.218 (.215) (37)	-.621 (.413) (27)	-.564 (.551) (4)	-.699 (.156) (6)	-.089 (.018) (2)	-.207 (.083) (6)
SP	-	-	-.526 (.316) (12)	-	-	-
RP	-	-.398 (.231) (177)	-.345 (.225) (16)	-.536 (.228) (20	0.50 (.137) (3)	-.313 (.199) (9)
RP, SP/RP	-.218 (.215) (37)	-.429 (.271) (204)	-.389 (.310) (20)	-.574 (.221) (26)	-.355 (.254) (5)	-.270 (.167) (15)

Notes: each cell defines the mean, standard deviation and sample size

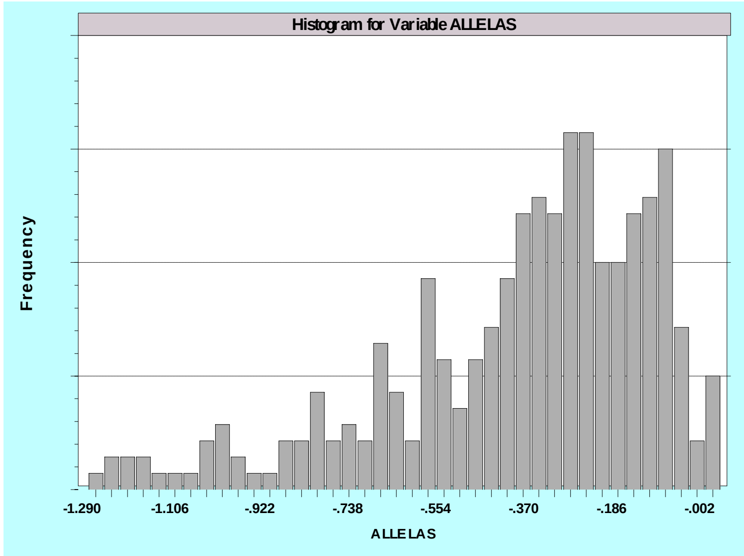


Figure 1: Elasticity profile of the full sample

3. The evidence

We estimated a large number of ordinary regression models[3], controlling for heteroskedasticity, in searching for statistically significant sources of explanation of systematic variation in mean estimates of direct elasticities for fare, in-vehicle time and headway. The final model is summarised in Table 3. Fourteen variables explained 32 percent of the variation in elasticity estimates across the sample. This suggests that there are a myriad of other systematic and non-systematic influences of mean estimates[4].

The selection of candidate influences is based on hypotheses that have either been tested or have arisen out of previous empirical studies. As an example, we hypothesise that the class of ticket (which carries a particular price structure) does have an influence of the behavioural response to public transport use. We expect, for example, all other factors held constant, (i) that those who choose multiride tickets are less sensitive to fare increases, because the price deal is more attractive than other classes; (ii) that a bus and a train are seen as offering different types of services and controlling for this is important in capturing responses to changes in fare and service levels; and (iii) the data specification paradigms (ie., stand alone SP, combined SP/RP and stand alone RP data) influence the evidence since there are mixtures of real and hypothetical

[3] Other variable assessed included locations (UK, USA), all day fares, SP separated from SP/RP, commuting vs. non-commuting, shopping trips, time series, before and after study, pensioner, short run vs. long run, and concession vs. non-concession. In meta analysis studies, it is common that representation of elasticities in each class may contributes to the lack of significance as much a genuine behavioural non-significance.

[4] When comparing the overall explanatory power of models herein with other meta analysis results, we have to be careful, since the much smaller sample sizes (e,g., 81 observation for fare elasticity in Holmgren (2007) might be expected to result in a higher overall fit (R^2 =0.56).

circumstances being studied, and there is evidence of hypothetical bias associated with choice experiment (see Hensher 2008).

Table 3: Sources of systematic variation in elasticites (319 observations)

Explanatory Variable	Parameter Estimate	T-Ratio	Mean of variable	VIF
Constant	-0.3973	-7.54	-	0.00
Fare elasticity specific dummy (1,0)	-0.03537	-0.837	-	1.86
In-vehicle time elasticity specific dummy (1,0)	-0.2494	-4.60	-	1.02
Bus mode dummy (1,0)[1]	-0.0616	-2.10	0.467	1.34
Train mode dummy (1,0) [1]	-0.10651	-32.96	0.295	1.12
Peak period elasticity (1,0) [2]	0.1990	6.853	0.341	1.05
All day period elasticity (1,0)[2]	0.0875	2.04	0.066	1.04
Ticket class – multi ride (1,0) [3]	-0.2471	-2.87	0.053	1.07
Ticket class - 1 hour (1,0) [3]	-0.51692	-2.13	0.0094	1.04
Ticket class – 4 hour (1,0) [3]	-0.62152	-3.75	0.013	1.94
Ticket class – day (1,0) [3]	-0.5279	-2.48	0.0063	1.36
Trip purpose – student travel (1,0)	0.1619	3.47	0.0094	1.32
Location Australia and USA (1,0)	0.0813	2.62	0.793	1.15
Distance (kms) dummy (1,0) [4]	0.1459	2.94	0.0094	3.41
Combined SP/RP dummy (1,0) [5]	0.0472	2.10	0.329	3.22
R-squared	0.32			

1 = relative to headway elasticity, 2 = relative to off-peak only, 3 = relative to single and weekly, 4 = relative to trips, 5 = relative to stand alone revealed preference

We investigated the prospects of multicollinearity, which can often be a concern in meta analysis using mean estimates from a sample of studies. A popular way to analyse multicollinearity is in terms of the effect of the intercorrelation of the regressors on the variance of the least squares parameter estimates. The variance inflation factor (VIF) is a measure of this effect[5].The optimal value for this statistic is 1.0, which occurs when the R^2 is zero or this variable is orthogonal to the other variables. There is no consensus on what values of the variance inflation factor merit attention, or on what one should do with the results. Some authors (e.g., Chatterjee and Price 1991) suggest that values in excess of 10 are problematic. In the current study we are well below this on all regressors (see last column of Table 3) and hence can safely reject the presence of multicollinearity.

The evidence suggests a number of key directional impacts, of which two are particularly important from a methodology point of view. There is evidence that models that use stand alone

[5] $VIF_i = 1/(1- R_k^2)$ where R_k^2 is the R^2 obtained when the kth regressor is regressed on the remaining variables.

RP tend to produce lower mean estimates than those that have combined RP and SP data. There are very few stand alone SP studies (12 associated with invehicle time and commuting), and a tested SP stand alone dummy variable was not significant6. There are some essential caveats to this – firstly many RP studies herein are earlier studies (i.e., 1970s in particular) than the majority of the SP/RP studies, and in general we see an increase in mean estimates over time. Drawing on a separate analysis of 152 observations (not reported herein), that had information to be able to identify the year of the study, all other factors remaining constant, the data suggest that as we move back from 2004, each year reduces the mean estimate by 0.00646 (given an overall average for the 152 data points in which the year is reported of -0.3905). In addition, it seems that the majority of studies, RP, SP and mixed SP/RP, are not calibrated7 to reproduce base population model shares, but that the SP studies in particular (representing all but 12 of the 74 SP plus SP/RP studies) reproduce stated choice shares which may be significantly at variance with market shares, and hence the uncalibrated RP constants in the SP models are behaviourally unhelpful. This makes the comparisons somewhat speculative at best, and indeed sends a message that all studies8 that report elasticities must ensure and report that the model constants are calibrated to market shares or totals. It would be unwise for readers to take away the message that SP/RP studies tend systematically to over- (or even under-) estimate elasticity estimates, which sadly appears to be a view in some research circles. The reason may be due to a common focus on establishing willingness to pay for specific attributes which does not require calibrated constants, unlike elasticity derivatives.

The other important finding is the tendency for fare elasticities to be very sensitive to the class of ticket type. Relative to a single and a weekly ticket, the most popular ticket types, we find a systematically higher mean estimate for multiride, one hour, four hour and all day ticket types. We were not been able to establish any significant variation between the use of unweighted average fares and ticket types, given that the contrast between an average fare and fare classes was not statistically significant.

Some inituitively plausible variations were established for peak, all day and off-peak estimates. Peak elasticities are lower on average than off-peak and all-day estimates, and all day estimates are lower than off-peak (due to inclusion of peak and off-peak). The peak estimates have a mean estimate that is on average 0.1958 lower than the overall mean of -0.408 (i.e., -0.2122). Bus specific elasticities are slightly lower than train specific elasticities, but both are higher relative to combined public transport, respectively by -0.0721 and -0.1101. This is an important finding, suggesting a downward bias in bus and train specific responsiveness when using an estimate based on ignoring the difference between a bus and a train.

[6] Excluding this dummy variable did not impact on the parameter estimate of SP/RP vs. RP.

[7] The secondary sources were checked to establish if calibration had occurred for the 74 elasticities that are SP or SP/RP. We found that the great majority of studies did not calibrate. This may be due to the fact that they are, in the majority, research studies by authors such as Hensher (1998), Douglas et al. (2003), Hensher and Louviere (1998), Hensher and King (1998), and IPART (1998.

[8] This includes RP studies, although we note than the RP studies typically have sample shares closer to population shares than do SP/RP and especially SP stand alone studies, where the elasticities are derived from the RP component of the SP/RP model..

After identifying a number of systematic sources of elasticity variation, we have included some elasticity-type dummy variables for fares, in-vehicle time and headway (the latter set to zero) to accommodate other sources of variation that are specific to fares, in-vehicle time and headways. As shown in Table 1, fare and in-vehicle time elasticities are on average greater than the headway elasticities, which is re-affirmed by the negative parameter estimates for the two constants in the model. Finally, estimates from USA and Australian cities are significantly lower, suggesting that the wealthier cities are less sensitive.

We also ran separate regression models for each of three types of direct elasticities, summarized in Table 4. Comparisons between the models are not straightforward, given that many of the fare-related variables are not applicable in the in-vehicle time and headway models. An important finding from the separate models is that the distinction between RP or SP/RP data has a much higher mean effect for each of the three elasticity types. Although one might expect some of these to be lower and some higher relative to the overall estimate in Table 1, the models are not strictly comparable because some variable are removed from some models. The overall message is clear however; importantly RP estimates are lower than combined SP/RP estimates (and most notably for in-vehicle time), ticket class effects are similar and ranked the same for fare elasticities, location is only significant for fares, and time of day elasticities are not significant for in-vehicle time and headway. The sample sizes are sufficiently small given the descriptive profiles in Table 2 of specific segments that behavioural inferences drawn from the in-vehicle and headway models must be cautioned.

Table 4: Sources of systematic variation in each type of elasticity (319 observations)

(t-ratio in brackets)

Explanatory Variable	Fare	In-vehicle time	Headway
Constant	-.455 (-15.5)	-.062 (-0.34)	-.518 (-4.5)
Fare elasticity specific dummy (1,0)	N/A	N/A	N/A
In-vehicle time elasticity specific dummy (1,0)	N/A	7	N/A
Bus mode dummy (1,0)[1]	-.05773 (-1.83)	-.414 (-2.8)	.074 (.87)
Train mode dummy (1,0) [1]	-.138 (-3.6)	-.413 (-2.6)	.145 (1.5)
Peak period elasticity (1,0) [2]	.201 (5.6)	-.090 (1.2)	.159 (2.6)
All day period elasticity (1,0)[2]	.111 (2.3)	.012 (.11)	-.061 (-.96)
Ticket class – multi ride (1,0) [3]	-.281 (-3.4)	N/A	N/A
Ticket class - 1 hour (1,0) [3]	-.5702 (2.3)	N/A	N/A
Ticket class – 4 hour (1,0) [3]	-.6639 (-3.9)	N/A	N/A
Ticket class – day (1,0) [3]	-.581 (2.32)	N/A	N/A
Trip purpose – student travel (1,0)	.1449 (3.01)	N/A	N/A
Location Australia and USA (1,0)	.1070 (2.9)	-.077 (-0.775)	No variation
Distance (kms) dummy (1,0) [4]	.149 (3.1)	Not known	No variation
Combined SP/RP dummy (1,0) [5]	.0925 (1.9)	.228 (2.5)	.178 (3.1)
R-squared	0.335	.118	.334
Sample Size	241	58	20

1 = relative to headway elasticity, 2 = relative to off-peak only, 3 = relative to single and weekly, 4 = relative to trips, 5 = relative to stand alone revealed preference

4. Conclusions

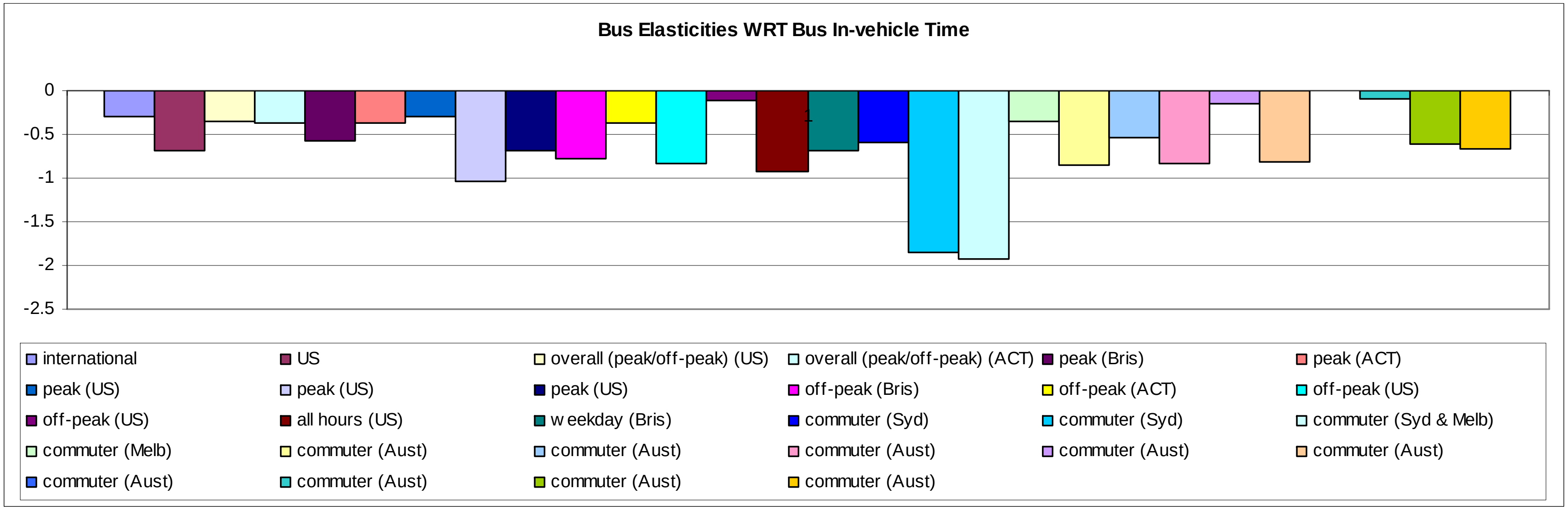
The analysis of 319 mean estimates of three classes of direct elasticities for public transport have identified some statistically significant influences that explain 32 percent of the systematic variation in mean elasticity estimates. The important questions to ask about the evidence are "what guidance does it provide when an analyst is using elasticities from secondary sources, instead of collecting new evidence from primary local sources?" and "what lessons can be used in the design and application of studies privileged to collect new primary data?".

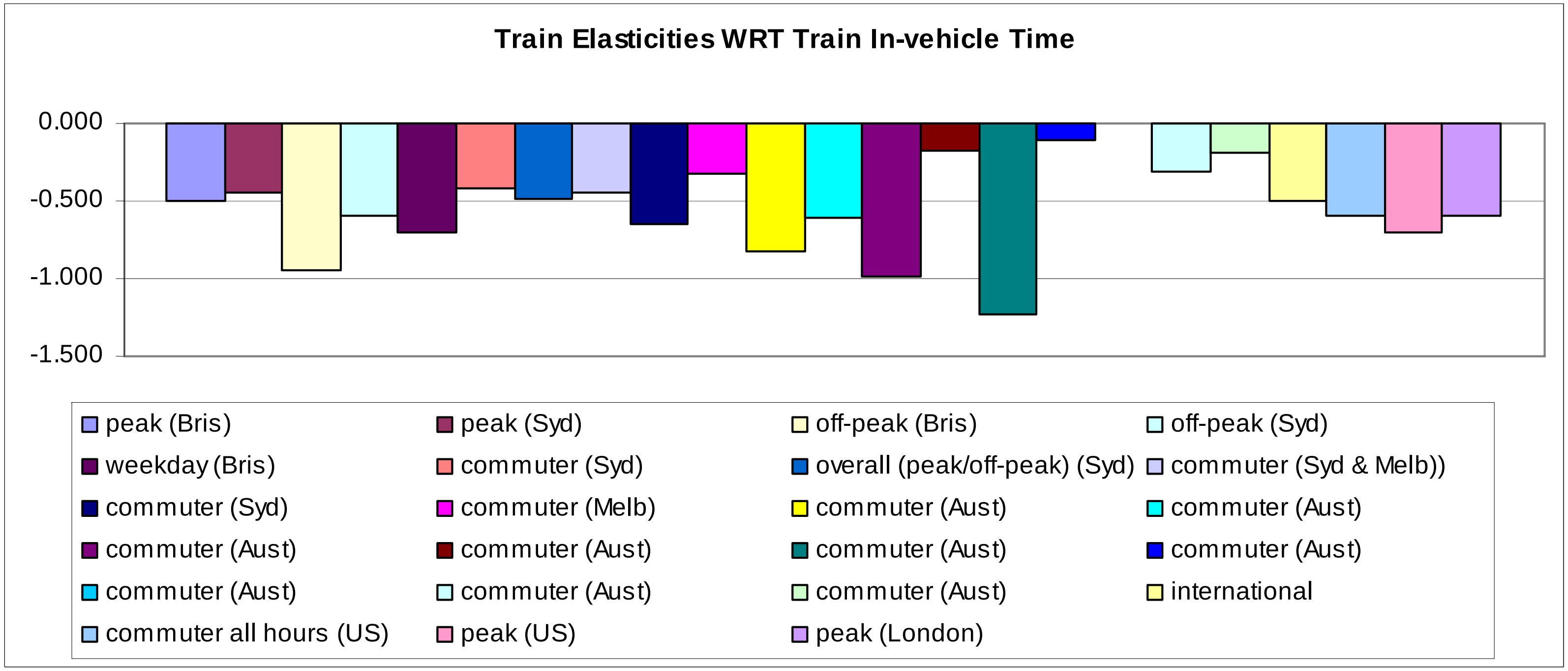
When one is evaluating the influence of pricing and service level policies on public transport patronage, in contexts where typically public transport has a relatively small share of the market, especially in countries where the data herein is predominantly sourced (i.e., USA, Australia, New Zealand, U.K. and a few car dominated European countries), the selection of a mean elasticity estimate can be the difference between a sizeable or an insignificant predicted modal switch away from or towards public transport.

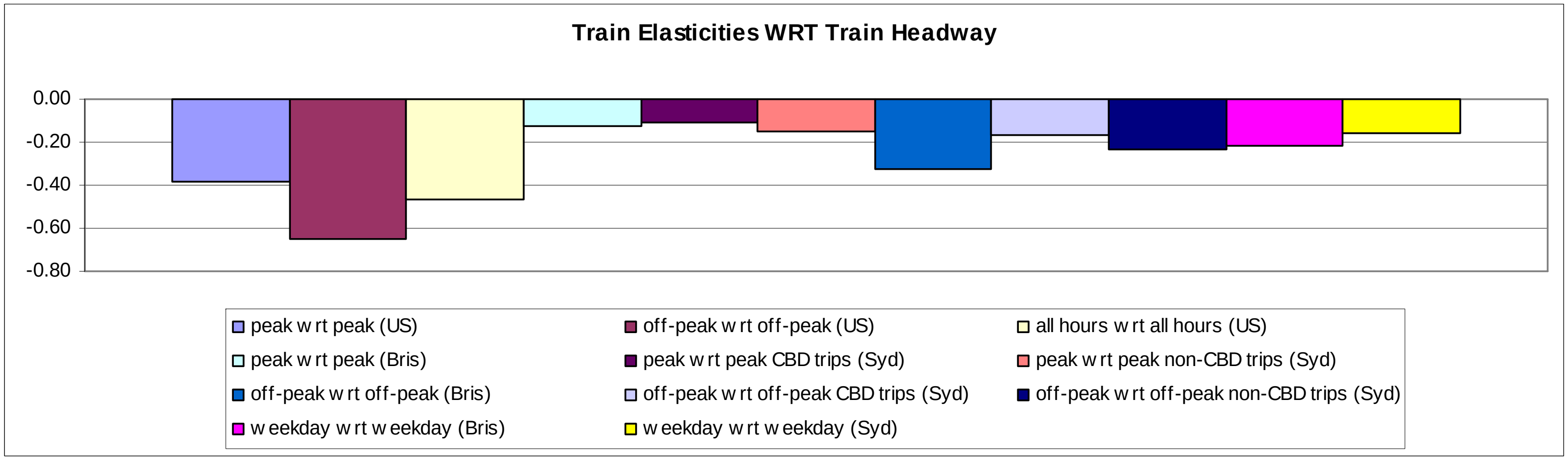
Our preference would always be to collect primary data as a basis for conclusions regarding effects of policy changes. The evidence herein offers at least three warning signals in the development of new data sources and in the selection of elasticities from secondary sources. First, drawing on public transport elasticities to use in a specific model context such as bus or train, will tend to over-estimate behavioural response. Second, if one believes that elasticities based on stand-alone RP data are 'better' estimates than those based on combined SP/RP data,, then RP estimates will be lower than the estimates reported from combined SP/RP data.. We caution that this is possibly not a criticism of the underlying behavioural content of SP data per se, but due in large measure to the absence of calibration designed to obtain the correct base market shares (compared to shares from stated responses), given the role that the dependent variable (e.g., choice probability) plays in the formula. The deviations from actual population shares are typically more pronounced in SP/RP data[9] than RP data; although RP data is not immune from this. Third, accounting for the type of ticket purchased has a clear influence on fare sensitivity. Although we cannot claim that using an average fare estimate in studies will tend to over- or under-estimate fare elasticities, the evidence supporting strong differences in behavioural response between ticket types is sufficiently revealing to warn against ignoring the class of ticket. Relative to a single and a weekly ticket, the most popular ticket types, we find a systematically higher mean estimate for multiride, one hour, four hour and all day ticket types; and with a growing interest in marketing such tickets, there is risk that using averages based typically on single fares, will under-estimate switching response.

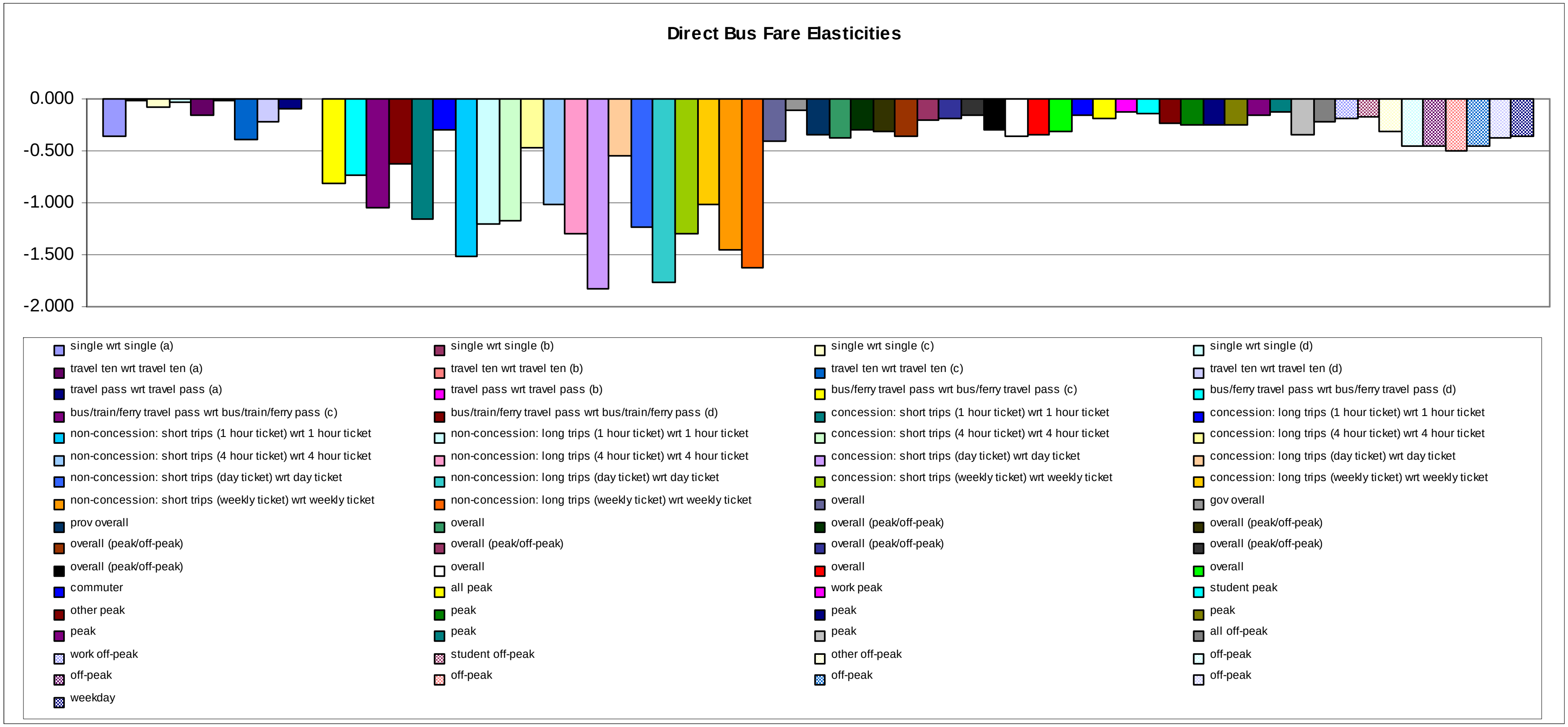
[9] This does not have to be the case; however it appears that large number of studies with an SP component often use quota sampling on segments, since smaller samples are collected (relying on the number of choice sets to produced good sized samples for model estimation), rather than Stand alone RP studies that have larger sample given that only one observation per person is obtained. These RP samples tend to reflect the actual market shares a lot closer or are subject to choice based sampled and weighted exogenous maximum likelihood estimation to account for endogenous sampling.

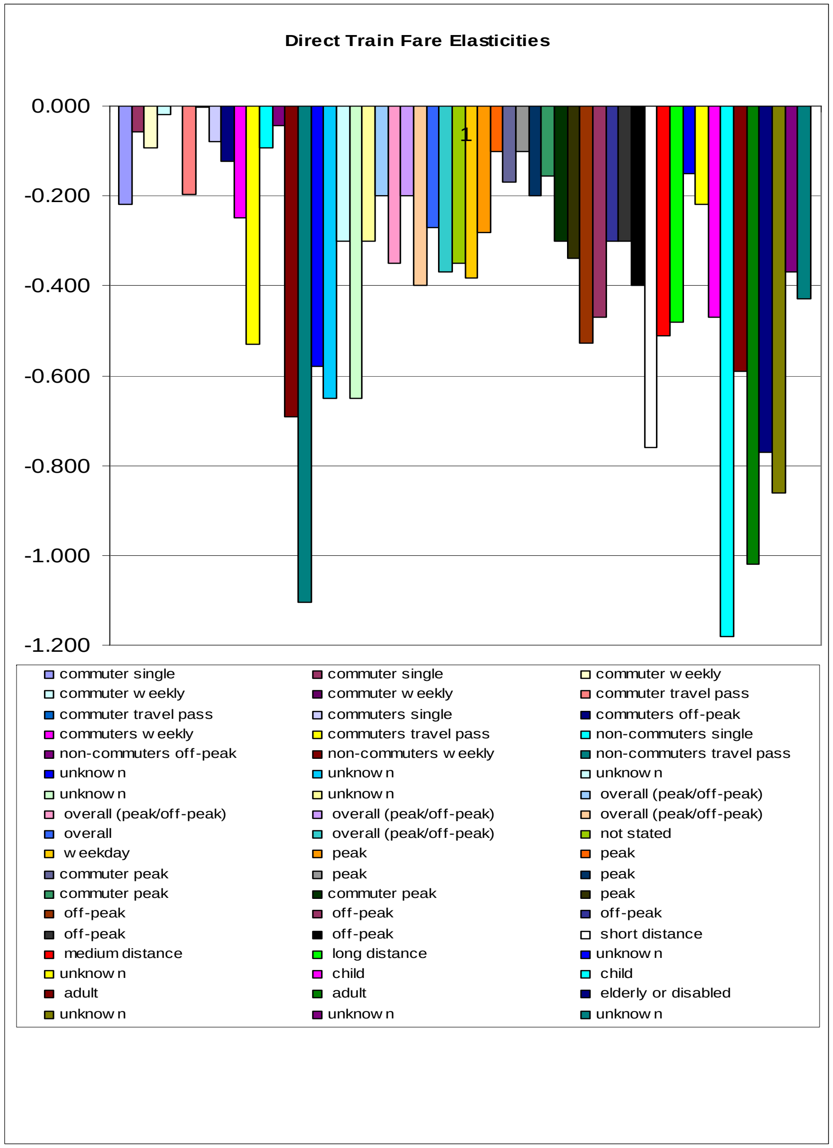
Appendix A: Profile of data by elasticity type




Train Elasticities WRT Train In-vehicle Time
0.000
-0.500
-1.000
-1.500
peak (Bris)
peak (Syd)
off-peak (Bris)
off-peak (Syd)
weekday (Bris)
commuter (Syd)
overall (peak/off-peak) (Syd)
commuter (Syd & Melb))
commuter (Syd)
commuter (Melb)
commuter (Aust)
commuter (Aust)
commuter (Aust)
commuter (Aust)
commuter (Aust)
commuter (Aust)
commuter (Aust)
commuter (Aust)
commuter (Aust)
international
commuter all hours (US)
peak (US)
peak (London)


Train Elasticities WRT Train Headway
0.00
-0.20
-0.40
-0.60
-0.80
peak w rt peak (US)
off-peak w rt off-peak (US)
all hours w rt all hours (US)
peak w rt peak (Bris)
peak w rt peak CBD trips (Syd)
peak w rt peak non-CBD trips (Syd)
off-peak w rt off-peak (Bris)
off-peak w rt off-peak CBD trips (Syd)
off-peak w rt off-peak non-CBD trips (Syd)
w eekday w rt w eekday (Bris)
w eekday w rt w eekday (Syd)


Direct Bus Fare Elasticities
0.000
-0.500
-1.000
-1.500
-2.000
single wrt single (a)
single wrt single (b)
single wrt single (c)
single wrt single (d)
travel ten wrt travel ten (a)
travel ten wrt travel ten (b)
travel ten wrt travel ten (c)
travel ten wrt travel ten (d)
travel pass wrt travel pass (a)
travel pass wrt travel pass (b)
bus/ferry travel pass wrt bus/ferry travel pass (c)
bus/ferry travel pass wrt bus/ferry travel pass (d)
bus/train/ferry travel pass wrt bus/train/ferry pass (c)
bus/train/ferry travel pass wrt bus/train/ferry pass (d)
concession: short trips (1 hour ticket) wrt 1 hour ticket
concession: long trips (1 hour ticket) wrt 1 hour ticket
non-concession: short trips (1 hour ticket) wrt 1 hour ticket
non-concession: long trips (1 hour ticket) wrt 1 hour ticket
concession: short trips (4 hour ticket) wrt 4 hour ticket
concession: long trips (4 hour ticket) wrt 4 hour ticket
non-concession: short trips (4 hour ticket) wrt 4 hour ticket
non-concession: long trips (4 hour ticket) wrt 4 hour ticket
concession: short trips (day ticket) wrt day ticket
concession: long trips (day ticket) wrt day ticket
non-concession: short trips (day ticket) wrt day ticket
non-concession: long trips (day ticket) wrt day ticket
concession: short trips (weekly ticket) wrt weekly ticket
concession: long trips (weekly ticket) wrt weekly ticket
non-concession: short trips (weekly ticket) wrt weekly ticket
non-concession: long trips (weekly ticket) wrt weekly ticket
overall
gov overall
prov overall
overall
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall
overall
overall
commuter
all peak
work peak
student peak
other peak
peak
peak
peak
peak
peak
peak
all off-peak
work off-peak
student off-peak
other off-peak
off-peak
off-peak
off-peak
off-peak
off-peak
weekday


Direct Train Fare Elasticities
0.000
-0.200
-0.400
-0.600
-0.800
-1.000
-1.200
1
commuter single
commuter single
commuter weekly
commuter weekly
commuter weekly
commuter travel pass
commuter travel pass
commuters single
commuters off-peak
commuters weekly
commuters travel pass
non-commuters single
non-commuters off-peak
non-commuters weekly
non-commuters travel pass
unknown
unknown
unknown
unknown
unknown
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall (peak/off-peak)
overall
overall (peak/off-peak)
not stated
weekday
peak
peak
commuter peak
peak
peak
commuter peak
commuter peak
peak
off-peak
off-peak
off-peak
off-peak
off-peak
short distance
medium distance
long distance
unknown
unknown
child
child
adult
adult
elderly or disabled
unknown
unknown
unknown

Appendix B: Key sources used to extra data

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