Airline profit maximization, cost pass-through and scarcity rents in capacity-constrained aviation systems

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Abstract Airport capacity limitations have been suggested to lead to reduced pass-through of airline cost changes, and increased airline profits. Theoretically, these outcomes arise from limited supply leading to profit-optimal passenger fares determined only by available capacity. Practically, however, outcomes depend on real-world airline networks, fleet and costs. In this paper we model airline competition across an existing network (Australian intercity domestic flights) with endogenously-generated fares and frequency to investigate this. Consistent with theory, we find less pass-through at airports with more stringent capacity constraints and where airlines are unequally-affected by cost changes. Per-passenger airline profit increases roughly linearly with constraint stringency.

Key words Airline competition; Airline costs; Cost pass-through; Scarcity rents; Profit optimization; Airport Capacity.

1. Introduction

Airline decisions about fares, frequency and aircraft utilisation are typically made on a profit- (or market share-) maximisation basis. This includes decisions about how best to react to cost increases and to what extent increases in operating costs should be passed through to the customers in terms of increased ticket prices as opposed to reducing own operating margins. At one extreme, 0 per cent cost pass-through indicates that airlines keep ticket prices constant when costs increase, accepting lower profit per passenger. At the other extreme, 100 per cent pass-through indicates that airlines add the full extra cost per passenger onto ticket prices, accepting a demand decrease and drop in overall ticket revenue. The level of pass-through can be important in evaluating the outcomes of policies that seek to change airline or passenger behaviour via airline operating costs (for example to promote new technology adoption or decrease demand) or evaluating fiscal policies such as fuel taxation.

Generally, cost pass-through depends on the relative elasticities of supply and demand. Because the cost of supply changes when airports reach capacity, cost pass-through will differ between congested and uncongested airports (Ernst & Young and York Aviation, 2008; Burghouwt et al. 2017). In 2008, up to 15 per cent of all global flights were from capacity-constrained airports, and this number is projected to rise significantly over time (Gelhausen et al. 2013; Boeing, 2018). A simplified depiction of this situation is shown in Figure 1.
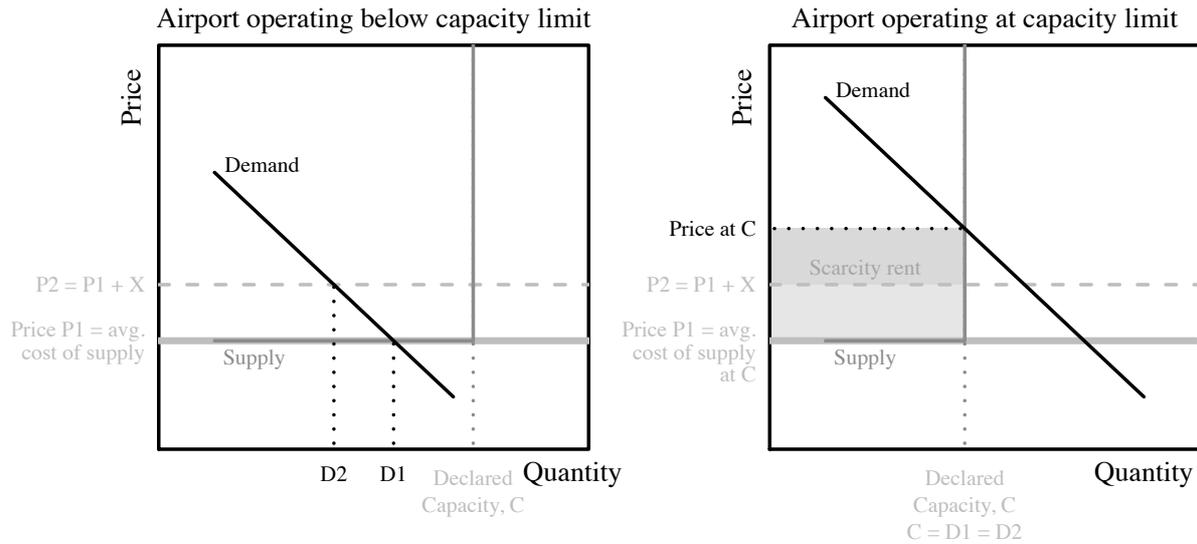
Figure 1. Variation of ticket prices with constrained supply. When the airport is at capacity, the supply curve becomes effectively vertical, so prices are set by the capacity rather than by the cost of supply.

When the airport is below capacity, extra passengers can be accommodated at similar per-passenger costs to current ones and the supply curve is roughly horizontal. If the cost of supply changes from P1 to P2 via the addition of an extra cost, X, this cost change is fully passed on to passengers and reduces demand (D1 to D2 in Figure 1). Once the airport is at capacity, extra passengers cannot be added, the supply curve is close to vertical, and no costs are passed through[1]. In this case the airline profit-optimal ticket price is set only by the constrained airport supply instead of marginal costs. Because the profit-optimal ticket price is above marginal costs, airlines can make extra profit (the scarcity rent) from operating at a constrained airport than they could if the airport was unconstrained (Button, 2005; ITF, 2009; Gillen & Starkie, 2016; Burghouwt et al. 2017)[2]. Although airports, in theory, could increase landing charges to take advantage of this, the extent to which airports can set landing charges

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[1] In practice, the average cost of supply will increase somewhat as the airport becomes close to capacity due to increases in average delay and delay-related costs. For simplicity, this effect is omitted from the diagram.

[2] Separately, Faber & Brinke (2007) argue that pass-through at Heathrow Airport, which is highly capacity-constrained, is effectively 0 per cent because landing and take-off slots at the airport can be traded; increases in costs for operating at Heathrow will be offset by a reduction in slot costs rather than a change in ticket price. However, EC (2011) found that slots change hands only infrequently at Heathrow, limiting this effect.

above their own operating costs is often constrained by regulation (Burghouwt et al., 2017). When airline operating costs change from P1 to P2, the profit-optimal fare remains constant, leading to 0 per cent pass-through (Ernst & Young and York Aviation, 2008). Instead, the scarcity rent (and airline profit) decreases. Demand remains unchanged.

Real-world aviation systems, of course, experience more complex conditions than this simple theoretical picture. Many other factors affect ticket pricing, and hence both levels of cost pass-through and scarcity rents. In particular, airlines consider profit on a whole-network basis rather than on an individual route basis; there are varying amounts of competition per route; scheduling must take into account fleet constraints and the requirements of both origin and destination airports; passenger ticket prices relate to itineraries rather than individual flight segments; and airlines with diverse fleets have some capability to increase seat capacity at constrained airports by switching their larger aircraft onto routes to and from that airport, potentially at the cost of using smaller-than-optimal aircraft elsewhere. These factors affect the extent to which the presence of capacity constraints influences fare.

Empirically, the amount by which airline profit margins and pass-through change at capacity-constrained airports is uncertain. Some studies of aviation cost pass-through suggest levels close to 100 per cent (Duplantis, 2010; Toru, 2011) and this is often used as an assumption in policy modelling (SEC, 2006). Anger & Köhler (2010) review literature examples of pass-through for emissions trading and find assumptions from 0-100 per cent, with several studies using values in the 30-50 per cent range. Wang et al. (2018) model pass-through as an elasticity-type term to total costs, implying rates of pass-through for a $100 cost increase per passenger typically 40-70 per cent. Evidence for logistical constraints leading to pass-through close to 0 per cent is found by other studies (Borenstein & Rose, 2014) and under some

circumstances rates of over 100 per cent are implied (Vivid Economics, 2007). Pass-through per route is also affected by the number of competitors (Ernst & Young and York Aviation, 2008), the price-sensitivity of passengers, airline business model (Vivid Economics, 2007), cross-subsidisation between routes (Scheelhaase & Grimme, 2007), whether airline costs increase or decrease (Wadud, 2015), and route closeness to break-even load factor (Koopmans & Lieshouwt, 2016). There is evidence that capacity-constrained airports have higher fares (Dresner et al., 2012; Burghouwt et al. 2017, Fukui, 2019). For example, it has been estimated that capacity constraints may increase fare by 10-40 per cent (Frontier, 2017). Greater delay-related costs may also apply at capacity-constrained airports, complicating outcomes (Zhang & Czerny, 2012). In contrast, CE Delft (2005) argue that empirical evidence suggests near-100 per cent pass-through at capacity-constrained airports, similarly to non-constrained ones.

Both cost pass-through and scarcity rents arise naturally from the assumption of airline profit maximisation. In real-world systems airlines may respond to changes in operating costs by changing fares or by other strategies, such as adjusting aircraft size or frequency on a route or even abandoning it completely. Modelling pass-through in realistic aviation systems therefore requires competition modelling which can jointly assess fare, frequency and fleet utilisation decisions. Several studies have been able to reproduce airline flight frequencies by modelling network-wide profit maximisation by competing airlines (Hansen, 1990; Wei & Hansen, 2007; Evans, 2014), including the impact of capacity constraints on frequency (Vaze & Barnhardt 2012, Evans & Schäfer, 2014), and other studies have considered the interaction of fare and frequency decisions (Brueckner 2010; Adler et al, 2010; Hansen & Liu 2015). However, only recently have models which are able to optimise profit accounting jointly for both airline fare and frequency decisions been developed and validated against real aviation systems (Doyme et al. 2019). Using these modelling advances, it is now possible to simulate

airport capacity constraints in a real network and evaluate their impact on pricing, revenues and profit. Considering each airline's full network allows the examination of factors that are not possible to evaluate when considering only a single route. For example, an airline may respond to an increase in landing costs by switching to less frequent flights with larger aircraft, and moving its smaller aircraft to other routes. Ticket prices on multiple routes may change as a result.

How airlines respond to cost changes has an important impact on the outcomes of policies that directly or indirectly affect airline costs, such as emissions trading, mandatory offsetting or biofuel requirements. For policies which aim to affect passenger behaviour by changing airline costs, knowledge of pass-through rates is vital in projecting policy outcome. As fuel can account for 30 per cent or more of airline costs (BTS, 2019), airline behaviour around fluctuations in oil prices also depends on the extent to which airlines pass on costs. In this paper, we apply a recently-developed, globally unique model of airline competition which endogenously generates fares and flight frequencies across networks of competing airlines (Doyme et al. 2018) to explore how airport capacity constraints affect pass-through and scarcity rents. This allows us to assess how theoretical outcomes are affected by real-world airline constraints in a way that has not previously been possible in the literature. Section 2 describes the airline competition model and how it is applied in this case, using the specific example of the Australian domestic aviation system and different scenarios for how much domestic capacity will be added by the 2025 expansion of Melbourne airport. By applying different types and levels of cost increase to different capacity and demand growth scenarios, we explore how the extent of capacity constraints affects airline profits and response to changes in cost. Section 3 discusses in detail how system fares, demand, pass-though and profits vary across the different scenarios modelled, and section 4 draws conclusions.
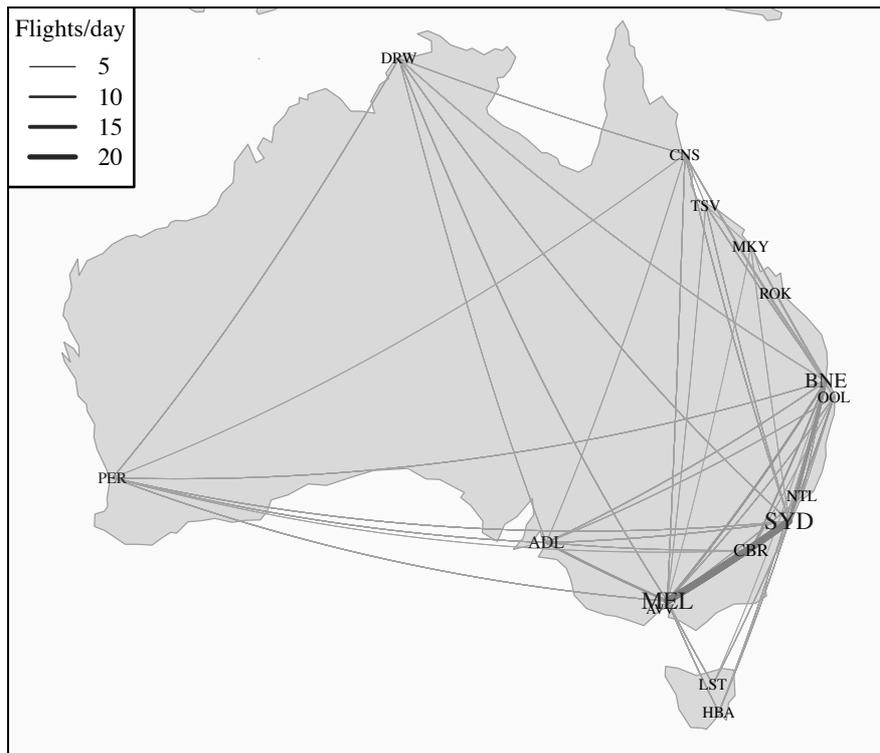
Figure 2. The route and airport network modelled in this study, showing flight frequencies in 2014. Airports are identified by 3-letter IATA Code (IATA, 2020)

2. Airline Competition Model

2.1 Baseline model

The Australian domestic aviation network is used as the baseline system in this study. This network is a useful environment for testing airline response to cost and capacity changes because it contains a mix of airport sizes, including airports with and without capacity constraints; the number of airports and carriers is relatively small, allowing rapid run times; the network is already highly connected, so network change is likely to have only a small impact; and it is largely self-contained, with relatively few journeys having both a domestic and international component. The modelled route network is shown in Figure 2. We model flights between cities and/or regions included in the AIM2015 database (Dray et al. 2019) and neglect smaller routes which are often subject to public service obligations and so have different competition characteristics. The detailed development and validation of the airline

competition model in this context for 2014 is described in Doyme et al. (2018). In summary, airline competition is modelled via a n-player non-cooperative game. In Australia, domestic flights are dominated by four airlines and/or their subsidiaries: Qantas, Virgin, and the two low-cost carriers Tigerair Australia and Jetstar Airways[3]. Each of these airlines in turn attempts to maximise its own profits across its network by changing two types of decision variable: itinerary-level fares, and segment-level flight frequency by aircraft of nine different size classes (detailed in Dray et al. 2019). In turn, passengers may choose to switch itinerary or carrier, or not to fly. The network-wide profit of airline *A* is modelled as:

$$P_A = \sum_{i \in ITN_A} fare_i \cdot pax_i + arev_A \cdot pax_A - \sum_{j \in SEG_A} \sum_{a \in AC_j} opcost_{a,j} \cdot freq_{a,j}$$

$$- \sum_{j \in SEG_A} \sum_{a \in AC_j} paxcost_{a,j} \cdot pax_{a,j}, \tag{1}$$

and consists of passenger fare revenue for each itinerary *i* plus per-passenger average ancillary revenues $arev_A$, minus per-flight costs ($opcost_{a,j}$) and per-passenger costs ($paxcost_{a,j}$) for each flight segment flown *j* with aircraft type *a* at frequency $freq_{a,j}$. Optimisation for each airline is carried out sequentially using IBM's CPLEX solver (IBM, 2017) and is repeated until changes in decision variables per iteration stability to below threshold values, allowing each airline to fully react to the choices of the other airlines. All costs are modelled in year 2015 US dollars.

This optimisation is subject to constraints, as detailed in Doyme et al (2018). In particular, airlines cannot schedule more flights out of an airport than there is capacity for:

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[3] These low-cost carriers are owned by Virgin Australia and Qantas, respectively. However, baseline operations are more accurately reproduced when they are modelled as independent entities, likely reflecting networks that have been structured to separate each airline's operations from those of its parent company.

$$\sum_{j \in SEG_p} \sum_{a \in AC_j} freq_{a,j} \leq capacity_p, \qquad (2)$$

where SEG_p is the set of all flight segments to or from airport p. Airport capacities for slot-controlled airports (8 of the 16 airports modelled, including the 6 busiest; IATA, 2019) are derived from typical hourly allocations of slots (Dray, 2020). For non-slot controlled airports they are derived from the airport's own hourly capacity assessment or typical capacities for airports with a similar runway layout (where no other assessment of capacity is available). However, the non slot-controlled airports modelled have available capacity well above current usage, and operate effectively without constraint. Spare capacity is allocated to airlines iteratively during the solution process until the capacity limit is reached or no more flights are required. In practice, this means that allocation of free slots for domestic flights at capacity-constrained airports is roughly in line with an airline's current presence at the airport. Although IATA slot guidelines specify that half of free slots should be offered first to new carriers and/or routes (IATA, 2019), this is likely to mainly affect international routes as most domestic airlines/alliances in Australia already operate at most major airports, and the domestic network is already highly-connected.

Additionally, airlines are limited by their fleet:

$$\sum_{j \in SEG_A} freq_{a,j} \cdot (time_j + ground_a) \leq (365 \times 24) \cdot fleet_{a,A}, \qquad (3)$$

where SEG_A is the set of all segments operated by airline A, $time_j$ is the flight time on segment j, $ground_a$ is the typical ground time between flights for aircraft of size a, and $fleet_{a,A}$ is airline A's available fleet of aircraft of size a. This means that airlines can respond to changes in cost or capacity by changing the aircraft size they use on different routes. However, changes in aircraft size on a given flight segment may require compensatory changes in aircraft size on other routes. Although airline fleets are typically planned years in advance (FlightGlobal,

2016), shorter-term changes in fleet are possible via leasing or second-hand aircraft purchase. We assume that airlines are able to anticipate broad trends in demand and will obtain new aircraft as needed, but that new aircraft are primarily chosen for fleet commonality (of the same broad type as those already in the airline's fleet or, for future years, as those on order) rather than being tailored to per-route cost minimisation (Brüggen & Klose, 2010).

Airline response is also affected by passenger response. Overall passenger demand for a given city-pair i, between origin city o_i and destination city d_i is modelled using the gravity-type model

$$D_i = e^{\eta}\left(P_{o_i}P_{d_i}\right)^{\alpha}\left(I_{o_i}I_{d_i}\right)^{\beta}\overline{fare}_{o_i,d_i}^{\gamma}\overline{time}_{o_i,d_i}^{\delta}drive_{o_i,d_i}^{\epsilon}e^{\left(\zeta\cdot special_{o_i,d_i}\right)}, \qquad (4)$$

where the variables P and I indicate greater metropolitan area population and income of the respective cities, *fare* and *time* give average (over all passenger-weighted itineraries) fare and time per city-pair journey, *drive* gives the drive time between the city pair, *special* is a binary variable indicating whether or not both cities have special characteristics that are likely to increase demand (capital cities, major tourist/business destinations), and coefficients α-η are determined via linear regression. For each city-pair, multiple itineraries may be available with different carriers. The market share MS_k of each itinerary k is given by

$$MS_k = e^{U_k}\Big/\sum_{l\in ITN_i} e^{U_l} \qquad (5)$$

where ITN_i is the set of all itineraries for city-pair i. The utility of each itinerary U_k is given by

$$U_k = \theta \cdot fare_k + \kappa \cdot time_k + \lambda \cdot ln(freq_k) + \mu \cdot nseg_k + ffx_A, \qquad (6)$$

where *fare_k* and *time_k* are the itinerary-specific fare and time of itinerary k; *freq_k* is the itinerary frequency (for multiple-leg itineraries, the smaller of the individual leg frequencies is used); *nseg_k* the number of flight legs; and *ffx_A* is an airline-specific fixed effect which captures

consumer preference for specific airlines (arising from, for example, reputation or frequent flyer programmes) which, along with coefficients θ-μ, is found by using linear regression via the Berkson-Theil method. These models are estimated and validated using data from the Sabre (2017) airline reservation dataset and city-level data as described in Dray & Doyme (2019); parameters for both regressions are given in Doyme et al. (2018). In practice, passengers may respond to changes in airline fare and frequency by switching itinerary (to another route or carrier) or not flying, and airlines take account of this in their profit optimisation. For example, an airline with a monopoly on a direct city-pair route can increase prices to a greater extent because passenger itinerary-switching options are limited.

Airline costs per segment are modelled by per-passenger (for example, per-passenger landing costs, marginal fuel costs), and per-flight components (for example, routing charges, cabin and flight crew costs, maintenance, capital costs, fuel costs for flying empty). Year-2014 enroute and landing costs by aircraft size are derived from RDC (2016), adjusted for typical discounts (Intervistas, 2018); other costs by aircraft size and carrier type are derived from US airline cost data (BTS, 2019) adjusted for Australian airlines (Qantas, 2015; Virgin Australia, 2015). Typical ancillary revenue per passenger (of around $40 USD) is also derived from airline financial reports. The model maximises gross airline profit and does not adjust for overhead-type costs[4].

2.2   Demand and capacity scenarios

Whether or not capacity constraints affect system outcomes depends on the level of demand. Melbourne airport (MEL) is currently (pre-Covid19) close to capacity. An extra runway is planned for 2025, taking overall hourly capacity from 50 to 90 flights (Melbourne

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[4] For comparison, US airline overheads on a per-passenger basis were around $33 in 2015 (Bureau of Transportation Statistics, 2019).

Airport, 2013). Slot control regulations in combination with the small number of Australian domestic carriers likely mean at least half of this new capacity will be taken by international flights (IATA, 2019). The current capacity available for domestic flights at MEL is around 34 flights per hour (Sabre, 2017), suggesting between 34 and 54 slots per hour may be available for domestic operations in 2025. At the same time, many projections exist for how fuel prices and Australian city-level population and income will change to 2025, implying a range of possible demand outcomes from stagnation to near-immediate full use of the new capacity (UN, 2017; OECD, 2019; ABS, 2017; O'Neill et al. 2013; EIA, 2019). To capture demand uncertainty, we take lower, upper and mid-range values from the range of socioeconomic projections available and use them to generate three demand scenarios for the Australian domestic network in 2025. We use this combination of uncertainty in demand with the range of possible year-2025 capacity values to generate a grid of possible future scenarios across demand and capacity, as illustrated in Table 1. The year-2020 third runway at Brisbane airport is included in all scenarios. The late-2026 anticipated opening of a second airport in Sydney is not included in this study but will be a factor in how demand and operations develop after the study year. In the baseline grid, all other costs are assumed to remain constant in real terms, and airline network structure and business models are also assumed unchanged. To estimate year-2025 fleets, we apply age-related retirement curves (Dray et al., 2019) to existing fleets and add known pre-2025 aircraft orders by airline and aircraft size (FlightGlobal, 2017). Any shortfall in total fleet size is assumed to be made up by the purchase and/or lease of second-hand aircraft of a similar size and age distribution to those already in each airline's fleet, as discussed above. For the Low, Mid and High demand scenarios these additional aircraft represent an extra 0, 7 and 20 per cent of the total fleet.

Table 1. Year-2025 scenario assumptions and baseline (no cost change) RPK outcomes.

Demand Scenario	Melbourne population, ratio with 2014	Melbourne GDP/capita, ratio with 2014	Fuel price, year 2015 USD/ gallon	MEL domestic capacity, flights/hr	Model system RPK at no cost change, bln[a]	References
Low	1.21	1.034[b]	4.8	34-54	46.4[c]	UN, 2017; O'Neill et al., 2013; EIA, 2019
Mid	1.26	1.15	2.7	34-54	61.8-65.1	UN, 2017; ABS, 2017; OECD, 2019; EIA, 2019
High	1.31	1.29	1.3	34-54	77.4-82.8	ABS, 2017; O'Neill et al., 2013; EIA, 2019

[a] For comparison, the year-2014 system RPK travelled (excluding charter, freight and PSO flights and domestic travel by international passengers) is 53 billion

[b] Given growth between 2014 and 2019, this scenario represents a recession in the 2020-2025 period (for example, an extended economic impact of Covid19).

[c] All scenarios are below capacity at low demand growth, so RPK is the same for each

In the Low Demand scenario, capacity limits at MEL are not reached even when domestic capacity remains at current levels. For the Mid Demand scenario, MEL is unconstrained at domestic capacity of 45 flights per hour and above, and in the High Demand scenario MEL is capacity-constrained even at 54 flights per hour.

2.3   Cost change cases

Cost pass-through may vary with the specific type of cost increase (Wang et al. 2017). Airline response may depend on what basis the additional costs are charged (for example, per flight, per passenger or per gallon fuel), their perceived volatility, and whether the charge is applied to all airlines equally (Koopmans & Lieshout, 2016). They may also be affected by harder-to-quantify factors, for example whether airlines receive incentives to operate at a specific airport, whether a route is being operated at a loss to gain market share from competing airlines, or whether the airline is hedging fuel costs. In this study we consider three main test cases:

- Case LC: an increase in per-passenger landing charges is applied at the constrained airport only. This mimics a situation where landing charges are increased before or during an airport expansion project to fund the construction work (FlightGlobal, 2018). We model a range of cost increases from $2.5- $17.5 USD per passenger. The lower end of this range is more likely for actual charge increases at MEL. The higher end is close to the upper end of values projected for London Heathrow (PWC, 2014).

- Case FP: an increase in fuel prices is applied across the entire network. This mimics situations where fossil Jet A prices increase, a carbon price is applied, or use of biofuels at higher cost than Jet A is mandated. The proportional impact of this cost change also depends on the baseline fuel price, which differs by scenario. We model a range of cost increases from $0.3-2.1 USD/gallon fuel ($0.1-0.7 USD/kg; equivalent to carbon prices of $30/tCO$_2$-$220/tCO$_2$; the upper end of the range is similar to 2014-2018 fuel price fluctuations).

- Case FP1: an increase in fuel prices across the network applied only to one specific airline. This mimics a case where a policy is applied on a basis which targets some operators but not others (for example, nationality or size of operator), or where airlines are differently-affected by a universal cost change because of different strategies (for example, hedging). The same range of values is used as in case FP, but we apply the extra charge only to the largest operator.

Each cost change case is applied to each scenario described in Section 2.2, leading to a 4-dimensional grid of models by socioeconomic scenario; capacity at MEL; level of cost increase; and type of cost increase. We neglect time lag and transition effects, and only consider the case where the system has reached a new equilibrium with the charge applied.

3. Results and Discussion

Airline revenue is primarily determined by number of passengers and typical fare per passenger. When airline costs change, both are affected. Figure 3 shows how airport-level demand, in terms of million passenger movements per annum (mppa), changes as costs, socioeconomic scenario, and capacity change[5]. Figure 4 shows corresponding changes in ticket price. Because airlines optimise profit over their whole networks, capacity or cost changes at a constrained airport also have second-order impacts at other airports within the system. Figure 3 and Figure 4 show outcomes at Melbourne airport (the capacity-constrained airport which is being expanded; (a) – (c)), Perth airport (an airport which is not capacity-constrained under any scenario; PER, (d)-(f)) and across the Australian domestic system ((g)-(i)). Demand varies by up to a factor of two for different socioeconomic scenarios, mainly due to the wide range in GDP modelled. In contrast, the cost changes modelled affect demand by under 10 per cent. The impact of cost increases on fare at an itinerary level is diverse and depends on factors such as the number of competing airlines per route, typical aircraft types used, and distance. Both fare and demand impacts are usually smaller when there is a capacity-constrained airport in the system. This is illustrated in Table 2 for scenarios at the upper end of cost change values.

Table 2. Illustrative average metrics for system response to different types of cost change with and without capacity constraints

Cost change	Airport	MEL is not capacity-constrained			MEL is capacity-constrained		
		Demand reduction, %	Fare increase, %	Effective pass-through, %	Demand reduction, %	Fare increase, %	Effective pass-through, %
$17.5 landing change increase (Case LC)	MEL	4.4-6.0	6.2-7.7	47-67	0.1-4.1	0.1-5.5	1-42
	MEL	7.1-7.2	11.8-12.8	79-81	0.2-6.9	2.8-12.0	25-75

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[5] Note that a single direct passenger journey counts as two passenger movements, one at the origin and one at the destination airport. For readability, not all scenarios modelled are plotted.

$2.1/gal fuel cost increase (Case FP)	PER	3.9-5.2	10.5-11.0	79-85	2.6-6.0	9.5-11.0	66-78
	System	6.3-6.5	11.3-12.4	82-84	3.1-6.3	5.6-11.8	42-79
$2.1/gal fuel cost increase to one airline only (Case FP1)[a]	MEL	1.4-3.6	2.9-6.6	23-45	-0.7-3.0	0.3-4.5	0-66
	PER	1.0-1.7	4.9-6.0	36-52	-0.9–3.3	0.0-7.2	5-45
	System	1.3-2.0	3.1-3.6	31-34	0.1-2.4	0.4-5.3	3-36

[a] Pass-through in this case is shown only for the affected airline; other metrics are across all airlines. Demand increases arise in two model runs from non-charged LCCs decreasing average fare on key routes.
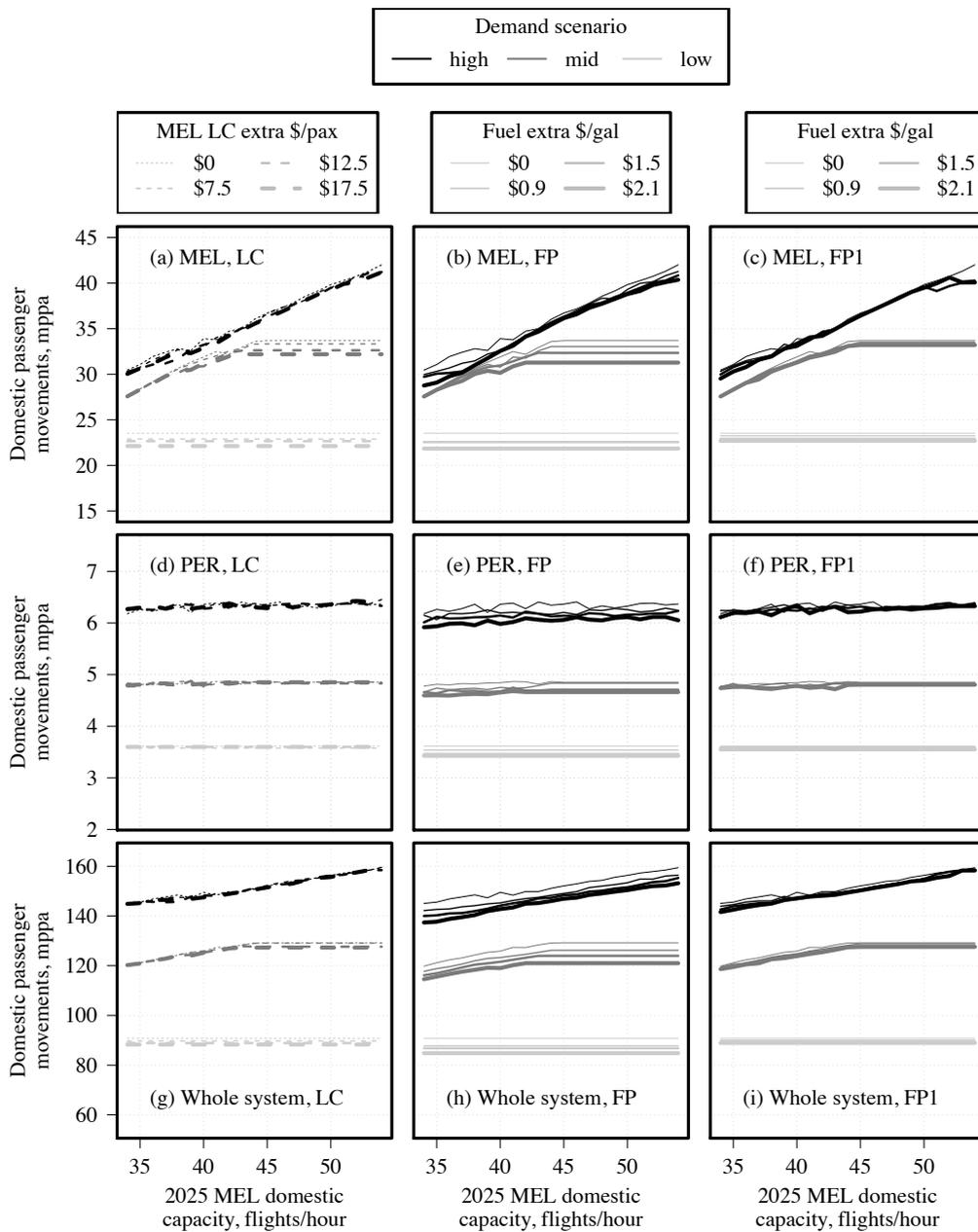

Figure 3. Passenger movements at Melbourne airport [(a)-(c)], Perth Airport [(d)-(f)] and the whole Australian domestic system [(g)-(i)] for each of the three cost change cases.

Figure 4 demonstrates the fare impact of cost changes, capacity constraints and underlying base cost levels per socioeconomic scenario. Across all scenarios, variation of up to around $100/ticket is observed. Average fares are higher when MEL is capacity-constrained (both at MEL and at other airports in the system), when baseline fuel costs are higher (for example, in the Low Demand Scenario), when additional charges are larger, and when those charges apply to more flights. In the case of fuel cost changes, impacts are also higher at airports, such as PER, with a greater average flight distance. However, even in the absence of extra charges fares are higher when MEL is capacity-constrained. Given the smaller impact on demand, this implies an increase in airline profit due to capacity constraint - scarcity rents, as discussed below in Section 3.2.
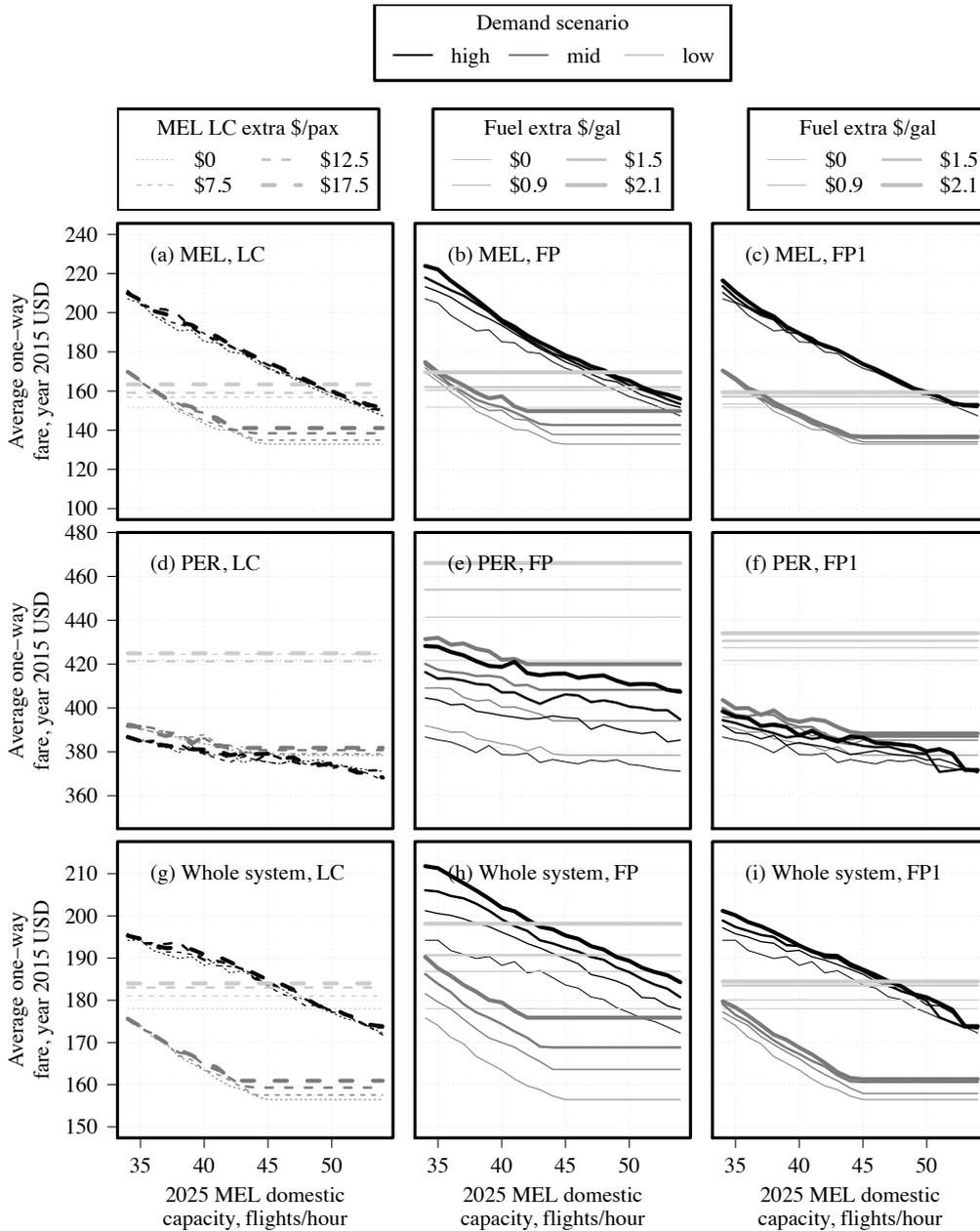
Figure 4. Average fares at Melbourne airport [(a)-(c)], Perth Airport [(d)-(f)] and the whole Australian domestic system [(g)-(i)] for each of the three cost change cases.

The extent of the fare premium depends on the level of constraint. For example, in the mid scenario with no extra charges, MEL domestic fares are 12 per cent higher if domestic capacity is 39 rather than 44 flights/hour, and 27 per cent higher in the case that domestic capacity is 34 flights/hour. This increase is approximately linear with the number of movements/hour that would need to be added for the airport to operate without constraint. For reference, PWC (2013), working with empirical fare data, find fare revenue per passenger mile

is 18 per cent higher for 'severely constrained' airports, and Frontier (2017) find fares at London Heathrow to be 24.4 per cent above those at less-congested European hub airports. These values are broadly consistent with those found here. A 24 per cent fare premium in the models used here maps roughly to capacity (in terms of slots/hour) which is 26 per cent short of what would be required to operate without constraints. Burghouwt et al. (2017) find a 10 per cent more stringent capacity constraint to be associated with a 1.4-2.2 per cent increase in fares at European airports, with a likely exponential relationship between capacity constraint and fare; however, they define the constraint level in terms of the Capacity Utilisation Index (CUI), a measure of how busy the airport's off-peak schedules are, which cannot be directly mapped onto the metrics used here[6]

3.1 Cost pass-through

Combining per-passenger increases in airline costs with changes in ticket price allows cost pass-through to be estimated. Because the model optimises profit across each airline's network, a change in fuel or landing costs may change frequency, load factor or aircraft type used per route as well as fare. This means that pass-through estimates are not presented under 'all-else-equal' conditions, and are prone to fluctuation due to corresponding changes in other elements of airline cost. Similarly, pass-through as a standalone metric does not fully capture system response, because airlines and routes which are not directly affected alter fares to take account of cost changes elsewhere.

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[6] As CUI approaches 1 at high constraint levels, an exponential relationship of fare to CUI may be fully consistent with a linear relationship between fare and shortfall in slots/hour.
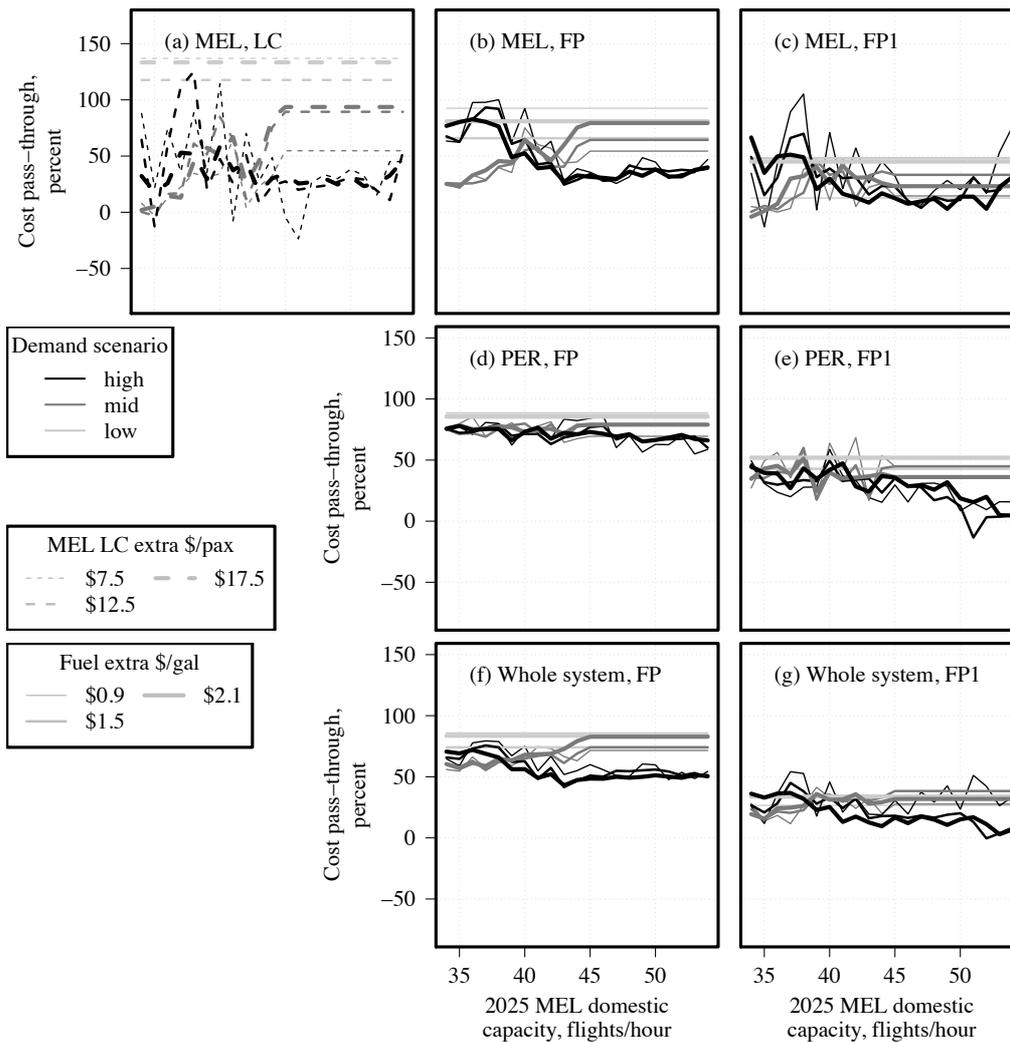
Figure 5. Effective cost pass-through rate at Melbourne airport [(a)-(c)], Perth Airport [(d)-(e)] and the whole Australian domestic system [(f)-(g)] for each of the three applicable cost change cases.

Figure 5 shows the approximate level of pass-through in the following cases: (a) for ticket prices from MEL from changing landing charges at MEL (case LC); (b),(d),(f) for ticket prices from MEL, PER and system-wide across all airlines, from changing fuel/carbon prices for all airlines (Case LC); (c),(e),(g) for ticket prices from MEL, PER and system-wide for the largest airline only, from changing fuel/carbon prices for that airline (Case LC1). Pass-through is typically 50-100 per cent in the case that MEL is unconstrained and all airlines are charged the same (for example, the Low demand scenario, case FP), and closer to 100 per cent for greater overall cost changes and higher baseline fuel cost. In case LC at Low demand some pass-through exceeding 100 per cent is also observed at MEL in combination with increases in

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use of the smallest (regional jet) aircraft sizes – that is, cost increases and associated demand decreases move the profit-optimal solution for MEL to one with smaller aircraft with higher per-passenger cost. Where MEL is moderately constrained (for example, Mid scenario, low/no capacity expansion) and all airlines are charged the same, pass-through at MEL decreases into the 0-50 per cent range. In the case that one airline experiences greater cost increases than others (Case FP1), pass-through for the affected airline is typically 50 per cent or below without constraints at MEL and 0-30 per cent with moderate constraints. These levels of pass-through are broadly consistent with expectations from economic theory (Figure 1). As discussed above, when an airport is at capacity, the supply curve becomes close to vertical and optimal ticket prices are determined by the level of constraint rather than by airline marginal costs. Therefore, changes in landing charges or fuel prices that impact on marginal costs are expected to have limited effect on ticket prices at congested airports.

In the case of extremely stringent capacity constraints at MEL and high cost changes, however, apparent pass-through level rises above 50 per cent once more. This somewhat counterintuitive outcome reflects the complex interaction of fare, flight frequency, costs and demand. When MEL is extremely capacity-constrained, it becomes profit-optimal to use twin-aisle aircraft on high-density short-haul routes rather than single-aisle aircraft at higher frequency. This effect has occurred, for example, on short-haul routes in Japan (Givoni & Rietvald, 2008). Under these circumstances, supply at the constrained airport has effectively increased; when using twin-aisle aircraft becomes part of profit-optimal solutions the supply curve is no longer vertical and a relationship between supply and demand is re-established. This, in turn, increases the apparent pass-through. For example, for MEL in Case FP at high demand, moving from 54 movements/hour capacity to 34 movements/hour increases pass-through from 31 per cent to 66 per cent, average seats per aircraft increase by 13 per cent, and

average fare increases by 43 per cent. However, this effect is somewhat dependent on the available fleet of the modelled airlines and the extent to which aircraft can be swapped between domestic and international routes, so it is unclear whether it is more widely applicable.
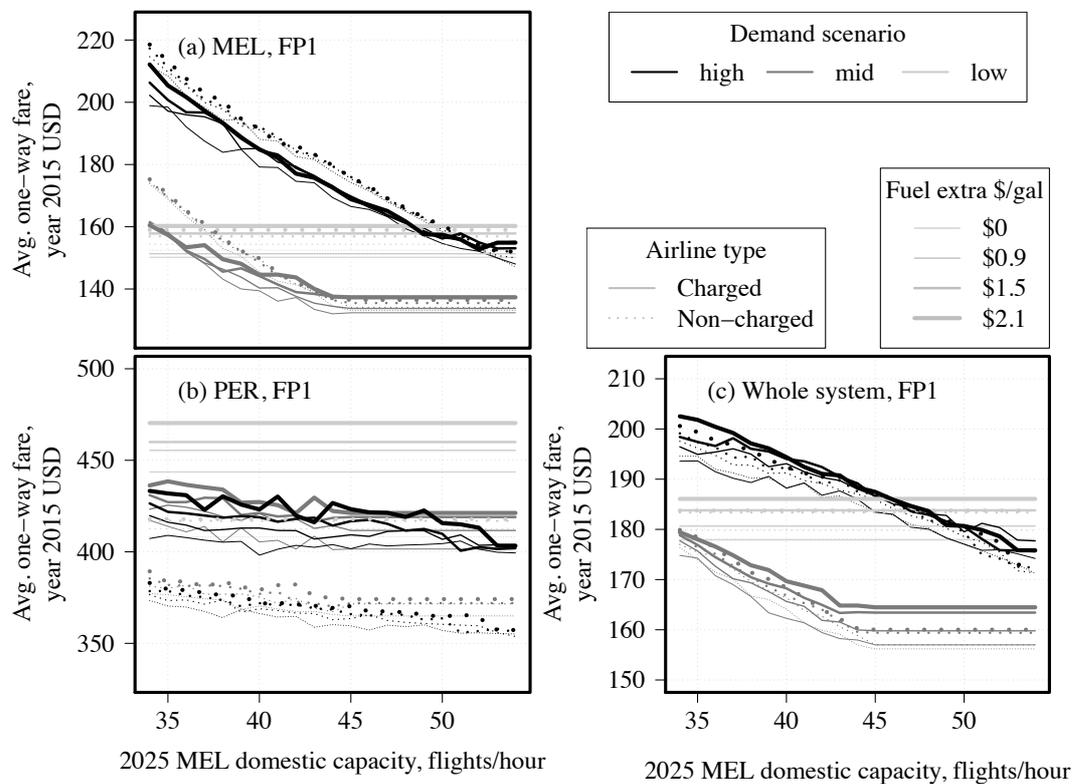

Figure 6. Fares by socioeconomic scenario, capacity, location and level of fuel charge for case FP1, comparing airlines which were subject to extra charges (solid lines) to those that were not (dotted lines).

Case FP1 also demonstrates the limitations of cost pass-through as a standalone metric. Figure 6 shows underlying fare trends by airline, separated into airlines which were subject to extra charges (solid lines), and those that were not (dotted lines). As the extra charge increases, fares increase at the affected airline. However, fares also typically increase at airlines which are not subject to extra charges. These airlines are taking the chance to increase their profits whilst still remaining cost-competitive. For example, in the High demand scenario with $2.1/gal fuel cost increase for one airline only at Melbourne, fares increase by up to 6.6 per cent for the affected airline, and by up to 3.3 per cent for the non-affected airlines. If all airlines

are equally affected by the fuel cost increase (Case FP), fare increases are up to 12.8 per cent and are similar across all airlines.

3.2 Scarcity rents

As discussed above, fares are typically greater, and cost pass-through lower, in the presence of capacity constraints. This is reflected in airline profits. Because airlines optimise profits across their networks, we compare system-wide profit per passenger in each situation. However, this is strongly influenced by capacity constraints at MEL. Around 20-30 per cent of domestic passenger movements across the different year-2025 scenarios are to or from MEL; in the High scenario, Sydney airport also experiences capacity constraints, so over half of system passenger movements are affected by capacity issues. Simulated outcomes are shown in Figure 7. Across the different cases modelled, the variable with the most notable effect on profit per passenger is capacity. For the range of extra charges and capacity examined, capacity limits have a much greater impact on profit per passenger than the level of pass-through of extra charges. In the Mid demand scenario, moving from unconstrained operation at MEL (44 movements/hour) to 10 movements/hour short of unconstrained operation (34 movements/hour) is associated with a whole-system increase in profit per passenger of 17 per cent. Because we assume no new domestic carrier enters the market to operate new domestic slots at MEL, this effect is purely associated with capacity constraints and does not reflect changes in the number of competing operators.
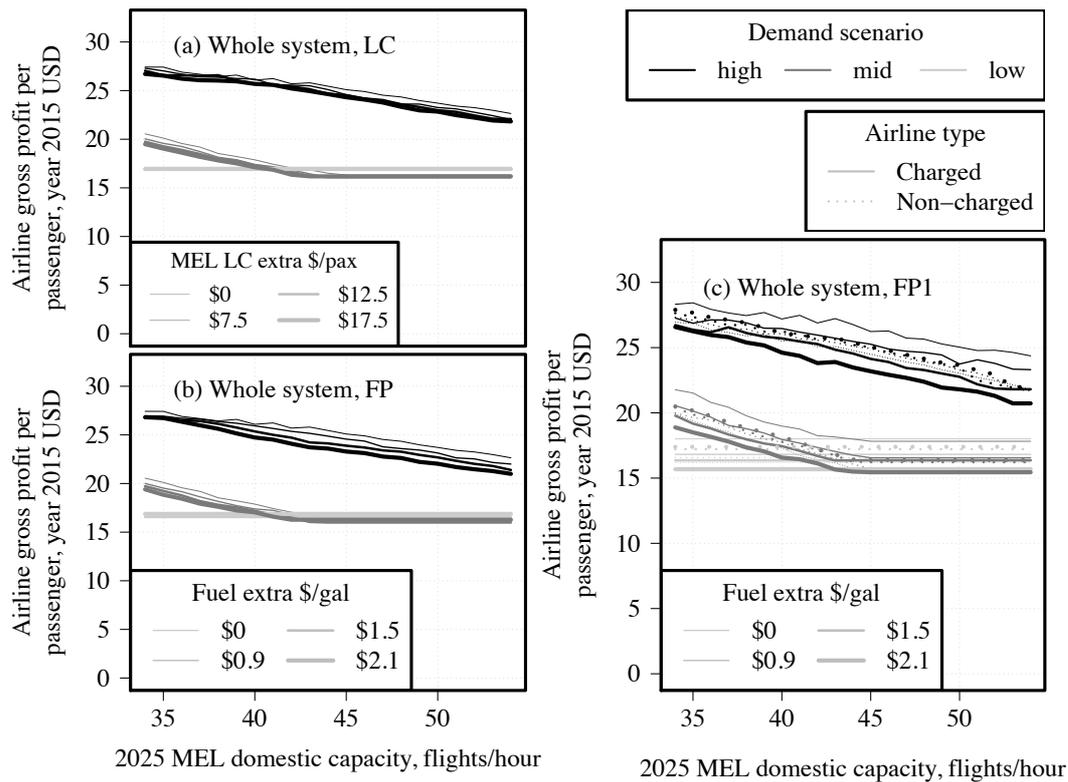
Figure 7. System gross profit per passenger with demand scenario, capacity, charge type ((a), all-airline landing charge increases at MEL; (b), all-airline fuel/carbon cost increases; (c) fuel/carbon cost increases for the busiest airline only, charged and non-charged airlines shown) and charge level.

Profits are also affected by the extra charges assumed in each case. This is because pass-through rates are typically below 100 per cent. Any costs not passed through lead to reductions in airline profit. When MEL is moderately capacity-constrained, pass-through rates are lower and there is a greater reduction in airline profits. Similarly, profits are lower when extra charges affect more flights. If extra costs apply unevenly to airlines, as in case FP1, profits for airlines with more extra costs decrease significantly due to the low pass-through rate. Profits for airlines which do not have extra costs increase in this situation, as they can increase fares and remain competitive. However, even in this case capacity still has a greater impact on per passenger profit than the range of extra charges modelled.

Airline net profit per passenger is typically small, cyclical, and frequently negative (Jiang & Hansman, 2006). Between 2013 and 2019, global average net airline profit per departing passenger for IATA member airlines was in the $3-10 range, although variation

between individual airlines can be considerably higher (IATA, 2019b). Because we do not model airline overhead costs in detail, Figure 7 reports gross profit per passenger. Overhead costs can vary significantly by airline, but if they are close to 13 per cent of total operating costs (ICAO, 2017), the baseline net profit per passenger modelled here is around $0-7/passenger depending on capacity constraints. Under these circumstances, airline profits may be dominated by scarcity rents, potentially leading to a reluctance to support expansion. Similarly, the higher levels of fuel charge modelled (more than doubling fuel costs in the High demand scenario) may completely wipe out airline profit, particularly in case FP1 where only one airline experiences them. This is a similar situation to that which airlines with unsuccessful hedging strategies were faced with in 2014-15 due to oil price fluctuations (Merkert & Swidan, 2019).

4.   Conclusions

In this paper, we applied a simulation model of airline profit maximisation to projections of the Australian domestic aviation system in 2025 to explore the interaction of airport capacity constraints with airline profit and cost pass-through, the first time that such a model has been used to examine these issues in real-world aviation systems with constraints derived from existing airlines. If airlines are assumed to set fares and frequency purely to optimise their profits, then the existence of a capacity-constrained airport in their network has a strong impact on both pass-through and profit. Under real-world conditions, pass-through of both increased landing charges and extra fuel costs is typically in the 50-100 per cent range when there are no capacity constraints and all airlines experience the same cost increase, although the exact value on a given route depends on route-specific factors such as the level of competition. When capacity constraints are introduced, or when only one of the competing airlines experiences the cost increase, pass-through is more typically in the 0-50 per cent range. When a single airline experiences a cost increase at a capacity-constrained airport, pass-

through is close to 0. These results are consistent both with economic theory and empirical studies of congested airports. We find a potential increase in pass-through with fuel cost increases in the case that capacity constraints become severe, due to airlines adopting high-cost methods which free up extra capacity (in particular, using twin-aisle aircraft on short-haul routes). However, pass-through on its own cannot fully reflect the underlying dynamics of situations where airlines can respond to cost changes by changing their operations as well as their fares. Similarly, pass-though is a flawed metric in the case that airlines are unequally affected by cost changes. In this case, airlines which experience no additional cost may still change their fares in response to action taken by their competitors, a response which cannot be captured by simple pass-through rates but requires a more nuanced consideration of the level of competition on each route.

Similarly, we find a strong linear relationship between the extent of system capacity constraints and overall gross profit per passenger; under the situations modelled here, airport capacity constraints are associated with significant scarcity rents. The modelling carried out here finds fare premiums for flying from a capacity-constrained airport of around 24 per cent for an airport which would need to add an extra 26 per cent to existing slots to operate without capacity constraints. These levels are broadly similar to those inferred for capacity-constrained airports from empirical fare data (PWC, 2013; Frontier, 2017). The extent of capacity constraints typically has a much greater impact on per-passenger profit than the level of cost pass-through under the range of capacities and cost increases modelled here.

The modelling in this research is simplified in a number of ways. We have assumed that the Australian domestic and international aviation systems can be fully separated; we have considered only a single class of air passengers, rather than dividing by socioeconomic status

or trip purpose; we have not modelled new carriers entering the system; and we have assumed that airlines base their decisions entirely on profit rather than, for example, seeking to optimise for market share or utilising non-profitable slots rather than lose them to a competitor. These assumptions in turn may affect system response. Although relatively few international passengers take an additional domestic flight leg compared to the numbers of purely domestic passengers (Sabre, 2017), excluding international-domestic and domestic-international passengers will lead to underestimates in flight frequency on routes to and from major international hub airports. A similar effect applies to domestic hub demand from domestic passengers who connect into the network modelled here via non-modelled small regional/PSO flights. This in turn likely leads to (small) underestimates in required domestic capacity, although general system behaviour should remain similar. Airlines faced with cost increases may also choose whether to pass on a greater amount of those costs onto routes and/or ticket types favoured by business passengers, who typically have lower price-sensitivity. This in turn may affect pass-through at airports which have higher-than-usual proportions of business or leisure passengers. The most likely case that an airline would optimise for market share is one in which a new airline is looking to expand its network. Although this does not apply in the specific situation modelled here, it may in other situations where airport capacity is a factor, particularly in airport expansions in rapidly-growing aviation systems where IATA new entrant slot preference rules apply (Dray, 2020). The intercity Australian domestic system is operated by relatively few carriers and is composed primarily of short- and medium-haul routes, so outcomes for systems with more carriers and/or longer-distance routes may also vary.

Broadly, however, we would expect the outcomes modelled here to be reflected in other aviation networks containing airports with capacity constraints. This has implications for aviation policy which seeks to influence airline or passenger behaviour by introducing extra

airline costs. For example, due to lower cost pass-through, demand reductions may be lower than anticipated for policies which increase costs at congested airports or which increase costs more for some airlines than others. Similarly, the impact of capacity expansion on reducing fares may lead to larger than anticipated increases in demand at expanded airports if it is not accounted for.

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