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Exploring net public transport expenditure in Australian cities

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Abstract

The NSW Treasury commissioned and collaborated with Veitch Lister Consulting (VLC) to explore net public transport expenditure per capita ("net PTE") in major Australian capital cities. The purpose of the research was to identify factors that are arguably outside the short-term control of state governments, including—but not limited to—geography, density, and congestion. To identify effects on net PTE, VLC developed a suite of regression models using detailed micro-data on public transport supply and demand. In these models, effects are identified from variation both within and between capital cities in Australia. Results identify several factors that give rise to relatively large differences in net PTE between Australian cities, which are robust to a range of controls, specifications, and controlling for endogeneity.

1 Introduction

NSW Treasury commissioned Veitch Lister Consulting (VLC) to assist in reviewing the Commonwealth Grant Commission's (CGC's) methodology for recurrent transport expenditure. In this paper, we consider whether there is evidence that non-policy factors affect net public transport expenditure per capita ("net PTE") in Sydney vis-à-vis other large capital cities in Australia. This chapter sets out the policy principles of the CGC, our methodology and theoretical foundations, as well as the specific non-policy factors we explore in the remainder of the report.

1.1 Policy principles and methodology

The CGC's approach to funding state governments is designed to deliver on the general principle of "horizontal fiscal equalisation" (HFE), which is defined as follows: *"State governments should receive funding from the Commonwealth such that, if each made the same effort to raise revenue from its own sources and operated at the same level of efficiency, each would have the capacity to provide services at the same standards"* (Commonwealth Grants Commission, 2002, p. 5).

We interpret these concepts in a PT context as:

- Fund levels of **PT supply** per capita that are consistent with underlying demand on a policy neutral basis;
- Not compensate states for differences in **PT productivity** arising from policy choices, such as ticketing systems; and
- Not compensate states for differences in **PT revenue** per capita arising from policy choices.

Our work seeks to disentangle the effects of different factors on net PTE, analysing supply, productivity, and revenue channels. We distinguish between *policy choices* and *non-policy factors*. In doing so, we adopt a specific interpretation of "non-policy factors" that reflects our focus on the process by which the Commonwealth Grants Commission (CGC) allocates GST revenues. In allocating funding for net PT expenditure, the CGC and state governments define "non-policy factors" as those that are beyond the control of PT planners. In this context, density and congestion are deemed to be non-policy factors, even if they are influenced by policies more generally. From the perspective of PT planners, causes of density and congestion—and the associated optimal policy responses, such as road pricing—are irrelevant. Over the medium and long term, all parties acknowledge that many of these so-called "non-policy" factors are at least partly within the control of state governments.

We consider three channels through which non-policy factors may affect net PTE, namely supply, productivity, and revenue:

- **Supply (or cost) models,** which analyse the effects of non-policy factors on the quantity of PT services delivered in Australian capital cities, measured at the level of SA2s;
- **Productivity models**, which analyse the effects of non-policy factors on the efficiency with which PT services operate in Australian capital cities, measured at the route-level. This model is substantially more complex than the other two so it is summarised in the Appendix; and
- **Revenue models,** which analyse the effects of non-policy factors on revenue from PT services in Sydney, also measured at the level of SA2s.

Our supply and productivity models capture the effects of non-policy factors on costs and use data sourced from General Transit Feed Specifications (GTFS) and the Census for the five largest capital cities, as defined by ABS's Greater Capital City Statistical Areas (GCCSA). Our revenue model, in contrast, makes use of (confidential) Opal ticketing data for Sydney.

Finally, we note that the policy context for this work is unique to Australia. The role of the CGC in allocating GST revenues to state governments, as well as the focus on net public transport expenditure per capita and the definition of non-policy factors, is not something that transfers to other jurisdictions. Partly for this reason, we identified relatively little literature of direct relevance to our research question.[1] The authors

[1] The study by Leland and Smirnova (2008) is perhaps the most relevant recent literature. Leland and Smirnova (2008) investigate the effects on PT *efficiency*, e.g. labour productivity, service efficiency, and cost efficiency, and *effectiveness*, e.g. vehicle utilisation, service effectiveness, and cost effectiveness. The study includes farebox recovery as a cost efficiency measures, as well as density of the service area as an explanatory variable. The latter is found to have a significant ($p < 0.01$) positive effect on farebox recovery, which aligns with our findings—noting the important distinction between

would welcome further direct correspondence from readers who are more familiar with the wider literature, especially as it relates to published academic work.

1.2 Theoretical and empirical underpinnings

At the most basic level, we treat net expenditure E as the result of two semi-independent (albeit linked) economic outcomes, namely gross costs, C, and fare revenue, R. That is,

$$E = C - R$$

We can further decompose gross costs into three major resource inputs:

- *Vehicle-hours* (h), which capture time-related costs, e.g. driver wages;
- *Vehicle-kilometres* (k), which capture distance-related costs, e.g. maintenance and fuel; and
- *Vehicles* (v), which capture vehicle-related costs, e.g. fleet and depots.

To arrive at total costs, each resource input is multiplied by its unit cost (γ_j) and summed. Intuitively, resource inputs will increase with demand, D. Moreover, resource inputs will be affected by policy choices, such as the distance between stops, and non-policy factors, such as geography. We denote policy choices and non-policy factors by the vectors X and Y, respectively. This implies a gross cost function:

$$C = \gamma_1 h(D, X, Y) + \gamma_2 k(D, X, Y) + \gamma_3 v(D, X, Y)$$

And similarly, $R = r(D, X, Y)$. Substituting these expressions into net expenditure and differentiating with respect to non-policy factor Y_j allows us to isolate the effect of the latter on net expenditure as follows:

$$\frac{\partial E}{\partial Y_j} = \left[\gamma_1 \frac{\partial h(\cdot)}{\partial Y_j} + \gamma_2 \frac{\partial k(\cdot)}{\partial Y_j} + \gamma_3 \frac{\partial v(\cdot)}{\partial Y_j}\right] - \frac{\partial r(\cdot)}{\partial Y_j}$$

This theoretical expression has a simple interpretation: The effect on net PTE, E, of a small change in non-policy factor, Y_j, is the sum of its effects on costs (hours, distance, and vehicles) minus its effects on revenue. On this theoretical basis, we proceed by estimating the effects of non-policy factors on costs and revenue separately before then combining the individual effects to arrive at the estimated total effect.

This decomposition is convenient for two reasons. First, and unlike the CGC, we do not have access to data on net PT expenditure for “Significant Urban Areas” (SUA) (Jacobs, 2018). Instead, we estimate cost effects for five cities and revenue effects for Sydney. Second, this approach allows us to make use of more granular microdata, which provides us with greater statistical power[2] and stronger identification[3].

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farebox recovery and net PT expenditure per capita. Specifically, and as later sections will show, we find it is possible for factors to lead to higher recovery as well as higher net PT expenditure.

2 We have larger samples than the CGC (1,000 SA2s or 100,000 PT services versus 70 SUAs).

3 We identify the effects of non-policy factors from variation that exists both *between* and *within* capital cities. As we have variation within cities, we can control for city-specific factors.

Our full study considered three model variants and various sensitivity tests (VLC, 2019).[4] Across the different variants and tests, we typically found consistent results. In the interests of brevity, this paper reports results for only a single variant for each of our supply, productivity and revenue models.

1.3 Non-policy factors

We are interested in non-policy factors that are largely beyond the control of state governments, at least in the short-run, and which may give rise to differences in net PTE. We identified the following non-policy factors as most relevant:

- **Transport outcomes,** such as road congestion and travel distances;
- **Economic geography**, such density and urban form; and
- **Physical geography**, such as barriers arising from water features and terrain.

Perfect measures for these non-policy factors do not exist. Instead, we developed metrics designed to capture the most salient aspects. The supply and revenue models in Sections 2 and 3, respectively, include the following two measures:

- **Density**, measuring the number of residents or jobs within a certain area, and
- **Congestion**, as measured by daily delay hours incurred by vehicles.

The productivity models presented in the Appendix operate at the level of individual PT service trip-IDs. In addition to density (or catchment) and congestion, we also test additional non-policy factors, namely: change in elevation and geographical deviation.

2. Supply Model

We model the effect of non-policy factors on PT gross costs (supply) for the five largest cities in Australia (GCCSAs) using SA2 seat-kilometres as a proxy.

2.1 Model

Data on the gross costs of operating PT within capital cities is not publicly available at the level of spatial detail (SA2s) required for our model. Instead, we approximate costs within and between cities using readily observed data on the supply of PT.

Our chosen PT supply indicator is *total seat-kilometres (seat-km)*. Seat-kms satisfies two criteria: First, it is mode-neutral and, second, it is a reasonable approximation for PT supply.[5] To estimate seat-km S_i in SA2 i, we multiply the number of vehicle kilometres k_i^m for each mode m with the seated vehicle capacity C^m of that mode.

We estimate PT vehicle capacities for each PT mode in each city from VLC's strategic transport models for 2016, as summarised in Table 1. These numbers denote approximate averages for each mode and city (NB: sensitivity tests using different

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4 Specifically, (1) Ordinary Least Squares (OLS) with robust standard errors (s.e.); (2) OLS with cluster-robust s.e.; and (3) Weighted Least Squares with cluster-robust s.e. Refer to the full report for further details on alternative model specifications.

5 In terms of the second criteria, we find an extremely high positive correlation (0.983) between seat-hrs and seat-kms at the SA2 level. This correlation, as well as our chosen model specification, discussed below, implies non-policy factors will have similar effects on seat-hrs as seat-km. While we do not have data on vehicle requirements, which is the third major cost driver noted in Section 1.2, we expect they will be determined largely by seat-kms and seat-hrs.

assumptions for vehicle capacity—specifically capacities that were consistent across cities—indicated that our results were not sensitive to the specific numbers assumed).

Table 1: Assumptions for Seated Public Transport Vehicle Capacities

City	Mode		
	Bus	**Tram**	**Heavy rail**
Sydney	52.5	239	1,165
Melbourne	50	115	875
SEQ	55	192	500
Perth	55	N/A	500
Adelaide	55	100	280

With these capacities we calculate our dependent variable S_i, and specify a basic model of PT supply. To start, we assume PT supply responds to density and congestion levels as follows:

$$S_i = \sum_m C^m k_i^m \ = \ F_i^q d_i^{\alpha_1} c_i^{\alpha_2}$$

Where d_i and c_i denotes density and congestion, respectively, and α_1 and α_2 denote parameters to be estimated. Taking logs yields an equation that is linear in parameters, formally:

$$\log S_i = \log F_i{}^q + \alpha_1 \log d_i + \alpha_2 \log c_i = f_i + \alpha_1 \log d_i + \alpha_2 \log c_i$$

Our priors are that PT supply increases with density and congestion, that is, $\alpha_1, \alpha_2 > 0$. The constant $\log F_i^q = f_i$ is a "supply shifter", or fixed effect, which captures average differences in levels of PT supply between the SA2s in area q. In the models below, we define q to be SA3s. Put another way, the fixed effects capture differences in average levels of PT across SA3s. Including SA3 fixed effects f_i means we identify effects of density and congestion from variation *between SA2s within an SA3*. In this way, the SA3 fixed effects help to control for unobserved determinants of PT supply, such as infrastructure, urban form, and policy choices.

One of the advantages of using a log-log model is the resulting estimates for α_1 and α_2 can be interpreted as "constant elasticities". These parameters provide a scale-invariant measure of the effects of explanatory variables that translates readily into relative percentage effects, including ultimately on costs.

2.2 Data

Our data was generated as follows:

- First, S_i is estimated by assigning route-kilometres by buses, trains and trams in GTFS data to individual SA2s (we exclude ferries for reasons of simplicity and non-materiality). For each mode and SA2, we then multiplied route kilometres by the vehicle seat capacities in Table 1;
- Second, we excluded extremely large and low density (less than 100 residents per square kilometre) SA2s from the sample and linked data on seat-km to Census data on the density of remaining SA2s, such as population, employment, and area (NB: We also estimated unrestricted models. Excluding large areas did not affect the estimated magnitude of the coefficients, while improving the statistical precision of our estimates); and

- Third, we extracted data on SA2 private vehicle delays from VLC's strategic transport models.

Summary statistics for key variables are summarised in Table 2, where each row relates to individual capital cities and the final row presents the average for the sample.

Table 2: Summary Statistics – Averages for Urban SA2s (minimum 100 residents/km2)

City	n	PT supply (S_i)	Population (p_i)	Employment (e_i)	Congestion (c_i)	Area A_i
Sydney	280	10,530,842	16,693	7,455	1,783	11.15
Melbourne	279	6,337,540	15,301	6,897	1,612	14.12
SE Qld	267	1,744,157	10,495	4,724	890	13.72
Perth	141	2,635,053	13,341	5,094	851	15.53
Adelaide	91	904,045	13,516	5,795	1,351	12.77
Sample	*1,058*	*5,327,325*	*14,042*	*6,161*	*1,351*	*13.30*

We emphasise the differences in population and employment in columns 4 and 5 of Table 2 are per SA2. That is, they are not densities. To arrive at average densities, one must divide by the final column of Table 2, which measures the areas of SA2s. The combined effects of differences in levels (columns 4 and 5) and areas (column 7) is that Sydney has population and employment densities that are 37% higher, on average, than Melbourne. In comparison, we find that PT supply in Sydney is 66% higher. The higher supply in Sydney is, we suggest, driven by our calculation of seat-kms and specifically the high capacity of heavy rail in Sydney. Note that average differences in supply are controlled for by our SA3 fixed effects. Hence the fact Sydney has higher average supply does not, in of itself, drive our findings. Rather, what matters is how supply varies with density between SA2s within SA3s.

2.3 Results

In this section we develop our baseline PT supply model. The first question we answer is how to define density. We investigated four alternative measures of SA2-level density: (1) average population, (2) population-weighted density, (3) average employment, (4) employment-weighted density. These were found to be strongly positively correlated (as expected), with (3) average employment density ultimately being selected as the simplest variable with highly significant results (VLC, 2019) (Table 3).

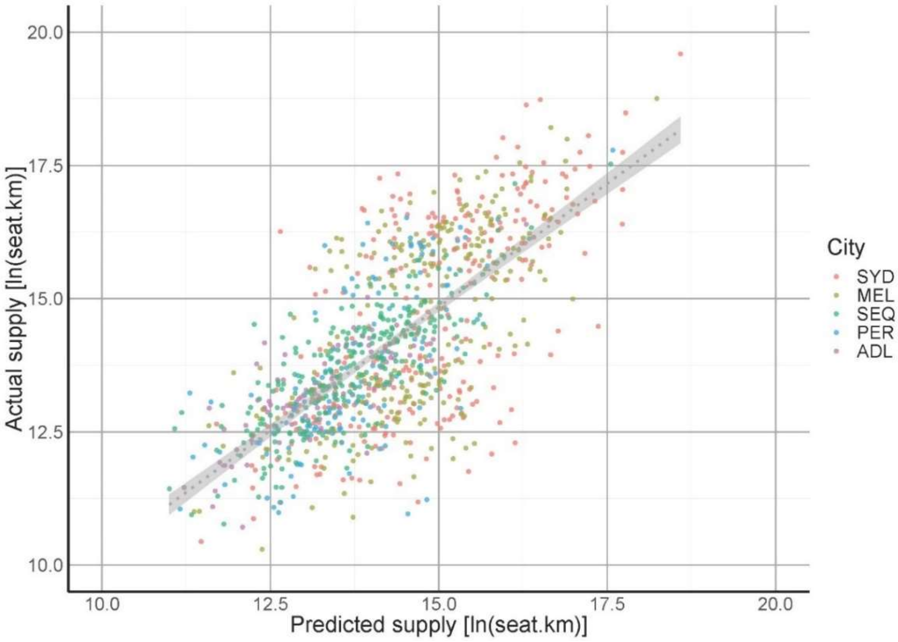
Table 3: Regression Results – Supply Model SA3 fixed effects

Parameters	Estimates
log(emp. density)	0.55 (0.06)***
log(delays)	0.42 (0.08)***
R^2	0.53
Notes: n = 1,058 obs. S.Es in brackets; ***p < 0.001, **p < 0.01, *p < 0.05. Model includes SA3 fixed effects.	

We find elasticities of seat-kms with respect to employment density and car delays of 0.55 and 0.42, respectively. Both coefficients are significant at the 0.1% level.

Inspection of model predictions, or "explanatory power", indications an R-squared value of 0.53 and a strong positive association between actual and predicted levels of PT supply with no obvious extreme values (Figure 1).

Figure 1: Supply Model – Model Fit (V2)



We confirmed the robustness of our results in two broad ways:

- First, we estimated models using alternative specifications for variables, e.g. different vehicle capacities, alternative fixed effects, and different congestion measures. We also tested the inclusion of labour and transport variables, such as workforce composition and trip length, respectively; and
- Second, we estimated an instrumental variables (IV) version of our model to control for potential endogeneity of our explanatory variables.

In all cases, we find that our baseline results are largely unchanged (VLC, 2019).

3. Revenue Model

We model the effect of non-policy factors on PT revenue in Sydney. Within the Sydney GCCSA, we use confidential disaggregated Opal demand and fare data supplied by Transport for NSW to estimate PT revenue for individual SA2s.

3.1 Model

Our dependent variable is total fare revenue for individual SA2s, R_i. We model R_i using a similar log-log model to that used in Section 2.1:

$$\log R_i = f_i^R + \beta_1 \log d_i + \beta_2 \log c_i$$

Where:

- R_i denotes fare revenue by SA2 i;
- f_i^R denotes SA3 fixed effects for SA2 i;
- d_i denotes employment density in SA2 i;
- c_i denotes total daily vehicle delay hours that are incurred in SA2 i; and
- β_1 and β_2 denote parameters to be estimated.

Our prior expectations are that revenue increases with employment density and car delays. We note here that local differences in average fare levels at a broader level are captured by the SA3 fixed effects. This will broadly control for average differences in fare revenue at the SA3 level that arise due travel patterns, modes, zones, and discounts (e.g. concessions). Hence, our estimated effects of density on fare revenue reflect the effects of variation between SA2s within SA3s.

3.2 Data

Summary statistics for our revenue data are in Table 4. While we do not have revenue data for other capital cities, we can apply the elasticities from our model to estimate the effect of non-policy factors on revenue in other cities. This assumes PT revenue in other cities responds to non-policy factors in a manner that is similar Sydney.[6]

Table 4: Summary Statistics for Revenue Model – Averages by Urban SA2

City	n	PT revenue (R_i)	Population (p_i)	Employment (e_i)	Congestion (c_i)	Area A_i
Sydney	280	10,530,842	16,693	7,455	1,783	11.15
Sample	*1,058*	*5,327,325*	*14,042*	*6,161*	*1,351*	*13.30*

3.3 Results

Regression results for the revenue model are summarised in Table 5. Our results suggest elasticities of PT revenue with respect to employment density and vehicle delays of 0.64 and 0.43, respectively. These coefficients are significant at the 0.1% level. In terms of model fit, we find an R-squared value of 0.59, with actual and predicted PT revenues showing a good alignment with no extreme values (Figure 2).

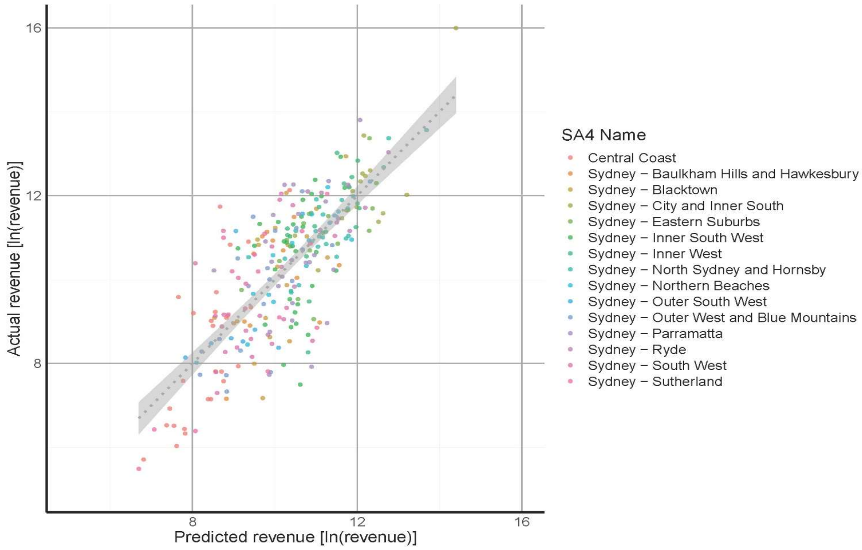
Table 5: Regression Results – Revenue Model (V2) with SA3 fixed effects

Parameters	Estimates
log(emp. density)	0.64 (0.10)***
log(delays)	0.43 (0.06)***
R^2	0.59

Notes: n = 280 obs. S.Es in brackets; ***p < 0.001, **p < 0.01, *p < 0.05. Model includes SA3 fixed effects.

[6] Readers may wonder if aggregate revenue data could be used to check this assumption. We see two problems with such an effort. First, we have defined cities as GCCSAs, which may or may not align with reported revenue data. Second, and perhaps more problematic, we have used SA3 fixed effects to control for average differences in fares within Sydney. Without having estimated similar fixed effects for the cities, we are unsure how to use our results to predict revenue at the SA2 level in other cities. Perhaps the best approach would be to estimate a model without fixed effects, although we feel this is unlikely to be representative due to potential differences in average fare levels between cities.

Figure 2: Revenue Model – Model Fit (V2)



We test the sensitivity of our revenue model to alternative specifications and estimate an instrumental variables version (VLC, 2019). Results from these tests were similar to those presented above for our baseline model.

4. Implications and Extensions

4.1 Implications

In this section, we work through the fiscal implications of our findings. To summarise, the effect of non-policy factors on net PT expenditure per capita is captured using three types of models:

- *Supply*, as measured in seat-km
- *Productivity*, as measured in vehicle-hours (speed) and vehicle-kilometres (route-kilometres)
- *Revenue*, as measured in monetary terms.

We examine the implications of these models for net PTE in each of the five cities for which we have data. To begin, we ignore productivity effects and instead focus on understanding the implications of the supply and revenue models, which consider the same non-policy factors, specifically employment density and car delays. Appendix A.3 extends this analysis to include productivity effects.

Whereas the revenue model is estimated in monetary terms, the PT supply is estimated in seat-km. For the purposes of our analysis, we assume seat-km exhibit a 1:1 relationship with costs. That is, a 1% increase in seat-km leads to a 1% increase in costs. As well as being simple, this approach has the advantage of being policy-neutral, in the sense it is unaffected by the costs of different modes.

Conceptually, our analysis then proceeds by comparing two scenarios: **actual values** in each city and the **sample average**. In the sample average scenario, the level for non-policy factors is defined by the average for our sample. That means all cities face the same non-policy factors, in terms of employment density and car delays. By extension, in the sample average scenario all cities will have the same net PTE.

We then calculate the effects of shifting each city from the sample average to their actual values. Differences in net PT expenditure per capita between the actual and average scenarios define the estimated effect of non-policy factors. The effects of non-policy factors on PT supply, or costs, per capita are estimated for each city in the actual (A) and sample (S) scenarios as follows:

$$\frac{S_A}{S_S} = \left(\frac{d_A}{d_S}\right)^{\alpha_1} \left(\frac{c_A}{c_S}\right)^{\alpha_2}$$

Where:

- S_A and S_S denote the supply, or cost;
- d_A and d_S denote average employment density;
- c_A and c_S denote congestion levels; and
- α_1 and α_2 denote elasticities for employment density and car delays from our supply model.

Using results from Table 3, we have $\alpha_4 = 0.55$ and $\alpha_5 = 0.42$.

Similarly, the fiscal implications of the revenue model for net PT expenditure are calculated as:

$$\frac{R_A}{R_S} = \left(\frac{d_A}{d_S}\right)^{\beta_1} \left(\frac{c_A}{c_S}\right)^{\beta_2}$$

Where:

- R_A and R_S denote revenue;
- d_A, d_S, c_A, and c_S are as defined above;
- β_1 and β_2 denote estimated elasticities for employment density and car delays from our revenue model.

Applying the above formulae to results from Table 5 ($\beta_1 = 0.64$ and $\beta_2 = 0.43$) and the first two columns of Table 6, we can then estimate the effects of non-policy factors on PT costs and revenue and, by extension, the change in net PTE. For all cities, we set the average index for costs and revenues to 100 and 25, respectively (NB: The choice of index has no effect, instead what matters is the relative change in costs to revenue between cities).

Table 6: Net PT Expenditure per capita – Effects of Non-policy Factors on Costs and Revenue

City	d_i	c_i	Costs	Revenues	Net Exp.	Change from Baseline
Sydney	1,610	1,790	133.31	34.30	99.01	+32%
Melbourne	1,413	1,624	118.90	30.23	88.67	+18%
SE Qld	1,013	881	77.16	18.97	58.19	-22%
Perth	523	854	52.50	12.20	40.30	-46%
Adelaide	661	1,356	72.49	17.25	55.24	-26%
Baseline	1,181	1,359	*100.00*	*25.00*	*75.00*	*0%*

This exercise shows that non-policy factors add an estimated 32% to Sydney's net PTE compared with the average within the sample. The same factors reduce Perth's net PTE by approximately 46%.

In Sydney's and Melbourne's cases, higher-than-average densities and congestion drive higher costs from additional PT services, which is only partly offset by extra revenue from these factors. SEQ has around average levels of density, but significantly lower congestion than average, while Adelaide has around average levels of congestion but is very low density. The estimated effects on net PT expenditure are similar for both cities at around 25% below average. In Perth's case both density and average congestion levels are well below average, resulting in a city that is relatively low net cost to service by PT.

4.2 Extensions

Our work could be extended in several ways, such as:

- *Develop a revenue model that includes other capital cities.* The confidential nature of PT ticketing data means that we were unable to estimate our revenue model for cities other than Sydney. The revenue model uses aggregate revenue by SA2s, so it may be possible for states to share revenue data while preserving the confidentiality of the underlying travel patterns.
- *Develop a monetary measure of supply at the SA2 level.* In formulating our supply model, we developed relatively innovative techniques for assigning PT supply (kilometres and hours) to SA2s, which in turn could be converted to seat-kms and seat-hrs. Further work could seek to monetise these supply measures by applying unit cost rates for each mode and jurisdiction. If this data was linked to revenue data at the SA2 level (as per the comment above), then it would be possible to model net PT expenditure at the SA2 level.
- *Incorporate ferries into our supply-side model.* Ferries were excluded from our supply-side model because their vehicle-kms largely fall outside of the SA2 that they service. Including them would require calculating their seat-kms and assigning them to the SA2s where they stop, rather than travel through.

Finally, we note that addressing the first and second points above presents the opportunity to integrate our revenue and supply models into one model of net PTE, like that used by the CGC although at a higher level of spatial detail. This approach would avoid the need to parse together results from two models and also reduce the CGC's reliance on revenue and cost information supplied and processed by states, potentially using different methodologies.

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Appendix: Productivity models

In this appendix we present models of the productivity of PT services in each of the five largest capital cities. We measure productivity in terms of average speed and route length. Our goal is to understand how these outcomes are affected by various non-policy factors. In the final section, we extend the analysis of the body of this paper by attempting to convert productivity impacts into a monetary value to understand the overall effect of non-policy factors on cost recovery.

A.1 Average speed

We first seek to explain how the speed of bus and tram services vary according to a range of policy and non-policy variables trips (we do not model the speed of heavy rail, which seems less likely to be affected by non-policy factors).

We build a dataset of service speeds for bus and tram/light rail services using GTFS (generalized transit feed specification) data for the five largest capital cities. We restrict our analysis to the relevant GCCSAs defined by ABS. We use scheduled GTFS data, rather than real-time data, which is not publicly available for all the cities we analysed.

We filtered out values that were considered erroneous and/or unrepresentative, specifically trip-IDs with:

- Average speeds in excess of 70 km/hr. Inspection suggests these trips are usually incorrectly coded by the agencies/operators.
- Trip-lengths shorter than 5km or longer than 50km, or that have durations less than 20 minutes or more than 2-hours. Inspection revealed that such trips are associated with atypical routes, such as inner-city circulators, or shuttles.
- Two or fewer stops. Many of these trips are short-running and point-to-point shuttle services, such as those provided for major sports events.
- Less than 100m (Euclidean distance) between the start and end stops, which were loops that were slow by design rather than due to non-policy factors.

These filters reduced the number of trip-IDs from 335,168 to 282,225, leaving us with 84% of the original data. We consider this to be a large and representative sample of PT services in the five capital cities.

A model of these average speeds, s, of bus or tram service trips i is specified as:

$$s_i^B = \alpha_0 + \alpha_1 \ln(l_i) + \alpha_2 \ln(d_i) + \alpha_3 p_i + \alpha_4 \ln(c_i) + \alpha_5^c D_i^c + \alpha_6^w D_i^w + \alpha_7^h D_i^h + \alpha_8^{cw} D_i^c D_i^w + \alpha_9^{ch} D_i^c D_i^h + \alpha_{10}^{wh} D_i^w D_i^h$$

Where:

- s_i^B is the average speed of trip i from the GTFS routes and timetables
- l_i is the route distance between the start and end of trip i [km]
- d_i is the average stop-spacing on trip i [km per stop]
- p_i is the population catchment (sum of the ABS meshblock populations whose centroids lie within 750m of stops on the trip, excluding overlaps)
- c_i is traffic congestion delays to private vehicles in SA1s that routes traverse (taken from VLC's Zenith transport models of 2016)
- D_i^c is a city categorical variable, where Sydney is the base category
- D_i^w is a weekday/weekend dummy variable (weekday is the base category)

- D_i^h are 24-four hourly categorical variables (0400-0500 is the base category)
- α's are regression parameters to be estimated.

The categorical variables D_i^c, D_i^w, and D_i^h allow average speeds to vary by city, between weekdays / weekends, and by hour of the day. The three pairwise interaction terms are interpreted as follows:

- $D_i^c D_i^w$ allows the average speed in each city to vary between weekdays/weekends;
- $D_i^c D_i^h$, allows the average speed in each city to vary by hour of day; and
- $D_i^w D_i^h$ allows average speed on weekdays/weekends to vary by hour of day.

We expect average speed will:

- Increase with route length, l_i, because longer routes tend to operate (1) in peripheral areas with less congestion or (2) where they have greater priority over general traffic,
- Increase with stop-spacing, d_i, because longer stop spacing allows vehicles to achieve a higher speed,
- Decline with catchment, p_i, as catchment is associated with increased PT demand. Services that experience greater demand will, on average, be expected to run more slowly due to longer dwell time,
- Decline with car congestion delays, c_i. We this effect will diminish at higher congestion levels, due to proactive policies, such as bus priority infrastructure. For this reason, we take the log of congestion.

Summary statistics show that Sydney operates the second highest number of bus and tram trips (services) after southeast Queensland (SEQ), which likely reflects the latter's extensive busway infrastructure (and associated high-frequency services) and limited heavy rail network (Table 7).

Table 7: Summary Statistics for Productivity Model – Bus and Tram Average Speed by SA2

Market	Mode	n [trips]	Average speed (s_i) [km.hr]	Route length (l_i) [km]	Stop-spacing (d_i) [km/stop]	Pop. Catchment (p_i) [people]	Congestion (c_i) [veh.hr]
Syd.	*Bus & Tram*	*188,587*	*22.369*	*17.598*	*0.528*	*75,808*	*1,933*
Mel.	Bus	149,966	23.458	16.690	0.417	51,336	1,099
	Tram	30,372	16.381	15.061	0.290	111,881	1,643
	Total	*180,338*	*22.266*	*16.416*	*0.396*	*61,533*	*1,190*
SE Qld	*Bus & Tram*	*322,119*	*24.346*	*17.788*	*0.736*	*46,758*	*1,504*
Perth	*Bus*	*95,598*	*25.322*	*15.921*	*0.443*	*34,348*	*741*
Adl.	*Bus & Tram*	*49,061*	*23.077*	*18.541*	*0.461*	*38,812*	*1,259*
Sample		*835,703*	*23.488*	*17.280*	*0.566*	*54,616*	*1,431*

After SEQ, the number of trips declines with city size. For average speed, we see that Sydney is the slowest of all cities, while Perth is the fastest. Although Sydney and Melbourne have similar average speeds, the former operates longer routes with larger distances between stops.

In terms of non-policy factors, the average bus / tram trip in Sydney has higher catchment and congestion levels than is found in the other cities. For example, average population catchment is 23% higher in Sydney than in Melbourne, while congestion is 29% higher in Sydney than in SEQ.

Regression results show both population catchment and congestion have the expected negative sign and are statistically significant ($p < 0.05$ or smaller) (Table 8). That is, higher population catchments and increased congestion leads to lower bus/tram speeds, which aligns with our priors.

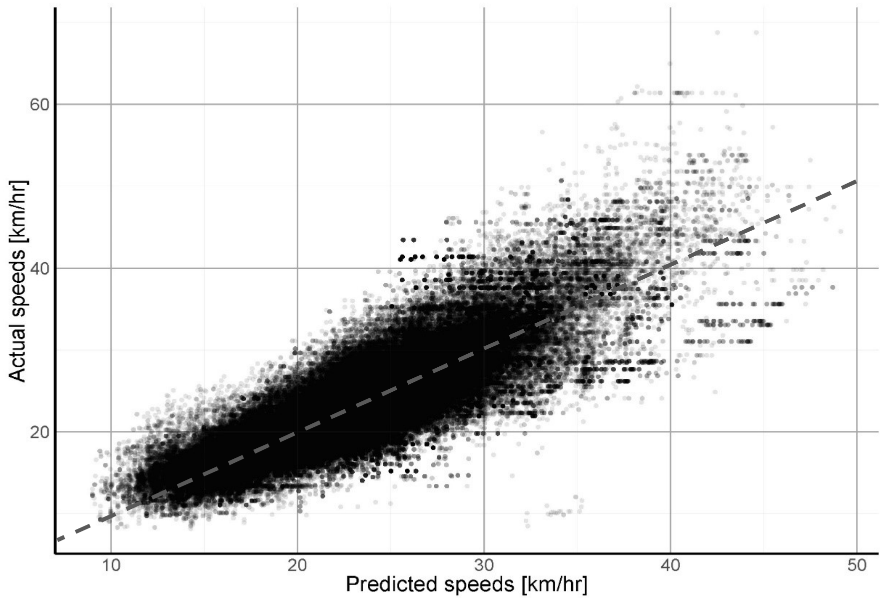
Table 8: Regression Results for Productivity Model – Bus and Tram Average Speed (V3)

ln(length) (l_i) [km]	8.39 (0.30)***
ln(stop-spacing) (d_i) [km/stop]	4.44 (0.54)**
Population Catchment (p_i) [per 1,000 people]	-0.10 (0.02)**
ln(congestion) (c_i) [veh.hrs]	-1.11 (0.32)*
R^2	0.70

Notes: n = 282,225. Standard errors in brackets; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All models include City x Weekend x Hour terms. Fixed effects are omitted but are available on request; inspection revealed a logical profile for hourly dummies.

To finish, we consider the overall explanatory power of the model. Figure 3 also illustrates predicted average speeds (horizontal axis) versus actual average speeds (vertical axis). Generally, we find a strong positive linear observation with clustering around the diagonal and few apparent extreme values. The model has an R-squared value of approximately 0.70.

Figure 3: Productivity Model – Bus and Tram Actual Speeds Model Fit (V3)



We considered several alternative specifications of the V3 Weighted model, with the regression results for these sensitivity tests confirming the lack of sensitivity to variable definitions selected; results are summarised in the full paper (VLC, 2019).

A.2 Route length

In this section we develop productivity models of route length, applied first for bus and tram, then heavy rail.

We specify a route length model that contains a set of general exogeneous controls, as well as our non-policy factors of interest:

$$l_i^B = \alpha_0 + \alpha_1 \bar{l}_i + \alpha_2 \bar{d}_i + \alpha_3 p_i + \alpha_4 \log c_i + \alpha_5 g_i + \alpha_6 z_i + \alpha_7^c D_i^c + \alpha_8^w D_i^w + \alpha_9^h D_i^h + \alpha_{10}^{cw} D_i^c D_i^w + \alpha_{11}^{ch} D_i^c D_i^h + \alpha_{12}^{wh} D_i^w D_i^h$$

Where l_i^B denotes the route distance between the start and end of trip i [km]; $\bar{l}_i$ denotes the Euclidean (or "crow flies") distance between the start and end of the route; and $\bar{d}_i$ denotes the number of stops. We also include four non-policy variables:

- **catchment** (p_i), defined in Section A.1
- log of **congestion** (c_i), defined in Section A.1
- absolute change in vertical **elevation**, z_i, an indicator of hilly terrain. We sum the (absolute) changes in vertical elevation between stops along the route, where elevation data is sourced from SRTM (NASA).
- geographical **deviation**, g_i, to measure the effect of geographical barriers, such as harbours and rivers. We subtract (1) the Euclidean distance from (2) the shortest network distance, from the start to the end of the route.

As in the speed model, D_i^c, D_i^w, and D_i^h denote categorical variables for city, weekday / weekends, and time of day, respectively. We include all pairwise interaction effects between categorical variables. α's denote regression parameters to be estimated.

We expect l_i^B will increase with Euclidean distance, $\bar{l}_i$, number of stops, $\bar{d}_i$, increase with barriers, g_i and elevation, z_i. We expect l_i^B will decrease with population catchment, p_i, because in dense areas routes do not need to travel as far to reach people, and, planners design shorter routes for reliability.

Summary statistics show that average bus and tram route length, Euclidean distance, and number of stops are similar in Sydney to other cities (Table 9). Comparing the number of stops across cities, we find that SEQ is the outlier with fewer stops per trip. Again, this likely reflects the effects of SEQ's extensive busways. For our new non-policy factors, we see that bus and tram routes in SEQ and Sydney tend to face greater geographical barriers and larger changes in vertical elevation than the average route.

Table 9: Summary Statistics for Productivity Model – Bus and Tram Route Length

Market	Mode	n [trips]	Length (l_i) [km]	Eu. Dist ($\bar{l}_i$) [km]	Stops ($\bar{d}_i$)	Catchment (p_i) [people]	Congestion (c_i) [veh.hr]	Deviation (g_i) [km]	Elevation (z_i) [km]
Syd.	*Bus & Tram*	*188,587*	*17.60*	*10.29*	*43.72*	*75,808*	*1,933*	*2.43*	*0.29*
Mel.	Bus	149,966	16.69	10.05	43.32	51,336	1,099	1.707	0.22
	Tram	30,372	15.06	12.03	51.65	111,881	1,643	1.609	0.27
	Total	*180,338*	*16.42*	*10.07*	*43.41*	*61,533*	*1,105*	*1.71*	*0.22*
SE Qld	*Bus & Tram*	*322,119*	*17.79*	*10.87*	*29.56*	*46,758*	*1,505*	*2.44*	*0.23*
Perth	*Bus*	*95,598*	*15.92*	*9.94*	*38.78*	*34,348*	*741*	*2.125*	*0.21*
Adl.	*Bus & Tram*	*49,061*	*18.54*	*12.10*	*45.55*	*38,812*	*1,262*	*2.02*	*0.25*
Sample		*835,703*	*17.28*	*10.59*	*37.96*	*54,616*	*1,432*	*2.22*	*0.24*

Regression results show geographical barriers and vertical elevation have the expected positive effect on route length ($p < 1\%$), population catchment has the expected negative effect ($p < 1\%$), and congestion is insignificant.

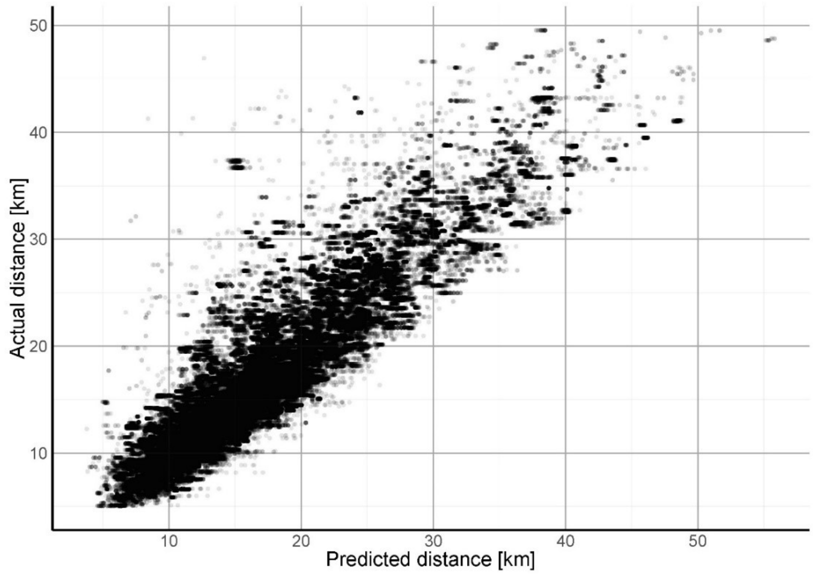
Table 10: Regression Results for Productivity Model (V3) – Bus and Tram Route Length

Euclidean distance	0.94 (0.07)***
Number of stops	0.14 (0.01)***
Population Catchment (p_i) [per 1,000 people]	-0.04 (0.01)**
ln(congestion) (c_i) [veh.hrs]	0.32 (0.16)
Deviation (g_i) [km per route]	0.34 (0.06)**
Elevation (z_i) [Δ height per route]	5.59 (1.21)**
R^2	0.83

*Notes: n = 282,225. Standard errors in brackets; ***p < 0.001, **p < 0.01, *p < 0.05. All models include City x Weekend x Hour terms*

The model route length has good explanatory power, with an R-squared value of 0.83. Predicted versus actual values show a strong positive association with most values clustered around the 45-degree line (Figure 4). We observe more variation on the upside, suggesting errors are heteroskedastic, supporting the use of robust standard error (V3).

Figure 4: Productivity Model – Bus and Tram Route Length Extended Model Fit



We use the same underlying data as described above to estimate a heavy rail route length model. Summary statistics are presented below in Table 11.

Table 11: Summary Statistics for Productivity Model – Heavy Rail Route Length

Market	n [trips]	Length (l_i) [km]	Eu. Dist ($\bar{l}_i$) [km]	Stops ($\bar{d}_i$)	Catchment (p_i) [people]	Congestion (t_i) [veh.hr]	Deviation (g_i) [km]	Elevation (z_i) [km]
Syd.	47,096	39.48	29.18	19.38	138,000	2,819	4.59	0.25
Mel.	57,240	31.12	25.55	18.75	93,000	2,312	2.60	0.19
SEQ	4,748	58.07	43.70	26.91	82,000	2,408	7.80	0.20
Perth	15,627	22.92	19.83	14.53	35,000	1,090	2.45	0.08
Adl.	3,572	27.53	22.75	17.61	35,000	1,061	2.63	0.17
Sample	*128,283*	*34.09*	*26.78*	*18.73*	*100,433*	*2,318*	*3.50*	*0.20*

Sydney operates the most kilometres (trips x length) by heavy rail, whereas SEQ operates the least. We note that the definition of a PT 'trip' (service) varies significantly between jurisdictions. For example, in SEQ all rail trips are through-routed across the city centre, which effectively halves the number of trips compared to a city like Perth, which does not. In terms of average route length, we find that Sydney is slightly longer than the sample average and has slightly more stops. As for non-policy factors, Sydney's population catchment, congestion levels, and elevation are higher than in other cities, whereas for deviation Sydney has the second largest after SEQ. While Sydney and SEQ appear to be outliers by this measure, most of the difference is explained by the length of rail trips in these cities, which are longer than average. Indeed, if we divide the deviation by the average route length to calculate deviation per kilometre travelled, then we find that the ratios for all five cities are much closer together.

Regression results show that route length tends to increase with Euclidean distance and the number of stops, as expected. For our four non-policy factors, coefficients for deviation and elevation are positive and statistically significant ($p < 0.1\%$), whereas those for catchment and congestion are not (Table 12).

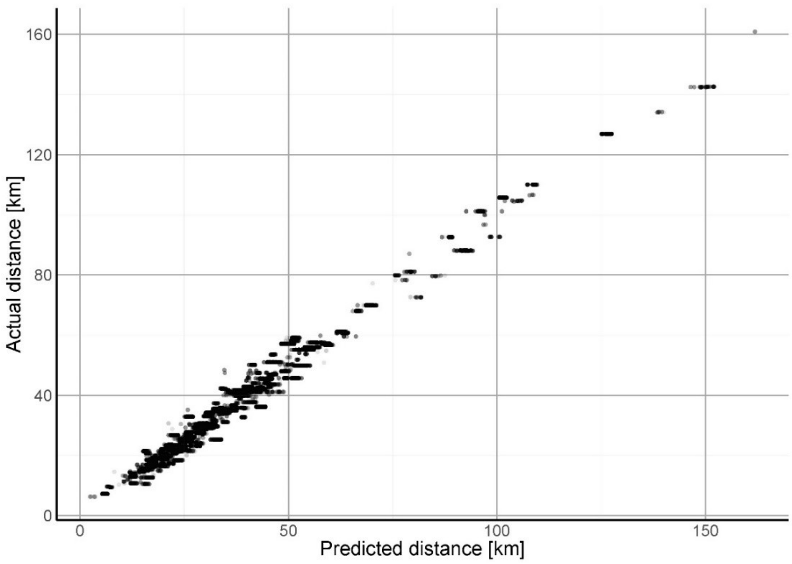
Table 12: Regression Results for Productivity Model – Heavy Rail Route Length

Euclidean distance	0.90 (0.02)***
Number of stops	0.17 (0.11)
Population Catchment (p_i) [per 1,000 people]	0.01 (0.01)
ln(congestion) (t_i) [veh.hrs]	0.41 (0.75)
Deviation (g_i) [km per route]	1.00 (0.13)**
Elevation (z_i) [Δ height per route]	12.80 (1.53)**
R^2	0.97

*Notes: n = 70,745. Standard errors in brackets; ***p < 0.001, **p < 0.01, *p < 0.05.*

In terms of explanatory power, we find both the Basic and Extended heavy rail route length V3 models have high R-squared values of 0.94 and 0.97, respectively. Model fit is illustrated in Figure 5. This reveals an excellent alignment between the predicted and actual values, with no extreme values.

Figure 5: Productivity Model – Heavy Rail Route Length Extended Model Fit (V3)



A.3 Refining cost recovery to account for productivity

Here we extend the analysis of cost recovery in Section 4.1 to account for our findings on the drivers of PT productivity (speed and route lengths). Using the results presented in Section A.1, we calculate the effect of non-policy factors on bus/tram and heavy rail productivity in each of our five cities by calculating the percentage change in average performance for bus/tram (speed and distance) and heavy rail route (distance). Estimated average productivity effects for each mode are summarised in Table 13.

Table 13: Bus/Tram and Heavy Rail Productivity – Effect of Non-policy Factors

City	Bus and Trams					Heavy rail		
	Speed (hours)		Distance		Cost Effect [%]	Distance		Cost Effect [%]
	KM/hr	%	KM	%		KM	%	
Sydney	-2.45	-10.4%	-0.39	-2.2%	4.38%	1.73	5.1%	2.54%
Melbourne	-0.49	-2.1%	-0.25	-1.5%	0.74%	-1.03	-3.0%	-1.51%
SE Qld	0.73	3.1%	0.33	1.9%	-1.00%	4.30	12.6%	6.31%
Perth	2.76	11.7%	0.41	2.4%	-4.78%	-2.59	-7.6%	-3.79%
Adelaide	1.72	7.3%	0.61	3.5%	-2.55%	-1.25	-3.7%	-1.84%

To put these effects on a monetary basis, we assume vehicle-hours and vehicle kilometres represent 50% and 30% of vehicle operating costs, respectively, based loosely on TfNSW (2016). (NB: Implying 20% is attributable to vehicle fleet, which we do not consider in our analysis and that is likely to make our estimates relatively conservative, in the sense that we underestimate productivity effects). Under these assumptions, non-policy factors are predicted to increase Sydney's bus and tram operating costs by 10.4% x 50% - 2.2% x 30% ≈ 4.38%. Similarly, for heavy rail we assume vehicle-kilometres represent 50% of total operating costs, such that non-policy factors are estimated to increase operating costs by 5.1% x 50% ≈ 2.54%.

We can then combine these productivity effects by assuming bus / tram and heavy rail operating costs represent 50% and 45% of total net PT expenditure, respectively, with the remainder attributable to ferries. Sydney's total percentage productivity loss attributable to non-policy factors can then be calculated as +3.24% (= 45% x 4.38% plus 50% x 2.54%).

We calculate productivity effects for each city using the same assumptions on relative operating cost splits between hours vis-à-vis kilometres and bus/tram vis-à-vis heavy rail, where the "productivity factor" (PF) represents the estimated net effect of non-policy factors on PT productivity. A PF smaller than one implies non-policy factors decrease PT productivity, and vice versa for a number greater than one. Our analysis suggests non-policy factors lead to PF in Sydney and Perth that are 3.2% and 4.1% lower and higher than average, respectively (Table 14).

Table 14: Calculating productivity factors

City	Fiscal effect			PF
	Bus/Tram	Rail	Total cost	
Sydney	1.97%	1.27%	3.24%	0.968
Melbourne	0.33%	-0.75%	-0.42%	1.004
SE Qld	-0.45%	3.15%	2.70%	0.973
Perth	-2.15%	-1.90%	-4.05%	1.040
Adelaide	-1.15%	-0.92%	-2.07%	1.021

Applying PFs to costs (revenue is left unchanged from that in Table 6), we find Sydney's net PT expenditure per capita is 38% higher than average once productivity effects are accounted for (Table 15). In contrast, non-policy factors *reduce* Perth net PT expenditure per capita from 46% to 49%. Taken together, these two results imply non-policy factors drive net PT expenditure per capita in Sydney 87% higher than in Perth. Non-policy factors also cause Sydney's net PT expenditure per capita to be 20% higher than Melbourne.

Table 15: Net PT Expenditure per capita – Adding Productivity Effects

City	Costs		Revenues	Net Expenditure		Effect	
	No PF	+PF		No PF	+PF	No PF	+PF
Sydney	133.31	137.78	34.30	99.01	103.48	+32%	*+38%*
Melbourne	118.90	118.40	30.23	88.67	88.17	+18%	*+18%*
SE Qld	77.16	79.31	18.97	58.19	60.33	-22%	*-20%*
Perth	52.50	50.46	12.20	40.30	38.26	-46%	*-49%*
Adelaide	72.49	71.02	17.25	55.24	53.78	-26%	*-28%*
Baseline	*100.00*		*25.00*	*75.00*		*0%*	