Information sheet

Australian Government

Department of Infrastructure, Regional Development and Cities

Bureau of Infrastructure, Transport and Regional Economics

An empirical analysis of route-based differences in Australian scheduled domestic passenger air fares

Summary

This paper provides an empirical analysis of factors affecting movements in Australian domestic commercial airfares and differences in fares across different routes, and provides some estimates of differences in fares across regional routes in Australia. The analysis was prepared by BITRE in response to a request from the Senate Standing Committee on Rural and Regional Affairs and Transport. BITRE's analysis considered movements in the lowest fare by fare class and airline across monitored domestic aviation routes, using unpublished data sourced from BITRE's monthly airfares collection (BITRE 2018).

BITRE's airfares collection comprised fares on the top-70 routes by passenger volume, which comprise large trunk commercial domestic aviation routes and next tier regional routes. Fares on lower-volume regional routes, by contrast, are less complete in the BITRE fares data set, and hence few such routes feature in the statistical analysis. An assessment of the relative difference in fares on regional routes is made by comparing actual fares for July 2018 with an estimate of fares predicted by the statistical analysis (discussed further below).

The analysis considered a range of potentially relevant factors, such as world oil prices, route distance, number of flights (by route), total route passengers, total number of route operators, route load factor and regional populations. Fares were compared across different routes by dividing the nominal fare by route distance (measured as the great-circle distance between airport pairs). The results show that all of these factors have a statistically significant impact on average fares, and together they explain close to 95 per cent of the variation observed in collected fares.

In summary, the key results from analysis of movements in best discount fares include:

- Distance – average fares decline with increasing route distance (i.e. the average fare per kilometre declines with increasing distance), implying the presence of scale economies in air operations with respect to route distance. Part of this would presumably be related to the ability to defray more fixed ground-based costs and take-off and landing costs over longer flight distance.

- Market size (number of passengers) – average fares also strongly decline with increasing market size, suggesting significant route-based scale economies.
- Competition (number of operators) – average fares were also found to decline significantly as the number of route operators increases. In other words, competition has a statistically significant effect in reducing average fares.
- Flights – average fares were found to increase as the number of flights on a route increased (other factors equal). The outcome presumably reflects a combined effect of the increased costs of adding flights and some dilution of the scale economies of increasing capacity utilisation.
- Load factor – despite reflecting both a combination of flights and passenger numbers, load factor was separately found to have a statistically significant but small positive impact on average fares.
- Oil prices – oil prices were found to have a statistically significant, but relatively small impact on best discount average airfares. This likely reflects a combination of the fact that fuel costs typically represent only a small share of total airline operating costs—fuel expenditures are around 20 per cent of total operating costs for major airlines in Australia—and also airline fuel hedging strategies, by which airlines aim to minimise the impact of future oil price movements.

After taking into account all of the factors above, the analysis suggests that there remain statistically significant differences in average fare levels across routes, and BITRE has identified three broad groups:

- *High-mark-up* routes (i.e. above average fare routes) – which feature predominantly longer-distance trunk routes to/from Perth, Darwin and Alice Springs, and also several routes servicing remote mineral industry locations (e.g. Karratha, Port Hedland, Newman, Weipa).
- *Mid-tier mark-up* routes – which include most of the higher volume (trunk) domestic commercial routes and several smaller-distance routes.
- *Low-mark-up* routes (i.e. below average fare routes) – which predominantly comprise shorter distance routes, such as Melbourne-Devonport, Melbourne-Burnie, Melbourne-Launceston and Coffs Harbour-Sydney, or longer-distance tourist-routes, such as Brisbane–Proserpine and Hervey Bay–Sydney. These former routes are all routes for which car, or ferry in the case of the Tasmanian routes, are a significant competitor.

In order to assess the relative level of fares on lower-volume regional routes, BITRE specifically collected a wider sample of fares for its July 2018 collection. The expanded collection covered over 280 separate domestic air routes, yielding useable fare information for approximately 245 routes.

BITRE then calculated the difference between the July 2018 best discount average fare for each route and the best discount average fare predicted by the preferred model specification. The resulting difference between the actual and modelled average fares represents then a measure of the relative route-specific difference after taking into account all other relevant factors. The results imply that while there are some apparent systematic differences in average fares for some routes or groups of routes—e.g. below-average fares on some subsidised routes and above-average fares on some regulated routes—for the large majority of routes, the estimated difference between actual and modelled fares are generally within the range of variation exhibited by major trunk routes. However, as these results are based on a one-month only snapshot of fares, they should not be treated as conclusive evidence of systematic differences in pricing across different routes.

1. Introduction

Australia's domestic aviation sector was deregulated in October 1989. Prior to deregulation, Australia's aviation market was a regulated duopoly with incumbents—Ansett Airlines and Trans Australia Airways (TAA)—shielded from new competitors on trunk routes and fares reviewed and set by the Federal Government's Independent Air Fares Committee (IAFC). Deregulation involved removing restrictions on new market entrants and letting airlines set fares unimpeded. Upon deregulation, fares decreased significantly across most routes, and most particularly on very long-distance routes.

BITRE monitoring of domestic air fares commenced in October 1992. Over the nearly 30 years since deregulation, while full economy and business class fares have increased slightly in real terms, real discount airfares have fallen almost 50 per cent below equivalent fares in 1993 (see Figure 1). The entry of low cost carriers in the early-2000s, initially Virgin Australia and subsequently Jetstar Airways and Tiger Airways, has resulted in increased competition on trunk many routes and periods of intense competition for market share which resulted in significant reductions in real airfares, particularly best discount fares. For example, the period between mid-2008 and mid–2011 exhibits significant reduction in both nominal and real best discount fares, before fares stabilised somewhat.

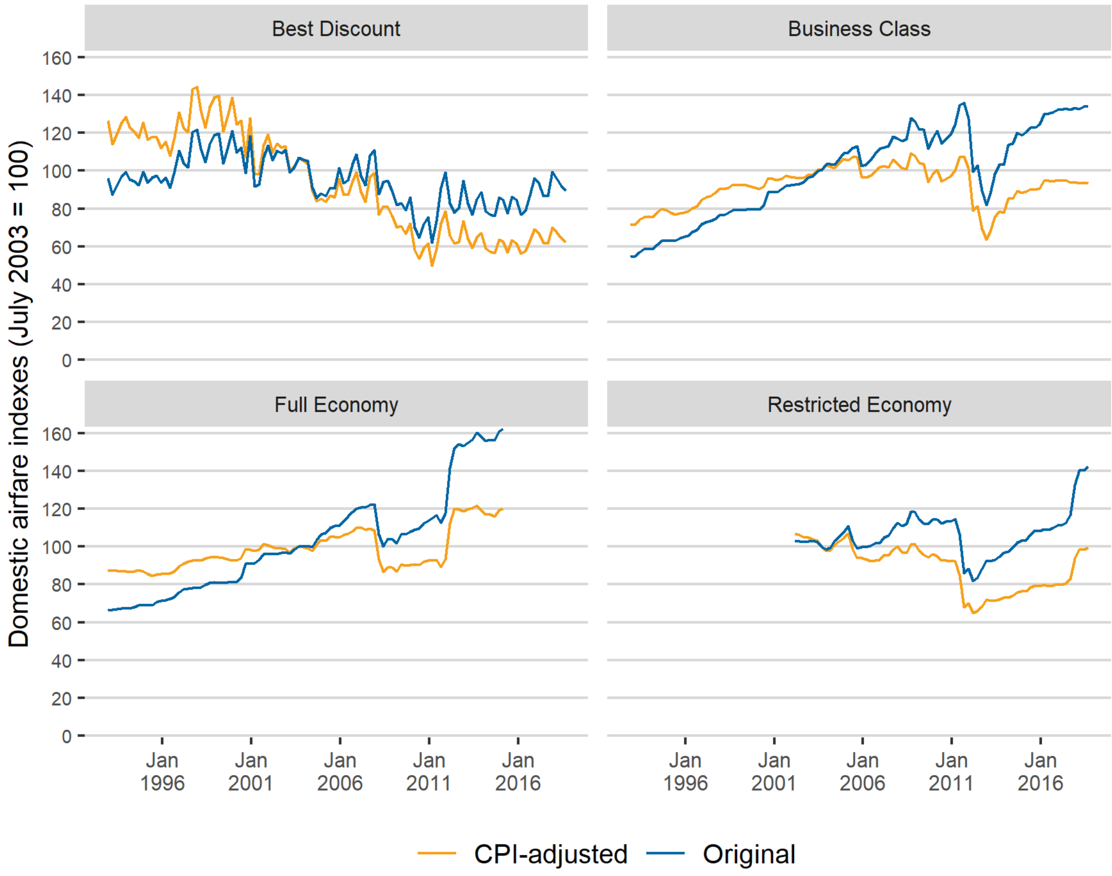
At the route-specific level, trend movements in fares vary across different routes, and in some cases are different from the national trends. This is addressed in subsequent sections. Note that all of the subsequent analysis of movements in fares presented in the remainder of this paper is in nominal terms (i.e. fares have not adjusted for inflation).

1.1 BITRE airfares collection

BITRE's airfares collection contains monthly records of the best available business, restricted economy and best discount fares for each airline across the 70-largest routes. Importantly, the fares recorded in the BITRE collection are the lowest available fare for each fare class on the last Thursday of each month, for a hypothetical trip in three weeks' time (i.e. the third Thursday of the following month). Hence, the BITRE's fares collection cannot provide any insight into the time-profile of fares for a particular flight in the lead up to flight departure (discussed further below).

Routes covered in BITRE's collection vary over the collection period, based on variations in the composition of the top 70 routes. In particular, the set of routes covered in BITRE's collection do not include many of the lower volume routes. The average fares for all routes covered by BITRE's fares collection, are shown in Appendix A.

Figure 1 Trends in nominal and real Australian domestic air fares, 1991 to present



Source BITRE (2018).

1.2 How airlines set fares?

Though detail about how Australian airlines set fares is not generally publicly available, from the outside it is apparent that most airlines today use 'sophisticated' yield management techniques to optimise operating revenues. Yield management techniques typically involve using historical utilisation data and real-time booking information to vary the menu of available fares, by fare class, for each flight up until the time bookings close. From an airline's perspective, aircraft seats on any particular flight are finite and limited-life resource—once the flight departs any unsold seats disappear. Therefore, it is in the airlines' interests to sell as many seats as possible at as high a price as possible to maximise revenue, hence the availability of 'last minute' and 'mystery' flight deals. The corollary to this is that as passenger bookings on any single flight increase, capacity diminishes and seats are likely to become more valuable and hence price can rise. Hence, any unanticipated increase in demand on a route can cause fares to increase significantly.

In the medium term airlines can vary the overall level of fares on a particular route by adding more capacity, through increasing the number of flights or operating larger aircraft. For example, competition for increased market share is conducted through increasing available seat capacity which has a flow-on effect to fares—in the short term, fares are subject to seat availability.

There are also different types of passengers, with different preferences with regard to price and service. Airlines take advantage of this by offering a mix of different fare classes. First/business class tickets, for example, cater for travellers who are relatively price insensitive, time sensitive (last-minute booking) and/or willing to pay a premium for extra services. Other travellers may be both price and time sensitive, for instance, business travellers able to book in advance, but not far enough in advance to secure the lowest fares. Leisure travellers, on the other hand are typically both price and time insensitive (by time of day rather than travel date), and seek the cheapest available fare.

As noted previously, BITRE's fares collection does not provide the multiple snapshots, over several points in time during each month, which would be needed to provide an indication of how fares change in the lead up to flight departure.[1] Moreover, multiple sampling of air fares at different points in time for a particular flight, does not provide the accompanying booking information necessary to fully understand the factors that influence the variation in fares observed by customers.

1.3 Air fares and airline cost structures

In markets where there is some degree of competition, or even risk of new market entry, changes in prices tend to reflect changes in input costs. The major input costs for airlines are capital, maintenance and parts, labour, fuel and air navigation and airport charges. Capital costs mainly comprise aircraft and airport terminal leasing costs. Labour includes pilots, aircraft cabin personnel, maintenance engineers and administrative staff. *Nominal* cost shares for Australia's two major domestic airlines, Qantas Group and Virgin Australia, in 2016–17 imply fuel costs represent between 17 and 21 per cent of total costs, labour is between 23.6 and 27.5 per cent, capital-related costs are around 34–35 per cent and other costs around 17 per cent for Qantas and 26 per cent for Virgin Australia.[2] (Appendix C provides Qantas and Virgin Australia's 2016–17 financial year operating cost shares.)

Input costs, and other factors, will vary across different routes, thereby resulting in some systematic differences in fares across routes. For example, fuel costs may be a higher share of variable costs for shorter distance routes than longer distance routes, due to the disproportionately higher fuel use involved in aircraft take-off/landing movements. Similarly, average fuel costs may be a lower share of overall costs on higher volume routes, where higher total fuel costs can be defrayed over proportionately more passengers. Increased route competition may lead to lower than average fares relative to routes where there is much less competition. Finally, variation in the characteristics

1. Presumably, with available fares increasing as flight occupancy increases as the flight departure time approaches, or decreasing if there is unexpected spare capacity.
2 These estimates are based on financial statements presented in the Qantas and Virgin Australia annual reports, and the categories may not be directly comparable, nonetheless they provide a rough indication of relative operating cost shares.

of aviation demand across different routes may also affect the level of fares. For example, on routes where there are fewer (or no) time-comparable modal alternatives, such as very-long distance routes, passenger demand may be less elastic—i.e. less responsive to changes in fares—airlines may be able to set prices with a small premium. Conversely, on routes where demand is more elastic—i.e. more responsive to changes in fares—fares may be comparatively lower.

1.4 Paper structure

The remainder of this paper is structured as follows. Section 2 outlines trends in average domestic airfares in Australia since 1992 and considers trends in fares across the various routes covered by BITRE's fares collection over that period. Section 3 briefly describes the analytical methodology used to modelling fares across different routes. Section 4 briefly outlines the key raw data and main data sources. Section 5 presents some of the key results. Section 6 uses the empirical results outlined in Section 5 to provide a comparison with fares on lower-volume, regional routes. Finally, Section 7 draws out some of the implications of the results and provides some concluding remarks.

2. Trends in Australian domestic airfares

2.1 Trends in airfares by route

Appendix Figure A.1 shows trends in best discount airfares since 1992, for all BITRE-monitored top-70 domestic aviation routes (by number of passengers). As a result of variation in the composition of the top-70 routes over that period, BITRE has collected fares on over 130 separate routes. Consequently, for the largest 30-odd routes BITRE's collection provides a complete record of the best available monthly airfare, on smaller volume routes (outside the top 30 or so routes), there are often significant periods for which no observations are available. Examples of the latter include Adelaide–Alice Springs, Adelaide–Kalgoorlie, Albury–Melbourne, Brisbane–Hobart, Carnarvon–Perth, Esperance–Perth, Melbourne–Burnie and Sydney–Norfolk Island, among others. For some of these smaller routes, there are likely to be insufficient observations to draw reliable conclusions about the factors influencing air fares on these routes.

Closer consideration of nominal fares by route suggests a few broad differences in fare trends across different routes. Firstly, across many routes, best discount fares have remained relatively stable, with little monthly variation—this appears to be particularly so on major intercapital routes, e.g. Sydney–Melbourne, Sydney–Brisbane, Melbourne–Brisbane, Adelaide–Brisbane, Sydney–Perth, etc. By contrast, on many lower-volume and/or non-intercapital routes, average best discount fares exhibit significantly more month-to-month variation. Examples include Sydney–Tamworth, Sydney–Port Macquarie, Sydney–Coffs Harbour, Sydney–Dubbo, Perth–Geraldton, Melbourne–Devonport, Melbourne–Hobart, Sydney-Albury and Adelaide–Port Lincoln.

Secondly, on many of the major intercapital routes, nominal average best discount fares exhibit no discernible trend, either up or down, over the observation period. However, for a small proportion of routes average best discount fares exhibit a long-term increasing trend (in nominal terms).

In many cases, there appears to be a spike (or peak) in fares before the route disappears from the records, which may reflect airlines attempting to improve profitability by lifting fares before abandoning a route, but it has not yet been verified whether this is indeed the case.

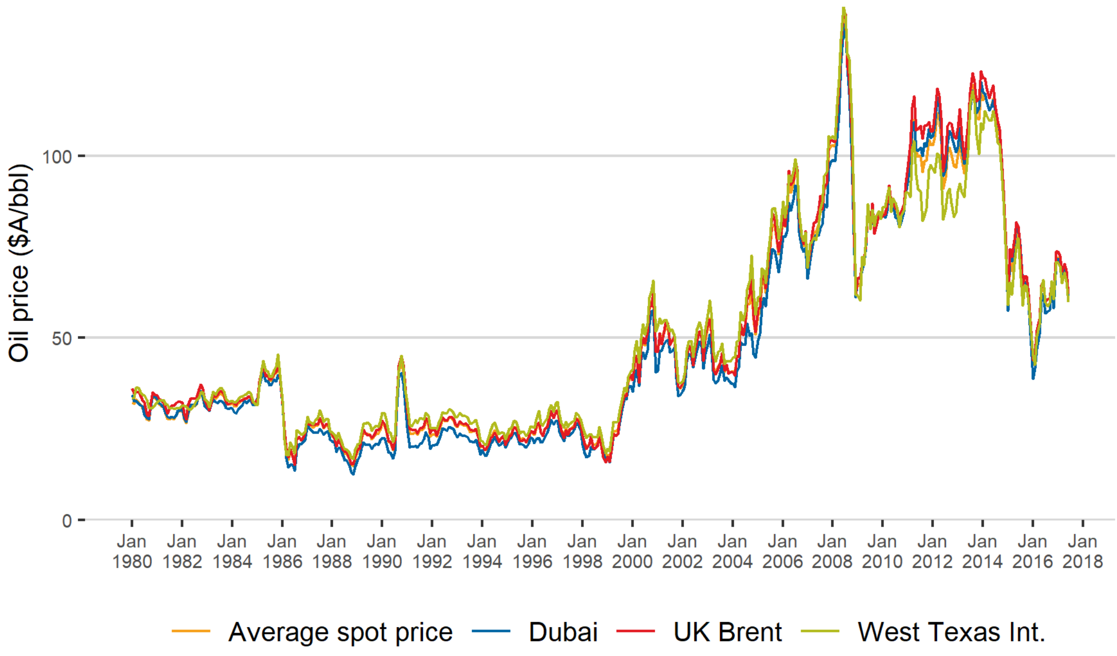
2.2 Australian air fares, crude oil prices and airline hedging

Figure 2 shows monthly world oil prices—including UK Brent, Dubai and West Texas Intermediate price indexes—since 1980. Notable features of historical trends in world oil prices include:

- oil prices averaged around $US 25 per barrel between 1986 and 1999
- oil prices averaged around $US 50 per barrel between 1999 and mid-2000s
- oil prices averaged around $US 100 per barrel between 2008 and 2015
- oil prices have, since 2015, declined to around $US 50-75 per barrel.

Significantly, average best discount (nominal) fares appear to exhibit far less month-to-month variation than world oil prices. This in part reflects the fact that, while fuel costs are presumably a significant share of individual flight costs, they comprise only a part of the total cost of air services—for example, as previously mentioned, Qantas and Virgin Australia's fuel costs are around 20 per cent of total operating costs.[3] Airline fuel hedging practices will also act to dampen the impact of changes in world oil prices on airline operating costs, and hence fares.

Figure 2 World oil prices, 1980–present



Source: World Bank (2018).

3 Qantas' 2016–17 Annual Report indicates aviation fuel costs were around 21 per cent of total operating expenditures and Virgin Australia's 2016–17 Annual Report implies fuel costs were around 19 per cent of its total operating costs. See Appendix C for further details.

2.3 Oil price hedging

Anecdotal evidence about airline pricing behaviour suggests that not only do airlines use yield management methods to maximise revenue for each flight, but airlines also forward hedge fuel purchases to protect against volatile movements in fuel prices. Hedging limits the fuel cost impact on airlines in periods of increasing fuel spot prices, but equally limits the scope for airlines to take advantage of future reductions in spot fuel prices.

Further, different airlines hedge to different extents and using different contracts/strategies. Details are typically not made publicly available as hedging potentially provides a competitive advantage, by enabling airlines to lower costs *vis-a-vis* their competitors. Qantas' annual report (Qantas 2017, p. 78) notes that fuel consumption may be hedged out to two years ahead within specific parameters, or more with management board approval. Similarly, Virgin Australia's annual report (Virgin Australia 2017, p. 79) notes that, subject to limits determined by its management board, it hedges anticipated fuel consumption to protect against sudden and significant increase in fuel prices whilst ensuring that the airline is not disadvantaged by a significant reduction in fuel prices.

This suggests that it should not surprise that fares exhibit little short-term (e.g. monthly or quarterly) correlation with changes in international crude oil spot prices, but one might expect some degree of longer-term correlation between average fares and long-term prevailing crude oil prices. It also suggests some degree of lagged ('sticky') relationship between fuel costs and crude oil spot prices. Other input costs may also exhibit a degree of 'stickiness', for example, wages tend to be agreed in two- or three-year contracts with annual increments.

3. Methodology

In this section, we outline the methodology used to analyse whether there are systematic difference in airfares across different routes. The analysis considers movements in the lowest fare on each route. Additional separate models, also by test for differences in fares across routes by fare class and airline. The data used for the analysis is sourced from the BITRE's monthly airfares collection (see Section 4).

Relevant factors considered in the analysis include:

- world oil prices (and exchange rates)
- route distances
- total flights (by route)
- total passengers (by route)
- total operators (by route)
- load factor
- regional populations.

For the models, with fares split by fare class and airline, we also include separate fare class and airline specific factors.

Differences in fares across different routes manifest as systematic differences in the modelled average fare level across routes and/or systematic differences in how fares change with respect to different factors across routes. We test these for systematic differences in these parameters to gauge whether, and if so, how large differing impacts are across routes.

4. Data

As previously noted, the BITRE's fares collection contains monthly records of the best available business, full economy (till February 2015), restricted economy (from March 2003) and best discount fares for each airline across the 70-largest routes. The collection extends back to October 1992. Routes covered in the collection vary over the collection period, in accord with variations in the top 70 routes. A full set of routes covered by BITRE's fares collection are listed in Appendix B. Importantly, the set of routes covered in BITRE's collection do not include many of the lower volume routes.

Airlines covered in BITRE's collection include:

- Qantas
- Jetstar Airways
- QantasLink
- Virgin Australia Airlines
- Tiger Airways
- Regional Express (Rex) Airlines

The fares data was combined with monthly BITRE data on passengers, flights, number of operators and load factors, by airline. World oil prices were sourced from the International Monetary Fund's (IMF) commodity database, which reports spot prices for UK Brent, Dubai and West Texas Intermediate crude oil. Regional populations were sourced from the Australian Bureau of Statistics' regional population data, and matched to airport according to BITRE-defined regional catchment areas.[4]

The data comprise an unbalanced time series cross-section data set, which may be estimated using panel data estimation methods. All models were estimated on log-transformed data, and hence all parameter estimates may be directly interpreted as elasticities.

4. Regional catchments were broadly defined as including the Greater Capital City Statistical Area for capital cities and all Statistical Area Level 2 areas within a 50-kilometre radius of regional airports.

5. Empirical results

5.1 Best discount fares by route

We first modelled movements in average best discount airfares (per route kilometre) across all Australian routes against the following factors:

- world oil prices (and exchange rates)
- route distances
- no. flights (by route)
- no. passengers
- no. operators
- load factor
- regional populations.

Averaging fares by route distance enables a more direct comparison of relative differences in fares across different distance routes. We tested the significance of all parameters and also tested for panel-data specific effects. The results imply there are statistically significant route-specific fixed effects—i.e. statistically significant differences in the average fare level across different routes—and also significant time-invariant fixed effects with respect to route distance. All other terms are also statistically significant. We also tested a dynamic specification, by including one-month lagged fares, but due to periodic gaps in the air fares data, the inclusion of a lagged dependent variable term significantly reduces the number of points and number of routes analysed in the model, and was not included in the final preferred specification.

Two sets of fixed effects are included in the preferred specification: i) route-specific dummy variables, and ii) seasonal (monthly) dummy variables. The preferred specification includes lagged oil prices.

We also tested the significance of adding airport-specific variables to the panel data model and replacing the route-specific variables with airport-specific variables. The first specification does not significantly improve the model fit. The second specification does not fit the data as well as the route-specific variable model, and, moreover, because of gaps in the data, airport-specific constants could not be estimated for all airports.

Table 1 shows summary estimation results, excluding route-specific fixed effects and time-specific dummy variables, for the preferred route-specific best discount fares model specification. The preferred specification includes a general time trend term, lagged oil prices (up to six months). Two sets of results are presented, ordinary least squares (OLS) and (feasible) generalised least squares (GLS) estimates, which better account for differences in variance across routes. (Appendix D provides a mathematical description of the preferred model specification and also some examples of how to interpret the model parameters.)

Table 1: Estimation results – best discount airfares by route

Dependent variable	log (Fare per km)	
Independent variables	OLS	GLS
Constant	-185.743***	-195.785***
	(11.771)	(10.654)
Log (Route distance)	-0.540***	-0.574***
	(0.035)	(0.027)
Route load factor	0.033***	0.026***
	(0.003)	(0.002)
Log (Avg. aircraft size)	2.011***	1.427***
	(0.188)	(0.149)
Log (Flights)	2.199***	1.583***
	(0.188)	(0.149)
Log (No operators)	-0.362***	-0.308***
	(0.012)	(0.012)
Log (Route passengers)	-2.315***	-1.751***
	(0.187)	(0.148)
Log (Trend)	24.695***	26.141***
	(1.553)	(1.404)
Log (Oil $price_t$)	-0.136***	-0.174***
	(0.033)	(0.025)
Log (Oil $price_{t-1}$)	0.543***	0.956***
	(0.206)	(0.161)
Log (Oil $price_{t-2}$)	-0.282	-0.701***
	(0.207)	(0.161)
Log (Oil $price_{t-3}$)	0.405**	0.390**
	(0.202)	(0.157)
Log (Oil $price_{t-4}$)	-0.657***	-0.205
	(0.201)	(0.155)
Log (Oil $price_{t-5}$)	0.638***	0.391**
	(0.200)	(0.153)
Log (Oil $price_{t-6}$)	-0.588***	-0.463***
	(0.136)	(0.104)
Summary statistics		
Observations	11,010	11,010
R^2	0.817	0.901
Adjusted R^2	0.816	0.900
Residual Std. Error (df = 10914)	0.256	0.081
F Statistic (df = 95; 10914)	514.418***	1,043.847***

Note: *Note: Significance levels:* *p<0.1, **p<0.05, ***p<0.01.

Source: BITRE estimates.

Information sheet

The model results show that both specifications fit the data quite well, the R^2 values imply the model explains over 96 per cent of the observed variation in average fares.[5] The GLS specification is preferred, as the estimates are both consistent and efficient.

All of the variables included in the model are statistically significant and the effects relatively consistent across all model variants. We briefly outline the key effects below.

The model results show that both specifications fit the data quite well, the R^2 values imply the model explains over 90 per cent of the observed variation in average best discount fares.[5] The GLS specification is preferred, as the estimates are both consistent and efficient.

All of the variables included in the model are statistically significant and the effects relatively consistent across all model variants. We briefly outline the key effects below.

Route distance

The estimated route distance elasticity is approximately -0.57, and implies that the average air fares decline by about 6 per cent for every 10 per cent increase in route distance.[6] In other words, average fares are generally lower for longer distance routes, all else equal. As previously mentioned, this accords with *a priori* expectations, as non-distance related flight costs can be defrayed over longer distances.

Number of passengers

The passenger volume parameter suggests there are significant scale economies in airline pricing, with average fares declining on more heavily trafficked routes. The impact is not only statistically significant but also substantial—for every one per cent increase in route passenger volume, average fares decline by around 1.75 per cent.

Number of route operators

There is also a statistically significant observed *competition effect*, with average fares declining with increasing number of airlines operating on a route. The implied elasticity is approximately -0.31, which implies that average fares on a route with three operators will be about 15 per cent lower than average fares on a route with just two operators, all else equal. Likewise, average fares on a route with four operators will be about 7 per cent lower than equivalent on a route with three operators.

Oil prices

The preferred model specification includes lagged oil price terms up to 6 months from the current period, all of which, with the exception of the two-period lag parameter, are statistically significant.

5. Note that there are approximately 11,000 usable observations in the data set, down from the approximately 20,900 observations in the raw data.
6. Appendix D provides a further explanation of why the model parameter estimates may be interpreted as elasticities and how to use elasticities.

While the significance of multiple lag effects appear consistent with the dynamic and potentially varying hedging strategies applied by different airlines, the estimated lag effects themselves alternate in sign, somewhat cancelling out over the entire period. The combined oil price impact (i.e. the sum of all current and lagged oil price terms) is +0.195, which implies that average air fares broadly increase on average with increases in world oil prices. Moreover the value of 0.195 is also broadly consistent with fuel's share (about 20 per cent) of airline operating costs (at least for full service airlines).

Number of flights and aircraft size

Conversely, average fares increase as the number of flights and the average aircraft size employed in each route increase, somewhat offsetting the scale economy effects. Both effects are statistically significant, with the elasticity of average fares to the number of flights approximately 1.6 (i.e. a 1.6 per cent increase in average fares for every one per cent increase in the number of flights) and the elasticity of average fares and average aircraft size 1.4.

Load factor

Average route load factor is also statistically significant and positive, implying that average fares increase as average aircraft occupancy increases, which accords with expectations.

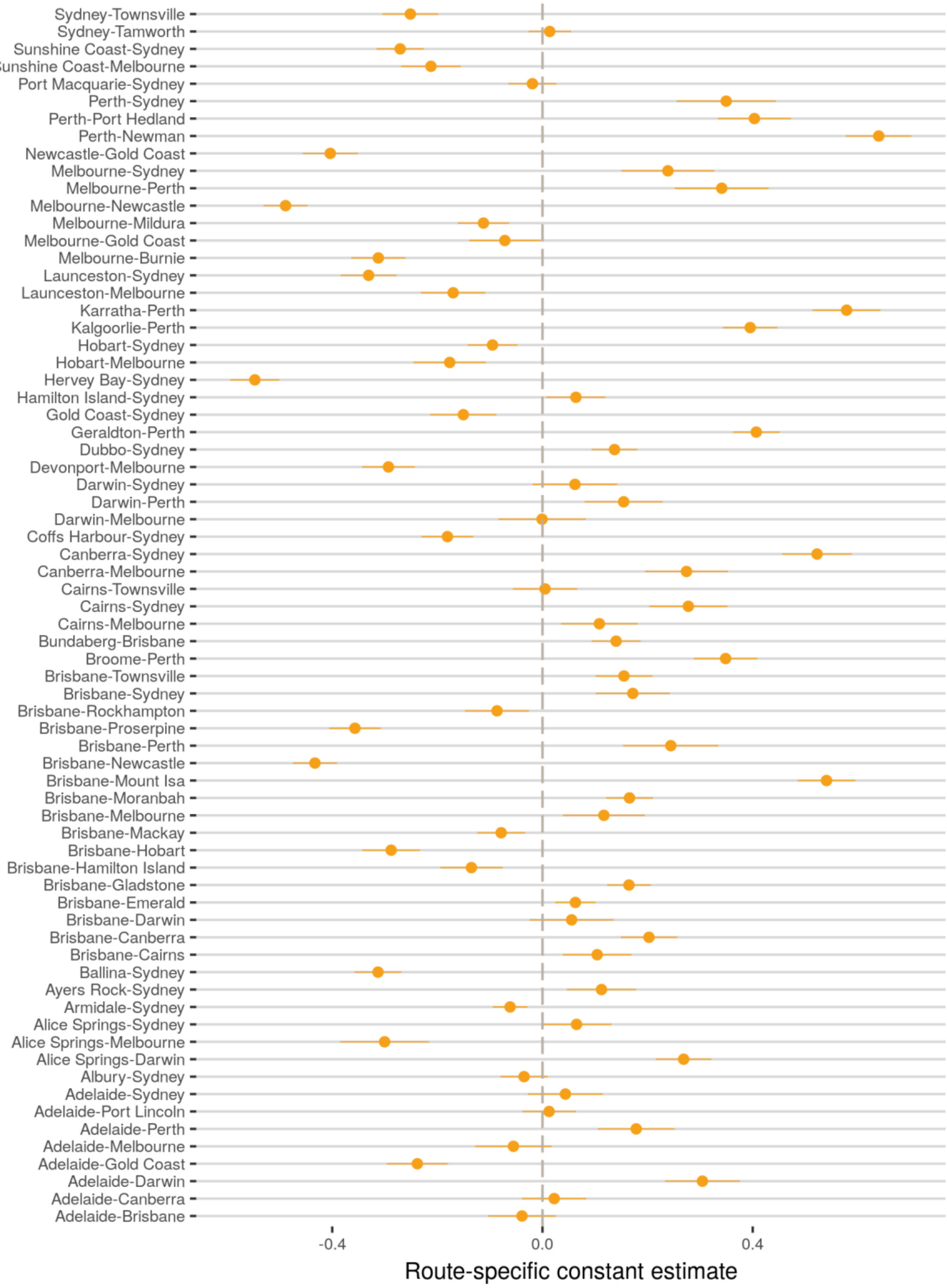
Route-specific fixed effects

Route-specific fixed effects (dummy variables) are statistically significant and imply there are systematic differences in average fares across routes, over and above the impacts of distance, oil prices, passenger numbers, competition, etc. outlined above. Figure 3, below, shows the route-specific fixed-effects parameter estimates, together with the two-standard error confidence interval, for each route.

Immediately apparent from the figure is the large spread of values and that only for a handful of routes are fixed effects not significantly different from zero. Examples of the latter include Sydney–Tamworth, Port Macquarie–Sydney, Darwin–Melbourne and Cairns–Townsville. Routes where average fares are systematically *below* average (i.e. where the route-specific constant is less than zero) include Hervey Bay–Sydney, Melbourne–Newcastle, Newcastle–Gold Coast and Brisbane–Newcastle—these routes have the largest negative fixed effects parameters. Conversely, routes where average fares are systematically *above* average (i.e. a route-specific constant greater than zero) include Perth–Port Hedland, Karratha–Perth, Brisbane–Mount Isa and Canberra–Melbourne—these routes are among the largest positive fixed effects parameter estimates.

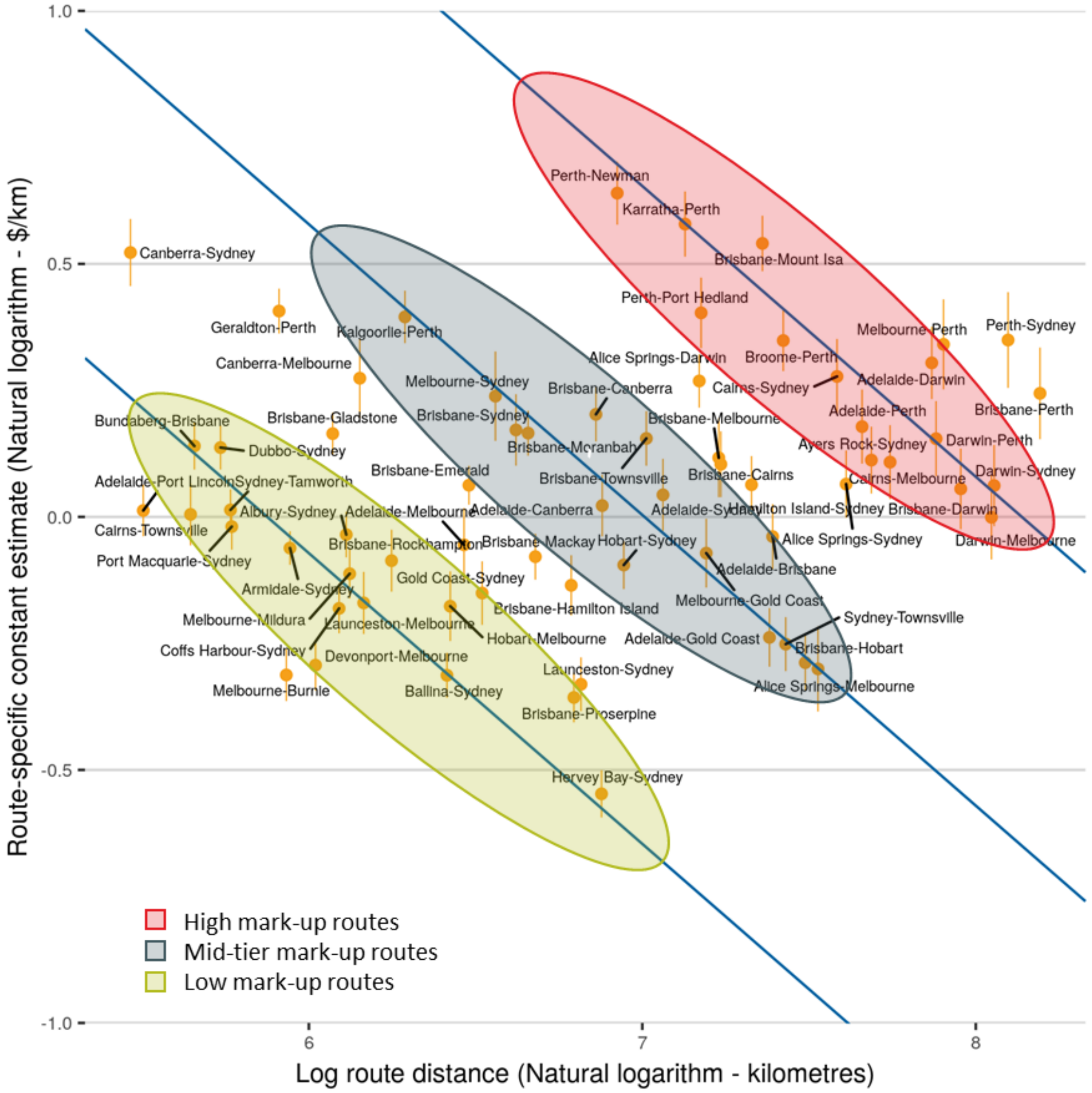
We also consider the route-specific constants against route distance in Figure 4, below, which yields some additional insights into how airfares vary across different commercial routes.

Figure 3 Route specific fixed effects - Best discount fares by route



Source: BITRE estimates.

Figure 4 Route specific fixed effects - Best discount fares by route and distance



Source: BITRE estimates.

In particular, we overlay the plot with several contour lines, with slope equal to the estimated distance elasticity, and group routes into three broad groups (highlighted by the shaded ellipses).[7]

The juxtaposition of the route-specific constants and distance elasticity contour lines suggests not only is there an inverse relationship between the average fare (per kilometre) and route distance, there is also an inverse relationship between the average fare *mark-up* (i.e. route-specific fixed effect) and route distance, such that the shorter the route distance, the higher the average fare mark-up. Moreover, there appear to be at least three, and possibly more, different groups of routes, which we characterise as follows:

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7 The three lines were subjectively chosen based on the observed distribution of route-specific fixed effect parameter estimates. The selected choice does not preclude the possibility that additional groups may better describe the distribution of average fare route-specific fixed effects. Consideration was given to using clustering techniques to more objectively group the results, but linear or planar analogues of point-base methods (e.g. centroid clustering, density clustering) were not readily apparent and developing such methods was beyond the scope of this work.

- *High-mark-up* routes – which feature Perth, Darwin and several remote mineral industry routes.
- *Mid-tier mark-up* routes – which include most of the higher volume (trunk) domestic commercial routes and several other smaller-distance routes.
- *Low-mark-up* routes – which include Bass Strait routes and some short regional or tourist routes, that are all shorter distance routes for which car, or ferry in the case of the Tasmanian routes, is a more significant competitor.

High-end mark-up routes include:

- Sydney/Melbourne/Brisbane/Adelaide–Perth
- Perth–Newman/Karratha/Broome/Port Hedland
- Sydney/Melbourne/Brisbane/Adelaide–Darwin
- Perth–Darwin
- Alice Springs–Darwin
- Sydney/Melbourne–Cairns
- Brisbane–Mount Isa

These routes are distinguished by either being longer-distance routes to/from Perth/Darwin/Alice Springs, or they are routes serving more remote mining centres (e.g. Newman, Karratha, Port Hedland, and Mount Isa).

Mid-tier mark-up routes, include many of the trunk domestic commercial routes:

- Sydney–Melbourne/Brisbane/Adelaide
- Melbourne–Sydney/Brisbane/Canberra
- Brisbane–Sydney/Melbourne/Adelaide/Canberra
- Adelaide–Sydney/Brisbane/Canberra
- Canberra–Melbourne/Brisbane/Adelaide (and Canberra–Sydney marginally)
- Gold Coast–Sydney/Melbourne

and some shorter-distance regional routes and longer-distance tourist routes, such as:

- Perth–Geraldton/Kalgoorlie
- Sydney/Brisbane–Hamilton Island
- Brisbane–Mackay/Emerald/Moranbah
- Hobart–Sydney/Brisbane

Thirdly, low-end mark-up routes include many shorter-distance regional and tourist routes, which appear to be more susceptible to greater competition from other modes, particularly private car travel. Such routes include:

- Melbourne–Adelaide
- Melbourne–Burnie/Devonport/Launceston/Hobart (ferry competition)

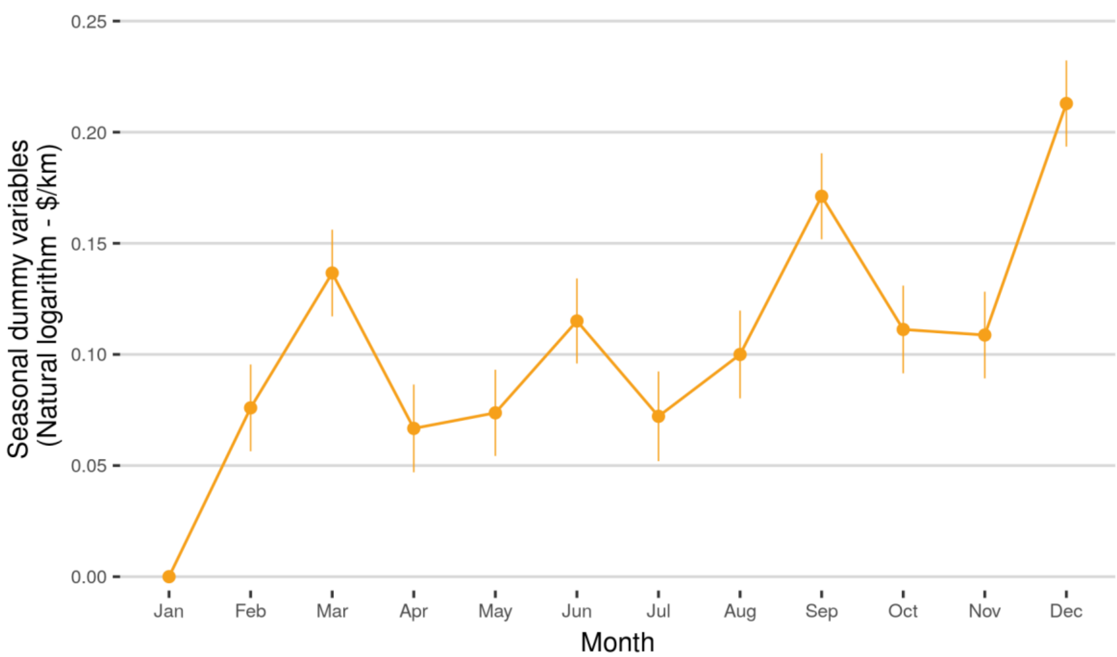
- Sydney–Albury/Ballina/Coffs Harbour/Hervey Bay/Armidale/Port Macquarie/Tamworth/Dubbo
- Brisbane–Bundaberg/Proserpine/Rockhampton
- Melbourne–Mildura

As already noted, data for many smaller-volume, regional routes is not available and hence it's not possible to draw any conclusions directly about relative fares for many smaller regional routes. (In Section 6, recent fares on smaller-volume, regional routes are compared with model-predicted fare levels.)

Seasonal effects

Seasonal effects are also statistically significant in fares. Figure 5 shows the seasonal (monthly) dummy variable estimates for fares by route. All monthly dummy variables are relative to January average fares. The results show a clear seasonal pattern, with fares on average higher in months including school/seasonal holiday periods—March, June, September and December. The vertical lines around each point estimate show the two-standard error confidence intervals for each estimate, and these show that the March, September and December fares are, on average, significantly above average fares in all other months. Similarly, fares for flights booked in January are significantly below average fares booked in all other months.

Figure 5 Monthly dummy variable estimates



Source: BITRE estimates.

5.2 *Best discount fares by route and airline*

BITRE's fares collection also includes the best available monthly fares by route and airline, and we used this data to also model variation in fares across routes and airlines, using the same explanatory variables used in analysing best discount fares by route (above). Again, for the purpose of the analysis, all fares were averaged by route distance.

The results imply there are statistically significant route- and airline-specific fixed effects—i.e. statistically significant differences in the average fare level across different routes and across different airlines—and also significant time-invariant fixed effects with respect to route distance. All other terms are also statistically significant. Three sets of fixed effects are included in the preferred specification[89]:

- route-specific dummy variables,
- airline-specific dummy variables, and
- seasonal (monthly) dummy variables.

Including airlines also allows for inclusion of more complex interactive effects, such as differences in how fares vary with distance across airlines. We tested the statistical significance of airline-specific effects with respect to distance, total route passengers, average route load factors, and the number of operators on the route.

While the empirical results are not included here, the best-performing model preferred specification 'explains' approximately 95 per cent of the observed variation in fares. Again, all of the variables included in the model were statistically significant and the effects relatively consistent across all model variants. The effects were also broadly similar to the 'all-airline' best discount model effects reported in Section 5.1 (above). In particular, the route-specific fixed effects (dummy variables) are similar to those for the 'all airline' model specification results. And, seasonal effects are also statistically significant and exhibit the same seasonal pattern exhibited in the 'all airline' specification results (above).

Airline-specific effects

Figure 6 shows various airline-specific composite effect estimates on average fares. The 'Airline constants' panel (top left) shows airline-specific constants for best discount fares by airline—the estimates imply Virgin Australia Airlines and SkyWest Airlines have systematically lower average fares than other airlines (all else equal), Tiger Airways have the next lowest average fares, while Regional Express have the highest average airfares.

The *distance* panel (top centre) shows how average fares vary with distance by airline.[10] The estimates imply that fares on Qantas, Virgin Australia and Regional Express decline more significantly with distance than fares for other airlines.

The *load factor* panel (top right) shows how average fares vary with load factor by airline. The

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8 We also tested a dynamic specification, by including one-month lagged fares, but due to periodic gaps in the air fares data, the inclusion of a lagged dependent variable term significantly reduces the number of points and number of routes analysed in the model.

9 Note that the data used in the route- and airline-specific best relates to fares since 2010, whereas the 'all airlines' route-based model estimates are based on data from 2001 onward.

10. Jetstar Airways is the reference airline in the model.

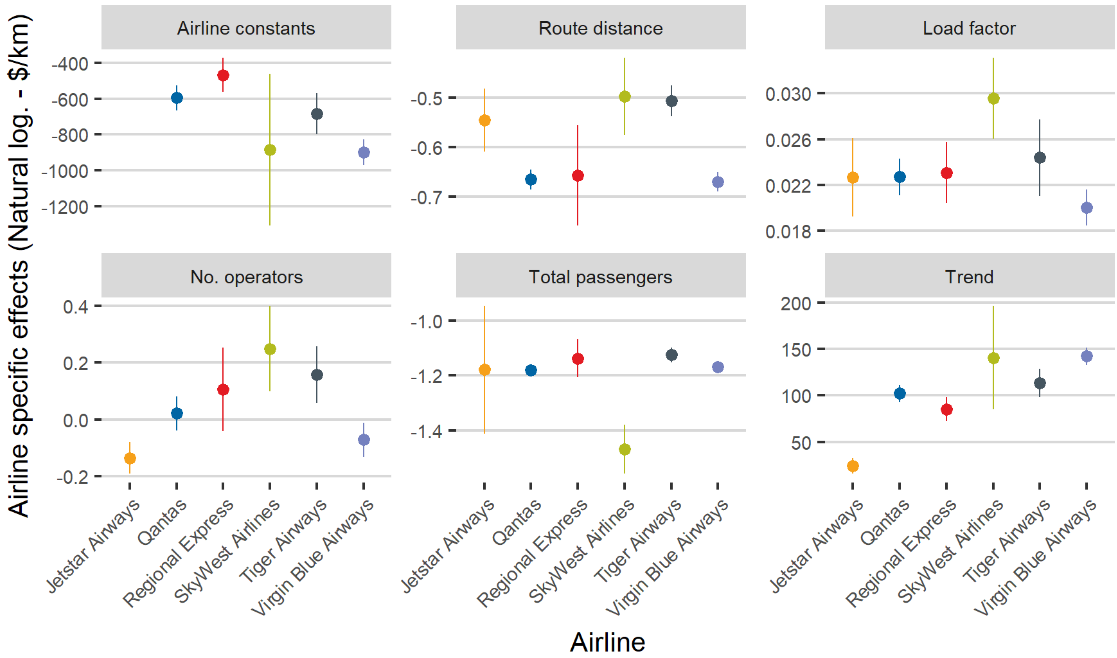
estimates imply that fares increase more rapidly with increasing load factor on SkyWest Airlines than on other airlines, while fares increase less rapidly with load factor on Virgin Australia Airlines.

The *no. operators* panel (bottom left) shows how average fares vary with the number of operators on a route. The results suggest that average fares charged by Jetstar Airways and Virgin Australia Airways decrease as the number of operators on a route increase, while Qantas fares do not vary with the number of operators. The results also suggest that fares on Regional Express, SkyWest Airlines and Tiger Airways increase as the number of operators increase. This counter-intuitive result may reflect the differing circumstances of these airlines. In the case of Tiger Airways, it has been the third or fourth competitor on routes it serves and it serves very few markets with fewer than three operators. For Regional Express and SkyWest Airlines, this result may be picking up other influences.

The *passengers'* panel (bottom centre) shows little difference across most airlines with respect to how average fares vary with route passenger volumes. The outlier is SkyWest Airlines, for which the model estimation results imply that average fares decline more sharply with increases in route passenger volumes than for other airlines.

Lastly, the *trend* panel (bottom right) shows how trends in (nominal) average fares have varied across airlines. The estimates imply that trend growth in average fares have been highest for Virgin Australia Airlines and SkyWest Airlines, while trend growth has been lowest for Jetstar Airways. The Virgin Australia Airlines results may reflect that airline's transition away from a low-cost airline and more towards a full-service model. The SkyWest Airlines' result may reflect the specific markets that this airline serves.

Figure 6 Airline specific effects, route- and airline-specific model specification



Source: BITRE estimates.

Information sheet

5.3 Best fare by route and fare class

BITRE's fares collection also includes best fare by route and fare class, and we also modelled variation in fares across routes by fare class, using the same set of explanatory variables used above. Again, for the purpose of the analysis, all fares were averaged by route distance.

The results imply there are statistically significant route- and fare class-specific fixed effects—i.e. statistically significant differences in the average fare level across different routes and, not surprisingly, by fare class—and also significant time-invariant fixed effects with respect to route distance. All other terms are also statistically significant. Three sets of fixed effects are included in the specification:

- route-specific dummy variables,
- fare class-specific dummy variables, and
- seasonal (monthly) dummy variables.

Jointly modelling all fare classes in the one specification allowed for estimation of cross-fare effects, such as differences in the behaviour of fares across different fare classes. We tested the statistical significance of fare class-specific effects with respect to distance, total route passengers, average route load factors, number of route operators, oil prices and seasonal differences.

While the empirical results are not included here, the best-performing model preferred specification 'explains' approximately 95 per cent of the observed variation in fares. Again, all of the variables included in the model were statistically significant and the effects relatively consistent across all model variants.

Fare class-specific effects

Figure 7 shows various fare class-specific composite effect estimates on average fares. The 'Fare class constants' panel (top left) shows fare type-specific constants relative to Business class fares.

The *distance* panel (top centre left) shows how average fares vary with distance by fare class. The estimates show that for all fare classes average fares decline with increasing route distance, but that restricted economy fares decline more significantly with distance than other fare classes. Discount fares decline the next most significantly, while business class fares decline least rapidly with respect to distance.

The *load factor* panel (top centre right) shows how average fares vary with route load factor by fare class. In contrast to the preceding estimation results, the estimates imply that discount and restricted economy fares decline with increasing route load factor, whereas business and full economy fares increase as route load factors increase.

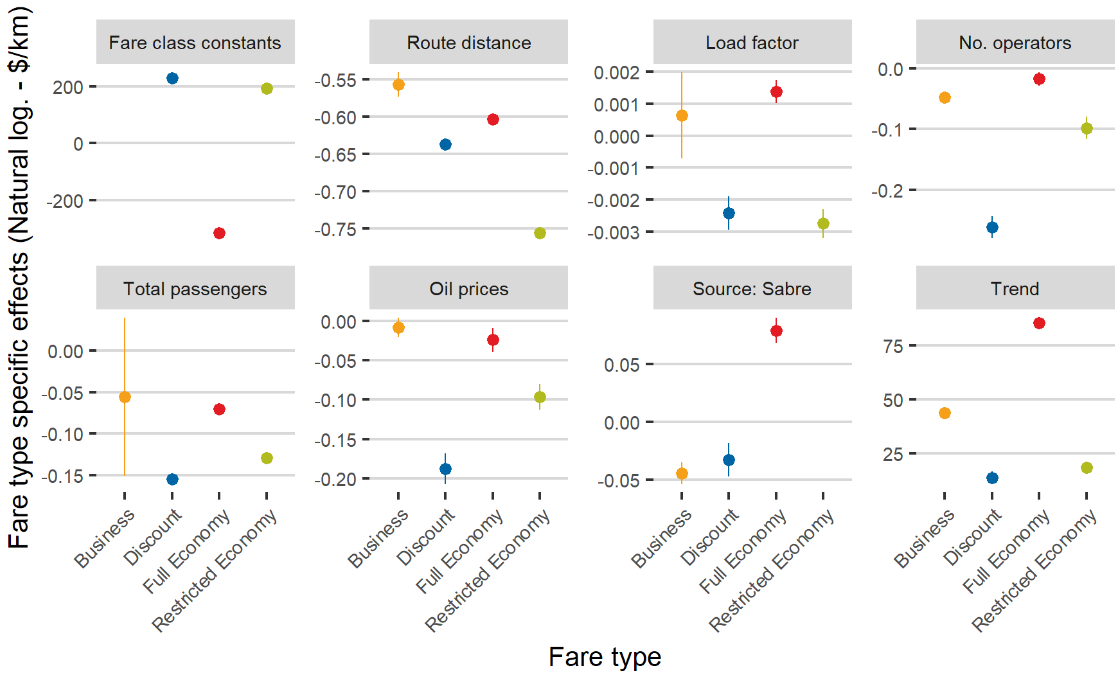
The *no. operators* panel (top right) shows how average fares vary by fare class with the number of operators on a route. The results, no surprisingly, suggest that average discount ticket fares decline most with the number of route operators. The number of route operators has the next largest effect on restricted economy fares. Business and full economy fares decline fare less with respect to the number of operators.

The *oil price* panel (bottom centre left) implies that business and full economy fares are relatively insensitive to changes in oil prices, while discount and restricted economy fares are most affected by changes in oil prices (although the parameter estimates are not of the expected sign).

The *source* panel (bottom centre right) accounts for the relative difference in fares captured using the different collection methods—i) Sabre, used for the earlier part of the collection, and ii) Internet. Restricted economy fares have only been available more recently, and so there is no applicable estimate. The results suggest that business and discount fares collected using the earlier Sabre system are systematically lower than more recent fares, but that the converse is true for full economy fares. Part of this effect may be reflecting slight growth in nominal fares over the sample period.

Lastly, the *trend* panel (bottom right) shows how trends in (nominal) average fares have varied across fare classes. The estimates imply that trend growth in average fares have been highest for full economy fares, while trend growth has been lowest for discount and restricted economy fares.

Figure 7 Fare class-specific impact estimates



Source: BITRE estimates.

6. Comparing fares on lower-volume regional routes

In order to assess the relative level of fares on lower-volume regional routes, BITRE collected a wider sample of fares as part of the July 2018 fares collection. The collected fares represent the cheapest fare available, by airline, across all city pairs with RPT domestic passenger traffic recorded in April 2018. The fares were for a prospective departure date of 26 July 2018 and return flight on 9 August 2018. The expanded collection covered over 280 separate domestic air routes, yielding useable fare information for approximately 245 routes.

BITRE then calculated the difference between the best discount average fare (divided by route distance) across each route and the best discount average fare predicted by the preferred model specification (outlined in Section 5, above), excluding the modelled route-specific factors. The resulting difference between the actual and modelled average fares represents a measure of the relative route-specific mark-up after taking into account all other relevant factors (i.e. distance, passenger volumes, number of operators, load factor and seasonal factors).

Because the estimates are based on a one-month snapshot of fares, the results may not reflect longer-term trend differences in fares across different routes. For example, unseasonably or unusually high bookings on any single route may result in higher than average available fares at the time of collection and, conversely, unusually low confirmed bookings on any route at the time of collection, may result in below average quoted fares. Also, the magnitude of the relationship between airfares and the various modelled factors (i.e. distance, passenger volume, load factor, aircraft size, etc.) may differ between the 'top-70' routes and lower-volume regional routes. Hence, the model may not predict fares on lower-volume regional routes as accurately as for the 'top-70' routes.

Moreover, where Commonwealth legislation ensures operation of interstate aviation services are unregulated, varying legislative and regulatory regimes apply to intrastate services in some states and territories, which may systematically affect fares across different routes. Section 6.1 (next) provides a short overview of the differing state/territory intrastate aviation regimes. Section 6.2 presents the results, grouped by the various intrastate regulatory regimes and interstate services.

6.1 State/territory intrastate aviation governance

New South Wales, Queensland, South Australia, Western Australia and the Northern Territory actively regulate commercial intrastate aviation services, applying varying regulatory controls and operating slightly different aviation support schemes within their respective jurisdictions. The following subsections outline the main features of aviation regulations in each jurisdiction. Victoria, and Tasmania do not or no longer have separate intrastate aviation legislation.

New South Wales

In New South Wales, all intrastate air services operate under the *Air Transport Act 1964 (NSW)*.[11] The Act also requires all operators operating air services from one place in NSW to another place in NSW to be licensed (with Transport for NSW). NSW aviation regulation limits competition on low volume routes (defined as routes with equal or fewer than 50,000 passengers per annum) 'that aren't always robust and may need protection to provide stability and encourage market development'. A five-year licence term currently applies. Regulated intrastate air routes in New South Wales currently include:

[11] NSW Regional aviation - https://www.transport.nsw.gov.au/operations/regional-air-operators (Accessed: 24 August 2018).

- Bathurst
- Bourke
- Brewarrina
- Broken Hill
- Casino
- Cobar
- Cooma
- Coonabarabran
- Coonamble
- Cootamundra
- Cowra
- Deniliquin
- Forbes
- Glen Innes
- Grafton
- Gunnedah
- Inverell
- Kempsey
- Lightning Ridge
- Lord Howe Island
- Maitland
- Merimbula
- Moree
- Moruya
- Mudgee
- Narrabri
- Narrandera
- Nyngan
- Parkes
- Scone
- Singleton
- Taree
- Walgett
- West Wyalong
- Wollongong
- Young

Unregulated intrastate routes in New South Wales (i.e. with more than 50,000 passengers per annum) include:

- Albury
- Armidale
- Ballina
- Cobar
- Coffs Harbour
- Cooma
- Dubbo
- Griffith
- Lismore
- Mudgee
- Narrabri
- Orange
- Port Macquarie
- Tamworth
- Wagga Wagga
- Williamtown

Queensland

Queensland Government regulated long distance air services

The Queensland Government regulates some regional air routes with low passenger volumes, with the right to operate air services on those routes allocated using a competitive open tender. As at August 2018, the following long distance intrastate routes were regulated:[12]

- Central 1: Brisbane–Roma–Charleville (QantasLink)
- Central 2: Brisbane–Barcaldine/Blackall–Longreach (QantasLink)
- Western 1: Brisbane–Toowoomba–St George–Cunnamulla–Thargomindah (Regional Express)
- Western 2: Brisbane–Toowoomba–Charleville–Quilpie–Windorah–Birdsville–Bedourie–Boulia–Mount Isa (Regional Express)
- Northern 1: Townsville–Winton–Longreach (Regional Express)
- Northern 2: Townsville–Hughenden–Richmond–Julia Creek–Mount Isa (Regional Express)
- Gulf: Cairns–Normanton–Mornington Island–Burketown–Doomadgee–Mount Isa (Regional Express)

The following routes, which were regulated prior to 1 January 2015, are unregulated as at August 2018:

12. Queensland Government Long distance air services - https://www.tmr.qld.gov.au/Travel-and-transport/Long-distance-air-services (Accessed: 24 August 2018).

- Cairns–Weipa
- Cairns–Horn Island
- Townsville–Cloncurry–Mount Isa.

Queensland Government Local Fare Scheme

The Queensland Government also operates the Local Fare Scheme[13], which is an airfare subsidy available to local residents in regional and remote Queensland communities, who have lived in a Local Fare Scheme region for three or more years. The scheme mainly applies to communities in Cape York, the Gulf of Carpentaria and the Torres Strait. Residents may receive a discount of up to $400 for return airfare bookings when travelling between designated airports. Designated airports include:

- Cape York: Aurukun, Coen, Kowanyama, Lockhart River, Northern Peninsula, Pormpuraaw and Weipa.
- Gulf of Carpentaria: Doomadgee and Mornington Island.
- Torres Strait: Horn (Ngurupai), Badu, Talbot (Boigu), Coconut (Poruma), Darnley (Erub), Mabuiag, Kubin, Murray (Mer), Saibai, Sue (Warraber), Yam (Iama) and Yorke (Masig) Islands.

South Australia

In South Australia, the *Air Transport (Route Licensing—Passenger Services) Act 2002 (SA)* provides the Minister with the power to declare a route between any two airports a 'declared route' and issue licenses to operate air services on the declared route. The purpose of the legislation is to establish, maintain, re-establish, increase or improve scheduled air services on the route. Under the legislation, the Minister is empowered to set conditions related to the allocation of licenses and conditions governing operations.

Currently, Adelaide–Port Augusta is the only intrastate route subject to a route service licence in South Australia, with thrice-weekly return services operated by Regional Express (DPTI 2017).

Western Australia

In Western Australia, the Minister for Transport has powers under the *Transport Coordination Act 1966* (WA) to license aircraft and place conditions on aircraft licenses to control where and when airlines may fly within the state. The purpose of the Act, and associated regulations, is to ensure that Western Australians are provided, as far as is practicable, with reliable, efficient and economic transport services. Under this legislation the Minister is empowered to regulate intrastate air routes by placing various conditions on aircraft licences. These can include conditions that restrict the area or frequency of airline operations or any other conditions considered in the public interest.

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13. Queensland Government Local Fare Scheme - https://www.tmr.qld.gov.au/Travel-and-transport/Local-Fare-Scheme-Far-North-Queensland.aspx (Accessed: 24 August 2018.)

Any condition placed on an aircraft licence may refer to the provision of RPT services, charter services, or both where applicable.

Air routes in WA which have insufficient passenger demand to support airline competition are regulated by the State Government, through the granting of monopoly rights to a single airline to operate on a particular RPT route. The following air routes are currently regulated:[14]

- Kununurra–Halls Creek–Balgo (Aviair)
- Perth–Learmonth (Exmouth) (QantasLink)
- Perth–Albany (Regional Express)
- Perth–Esperance (Regional Express)
- Perth–Monkey Mia–Carnarvon (Regional Express)
- Perth–Leonora–Laverton (Skippers Aviation)
- Perth–Meekatharra–Mt Magnet–Wiluna (Skippers Aviation)

Northern Territory

The Northern Territory Government is responsible for developing aviation policy, supporting the development of domestic and international air service routes, and off-airport land use planning in the Northern Territory (NT). The Northern Territory government also provides funding support for 70 regional and remote aerodromes throughout the Territory.

The Northern Territory Government also provides financial support for scheduled air services between Darwin–Katherine–Tennant Creek–Alice Springs, and return. The service currently operates three times a week (Monday, Wednesday and Friday).[15] Regular scheduled intrastate passenger air services operate between Darwin and the following regional centres:

- Katherine
- Tennant Creek
- Garden Island
- Bathurst Island
- Snake Bay
- Croker Island
- South Goulburn Island
- Maningrida
- Elcho Island
- Milingimbi
- Gove
- Ramingining
- Lake Avella
- McArthur River
- Groote Eylandt

Australian Government Remote Air Services Subsidy Scheme

Lastly, for completeness, the Commonwealth Remote Air Services Subsidy (RASS) Scheme is part of the Australian Government's Regional Aviation Access Programme (RAAP). RASS subsidises a regular weekly air transport service for the carriage of passengers and goods to communities in remote and isolated areas of Australia. The RASS Scheme provides some 372 communities in

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14. Air Services in Western Australia - https://www.transport.wa.gov.au/aviation/air-services-in-western-australia.asp (Accessed: 24 August 2018)
15. Northern Territory regional trial air service, https://dipl.nt.gov.au/transport/transport-reviews-and-consultations/nt-regional-trial-air-service (Accessed: 24 August 2018).

remote and isolated areas of Australia with improved access through the subsidy of a regular air transport service. This includes 266 directly serviced locations and a further 106 neighbouring communities that receive mail through RASS ports. (A RASS community is typically a cattle station or an Indigenous community with a population ranging from six people to approximately 200 people.)

The BITRE's augmented fares collection did not cover flights to/from RASS Scheme airports and hence these are not considered further here.

6.2 Route-specific difference between actual and modelled fares

Figure 8, below, shows the estimated difference between actual and modelled average return airfares, for the month of July 2018, grouped according to the jurisdiction and regulatory regime governing each route. As previously noted, the estimated difference between the actual and modelled fares provides an implicit indicator of the relative fare mark-up across different routes. (Appendix B provides complementary bar plots of the same data and a labelled version showing the estimated difference for each available route – Figure B.2.) For the purposes of comparison, Figure 8 also includes several average fare–distance contour lines, based on the modelled relationship between average fares and route distance, which show lines along which average fares are equivalent for different length routes.

The results imply some apparent systematic differences in average fares for some routes and groups of routes, but that for the broad majority of routes, including lower-volume regional routes, estimated differences between actual and modelled fares are within the range of variation of that for major routes.

Some notable results include:

- Queensland Local Fare Scheme (LFS) routes tend to be among the lowest fare mark-up routes. This is exhibited by the 'convex hull' of the difference between actual and modelled fares for these routes (the grey-shaded region in the top-right panel shown in Figure 8) lying to the lower left of all other route groups and the prevalence of Queensland LFS routes in the lower left portion of this area. Some of the lowest mark-up routes include: Baidu Island–Mabuiag Island, Darnley Island–Yorke Island, Boigu Island–Saibai Island, Saibai Island–Yam Island, Coconut Island–Yam Island, and Coconut Island–Yorke Island.
- In contrast, Queensland regulated routes include some of the highest apparent fare mark-up routes across Australia—exhibited by the convex hull of fares for these routes (the red-shaded region in the top-right panel in Figure 8). Examples of apparent high fare mark-up routes include: Boulia–Mount Isa, Bedourie–Boulia, Cunnamulla–Thargomindah, Bedourie–Birdsville, Mount Isa–Julia Creek, Brisbane–Barcaldine, Cunnamulla–Saint George and Townsville–Winton. Note, however, this group also includes some apparent low fare mark-up routes, such as Cairns–Thursday Island, Brisbane–Roma, Hughenden–Richmond and Julia Creek–Richmond.

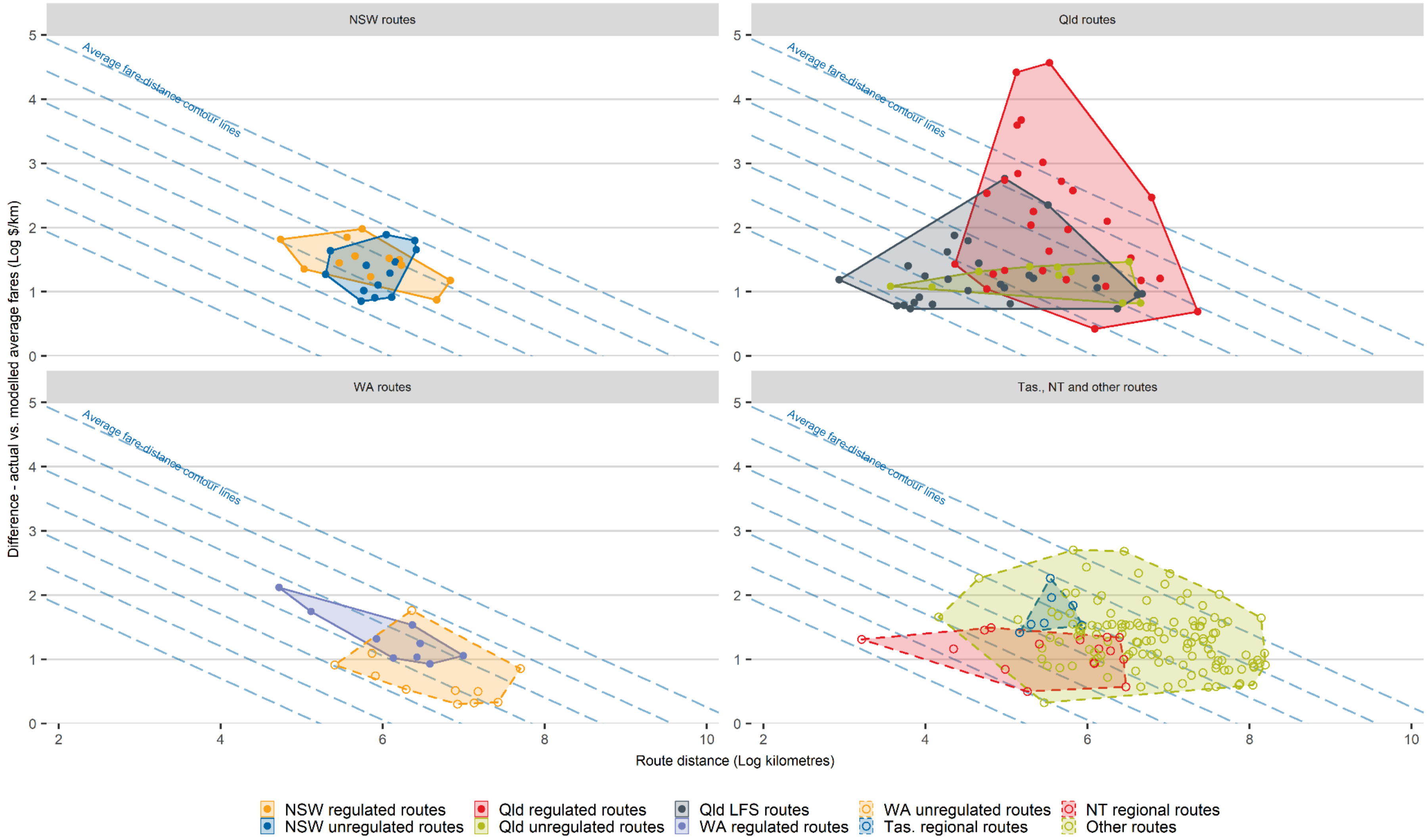
- Northern Territory (NT) regional routes also feature among the lower-end fare mark-up routes, exhibited by the convex hull of these routes (the red dashed-line and shaded region in the bottom-right panel in Figure 8) also lying towards the lower-left quadrant. Examples of low fare mark-up routes include: Garden Point–Snake Bay, Bathurst Island–Darwin, Elcho Island–Maningrida, Darwin–Gove, Darwin–Ramingining, Darwin–Milingimbi, Darwin–Snake Bay and Darwin–Garden Point.
- Fares on NSW regulated and unregulated routes are adjacently clustered, broadly parallel to the average fare–distance contours, suggesting average fares are broadly similar across regulated and unregulated routes in that jurisdiction (top-left panel in Figure 8). Among the lower average fare NSW intrastate routes are: Sydney–Wagga Wagga, Sydney–Dubbo, Sydney–Tamworth and Sydney–Port Macquarie and Sydney–Albury.
- Fares on services to and from Bass Strait islands (King and Flinders Islands), grouped as Tasmanian regional routes in Figure 8 (bottom-right), appear to be around average fares on a per route kilometre basis. Other Bass Strait routes—e.g. Melbourne–Hobart/Burnie/ Launceston and Sydney–Hobart/ Launceston—are also around average fares.
- Like NSW, fares on WA regulated and unregulated routes are also adjacently clustered, also broadly parallel to the average fare–distance contours, suggesting average fares are broadly similar across regulated and unregulated routes in that jurisdiction (bottom-left panel in Figure 8). Among the lower average fare WA intrastate routes implied by the analysis are: Perth–Port Hedland, Perth–Broome, Perth–Karratha, Perth–Paraburdoo, and Perth–Kalgoorlie. These outcomes are addressed further next.

Further inspection of the Figure 8 (and also Figure B.2), also provides some similarities and contrasts with the results reported in Section 5.1. For example:

- The implied mark-up (i.e. divergence between actual and modelled fares) for long-distance routes between Perth to northern Western Australian airports are much less than that implied by the model results. Examples include: Perth–Port Hedland, Perth–Broome, Perth–Karratha, Perth–Paraburdoo, Perth–Kalgoorlie, and Perth–Kununurra.
- On the other hand, a number of the longer-distance routes, still appear among the higher mark-up routes. For example, Brisbane–Darwin, Brisbane–Port Hedland, Cairns–Perth, Perth–Sydney, Canberra–Perth, Brisbane–Perth, Darwin–Sydney, Darwin–Melbourne, Melbourne–Townsville appear among the higher fare mark-up routes.
- Routes to and from Avalon Airport also feature among higher mark-up routes, including Avalon–Sydney, Avalon–Adelaide, Avalon–Gold Coast.

Again, it is important to remember that these results are based on a one-month snapshot of fares, and hence may not reflect longer-term systemic differences in fares across routes. While these initial results may make intuitive sense—e.g. below-average average fares on subsidised routes, higher-than-average average fares on some regulated routes—a longer-term time series set of observations would be necessary to more conclusively estimate systematic differences in average fares across routes.

Figure 8 Grouped difference between actual and modelled domestic return airfares, by route distance July 2018



Note The average fare–distance contours (dashed lines) represent lines along which average fares are 'equivalent' for different distance routes. Source: BITRE estimates.

7. Implications and concluding remarks

The analysis presented in this paper suggests that regional airfares respond largely as expected in a competitive market. In particular, the analysis found:

- significant distance-based scale economies in the provision of aviation services, hence average fares generally decline with increasing route length
- strong market-based scale economies in aviation services, with average fares strongly declining with increasing market size (as measured by the number of passengers)
- competition (i.e. number of operators) has a significant impact on average fares, with fares declining significantly with increasing numbers of route operators.
- oil prices have a statistically significant, but relatively small impact on average airfares, which appears to reflect that fuel costs are typically around 20 per cent of total operating costs of major airlines and also airline fuel hedging practices.
- the number of flights has a positive impact on average fares, presumably reflecting the increased costs of adding flights, and some dilution of the scale economies from increasing capacity utilisation.

Moreover, the analysis also suggests there are statistically significant differences in average fare levels across routes, which also appear correlated with the degree of competition and also the availability of alternative transport options for travellers. BITRE identified three broad groups of routes:

- *High-mark-up* routes (i.e. above average fare routes) – which feature predominantly longer-distance trunk routes to/from Perth, Darwin and Alice Springs, and also several routes services remote mineral industry locations (e.g. Karratha, Port Hedland, Newman, Weipa). For these routes, there are no time-competitive alternatives to air transport and demand may be less responsive to price changes, enabling airlines to price accordingly.
- *Mid-tier mark-up* routes – which include most of the higher volume (trunk) domestic commercial routes and several smaller-distance routes.
- *Low-mark-up* routes (i.e. below average fare routes) – which predominantly comprise shorter distance routes, such as Melbourne-Devonport, Melbourne-Burnie, Coffs Harbour-Sydney, Hervey Bay-Sydney and Melbourne-Launceston. These routes are all routes for which car, or ferry in the case of the Tasmanian routes, is a more significant competitor.

Examination of actual and modelled fares across a broader selection of routes, including lower-volume regional routes, imply that while there are some apparent systematic differences in average fares for some routes or groups of routes—e.g. below-average fares on some subsidised routes and above-average fares on some regulated routes—for the broad majority of routes the estimated difference between actual and modelled fares are generally within the range of variation exhibited by major trunk routes. However, as these results are based on a one-month only snapshot of fares (July 2018), they may reflect unaccounted for one-off effect, and should not be treated as conclusive evidence of systematic differences in pricing across different routes.

Overall, the results of this analysis show that measures that:

- increase effective competition on routes
- increase competition from other transport modes
- increase passenger volumes through airports

are most likely to put downward pressure on regional airfares.

Appendix A – BITRE best discount fares by route

Figure A.1 Average best discount fares, by route

Figure A.1 Average best discount fares, by route (continued)

Figure A.1 Average best discount fares, by route (continued)

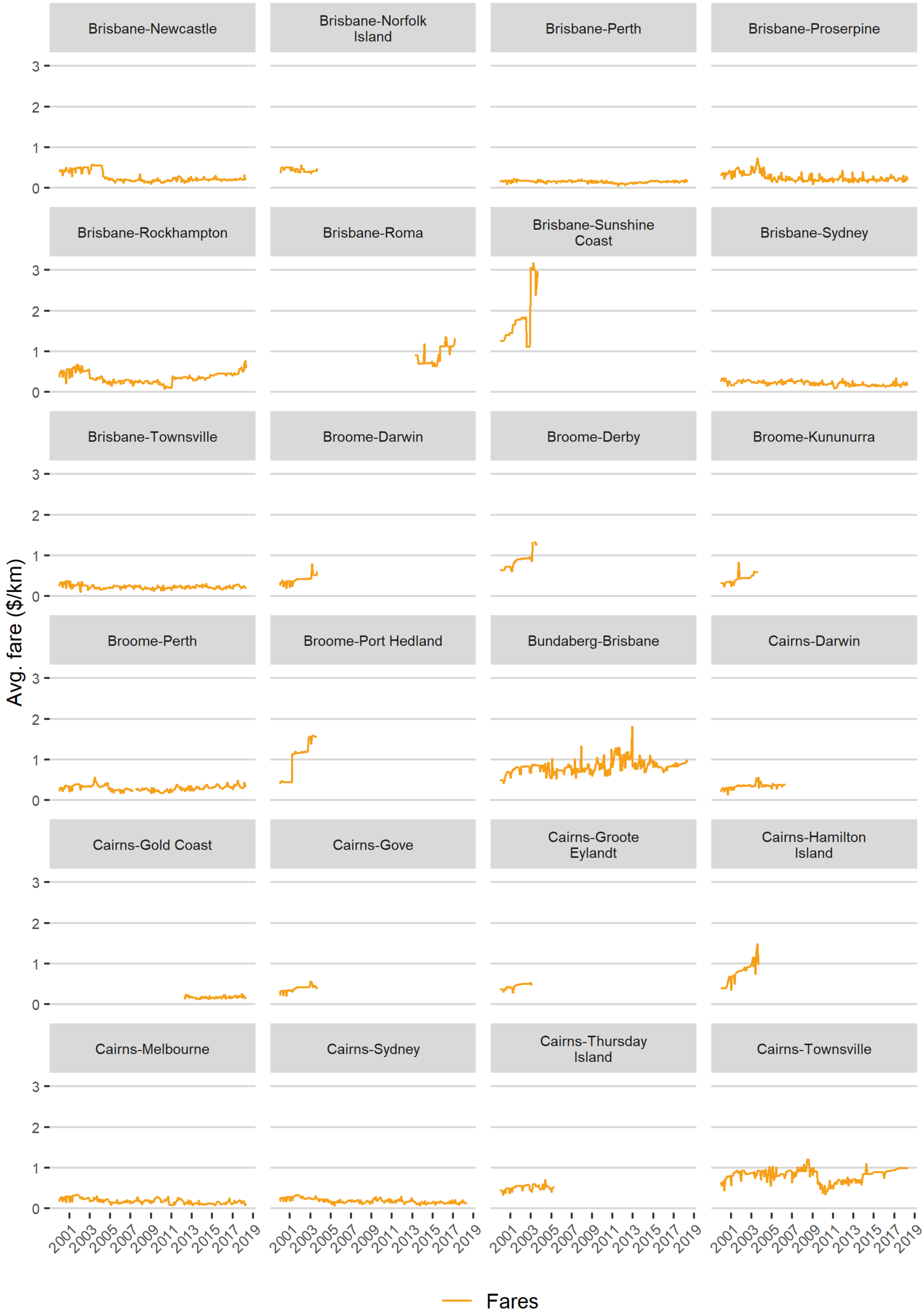


Figure A.1 Average best discount fares, by route (continued)

Figure A.1 Average best discount fares, by route (continued)

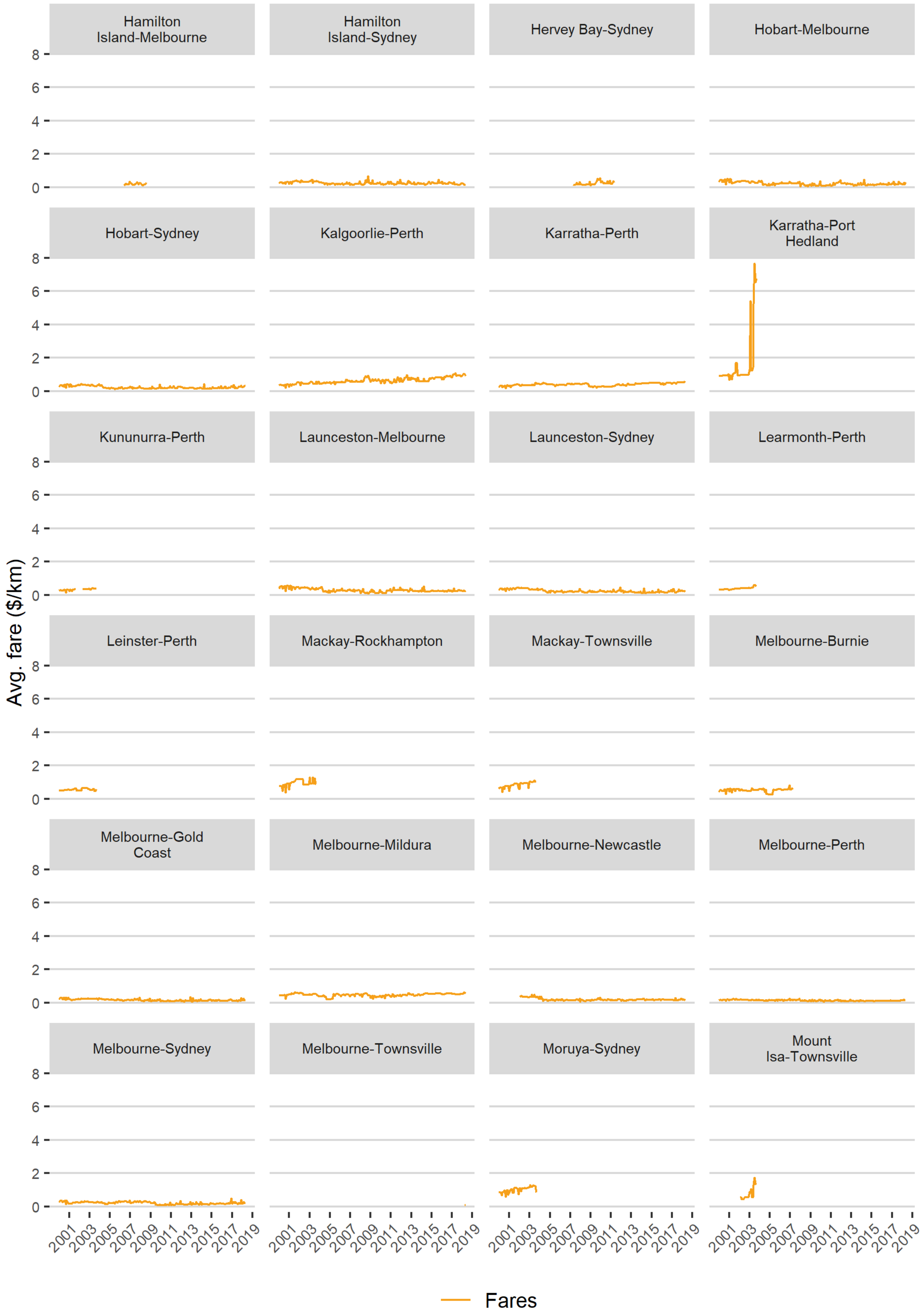


Figure A.1 Average best discount fares, by route (continued)

Source BITRE (2018).

Appendix B Implied route-specific differences in fares

Figure B.1 Difference between actual and modelled return airfares, by route, July 2018

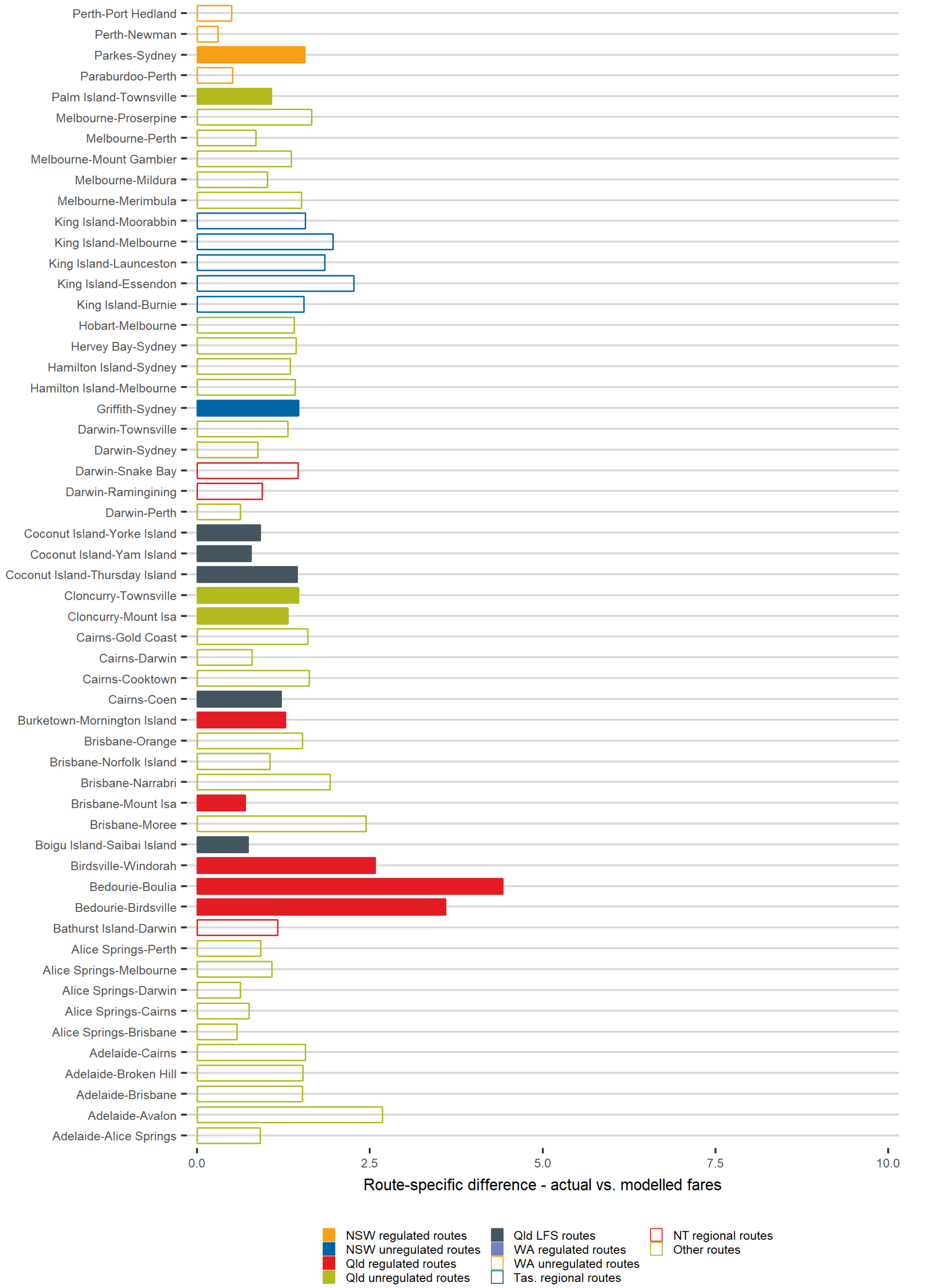
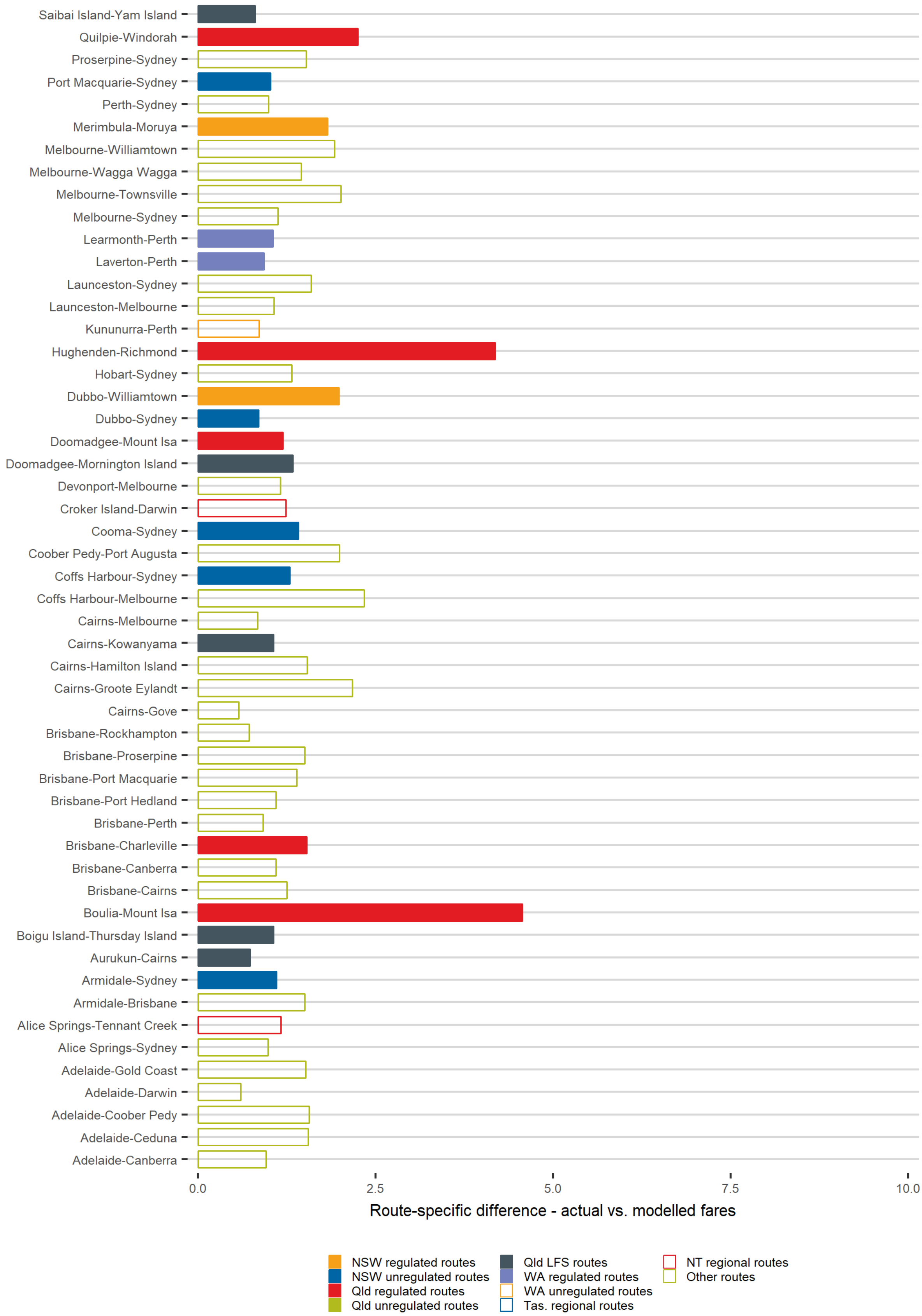
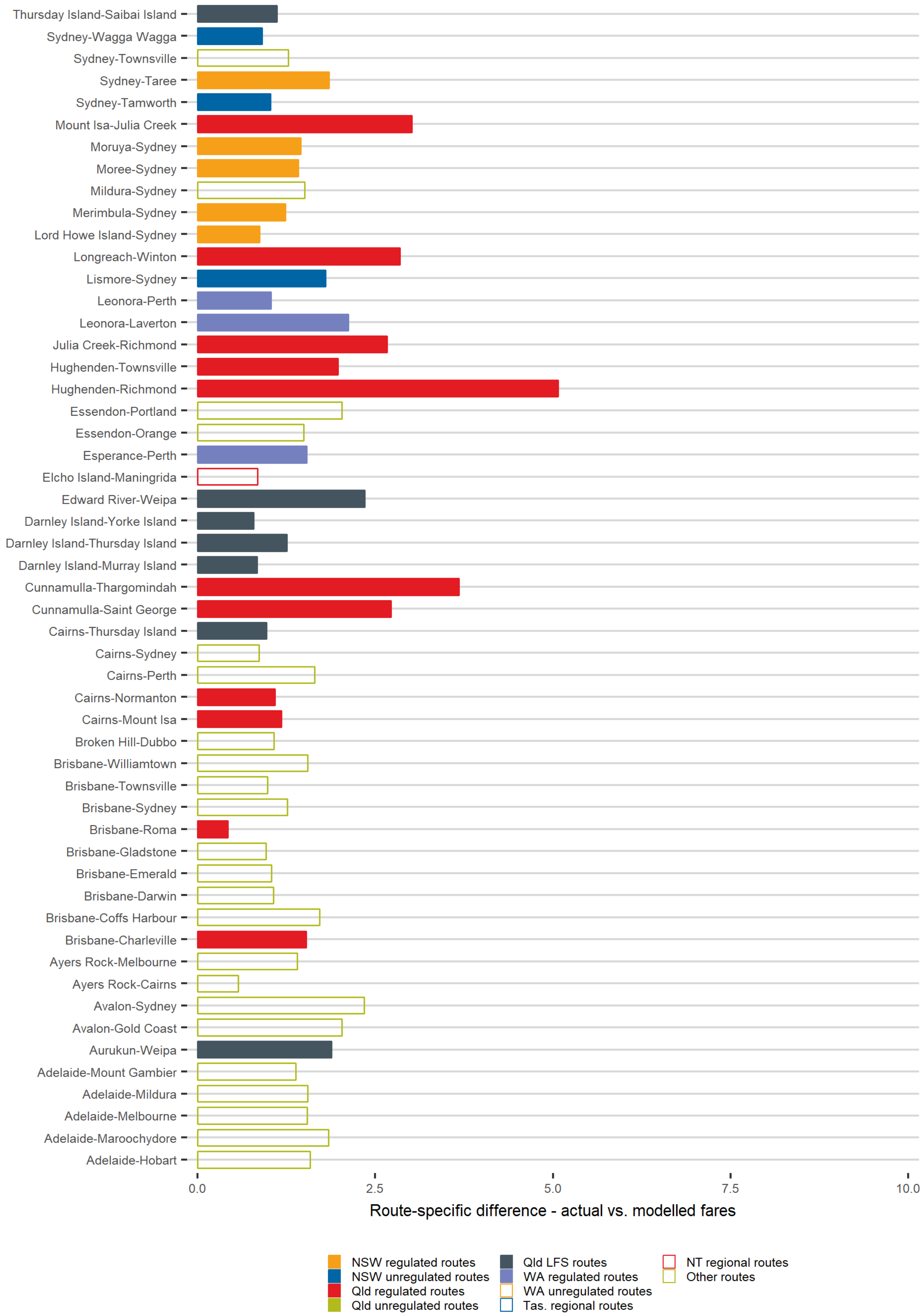


Figure B.1 Difference between actual and modelled return airfares, by route, July 2018 (continued)



Source BITRE estimates.

Figure B.1 Difference between actual and modelled return airfares, by route, July 2018 (continued)



Information sheet

Figure B.1 Difference between actual and modelled return airfares, by route, July 2018 (continued)

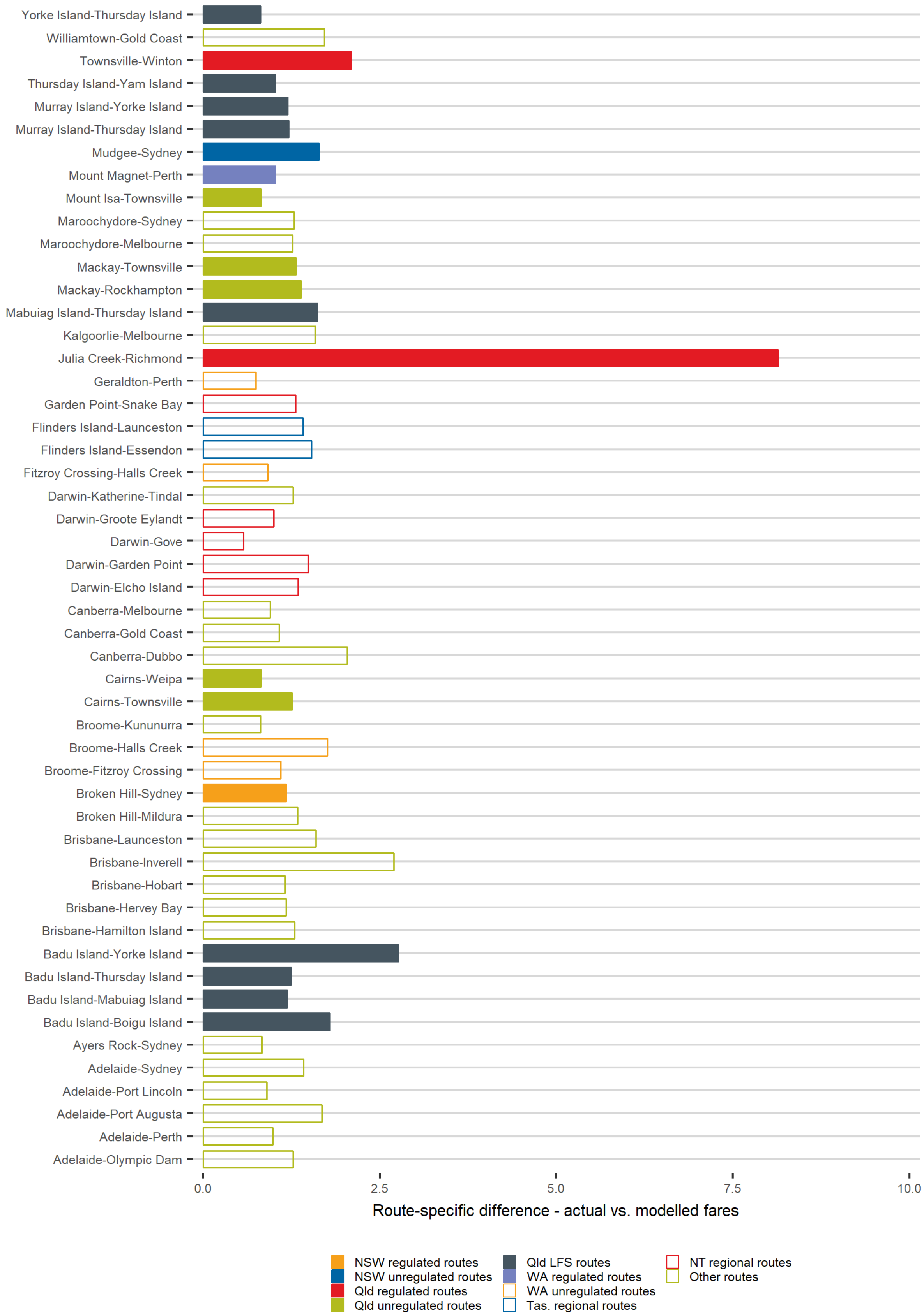
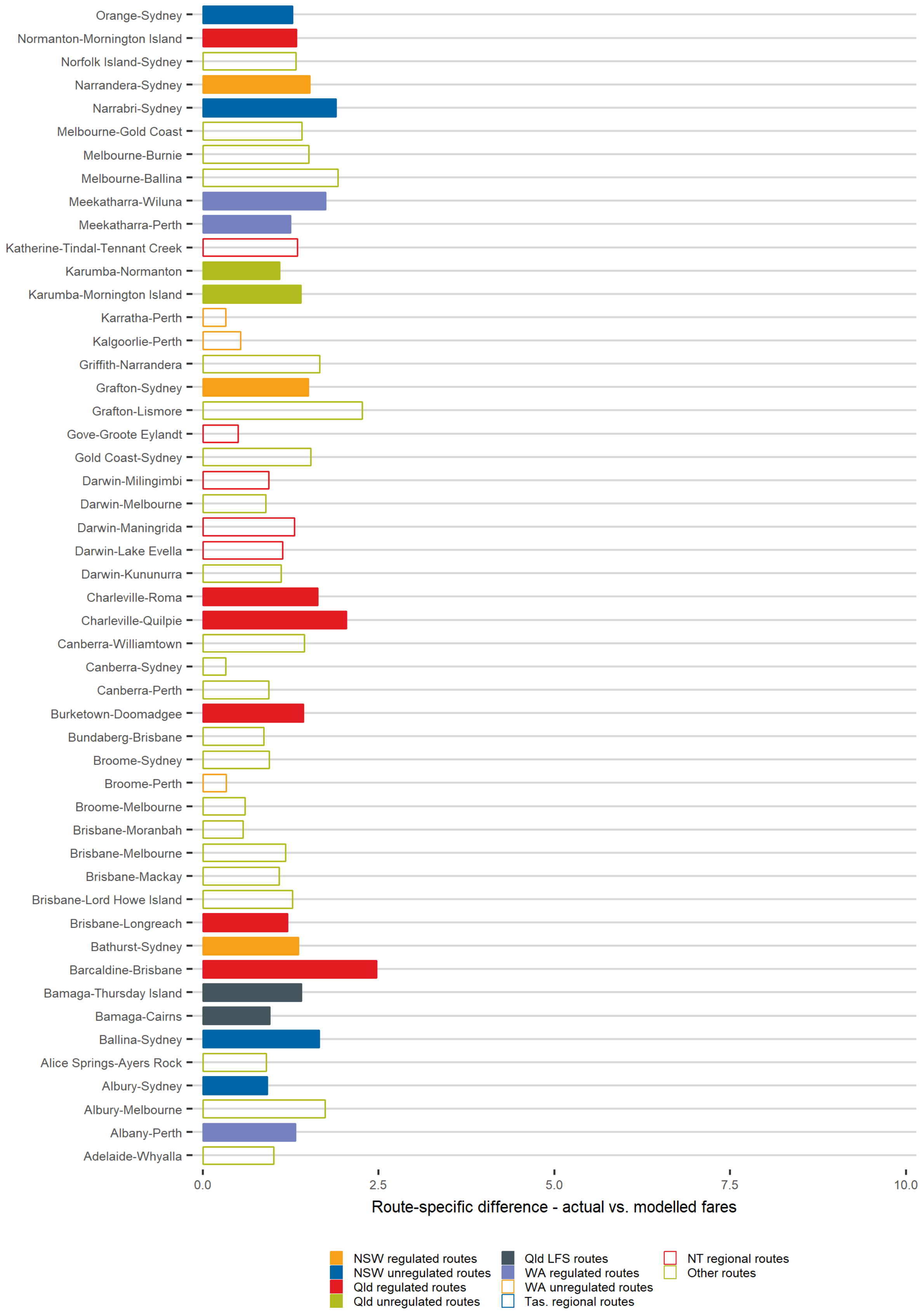
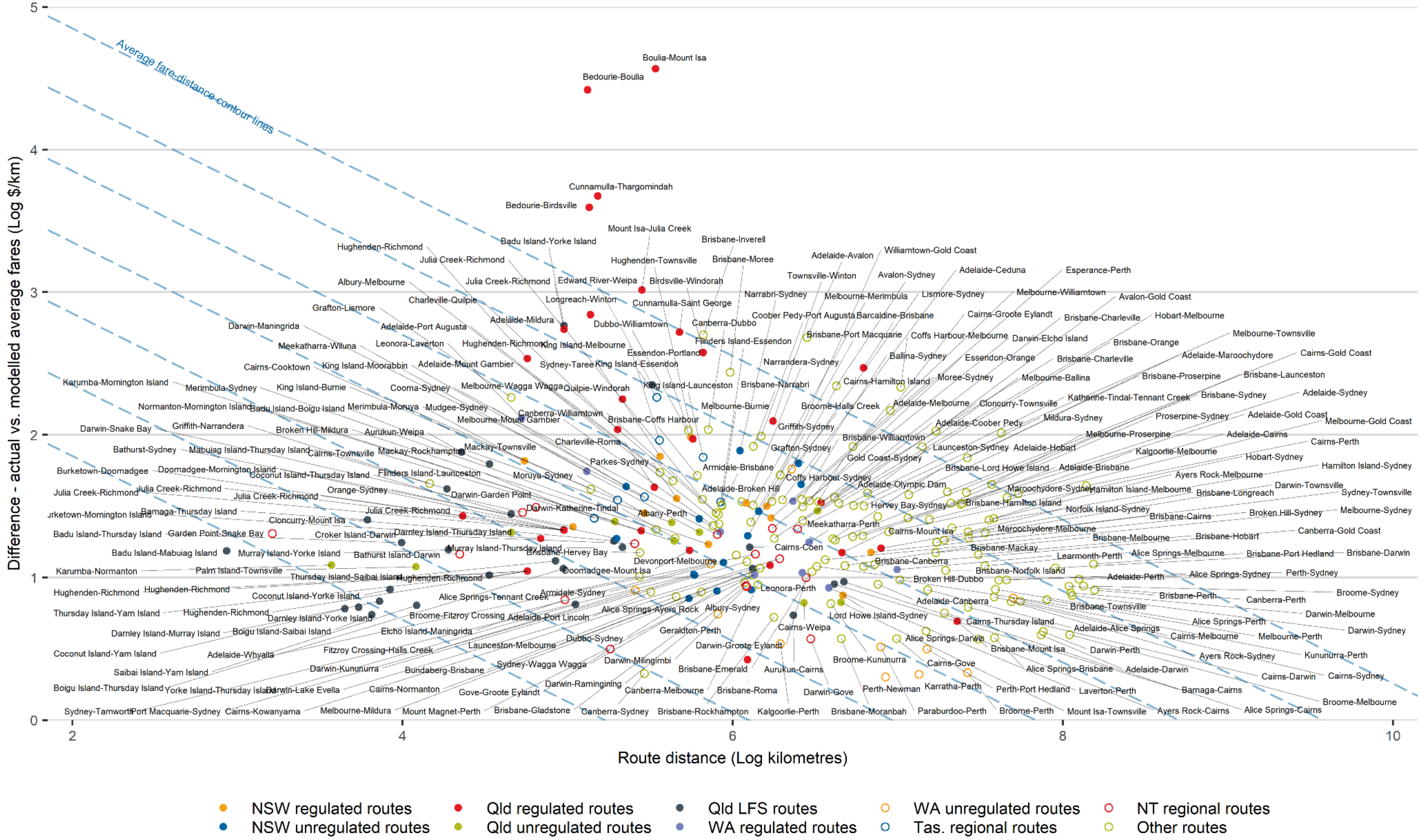


Figure B.1 Difference between actual and modelled return airfares, by route, July 2018 (continued)



Source BITRE estimates.

Figure B.2 Estimated difference between actual and modelled domestic return airfares, by route, July 2018



Note The average fare–distance contours (dashed lines) represent lines along which average fares are 'equivalent' for different distance routes. Source: BITRE estimates.

Appendix C Australian airline operating cost shares

Table C.1 Australian domestic airline operating costs

Cost component	Qantas		Virgin Australia	
	Cost	Cost share	Cost	Cost share
	($m)	(%)	($m)	(%)
Labour	4 033	27.5	1 219.2	23.6
Fuel	3 039	20.7	866.7	16.8
Aircraft operating costs[a]	3 436	23.4	1 023.8	19.8
Depreciation & amortisation	1 382	9.4	309.7	6.0
Non-cancellable aircraft leases	356	2.4	420.3	8.1
Other	2 441	16.6	1 331.5	25.7
Total	14 687	100	5 171.2	100

a. Includes airport charges, navigation and station operations.

Sources: Qantas Group (2017), Virgin Australia Airlines (2017) and BITRE estimates.

Appendix D Preferred empirical model specification

The preferred empirical model specification is shown in the equation below. For the models, with fares split by fare class and airline, we also include separate fare class and airline specific factors.

The simple static empirical model specification is:

$$y_{it} = \alpha_i + \beta x_{it} + \sum_{j=0}^{J} \gamma_j w_{t-j} + \delta z_i + \varepsilon_{it}, \quad \varepsilon_{it} \sim \text{iid}(0, \Omega)$$

where

y_{it} – denotes the natural logarithm of average fare per route kilometre for route i at time t.

x_{it} – denotes the natural logarithm of route-specific factors—i.e. total flights, total passengers, total operators and load factor—for route i at time t.

w_t – denotes the natural logarithm of airline inputs costs at time $t-j$—the current analysis includes only oil prices.

z_i – denotes the logarithm of time-invariant route-specific variables (e.g. route distance)

α_i, β, γ_j and δ – are model parameters.

ε_{it} – denotes the random error, which is assumed to be distributed with mean zero and variance–covariance matrix Ω.

Understanding and interpreting the parameter estimates

Because the model variables are specified in natural logarithms, the parameter estimates may be directly interpreted as *elasticities*. Elasticities are 'unit-free' measures of the responsiveness of an economic measure of interest to a change in another factor favoured for used in economic

Information sheet

analysis, as they provide a readily interpretable means of relating responsiveness without also needing to specify units of measure. To see this, shows the equation below provides the elasticity of demand (q) with respect to price (p), denoted by (η), which equals the percentage change in demand ($\Delta q/q$) divided by the percentage change in price ($\Delta p/p$), which (in the limit) is equivalent to the ratio of the natural logarithm of demand ($\log q$) with respect to the natural logarithm of price ($\log p$):

$$\eta_{it} = \frac{\Delta q/q}{\Delta p/p} \approx \frac{\log q}{\log p}$$

A couple of examples may help understand how to use the model elasticities. For example, the route distance parameter value (elasticity) in the preferred model specification, reported in Table 1, was –0.574. This means that for every 10 per cent increase in route distance, the average fare (i.e. nominal fare per route kilometre) decreases by 5.7 per cent (i.e. –0.574 x 10 = –5.74). Similarly, the market size parameter (i.e. total route passengers) parameter value (elasticity) in the preferred model specification was –1.751. This may be interpreted as, for a 10 per cent increase in the size of a market, the average fare would be 17.5 per cent lower (i.e. –1.751 x 10 = –17.5).

Note, as load factor is already defined in percentage terms (the maximum possible load factor is 100 per cent), it is included in the model specification in raw form (i.e. not transformed by the natural logarithm). The parameter estimate (0.026) is still interpreted as an elasticity, as changes in load factor are in percentage terms.

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