Market Power Spillovers Across Airline Routes

Rebekah Dix Roi Orzach [*]

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Abstract

Horizontal merger analysis focuses on predicting price changes of the merging firms' substitutable products. However, many firms produce multiple products that are neither substitutes nor complements in consumer demand but related through supply-side factors like capacity constraints or economies of scale. We show that prices of products that are related through supply-side factors may adjust after changes in competition (e.g., mergers and entry), so that estimating the full consumer surplus effect of changes in competition requires including the effects on products related through supply-side factors. We provide empirical evidence for the quantitative importance of these spillovers due to capacity constraints in the airline industry, showing that estimates of consumer surplus changes based on the directly affected substitutable products alone understate the consumer surplus benefits of entry by low-cost carriers by an average of 12 percent and understate the anti-competitive harm to consumer surplus from recent mergers by an average of 57 percent.

1 Introduction

The first step in investigating proposed horizontal mergers for competitive harm is defining the relevant product market, which typically consists of products that both of the merging firms produce and are seen by consumers as close substitutes.[1] Standard

[*]Department of Economics, Massachussetts Institute of Technology; rdix@mit.edu, orzach@mit.edu.
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[1]When discussing market definition, the Horizontal Merger Guidelines state: "Market definition focuses solely on demand substitution factors, i.e., on customers' ability and willingness to substitute away from one product to another in response to a price increase or a corresponding non-price change such as a reduction in product quality or service." (US Department of Justice, 2010, Page 7).

horizontal merger analysis then proceeds by predicting merger induced price changes of the products in this market. However, many firms produce multiple products that need not be substitutes from the perspective of consumer demand, which often results in these non-substitutable products being ignored in merger analysis. This paper highlights the potential for price changes of products that are neither substitutes nor complements with the products traditionally thought to be affected by the merger but are related though supply-side factors. We will emphasize one such form of interrelated costs: capacity constraints. We show that estimating the full consumer surplus effect of changes in competition (e.g., mergers and entry) requires estimating the price changes of products that are related through supply-side factors. Given limited antitrust agency resources for investigating mergers and potentially calculating damages, it is important to understand the full scope of the effects of changes in competition in order to efficiently target enforcement. Our work suggests that ignoring products related through supply-side factors underestimates consumer surplus effects of changes in competition.

The idea that shocks to one product could affect other products of multiproduct oligopolists because of interrelated costs across products was argued as early as Bulow et al. (1985), who showed this relation when there are economies of scale in production. This spillover can also occur with capacity constraints. Consider a firm producing two different products that share capacity but are neither substitutes nor complements from the perspective of consumer demand. Suppose there is a positive shock to the demand of product 1. The firm had previously set their quantities of products 1 and 2 to equate the marginal revenue of each product to the marginal cost of capacity. Now, due to the demand shock, in the absence of capacity constraints, they would want to increase their quantity of product 1 and keep their quantity of product 2 the same.[2] This would violate their capacity constraint and hence they would prefer to increase their quantity of product 1 and decrease the quantity of product 2. This will increase the price of both products in equilibrium. A similar logic applies to price effects of changes in market structure like entry of competing products or mergers of rivals.

The industrial organization literature seeking to estimate the consumer surplus effects of changes in market structure has generally ignored the effects on products related through supply-side factors. This paper provides empirical evidence for the importance of these spillovers across distinct demand markets via costs in the airline industry. While we focus on airlines, the effects we highlight in this paper may also be present in other industries, such as manufacturing firms whose multiple products share factory capacity.

[2] In other words, the opportunity cost of a unit of capacity has increased because of the positive demand shock.

Airlines offer many products (flights) that face interrelated costs. In particular, airlines face rigid short-run capacity constraints (e.g., the airline can not add a few seats to an already booked flight, it must schedule a new flight entirely), and seats on any given flight are used by consumers who purchased different itineraries (e.g., those flying direct and those flying indirect). We show in a stylized theoretical model that shocks to the demand of a direct route will affect the fares of indirect routes, and that the pass-through of these shocks will be positive with capacity constraints.[3] We also expect shocks to have persistent effects through opportunity costs of capacity because of capacity adjustment costs and indivisibility. We provide further support for this result by discussing Airline Revenue Management systems and how they imply positive pass-through of shocks. To empirically measure this pass-through, or spillover, of shocks to one product to other products that share capacity constraints, we focus on the propagation of demand and competition shocks throughout airline networks. In particular, we show that the fares of nonstop routes and the indirect routes using these routes as legs will not only be positively correlated, but that shocks to nonstop routes will also cause fare changes on indirect routes.

The paper is organized as follows. We first develop a simple model of airline pricing decisions for direct and indirect flights in a hub-and-spoke network with fixed capacity (Section 2). We show that there is a positive pass-through rate from a shock to a direct flight to the fares of indirect flights using this direct flight as a leg. To provide further support for positive pass-through of shocks, we discuss Airline Revenue Management systems and how the heuristics they use to price flights imply positive pass-through. We provide descriptive evidence of positive pass-through by showing there is a positive correlation between the prices of indirect flights and their nonstop legs using a large sample of indirect one-stop itineraries flown between 1990 and 2016 (Section 3).

We conduct three exercises to provide causal estimates of pass-through of shocks to one product to a firm's other products related through shared capacity constraints. First, in Section 4, we exploit route-level demand shocks to argue that shocks to nonstop flights cause price changes to the indirect flights that use the nonstop flight as a leg.

Second, in Section 5, we examine the impact of entry events of low-cost carriers. After entry into a nonstop route, connecting flights using this nonstop route as a leg also experience fare changes. We estimate positive pass-through using entry onto a route as an instrument for direct fare changes. A first-order approximation suggests that estimates of consumer surplus increases after these entry events based solely on nonstop route effects

[3] In the language of opportunity costs, a positive demand shock to a direct route increases the opportunity cost of a seat on that route, implying that indirect fares will also increase.

may understate welfare effects by as much as 15 percent.

Third, in Section 6, we study a series of airline mergers that have occurred since 2005. While the merging airlines overlapped on very few direct routes, we show that many more indirect routes containing these direct routes as legs also experienced price changes after the merger, even though the merger did not cause a change in ownership structure on these indirect routes. The same approximation suggests that estimates of consumer surplus decreases after these merger events based solely on nonstop route effects may understate welfare effects by as much as 100 percent, with a median understatement of 57 percent. Together, these results demonstrate how positive pass-through between direct and indirect fares causes traditional estimates of consumer surplus effects of airline entry events and mergers to be underestimated.

This paper contributes to several literatures. First, we provide alternative mechanisms and results for how shocks propagate through airline networks compared to a literature that has focused on modelling the relationships between fares within an airline network due to economies of density. Theoretical work in this literature (e.g., Brueckner and Spiller, 1991) predicts that increased competition in one particular market of a hub-and-spoke network is likely to have negative welfare effects on other routes under the assumption of economies of density. This happens since reduced demand in one market increases costs in connected markets. Our paper provides evidence that the opposite result can happen and be quantitatively important in the analysis of merger and entry events when airlines face capacity constraints (without the assumption of economies of density).[4] We show theoretically and verify empirically that in the presence of capacity constraints or sufficiently large costs of adjusting capacity there is a *positive* pass-through rate between the fares of direct flights and indirect flights using those direct flights as a leg, implying that changes in competition will be amplified throughout the spokes of the airline network. Empirical work (Brueckner et al., 1992; Brueckner and Spiller, 1994; Bamberger and Carlton, 2002; Berry et al., 2006) shows that airline fares depend on airline network characteristics, attributing the finding to economies of density. We provide empirical evidence of a specific relationship between fares that occurs because of the airline network structure, namely that there is positive pass-through between direct and indirect fares. The closest paper to ours is White (2020), which develops a structural model to estimate the pass-through of taxes to directly taxed routes allowing for spillovers to other routes via economies of scale. We instead focus on estimating pass-through after changes

[4]When an airline hits a capacity constraint this can be viewed as an extreme case of diseconomies of scale/density. However, the existence of capacity constraints and multiple products sharing capacity in the presence of uncertain demand creates opportunity costs of capacity before the constraint is hit.

in competition and demonstrate how this pass-through depends on products' interrelated costs without assuming economies of scale.

Our work also identifies an important missing aspect of the analyses of competitive changes in airline markets. Many papers have estimated the impact of airline mergers on the fares of routes that the merging airlines both operated before the merger (Borenstein, 1990; Werden et al., 1991; Peters, 2006; Luo, 2014; Hüschelrath and Müller, 2014; Carlton et al., 2019; Das, 2019; Orchinik and Remer, 2020). Our paper shows that many more indirect flights also experienced fare changes after mergers despite the mergers causing no change in the number of competitors providing the indirect flights. The mergers we study exhibit mean fare increases on direct routes, and the anti-competitive effects of these increases are understated when the propagation of shocks from nonstop to connecting routes is ignored. On the extensive margin, recent work has also estimated how airlines change their service selection after a merger. Li et al. (2021) study an airline's incentive to provide nonstop versus connecting service after a merger, and Ciliberto et al. (2021) study an airline's incentive to provide nonstop service, allowing for self-selection into the market, after the American and US Airways merger. When airlines stop servicing a direct route after a merger, we show that many indirect routes that used this direct route as a leg are also cancelled. This can be viewed as the pass-through of an infinite fare change on the direct route to related indirect routes.

Similarly, previous papers estimate the price effects of low-cost carrier (LCC) entry (Morrison, 2001; Brueckner et al., 2013; Tan, 2016) and potential entry (Goolsbee & Syverson, 2008) on nonstop routes. Our paper expands the analysis of low-cost carrier entry events to calculate fare changes on indirect routes that did not experience a change in the number of competitors following such entry events. After LCC entry onto a nonstop route, we find changes in average carrier level fares (specifically, carriers other than the entrants, including legacy carriers) on nonstop routes that were passed through to connecting routes. Again, we find that consumer surplus effects of entry events are understated when the propagation of shocks from nonstop to connecting routes is ignored.

Finally, this paper is related to theoretical and empirical work about pass-through. Notably, Weyl and Fabinger (2013) characterize the incidence and pass-through of taxes to prices in imperfectly competitive models, White et al. (2019) estimate the pass-through of taxes to airline fares abstracting away from airline networks, and Gayle and Lin (2021) estimate the pass-through rate of changes in crude oil prices to airfare. We study the pass-through in a different but related setting, focusing on the pass-through of nonstop to connecting fares.

2 Model

We present a simple model to show how shocks to one product can propagate to other products that are related through shared capacity. We develop this model in the context of airlines to illustrate how demand shocks to nonstop routes can affect the fares of connecting routes using the nonstop routes as legs despite their associated demands being independent.

Consider the hub-and-spoke network of a monopolist airline. Denote the hub by h and a spoke by s_i, where $i = 1, \ldots, n$. The airline offers both direct (nonstop) and indirect (connecting) flights. The direct flights operate between each spoke airport and the hub: the direct flight between s_i and h is denoted by $s_i \to h$. For simplicity, we will model the airline network as undirected: for example, the flight from $s_1 \to h$ is the same as $h \to s_1$. Indirect flights operate between spoke airports with a connection, or layover, at the hub airport: the indirect flight between spoke s_i and spoke s_j has a layover at the hub h and is denoted by $s_i \to h \to s_j$. Assume the demand for route m (either direct $s_i \to h$ or indirect $s_i \to h \to s_j$) is linear and given by[5]

$$q_m = \alpha_m - p_m.$$

Suppose that the capacity of direct flight m is given by κ_m and the cost of setting this level of capacity is $c\kappa_m$. Notably, capacity on a direct flight is also used for the indirect flights using the direct flight as a leg. That is, capacity on the direct flight $s_i \to h$ is also used for all $s_i \to h \to s_j$ flights.

Next, suppose there is a shock on route $s_1 \to h$ that increases $\alpha_{s_1 \to h}$ by $\epsilon > 0$.[6] We study how prices adjust throughout the network. The crucial factor in determining whether the prices of flights other than $s_1 \to h$ are affected is the airline's ability to adjust capacity.

If capacity can be re-adjusted instantaneously with no adjustment costs, then the price along the affected route $s_1 \to h$ will increase by $\frac{\epsilon}{2}$ and all other prices in the network will not change.[7] In the short run, the ability to immediately and costlessly adjust capacity

[5]This demand system assumes symmetric price sensitivities on the spokes. We study examples with heterogeneous demand functions in Appendix B and show that our main conclusion of positive pass-through to indirect routes using the shocked direct route as a leg is robust. However, some secondary implications of the model, discussed later in this section, are not robust to such heterogeneity.

[6]We consider ϵ small to ensure that the response of the airline is to continue offering all flights and only adjust the allocation of tickets from direct to indirect flights. This also ensures first-order conditions remain sufficient. Furthermore, considering ϵ shocks allows our results to generalize to any demand system featuring downward sloping demand.

[7]This result and all other results in this section are proved in Appendix A.

is not a reasonable assumption in the airline industry. On the intensive margin, it is not feasible to add more seats to planes. On the extensive margin, quickly adjusting flight schedules or procuring more planes may not be feasible. We will instead study the case in which capacity remains fixed before and after the shock, although results will be similar for cases in which capacity adjustments occur after the shock but are costly.[8]

To determine how the shock to one direct route propagates through the network, it is helpful to consider the following four types[9] of routes:

1. The direct route that experienced the shock ($s_1 \to h$),
2. Indirect routes that use the route in case (i) as a leg ($s_1 \to s_j, j \neq 1$),
3. Direct routes that are legs of routes in case (ii) ($s_j \to h, j \neq 1$),
4. Indirect routes that use direct routes in case (iii) as a leg ($s_j \to s_k$, $j, k \neq 1$) and do not use the $s_1 \to h$ route as a leg.

We summarize how the price of each type of route changes after the demand shock in the following proposition.

Proposition 1. If capacity constraints bind,[10] the changes in prices for routes of each type are given by

1. an increase of $\frac{2n+1}{4n-2}\epsilon$
2. an increase of $\frac{2n-3}{(2n-2)(2n-1)}\epsilon$
3. a decrease of $\frac{1}{(2n-2)(2n-1)}\epsilon$
4. a decrease of $\frac{1}{(n-1)(2n-1)}\epsilon$.

This proposition shows how the positive demand shock to the $s_1 \to h$ (type 1) flight results in price increases on the $s_1 \to h$ flight and also all indirect flights using this flight as a leg (type 2). Demand shocks on the type 1 route cause the airline to shift seats from type 2 to type 1, causing price increases on type 2. That is, there is positive pass-through between the price change on the $s_1 \to h$ direct flight and the price changes all indirect flights using this direct flight as a leg. When there are fewer seats for type 2, this increases seats for types 3 and 4, which causes their prices to decrease. While this proposition predicts price changes on flights of type 3 and 4, this paper will focus on testing the positive pass-through implied by parts 1 and 2 of the proposition. Developing identification strategies

[8]Capacity adjustment costs and indivisibility are forces that will make such shocks persist and have long-run effects.

[9]Note that the union of these four groups is all the routes in the network.

[10]Equivalently, if the airline is starting at initially optimal capacity choices.

for examining price changes on the routes in cases 3 and 4 is left to future work.[11] An additional challenge of studying routes of types 3 and 4 is that with heterogeneous demand elasticities on the spokes it is possible that the sign of the fare change on route types 3 and 4 is ambiguous. We discuss this possibility in Appendix B.

2.1 Airline Revenue Management Systems

The simple model above demonstrates how shocks to a direct route can propagate through an airline network with fixed capacity and gives the prediction of positive pass-through of shocks from direct to indirect routes. Institutional details of how airline fares are set provide further support for this result.

Airline revenue maximization is a highly complex network optimization problem because of the number of products offered, price discrimination, and competition, among other factors. Talluri et al. (2008) write that in "the network case exact optimization is, for all practical purposes, impossible." The complexity of the revenue maximization problem and the airlines' focus on price discrimination on direct routes has led airlines to rely on various heuristics to maximize their revenues over their networks.

While the pricing software currently in operation is proprietary and extremely complicated, [12] we enumerate some of the principles used to price indirect (one-stop) flights. The discussion in this section follows Belobaba et al. (2015). The fundamental challenge in pricing an indirect route is that every seat occupied by an indirect passenger removes one seat on each of the nonstop flights forming the legs of the indirect route. Given how airline demand is inherently random (e.g., demand depends on whether inelastic business travelers decide to purchase tickets), the pricing decision of the indirect flight needs to intricately depend on the characteristics of the direct flights in order to maximize revenue.

Airlines use heuristics to price direct flights. The primary objective of these heuristics is to ensure that high yield business or long-haul travelers have seats available if and

[11] We do not test the predictions of the price changes of routes of types 3 and 4 because if we attempted to document price changes on these routes we would have no control routes, as the flights in cases 1 through 4 are an exhaustive list of all flights in this example network. Furthermore, the predicted price changes on these routes are relatively small in magnitude. Since the average number of flights out of an airport (n in our model) is greater than 20, the changes in prices for flight types 3 and 4 would be on the order of $\frac{1}{400}$, which should not affect our analysis if we use these as control routes. However, one might note that routes of types 3 and 4 are on the order of $\frac{1}{n^2}$ but there are n^2 of them. Even if price changes are small on these flights, since there are many flights, they could aggregate to meaningful price changes. In reality, airline networks are more complicated than our simple model and it is not clear in all cases how to define routes of types 3 and 4.

[12] One example of such software primarily used for research and testing new heuristics is The Passenger Origin-Destination Simulator (PODS): http://podsresearch.com/pods.html.

when they show up to buy. For simplicity, we will assume the airline pricing system includes only two price points, one (higher) price point intended for business travelers (which, for example, does not require consumers to purchase 21 days in advance) and one lower price point with many restrictions.[13] We can think of these price points as being defined by how many (and what type) of competitors are present in this market, along with the demand conditions along this route. These price points are determined before any tickets are sold, are generated solely by route-level characteristics, and generally are not modified absent changes in competition or demand on the route. Given these price points, when tickets begin to be sold, the Revenue Management (RM) system decides how many tickets to set aside for each of the price points. If demand is such that more than the expected number of tickets have already been bought at the higher price point, the RM system may decide no longer to sell the lower priced tickets. Selling more of the lower priced tickets results in guaranteed sales, but may result in an inability to sell a seat to a highly inelastic business traveler the day before the flight. The RM software's job is to find a quantity to balance these effects.

The indirect flight pricing is based on a similar principle. Multiple price points are determined before demand is realized based on route-level characteristics. These are referred to as "fare buckets" in RM systems. As demand begins to be realized, the trade-off the RM considers for indirect routes is that each additional seat used to occupy an indirect route removes a seat from a direct route. If the expected marginal revenue of a direct flight is higher than expected, the RM may reduce the number of seats available to indirect passengers at the lower price point, or even remove this price point all together, i.e. closing this fare bucket.

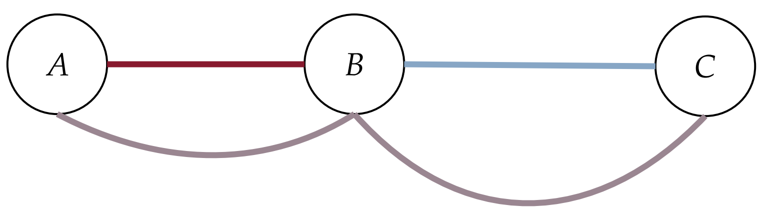


Figure 1: Correlation between direct and indirect fares.

When there is a shock to a direct market that does not explicitly affect the indirect route, we would expect to see prices change on the indirect route due to this network pricing problem. For example, consider what happens when Southwest (WN) enters an

[13]In reality, there will be many more price points, but the description with only two points will suffice for the intuition.

$A \to B$ market United (UA) operates as shown in Figure 1. Due to the increase in competition, UA may lower both their price points in this market (which would in turn lower the average fare) to match WN's fares. In doing so, the expected marginal revenue of UA's seat on this market decreases. Now, when considering UA's pricing for their indirect flight $A \to B \to C$, note that the price points available have not changed since neither the competition nor demand on this route changed. However, the RM calculation will change. Since the expected marginal revenue on the direct route has decreased, the RM will sell more of the lower price point tickets on the indirect route. Hence when we look at average fares on a given market, the average fare will decrease. Through this mechanism we claim a price change on a direct route will *cause* a price change on an indirect route.

3 Data and Descriptive Statistics

We now turn to an empirical analysis of the relationship between indirect fares and direct fares of flights forming the legs of indirect flights. We begin by describing our data and provide descriptive evidence of positive pass-through between fare changes on direct and indirect routes. We then conduct three exercises to estimate pass-through after demand shocks, entry events, and mergers.

3.1 Data

We use two main datasets in our analysis. First is the U.S. Department of Transportation's Airline Origin and Destination Survey (DB1B).[14] The DB1B includes a 10% random sample of all domestic airline tickets used in each quarter. We restrict the sample to round-trip coach tickets.[15] We calculate average fares and the total number of passengers for each route-operating carrier-quarter combination. Many previous papers study average fares on a route-quarter combination. However, given the self-selective price discrimination, loyalty programs, and heuristics used by airlines, we think it is more informative to focus on carrier-specific fares. For direct flights, a route is defined by an airport origin-destination pair. For indirect flights, we restrict to tickets with at most one connection, and hence a route consists of an origin-layover-destination airport tuple.[16] For our main

[14]We use Severin Borenstein's cleaned DB1B data, provided by the NBER, available here: https://www.nber.org/research/data/department-transportation-db1adb1b.

[15]For Southwest, we include all fare classes since fares were coded as First-Class for the early years of Southwest's operations.

[16]In principle, the mechanisms we describe will also be important for flights with multiple connections. We focus our empirical analysis on indirect flights with one layover for simplicity.

analyses, we use data from 1990 to 2016. We include all carriers present in the DB1B in our sample.

Second, we use the Air Carrier Statistics database (T100), which provides aggregate traffic statistics on a segment (flight) level. The T100 contains monthly data on number of departures, seats, passengers, and other statistics, at a carrier-route-aircraft type level. A main limitation with the T100 is that it does not record information on the number of passengers flying on direct versus indirect itineraries on a given flight. We are limited to using the number of tickets and total passenger variables observed in the DB1B to measure quantity of indirect passengers. The DB1B is a random sample of tickets rather than a census, so the coverage of indirect flights may be noisy, especially for thinly travelled routes. In general, an indirect itinerary will have fewer consumers than a direct route, so a 10% random sample will be more likely to miss an indirect route.

Table 1 provides summary statistics for the general sample, used in Section 3.2 to provide descriptive evidence of positive pass-through, and for the Denver sample, used in Section 4, to provide causal estimates of pass-through using demand shocks for flights to Denver. Further details about our data construction process are in Appendix C.

Table 1: Sample Descriptive Statistics
(1990 Q1 to 2016 Q4)

	# Obs Control	**Mean** Control	**StdDev** Control	**# Obs** Treatment	**Mean** Treatment	**StdDev** Treatment
General Sample						
Indirect ($A \rightarrow B \rightarrow C$) Routes						
Fare ($)	379776	195.42	61.9			
Fare Change ($)	379776	5.07	44.32			
Fare Change (%)	379776	4.8	22.51			
Pax Change (%)	379776	17.78	66.47			
Direct ($A \rightarrow B$) Legs						
Fare ($)	30814	184.15	66.44			
Fare Change ($)	30814	8.23	37.94			
Fare Change (%)	30814	4.86	21.37			
Pax Change (%)	30814	14.1	41.49			
Seats Change (%)	30814	3.41	26.44			
HHI (Seats)	30814	0.74	0.25			
Denver Sample						
Indirect ($A \rightarrow B \rightarrow C$) Routes						
Fare ($)	382160	196.82	64.72	26740	203.56	62.78
Fare Change ($)	382160	-2.66	34.76	26740	-2.11	36.29
Fare Change (%)	382160	0.07	16.71	26740	0.76	16.55
Pax Change (%)	382160	23.31	52.34	26740	35.43	60.44
Direct ($A \rightarrow B$) Legs						
Fare ($)	34473	188.6	70.5	2254	183.59	45.53
Fare Change ($)	34473	-2.57	21.49	2254	0.59	19.58
Fare Change (%)	34473	-1.41	12.0	2254	0.42	10.75
Pax Change (%)	34473	12.94	30.3	2254	7.77	28.18
Seats Change (%)	34473	5.08	15.53	2254	5.79	16.44
HHI (Seats)	34473	0.75	0.24	2254	0.59	0.25

Notes: The first and second panels give descriptive statistics for the General sample used in Section 3.2 and the Denver sample used in Section 4, respectively. For the General sample, differences are calculated year over year. For the Denver sample, differences are calculated between quarter 2 and quarter 1 of each year. Both samples include all carriers present in the DB1B and include data from 1990 to 2016. # Obs tells the number of unique (route, operating carrier, year) tuples we observe in the data. Denver's price changes are defined as Q2 less Q1, so Denver includes 1990 data separately from 1991 data, whereas the general sample does not. Combining this with the fact that all the control routes remain the same post 1990 explains why the Denver sample has more observations. All fares are nominal.

3.2 Descriptive Evidence of Pass-through

Let $p_{A\to B,i,y,q}$ denote the fare of route $A \to B$ by carrier i in year y and quarter q, given in dollars. Let $\Delta_y p_{A\to B,i,y,q} = p_{A\to B,i,y+1,q} - p_{A\to B,i,y-1,q}$ be the change in fare from year $y-1$ quarter q to $y+1$ quarter q.[17] Unlike the majority of the literature, we use carrier-specific prices. As an example of why this is the correct specification for our analysis, suppose both Delta and Southwest are offering the direct leg. Delta's own price is a much more reasonable predictor of their marginal revenue for that leg (which as discussed in Section 2.1 will impact the price of the indirect flight) than the quantity-weighted market price. To characterize the relationship between direct $A \to B$ and indirect $A \to B \to C$ fare changes, we estimate the following regression

$$\Delta_y p_{A\to B\to C,i,y,q} = \beta_p \Delta_y p_{A\to B,i,y,q} + \delta_y + \alpha^A + \alpha^C + \alpha^i + \epsilon_{A\to B\to C,i,y,q} \tag{1}$$

where δ_y is a year fixed effect, α^A is an origin fixed effect, α^C is a destination fixed effect, and α^i is a carrier-specific fixed effect. [18] We will weight the above equation by how many tickets we observe for the indirect $A \to B \to C$ route.[19] The coefficient of interest is β_p, which we will refer to as the direct-fare pass-through rate.

In a correct specification, this can be interpreted as the causal effect of an increase in the price of the direct route on the indirect route. However, Equation 1 suffers from simultaneity issues. For example, there could be shocks to airlines' costs (such as changes in the price of oil) that affect both the price of the direct and indirect routes.

We defer causal inference for later sections and estimate Equation 1, noting that these results do not have a causal interpretation because of the endogeneity of $\Delta_y p_{A\to B,i,y,q}$. We take all indirect (one-stop) itineraries in the DB1B between 1990 and 2016 and calculate $\Delta_y p_{A\to B\to C,i,y,q}$ as the change in fare on that flight from quarter 2 of year $y+1$ to quarter 2 of year $y-1$ (i.e., $q = 2$). [20] Similarly, we calculate $\Delta_y p_{A\to B,i,y,q}$ as the change in fare on

[17] We include one of our regressions from Section 4 in percentages rather than levels as a robustness check, although the RM pricing theory does predict levels should be the relevant variable. This is Table 6 in the Appendix.

[18] These fixed effects are designed to pick up that different segments (either by location or by carrier choice) of the market may have different demand over time. One would additionally include a layover fixed effect to accommodate the idea that if airport B has a cost shock that it will affect indirect prices. However, this is exactly what β_p is designed to pick up, since that shock will also affect the direct route fare $\Delta p_{A\to B,i,y,q}$. However, including an airport B fixed effect does not affect our results.

[19] We note that this may be an endogenous measure and we will present robustness checks in footnote 28 where we weight by lagged tickets.

[20] We use quarter 2 for our analysis to avoid demand changes due to summer and holiday travel given that quarter 2 has less seasonal travel. Additionally the results are robust to the size of the time window, and this version is chosen to be consistent with later sections. Since we focus on quarter 2, we do not include a quarter fixed effect. However, using all quarters in the analysis and including a quarter fixed effect gives

the direct $A \to B$ flight that is the first leg of the $A \to B \to C$ flight from quarter 2 of year $y+1$ to quarter 2 of year $y-1$. Opportunity costs of capacity and RM pricing predict that the change in fare on the $A \to B$ leg, $\Delta_y p_{A\to B,i,y,q}$, will have a positive correlation with the change in fare on all indirect flights containing this direct flight as a leg.

Table 2 presents these results. Across all specifications, we observe a positive and statistically significant coefficient β_p on $\Delta_y p_{A\to B,i,y,q}$. Column (1) gives estimates of pass-through without fixed effects, and Column (2) includes all fixed effects discussed in Equation 1. We observe that the positive correlation remains after including this set of fixed effects. This is consistent with a positive pass-through rate from direct to indirect flights. In Column (3), we additionally control for the fare change on the $B \to C$ leg, and find that the correlation between the indirect fare change and the changes of each of its legs are approximately equal.

Table 2: OLS estimates of pass-through for all one-stop itineraries 1990-2016 (Q2)

	Change in Indirect Fare (\$) $\Delta_y p_{A\to B\to C,i,y,2}$		
	(1)	(2)	(3)
Intercept	4.311		
	(0.068)		
$\Delta_y p_{A\to B,i,y,2}$	0.235	0.151	0.130
	(0.002)	(0.002)	(0.002)
$\Delta_y p_{B\to C,i,y,2}$			0.129
			(0.002)
Origin		Yes	Yes
Destination		Yes	Yes
Year		Yes	Yes
Carrier		Yes	Yes
Estimator	OLS	OLS	OLS
N	379,776	379,748	379,748
Adjusted R^2	0.046	0.141	0.152

Notes: In all tables, robust standard errors are in parentheses.

similar results.

4 Identifying Pass-through with Regional Demand Variation

We next turn to the endogeneity and simultaneity concerns of Equation 1 estimated in Section 3.2. For example, there could be shocks to airlines' costs (such as oil price changes) that affect the price of both the direct and indirect routes. To address these, we use an instrumental variables approach that exploits seasonal variation in demand for nonstop flights to Denver because of the ski season. The ski season in Denver peaks in the first quarter, ending by early April.[21] We therefore expect demand for direct flights to Denver during quarter 1 to consist of many travellers seeking to ski. In quarter 2, we would expect this ski season demand to decrease yielding price changes on these direct flights. Importantly, there are many indirect flights that have layovers in Denver,[22] and indirect travellers generally do not consider the ski characteristics of their layover cities. Opportunity costs of capacity and RM pricing heuristics imply increases in the fares of direct flights to Denver during the ski season will be passed through to the fares of indirect flights that have layovers in Denver.

We estimate the pass-through of direct fare changes between quarter 1 and quarter 2 to indirect fare changes for indirect itineraries in the DB1B from 1990 to 2016. We instrument for direct fare changes using snowfall in Denver in quarter 4 of the previous year interacted with an indicator for the direct flight having a layover in Denver.[23] This instrument is meant to capture that demand for nonstop routes to Denver will be shifted by the ski season and reflected in nonstop fares. High snowfall at the end of December foreshadows a strong skiing season in the new year. Thus, this instrument is correlated with demand (and hence prices) for direct flights to Denver. We will discuss below why we expect this instrument to be uncorrelated with demand (and hence prices) for indirect flights with a layover in Denver except for its effect on direct flight prices.

Our estimation equations are now based on $\Delta_q p_{A\to B\to C,i,y,2} \equiv p_{A\to B\to C,i,y,2} - p_{A\to B\to C,i,y,1}$ representing the change in fare from quarter 2 to quarter 1 in year y. Our first- and second-stage estimating equations are as follows:

$$\Delta_q p_{A\to B\to C,i,y,2} = \beta_p \Delta_q p_{A\to B,i,y,2} + \delta_y + \alpha^A + \alpha^C + \alpha^i + \epsilon_{A\to B\to C,i,y,2} \quad (2)$$

$$\Delta_q p_{A\to B,i,y,2} = \gamma Z_{A\to B,y,2} + \delta_y + \alpha^A + \alpha^i + \epsilon_{A\to B,i,y,2} \quad (3)$$

[21]This can be seen by the average closing dates of Colorado ski resorts: https://www.uncovercolorado.com/colorado-ski-resorts-season-opening-closing-dates/.

[22]Denver is a hub for United and Frontier (and Continental pre-merger) in addition to being a focus city for Southwest.

[23]The snowfall data was obtained from https://www.weather.gov/bou/seasonalsnowfall.

where $Z_{A \to B,y,2}$ is the set of instruments we include for the direct $A \to B$ fare.

The exclusion restriction requires that demand (and hence fares) for indirect flights with layovers in Denver do not change because the ski season except through the fare changes that occur on the direct legs. There are indirect flights to other ski destinations with a layover in Denver that would violate the exclusion restriction, since the demand for these indirect flights will be dependent on the ski season. Therefore, we remove any indirect flights with a layover in Denver that continue onto (or start at) airports that are themselves skiing destinations.[24] Once we make this restriction, we would not expect demand for the indirect flights to change because of the ski season.[25] One additional concern is whether in general there is less travel from some airport A in quarter 1 compared to quarter 2 (e.g., no one wants to leave California in the winter) and hence this mechanically causes a correlation between the price changes of $A \to B$ and $A \to B \to C$.[26] To correct for this, we include origin and destination fixed effects to account for local demand fluctuations at A and aggregate changes from quarter 1 to quarter 2.

Using snowfall in Denver in quarter 4 of the previous year interacted with an indicator for whether the indirect flight has a layover at Denver as an instrument for direct fare changes is plausibly exogenous. Since snowfall in quarter 4 will be idiosyncratic around locations, if Denver gets more snow, this should not cause any shift in demand for the price of the flight from, for example, Seattle to Denver to Boston. Additionally, quarter 4 snowfall will not alter airline travel in quarter 1 since the airport will be able to shovel it away, however this does satisfy the relevance condition, since ample snow in quarter 4 on the slopes will accumulate and cause more travellers to want to travel to Denver for the ski season. We also include the square of snowfall interacted with an indicator for whether the indirect flight has a layover at Denver, which for similar reasons satisfies the exclusion restriction and allows us to capture non-linearity in the relationship between direct flight demand and snow. High snowfall years are associated with very good skiing, but the relationship between snowfall and the quality of skiing need not be linear. As is shown in Table 3, the squared term is in fact negative.

Descriptive statistics for the sample after removing routes that potentially violate the exclusion restriction (routes with destinations that themselves are skiing destinations) are

[24] The airports we exclude are ASE, TEX, HDN, EGE, DRO, GUC, GJT, SLC, SUN, MTJ, JAC, RNO, BZN, BTV, and MMH.

[25] Some travellers might try to avoid layovers in Denver in the winter, which would decrease demand for indirect flights through Denver. As a robustness check we use snowfall in the previous quarter as the only instrument and then include fixed effects for layover in the second stage and get an estimated pass through of 0.194 which is in line with those reported in Table 3.

[26] However, our exclusion restriction only requires that travel from, e.g. California, to any location besides Denver is independent of snowfall in Denver.

given in the second panel of Table 1. There are 99 $A \to$ Denver routes that generate 2345 $A \to$ Denver $\to C$ routes.

We estimate Equations 2 and 3 and present results in Table 3. Column (1) estimates pass-through by OLS (Equation 1). Column (2) presents IV estimates using an indicator for the indirect flight having a layover at Denver interacted with Denver snowfall and snowfall squared as instruments, and Column (3) contains the first-stage of this regression.

Table 3: Denver pass-through

	Change in Indirect Fare (\$) $\Delta_q p_{A\to B\to C,i,y,2}$		Change in Direct Fare (\$) (First-Stage, $\Delta_q p_{A\to B,i,y,2}$)
	(1)	(2)	(3)
$1_{B=\text{Denver}} \times \Delta_q p_{A\to B,i,y,2}$	0.216		
	(0.009)		
$\Delta_q p_{A\to B,i,y,2}$		0.194	
		(0.095)	
Denver Snowfall			0.472
			(0.026)
Denver Snowfall^2			-0.016
			(0.001)
Origin	Yes	Yes	Yes
Destination	Yes	Yes	Yes
Year	Yes	Yes	Yes
Carrier	Yes	Yes	Yes
Layover		Yes	
Estimator	OLS	IV	OLS
N	408,878	408,877	408,878
First-stage F statistic		126.563	

As expected, the first-stage regression produces a strong first-stage F-statistic. Here, direct flights to Denver experience a drop in fare between quarter 1 and quarter 2 at average snowfall levels. Additionally, our first-stage shows price differences are maximized when snowfall is 14.75 inches (the mean snowfall for a given year in Denver is approximately 21 inches). We estimate a statistically and economically significant pass-through rate.[27,28] Column (2) implies that a one-dollar increase in the fare of a direct leg results in

[27] An airline may not wish to increase the price of an indirect flight to be higher than either of the legs' price (or else a "hidden city" arbitrage is available). When we restrict our sample to contain only hidden city tickets, the positive pass-through rate remains and is 0.352 . An airline also may not want to decrease the price of an indirect flight so that it now competes with a direct flight it offers. When we restrict to this sample of indirect flights that have direct flight competition, the pass-through rate is 0.473 .

[28] As mentioned before, we weight by number of passengers, which may be viewed as endogenous. As a robustness check we run this specification weighted by number of passengers in the previous year and get 0.22 .

a 20-cent increase in the indirect fare.[29]

5 Pass-Through after Entry Events

In this section, we study how pass-through alters the estimates of the consumer surplus benefits of entry by a low-cost carrier. While the setting in Section 4 provided clean variation in the prices of direct flights and allowed us to provide causal estimates of pass-through, the pass-through of direct flight prices to indirect flight prices because of seasonal variation in demand is not necessarily of independent interest.

When an airline enters a nonstop route, positive pass-through from fare changes on that nonstop route to indirect routes implies that any indirect route that uses this nonstop route as a leg will also experience a change in fare. When entry causes fare decreases, ignoring the pass-through of fare changes to indirect routes will result in underestimation of the benefits of entry.

We analyze entry by two low-cost carriers between 1990 and 2016: Southwest and Spirit. As in Section 4, we instrument for direct fare changes using exogenous changes to direct route fares. Here, we use entry by one of these low-cost carriers as the shock to direct fares of the incumbent carriers. More precisely, we instrument for the change in direct fare with an indicator for whether Southwest (Spirit) entered that route during a given quarter. Standard economic theory would suggest that an additional competitor in a market will cause price changes for the incumbents, and hence our instrument satisfies the relevance restriction. We discuss the instrument's exclusion restriction after we outline how we construct our sample of treatment and control routes.

Our sample of treatment routes (i.e., those routes that receive a non-zero value of the instrument) experiencing entry events is constructed as follows.[30] We define Southwest (Spirit) as having entered a direct route, $A \rightarrow B$ in period t (where a period is a year, quarter tuple) if they operate at least 30 direct flights on that route in period t and did not do so in any previous period.[31] We then remove all indirect routes $A \rightarrow B \rightarrow C$ for which Southwest (Spirit) also contemporaneously entered any competing $A \rightarrow C$ service (direct and indirect via any airport B).[32] This eliminates spatial correlation in entry patterns. Our

[29] There is nothing particularly special about the Denver demand shock, and in principle any layover location could have shifts in the demand curve that would move direct fare prices. We do this in Appendix Table 7, yielding coefficient 0.431 .

[30] Descriptive statistics for this sample are provided in Table 8 in the Appendix.

[31] Since Southwest merged with Airtran in 2011, for all flights after 2011, we do not code it as entry if Airtran previously operated this route. We estimate pass-through rates after this merger in Section 6.

[32] For part of our sample, Southwest sold tickets for individual legs of flights, so the DB1B data did not record any connecting (indirect) itineraries. For this reason, we also remove any $A \rightarrow B \rightarrow C$ flights where

sample of control routes (i.e., those routes that receive a zero value of the instrument) includes all other indirect routes in the DB1B.[33]

The routes Southwest (Spirit) chooses to enter are not exogenous. One potential exclusion restriction violation is that a carrier enters $A \rightarrow B$ because of an increase in profitability in city A (e.g., Tesla's headquarters move to Austin). However, this would imply that the prices carriers can charge out of A have increased. Hence, absent positive pass-through, we would expect the prices of $A \rightarrow B \rightarrow C$ to go up due to the increased profitability but the prices of $A \rightarrow B$ to go down due to the entry. These two prices moving in the opposite direction would, if anything, bias our estimates of pass-through downward. Spatial correlation in entry could also violate the exclusion restriction. For example, Goolsbee and Syverson (2008) document that Southwest is much more likely to enter a route which they are already operating other routes out of both endpoints. Namely, if Southwest (Spirit) entered $A \rightarrow B$ at period t, they may have also entered $A \rightarrow C$ in period t, which could affect $A \rightarrow B \rightarrow C$ fares. We explicitly exclude such entry events from our sample. Similarly, another potential exclusion restriction violation is, after entry onto $A \rightarrow B$, other fares of rivals on $B \rightarrow C$ drop since Southwest may now be a *potential* entrant on $B \rightarrow C$. In some cases, Southwest may have already been operating other flights out of airports A, B, and C, so their status as a potential entrant on $B \rightarrow C$ would not change after entering $A \rightarrow B$. One would additionally include an airport B fixed effect or control for $\Delta p_{B \rightarrow C}$ to prevent violations of the exclusion restriction. We find that including an airport B fixed effect and controlling for $\Delta p_{B \rightarrow C}$ does not quantitatively change our estimates of pass-through.[34]

Figure 2 shows the entry of Southwest onto nonstop routes between 1990 and 2016, and Figure 3 shows the changes in nonstop and connecting fares for that same period after Southwest entry events.[35] In our sample, entry onto 173 $A \rightarrow B$ routes by Southwest and Spirit affected 1483 $A \rightarrow B \rightarrow C$ indirect routes (after excluding the $A \rightarrow C$ routes discussed above).[36]

Southwest also started operating $B \rightarrow C$. Spirit connecting itineraries are explicitly coded as indirect, so we additionally report pass-through estimates for Spirit. In this case, we do not have concerns about knowing the identity of indirect flights in the DB1B data.

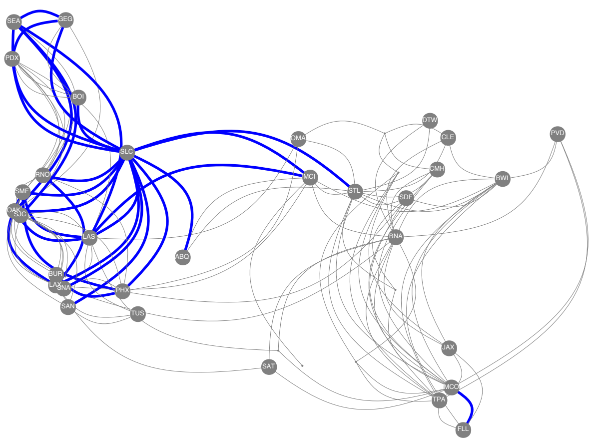
[33] Previous airline merger retrospectives typically choose control routes by matching on observables. To avoid issues with selection, we include a large control group (i.e., essentially all indirect flights not in the treatment group). There could be entry (or other shocks) happening on the control routes, which would bias our estimates of pass-through downwards.

[34] However, due to the similar endogeneity concerns, an instrument would also be required for $\Delta p_{B \rightarrow C}$. We explore this in ongoing work.

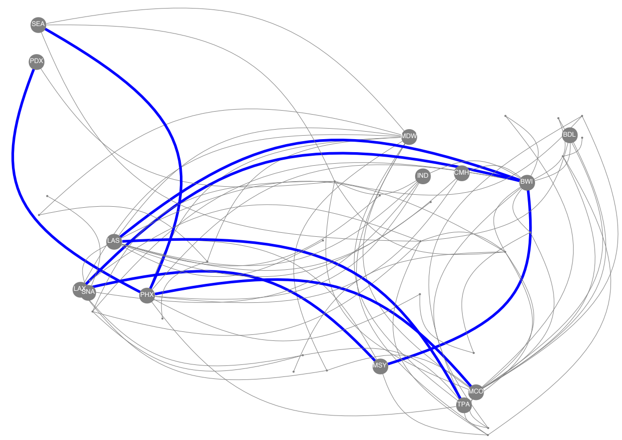
[35] It is important to note while the theory predicts a positive relationship between the prices of direct and indirect routes, due to idiosyncratic factors on each route, it is possible to observe routes where the direct route had a fare increase but the indirect had a fare decrease or vice versa.

[36] For brevity we only show these figures for Southwest entry events – figures for Spirit show the same

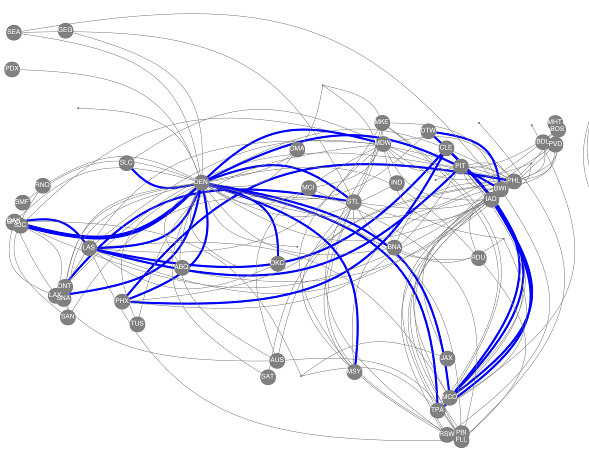
Figure 2: Southwest entry into nonstop markets: 1990 - 2016



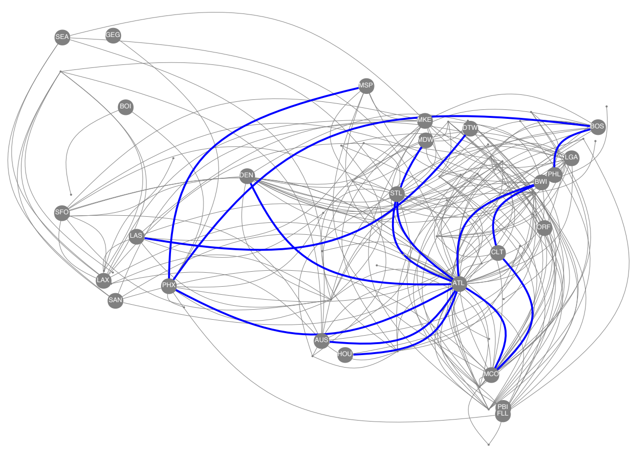
(a) 1991 Q1 - 1997 Q3



(b) 1997 Q4 - 2003 Q4



(c) 2004 Q1 - 2010 Q2



(d) 2010 Q3 - 2016 Q3

Notes: Direct routes that generated indirect routes satisfying our sample criteria are colored in blue. Direct routes that did not generate indirect routes satisfying our sample criteria are highlighted in grey.

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qualitative patterns.

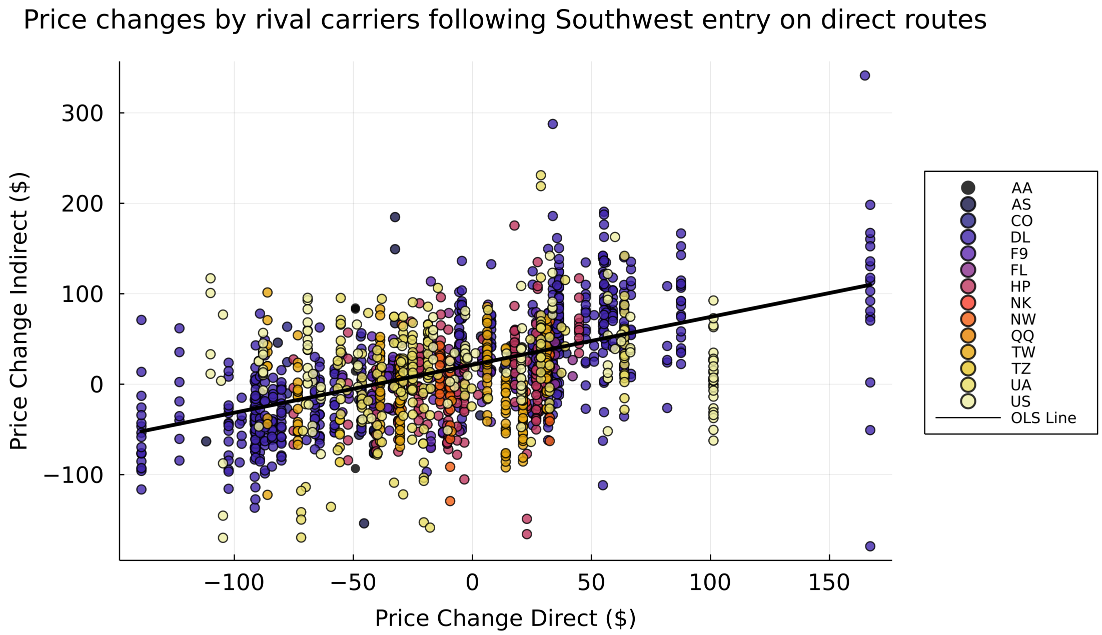


Figure 3: Correlation between direct and indirect fare changes following Southwest entry

We will use

$$\Delta_y p_{A\to B\to C,i,y,q} = \beta_p \Delta_y p_{A\to B,i,y,q} + \delta_{y,q} + \alpha^A + \alpha^C + \alpha^i + \epsilon_{A\to B\to C,i,y,q} \quad (4)$$

$$\Delta_y p_{A\to B,i,y,q} = \gamma 1_{\text{Entry by Carrier on route},i,y,q} + \delta_{y,q} + \alpha^A + \alpha^i + \epsilon_{A\to B,i,y,q} \quad (5)$$

as our estimating equations, where $\delta_{y,q}$ is a quarter-year fixed effect to control for both time and seasonal trends. Recall that $\Delta_y p_{A\to B,i,y,q} \equiv p_{A\to B,i,y+1,q} - p_{A\to B,i,y-1,q}$ is defined as the difference in the average prices for carrier i in the quarter that occurred one year after entry to the quarter one year before. [37]

Table 4 presents our estimates of pass-through. Columns (1) and (2) contain the OLS estimates of pass-through in Southwest and Spirit entry events. Columns (3) and (4) report the IV estimates for Southwest and Spirit respectively. A reason the pass-through estimates are different for Southwest and Spirit, and different from the estimate in our Denver case study, is that in practice many route-level characteristics will go into the RM pricing heuristics which determine pass-through. These include the elasticities of the direct/indirect travelers, the fraction of connecting passengers, the probability of a flight being full, and many other aspects of a specific route. Hence as we change the set of indirect routes we consider, we would expect the estimated pass-through rate to change.

[37] As a robustness check, we do the same analysis looking two years ahead and two years back, getting pass-through rates 0.095 and 0.191 for Southwest and Spirit, respectively. We do expect these pass-through estimates to be attenuated since they use fare data further away from the competition shock.

Table 4: Entry pass-through

	Change in Indirect Fare (\$) $\Delta_y p_{A\to B\to C,i,y,q}$				Change in Direct Fare (\$) First-Stage, $\Delta_y p_{A\to B,i,y,q}$	
	OLS Southwest	OLS Spirit	IV Southwest	IV Spirit	Southwest	Spirit
$1_{\text{Entry } A\to B} \times \Delta_y p_{A\to B,i,y,q}$	0.086	0.073				
	(0.003)	(0.005)				
$\Delta_y p_{A\to B,i,y,q}$			0.128	0.225		
			(0.006)	(0.013)		
$1_{\text{Entry } A\to B}$					-24.863	-12.298
					(0.130)	(0.136)
Origin	Yes	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes	Yes
Carrier	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	IV	IV	OLS	OLS
N	1,258,944	1,372,638	1,258,944	1,372,638	1,258,944	1,372,638
First-stage F statistic			567.091	251.780		

Notes: Column (1) and (2) present OLS estimates of pass-through. Columns (3) and (4) present IV estimates of pass-through, where the first-stages are given by Columns (5) and (6) respectively.

As expected, the first-stages (Columns 5 and 6) show that, in fact, entry by these disruptive carriers resulted in large fare decreases by incumbents. While previous work has estimated positive welfare effects for direct passengers on these entered routes, our estimates of positive pass-through to indirect routes suggest there are additional welfare gains created for passengers on the indirect routes affected by entry onto one of the legs of the itinerary.

The simplest way to show the relative importance of these calculations for consumer surplus (CS) is through the following first-order approximation to the change in consumer surplus due to indirect routes versus direct routes:

$$\frac{\text{Indirect CS Gain}}{\text{Direct CS Gain}} \approx \frac{\text{Price Change Indirect} \cdot \text{Number of Indirect Passengers}}{\text{Price Change Direct} \cdot \text{Number of Direct Passengers}} \tag{6}$$

$$= \text{Pass-through Rate} \cdot \frac{\text{Number of Indirect Passengers}}{\text{Number of Direct Passengers}} \tag{7}$$

This is a scale-free measure that compares the changes to consumer surplus on indirect and direct routes. It tells us the understatement in consumer surplus changes that comes from ignoring the effects on indirect routes sharing legs with affected direct routes. We simply take the ratio of indirect fare changes weighted by the number of indirect passengers to the direct fare changes weighted by the number of direct passengers. In Equation 6, we can substitute the estimated pass-through rate to get Equation 7. Next, we can observe the ratio of connecting travel in the data. Multiplying the two we get 0.098 for Southwest and 0.156 for Spirit. These are conservative estimates, since we remove many indirect routes from consideration in our sample creation. Additionally, we do not have data for international indirect flights that begin with a domestic leg which would similarly experience a pass-through and potentially contain a larger fraction of connecting passengers.

6 Pass-Through after Merger Events

The pass-through of changes in direct fares to indirect fares may also be an important factor in the evaluation of mergers in the airline industry. Previous airline merger retrospectives study price and quantity effects for routes that the merging firms both operated before the merger. However, there are many indirect flights that did not experience a change in competition due to the merger that we would, nonetheless, predict to have fare changes after the merger. This happens when a leg of an indirect route experiences a reduction in competition due to the merger and thus the entire indirect flight likely experiences fare changes.

We study five consummated mergers since 2005: US Airways and America West (2005); Delta and Northwest (2009); United and Continental (2010); Southwest and Airtran (2011); and US Airways and American (2013). Our sample of indirect routes consists only of indirect routes where both firms operated the $A \to B$ leg but only one operated the $B \to C$ leg. Therefore, only one of the merging airlines would have operated the $A \to B \to C$ route before the merger. We estimate the pass-through of fare changes (between approximately one year before and after the date the merger was closed)[38] on the direct route to the indirect route. By and large, the airline mergers that are not blocked by the DOJ are a selected sample because they have few direct overlap routes.[39] However, a single direct route can serve as a leg for many indirect routes, so we would predict many more routes to experience price changes after mergers than just the nonstop routes both airlines operated before the merger. For example, Delta and Northwest simultaneously operated on only five nonstop markets, but an additional 139 indirect routes may have

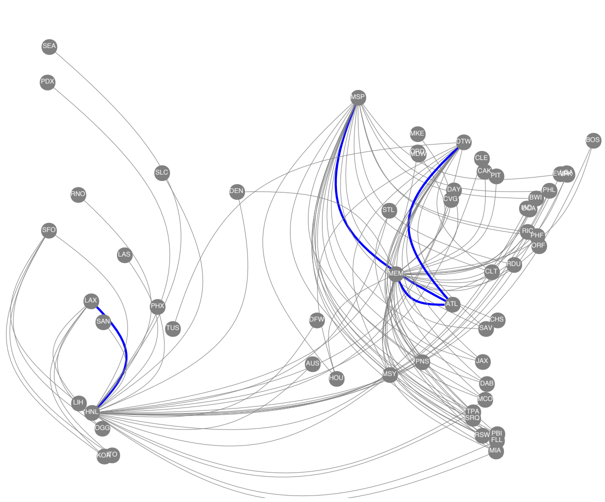
[38]The exact pre- and post- time periods are given in Table 5. For each merger we use quarter 2 fares to avoid capturing changes due to holiday travel.

[39]Some airline merger retrospectives also consider the price effects realized on indirect overlaps routes (Luo, 2014). We will not focus on these routes but rather consider the spillover onto indirect routes that did not experience a change in competition due to the merger.

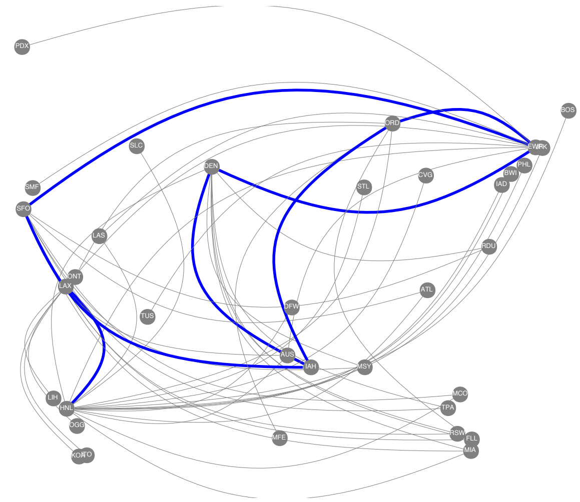
price changes induced by the reduction in competition of the nonstop route experiencing a merger that is a leg of the connecting itinerary. The number of direct overlap routes and indirect routes we predict will be affected by each merger are given in Table 5.

Figure 4 shows, for each merger we consider, the nonstop routes the merging airlines both operated before the merger (in blue) and the indirect routes that only one of the merging airlines operated before the merger that use one of the overlap nonstop routes as a leg (in grey).

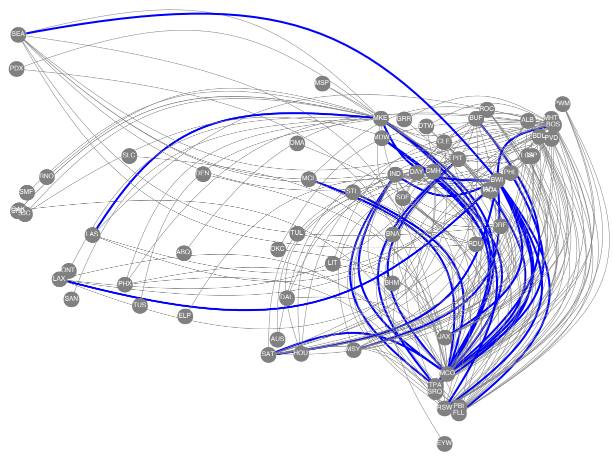
Figure 4: Merger overlap direct routes and affected indirect routes



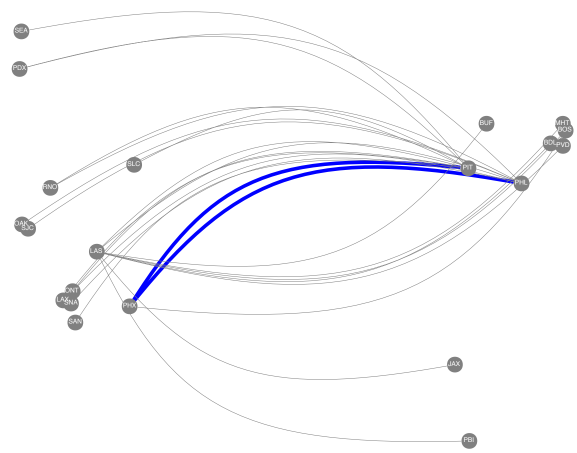
(a) Delta/Northwest



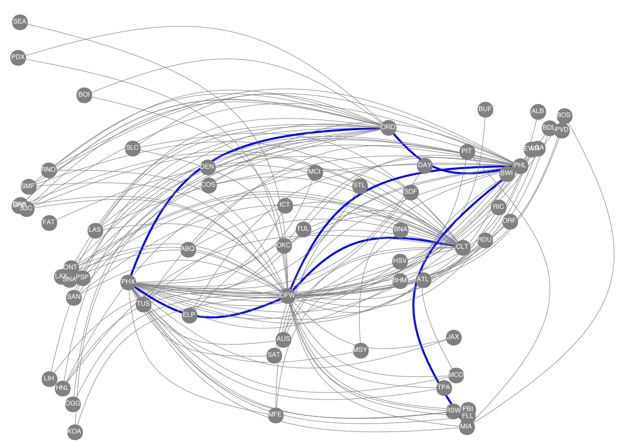
(b) United/Continental



(c) Southwest/Airtran



(d) US Airways/America West



(e) US Airways/American Airlines

Notes: Routes that both airlines operated before the merger are in blue. Indirect routes satisfying our sample criteria are in grey.

We use an instrumental variables approach similar to our analysis of entry events in Section 5 to estimate direct fare pass-through after merger events. We estimate equations 2 and 3 for each merger, where now the change in prices are calculated by taking the difference in prices approximately a year before the merger announcement date and a year after the merger closing date. We use an indicator for whether both of the merging airlines operated that direct route pre-merger, as well as functions of the pre-merger HHI (calculated with respect to seats) on the overlapping routes to instrument for direct fare changes. We discuss the construction of our estimation sample in detail before discussing the relevance and validity of these instruments.

Our estimation sample is constructed as follows. Indirect routes $A \to B \to C$ in the treatment group (e.g., receive a non-zero value of the instrument) are those that were operated by (only) one of merging carriers before merger (i.e., only one of the merging firms operated $B \to C$) and had an $A \to B$ leg that both of the merging carriers operated. We exclude indirect routes $A \to B \to C$ where both of the merging firms offered $A \to C$ since $A \to B \to C$ and $A \to C$ can be viewed as substitutes and would therefore likely experience price changes after the merger. The fare of $A \to B \to C$ changing because of a change in competition on $A \to C$ would be a violation of the exclusion restriction, which requires that the merger can only affect the fares of $A \to B \to C$ through its effect on the fares of $A \to B$. All other indirect routes in the DB1B are in the control group (e.g., receive a zero value of the instrument).

This exclusion is hard to defend for mergers in general. When airlines engage in these multi-billion dollar mergers, they do so to increase their route network, monopoly power, and clientele base. In this sense, we do not worry about the particular selection of the routes that both carriers overlapped on. However, the exclusion restrictions for the instruments in this case are hard to defend, as it requires that the only reason that indirect fares change after merger is because of price changes on one of its direct legs. When two airlines merge, aside from greater pricing power, there is a potential for re-hubbing and an overhaul of the route network. Airlines are competing on networks, thus the merger can also cause other carriers to drastically change their route networks. Given this concern, our results on merger pass-through rates should be viewed as suggestive rather than causal. [40]

We will proceed assuming that the only effects of the merger operate through the internalization of competitive effects, which implies that indirect fares will change after the

[40] As mentioned, the exact pass-through will differ depending on the route, time, and carrier, so it is fruitful to measure the pass-through on the merger routes. However, implicitly a regulator could estimate pass-through on one set of routes and apply this estimate to the proposed overlap routes to predict fare changes.

merger only because of changes in direct fares. Regardless of whether this is the correct interpretation of why indirect route fares change after mergers, we believe it is still important to examine whether many indirect routes did indeed experience fare changes after mergers that were not documented in previous studies because they did not experience a change in competition due to the merger. Figure 5 graphs the changes in direct and indirect fares after the set of mergers we consider. The figure also illustrates the positive correlation between direct and indirect fare changes, pooling data across all mergers. The intercept of this OLS regression line is near zero, which suggests that when there were no fare changes on direct routes, indirect routes also did not experience price changes.

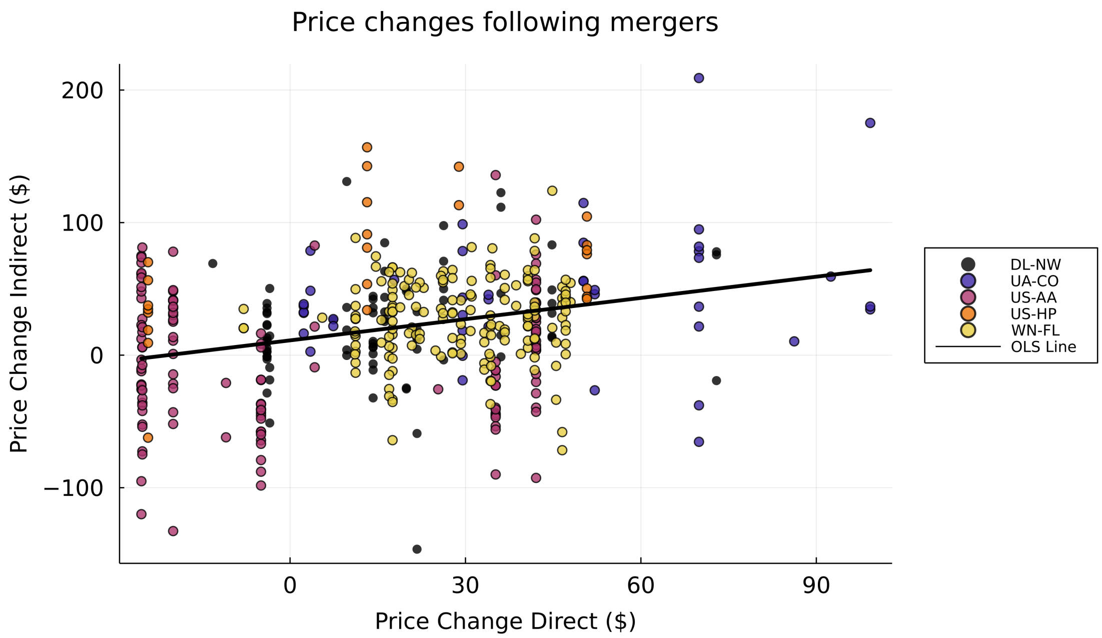


Figure 5: Correlation between direct and indirect fare changes

Table 5 presents descriptive statistics and pass-through rates for the mergers we consider. [41] In the estimation of Equations 2 and 3, we use the following set of instruments

$$Z_{A\to B,y,q} = \left\{1_{\text{Merger on } A\to B}, 1_{\text{Merger on } A\to B} \times HHI_{A\to B}, (1_{\text{Merger on } A\to B} \times HHI_{A\to B})^2\right\}$$

Despite many more indirect routes being affected than direct routes, our sample size is much smaller than the ski season and entry applications studied above, which considered many years of flights. This leads to weaker first-stage estimates. Additionally, the mergers that are cleared (and hence appear in our sample) are selected because they have few direct overlap routes and purported cost synergies yielding minimal fare changes, which

[41] Additional detail about the overlap routes is given in Table 9 of the Appendix.

weakens the variation in direct fare changes. Nonetheless, for each merger we estimate a positive pass-through rate. These estimates are statistically significant for a subset of the mergers.

In the case of direct fare increases after a merger, these estimates suggest that the anti-competitive effects of mergers have been underestimated when the spillover to indirect routes is ignored. We observe average direct fare increases for each merger we consider.[42] As in Section 5, we can calculate the proportion of welfare changes that are attributable to the indirect routes using Equation 7. These estimates are in the row titled "Indirect Welfare Proportion" of Table 5, ranging between .19 and 1.10. Since the ratio of connecting passengers to direct passengers can be arbitrarily large, it is possible to get welfare proportions above 1. Our estimate of 1.10 for the United Continental merger suggests that welfare estimates could be off by nearly 50%.

After a merger, the merging airlines may reconfigure their network by adding new routes and ceasing to operate others. We can view $A \rightarrow B$ no longer being offered as an increase in that route's price to infinity. The pass-through of this price to indirect $A \rightarrow B \rightarrow C$ routes is mechanically also infinity as these routes, too, are no longer operated. Importantly, one $A \rightarrow B$ route can serve as the first leg of many indirect routes, so the welfare effects of network changes may be misstated if the these indirect routes are not considered.[43] As an example, after the Delta-Northwest merger, Delta ceased to offer 236 $A \rightarrow B$ routes, which in turn ended 878 $A \rightarrow B \rightarrow C$ routes.[44] Table 10 in the Appendix provides similar calculations for other mergers.

[42]While some previous merger retrospectives of airline mergers have not found evidence of fare increases, we find fare increases when we look at carrier-level fares rather than industry aggregates, which, given self-selective price discrimination, may be the better metric. Furthermore, RM pricing heuristics imply that an airline's own nonstop fares will be relevant for setting the fares of indirect routes.

[43]We do not include $A \rightarrow B$ routes that are no longer offered after the merger in our analysis in Table 5 since we do not observe fares in the pre- and post-merger periods.

[44]We say a route is not operated if the same carrier stopped operating that route. However, it is possible that regional jets started operating the route after the merger, in addition to other potential network structure changes.

Merger	DL-NW	UA-CO	WN-FL	US-HP	US-AA
Date Closed	12/31/2009	10/1/2010	5/2/2011	9/27/2005	12/9/2013
# Direct Overlap $A \leftrightarrow B$ Markets	5	7	26	3	6
# $A \to B \to C$ Routes	77	42	167	24	127
IV Pass-Through Estimate	0.84	0.57	0.14	0.27	0.39
IV Pass-Through SE	0.45	0.23	0.39	0.18	0.14
First-Stage F	4.14	11.98	6.08	13.27	44.52
OLS Pass-Through Estimate	0.76	0.29	0.03	0.82	-0.04
Mean Direct Fare Change ($)	17.87	38.64	28.31	29.22	3.85
Mean Indirect Fare Change ($)	22.46	46.18	27.0	66.93	-3.7
Mean Direct Pax Change (Level)	3453.25	-805.48	573.59	-1086.25	-588.58
Mean Indirect Pax Change (Level)	-88.31	-220.48	31.32	-387.5	-167.64
Indirect Welfare Proportion	0.76	1.15	0.29	0.31	0.25
Pre-Period Year	2007	2009	2010	2004	2012
Post-Period Year	2010	2011	2012	2006	2014
Quarter	2	2	2	2	2

Table 5: Merger pass-through

7 Conclusion

In this paper, we demonstrated that considering products related through supply-side factors like capacity constraints is important for estimating the full consumer surplus effects of changes in competition. Focusing on the airline industry, we showed that a change in price on a direct route can propagate to many indirect routes using this direct route as a leg. Ignoring price changes on these additional routes can yield severe underestimates of the consumer surplus impacts of mergers and entry events. Our work also suggests that additional routes must be considered to evaluate the effects of codesharing[45] or vertical integration.[46]

[45]Gayle (2013) shows that after the airlines serving legs of indirect routes enter into codeshare agreements, the prices of the indirect flights composed of these legs may decrease, an effect attributed to the elimination of double marginalization. Gayle (2013) focuses on indirect flights where both legs were impacted by codeshare agreements, while we will study the propagation of shocks that only occur on one leg. Our main result of positive pass-through between direct and indirect fares suggests that to fully evaluate the welfare effects of codesharing agreements, it is important to estimate the effects on indirect routes where only one leg was impacted by the codeshare

[46]Forbes and Lederman (2009) study incentives for vertical integration in the airline industry, finding that airlines are more likely to own regional partners operating flights on city pairs that are more integrated into the airline's overall network. They suggest these flights are more likely to impose externalities on other flights via connecting passengers, creating incentives for integration. Our result of positive pass-through from shocks on nonstop routes to connecting routes provides another example of such an externality.

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A Proofs

This section presents the proof of the proposition in Section 2. We first state and prove one lemma.

Lemma 2. Given the demand parameter for each market α^m and the cost of capacity $c\kappa$ the quantity that each flight will use is

$$q^m_{\text{pre}} = \left\{ \begin{array}{ll} \frac{\alpha^m - c}{2}, & \text{if m is direct} \\ \frac{\alpha^m - 2c}{2}, & \text{if m is indirect} \end{array} \right\}$$

This is just the standard monopoly pricing formula, except that indirect flights have double the associated costs because they use capacity on two different legs. One can see that there is no relationship between the prices of a given flight with any other flight. This is why if capacity was able to adjust costlessly there would be no changes in prices of any of the other legs.

Proof of Proposition 1. Given the capacities calculated in Lemma 2 we will calculate how the prices change given the demand shock on the $s_1 \to h$ market. Since the capacities were chosen given the costs associated with the planes, but now these are fixed, an ϵ change in any of the demand conditions will still result in all the capacity constraints being binding across the flights. This results in the constrained optimization problem of the airline having two types of constraints binding: the capacity constraints on any given leg, and that the marginal revenue of an indirect flight equates to the sum of the marginal revenues for the two direct flights.

$$\begin{aligned} \sum_{i \neq j} q^{s_j \to s_i} + q^{s_j \to h} &= \sum_{i \neq j} \frac{\alpha^{s_j \to s_i} - 2c}{2} + \frac{\alpha^{s_j \to h} - c}{2} \quad \forall j \\ \alpha^{s_j \to s_i} - 2q^{s_j \to s_i} &= \alpha^{s_j \to h} - 2q^{s_j \to h} + \alpha^{s_i \to h} - 2q^{s_i \to h} \quad \forall 1 < i < j \\ \alpha^{s_j \to s_1} - 2q^{s_j \to s_1} &= \alpha^{s_j \to h} - 2q^{s_j \to h} + \alpha^{s_1 \to h} + \epsilon - 2q^{s_1 \to h} \quad \forall j > 1 \end{aligned}$$

One can see this yields exactly the same number of constraints as quantity decisions. One can now check that the solution to the above system of equalities is

$$q^m_{\text{post}} = q^m_{\text{pre}} + \left\{ \begin{array}{ll} \frac{2n-3}{4n-2}\epsilon, & \text{if case 1} \\ -\frac{2n-3}{(2n-2)(2n-1)}\epsilon, & \text{if case 2} \\ \frac{1}{(2n-2)(2n-1)}\epsilon, & \text{if case 3} \\ \frac{1}{(n-1)(2n-1)}\epsilon, & \text{if case 4} \end{array} \right\}.$$

We will proceed by replacing the proposed solution into the constraints. Note we only need to check that the ϵ's match up since all the terms involving the other constants equate by assumption.

First set of constraints:

It is helpful to break up in the case of $j = 1$ and $j \neq 1$.

$j = 1$**:** Checking that total seats sold along the flight from $s_1 \to h$ remains the same:

$$-\sum_{i \neq 1} \frac{2n-3}{(2n-2)(2n-1)}\epsilon + \frac{2n-3}{4n-2}\epsilon = \epsilon\big(-(n-1)\frac{2n-3}{(2n-2)(2n-1)} + \frac{2n-3}{4n-2}\big)$$
$$= \epsilon(-\frac{2n-3}{2(2n-1)} + \frac{2n-3}{4n-2}) = 0.$$

$j \neq 1$**:** Checking that total seats sold on flights from each $s_j \to h$ remains the same. There are three types of routes here: cases $2, 3, 4$. There is only one case 2 flight on this route. There is also only one case 3 flight and $n-2$ case 4 flights on this route. This causes an aggregate capacity change of

$$-\frac{2n-3}{(2n-2)(2n-1)}\epsilon + \frac{1}{(2n-2)(2n-1)} + (n-2)\frac{1}{(n-1)(2n-1)}\epsilon$$
$$= \frac{\epsilon}{(n-1)(2n-2)}(-(2n-3) + 1 + 2(n-2)) = 0.$$

Second set of constraints: Since the α's are constants, we again only need to match the ϵ's. It is thus equivalent to check:

$$q^{s_j \to s_i} = q^{s_j \to h} + q^{s_i \to h} \quad \forall 1 < i < j.$$

One can see that this is true because the LHS is a case (4) flight and the RHS are both case (3) flights. We can can see case (4) responds twice as much as case (3).

Final set of constraints: It is again equivalent to checking the ϵ's match in the simplified system

$$q^{s_j \to s_1} = q^{s_j \to h} + q^{s_1 \to h} - .5\epsilon \quad \forall j > 1.$$

The LHS is a case (2) flight, while the RHS is composed of a case (1) flight and a case (3) flight. We can simplify this to be

$$-\frac{2n-3}{(2n-2)(2n-1)}\epsilon \stackrel{?}{=} \frac{2n-3}{4n-2}\epsilon + \frac{1}{(2n-2)(2n-1)}\epsilon - .5\epsilon$$

$$\iff -\frac{2n-2}{(2n-2)(2n-1)} \stackrel{?}{=} \frac{2n-3}{4n-2} - .5$$
$$\iff 0 = \frac{1}{2n-1} + \frac{.5(2n-3)}{2n-1} - .5 \iff 0 \quad = 1 + n - 1.5 - .5(2n-1).$$

Now that we know these are the correct quantities we can simply substitute them into the demand equations to get the prices displayed in Proposition 1.

□

B Asymmetric Route Networks

Here we will consider two asymmetric route networks, R_1, R_2, in which we remove some of the routes from the main analysis in Section **??**. This can be thought of as stemming from a few different reasons: 1) these route simply do not exist for any carrier 2) a low cost carrier offers this route and is thus not carried by a legacy 3) the passengers are sufficiently inelastic where the airline does not change quantity in response to network shocks. The two networks are $R_1 = \{s_1 \to h, s_1 \to s_2, s_2 \to s_3, s_3 \to h\}$ and $R_2 = \{s_1 \to h, s_1 \to s_2, s_2 \to s_3, s_3 \to 4, s_4 \to h\}$. Assume the demand for all the flights is $q(p) = 1 - p$, and again there is a shock that increases the intercept for the $s_1 \to h$ flight by ϵ. In route network R_1 the quantity effects are $\Delta q^{1,h} = \Delta q^{2,3} = -\Delta q^{1,2} = -\Delta q^{3,h} = \frac{\epsilon}{8}$. Meanwhile for route network R_2 we have $\Delta q^{1,h} = \Delta q^{2,3} = \Delta q^{4,h} = -\Delta q^{1,2} = -\Delta q^{3,4} = \frac{\epsilon}{10}$. This shows that for routes of types (3) and (4) as defined in Section **??** the signs are ambiguous and are a function of the specific network structure.

Proof of Route 1. The quantity constraints continue to bind which implies

$$\Delta q^{1,h} = -\Delta q^{1,2}$$
$$\Delta q^{1,2} = -\Delta q^{2,3}$$
$$\Delta q^{2,3} = -\Delta q^{3,h}.$$

Additionally the marginal revenues must equate which yields the following equation

$$\text{MR}^{1,2} = \text{MR}^{1,h} + \text{MR}^{2,3} - \text{MR}^{3,h}$$
$$\iff \Delta q^{2,3} + \Delta q^{1,h} = \Delta q^{1,2} + \Delta q^{3,h} + \frac{\epsilon}{2}.$$

Combining these four equations yields the result. □

Proof of Route 2. Similarly we know all the quantity constraints continue to bind which implies

$$
\begin{aligned}
\Delta q^{1,h} &= -\Delta q^{1,2} \\
\Delta q^{1,2} &= -\Delta q^{2,3} \\
\Delta q^{2,3} &= -\Delta q^{3,4} \\
\Delta q^{3,4} &= -\Delta q^{4,h}.
\end{aligned}
$$

Here the marginal revenue constraint is

$$
\begin{aligned}
& \mathrm{MR}^{1,2} = \mathrm{MR}^{1,h} + \mathrm{MR}^{2,3} - \mathrm{MR}^{3,4} + \mathrm{MR}^{4,h} \\
\iff & \Delta q^{2,3} + \Delta q^{1,h} + \Delta q^{4,h} = \Delta q^{1,2} + \Delta q^{3,4} + \frac{\epsilon}{2}.
\end{aligned}
$$

Combining these five equations yields the result. □

C Data Construction

We begin with the Department of Transportation Databank 1B (DB1B), as processed by Severin Borenstein and archived on the NBER website. As noted by Borenstein and many other airline researchers, the DB1B data are not scrubbed for many errors. To minimize noise, we impose the following additional criteria. We keep tickets with prices between \$20 (already imposed in Borenstein's version) and \$5000. The reason for our \$5000 threshold is that for certain cities there are many coach tickets that are sold for exactly this amount despite the median fare being less than \$200, so we remove these tickets. We restrict the analysis to coach tickets for all carriers except Southwest. Southwest in particular classifies all their tickets as first class, despite having no first class cabin, and hence we include all their tickets.

We include indirect routings only if the carrier reports at least 10 tickets in a quarter (roughly one passenger per day given the 10% sampling in the DB1B). We include direct routes if they have at least 30 departures, as observed in the T100, for that carrier-quarter (roughly 2 flights per week).

We merge the data from the DB1B and T100 to create one data file. In our econometric framework we use the HHI of available sets on direct routes, and we calculate this using the number of seats flown from the T100. Using number of seats (capacity) in our measure of HHI seemed closest to our analysis based on airline capacity. When calculating carrier-specific prices we use the mean fare as observed in the DB1B.

D Robustness Checks

D.1 Demand Shock Regression using Percents

While the ARM heuristics described in Section 2.1 imply a relation between fare levels in dollars, Table 6 reports a regression (analogous to the levels regression performed in Section 4) based on percent changes in prices to illustrate the robustness of pass-through results using this alternative measure and implicit weighting across observations.

	$\%\Delta_q p_{A\to B\to C,i,y,2}$		Change in Direct Fare (\$) (First-Stage, $\%\Delta_q p_{A\to B,i,y,2}$)
	(1)	(2)	(3)
$1_{B=\text{Denver}} \times \%\Delta_q p_{A\to B,i,y,2}$	0.247		
	(0.007)		
$\%\Delta_q p_{A\to B,i,y,2}$		0.273	
		(0.077)	
Denver Snowfall			0.002
			(0.000)
Denver Snowfall^2			-0.000
			(0.000)
Origin	Yes	Yes	Yes
Destination	Yes	Yes	Yes
Year	Yes	Yes	Yes
Carrier	Yes	Yes	Yes
Estimator	OLS	IV	OLS
N	408,878	408,878	408,878
First-stage F statistic		156.915	

Table 6: Denver Regression with Percent Price Changes

To consider why levels is the correct interpretation, consider an indirect flight from Boston to Moscow with a layover in New York. If the flight from Boston to New York increases by 5%, \$10, meanwhile the New York to Moscow flight decreases by 2%, or \$50, it is clear to see that the indirect flight should decrease in price when thinking about opportunity costs. Doing the analysis in percents would yield the wrong conclusion.

D.2 General Layover Regression

Using Denver as an instrument provides a clear interpretation of demand shocks due to the ski season. However, in principle, any layover location could have shifts in the demand curve that would move direct fare prices. This specification is given by the following second- and first-stage estimating equations respectively:

$$\Delta_q p_{A\to B\to C,i,y,2} = \beta_p \Delta_q p_{A\to B,i,y,2} + \delta_y + \alpha^A + \alpha^C + \alpha^i + \epsilon_{A\to B\to C,i,y,2}, \tag{8}$$

$$\Delta_q p_{A\to B,i,y,2} = \gamma Z_{A\to B,y,2} + \delta_y + \alpha^A + \alpha^i + \epsilon_{A\to B,i,y,2}, \tag{9}$$

where $Z_{A\to B,y,2}$ is the layover airport of the indirect flight (i.e., airport B).

While using demand shifts at all layover airports yields more power in the first stage of the regression, it is harder to ensure the exclusion restriction is satisfied. With Denver, we could make sure that flights that continued on to ski destinations were excluded. It would be harder to know exactly why, for example, Phoenix had a shift in demand and ensure this was exogenous to indirect routes. Our pass-through estimate in this specification, including all layover locations, is 0.431 . The fixed effects for the ten largest airports in are given in Table 7.

Table 7: Fixed Effects for 10 Largest Airports

ATL	1.54
DEN	4.29
CLT	−3.59
PHX	−3.94
STL	−3.77
MSP	2.95
DTW	4.65
PIT	−0.63
SFO	6.17
CVG	−3.09

As a general pattern, it appears that warmer cities (e.g., PHX) had more travel in Q1 than Q2 (i.e., a positive demand shock in Q1) relative to colder cities (e.g., MSP), which experienced the opposite.

D.3 Entry Descriptive Statistics

Consistent with our presumption that capacity increased after the entry events, we see in the data that the treatment routes significantly increased their capacity and this lead to more passengers using both the direct and the indirect legs. Descriptive statistics for our entry sample are given in Table 8 below.

Table 8: Entry Sample Descriptive Statistics

	# Obs `Control`	**Mean** `Control`	**StdDev** `Control`	**# Obs** `Treatment`	**Mean** `Treatment`	**StdDev** `Treatment`
Indirect ($A \to B \to C$) Routes						
Fare ($)	977564	192.07	62.32	1533	189.53	59.11
Fare Change ($)	977564	4.73	53.79	1533	12.62	56.81
Fare Change (%)	977564	5.65	27.85	1533	9.08	30.55
Pax Change (%)	977564	26.08	81.06	1533	47.82	110.23
Direct ($A \to B$) Legs						
Fare ($)	84760	178.07	62.82	191	177.95	55.84
Fare Change ($)	84760	12.41	47.28	191	-8.51	54.46
Fare Change (%)	84760	7.69	27.5	191	-5.24	30.36
Pax Change (%)	84760	28.07	82.65	191	73.21	184.07
Seats Change (%)	84760	6.06	34.17	191	10.83	33.84
HHI (Seats)	84760	0.75	0.24	191	0.73	0.24

Notes: Descriptive statistics for the entry sample used in Section 5. This sample pools Southwest and Spirit entry events. # Obs tells the number of unique (route, operating carrier, year) tuples we observe in the data.

D.4 Merger Overlap Route Descriptive Statistics

Table 9 provides descriptive statistics for the nonstop overlap in our sample of mergers.

$A \leftrightarrow B$	$\lvert A \leftrightarrow B \leftrightarrow C \rvert$	**Merger**	$\Delta p_{A\to B,Mkt}$	$\Delta p_{A\to B\to C,Mkt}$	$\Delta p_{A\to B,M}$	$\Delta p_{A\to B\to C,M}$	$\%\Delta q_{A\to B,Mkt}$
MSP ATL	15.00	DL-NW	2.23	1.60	24.31	19.84	35.87
MEM ATL	24.00	DL-NW	0.25	0.37	3.10	-0.20	-7.90
DTW ATL	12.00	DL-NW	3.01	3.31	7.47	5.51	102.14
SFO HNL	10.00	DL-NW	0.97	2.09	NaN	NaN	7.38
LAX HNL	16.00	DL-NW	1.00	1.57	7.21	14.26	6.31
ORD EWR	6.00	UA-CO	1.26	5.76	3.52	11.63	-24.67
LAX HNL	15.00	UA-CO	2.45	2.99	11.31	11.32	9.30
SFO IAH	9.00	UA-CO	7.77	9.33	7.77	9.33	-1.42
ORD IAH	3.00	UA-CO	17.37	7.46	17.37	7.46	92.79
IAH DEN	7.00	UA-CO	4.22	4.50	4.22	4.50	24.59
EWR DEN	1.00	UA-CO	86.22	10.41	86.22	10.41	-34.96
SFO EWR	1.00	UA-CO	92.48	59.28	92.48	59.28	15.74
STL MCO	5.00	WN-FL	4.27	9.00	4.27	9.00	11.70
MKE LAS	14.00	WN-FL	1.17	2.24	1.17	2.24	19.76
RSW MDW	8.00	WN-FL	3.47	4.09	3.47	4.09	51.81
JAX BWI	11.00	WN-FL	3.80	2.75	3.80	2.75	24.71
TPA BWI	9.00	WN-FL	3.14	3.25	3.14	3.25	1.27
LAX BWI	4.00	WN-FL	4.15	9.27	4.15	9.27	106.29
MDW MCO	1.00	WN-FL	5.51	28.25	5.51	28.25	-4.56
BWI BOS	21.00	WN-FL	0.63	1.10	0.63	1.10	1.89
FLL BWI	11.00	WN-FL	1.42	0.86	1.42	0.86	-7.97
SEA BWI	6.00	WN-FL	7.76	0.10	7.76	0.10	55.05
SAT BWI	13.00	WN-FL	3.18	2.88	3.18	2.88	21.54
MCO BUF	3.00	WN-FL	6.95	8.06	6.95	8.06	-2.40
SAT MCO	5.00	WN-FL	9.29	4.14	9.29	4.14	15.71
RSW BWI	6.00	WN-FL	4.94	1.71	4.94	1.71	-8.09
PIT MCO	3.00	WN-FL	8.61	10.27	8.61	10.27	-11.87
MCO BWI	8.00	WN-FL	4.19	2.29	4.19	2.29	-14.06
MCO CMH	3.00	WN-FL	7.39	9.30	7.39	9.30	14.32
MCO IND	1.00	WN-FL	26.21	63.24	26.21	63.24	-8.77
MCO MCI	3.00	WN-FL	12.98	8.48	12.98	8.48	-4.17
MSY BWI	8.00	WN-FL	4.28	3.28	4.28	3.28	42.35
IND BWI	10.00	WN-FL	4.71	3.20	4.71	3.20	33.26
MKE BWI	6.00	WN-FL	6.12	5.94	6.12	5.94	-3.60
TPA PIT	1.00	WN-FL	34.09	0.97	34.09	0.97	-0.37
TPA IND	3.00	WN-FL	7.18	10.50	7.18	10.50	30.51
TPA MKE	2.00	WN-FL	15.08	32.32	15.08	32.32	-5.31
PHL MCO	2.00	WN-FL	7.34	34.38	7.34	34.38	-24.45
PHX PHL	9.00	US-HP	1.94	11.18	1.94	11.18	-21.12
PHL LAS	7.00	US-HP	7.25	9.43	7.25	9.43	6.53
PIT PHX	8.00	US-HP	-3.04	3.50	-3.04	3.50	-1.01
DFW CLT	41.00	US-AA	-0.32	-0.41	-0.32	-0.41	10.74
PHL DFW	19.00	US-AA	-1.34	1.10	-1.34	1.10	4.36
PHX DFW	45.00	US-AA	0.90	-0.05	0.90	-0.05	11.32
PHL MIA	5.00	US-AA	-0.24	-0.43	-0.24	-0.43	14.78
PHX ORD	16.00	US-AA	-1.58	-1.31	-1.58	-1.31	10.17
PHL ORD	1.00	US-AA	25.34	-25.74	25.34	-25.74	0.66

Table 9: Merging firms overlap routes and descriptive statistics for bidirectional direct markets. One carrier has a hub at either airport: blue. Two carriers have hubs at either airport: Red. Three carrier hub: Green. Four carrier hub: orange. Fare changes are given in dollars, calculated post minus pre-merger weighted by the number of passengers. *Mkt* calculates a market average, and *M* calculates an average for the merging firms. The final column gives the percent change in capacity at a market level.

D.5 Route Creation and Destruction after Mergers

Merger	DL-NW	UA-CO	WN-FL	US-HP	US-AA
Created $A \to B$	40.00	35.00	86.00	41.00	50.00
Created $A \to B \to C$	115.00	38.00	344.00	130.00	99.00
Destroyed $A \to B$	236.00	48.00	114.00	84.00	34.00
Destroyed $A \to B \to C$	878.00	70.00	237.00	364.00	35.00

Table 10: Route creation and destruction by merging firms after merger.