Elasticity of Demand for Sydney Public Transport

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IPART

FINAL REPORT

Prepared by:

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1. EXECUTIVE SUMMARY

Cambridge Economic Policy Associates Pty Ltd (CEPA) and the Hensher Group Pty Ltd (Hgroup) have prepared this report for the Independent Pricing and Regulatory Tribunal (IPART) of New South Wales on the elasticity of demand for public transport in Sydney and the surrounding areas. IPART plans to use these elasticities as an input into the next review of public transport fares.

In this study we use high frequency Opal data provided by Transport for New South Wales (TfNSW) to estimate a range of values for each of the following price elasticities for Sydney and its surrounds:

- **Own point price elasticity by time of travel for each mode of public transport** by which we mean the percentage change in demand for a mode e.g. rail, in response to a percentage change in price.
- **Cross-price elasticities for each mode of public transport and alternative travel modes by time of travel** (where possible). Cross price elasticities measure, for example, how rail demand is affected by a change in bus prices.

In addition, we assess how the elasticities discussed above differ by a number of factors, including but, not limited to, journey length, type of traveller (e.g. adult, child/youth, etc.), and location.

To conduct the study, we originally anticipated using a log-log model as our primary modelling approach as it would allow us to estimate a wide range of demand elasticities, including cross-elasticities with other forms of transport, such as car. However, we found that the log-log model was unable to produce reliable demand elasticity estimates for our dataset because of strong correlations between fares of different public transport travel modes.

However, an alternative modelling method – aggregate share logit model – was able to produce robust demand elasticity estimates of the expected sign and magnitude. We therefore use this modelling approach as our main estimation tool.

We have complimented the aggregate share logit model results with separate analysis estimating cross elasticities of demand for private car, as well as a corridor analysis of the most relevant corridors for ferry and light rail.

All the model results for this study have been carefully reviewed; only elasticity estimates which have the correct sign, are of a sensible magnitude, and are statistically significant at a 5 percent level have been included in the report. Therefore, we consider that all the results presented in this result are sufficiently robust for IPART to use as part of its next fare review.

More detailed findings are presented in the main body of the report. But overall, we find:

- The magnitudes of our elasticity estimates are in line with expectations, largely falling in the range of 0 to -1 for own-price elasticities and 0 to 1 for cross-price elasticities. The exception being ferry demand along the "Parramatta – Circular Quay" corridor, which we found to be relatively more elastic than other transport modes perhaps because these travellers have a higher number of alternative public transport modes available compared to the average traveller in the Opal network.
- The responsiveness of public transport demand with respect to price increases with journey length, with the largest elasticities for journeys in distance band 4 (>20km).
- Elasticities are lower for weekend travel compared with weekday travel. This may be the result of the weekly cap and/or weekly travel reward that means travellers do not incur any additional cost

(or only 50% of cost) for travelling on weekends if they have already reached the weekly cap (or accumulated 8 paid journeys) by the end of Friday, as well as the $2.50 fare cap on a Sunday.

- Demand for public transport is most responsive to changes in price in the hour after the peak period, which may be because travel during this time is less necessary / routine
- Multimodal journey demand is most responsive to changes in price for child/youth and senior/pensioner travellers, which suggests that these passenger types have reacted positively to the multimodal rebate that was introduced in September 2016.

Overall, we were successful in producing a wide range of robust elasticity estimates that IPART can use in its next fare review. However, data limitations, limited fare changes, similar fare change for all public transport modes, and other factors mean we have been unable to produce robust elasticity estimates for a number of journey types. Most notably for light rail journeys, where a combination of fewer data observations and a lack of variation in fare for travellers along the "Central – Dulwich Hill" corridor resulted in us not being able to produce robust elasticity estimates. The provision of Opal data at a higher level of disaggregation and for a longer time period may solve some of these issues.[1] However, there is no guarantee that more disaggregated data will solve the issues due to the presence of other detrimental factors, such as high correlation observed in the data and because there has only been minor changes to public transport fare structure in New South Wales (NSW) in the last three years.

[1] Due to data confidentiality reasons, TfNSW were unable to provide us with the tap-on tap-off level data, that may have allowed for a better aggregation of the data.

2. INTRODUCTION

In 2012 Transport for New South Wales (TfNSW) began rolling out the electronic tap-on tap-off "Opal Card" for fare payment on public transport in the greater Sydney area. This rollout was completed on 1 August 2016 and paper tickets were no longer accepted. The Opal system records data allows the assessment of changes in demand and estimation of the elasticity[2] of demand in response to price changes.

Cambridge Economic Policy Associates Pty Ltd (CEPA) and the Hensher Group Pty Ltd (Hgroup) have prepared this report for the Independent Pricing and Regulatory Tribunal (IPART) of New South Wales on the elasticity of demand for public transport in Sydney and the surrounding areas. IPART plans to use these elasticities as an input into the next review of public transport fares.

Public transport is essential for ensuring any modern city is both liveable and productive. It helps people get around while also reducing the number of cars on the road. Public transport in Sydney has been expanding its services and reach, increasing public transport options, but also increasing the overall efficient cost per trip. This cost is covered by both the fares collected on the network and contributions from the taxpayer. IPART's challenge is to set fares in a way that efficiently shares the cost between those who use Opal services and the taxpayer more broadly, considers how best to share the cost between travellers who use the network differently (e.g. those who travel short vs. long distances), and how to encourage the efficient use and delivery of public transport services, ensuring the best service for the lowest cost. An important input to this process is understanding how travellers change their behaviour in response to changes in price. While it may seem to make sense to shift more of the cost to those using the service, increasing fares may lead people to opt out of public transport altogether, which may lead to a rise in externality costs as the use of private transport (e.g. private car) rises. Understanding how users react to changes in the price by estimating their elasticity of demand for public transport is therefore an essential input into setting Opal fares.

In this study we use anonymized data provided by Transport for New South Wales (TfNSW) to estimate a range of values for each of the following price elasticities for Sydney and its surrounds:

- Own point price elasticity by time of travel for each mode of public transport by which we mean the percentage change in demand for a mode e.g. rail, in response to a percentage change in price (holding all other factors constant).
- Cross-price elasticities for each mode of public transport and alternative travel modes by time of travel (where possible). Cross price elasticities measure, for example, how rail demand is affected by a change in bus prices (holding all other factors constant).

In addition, we assess how the elasticities discussed above differ by:

- Journey length – Public transport elasticities may vary with journey length (associated with all modes used) and may differ between public transport modes. Four distance bands are examined in this study: 0-3km, 3-8km, 8-20km and more than 20km, which were selected based on the Opal card distance bands and the length of journeys taken.[3]

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[2] Elasticity of demand measures how sensitive demand is for a given good or service, in this case public transport, to changes in its price.

[3] Given the nature of Opal data, however, we are not able to capture door-to-door journeys or trips taken outside of the Opal network.

- Type of traveller/Opal card type – We expect there may be differences in elasticities across different types of travellers/opal card classes, e.g., adult, child/youth, concession, and senior/pensioner.
- Location – Generally we expect that individuals who have access to a greater number of alternative travel modes/options will have higher elasticities (i.e., greater sensitivity to price change and propensity to switch) than individuals who have few alternatives available.

Overall, this study produces a wide range of disaggregated elasticity estimates, which was made possible by the availability of high frequency Opal data. This will enable IPART / transport providers to optimise the price and subsidy levels at a more disaggregated level than was previously possible.

This report describes our key findings and the method we used to estimate the elasticities. The remainder of the report is structured as follows:

- Section 3 describes the data used to conduct the study.
- Section 4 outlines the methods used in this study.
- Section 5 presents our model results.
- Section 6 concludes the report by comparing results from our study with findings identified from the literature.

A series of annexes follow the main report:

- ANNEX A presents details of the literature used within this study.
- ANNEX B provides further details of our methodological approach.
- ANNEX C presents additional data exploratory analysis.
- ANNEX D includes additional aggregate share model results for child/youth, concession, and senior/pensioner passenger types.
- ANNEX E provides further details of our literature review.
- ANNEX F sets out analysis undertaken by Hgroup on the volume of public transport and car journeys.

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3. DATA

For this study, TfNSW has provided us with a 50 percent random sample of anonymised and time-truncated transactional Opal data for a period of approximately 18 months from the 1 August 2016 (when paper tickets were no longer sold or accepted). We note that, TfNSW aggregated the data to alleviate its internal concerns about individual passengers being identified in the data set. This aggregation anonymised the records but still provided us with a significant amount of information about journeys and trips taken by passengers. In addition, while the aggregation restricted the range of estimation approaches we could use, we do not believe it had a significant bearing on our findings.

Most of our analysis is conducted on the four-and-a-half-month period from 1 August 2016 to 20 December 2016, a period during which there was a significant change to prices, but service levels and the overall level of demand are relatively stable. This avoids mistaking a demand response to a change in the service level / quality (e.g. more frequent or reliable service) for a demand response to a change in price. It also helps to satisfy the underlying constrained demand assumption of the aggregate share model, which we use as the main estimation method for this study and is discussed in Section 4.

The introduction of Opal system and the large dataset that it provides, should enable the estimation of demand elasticities that are more reliable and accurate than has previously been the case.[4]

3.1. OPAL DATA SPECIFICATION

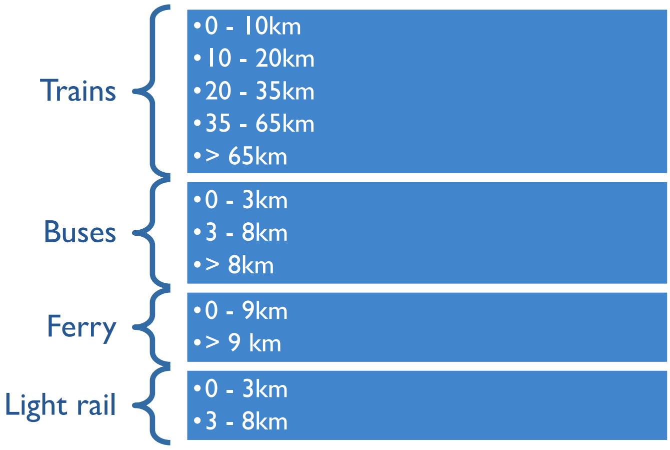
The Opal data provides a range of information, such as:

- Journey distance.
- Passenger type.
- Type of day.
- Mode of public transport.
- Time band.

Given the current and past distance-bands used in the Opal system, journey length will be a significant driver of the price of a public transport journey. The current distance bands used in the Opal system, for fares, are depicted in the diagram below.

[4] Technically a larger dataset of accurate records should lead to more precise estimates.

Figure 3.1: Current distance bands used in the Opal system



Source: CEPA and Hgroup

Based on the above and an examination of the number of journeys taken in each distance band, we identified that four distance bands would provide an appropriate level of aggregation:

- 0 – 3km
- 3 – 8km
- 8 – 20km
- >20km

The other characteristics the Opal data provides, as described in Figure 3.2 below. These characteristics can be used to estimate elasticities under different parameters, such as the elasticity of adult weekday train journeys taken in the AM peak time period with respect to price. Public holidays are excluded from the descriptive analysis as they tend to follow a very different demand profile (see Annex C for more details).[5]

[5] In addition, there were only four public holidays in the data series selected, providing insufficient observations for statistical significance.

Figure 3.2: Opal data characteristics

Passenger type

- Adult
- Child / youth
- Concession
- Senior / Pensioner

Type of Day

- Weekday
- Saturday
- Sunday

Mode of Public Transport

- Train
- Bus
- Light Rail
- Ferry
- Multimodal (Bus + Train)
- Multimodal (Other)

Time Band

- Morning (before 6:00)
- Pre AM peak (6:00 - 7:00)
- AM peak (7:00 - 9:00)
- Post AM peak (9:00 - 10:00)
- Inter-peak (10:00 - 14:30)
- Pre PM peak (14:30 - 15:30)
- PM peak (15:30 - 18:30)
- Post PM peak (18:30 - 19:30)
- Evening (after 19:30)

Source: CEPA and Hgroup

3.1.1. Subsets

Given the information included in the Opal data, the maximum number of combinations of user/card type, public transport mode, day of week, time bands, and distance bands is high: 4 card types × 6 modes × 3 type of day x 9 time bands × 4 distance bands = 2,592 combinations. For practical reasons, we analysed a subset of possible combinations, based on the following observations:

- Most multimodal journeys involve using a train and bus. Other multimodal journeys are unpopular, so our analysis only considered train and bus multimodal journeys.

- Based on the distance bands offered by each public transport mode it does not make sense to estimate direct elasticities for all four distance bands for every mode of public transport. For example, we didn't observe any light rail journeys that were >8km.

- Bus, light rail, and ferry fares do not change during the peak/off peak periods. Customers will not shift their travel from peak to off-peak because of price differences. This is also true for weekend travel, where all train journeys are classified as off-peak. Therefore, it is sensible to estimate direct time band elasticities for train and multimodal journeys on weekdays only.

- We reduced the number of time bands for train and multimodal journeys in order to produce meaningful results. To maximise the use of the data available, we use six time bands: Pre AM peak (6:00 – 7:00); AM peak (7:00 – 9:00); Post AM peak (9:00 – 10:00); Pre PM peak (14:30 – 15:30); PM peak (15:30 – 18:30); and Post PM peak (18:30 – 19:30). This approach captures train users switching the time they travel to save money by moving from peak to off-peak periods.

3.1.2. Limitations of Opal data

There are three important limitations or challenges to using Opal data in this study:

- Opal data does not include information on the non-public transport portion of any journey, such as taking a private car, taxi, or walking. Opal data cannot therefore be used on its own to determine cross elasticities between public transport and alternative travel modes.

- Opal data does not contain information on service quality, including aspects like quality/accessibility of trains and buses themselves (likelihood of getting a seat, likelihood of transport mode having A/C etc.), ease and convenience of use, and frequency of specific services, which may affect elasticities.

- Opal data alone will not give an Origin – Destination (O-D) elasticity if one of the trip legs is a non-Opal trip leg. O-D elasticities for these types of journeys are out of scope for this study.

3.2. ADDITIONAL DATA SOURCES

Given the limitations of Opal data, we considered a variety of other data sources that may give information on:

- **Driving:** In order to approximate for the cost of driving, we obtained data on the price of fuel in the New South Wales area from FuelCheck, hosted on the NSW Government Data website.[6] Prices of different fuel types were weighted to obtain a weighted average fuel price based on recent data on the consumption of different fuels in New South Wales:[7]

- **Service Quality / Level:** We obtained service kilometre data to proxy for changes in the service level using publicly available General Transit Feed Specification (GTFS) data from the TfNSW Open Data Website[8], which provides the number of service kilometres per day, and per time of day, for different public transport modes.[9] However, this information source is based on public transport timetables, and therefore does not take into account whether services actually run, or how punctual they are when they do. Hence, the absence of real time service quality / level data from Opal remains a limitation to this study.

- **Cycling:** Based on online research, we did not find any significant expansion of the Sydney cycling network during the time period available for this study. Calculating cross-price elasticities with cycling was therefore not feasible.

3.3. DATA EXPLORATORY ANALYSIS

We conducted initial data exploratory analysis to assess the data available and to check the validity of any assumptions made. Our findings from this analysis are discussed below.

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[6] Source: https://data.nsw.gov.au/data/dataset/fuel-check

[7] Sources: (i) Department of Infrastructure, Regional Development and Cities (2017). Fuel economy of Australian passenger vehicles - a regional perspective; (ii) Money costs (Dec 2016). Regular unleaded petrol facing crackdown.

[8] Source: https://opendata.transport.nsw.gov.au/dataset/timetables-complete-gtfs

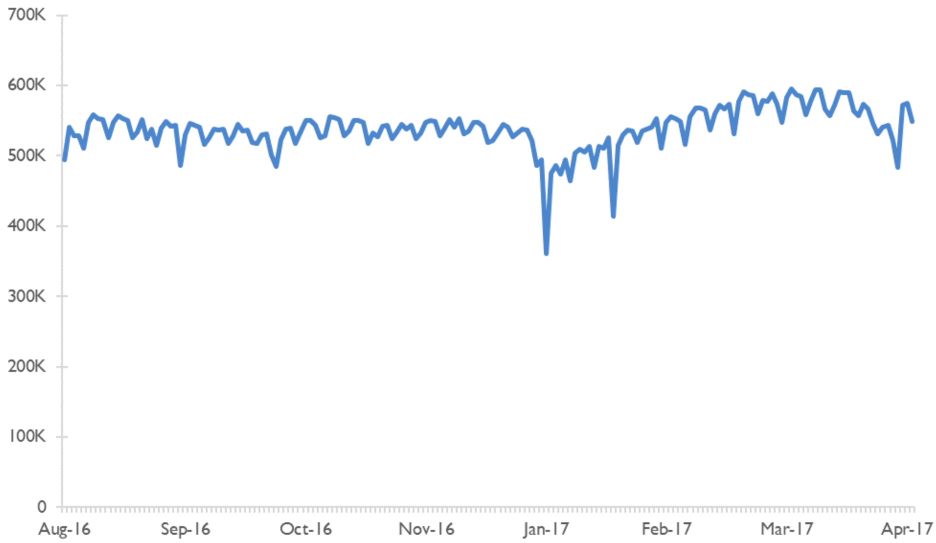
[9] Note, we have found three timetable periods on TfNSW's Open Data website: 29 August 2016 to 27 November 2017; 5 July 2017 to 3 September 2017; and 19 March 2018 to 17 June 2018.

3.3.1. Validity of model assumptions

To evaluate the validity of the constrained demand assumption underlying the aggregate share model used for this study (discussed in Section 4 below), we examined the total number of daily weekday journeys over the period from August 1st 2016 to April 30th 2017.[10]

To estimate precise elasticities, we need there to be variation in demand between different modes (i.e. travellers switching modes as a result of a price change) but stable demand at a total public transport level. As shown in the figure below, there is a clear increase in total number of journeys on public transport following the start of 2017.

Figure 3.3: Total number of journeys per day by 50 percent of fee-paying travellers from 1st August 2016 to April 20th 2017 (excluding weekends and Public Holidays)[11]



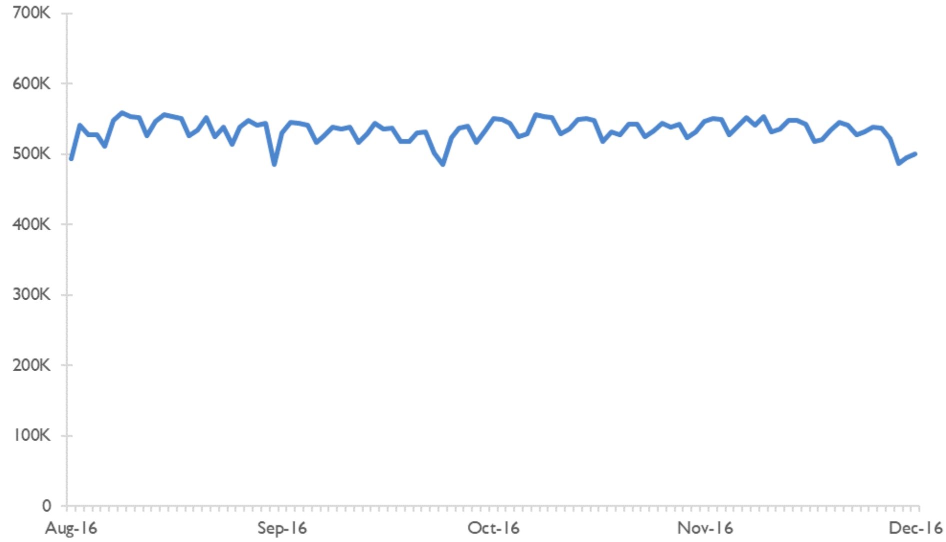
Source: CEPA and Hgroup analysis

We therefore narrowed the period we examined to the more stable period of August 1st 2016 to December 20th 2016, shown in Figure 5.2 below.

[10] Annex C provides additional data on the total number of journeys for each day of the week, including and excluding bank holidays.

[11] For more information on why public holidays were excluded, see Annex C.

Figure 3.4: Total number of journeys per day by 50 percent of fee-paying travellers from 1st August 2016 to 20th December 2016 (excluding weekends and Public Holidays)

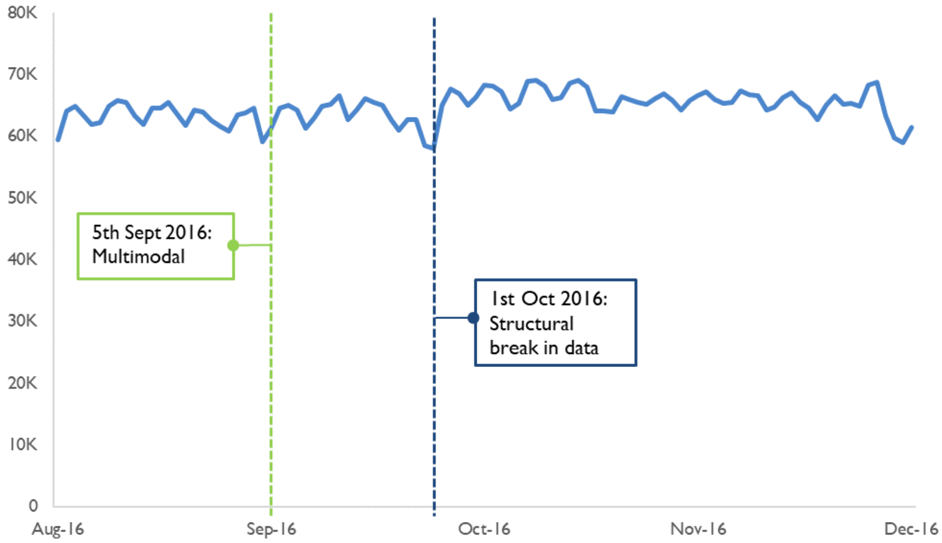


Source: CEPA and Hgroup analysis

This stability indicates that while travellers may have changed public transport modes and/or conducted a greater number of multimodal journeys as a result of the price change, they were not opting out of the public transport system. Additionally, large numbers of additional travellers were not choosing to enter the public transport system as a result of a price change during this period.

We also examined the variability of demand between public transport modes, i.e. can we see demand response following a change in price. Variability is crucial to determine whether we are able to estimate precise and reliable demand elasticities. The figure below shows the total daily weekday journeys for multimodal journeys only, which had a price reduction via a rebate introduced on 5th September 2016.

Figure 3.5: Total number of multimodal journeys per day by 50 percent of fee-paying travellers from 1st August 2016 to 20th December 2016 (excluding weekends and public holidays)



Source: CEPA and Hgroup

In the figure we can see a structural break in the data following the introduction of the multimodal rebate. In the period before the rebate the total number of multimodal journeys per day tends to be between 60,000 and 65,000. Following the break, we see a step change in the data, and the total number of multimodal journeys per day is now much closer to 70,000.[12] This variability, in conjunction with figures 5.1 and 5.2 above, indicates that the multimodal rebate had an impact on demand that was not caused by a change in demand for public transport more generally.

3.3.2. Journey fare variability

We have also assessed the variability of Opal fares over time by considering how the average Opal fare per journey on working Mondays has changed between August 2016 and April 2017. Our analysis is depicted in the figures below (relative to average fares in August 2016). In considering these results it is important to note that a multimodal rebate (or Opal Transfer Discount) was introduced in September 2016. It provides adult Opal card holders with a $2 discount for every transfer between train, ferry, bus, and light rail as part of one journey within 60 minutes from the last tap off. Similarly, child/youth, senior/pensioner and concession Opal card holders obtain a $1 discount for every transfer between modes. Once a traveller reaches the weekly travel reward cap of half-price travel (after 8 paid trips in one week), the multimodal rebate reduces by 50 percent. As a result of this decrease in the cost of multimodal journey, TfNSW recently found evidence of a significant increase in inter-modal transfer.[13]

The figures below demonstrate the impact of the rebate on the average public transport fares. They show the significant decrease in the average fare of a multimodal journey following the introduction of the rebate. There are also increases in the average fare of other journey types, which is likely to be driven by the introduction of the multimodal rebate (i.e. more travellers choosing to travel using more than one mode of public transport given the price saving).

Overall, this analysis shows that there is sufficient Opal fare change in the data selected to assess elasticities.

[12] Based on a 50% sample of journeys.

[13] Source: https://www.transport.nsw.gov.au/newsroom-and-events/media-releases/opal-customers-save-120-million-12-months

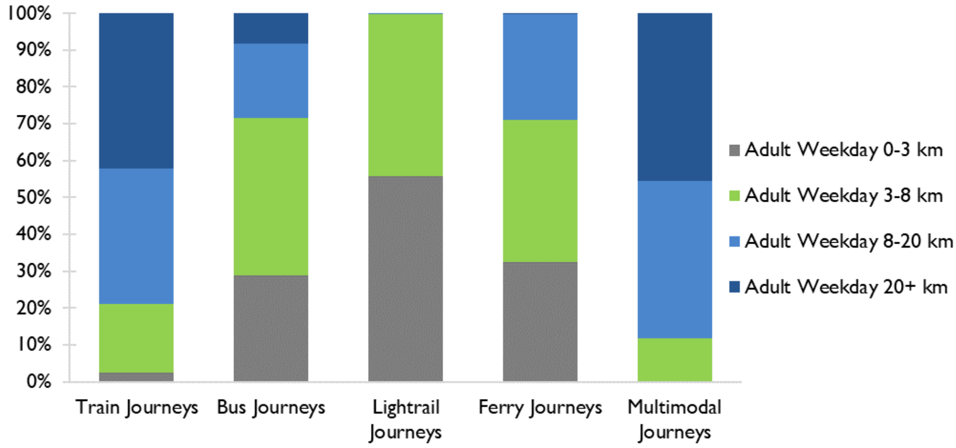
Figure 3.6: Average Opal fare per journey on working Mondays between August 2016 and April 2017 (base =1 in August 2016)

Source: CEPA and Hgroup analysis

3.3.3. Modes by distance bands

Demand elasticities cannot be calculated for all combinations of transport modes and distance bands, as some modes have few observations for certain distance bands, i.e. they are journeys that are rarely or never made. The figure below presents the breakdown of adult weekday journeys for each of the four distance bands (0-3km, 3-8km, 8-20km and 20+km) between August 2016 and May 2017.

Figure 3.7: Breakdown of adult weekday journeys for each of the four distance bands (0-3km, 3-8km, 8-20km and 20+km) between August 2016 and May 2017



Source: CEPA and Hgroup analysis

The figure shows that there are no light rail journeys beyond 8km; the majority of ferry journeys are below 20km; and the majority of multimodal journeys are 3km or above. As a result, we do not estimate demand elasticities for light rail journeys of more than 8km, ferry journeys of more than 20km, or multimodal journeys of less than 3km.

In addition, we do not estimate elasticities for mode / distance band combinations with relatively few journeys. For example, train journeys of less than 3km make up approximately 2 percent of total adult weekday journeys in the period studied.

4. MODELLING METHODS

We attempted to use two different modelling methods for this study. These are discussed below.

4.1. Log-log model

The **log-log model** is a linear regression model, which aims to explain the relationship between a dependent variable (e.g. number of train journeys) and one or more explanatory variables (e.g. total fares collected for different public transport modes). By taking the log transformation of the dependent and explanatory variables we are able to interpret the estimated coefficients of the regression model as elasticities.

Therefore, the estimated coefficient on the explanatory variable represents the expected percentage change in the dependent variable (i.e. demand) if the explanatory variable increases by 1% (i.e. fares). An illustrative example is presented below.

Table 4.1: Illustrative example of an estimated log-log model

Log (Train Journeys) = 8.20 – 0.15 Log (Train Fares) + 0.05 Log (Bus Fares)
• In this example, the natural log of train journeys (dependent variable) has been regressed on the natural log of train fares and the natural log of bus fares (explanatory variables). • The estimated coefficient on train fares represents the own price elasticity of train journeys. In this illustrative example, a coefficient of -0.15 indicates that a 1% increase in train fares leads to a 0.15% decrease in demand for train journeys. • The estimated coefficient on bus fares represents the cross-price elasticity of train journeys with respect to bus fares. In this illustrative example, a coefficient of 0.05 indicates that a 1% increase in bus fares leads to a 0.05% increase in demand for train journeys.

Source: CEPA and Hgroup analysis

One benefit of the log-log modelling method is that it allows total public transport demand to change over time. In technical terms, it assumes that public transport demand is unconstrained. This means, for example, that if the public transport service level, and in turn public transport demand, increased at one point in time as a result of an increase in the number of trains / buses in the network, it is still technically feasible to estimate accurate elasticities providing we can include an explanatory variable in the model that captures the change in the service level.

In addition to the service level, other explanatory variables that may have an impact on demand for public transport can also be easily included in the log-log model. The table below gives further details of control variables that could be included, their expected sign, and information on their availability for this analysis.

Table 4.2: Control variables

Control Variable	Expected Sign	Data source
Cost of car	Positive	We used fuel data from the publicly available 'FuelCheck' source to control for this.
Service quality (quantity)	Positive	We have used publicly available GTFS data to control for the service level, but the absence of real time service quality/quantity data remains a limitation of this study.
Time index	Ambiguous	No data source required.

Control Variable	Expected Sign	Data source
Cycleway expansion	Negative	We did not find any significant Cycleway expansion that occurred during our specified time period.
Cost of taxi/uber	Positive	Not included as there is insufficient data publicly available.

Source: CEPA and Hgroup analysis

While log-log models are preferable for being able to include a variety of control variables and their relative flexibility, when used to estimate elasticities of demand for public transport they can suffer from issues of multicollinearity and endogeneity. Unlike other goods that have daily or even hourly price variation, public transport fares tend to be set centrally and have little variation over time. As a result, public transport fares tend to follow similar patterns, with fares of all modes changing at the same time and more often than not going in the same direction. Given that we are attempting to explain the variation in public transport demand with the variation in public transport fares, it is unsurprising that the fare explanatory variables of different public transport modes will be highly correlated. Depending on the severity of the multicollinearity problem, this can lead to inaccurate and unexpected parameter estimates (i.e. elasticity estimates).

A further limitation of estimating log-log models for public transport demand is fare endogeneity. This is because fares tend to be set as a function of the number of journeys. For example, peak fares are set higher because more people travel at that time and the need for travel is more essential. Whereas, off-peak fares are set relatively lower as less people travel during these times, and journeys that are taken may be less essential. When we explore the data, this may look like more people want to travel when fares are higher, giving a counterintuitive positive elasticity. This problem is exacerbated by the log-log model specification, which includes total journeys on the left-hand side of the model and aggregate fares on the right-hand side of the model. This means that the total number of journeys is included on both sides of the equation. Hence, if demand goes up as a result of factors other than price then this will lead to a positive relationship between aggregate fares and total journeys unless the cause of the demand change is appropriately controlled for. The inclusion of the time trend and service kilometre variable will partially pick up some of these factors but are unlikely to capture them all.

These issues of multicollinearity and endogeneity can limit the results produced by the log-log model, depending on how prevalent they are in a given dataset.

4.2. AGGREGATE SHARE MODEL

We also conducted elasticity analysis using the **aggregate share model,** which is often viewed as a more sophisticated and precise approach to estimating elasticities. The model interprets the data as the result of an individual discrete choice process in which a traveller decides among different public transport alternatives. In this case the choices available to the traveller are train, bus, multimodal (bus and train), light rail and ferry. This model estimates the probability that a traveller will change public transport modes / time of travel given a change in the price of its current choice of public transport or alternative choices. These probabilities can be interpreted as elasticities and can be compared to alternative approaches to estimate price demand elasticities such as the log-log model.

Importantly, the aggregate share model is widely used to mitigate for key limitations of the log-log model, namely high multicollinearity and endogeneity. For example, de Grange et al (2013) studied the case study of the integrated public transport system in Santiago, Chile (known as Transantiago) and failed to obtain sensible elasticity estimates using the log-log model but obtained sensible and significant estimates using the aggregate share model.

While this model can produce more reliable results, it requires the use of the assumption that the total number of public transport journeys is fixed (i.e. total public transport demand is constrained). This assumption has the following implications:

- We assume that the total level of public transport demand remains fixed during the time period studied. This is a strong assumption to make but is more reasonable when considering a shorter period of time over which service level/quality is relatively constant. For this reason, we focus the aggregate share model analysis on the relatively stable period August to December 2016.
- The aggregate share model excludes the possibility that trips could be taken by modes other than public transport, e.g. private car, walking, taxi, or cycling, and excludes the possibility that the individual will choose not to travel at all, given a price change. It may not be realistic to assume that travellers do not consider switching to alternative non-public transport modes given an increase in price or consider switching to public transport modes given a decrease in price. These considerations may be more prevalent for certain travellers. For example, those who travel in distance band 1 (0-3km) may be more sensitive to public transport price changes than those who travel further to get to work (distance bands 2-4) as they may deem walking as an attractive and realistic alternative to public transport. However, as above, this assumption is made weaker by opting for a period in time with relatively stable total public transport demand. We carefully consider these in Section 5.
- We are unable to estimate cross elasticities with non-public transport modes, such as private car, walking and cycling using Opal data since these transport modes are not included.

In addition to the above, when we implement the aggregate share model we also have to consider the data available, which is a significant determinant of what elasticities can feasibly be estimated using the aggregate share model. For example, given there are no light rail journeys beyond 8km it is not possible to estimate elasticities for light rail journeys in distance bands 3 and 4. Similarly, the absence of service level and quality data in Opal means we are unable to understand the impact of service quantity and quality on public transport demand using the aggregate share model. These practical considerations are important to take into account when exploring the model results presented in Section 5.

4.3. MODEL APPROACH APPLIED

We originally anticipated using the log-log method as our primary approach, as it would allow us to estimate a wider range of demand elasticities, including cross-elasticities with other forms of transport, such as car. However, we found that the log-log model was unable to produce precise demand elasticity estimates for our dataset because the data is so highly correlated. Annex C provides further details. The aggregate share logit model, however, was able to produce precise demand elasticity estimates of the expected sign and magnitude. We therefore use this modelling approach as our main estimation tool noting that the strong demand assumption (in part dictated by available data) has implications for the interpretation of results.

The results of our aggregate share modelling for train, bus and multimodal journeys are presented in Section 5.1.2. We have complimented the aggregate share logit model with separate analysis estimating cross elasticities of demand for private car, as well as a corridor analysis of the most relevant corridors for ferry and light rail.

4.3.1. Corridor analysis for light rail and ferry journeys

The main aggregated dataset was used to estimate models for train, bus and multimodal journeys, and a separate 'corridor' analysis was undertaken for light rail and ferry journeys given that not all individuals have the option of choosing to travel by these modes and Opal data does not capture the number of different modes available at any given station. This process involved:

- identifying the most appropriate corridors (i.e. those with the most public transport options to choose from);
- creating two additional aggregated data sets by matching origin and destinations for journeys taken in these corridors; and
- estimating light rail and ferry own- and cross-price elasticities using the aggregate share model.

Our assessment of potential options highlighted the following corridors as the most appropriate for our analysis:

- **Ferry:** Circular Quay – Parramatta/Northwest corridor appears to be the best for ferry as travellers have a number of travel options to choose from:
    - Distance band 1 (<3km): travellers have ferry, bus, and light rail to choose from.
    - Distance band 2 (3 – 8km): travellers have ferry, bus, and train to choose from, with train split further into different time periods (pre peak, peak, and post peak).
    - Distance band 3 (8 – 20km): travellers have ferry, bus, train and multimodal (bus and train) to choose from, with train and multimodal split further into different time periods (pre peak, peak, and post peak).
    - Distance band 4 (>20km): very few ferry journeys are taken in distance band 4 along this corridor. Therefore, we omit these journeys from our analysis.
- **Light Rail:** Central – Dulwich Hill has the most public transport options to choose from:
    - Distance band 1 (<3km): travellers have ferry, bus, and light rail to choose from.
    - Distance band 2 (3 – 8km): travellers have ferry, bus, and train to choose from, with train split further into different time periods (pre peak, peak, and post peak).
    - Distance band 3 (8 – 20km) and Distance band 4 (>20km): very few light rail journeys are taken in distance bands 3 and 4. Therefore, we omit these journeys from our analysis.

Both corridors are illustrated in Annex B.3, and the results of our corridor analysis are presented in Section 5.1.3.

4.3.2. Estimating cross-elasticities of demand for private car

As our log-log model did not produce sensible cross elasticities of demand for private car using a combination of Opal and Sydney fuel cost data, we therefore complement our elasticity results from the aggregate share model with private car cross elasticity estimates obtained from a previous study completed by members of this project team.[14] These results are an important addition to the main public transport elasticity results presented in this report given IPART's approach of setting fares by calculating the efficient subsidy to offset the externalities of car travel. The study developed mode and time of day choice models that can be used within travel demand management and policy evaluation. Understanding what drives individual's choice of when to travel and what transport mode to use has been found to be a key determinant of the success of travel demand management in congested/crowded areas.

Data for the study was collected from a computer-assisted personal interview (CAPI) survey, which was purposefully designed to collect data for the development of mode and time of day joint choice models. The survey was conducted at 8 different interview sites, which were selected to provide a good mix of travel modes and to cover the Sydney Greater Metropolitan Area (SGMA). A sample of 1,221 interviews were used, spreading equally across six travel purposes (to work, from work, education, shopping, personal business, and social), which was considered to be sufficient to produce robust elasticity estimates. The use of primary research for this study eliminated the issue of collinearity and endogeneity identified in the Opal data; and also meant that private car could be considered alongside public transport journeys, which was important given the context of the study (i.e. what leads to effective travel demand management?).

As part of the study, robust cross-elasticity estimates were produced for private car with bus and train journeys, and for six different time periods: before 7am, 7-9am, 9am-3pm, 3-4pm, 4-6pm and after 6pm. While these time periods differ slightly from those used for the analysis conducted for this study, we consider they provide very useful information on responsiveness of change in public transport demand to a change in the cost of private car, which IPART can potentially use as part of their fare review. The study, however, is unable to provide cross elasticities for private car with ferry, light rail, or multimodal journeys, and may be interesting to assess in future research.

Overall, Ho, C. and Hensher, D.A. (2016) study allowed for estimation of sensible and precise cross elasticities with private car for bus and train journeys, and the results are presented in Section 5.1.4.

[14] Please see Ho and Hensher (2016) for further detail.

5. MODEL RESULTS

This section presents our model results. The main aggregated dataset was used to estimate models for train, bus, and multimodal journeys, and as discussed above a separate 'corridor' analysis was undertaken for light rail and ferry journeys. Therefore, three different aggregated datasets were used within the model estimation process. The main aggregated dataset was used to estimate elasticities for train, bus, and multimodal journeys (see Section 5.1.2); and two corridor datasets were used to estimate elasticities for light rail and ferry (see Section 5.1.3). As discussed, using Opal data does not allow us to directly estimate cross-elasticities with other modes of transport such as private car. Therefore, a separate analysis was conducted to estimate cross elasticities with private car, and the results of this analysis are presented in Section 5.1.4.

Annex F presents an additional piece of analysis Hgroup has produced for IPART, which estimates quantities of car and public transport journeys for all combinations of time period and distance band considered in this report.[15] This information can be used by IPART alongside the elasticity estimates presented in this report as an input into its fares optimisation model.

An illustration of how the elasticity estimates should be interpreted is presented in the textbox below.

Box 1: Illustrative elasticity example - a 1% increase in peak adult train fares in distance band 3-8km

All else equal, the results presented below indicate that a 1% increase in peak adult train fares in distance band 3-8km leads to a:

- 0.105% decrease in peak adult train journeys in distance band 3-8km.
- 0.036% increase in pre-peak adult train journeys in distance band 3-8km.
- 0.052% increase in post-peak adult train journeys in distance band 3-8km.
- 0.072% increase in adult bus journeys in distance band 3-8km.
- 0.039% increase in adult pre-peak multimodal (bus+train) journeys in distance band 3-8km.
- 0.045% increase in adult peak multimodal (bus+train) journeys in distance band 3-8km.
- 0.047% increase in adult post-peak multimodal (bus+train) journeys in distance band 3-8km.

Source: CEPA and Hgroup analysis

The remainder of this section presents our elasticity results, and is divided into four parts:

- Assessment of the appropriateness of the underlying assumptions made within the model development process.[16]
- Analysis of train, bus and multimodal elasticities using the main aggregated dataset.
- Analysis of light rail and ferry elasticities using the corridor aggregated datasets.
- Analysis of cross elasticities with private car.

We understand the importance of the outputs of this study for the next fare review IPART conduct. For these reasons, we only include elasticity estimates in this report which are both sensible in magnitude and statistically significant at a 5 percent level. In cases it has not been possible to produce robust elasticity estimates, we suggest that IPART consider the appropriateness of using other robust elasticity estimates

[15] Annex F was prepared and quality assured independently by Hgroup.

[16] The same assumptions are made within the main train, bus and multimodal journey analysis and the ferry and light rail corridor analysis.

presented in this report as a 'proxy'. For example, is might be appropriate / sensible to use own price ferry adult weekday elasticities as a proxy for own price ferry child weekday elasticities?

5.1. APPROPRIATENESS OF UNDERLYING ASSUMPTIONS

There are key assumptions underlying the model results presented below:

- The constrained demand assumption of the aggregate share model.
- The selected time band level.

The appropriateness of each assumption is discussed in turn below. Overall, we consider that the model results presented in this report are not undermined by the underlying assumptions made.

5.1.1. Constrained demand

The aggregate share model is able to produce precise and robust elasticity estimates in the presence of severe multicollinearity. As discussed above, however, this approach is limited by the constrained demand assumption; and the associated independence from irrelevant alternative (IIA) assumption under the multinomial logit (MNL) form, which is relaxed under more advanced model forms such as mixed logit.

The IIA assumption states that any item added to the set of choices will decrease all other items' likelihood of been chosen by an equal fraction. For example, consider that a person can travel to work either by car or by a blue bus, and the probability of each model of travel is 1/2. Now suppose the person can now also travel by red bus as the bus company has introduced a new fleet of buses on the network. We may expect that the probability of taking a blue bus is equal to taking a red bus. Given this scenario, the IIA assumption would assume that the car is chosen with probability a 1/3, a blue bus 1/3, and a red bus 1/3. As a result, we would effectively rule out the use of cars by increasing the number of colours used by the bus company. In reality, however, it is more likely that the original bus travellers would divide their travel equally between blue and red buses, meaning that the probability or travelling by car or by bus remains equal (1/2 versus 1/2). But this would violate the IIA assumption as the probability of travelling by car versus traveling by blue bus would become 1/2 versus 1/4. Therefore, the IIA assumption may not be appropriate in certain scenarios.

We tested the validity and appropriateness of the constrained demand and IIA assumptions using statistical and practical reasoning. As part of the data exploratory analysis in Section 3.3 we examined the total number of daily weekday journeys and found that total public transport demand during the period August 1st 2016 to December 20th 2016 was relatively stable. From a statistical and practical perspective, this evidence gave us confidence that the constrained demand assumption was not violated by the data. We also estimated more advanced models that relax the IIA assumption but found that these models did not provide any statistical improvement over the standard MNL model, which is arguably more transparent and easier to understand than more advanced model forms such as mixed logit. Taking these two pieces of evidence into account, we consider that our elasticity results are not significantly undermined by the underlying IIA assumption of the MNL form or the constrained demand assumption of the aggregate share model in general.

5.1.2. Selected time band level

The model estimation process we followed was the same when using all three datasets and involved estimating elasticities at different combination levels using the aggregate share model until we arrived at the most robust model specification, which is reflected in the model results presented. One key assumption was made with regards to the most appropriate time band level. In particular, AM and PM Pre/Peak/Post periods have been pooled (e.g. Trains Pre Peak = Trains AM Pre Peak + Trains PM Pre Peak) when estimating the models.

This decision makes sense from a behavioural perspective as individuals may be incentivised to switch their travel from the peak period to pre and post peak periods given that their day is unlikely to be overly affected by moving their travel time one hour before or after peak times. In addition, by pooling AM and PM periods we are effectively assuming that travellers are equally sensitive to fare changes in the morning and afternoon. This is a modelling technique that is widely used to increase the number of observations (for statistical significance) while still capturing the underlying behaviour of travellers.[17] Therefore, we do not consider that this assumption undermines the elasticity estimates presented in this report.

5.2. Train, bus and multimodal results

The figures below present own-price and cross-price elasticity estimates for adult weekday, Saturday (and public holidays), and Sunday train, bus and multimodal (MM) journeys in distance bands 1 to 4.[18] Public holidays are combined with Saturday journeys to reflect the similar service levels and fare between them, while Sunday journeys are modelled separately to reflect the $2.50 fare cap that applies to all travellers.[19]

We focus on adult elasticities here but elasticities for other passenger types – child/youth, concession, and senior/pensioner – are presented in Annex D and are largely in line with those presented for adult travellers.

Own-price elasticities are on the diagonal and are expected to be negative, and all other elasticities are cross-elasticities and are expected to be positive. For example, an own price elasticity of -0.069 for peak train journeys in distance band 1 (<= 3km) suggests that a 1% increase in peak train fares, all other influences held constant, leads to a 0.069% decrease in peak train journeys. Whereas, a cross price elasticity of 0.061 between peak train fares (row) and bus journeys (column) suggests that a 1% increase in peak train fares leads to a 0.061% increase in bus demand.

[17] We also tested models when AM and PM were treated separately but found that the model results were not as significant/reliable as when they were considered in combination.

[18] Pre Peak is defined as 06:00 to 07:00 & 14:30 to 15:30. Peak is defined as 07:00 to 09:00 & 15:30 to 18:30. Post Peak is defined as 09:00 to 10:00 & 18:30 to 19:30. Public holidays have been combined with Sunday journeys to reflect the similar service levels.

[19] We also ran models with public holiday combined with Sunday journeys and found there was not a significant difference in the results, which is likely to be because there are only four public holidays in the four and a half year period selected. However, we consider that behaviourally it makes more sense to combine public holiday journeys with Saturday journeys. The same approach is also applied within the corridor analysis below.

Adult Journeys in Distance Band 1 (0-3km) – Elasticity Estimates

Figure 5.1: Adult weekday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.005	0.000	0.000	0.001
Train Peak	0.011	-0.069	0.016	0.061
Train Post Peak	0.006	0.008	-0.215	0.035
Bus	0.109	0.132	0.164	-0.183

Source: CEPA and Hgroup analysis using Opal data

Figure 5.2: Adult Saturday (and public holiday) journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.037	0.002	0.002	0.008
Train Peak	0.007	-0.039	0.008	0.028
Train Post Peak	0.006	0.006	-0.071	0.021
Bus	0.091	0.092	0.098	-0.142

Source: CEPA and Hgroup analysis using Opal data

Figure 5.3: Adult Sunday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.799	0.092	0.098	0.114
Train Peak	0.275	-0.618	0.285	0.316
Train Post Peak	0.140	0.136	-0.746	0.166
Bus	0.380	0.356	0.388	-0.576

Source: CEPA and Hgroup analysis using Opal data

Adult Journeys in Distance Band 2 (3-8km) – Elasticity Estimates

Figure 5.4: Adult weekday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.008	0.001	0.001	0.001	0.001	0.001	0.001
Train Peak	0.036	-0.105	0.052	0.072	0.039	0.045	0.047
Train Post Peak	0.020	0.024	-0.370	0.041	0.022	0.026	0.027
Bus	0.209	0.254	0.313	-0.413	0.226	0.265	0.279
MM Pre Peak	0.000	0.000	0.000	0.000	-0.005	0.000	0.000
MM Peak	0.005	0.006	0.007	0.010	0.006	-0.116	0.007
MM Post Peak	0.001	0.001	0.001	0.002	0.001	0.001	-0.150

Source: CEPA and Hgroup analysis using Opal data

Figure 5.5: Adult Saturday (and public holiday) journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.051	0.004	0.005	0.008	0.005	0.005	0.005
Train Peak	0.014	-0.052	0.015	0.028	0.015	0.015	0.015
Train Post Peak	0.011	0.011	-0.097	0.021	0.011	0.011	0.011
Bus	0.147	0.150	0.157	-0.275	0.152	0.152	0.152

Source: CEPA and Hgroup analysis using Opal data

Figure 5.6: Adult Sunday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.017	0.002	0.002	0.002	0.003	0.003	0.003
Train Peak	0.005	-0.013	0.005	0.005	0.007	0.007	0.007
Train Post Peak	0.003	0.003	-0.015	0.002	0.004	0.004	0.004
Bus	0.007	0.007	0.006	-0.014	0.009	0.009	0.009

Source: CEPA and Hgroup analysis using Opal data

Adult Journeys in Distance Band 3 (8-20km) – Elasticity Estimates

Figure 5.7: Adult weekday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.020	0.003	0.003	0.001	0.003	0.003	0.003
Train Peak	0.162	-0.149	0.173	0.030	0.176	0.184	0.187
Train Post Peak	0.076	0.081	-0.644	0.016	0.083	0.088	0.089
Bus	0.162	0.178	0.194	-0.289	0.176	0.190	0.193
MM Pre Peak	0.000	0.000	0.000	0.000	-0.011	0.000	0.000
MM Peak	0.024	0.025	0.025	0.004	0.026	-0.245	0.027
MM Post Peak	0.005	0.005	0.005	0.001	0.005	0.005	-0.326

Source: CEPA and Hgroup analysis using Opal data

Figure 5.8: Adult Saturday (and public holiday) journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.105	0.018	0.018	0.003	0.020	0.020	0.020
Train Peak	0.060	-0.085	0.061	0.010	0.066	0.066	0.066
Train Post Peak	0.043	0.043	-0.185	0.007	0.047	0.047	0.047
Bus	0.118	0.119	0.124	-0.219	0.123	0.123	0.123

Source: CEPA and Hgroup analysis using Opal data

Figure 5.9: Adult Sunday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.017	0.002	0.002	0.002	0.003	0.003	0.003
Train Peak	0.005	-0.014	0.005	0.005	0.008	0.008	0.008
Train Post Peak	0.003	0.003	-0.015	0.003	0.004	0.004	0.004
Bus	0.007	0.007	0.007	-0.014	0.010	0.010	0.010

Source: CEPA and Hgroup analysis using Opal data

Adult Journeys in Distance Band 4 (>20km) – Elasticity Estimates

Figure 5.10: Adult weekday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.036	0.005	0.003	0.001	0.007	0.006	0.006
Train Peak	0.258	-0.200	0.147	0.046	0.287	0.250	0.240
Train Post Peak	0.085	0.068	-0.597	0.017	0.094	0.083	0.080
Bus	0.243	0.205	0.156	-0.339	0.270	0.246	0.235
MM Pre Peak	0.001	0.001	0.000	0.000	-0.019	0.001	0.001
MM Peak	0.040	0.032	0.023	0.007	0.045	-0.329	0.038
MM Post Peak	0.007	0.006	0.004	0.001	0.008	0.007	-0.424

Source: CEPA and Hgroup analysis using Opal data

Figure 5.11: Adult Saturday (and public holiday) journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.160	0.027	0.025	0.004	0.037	0.037	0.037
Train Peak	0.090	-0.127	0.080	0.013	0.118	0.118	0.118
Train Post Peak	0.058	0.057	-0.251	0.009	0.076	0.076	0.076
Bus	0.112	0.109	0.102	-0.205	0.138	0.138	0.138

Source: CEPA and Hgroup analysis using Opal data

Figure 5.12: Adult Sunday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.019	0.002	0.002	0.002	0.003	0.003	0.003
Train Peak	0.006	-0.015	0.006	0.006	0.008	0.008	0.008
Train Post Peak	0.003	0.003	-0.017	0.003	0.004	0.004	0.004
Bus	0.007	0.007	0.007	-0.014	0.010	0.010	0.010

Source: CEPA and Hgroup analysis using Opal data

Overall, we consider that the results from the aggregate share model presented above are sufficiently robust for IPART to use as part of its next fare review. This is evidenced by:

- All own-price elasticities are negative, and all cross-price elasticities are positive as expected.

- All elasticities are statistically significant at a 5 percent level or better, which results in narrow confidence bands[20], and provides reassurance that the elasticity estimates are precise.
- Given the expected sign of the elasticity, all elasticity estimates fall within the -1 to 1 range identified from the literature review (see Annex E for more details).

In Section 6 we provide further discussion of our results and combine them with the findings from the literature review.

5.3. Ferry and light rail corridor model results

This section presents the results of our ferry and light rail corridor analysis. It is important to note that we have been unable to produce as many robust elasticity estimates within this analysis, which is somewhat the result of a lower number of observations. As a result, a number of elasticities we estimated were found not be statistically significant and are not published in this report.

Taking the above into account, we were unable to produce any robust elasticity estimates within our light rail corridor analysis (along the inner west light rail). In addition to fewer observations, another contributing factor for why we obtained insignificant elasticities is the lack of variation in fare for travellers along this corridor over the period studied. For example, light rail and bus journeys have the same fare and use the same distance band, and therefore the decision by the traveller on which transport mode to choose is likely to the result of something other than the fare., e.g. mode that is closest to the traveller's home or will get the traveller closest to their end destination. In other words, fare is not the main driver of mode choice, and this is reflected in the model results. Therefore, we have chosen not to present any elasticity results from our light rail corridor analysis.

As a result, the results presented in the figures below relate to our ferry corridor analysis (Parramatta – Circular Quay).[21] We have successfully estimated robust own-price and cross-price ferry elasticity estimates for adult weekday and Saturday (and public holidays) journeys in distance bands 1 to 3.[22]

We have been unable to produce robust elasticity estimate for adult Sunday journeys, which is most likely the result of the $2.50 Sunday fare cap. In addition, we were unable to produce robust and significant elasticity estimates for child/youth, concession, and senior/pensioner travellers within the ferry corridor analysis, which is likely to be the result of fewer observations for these groups.

Nevertheless, we consider that the results presented below are a welcomed complement to the train, bus, and multimodal journey results, and demonstrate further that this study has been able to produce robust elasticity results using Opal data that has not been achieved before.

Elasticity estimates highlighted in blue are ferry own-price elasticities, with the remainder being cross-elasticities with other public transport modes (when applicable). As before, own price elasticities are expected to be positive and cross-price elasticities are expected to be negative.

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[20] We used the Delta test to obtain standard errors in order to obtain t-values and confidence limits, as used in Hensher et al (2015).

[21] Pre Peak is defined as 06:00 to 07:00 & 14:30 to 15:30. Peak is defined as 07:00 to 09:00 & 15:30 to 18:30. Post Peak is defined as 09:00 to 10:00 & 18:30 to 19:30. Public holidays have been combined with Saturday journeys to reflect the similar service levels.

[22] Adult weekday journeys in distance band 1 are not statistically significant and are not presented.

Hence, an own price elasticity of -1.247 for ferry journeys in distance band 2 suggests that a 1% increase in ferry fares leads to a 1.247% decrease in ferry journeys. This result suggests that ferry demand is relatively elastic compared with other public transport journeys, which may be reflective of the greater number of public transport choices available to travellers along this corridor compared to majority of travellers in the Opal network. A cross price elasticity of 0.361 between ferry fares (row) and bus journeys (column) suggests that a 1% increase in ferry fares leads to a 0.361% increase in bus demand.

5.3.1. Ferry journey elasticity results

Figure 5.13: Adult weekday ferry journeys – elasticity estimates using the aggregate share model (fares in row, demands in column)

	Bus	Ferry	Train Pre Peak	Train Peak	Train Post Peak	MM
Distance Band 2 (3 - 8km)	0.361	-1.247	0.500	0.461	0.492	
Distance Band 3 (8 - 20km)	0.240	-1.510	0.687	0.733	0.692	1.309

Source: CEPA and Hgroup analysis using Opal data

Figure 5.14: Adult Saturday (and public holiday) ferry journeys – elasticity estimates using the aggregate share model (fares in row, demands in column)

	Bus	Ferry	Train Pre Peak	Train Peak	Train Post Peak	MM
Distance Band 1 (<3km)	0.107	-0.201	0.240			
Distance Band 2 (3 - 8km)	0.056	-0.201	0.102	0.098	0.098	
Distance Band 3 (8-20km)	0.042	-0.174	0.076	0.089	0.087	0.173

Source: CEPA and Hgroup analysis using Opal data

Overall, we consider that the elasticity results presented above from the ferry corridor analysis are sufficiently robust for IPART to use as part of the next fare review. This is evidenced by:

- All elasticity results presented have the correct sign (i.e. negative for own-price elasticities and positive for cross-price elasticities).
- All elasticity results are statistically significant at a 5 percent level or better.
- While the estimated own-price ferry elasticities go beyond the range identified in the literature, they are also in line with two key findings from our literature review: (i) the responsiveness of demand to changes in fares increases with the number of public transport modes alternatives; and (ii) elasticities tend to be higher if the starting fare is higher (ferry prices are higher than other transport modes for comparable journey lengths).

It is important to note that the presented ferry journey elasticity estimates are for the Circular Quay – Parramatta/Northwest corridor. Therefore, there is a question on whether these results can be transferred to other ferry routes. This is likely to depend on the range of other public transport options available along the various ferry routes. The main reason for selecting the Parramatta River route was because travellers along this route have multiple transport options to choose from. Therefore, the results may be applicable to Inner Harbour routes where most travellers have bus and train as travel options in addition to ferry. However, the results may not be as transferable to Manly routes where ferry has a clear advantage over bus from a travel time perspective and travelling by train is not an option. In addition, Manly attracts tourists and its residents have higher than average income levels. All three of these factors could lead to lower ferry elasticities for Manly routes relative to journeys along the Circular Quay – Parramatta/Northwest corridor. To verify these hypotheses, we would need to estimate elasticities for additional ferry routes and compare results, which is outside the scope of this study but may provide opportunity for further study.

In Section 6 we provide further discussion of our results and combine them with the findings from the literature review that we have also conducted.

5.4. CROSS PRICE ELASTICITY WITH PRIVATE CAR RESULTS

The figure below presents cross elasticity estimates with private car for bus and train journeys for different time periods in the day. In comparison with the other analysis presented in this report, we can apply the following approximation:

- Before 7am = "Pre AM Peak";
- 7-9am = "AM Peak";
- 9am-3pm = "Interpeak";
- 3-4pm = "Pre PM Peak";
- 4-6pm = "PM Peak"; and
- after 6pm = "Post PM Peak".

These elasticity estimates were derived using the same dataset and modelling approach used by Ho and Hensher in their 2016 paper[23], which was presented at the world conference on transport research (WCTR) in Shanghai in July 2016.[24] All results presented are significant at a 5 percent level or better, and we consider are sufficiently robust to be used by IPART in the next fare review.

The elasticity estimates presented below refer to the responsiveness of private car demand with respect to changes in public transport fares. This aligns with IPART's socially optimal tariff model, which among other things aims to assess how fares influence people's decision to use private cars versus public transport, and the impacts on congestion when public transport fares are increased or decreased.[25]

Overall, the responsiveness of private car demand with respect to changes in public transport fares is very small (i.e., demand for private car appears to be very insensitive to the cost of using public transport). This reflects the fact that Sydney residents are quite dependent on private car.[26]

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[23] The mixed logit model was used and calibrated to existing modal shares at the population level. These are the weighted mean estimates where the weights are from individual probabilities of choosing each mode, summed across the population and averaged.

[24] Ho and Hensher (2016).

[25] IPART (2016).

[26] Ho and Mulley (2013b).

Figure 5.15: Car demand elasticity with respect to public transport fares (public transport fares in rows, private car demand in columns)

	Car before 7am	Car 7-9am	Car 9am-3pm	Car 3-4pm	Car 4-6pm	Car after 6pm
Bus before 7am	0.0050	0.0030	0.0003			
Bus 7-9am	0.0030	0.0050	0.0020			
Bus 9am-3pm		0.0008	0.0030	0.0020	0.0002	
Bus 3-4pm			0.0020	0.0030	0.0010	
Bus 4-6pm			0.0010	0.0020	0.0040	0.0020
Bus after 6pm					0.0010	0.0030
Train before 7am	0.0130	0.0050	0.0005			
Train 7-9am	0.0070	0.0130	0.0030			
Train 9am-3pm	0.0001	0.0002	0.0050	0.0030	0.0003	
Train 3-4pm			0.0006	0.0030	0.0020	
Train 4-6pm			0.0005	0.0100	0.0160	0.0060
Train after 6pm					0.0020	0.0120

Source: CEPA and Hgroup analysis

6. DISCUSSION OF RESULTS

To establish a cross-check for our analysis, we conducted a literature review to identify a range of published elasticity estimates for public transport and key issues relating to elasticity estimates.[27] The table below presents a summary of the transport (own-price) demand elasticities from recent literature.

Table 6.1: Literature review summary table

Author	Type of Elasticity	Estimate
de Grange et al (2013)	Metro off-peak	-0.186 to -0.233
	Metro peak	-0.557 to -0.588
	Bus off-peak	-0.34 to -0.354
	Bus peak	-0.286 to -0.309
Cipriani et al (2010)	Bus (lowest income)	-1.10
	Bus (middle income)	-0.96
	Bus (high income)	-0.61
Deb and Filippini (2013)	Bus (short-term)	-0.289
	Bus (long-term)	-0.523
WSP Group and Parsons Brinckerhoff (2016)	Bus (16 – 18 years old, West Yorkshire)	-0.44
	Bus (16 – 18 years old, London)	-0.52
	Bus (18 – 22 years old, West Yorkshire)	-0.81
	Bus (18+ years old, London)	-0.66
Holmgren (2013)	Urban public transit	-0.4
Cats et al (2010)	Urban public transit	-0.01
Littman (2017)	Bus (Australia)	-0.29
	Rail (Australia)	-0.35
	Bus (US)	-0.58
	Rail (US)	-0.86

Source: CEPA and Hgroup analysis

There are several key themes that come out of literature review and it is important to understand these in order to use them as a cross-check to our model results. These are summarised in the table below.

Table 6.2: Key themes and trends highlighted in the literature review

Theme	Finding
Type of traveller	• Travellers with alternative travel options are more sensitive to price. • Travellers with relatively low incomes (e.g. concession; seniors/pensioner) tend to more responsive to price changes.
Time of day	• Peak travel is generally less price sensitive than off-peak travel.
Type of day	• Weekend travel tends to be more price sensitive than weekday travel.

[27] More details of our literature review can be found in Annex E.

Theme	Finding
Geography	• Large cities tend to have lower elasticities as more travellers are dependent on public transport.
Starting price level	• Elasticities tend to be higher if the starting fare was higher.
Direction of price change	• Fare increases tend to have a greater impact than on demand than price decreases.
Time period	• The impact of a price change tends to increase with time as travellers make lifestyle choices in response to the cost of travel.
Type of public transport	• Elasticities can differ between transport if they serve different markets (e.g. individuals with different income levels).

Source: CEPA and Hgroup analysis

For comparison purposes, the tables below present own price elasticities for adult, child/youth, concession and senior/pensioner weekday train, bus, and multimodal passenger journeys in distance bands 1 to 4 from the analysis conducted for this study. Ferry and light rail elasticity estimates are excluded as these transport modes were not considered in the literature. In addition, it is not possible to estimate robust elasticities for multimodal journeys in distance band 1, and own price multimodal elasticities for concession travellers in distance bands 2 to 4, because of low journey numbers.

All the elasticity estimates presented in the tables below are statistically significant and sensible in magnitude when cross checked against the literature. Therefore, like those presented in Section 5, we consider that these results are sufficiently robust to be used by IPART in the next fare review.

Figure 6.1: Adult, child/youth, concession and senior/pensioner weekday journeys in distance band 1 (0-3km) – own price elasticity estimates for train and bus journeys

Mode / Passenger Type	Adult	Child / Youth	Concession	Senior / Pensioner
Train Pre Peak	-0.005	-0.071	-0.018	-0.123
Train Peak	-0.069	-0.032	-0.044	-0.132
Train Post Peak	-0.215	-0.070	-0.120	-0.153
Bus	-0.183	-0.019	-0.114	-0.068

Source: CEPA and Hgroup analysis using Opal data

Figure 6.2: Adult, child/youth, concession and senior/pensioner weekday journeys in distance band 2 (3-8km) – own price elasticity estimates for train, bus and multimodal journeys

Mode / Passenger Type	Adult	Child / Youth	Concession	Senior / Pensioner
Train Pre Peak	-0.008	-0.069	-0.032	-0.077
Train Peak	-0.105	-0.031	-0.071	-0.113
Train Post Peak	-0.370	-0.068	-0.206	-0.066
Bus	-0.413	-0.034	-0.316	-0.104
MM Pre Peak	-0.005	-0.168		-0.164
MM Peak	-0.116	-0.116		-0.130
MM Post Peak	-0.150	-0.124		-0.171

Source: CEPA and Hgroup analysis using Opal data

Figure 6.3: Adult, child/youth, concession and senior/pensioner weekday journeys in distance band 3 (8-20km) – own price elasticity estimates for train, bus and multimodal journeys

Mode / Passenger Type	Adult	Child / Youth	Concession	Senior / Pensioner
Train Pre Peak	-0.020	-0.175	-0.087	-0.084
Train Peak	-0.149	-0.063	-0.136	-0.118
Train Post Peak	-0.644	-0.176	-0.456	-0.073
Bus	-0.289	-0.157	-0.292	-0.107
MM Pre Peak	-0.011	-0.400		-0.141
MM Peak	-0.245	-0.279		-0.132
MM Post Peak	-0.326	-0.319		-0.110

Source: CEPA and Hgroup analysis using Opal data

Figure 6.4: Adult, child/youth, concession and senior/pensioner weekday journeys in distance band 4 (>20km) – own price elasticity estimates for train, bus and multimodal journeys

Mode / Passenger Type	Adult	Child / Youth	Concession	Senior / Pensioner
Train Pre Peak	-0.036	-0.232	-0.140	-0.104
Train Peak	-0.200	-0.083	-0.182	-0.124
Train Post Peak	-0.597	-0.228	-0.475	-0.091
Bus	-0.339	-0.170	-0.311	-0.111
MM Pre Peak	-0.019	-0.428		-0.160
MM Peak	-0.329	-0.330		-0.140
MM Post Peak	-0.424	-0.374		-0.130

Source: CEPA and Hgroup analysis using Opal data

The remainder of this section compares the model results from this study with the findings from the literature review.

At an overall level we find the magnitude of our own-price elasticities are generally in line with the literature, falling in the range of 0 and -1. This suggests that demand for public transport is inelastic (i.e. not very responsive to changes in price). The exception being ferry demand, which we found to be relatively more elastic than other transport modes (see Section 5.1.3 for more details). We consider that this is largely caused by the relatively higher number of alternative public transport modes available to ferry travellers compared to the average traveller in the Opal network, and ferry fares are much higher than other public transport fares.

Comparing elasticities across passenger types, except for the pre peak period when adult demand is very price inelastic, we find that adult travellers are generally more responsive to changes in price than other passenger types. This finding is somewhat against the literature, which suggests that travellers with lower incomes (i.e. child/youth, concession, and senior/pensioner) tend to be more responsive to changes in price. However, this may be because the starting price of adult fares are higher than other passenger types, which leads to higher elasticities according to the literature. That is, a 10% increase in adult train fare during the peak for short distance band (<=10 km) results in an increase of 35 cents in price while a 10% increase translates to 17 cents for concession travellers. It might also be the result of the $2.50 daily travel cap for senior/pensioner travel, which means that travel is effectively free for many journeys.

Turning to time of day, the literature review suggested that off-peak travel was more responsive than peak travel as the latter is more routine and necessary. Our results indicate that Post Peak train and multimodal journeys are more responsive to changes in price than Peak train and multimodal journeys, which is in line with the literature. However, our results also indicate that Pre Peak train and multimodal journeys are the least responsive to changes, which is not supported by the literature. This is likely to be because the number of Pre Peak journeys are relatively low, which in turn may mean that those who travel during these times are doing so out of necessity, and are unable to easily change their travel time, i.e. working hours.

To examine how the magnitude of elasticities changes with journey length, Figure 6.5 below summarises adult weekday elasticities across all four distance bands. Comparing elasticities across distance bands highlights that the responsiveness of public transport demand with respect to price tends to increase with journey length. In other words, demand for travel in distance band 1 (0-3km) is the least responsive to changes in price and demand for travel in distance band 4 (>20m) is the most responsive to changes in price.

Figure 6.5: Adult weekday elasticities by distance band

Mode / Distance Band	Distance Band 1	Distance Band 2	Distance Band 3	Distance Band 4
Train Pre Peak	-0.005	-0.008	-0.020	-0.036
Train Peak	-0.069	-0.105	-0.149	-0.200
Train Post Peak	-0.215	-0.370	-0.644	-0.597
Bus	-0.183	-0.413	-0.289	-0.339
MM Pre Peak		-0.005	-0.011	-0.019
MM Peak		-0.116	-0.245	-0.329
MM Post Peak		-0.150	-0.326	-0.424
Average	-0.118	-0.167	-0.241	-0.278

Source: CEPA and Hgroup analysis using Opal data

On average, demand for multimodal journeys is most responsive to changes in price for child/youth and senior/pensioner travellers, which implies that these passenger types have reacted positively to the multimodal rebate that was introduced in September 2016. However, in contrast, demand for train and bus journeys are more responsive than multimodal journeys to changes in price for adult passengers, which suggests that the multimodal rebate has had as smaller positive effect for adult passengers.

When considering weekend travel, elasticities are lower across all distance band elasticities compared with weekday travel, which is against the findings of the literature review. However, this may be the result of the weekly cap, which means that travellers do not incur any additional cost for travelling on weekends if they have already reached the weekly cap by the end of Friday. Furthermore, elasticities are smallest in magnitude for Sunday journeys, which is perhaps not surprising given the $2.50 fare cap that applied to all travel. As expected, we do not see any substantial difference between pre, peak, and post periods given that fares do not change throughout the day during the weekend.

Our corridor analysis for ferry journeys confirmed that location is an important determinant of elasticity size. In particular, we found that travellers who travel along the "Parramatta – Circular Quay" corridor tend to have more alternative transport modes available than the average traveller on the Opal network, which leads to higher elasticities. This supports the key finding from the literature, which highlighted that individuals who have access to a greater number of alternative travel modes/options will have a greater sensitivity to price change and propensity to switch than individuals who have few alternatives available

Two remaining themes from the literature are regarding the direction of the change in cost and the time period.

- Direction of change - the literature found that an upwards increase in price will tend to have a larger impact on demand than a price decrease. In our analysis, we have assumed that the effect of an increase or decrease in prices is equal. Therefore, we are unable to say whether the magnitude of estimated elasticities is higher following a price increase compared with a price decrease. However, the elasticities we have estimated for this study can be used to assess the impact of fare increases or decreases on demand.

- Time period – the literature suggests that the impact of a price change will increase with time. More specifically, Litman (2017) claims that price impacts typically triple in the long run.[28] Given that the results presented in this report are short term elasticity estimates, it is likely that the elasticity estimates derived for this study underestimate the long-term impact of the multimodal rebate.

[28] Litman (2017).

ANNEX A REFERENCES

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ANNEX B DETAILED METHODOLOGY

We provide further details of our methodology below.

B.1. LOG-LOG MODELLING METHOD

The log-log regression model is the traditional method of estimating price elasticities of demand, which can be written as follows:[29]

$$\log(y_t^m) = \beta_0^m + \sum_m \beta_{fare}^m \log(Fare_t^m) + \sum_k \beta_k^m \log(x_{kt}^m) + \varepsilon_t^m \qquad (1)$$

Where y_t^m is the number of journeys by mode *m* observed in period *t*;

$Fare_t^m$ is the total fare-box revenue collected by mode *m* in period *t*;

x_{kt}^m is the set of *K* control variables;

ε_t^m is the statistical error term; and

$\beta's$ is the set of parameters to be estimated.

With this specification, the parameter β_{fare}^m, associated mode *m,* is its own-price elasticity of demand while the parameters for the alternative services (alternative mode or period) are cross-elasticities.

Note that the log-log linear regression model uses a time indicator (e.g., time index from the first month of the Opal data series) as one of the control variables in equation (1), its accompanying parameter indicates the trend in the demand for public transport, allowing for the parameters associated with the fare variables to be interpreted as the unbiased price elasticities.

Data needed for estimating equation (1) was aggregated from the Opal unit record data (Table 2.1) provided by TfNSW. Specifically, the unit record/trip leg Opal data were first restructured to journey data (linking trip legs into journeys) then aggregated to obtain the total fares (public transport price) and journey numbers (public transport demand) for each mode (and combination of them), each time period, each user type (card type) and each distance band. This aggregation method was successfully used in Ho and Mulley (2013a) for the estimation of elasticities of Sydney bus demand, accounting for many major events occurred in the period of the data.

High correlation between explanatory variables indicates multicollinearity and may prevent the precise estimation of price demand elasticities using the log-log modelling method. The figure below presents the correlation matrix for all fares and all journeys of train, bus, and multimodal journeys. Variables which are correlated by more than 80% are highlighted in red.

The correlation matrix demonstrates that:

- Fares of different modes are highly correlated in several cases. In particular, train and multimodal fares are highly correlated in all six time bands presented above. While this is not necessarily

[29] This is a generalised formula that can be modified to also include specific distance bands and traveller types.

surprising given that all multimodal journeys will include a train trip, the level of correlation is higher than we could have anticipated.

- There appears to be significant correlation between time periods of the same mode, which makes it difficult to obtain time-of-day cross-elasticities. For example, the correlation between adult train AM and PM peak train fares is equal to one, which is what was expected.

The combination of these two effects has led to a high degree of multicollinearity in the model, which reduces the precision of the parameter estimates when using a linear regression model, such as the log-log model. Overall, the level of multicollinearity between fares is higher than we anticipated, and this is reflected in the log-log model results, which more often than not produces an unexpected sign, i.e. positive own elasticities and negative cross-elasticities.

Table 6.3: Correlation matrix

	T Pre-AM	B Pre-AM	MM Pre-AM	T AM	B AM	MM AM	T Post-AM	B Post-AM	MM Post-AM	T Pre-PM	B Pre-PM	MM Pre-PM	T PM	B PM	MM PM	T Post-PM	B Post-PM	MM Post-PM
T Pre-AM	1																	
B Pre-AM	0.27	1																
MM Pre-AM	0.99	0.31	1															
T AM	0.93	0.56	0.95	1														
B AM	-0.05	0.92	-0.04	0.21	1													
MM AM	0.87	0.54	0.92	0.98	0.18	1												
T Post-AM	0.71	0.67	0.77	0.91	0.35	0.94	1											
B Post-AM	-0.43	0.58	-0.44	-0.27	0.84	-0.33	-0.18	1										
MM Post-AM	0.80	0.42	0.86	0.90	0.07	0.95	0.94	-0.44	1									
T Pre-PM	0.95	0.44	0.96	0.98	0.10	0.95	0.89	-0.36	0.92	1								
B Pre-PM	-0.38	0.63	-0.39	-0.20	0.85	-0.25	-0.11	0.98	-0.38	-0.29	1							
MM Pre-PM	0.94	0.38	0.97	0.97	0.02	0.97	0.88	-0.44	0.95	0.99	-0.38	1						
T PM	0.95	0.52	0.96	1.00	0.19	0.96	0.88	-0.27	0.89	0.98	-0.21	0.97	1					
B PM	-0.11	0.88	-0.10	0.14	0.98	0.10	0.26	0.88	-0.02	0.03	0.91	-0.05	0.12	1				
MM PM	0.92	0.48	0.95	0.99	0.12	0.99	0.91	-0.36	0.93	0.97	-0.29	0.98	0.98	0.05	1			
T Post-PM	0.79	0.68	0.83	0.95	0.36	0.95	0.97	-0.14	0.91	0.93	-0.06	0.91	0.94	0.29	0.94	1		
B Post-PM	-0.21	0.77	-0.22	-0.01	0.94	-0.07	0.08	0.94	-0.19	-0.11	0.96	-0.20	-0.02	0.97	-0.11	0.13	1	
MM Post-PM	0.81	0.54	0.86	0.94	0.19	0.98	0.96	-0.32	0.96	0.93	-0.24	0.95	0.93	0.12	0.97	0.97	-0.05	1

T = Train, B = Bus, MM = Multimodal

Source: CEPA and Hgroup

Because of the high collinearity and fare endogeneity, we were unable to produce precise and sensible demand elasticity estimates using the log-log modelling approach.

This is illustrated in the example below, which presents elasticity estimates for adult weekday journeys in distance band 2 (3-8km) for train, bus, and multimodal journeys.[30] Own-price elasticities are on the diagonal and are expected to be negative, and all other elasticities can be interpreted as cross-elasticities and are expected to be positive. Elasticity estimates with green font highlight that the elasticity estimate is statistically significant at a 10 percent level.[31]

Figure 6.6: Adult weekday journeys in distance band 2 (3-8km) elasticity estimates using the log-log model (fares in row, demands in column)

	T Pre Peak	T Peak	T Post Peak	B Pre Peak	B Peak	B Post Peak	MM Pre Peak	MM Peak	MM Post Peak
T Pre Peak	0.379***	-0.434***	-0.565***	-0.394***	-0.259***	-0.464***	-0.665***	-0.486***	-0.705***
T Peak	-0.113	0.442**	-0.194	-0.177	-0.461***	-0.146	0.027	-0.217	0.421
T Post Peak	0.144	0.203	1.154***	0.137	0.157	0.127	0.379	0.368	0.251
B Pre Peak	0.278**	0.195*	0.253**	1.148***	0.099	0.182**	0.953***	0.701***	0.839***
B Peak	-0.481***	-0.207	-0.397***	-0.316***	0.850***	-0.326***	-0.529**	-0.258	-0.536**
B Post Peak	-0.175	-0.268**	-0.182*	-0.184**	-0.240***	0.822***	-0.187	-0.284	-0.159
MM Pre Peak	0.146***	0.149**	0.141***	0.121***	0.143***	0.145***	0.552***	-0.260***	-0.346***
MM Peak	0.073	0.042	0.049	0.028	-0.003	0.031	-0.223	0.616***	-0.355**
MM Post Peal	-0.145***	-0.119**	-0.120**	-0.113***	-0.101**	-0.119***	-0.249**	-0.153	0.694***
T = Train, B = Bus, MM = Multimodal									
*10% significant, ** 5% significant, *** 1% significant									

Source: CEPA and Hgroup

These results show that all own-price elasticities, and the majority of cross-price elasticities, have the unexpected sign. Similar results were obtained with various different model specifications. This is a clear indication that severe multicollinearity and endogeneity are significantly affecting the model estimation results.

We introduced a service level variable, constructed using GTFS data that is available from the TfNSW Open Data Website, to control for changes in journey numbers caused by changes in the underlying service level rather than changes in the price of travel. However, the multicollinearity and endogeneity were so severe that this did not improve the results of the log-log model.

The aggregate share model, by contrast, can produce precise and robust elasticity estimates in the presence of severe multicollinearity. More details on the aggregate share model is discussed below.

[30] Light rail and ferry elasticities are being examined as part of a separate analysis give that these modes of transport are only available for a restricted set of individuals.

[31] For this model run AM and PM Pre/Peak/Post periods have been combined (e.g. Trains Pre Peak = Trains AM Pre Peak + Trains PM Pre Peak). Although, models have been run at a number of different combination levels and have produced comparable results using the log-log modelling method.

B.2. THE AGGREGATE SHARE LOGIT MODEL

The aggregate share logit model is perhaps a more advanced method for estimating price elasticities. Applying this method to the Opal data, the model derivation starts with a specification of the utility the travel public derive from mode *m* in period *t* as follows:[32]

$$\begin{aligned} U_t^m &= \beta_0^m + \beta_{fare}^m Fare_t^m + \sum_k \beta_k^m x_{kt}^m + \varepsilon_t^m \\ &= V_m^t + \varepsilon_t^m \end{aligned} \tag{2}$$

Where V_m^t is observable utility component; ε_t^m is the unobservable and random utility. Other notations are as same as above.

The proportion (i.e., aggregate probability or share) of the travelling public that choose mode *m* in period *t* can then be written as (see for example Hensher et al, 2015):

$$p_t^m = \frac{\exp(V_m^t)}{\sum_{m',t'} \exp(V_{m'}^{t'})} \tag{3}$$

To estimate equation (3) we interpret the aggregate trips in each mode *m* and period *t* as the sum of individual choices to be explained by the discrete choice model as a function of fares. In other words, the number of trips for each mode and period are the aggregated choices of individuals, all facing the same fares in each distance band in each day.

The own-price elasticity of mode *m* in period *t* is determined by:

$$E_t^m = \frac{\partial p_m^t / p_m^t}{\partial x_t^m / x_t^m} = \beta_{Fare}^m x_t^m (1 - p_m^t) \tag{4}$$

The cross-fare elasticity of mode *m* in period *t* with respect to change in fare of mode *m'* in period *t* is determined by:

$$E_t^{m,m'} = \frac{\partial p_m^t / p_m^t}{\partial x_t^{m'} / x_t^{m'}} = -\beta_{Fare}^{m'} x_t^{m'} (1 - p_t^{m'}) \tag{5}$$

As discussed above, the Opal data required for the estimation of the discrete choice model in equation (3) are the total number of journeys observed for each user type (i.e., card holder), each mode (or combination of mode), each period, and each distance band.

For the aggregate share logit modelling method, we considered which econometric model would be most appropriate. Multinomial logit is the most popular choice and was the main modelling method used by Grange et al. (2013). We therefore used multinomial logit for this study, with the results used as a cross-check against the log-log modelling results.

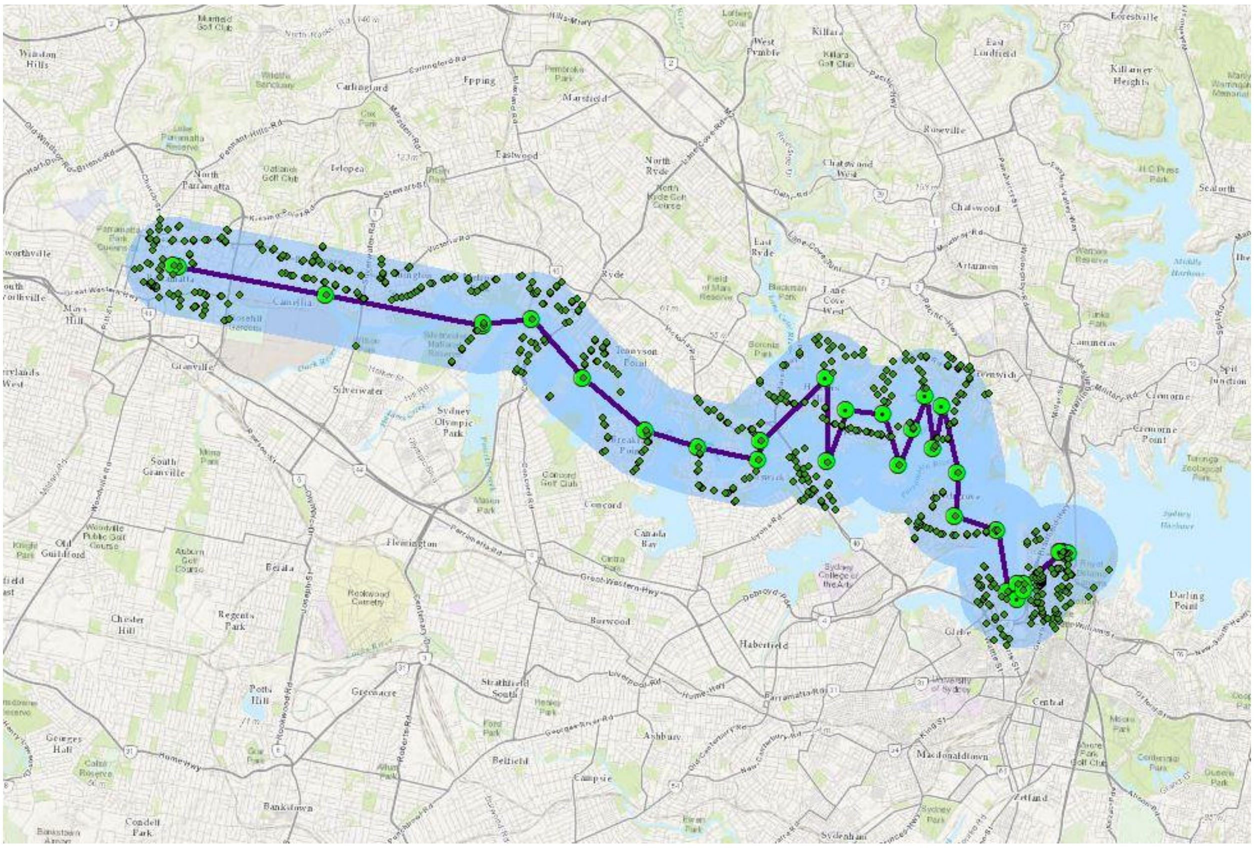
One limitation of multinomial logit is the underlying assumption of independent from irrelevant alternative (IIA), which means the cross-price elasticities are symmetric and when added to the direct-price elasticities

[32] This is a generalised formula that can be modified to also include specific distance bands and traveller types.

they sum to one. We therefore tested the appropriateness of the IIA assumption after estimating each model, and if the test result indicates the IIA assumption was not valid we used the mixed logit estimation if possible. Mixed logit is a more complex and flexible alternative to multinomial logit estimation but has significantly greater data requirements and was not always feasible (see Hensher et al. (2015) and Hensher and Greene (2003) for more details).

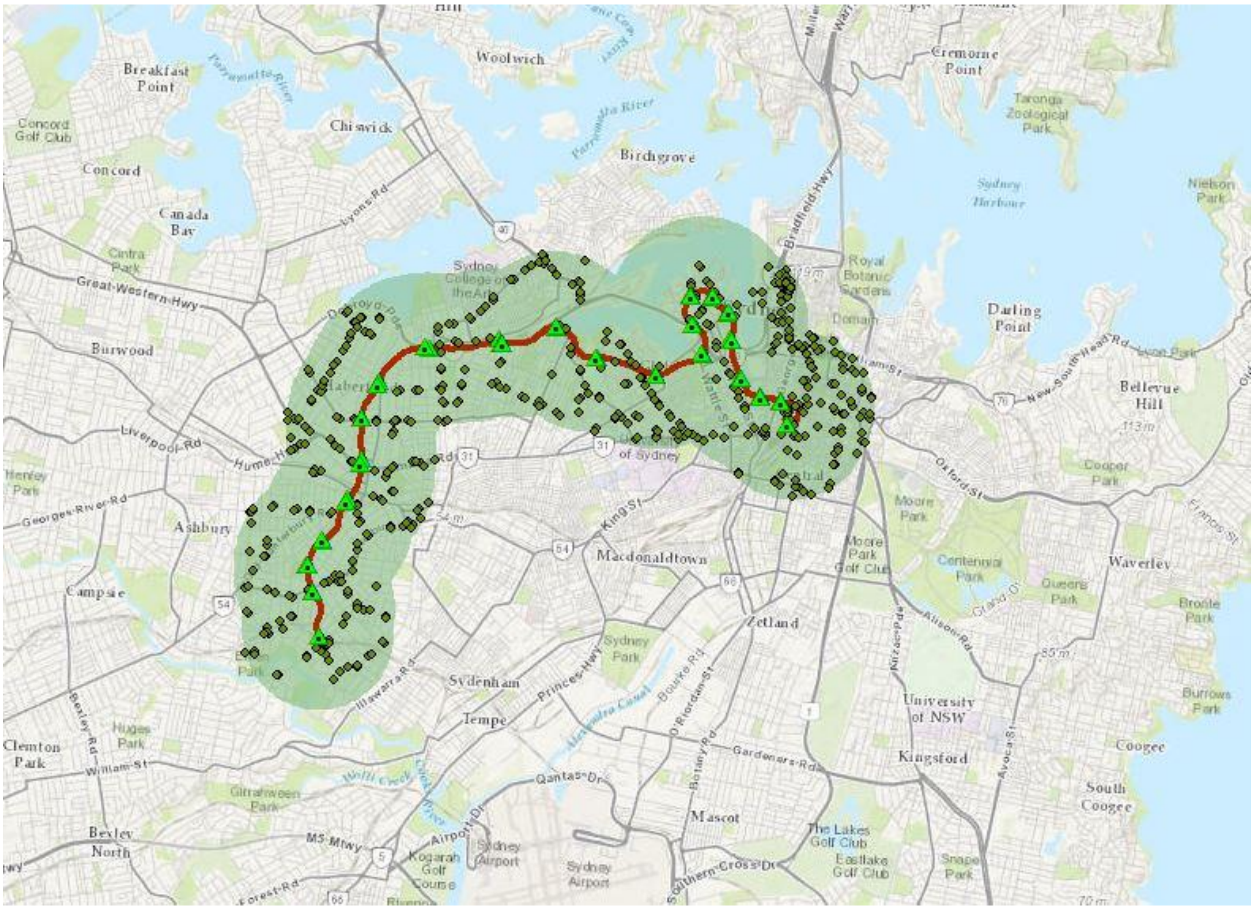
B.3. CORRIDOR ANALYSIS – ILLUSTRATIONS OF CHOSEN CORRIDORS

Figure 6.7: Ferry corridor: Parramatta – Circular Quay



Source: CEPA and Hgroup analysis

Figure 6.8: Light Rail Corridor: Along the Inner West Light Rail



Source: CEPA and Hgroup analysis

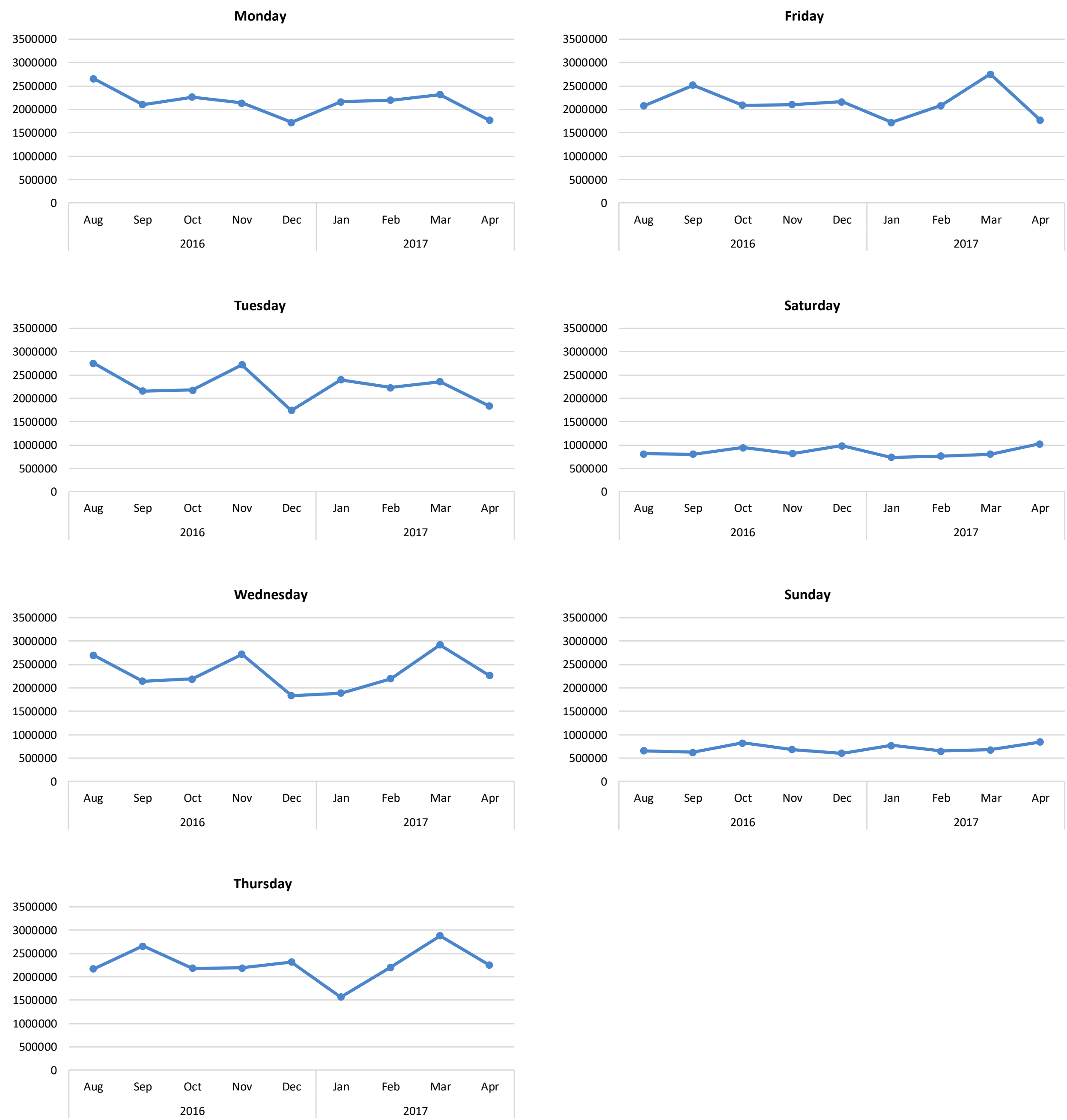
ANNEX C ADDITIONAL DATA ANALYSIS

The figures below indicate that it is important to exclude public holidays from the analysis as their demand profile clearly differs from the other profiles and distorts weekday demand profiles when they are included in the data.

Secondly, weekday and weekends appear to have different demand profiles, and therefore probably require separate treatment.

Finally, when controlling for public holidays, weekday demand appears to be relatively stable over time, particularly between August 2016 and December 2017, which is the main period of focus of our analysis.

Figure 6.9: Total number of journeys per day by 50 percent of fee-paying travellers over the period August 2016 to April 2017 (including public holidays).



Source: CEPA and Hgroup

Figure 6.10: Total number of journeys per day by 50 percent of fee-paying travellers over the period August 2016 to April 2017 (excluding public holidays).

Source: CEPA and Hgroup

ANNEX D ADDITIONAL MODEL RESULTS

This annex presents model results that should be considered alongside those presented in Section 5.

D.1. TRAIN, BUS AND MULTIMODAL: ADDITIONAL RESULTS

This section presents the remaining aggregate share modelling results for passenger types child/youth, concession, and senior/pensioner.

D.1.1. Child/Youth elasticity results

Child/Youth Journeys in Distance Band 1 (0-3km) – Elasticity Estimates

Figure 6.11: Child/Youth weekday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Trains Pre Peak	Trains Peak	Trains Post Peak	Bus
Trains Pre Peak	-0.071	0.004	0.004	0.011
Trains Peak	0.007	-0.032	0.007	0.018
Trains Post Peak	0.004	0.003	-0.070	0.010
Bus	0.019	0.018	0.018	-0.019

Source: CEPA and Hgroup analysis using Opal data

Figure 6.12: Child/Youth Saturday (and public holiday) journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-1.509	0.113	0.110	0.198
Train Peak	0.389	-1.190	0.330	0.587
Train Post Peak	0.182	0.158	-1.361	0.285
Bus	0.980	0.850	0.859	-1.015

Source: CEPA and Hgroup analysis using Opal data

Figure 6.13: Child/Youth Sunday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.477	0.045	0.047	0.056
Train Peak	0.154	-0.448	0.164	0.192
Train Post Peak	0.094	0.096	-0.504	0.119
Bus	0.265	0.266	0.282	-0.343

Source: CEPA and Hgroup analysis using Opal data

Child/Youth Journeys in Distance Band 2 (3-8km) – Elasticity Estimates

Figure 6.14: Child/Youth weekday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.069	0.004	0.004	0.009	0.005	0.005	0.005
Train Peak	0.007	-0.031	0.007	0.016	0.009	0.008	0.008
Train Post Peak	0.004	0.003	-0.068	0.008	0.005	0.004	0.004
Bus	0.025	0.024	0.025	-0.034	0.032	0.029	0.030
MM Pre Peak	0.003	0.003	0.003	0.007	-0.168	0.004	0.004
MM Peak	0.007	0.006	0.006	0.015	0.008	-0.116	0.008
MM Post Peak	0.002	0.002	0.002	0.004	0.002	0.002	-0.124

Source: CEPA and Hgroup analysis using Opal data

Figure 6.15: Child/Youth Saturday (and public holiday) journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.126	0.012	0.012	0.010	0.014	0.014	0.014
Train Peak	0.041	-0.108	0.043	0.034	0.049	0.049	0.049
Train Post Peak	0.020	0.021	-0.130	0.016	0.023	0.024	0.024
Bus	0.070	0.075	0.074	-0.110	0.081	0.082	0.082

Source: CEPA and Hgroup analysis using Opal data

Figure 6.16: Child/Youth Sunday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.047	0.005	0.004	0.004	0.005	0.006	0.006
Train Peak	0.014	-0.039	0.013	0.012	0.014	0.018	0.018
Train Post Peak	0.008	0.008	-0.041	0.007	0.008	0.010	0.010
Bus	0.025	0.025	0.024	-0.040	0.025	0.032	0.032

Source: CEPA and Hgroup analysis using Opal data

Child/Youth Journeys in Distance Band 3 (8-20km) – Elasticity Estimates

Figure 6.17: Child/Youth weekday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.175	0.026	0.025	0.005	0.027	0.028	0.028
Train Peak	0.048	-0.063	0.046	0.008	0.049	0.051	0.051
Train Post Peak	0.023	0.023	-0.176	0.004	0.024	0.025	0.025
Bus	0.117	0.108	0.113	-0.157	0.144	0.138	0.138
MM Pre Peak	0.018	0.018	0.018	0.004	-0.400	0.020	0.021
MM Peak	0.039	0.039	0.038	0.008	0.043	-0.279	0.043
MM Post Peak	0.010	0.010	0.010	0.002	0.011	0.011	-0.319

Source: CEPA and Hgroup analysis using Opal data

Figure 6.18: Child/Youth Saturday (and public holiday) journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.151	0.015	0.015	0.010	0.019	0.019	0.019
Train Peak	0.050	-0.129	0.053	0.037	0.068	0.068	0.068
Train Post Peak	0.024	0.025	-0.155	0.018	0.033	0.032	0.032
Bus	0.080	0.085	0.084	-0.128	0.105	0.105	0.105

Source: CEPA and Hgroup analysis using Opal data

Figure 6.19: Child/Youth Sunday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.052	0.005	0.005	0.005	0.007	0.007	0.007
Train Peak	0.015	-0.044	0.015	0.014	0.022	0.021	0.021
Train Post Peak	0.009	0.009	-0.046	0.008	0.012	0.012	0.012
Bus	0.027	0.028	0.027	-0.045	0.039	0.037	0.037

Source: CEPA and Hgroup analysis using Opal data

Child/Youth Journeys in Distance Band 4 (>20km) – Elasticity Estimates

Figure 6.20: Child/Youth weekday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.232	0.036	0.031	0.007	0.029	0.035	0.034
Train Peak	0.059	-0.083	0.063	0.012	0.056	0.068	0.067
Train Post Peak	0.026	0.032	-0.228	0.006	0.026	0.030	0.030
Bus	0.114	0.126	0.120	-0.170	0.136	0.146	0.142
MM Pre Peak	0.017	0.020	0.018	0.005	-0.428	0.021	0.020
MM Peak	0.040	0.049	0.043	0.010	0.041	-0.330	0.047
MM Post Peak	0.010	0.012	0.011	0.003	0.010	0.012	-0.374

Source: CEPA and Hgroup analysis using Opal data

Figure 6.21: Child/Youth Saturday (and public holiday) journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.194	0.016	0.017	0.015	0.030	0.030	0.030
Train Peak	0.053	-0.170	0.057	0.051	0.104	0.103	0.103
Train Post Peak	0.025	0.027	-0.198	0.024	0.050	0.049	0.049
Bus	0.080	0.087	0.087	-0.145	0.155	0.154	0.154

Source: CEPA and Hgroup analysis using Opal data

Figure 6.22: Child/Youth Sunday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.067	0.006	0.006	0.006	0.010	0.009	0.009
Train Peak	0.017	-0.053	0.017	0.017	0.029	0.026	0.026
Train Post Peak	0.010	0.010	-0.055	0.010	0.016	0.015	0.015
Bus	0.026	0.027	0.026	-0.044	0.043	0.040	0.040

Source: CEPA and Hgroup analysis using Opal data

D.1.2. Concession elasticity results

Concession Journeys in Distance Band 1 (0-3km) – Elasticity Estimates

Figure 6.23: Concession weekday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.018	0.001	0.001	0.003
Train Peak	0.005	-0.044	0.006	0.027
Train Post Peak	0.004	0.004	-0.120	0.019
Bus	0.104	0.112	0.133	-0.114

Source: CEPA and Hgroup analysis using Opal data

Figure 6.24: Concession Saturday (and public holiday) journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.029	0.001	0.001	0.004
Train Peak	0.007	-0.042	0.008	0.025
Train Post Peak	0.005	0.005	-0.063	0.016
Bus	0.048	0.049	0.051	-0.058

Source: CEPA and Hgroup analysis using Opal data

Figure 6.25: Concession Sunday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.259	0.022	0.022	0.026
Train Peak	0.080	-0.203	0.077	0.093
Train Post Peak	0.044	0.042	-0.235	0.052
Bus	0.140	0.134	0.135	-0.168

Source: CEPA and Hgroup analysis using Opal data

Concession Journeys in Distance Band 2 (3-8km) – Elasticity Estimates

Figure 6.26: Concession weekday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.032	0.002	0.002	0.003	0.002	0.002	0.002
Train Peak	0.016	-0.071	0.020	0.035	0.016	0.016	0.016
Train Post Peak	0.011	0.012	-0.206	0.025	0.011	0.011	0.011
Bus	0.217	0.234	0.276	-0.316	0.215	0.215	0.215

Source: CEPA and Hgroup analysis using Opal data

Figure 6.27: Concession Saturday (and public holiday) journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.035	0.002	0.002	0.004	0.002	0.002	0.002
Train Peak	0.010	-0.049	0.010	0.025	0.010	0.010	0.010
Train Post Peak	0.006	0.006	-0.073	0.016	0.006	0.007	0.007
Bus	0.074	0.077	0.080	-0.114	0.075	0.077	0.077

Source: CEPA and Hgroup analysis using Opal data

Figure 6.28: Concession Sunday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.156	0.013	0.013	0.011	0.014	0.015	0.015
Train Peak	0.047	-0.123	0.046	0.041	0.052	0.055	0.055
Train Post Peak	0.025	0.025	-0.140	0.022	0.028	0.030	0.030
Bus	0.084	0.083	0.083	-0.132	0.092	0.098	0.098

Source: CEPA and Hgroup analysis using Opal data

Concession Journeys in Distance Band 3 (8-20km) – Elasticity Estimates

Figure 6.29: Concession weekday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.087	0.010	0.010	0.002	0.010	0.010	0.010
Train Peak	0.098	-0.136	0.102	0.018	0.102	0.102	0.102
Train Post Peak	0.062	0.062	-0.456	0.012	0.064	0.064	0.064
Bus	0.209	0.213	0.227	-0.292	0.215	0.215	0.215

Source: CEPA and Hgroup analysis using Opal data

Figure 6.30: Concession Saturday (and public holiday) journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.092	0.011	0.011	0.002	0.012	0.012	0.012
Train Peak	0.065	-0.099	0.066	0.012	0.072	0.071	0.071
Train Post Peak	0.041	0.041	-0.174	0.007	0.045	0.045	0.045
Bus	0.131	0.135	0.138	-0.201	0.140	0.139	0.139

Source: CEPA and Hgroup analysis using Opal data

Figure 6.31: Concession Sunday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.178	0.015	0.015	0.012	0.020	0.020	0.020
Train Peak	0.054	-0.140	0.053	0.043	0.072	0.070	0.070
Train Post Peak	0.029	0.029	-0.159	0.023	0.039	0.038	0.038
Bus	0.091	0.090	0.089	-0.147	0.121	0.118	0.118

Source: CEPA and Hgroup analysis using Opal data

Concession Journeys in Distance Band 4 (>20km) – Elasticity Estimates

Figure 6.32: Concession weekday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.140	0.015	0.012	0.003	0.020	0.020	0.020
Train Peak	0.129	-0.182	0.098	0.024	0.156	0.156	0.156
Train Post Peak	0.063	0.059	-0.475	0.012	0.076	0.076	0.076
Bus	0.230	0.218	0.181	-0.311	0.275	0.275	0.275

Source: CEPA and Hgroup analysis using Opal data

Figure 6.33: Concession Saturday (and public holiday) journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.147	0.016	0.015	0.003	0.022	0.022	0.022
Train Peak	0.095	-0.145	0.085	0.016	0.122	0.122	0.122
Train Post Peak	0.056	0.053	-0.239	0.009	0.072	0.071	0.071
Bus	0.133	0.128	0.123	-0.200	0.165	0.164	0.164

Source: CEPA and Hgroup analysis using Opal data

Figure 6.34: Concession Sunday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.216	0.015	0.015	0.016	0.029	0.028	0.028
Train Peak	0.051	-0.174	0.055	0.057	0.103	0.101	0.101
Train Post Peak	0.027	0.029	-0.192	0.031	0.056	0.055	0.055
Bus	0.084	0.089	0.090	-0.160	0.169	0.165	0.165

Source: CEPA and Hgroup analysis using Opal data

D.1.3. Senior/Pensioner elasticity results

Senior/Pensioner Journeys in Distance Band 1 (0-3km) – Elasticity Estimates

Figure 6.35: Senior/Pensioner weekday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.123	0.013	0.005	0.015
Train Peak	0.008	-0.132	0.017	0.055
Train Post Peak	0.003	0.015	-0.153	0.017
Bus	0.023	0.126	0.047	-0.068

Source: CEPA and Hgroup analysis using Opal data

Figure 6.36: Senior/Pensioner Saturday (and public holiday) journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-1.732	0.108	0.097	0.216
Train Peak	0.331	-1.310	0.301	0.490
Train Post Peak	0.133	0.131	-1.502	0.237
Bus	1.320	0.965	1.066	-0.894

Source: CEPA and Hgroup analysis using Opal data

Figure 6.37: Senior/Pensioner Sunday journeys in distance band 1 (0-3km) – elasticity estimates using the aggregate share model for train and bus journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus
Train Pre Peak	-0.867	0.075	0.078	0.108
Train Peak	0.239	-0.680	0.200	0.245
Train Post Peak	0.117	0.094	-0.790	0.129
Bus	0.616	0.438	0.491	-0.460

Source: CEPA and Hgroup analysis using Opal data

Senior/Pensioner Journeys in Distance Band 2 (3-8km) – Elasticity Estimates

Figure 6.38: Senior/Pensioner weekday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.077	0.007	0.009	0.007	0.003	0.010	0.006
Train Peak	0.042	-0.113	0.038	0.027	0.011	0.041	0.025
Train Post Peak	0.008	0.006	-0.066	0.005	0.002	0.008	0.005
Bus	0.117	0.085	0.108	-0.104	0.031	0.117	0.071
MM Pre Peak	0.008	0.006	0.008	0.006	-0.164	0.009	0.006
MM Peak	0.018	0.013	0.017	0.011	0.004	-0.130	0.010
MM Post Peak	0.007	0.005	0.006	0.004	0.002	0.007	-0.171

Source: CEPA and Hgroup analysis using Opal data

Figure 6.39: Senior/Pensioner Saturday (and public holiday) journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.033	0.003	0.003	0.002	0.004	0.004	0.004
Train Peak	0.009	-0.032	0.009	0.008	0.012	0.012	0.012
Train Post Peak	0.004	0.004	-0.035	0.003	0.005	0.005	0.005
Bus	0.019	0.021	0.020	-0.025	0.025	0.025	0.025

Source: CEPA and Hgroup analysis using Opal data

Figure 6.40: Senior/Pensioner Sunday journeys in distance band 2 (3-8km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.013	0.001	0.001	0.001	0.002	0.002	0.002
Train Peak	0.003	-0.013	0.004	0.003	0.005	0.005	0.005
Train Post Peak	0.002	0.002	-0.014	0.002	0.002	0.002	0.002
Bus	0.007	0.008	0.008	-0.011	0.011	0.011	0.011

Source: CEPA and Hgroup analysis using Opal data

Senior/Pensioner Journeys in Distance Band 3 (8-20km) – Elasticity Estimates

Figure 6.41: Senior/Pensioner weekday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.084	0.007	0.010	0.006	0.015	0.011	0.013
Train Peak	0.042	-0.118	0.039	0.024	0.058	0.041	0.051
Train Post Peak	0.008	0.006	-0.073	0.005	0.012	0.008	0.010
Bus	0.108	0.073	0.100	-0.107	0.149	0.106	0.130
MM Pre Peak	0.008	0.006	0.008	0.004	-0.141	0.008	0.010
MM Peak	0.018	0.012	0.017	0.010	0.025	-0.132	0.022
MM Post Peak	0.005	0.003	0.004	0.002	0.006	0.004	-0.110

Source: CEPA and Hgroup analysis using Opal data

Figure 6.42: Senior/Pensioner Saturday (and public holiday) journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.037	0.003	0.003	0.003	0.004	0.004	0.004
Train Peak	0.010	-0.037	0.011	0.009	0.014	0.014	0.014
Train Post Peak	0.004	0.005	-0.040	0.004	0.006	0.006	0.006
Bus	0.021	0.024	0.023	-0.028	0.029	0.029	0.029

Source: CEPA and Hgroup analysis using Opal data

Figure 6.43: Senior/Pensioner Sunday journeys in distance band 3 (8-20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.015	0.001	0.001	0.001	0.002	0.002	0.002
Train Peak	0.004	-0.015	0.004	0.004	0.006	0.006	0.006
Train Post Peak	0.002	0.002	-0.016	0.002	0.003	0.003	0.003
Bus	0.008	0.010	0.009	-0.012	0.013	0.013	0.013

Source: CEPA and Hgroup analysis using Opal data

Senior/Pensioner Journeys in Distance Band 4 (>20km) – Elasticity Estimates

Figure 6.44: Senior/Pensioner weekday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.104	0.009	0.013	0.007	0.020	0.014	0.017
Train Peak	0.043	-0.124	0.041	0.024	0.064	0.045	0.055
Train Post Peak	0.011	0.007	-0.091	0.006	0.015	0.011	0.013
Bus	0.110	0.073	0.104	-0.111	0.162	0.115	0.140
MM Pre Peak	0.009	0.006	0.009	0.005	-0.160	0.010	0.012
MM Peak	0.019	0.012	0.018	0.010	0.028	-0.140	0.025
MM Post Peak	0.005	0.003	0.005	0.003	0.008	0.006	-0.130

Source: CEPA and Hgroup analysis using Opal data

Figure 6.45: Senior/Pensioner Saturday (and public holiday) journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.049	0.004	0.004	0.004	0.006	0.006	0.006
Train Peak	0.012	-0.047	0.013	0.012	0.019	0.019	0.019
Train Post Peak	0.005	0.006	-0.052	0.005	0.008	0.008	0.008
Bus	0.022	0.025	0.024	-0.030	0.034	0.034	0.034

Source: CEPA and Hgroup analysis using Opal data

Figure 6.46: Senior/Pensioner Sunday journeys in distance band 4 (>20km) – elasticity estimates using the aggregate share model for train, bus and multimodal journeys (fares in row, demands in column)

	Train Pre Peak	Train Peak	Train Post Peak	Bus	MM Pre Peak	MM Peak	MM Post Peak
Train Pre Peak	-0.021	0.002	0.002	0.002	0.003	0.003	0.003
Train Peak	0.005	-0.020	0.006	0.005	0.008	0.008	0.008
Train Post Peak	0.002	0.003	-0.021	0.003	0.004	0.004	0.004
Bus	0.009	0.010	0.010	-0.013	0.014	0.014	0.014

Source: CEPA and Hgroup analysis using Opal data

ANNEX E LITERATURE REVIEW

To establish whether our results are in line with other published studies, we conducted a literature review to identify a range of published elasticity estimates for public transit. Overall, our literature review suggested price elasticities of demand for public transport tend to fall between -1 and -1.

E.1. TRANSIT LITERATURE

de Grange et al's 2013 paper studying the Santiago metro system conducted a literature review with a similar scope. Based on 19 papers the authors found that in general, public transport elasticities ranged between -0.3 and -0.5. Their own analysis found Metro elasticities to be between -0.186 (off-peak) to -0.588 (peak), and bus elasticities to be between -0.354 (off-peak) to -0.286 (peak).

Using this paper as a starting point, we have focussed our literature review on papers published after 2011. The literature we reviewed provided broadly comparable results to the Santiago study, with nearly all transport elasticities falling between a slightly wider range of 0 and -1:

- Considering the bus network in Zagreb, Croatia, Cipriani et al (2012) found a price elasticity of demand ranging from -0.61 for high income to -1.10 for lowest income bus users.
- Looking at short and long-term elasticities of bus transport demand in India, Deb and Filippini (2013) found short term elasticities to be -0.289 and long-term elasticities to be -0.523.
- A study by WSP group and Parsons Brinckerhoff (2016) found the elasticity for young bus users to be between -0.6 and -0.8, which they note is higher than is found across the total population, suggesting that young people are more sensitive to price changes.
- Finally, Holmgren (2013), using panel data from Swedish counties, found that fare elasticities for public transport were -0.4.

E.2. AUSTRALIAN CONTEXT

In 1996, Hensher and Raimond[33] conducted a comprehensive review of transport elasticities and cross elasticities in the Sydney region for IPART. The authors found:

- The elasticities for Travel Pass rail travel were -0.529 for commuters and -1.103 for non-commuters.
- The elasticities for weekly rail travel were -0.25 and -0.691 for commuters and non-commuters respectively.
- The elasticities for bus usage were -0.383 for those using a TravelTen pass, and -0.822 for those using a Bus/Train/Ferry Travel Pass.

In a more recent study, Littman (2017) found Australian bus demand elasticity to be -0.29 and rail demand elasticity to be -0.35. These results are broadly in line with the above.

[33] Hensher and Raimond (1996).

E.3. OTHER FACTORS

In addition to factors of price, our literature review suggested several other factors that can affect elasticities, including:

- **Type of traveller.** People with alternative travel options may be more sensitive to price (e.g. if they own a car) and certain demographics may be more dependent on public transit (e.g. those with lower income, students, seniors etc.). For example, in Cipriani et al (2010) lowest income bus users had an elasticity of -1.10 versus -0.61 of highest income users.
- **Type of trip.** Non-routine trips tend to be more price sensitive than routine trips. Non-routine trips are more likely to happen during off-peak periods, and we can see this in de Grange et al (2013) where off peak bus trips had an elasticity of approximately -0.35 and peak bus trips were less responsive at approximately -0.3.
- **City geography.** Large cities tend to have lower elasticities due to more travellers who are dependent on public transport. We can see this in the study by WSP Group (2016), where the elasticity for youth concessions was -0.81 in West Yorkshire versus -0.66 in London.
- **Component and level of cost/price that changes.** Price can include not just fare price but also travel times and comfort, which can have a bigger effect on elasticities than just the fare. For example, in Guo and Wilson (2017), the authors do not estimate price elasticity but find that the inconvenience of a transfer does impose a cost to travellers. Furthermore, elasticities increase as fares increase, meaning elasticity may be higher if starting fare was higher.
- **Direction of change in cost.** Elasticity is often not symmetrical, and fare increases generally have a greater impact on number of trips than corresponding fare decreases. Cats et al (2010) was the only study reviewed that directly examined the impact of a fare decrease, of €1 to 0, and found the elasticity to be -0.01, much closer to zero than other elasticities reported.
- **Period.** The impact of a price changes tends to differ between the short term and the long term, generally growing over time as people make lifestyle choices in response to the cost of travel. Deb and Filippini (2013) demonstrate this, with elasticities for bus travel being -0.29 and ten years later had grown to -0.52.
- **Type of public transport**. Elasticities tend to differ between, for example, bus and Metro demand, primarily because they serve different markets. Littman (2017) shows this for the US market, where bus elasticities are -0.58 and rail elasticities are significantly larger at -0.86.

ANNEX F NUMBER OF PUBLIC TRANSPORT AND CAR JOURNEYS

In addition to the elasticities presented in the main report, IPART want to estimate demand quantity, which is part of the input to IPART's fare optimisation model. This annex has been produced by Hgroup and provides an analysis of the quantity of car and public transport journeys for all combinations of time period and distance band provided in the main report.[34]

The number of public transport journeys is estimated from the Opal data used in the main report. In estimating the number of train, bus, ferry, light rail, multimodal bus-train journeys for each of the 24 combinations (3 time periods × 4 distance bands × 2 day of week = 24), the Opal data is scaled up by a factor of two since this dataset represents 50 percent of total fare-paying Opal card holders. It is also noted that this exercise uses only the first 4.5 months of Opal data (from 1st August to 20 Dec 2016 inclusive), consistent with the main study.

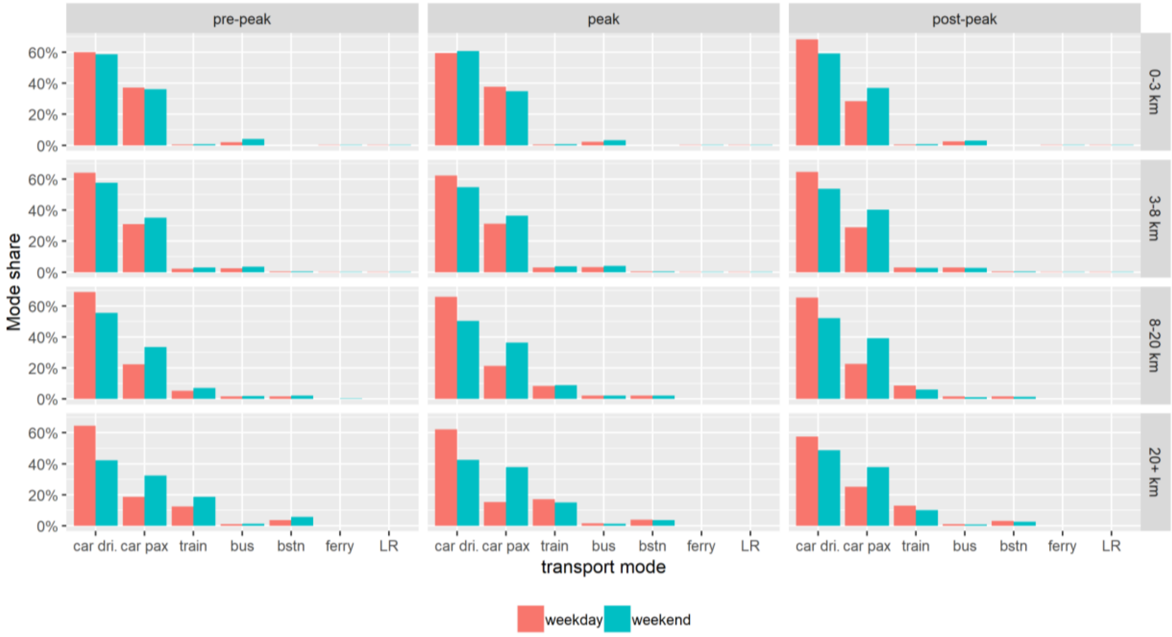
The number of car journeys is estimated from the 3-year pooled Sydney Household Travel Survey data (HTS 2014/15 – 2016/17), weighted to the population demand based on the journey to work data from the 2016 Census. This weighting process is done by TfNSW to ensure that the 3-year pool HTS sample is representative of the population, in terms of both personal and trip characteristics (i.e., time, distance, mode). Time bands and distance bands are defined based on departure time of each car journey, consistent with the definition used for public transport journeys.

Tables 6.4 to 6.6 provide the number of journeys by mode and time period on an average weekday and weekend in 2016 for each of the four distance bands. Figure 6.47 validates the results using mode share. The results are sensible, with trains accounting for a larger market share of long distance travel but in general cars (driver and passengers) are the dominating modes. As expected, car passenger journeys are more popular on the weekend than on weekdays. Overall, the total number of public transport and car journeys generated by the residents of Sydney Greater Capital City Statistical Area are in line with the latest HTS summary report[35] with an average weekday having 17.3 million journeys and an average weekend having 14.8 million journeys.

[34] This annex was prepared by Hgroup with no input or quality assurance from CEPA.

[35] Transport for NSW (2014). Household Travel Survey Report: Sydney 2012/13. Bureau of Transport Statistics

Figure 6.47: Mode share of journeys on an average weekday and weekend in 2016 by time period and distance band



Source: Hgroup analysis

Table 6.4: Number of journeys up to 3 km by transport mode on an average weekday and weekend: estimated from the Sydney HTS (3 years pooled 2014/15 – 2016/17, weighted to 2016 Census) and Opal data 2016

Distance	Time period	Mode	Average weekday	Average weekend
0-3 km	pre-peak	bus-train	104	82
0-3 km	pre-peak	bus	16,148	13,814
0-3 km	pre-peak	car driver	473,298	203,820
0-3 km	pre-peak	car passenger	293,680	125,412
0-3 km	pre-peak	ferry	476	544
0-3 km	pre-peak	light rail	654	536
0-3 km	pre-peak	train	2,922	2,778
0-3 km	peak	bus-train	246	216
0-3 km	peak	bus	54,012	43,316
0-3 km	peak	car driver	1,486,845	792,613
0-3 km	peak	car passenger	945,500	455,824
0-3 km	peak	ferry	2,522	2,192
0-3 km	peak	light rail	2,294	1,826
0-3 km	peak	train	9,220	8,110
0-3 km	post-peak	bus-train	84	76
0-3 km	post-peak	bus	17,756	16,090
0-3 km	post-peak	car driver	469,341	324,694
0-3 km	post-peak	car passenger	195,663	201,923
0-3 km	post-peak	ferry	548	626
0-3 km	post-peak	light rail	736	660
0-3 km	post-peak	train	3,394	3,306

Note: IPART may wish to round these figures when using them in its model.

Source: Hgroup analysis

Table 6.5: Number of journeys betwee 3 and 8 km by transport mode on an average weekday and weekend: estimated from the Sydney HTS (3 years pooled 2014/15 – 2016/17, weighted to 2016 Census) and Opal data 2016

Distance	Time period	Mode	Average weekday	Average weekend
3-8 km	pre-peak	bus-train	2,058	1,790
3-8 km	pre-peak	bus	16,456	14,160
3-8 km	pre-peak	car driver	410,801	232,677
3-8 km	pre-peak	car passenger	198,171	141,915
3-8 km	pre-peak	ferry	464	428
3-8 km	pre-peak	light rail	332	286
3-8 km	pre-peak	train	13,438	12,212
3-8 km	peak	bus-train	8,400	6,494
3-8 km	peak	bus	72,984	54,074
3-8 km	peak	car driver	1,402,012	723,550
3-8 km	peak	car passenger	701,694	481,535
3-8 km	peak	ferry	2,928	2,026
3-8 km	peak	light rail	1,926	1,368
3-8 km	peak	train	65,798	50,202
3-8 km	post-peak	bus-train	1,966	1,786
3-8 km	post-peak	bus	18,348	16,228
3-8 km	post-peak	car driver	400,425	316,301
3-8 km	post-peak	car passenger	179,318	236,725
3-8 km	post-peak	ferry	418	352
3-8 km	post-peak	light rail	390	376
3-8 km	post-peak	train	18,280	16,080

Note: IPART may wish to round these figures when using them in its model.

Source: Hgroup analysis

Table 6.6: Number of journey between 8 and 20 km by transport mode on an average weekday and weekend: estimated from the Sydney HTS (3 years pooled 2014/15 – 2016/17, weighted to 2016 Census) and Opal data 2016

Distance	Time period	Mode	Average weekday	Average weekend
8-20 km	pre-peak	bus-train	8,228	6,736
8-20 km	pre-peak	bus	8,002	5,944
8-20 km	pre-peak	car driver	358,343	183,800
8-20 km	pre-peak	car passenger	116,618	110,349
8-20 km	pre-peak	ferry	698	698
8-20 km	pre-peak	light rail	4	4
8-20 km	pre-peak	train	27,796	23,014
8-20 km	peak	bus-train	31,596	23,122
8-20 km	peak	bus	34,398	23,094
8-20 km	peak	car driver	1,020,182	525,720
8-20 km	peak	car passenger	330,589	379,408
8-20 km	peak	ferry	2,294	2,036
8-20 km	peak	light rail	10	12
8-20 km	peak	train	128,878	93,128
8-20 km	post-peak	bus-train	6,262	5,540
8-20 km	post-peak	bus	6,396	5,346
8-20 km	post-peak	car driver	243,023	225,887
8-20 km	post-peak	car passenger	84,338	169,872
8-20 km	post-peak	ferry	552	606
8-20 km	post-peak	light rail	6	6
8-20 km	post-peak	train	31,724	26,616

Note: IPART may wish to round these figures when using them in its model.

Source: Hgroup analysis

Table 6.7: Number of journeys longer than 20 km by transport mode on an average weekday and weekend: estimated from the Sydney HTS (3 years pooled 2014/15 – 2016/17, weighted to 2016 Census) and Opal data 2016

Distance	Time period	Mode	Average weekday	Average weekend
20+ km	pre-peak	bus-train	12,420	9,212
20+ km	pre-peak	bus	3,328	2,132
20+ km	pre-peak	car driver	221,770	68,342
20+ km	pre-peak	car passenger	64,290	52,330
20+ km	pre-peak	ferry	20	14
20+ km	pre-peak	train	42,478	30,192
20+ km	peak	bus-train	34,418	24,500
20+ km	peak	bus	13,170	8,060
20+ km	peak	car driver	552,894	288,430
20+ km	peak	car passenger	136,186	255,485
20+ km	peak	ferry	36	28
20+ km	peak	train	151,256	101,342
20+ km	post-peak	bus-train	6,152	5,368
20+ km	post-peak	bus	2,072	1,480
20+ km	post-peak	car driver	109,704	99,090
20+ km	post-peak	car passenger	47,864	76,718
20+ km	post-peak	ferry	22	16
20+ km	post-peak	light rail	0	0
20+ km	post-peak	train	24,722	20,750
20+ km	pre-peak	bus-train	12,420	9,212
20+ km	pre-peak	bus	3,328	2,132

Note: IPART may wish to round these figures when using them in its model.

Source: Hgroup analysis

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