Market Power Spillovers Across Airline Routes

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Abstract

Airlines operate complicated flight networks, often utilizing hub-and-spoke systems to efficiently route connecting travelers and optimize costs. Despite the prevalence of connecting travelers—accounting for approximately one-third of passenger itineraries—most analyses of the welfare effects of changes in competition focus on nonstop routes. We show that when firms face capacity constraints or adjustment costs, a price decrease on a direct route may incentivize firms to decrease prices on indirect routes using this route as a leg. We document that this pass-through is positive using the price effects of low-cost carrier entry and airline mergers: connecting fares decrease after low-cost carrier entry on one of the legs and increase after a merger of carriers that competed on one of the legs. Our findings demonstrate that ignoring these network effects leads to significantly underestimating changes in consumer surplus—by up to 115%—in response to changes in competition. Thus, considering full airline networks is essential to accurately estimating the impact of changes in competition on consumers.

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1 Introduction

Airlines operate complicated flight networks, often utilizing a hub-and-spoke system to route connecting travelers through hubs in order to reduce costs and enhance service frequency. Despite the importance of network structure in airline industry outcomes and the fact that nearly one-third of passengers travel on connecting itineraries, most analyses of the price effects of changes in competition through airline entry and merger events abstract from the fact that airlines are competing on networks rather than on a route-by-route basis. In doing so, economists have often ignored how shocks to one route might propagate to other routes through these network connections.

An important exception to work studying airline competition route-by-route is a set of papers starting with Brueckner and Spiller (1991). This literature assumes airlines benefit from economies of density or scale that arise at the service-segment level, where several different city-pair routes may share capacity. The economies of density imply that increased competition in one direct (spoke) city-pair market of a hub-and-spoke network leads to price increases on indirect routes that share the same service segments but did not have a change in competition. These effects arise because increased competition in a non-stop market (e.g., entry by a low-cost carrier) will cause the incumbent airlines in that market to reduce their quantity in that market, which then increases marginal costs and prices in the related indirect markets. In turn, reductions in the incumbents' quantities on the indirect routes, may lead to further quantity reductions and price increases on other direct routes that share other service segments with those indirect routes. The existence of such effects would imply that estimates of the benefits of entry or of the costs of merger-induced price increases based only on the immediately affected markets would overstate the true overall effects.

In this paper, we highlight a new effect that results in the opposite prediction: when firms face capacity constraints or adjustment costs, a decrease in price on a direct route may incentivize firms to decrease price on indirect routes sharing a service segment (a "leg") with that direct route. This prediction follows from an opportunity cost effect. The opportunity cost effect is driven by two forces. First, every seat taken by a passenger on an indirect flight could be sold to direct passengers, and second, an inability to adjust capacity costlessly. When these forces interact, a decrease in the marginal revenue of a direct passenger (e.g. from changes in competition) leads the airline to sell more tickets to indirect passengers, lowering the price of the indirect flight. In turn, this change can lead to further price reductions on direct routes that share service segments with the affected indirect routes.

We empirically document that the opportunity cost effect dominates after changes in market structure due to entry and merger events, resulting in positive *pass-through* of competition shocks on direct flights to the fares of indirect flights, even though the indirect flights themselves did not experience a change in competition. We provide further support for this result by discussing Airline Revenue Management systems and how the heuristics they use to set fares are consistent with the positive relationship we observe between direct fares and indirect fares.

To build intuition, consider the short-run effects of a change in competition on a route. Here, the airline's choice of capacity on that and all neighboring routes can be thought of as fixed. Hence, in the short run, the opportunity cost effect will dominate, creating positive pass-through. As the time horizon expands and firms have a greater ability to adapt to the change in market structure, the economies of scale effect in Brueckner and Spiller (1991) strengthens. However, capacity changes being easier in the long run than the short run need not imply making these changes is profitable for the airline. For instance, if capacity adjustments are costly or must be made in discrete quantities (e.g., the airline cannot add a few seats to an already full route, it must schedule a new flight entirely), then airlines may rationally choose not to change capacity. In such cases, the opportunity cost effect may continue to be the empirically relevant effect even in the long run.

In contrast to the implications following from economies of density, positive pass-through of shocks on direct flights to indirect flights implies that ignoring such spillovers results in underestimating the consumer surplus effects of changes in competition. This fact can have important implications for antitrust enforcement; for example, given limited antitrust agency resources for investigating mergers, it is important to consider the full scope of the likely effects of changes in competition to appropriately target enforcement.

The paper is organized as follows. We begin in Section 2 by developing a simple model of a multi-product firm that faces a shock to one product. We characterize how this shock affects the price of the firm's other product, highlighting the trade-off between the economies of scale effect (induced by exogenously allowing for economies of scale in firm production) and the opportunity cost effect (induced by capacity adjustment costs). We provide conditions on the magnitude of economies of scale and adjustment costs under which there is positive pass-through of a shock to one product to the price of the other product. We then discuss Airline Revenue Management systems and how the heuristics they use to price flights are consistent with the opportunity cost effect, implying positive pass-through.

Our empirical analysis is contained in Sections 3-5. In Section 3, we first 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.

In Section 4, we examine the impact of low-cost carrier (LCC) entry events. 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 may understate welfare effects by as much as 50%. We then provide evidence consistent with high capacity adjustment costs by showing that there was insignificant capacity adjustment by incumbents after LCC entry events. Finally, we document that after entry by some LCCs, pass-through rates remain positive many years after the initial entry event, whereas some pass-through rates become noisily estimated as the entry instrument loses power.

In Section 5, we study a series of airline mergers that have occurred since 2005. Although 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 115%, with a median understatement of 31%.

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, as noted above, we highlight the importance of capacity constraints and adjustment costs for how shocks propagate through airline networks compared to a literature that has focused on modeling the relationships between fares within an airline network due to economies of density.[1] This difference leads to dramatically different predictions about the propagation of shocks.[2] This paper also identifies an important missing aspect in the analyses of competitive changes, such as mergers, in airline markets (see, for example, Borenstein, 1990; Werden et al., 1991; Peters, 2006; Luo, 2014; Hüschelrath and Müller, 2014; Carlton et al., 2019; Das, 2019;

[1]This literature includes both theoretical work (e.g., Brueckner and Spiller, 1991) and empirical work (Brueckner et al., 1992; Brueckner and Spiller, 1994; Bamberger and Carlton, 2002; Berry et al., 2006) focused on the effects of changes in competition. Also closely related 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.

[2]We compare our empirical strategy with the that of Brueckner et al. (1992) and Brueckner and Spiller (1994) in Section 4.

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.

Similarly, previous papers estimate the price effects of low-cost carrier entry (Morrison, 2001; Brueckner et al., 2013; Tan, 2016) and potential entry (Goolsbee and 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 were passed through to connecting routes. We show that the consumer surplus effects of entry events are understated when the propagation of shocks from nonstop to connecting routes is ignored.

This paper also contributes to a literature in economics that has analyzed the implications of Airline Revenue Management systems for consumer welfare in airline markets, including Hortaçsu et al. (2021) and Williams (2022). We highlight how the heuristics airlines use to set fares have implications for estimating the welfare effects of changes in competition.

Finally, this paper is related to theoretical and empirical work on 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, 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

In this section, we develop a model of a multi-product firm to show how a demand shock to one product can affect other products that face interrelated costs. The model builds upon Brueckner and Spiller (1991) by explicitly incorporating capacity adjustment costs in addition to economies of scale. Although still stylized, the model helps disentangle the economies of scale effect with the capacity constraint effects we study.

There are two products, $i \in \{1, 2\}$, which the firm produces Q_1 and Q_2 units of, respectively.[3] Production of these two products faces a common cost function $c(\cdot)$, so the cost of producing Q_1, Q_2 units is given by $c(Q)$, where $Q = Q_1 + Q_2$. We assume that the

[3] Adding more products does not fundamentally change the analysis.

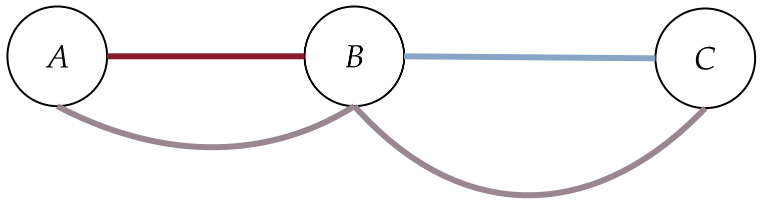


Figure 1: Correlation between direct and indirect fares.

cost function has the following parametric form, $c(Q) = \frac{Q^\beta}{\beta}$. We focus on the case where the firm has economies of scale in production, $\beta < 1$.[4]

Although the products are related through supply costs, each product $i \in \{1, 2\}$ has an independent inverse demand curve $P_i(Q_i)$. The only assumption we make on P_i is that $P_i(Q_i)$ is decreasing and that the resulting revenue curve $Q_i P_i(Q_i)$ is concave with a strictly interior optimum. These assumptions ensure that the solution to our problem corresponds to a unique solution to the first-order condition.

To study the relationship between direct and indirect fares in the airline industry, product 1 can be viewed as a direct flight from airport A to airport B, and product 2 can be viewed as an indirect flight from airport A to airport C with a layover at airport B, as shown in Figure 1.

We analyze how a firm in such an environment adapts its prices of product 2 when a demand shock occurs only to product 1. In particular, suppose that an unexpected inverse demand shock occurs, shifting the demand of product 1 such that $P_1^{\text{new}}(Q_1) = P_1(Q_1) + \epsilon$ with $\epsilon > 0$. With no cost to changing capacity, this mimics the setup in Brueckner and Spiller (1991). In this case, the model predicts that due to the increase in demand, the firm increases the quantity supplied in market 1. This decreases the marginal cost for quantity in market 2 and the decreased marginal cost is passed onto the consumers in terms of lowered fares. Hence, the unaffected market has a predicted price decrease.

However, within the airline industry and many others, it is not costless to adjust capacity. To model this, we assume that firms can adjust their capacity from Q_{old} to Q_{new} and incur adjustment cost $\mu f(Q_{\text{new}} - Q_{\text{old}})$, while paying $c(Q_{\text{new}})$ for this new capacity. Note that after setting $\mu = 0$, the firm does not experience adjustment costs and the analysis is unchanged from the preceding paragraph. To proceed with our first-order condition approach, we assume that $f()$ is symmetric, convex, and satisfies $f'(0) = 0$.

In summary, the timing of the pricing game we will consider is as follows:

[4] If there were instead diseconomies of scale, then costs would increase after increasing quantity, providing an incentive for the firm to increase prices. This diseconomies of scale effect would then give the same prediction as the opportunity cost effect. We do not focus on this case theoretically as there is no ambiguity, and as documented in Brueckner et al. (1992) there are, if anything, economies of density.

(i) The firm chooses how many units Q_i to produce for products $i \in \{1, 2\}$ at cost $c(Q) = \frac{Q^\beta}{\beta}$ where $Q = Q_1 + Q_2$.

(ii) An unexpected demand shock occurs to product 1 shifting the inverse demand curve as follows: $P_1^{\text{new}}(Q_1) = P_1(Q_1) + \epsilon$ with $\epsilon > 0$.

(iii) The firm can adjust its total capacity at cost $c(Q_{\text{new}}) + \mu f(Q_{\text{new}} - Q_{\text{old}})$.

(iv) The firm sets updated prices in accordance with maximizing their revenue given their new capacity.

This model aims to differentiate between two different factors that affect the pricing decision. The first factor is the *economies of scale effect*, namely if the economies of scale are sufficiently strong and adjustment costs are sufficiently small, the firm is incentivized to increase total capacity. This decreases the marginal cost of capacity, which decreases the price of the second product.

The second factor is the *opportunity cost effect*. This force is most easily seen when capacity cannot be adjusted, i.e. $\mu = \infty$. When the demand shock occurs on product 1, this increases the marginal revenue of product 1, and since it is impossible to adjust capacity the firm will choose the quantities of the two products to equate their marginal revenues. Before the shock, the firm equalized the marginal revenues of the two products. Now, post-shock, the marginal revenue of product 1 increases at the pre-shock quantities, so the marginal revenue of product 2 must go up, implying the quantity of product 2 must decrease, thus causing a price increase.

When does each effect, namely economies of scale or opportunity cost, dominate? Intuitively, β scales the strength of the economies of scale effect and μ scales the strength of the opportunity cost effect. One interpretation of μ is the time horizon. For instance, the day after the shock, it would be extremely costly to change capacity resulting in μ being large. However, if the time horizon is many years μ is likely smaller.[5] However, even in the long run, capacity adjustments may be costly. If the firm procures another plane for this route, it must integrate that plane into its overall flight network, which will be costly due to both procurement and planning costs. Hence, we can vary μ to analyze the short-run and long-run effects of demand shocks. In the long run, the comparison is ambiguous and depends on how costly capacity changes are. In the very short run, when capacity changes are extremely costly $\mu \gg 0$, we expect the opportunity cost effect to dominate.

We now analyze the trade-off between the opportunity cost and economies of scale

[5]One interpretation is that every time period after the shock the firm can pay the adjustment cost. As $f'(0) = 0$, in the long-term eventually the firm will fully adjust its capacity.

effects in the long run. For convenience, we will normalize the quantity such that in the pre-shock period the total quantity is 1.[6] Proposition 1 gives necessary and sufficient conditions on the parameters μ and β for the price of product 2 to increase after a positive demand shock to product 1. All proofs are given in Appendix A.

Proposition 1. Given inverse demand curves $P_1(Q_1), P_2(Q_2)$, when the firm experiences a demand shock for product 1, the price change for product 2, defined as $\Delta(\mu, \beta)$, has the following properties:

(i) $\Delta(\cdot, 1) \geq 0$ and $\Delta(0, \cdot) \leq 0$.

(ii) Holding fixed the quantities before the shock, we have $\frac{\partial \Delta}{\partial \mu} \geq 0$ and $\frac{\partial \Delta}{\partial \beta} \leq 0$.

The intuition behind statement (i) is that when $\beta = 1$, the economies of scale effect has been shut down and the opportunity cost effect is nonzero, causing a price increase (positive pass-through). Furthermore, when $\mu = 0$ capacity can be adjusted costlessly, and thus the economies of scale effect dominates, causing a price decrease (negative pass-through).

Statement (ii) has a similar intuition: when μ increases (holding β fixed), the opportunity cost effect becomes stronger, thus the price increases become larger. Similarly, when β increases, the economies of scale effect becomes smaller, and the price decreases become smaller. Hence, depending on the magnitude of μ and β, the price change of product 2 after a demand shock to product 1 may, in fact, be ambiguous. In the remainder of this paper, we test for the sign and magnitude of this effect.

2.1 Airline Revenue Management Systems

The simple model above demonstrates how shocks to a direct route can propagate through an airline network and presents a trade-off between an economies of scale effect and an opportunity cost effect governed by capacity adjustment costs. In this section, we summarize institutional details of how airline fares are set and argue that they suggest that the opportunity cost effect will generally dominate, so that pass-through of shocks from direct to indirect routes will be positive.

Airline revenue maximization is a highly complex network optimization problem due to the number of products offered, price discrimination, and competition, among other

[6]This assumption is not necessary for our main conclusions. This assumption allows the total market capacity in the pre-period to be independent of the economies of scale present. If not, the degree to which there are economies of scale changes based on where the original quantity is on the marginal revenue curve, which would contaminate the opportunity cost effect. To compute this normalization, do the following: if quantities before the shock were y, precompose P_i, $c()$, and $f()$ with $g(x) = \frac{x}{y}$.

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 focus of airlines on price discrimination on direct routes have led airlines to rely on various heuristics to maximize their revenues over their networks.

While the pricing software currently in operation is proprietary and complicated, [7] 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 that realized 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 when they show up to buy. For simplicity, we will assume that 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.[8] 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 not 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.

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 called "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

[7]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.

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

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.

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 $A \to B$ 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 in turn would lower the average fare) to compete with 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 the 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. Therefore, when we look at average fares on a given market, the average fare will decrease. Through this mechanism, we claim that a price change on a direct route will *cause* a price change on an indirect route. This mechanism also motivates our estimation equations, which we discuss in more detail in the next section.

3 Data and Descriptive Statistics

We now turn to an empirical analysis of the relationship between indirect fares and direct fares of flights that form 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 two exercises to estimate pass-through after entry events by LCCs 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).[9] The DB1B includes a 10% random sample of all domestic airline tickets used in each quarter. We restrict the sample to round-

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

trip coach tickets.[10] We calculate average fares and the total number of passengers for each route-operating carrier-quarter combination.[11] 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.[12] For our main analysis, 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 of the T100 is that it does not record information on the number of passengers flying 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 the 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 traveled 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 entry sample, used in Section 4, to provide causal estimates of pass-through after entry by LCCs. Further details about our data construction process are provided in Appendix B.

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

[11] 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.

[12] 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.

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 ($A \to B \to C$) Routes						
Fare ($)	1380880	193.53	61.74			
Fare Change ($)	1380880	4.52	46.0			
Fare Change (%)	1380880	4.75	23.65			
Pax Change (%)	1380880	17.61	66.55			
Direct ($A \to B$) Legs						
Fare ($)	115385	181.53	64.84			
Fare Change ($)	115385	7.75	38.63			
Fare Change (%)	115385	4.6	22.03			
Pax Change (%)	115385	15.36	61.16			
Seats Change (%)	115385	3.15	25.45			
HHI (Seats)	115385	0.74	0.25			
Entry Sample						
Indirect ($A \to B \to C$) Routes						
Fare ($)	484262	200.4	71.44	2464	210.24	74.29
Fare Change ($)	484262	7.05	47.59	2464	5.44	49.47
Fare Change (%)	484262	6.11	23.33	2464	5.16	21.66
Pax Change (%)	484262	14.36	68.73	2464	16.49	73.81
Direct ($A \to B$) Legs						
Fare ($)	49333	201.71	70.94	276	229.27	67.82
Fare Change ($)	49333	10.45	41.73	276	-20.93	49.9
Fare Change (%)	49333	5.95	23.58	276	-11.36	29.54
Pax Change (%)	49333	11.0	48.48	276	15.73	40.77
Seats Change (%)	49333	0.73	25.62	276	5.38	23.48
HHI (Seats)	49333	0.72	0.24	276	0.7	0.25

Notes: The first (General Sample) and second (Entry Sample) panels give descriptive statistics for the general sample used in Section 3.2 and the entry sample used in Section 4, respectively. For both samples, differences are calculated as one year after minus one year before a given time (e.g., 2016 Q4 $-$ 2014 Q4, 2016 Q3 $-$ 2014 Q3, $\ldots$). 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. 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.[13] 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. Let $\%\Delta_y p_{A\to B,i,y,q}$ denote the change in fare in percents. To characterize the relationship between the direct $A \to B$ and indirect $A \to B \to C$ fare changes, we estimate the following regression

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

where $\alpha^{y,q}$ is a year-quarter fixed effect to control for both time and seasonal trends, α^A is an origin fixed effect, α^C is a destination fixed effect, and α^i is a carrier fixed effect.[14] We will weight the above equation by how many tickets we observe for the indirect $A \to B \to C$ route in the pre-period, year $y-1$ quarter q. 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 due to 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 q of year $y+1$ to quarter q of year $y-1$. Similarly, we calculate $\Delta_y p_{A\to B,i,y,q}$ as the change in fare on the direct $A \to B$ flight that is the first leg of the $A \to B \to C$ flight from quarter q of year $y+1$ to quarter q 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

[13] 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 that 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.

[14] 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, and we include this robustness check in Section 4.

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

	Change in Indirect Fare ($) $\Delta_y p_{A \to B \to C,i,y,q}$			Change in Indirect Fare (%) $\%\Delta_y p_{A \to B \to C,i,y,q}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	3.838			0.037		
	(0.037)			(0.000)		
$\Delta_y p_{A \to B,i,y,q}$	0.240	0.176	0.150			
	(0.001)	(0.001)	(0.001)			
$\Delta_y p_{B \to C,i,y,q}$			0.148			
			(0.001)			
$\%\Delta_y p_{A \to B,i,y,q}$				0.211	0.162	0.136
				(0.001)	(0.001)	(0.001)
$\%\Delta_y p_{B \to C,i,y,q}$						0.133
						(0.001)
Origin		Yes	Yes		Yes	Yes
Destination		Yes	Yes		Yes	Yes
Carrier		Yes	Yes		Yes	Yes
Year Quarter		Yes	Yes		Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	1,380,880	1,380,871	1,380,871	1,380,880	1,380,871	1,380,871
Adjusted R^2	0.046	0.131	0.145	0.042	0.133	0.147

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

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. Columns (4)-(6) present the same set of regressions in percents. The results are similar to the regressions in levels.

4 Pass-Through after Entry Events

In this section, we present estimates of pass-through from direct to indirect fares after one type of competition shock: entry by LCCs.[15] We provide suggestive evidence that

[15]Section 5 presents estimates of pass-through after a different type of competition shock, mergers. In addition to estimating pass-through after competition shocks, we also estimate pass-through after demand shocks as a robustness check in Appendix C.1. We find similar estimates of pass-through after demand shocks.

Table 3: Low-cost carrier entry events

Airline	Code	Entry Date
Frontier	F9	1994
JetBlue	B6	2000
Southwest	WN	1971 (1990)
Spirit	NK	1992

Notes: This table includes the set of LCCs included in the analysis and the year of their entry. For Southwest, the first year is the year of entry and the second year is the year we start considering entry, since we consider data starting in 1990.

positive pass-through is driven by firms' inability to adjust capacity costlessly. We then quantify the understatement to estimates of consumer surplus that results from ignoring positive pass-through from direct to indirect routes.

4.1 Pass-Through Estimation

We analyze the entry of LCCs between 1990 and 2016. The carriers whose entry events we study and their first date of entry are shown in Table 3.[16] While Section 3.2 provided descriptive evidence of pass-through in general, Equation 1 suffers from concerns of endogeneity and simultaneity. 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, where we instrument for direct fare changes using exogenous changes to direct route fares. Here, we use the entry of one of these low-cost carriers as the shock to the direct fares of the incumbent carriers. More precisely, we instrument for the change in direct fare with an indicator for whether an LCC entered that route during a given quarter. Standard economic theory suggests 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.

We first discuss the construction of our pooled sample (i.e., consider entry events by all the carriers in Table 3). Our sample of treatment routes (i.e., those routes that receive a nonzero value of the instrument) experiencing entry events is constructed as follows.

[16]This list includes all low-cost carriers (not regional carriers) that entered between 1990 and 2016, with the exception of Allegiant Air and Sun Country. We exclude Allegiant Air because after removing routes that violate the exclusion restriction (described in the sample creation part of this section), fewer than 10 treatment routes remain for the analysis. We exclude Sun Country as a majority of their routes are offered seasonally (i.e., not persistent entry). Avelo Airlines and Breeze Airways entered after the end of our sample.

We define an LCC as having entered a direct route $A \to B$ in period t (where a period is a year, quarter tuple) if that carrier operates at least 30 direct flights on that route in period t and did not do so in any previous period.[17] We then remove all indirect routes $A \to B \to C$ for which a LCC also contemporaneously entered any competing $A \to C$ service (direct and indirect via any airport D). Therefore, indirect $A \to B \to C$ routes in our treatment sample did not also simultaneously experience entry onto $B \to C$.[18] This eliminates spatial correlation in entry patterns. Our sample of control routes (i.e., those routes that receive a zero value of the instrument) includes all other indirect routes in the DB1B.[19]

We also consider treatment samples that restrict to only routes entered by a particular LCC.[20] This allows us to separately estimate pass-through rates for each set of entry events. The treatment samples for these cases are constructed analogously to the above but restrict entry to a particular carrier.

The routes the LCCs choose to enter are not exogenous. One potential exclusion restriction violation of using entry on $A \to B$ as an instrument for direct fares on that route is that a carrier enters $A \to B$ because of an increase in profitability in city A (e.g., Tesla's headquarters move to Austin). However, this would imply that the prices that carriers can charge out of A have increased. Therefore, absent positive pass-through, we would expect the prices of $A \to B \to C$ to increase due to increased profitability but the prices of $A \to B$ to decrease 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 that they are already operating other routes out of both endpoints. That is, if Southwest entered $A \to B$ in period t, they may also have entered $A \to C$ in period t, which could affect $A \to B \to C$ fares. We explicitly exclude such entry events from our sample.

Similarly, another potential violation of the exclusion restriction is that, after entry into $A \to B$, other rival fares in $B \to C$ drop as Southwest may now be a *potential* entrant on $B \to C$. In some cases, Southwest may already have been operating other flights out

[17] 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 5.

[18] 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 $A \to B \to C$ flights where Southwest also started operating $B \to C$.

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

[20] There could, however, still be simultaneous or subsequent entry by *other* LCCs.

of airports A, B, and C, so its status as a potential entrant in $B \rightarrow C$ would not change after entering $A \rightarrow B$. In addition, a fixed effect for B or control for $\Delta p_{B \rightarrow C}$ could be used 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.[21]

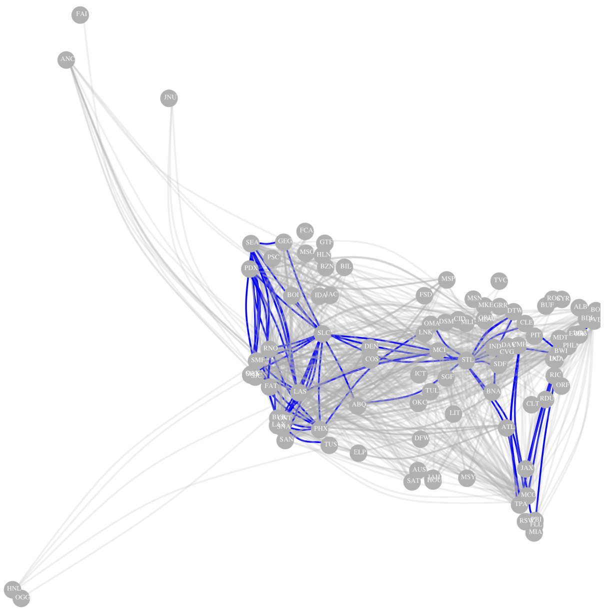
To show the number of indirect routes we would predict to also experience fare changes due to positive pass-through, Figure 2 plots the entry of Southwest into nonstop routes between 1990 and 2016, with entry into nonstop markets in blue and indirect routes sharing a leg with direct routes in gray. In our sample, entry onto 157 $A \rightarrow B$ routes by Southwest affected 1703 $A \rightarrow B \rightarrow C$ indirect routes.[22] Figure 3 shows a binscatter of the changes in nonstop and connecting fares by rival (i.e., not Southwest) carriers after Southwest entry events onto those direct routes.[23]

[21]For the pooled regression these yield pass-through estimates of 0.136 and 0.123 , respectively. However, due to similar endogeneity concerns, an instrument would also be required for $\Delta p_{B \rightarrow C}$.

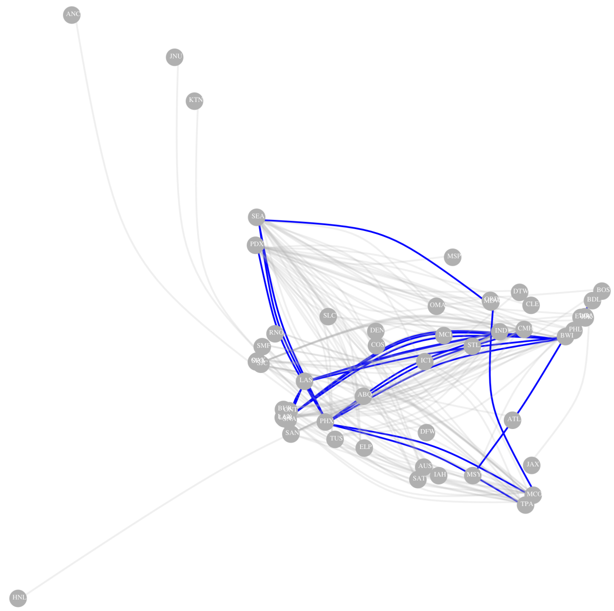
[22]These routes are calculated after excluding the $A \rightarrow C$ routes discussed above that may violate the exclusion restriction for the instrument. Therefore, these numbers are lower bounds on the number of indirect routes that could have experienced fare changes after direct entry events because of positive pass-through.

[23]For brevity we only show these figures for Southwest entry events – figures for other LCCs show the same qualitative patterns.

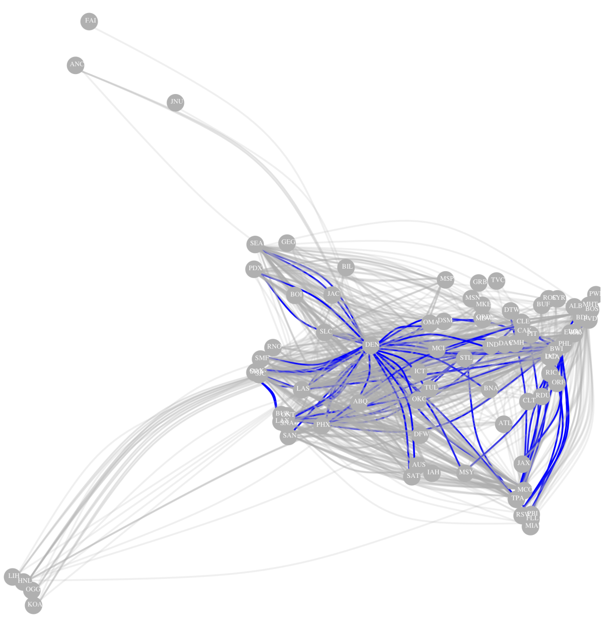
Figure 2: Southwest entry into nonstop markets: 1990 - 2016



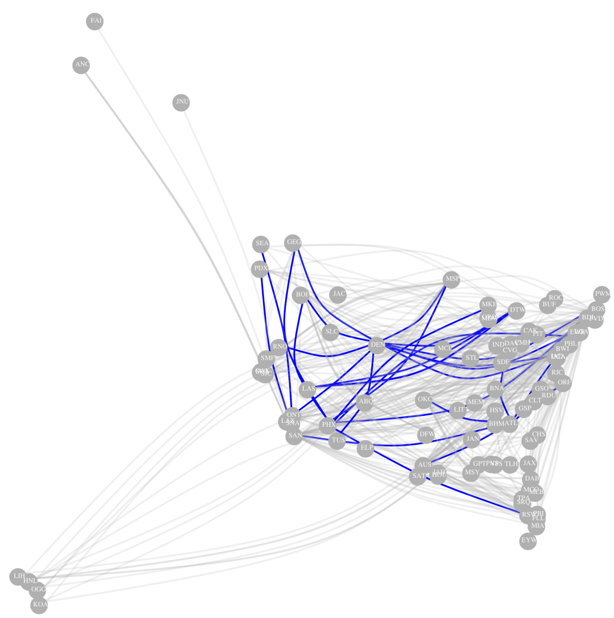
(a) 1991 Q1 - 1997 Q3



(b) 1997 Q4 - 2003 Q4



(c) 2004 Q1 - 2010 Q2



(d) 2010 Q3 - 2016 Q3

Notes: Direct routes (i.e., $A \to B$) that Southwest entered in the given time period are colored in blue. Indirect routes (i.e., $A \to B \to C$) that we predict to experience fare changes because of entry onto $A \to B$ are colored in grey, where we plot the $A \to C$ component of the route.

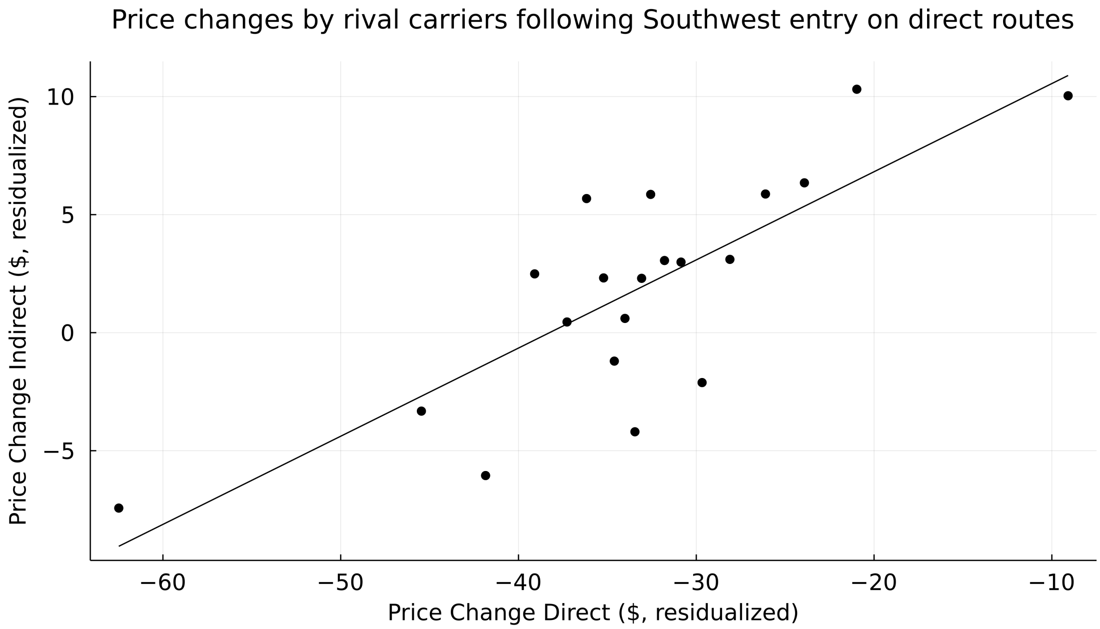


Figure 3: Notes: Binscatter of the fare changes on direct routes versus indirect for direct routes that experienced Southwest entry. We include origin, destination, carrier, and time (year-quarter) fixed effects.

Our estimation equations are

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

$$\Delta_y p_{A\to B,i,y,q} = \gamma 1_{\text{Entry by Carrier on route},i,y,q} + \alpha^{y,q} + \alpha^A + \alpha^i + \epsilon_{A\to B,i,y,q}. \tag{3}$$

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.[24]

Table 4 presents OLS estimates of pass-through. More formally, the estimating equation is exactly that of Equation 2 except the price change is multiplied by the indicator for entry. We present an estimate of pass-through for each carrier separately and a pooled regression. Each carrier caters to a different demographic of customers, implying different cross-price elasticities and routes. Therefore, pass-through rates may differ across carriers. The results are consistent with positive pass-through to indirect fares after entry events onto direct routes, but may be subject to endogeneity concerns.

To understand the changing sample sizes across specifications, note that our sample construction states that if carrier i enters route $A \to B$ and $A \to C$ at time t, this route is

[24]Throughout the paper we weight the regressions by the number of passengers in the pre-period, i.e. before the shock. As a robustness check, we ran an unweighted regression for the pooled results to find an even higher pass-through of 0.163 . This is because smaller routes are more likely to be capacity constrained and thus exhibit larger pass-through.

Table 4: Entry pass-through estimates: OLS

	Change in Indirect Fare ($) $\Delta_y p_{A\to B\to C,i,y,q}$				
	Pooled	Frontier	Jetblue	Southwest	Spirit
$\Delta_y p_{A\to B,i,y,q}$	0.109	0.167	0.103	0.184	0.173
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Estimator	OLS	OLS	OLS	OLS	OLS
N	486,706	1,036,162	659,969	1,259,649	1,240,545
First-stage F statistic					

Notes: All regressions include origin, destination, carrier, and time (year-quarter) fixed effects.

removed from our treatment group (as this route would violate the exclusion restriction). Furthermore, since $A \to B$ experienced entry on the route, $A \to B \to C$ does not belong in the control group either, as this would bias the first-stage regression, and thus it is removed from the control group as well. Since different carriers have different entry patterns, this results in asymmetric sample sizes across carriers. As the pooled sample imposes these restrictions across all carriers, it has the smallest sample size.

To address endogeneity concerns, we present results from instrumental variable regressions. Tables 5 and 6 present the first stage in dollars and percents, respectively,[25] showing how much direct fares decreased after entry by LCCs. Across the different carriers, incumbent fares dropped between 5% and 21% after LCC entry, with Southwest entry events having the largest effect.

[25]We include percents to show robustness of the results to controlling for distance, however, we believe the correct interpretation is dollars. Consider an $A \to B \to C$ flight where the $A \to B$ flight experienced a price drop from 1000 dollars to 900 but the $B \to C$ flight experienced a price increase from 100 to 150 dollars. Using percents in the analysis would suggest the indirect flight price should go up; however, the effective marginal cost went down. Hence, dollars is the correct interpretation.

Table 5: Entry pass-through first-stage estimates: Levels

	$\Delta_y p_{A\to B,i,y,q}$				
	Pooled	Frontier	Jetblue	Southwest	Spirit
$1_{\text{Entry } A\to B}$	-26.269				
	(0.759)				
$1_{\text{Entry } A\to B}$		-32.837	-39.720	-39.824	-13.072
		(1.646)	(1.970)	(0.876)	(0.863)
Estimator	OLS	OLS	OLS	OLS	OLS
N	486,706	1,036,162	659,969	1,259,649	1,240,545
F	1197.134	398.145	406.523	2068.427	229.656

Notes: All regressions include origin, destination, carrier, and time (year-quarter) fixed effects.

Table 6: Entry pass-through first-stage estimates: Percents

	$\%\Delta_y p_{A\to B,i,y,q}$				
	Pooled	Frontier	Jetblue	Southwest	Spirit
$1_{\text{Entry } A\to B}$	-11.618				
	(0.378)				
$1_{\text{Entry } A\to B}$		-15.672	-13.279	-21.337	-5.448
		(0.907)	(0.984)	(0.499)	(0.476)
Estimator	OLS	OLS	OLS	OLS	OLS
N	486,706	1,036,162	659,969	1,259,649	1,240,545
F	943.243	298.504	182.168	1826.694	130.914

Notes: All regressions include origin, destination, carrier, and time (year-quarter) fixed effects.

Tables 7 and 8 present IV estimates of pass-through in dollars and percents, respectively. Table 7 shows that a 1 dollar decrease in fares on the direct route causes a 14 cent decrease in fares in the pooled sample and between a 10 cent and 31 cent decrease in fares after entry by the different LCCs in our sample. Table 8 shows similar results in percents.

Table 7: Entry pass-through second-stage: Levels

	Change in Indirect Fare ($) $\Delta_y p_{A\to B\to C,i,y,q}$				
	Pooled	Frontier	Jetblue	Southwest	Spirit
$\Delta_y p_{A\to B,i,y,q}$	0.136	0.178	0.311	0.106	0.174
	(0.031)	(0.056)	(0.054)	(0.025)	(0.073)
Estimator	IV	IV	IV	IV	IV
N	486,706	1,036,162	659,969	1,259,649	1,240,545
First-stage F statistic	1198.464	398.383	406.862	2069.500	229.774

Notes: All regressions include origin, destination, carrier, and time (year-quarter) fixed effects.

Table 8: Entry pass-through second-stage: Percents

	Change in Indirect Fare (%) $\%\Delta_y p_{A\to B\to C,i,y,q}$				
	Pooled	Frontier	Jetblue	Southwest	Spirit
$\%\Delta_y p_{A\to B,i,y,q}$	0.130	0.049	0.253	0.137	0.252
	(0.034)	(0.059)	(0.080)	(0.024)	(0.089)
Estimator	IV	IV	IV	IV	IV
N	486,706	1,036,162	659,969	1,259,649	1,240,545
First-stage F statistic	944.291	298.682	182.319	1827.642	130.981

Notes: All regressions include origin, destination, carrier, and time (year-quarter) fixed effects.

These regressions suggest that when an LCC enters a route, the indirect routes serviced by incumbent carriers using this route as a leg exhibit price decreases. This result of positive pass-through predicts the opposite relationship between direct and indirect fares to the force illustrated in Brueckner et al. (1992), which predicts negative pass-through stemming from economies of scale. Brueckner et al. (1992) regresses indirect route fares on measures of network interconnectivity and shows that fares are lower on denser networks, which suggests economies of scale are present in airline networks. However, Brueckner et al. (1992) does not directly estimate pass-through after entry events. Tables 7 and 8 do not imply that economies of scale do not exist, but do suggest that the opportunity cost effect dominates after entry events by LCCs.

4.2 Capacity and Pass-through

The simple theory in Section 2 predicts that positive pass-through stems from an airline's inability to costlessly adjust capacity across its routes. Standard economic theory

Table 9: Entry pass-through second-stage

	$\Delta_y s_{A\to B,y,q}$	$\%\Delta_y s_{A\to B,y,q}$	$\Delta_y s_{B\to C,y,q}$	$\%\Delta_y s_{B\to C,y,q}$
	(1)	(2)	(3)	(4)
$1_{\text{Entry } A\to B}$	1294.136	0.013	-1313.250	-0.058
	(841.542)	(0.020)	(1258.757)	(0.031)
Carrier	Yes	Yes	Yes	Yes
Year Quarter	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS
N	49,609	49,609	49,466	49,466

Notes: All regressions include origin, destination, carrier, and time (year-quarter) fixed effects.

predicts that following entry into a market, all remaining firms will have an incentive to decrease their quantity. Hence, if capacity was costless to adjust, we would expect to see all incumbent carriers decreasing their capacity in this market following entry by a low-cost carrier into the $A \to B$ market. This section provides evidence of limited capacity adjustment after entry by LCCs, which is consistent with adjustment costs and frictions.

We estimate the following equation

$$\Delta_y q_{A\to B,i,y,q} = \kappa 1_{\text{Entry by Carrier on } A\to B,i,y,q} + \alpha^{y,q} + \alpha^i + \epsilon_{A\to B,i,y,q}, \tag{4}$$

where $\Delta_y q_{A\to B,i,y,q}$ is the change in seats (capacity) offered by carrier i on route $A \to B$ from year $y+1$ quarter q to year $y-1$ quarter q, calculated from the T100. We estimate this equation for both levels and percents of capacity changes. $1_{\text{Entry by Carrier on } A\to B,i,y,q}$ is an indicator for whether a LCC entered route $A \to B$ at year y quarter q. We include year-quarter fixed effects to capture aggregate trends in capacity adjustment and carrier fixed effects to control for how different carriers may be differently able to adjust to capacity changes (e.g., based on the size of their fleets).

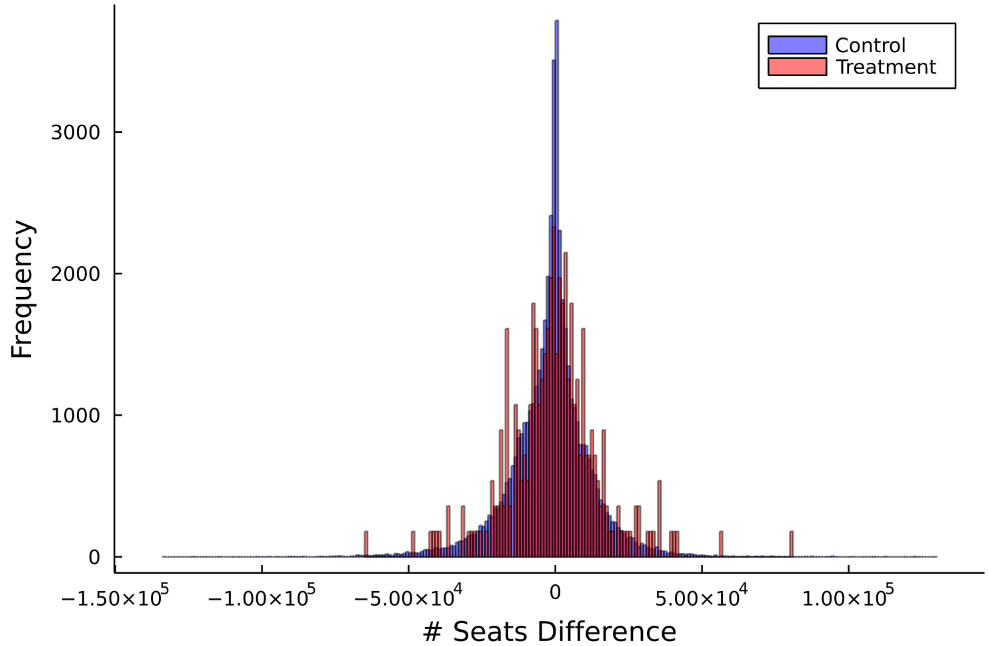
We additionally estimate Equation 4 for changes in capacity on the $B \to C$ legs of the $A \to B \to C$ routes,

$$\Delta_y q_{B\to C,i,y,q} = \kappa 1_{\text{Entry by Carrier on } A\to B,i,y,q} + \alpha^{y,q} + \alpha^i + \epsilon_{A\to B,i,y,q}. \tag{5}$$

If adjustment costs are sufficiently large, we expect there to be small (or zero) changes in capacity on the $B \to C$ markets as well.

Table 9 presents the results. Absent capacity adjustment costs, we would expect a negative estimate of κ on the $A \to B$ market. Columns (1) and (2) present estimates of κ

Figure 4: Distributions of capacity changes on control and treatment routes



Notes: To allow for a natural comparison between the two sets of routes (those routes that did and did not experience entry by LCC) on the same figure, we duplicate each control route n times where n is the floor of $\frac{\text{Number of Control Routes}}{\text{Number of Treatment Routes}}$.

in Equation 4 in levels and percents, respectively. We estimate a κ that is not statistically different from zero on the $A \rightarrow B$ market for capacity changes measured in both levels and percents. Columns (3) and (4) present estimates of κ in Equation 5 in levels and percents, respectively. We again find estimates of κ that are not statistically different from zero on $B \rightarrow C$ routes.

While these results are consistent with non-zero capacity adjustment costs, Equations 4 and 5 only test whether the mean changes in capacity on $A \rightarrow B$ routes were different on routes that experienced LCC entry versus those that did not. We can additionally compare the distributions of capacity changes. At any given time and market, we expect there to be capacity changes for idiosyncratic reasons. Comparing distributions of capacity changes on routes that did and did not experience LCC entry provides an informal test of whether airlines differentially adjusted capacity in response to this entry. Figure 4 presents these results. The distributions of capacity changes on direct routes that did and did not experience LCC entry are not significantly different.

4.3 Dynamic Pass-through

The section studies whether the pass-through estimates from Section 4.1 persist over time. The theory presented in Section 2 suggests that the longer the time horizon since the initial shock, the lower the adjustment costs, and hence we expect pass-through to decrease over time. We estimate Equation 2 again, however now instead of calculating fare differences based on comparing fares 1 year after the entry event to 1 year before, we use fares further after the entry event.

However, our estimates of these dynamic pass-through rates are subject to selection issues and diminishing relevance of the entry instrument. To satisfy the exclusion restriction in the sample construction detailed in Section 4.1, we restricted our sample to $A \to B \to C$ routes for which the carrier did not enter any $A \to D \to C$ routes. If we did not make this restriction, then the prices may change on $A \to B \to C$ due to the direct competition from the $A \to D \to C$ route as opposed to solely pass through of shocks from $A \to B$ to $A \to B \to C$. Doing so over a one-year horizon induces less sample selection than doing so over a two or more year horizon. Hence, the further the time horizon, the larger the sample selection. Note then that our treatment routes will have disproportionately less competition than other routes, which biases our sign towards null or negative pass-through.

Further, the relevance restriction is also less likely to be satisfied. For instance, in the long run, entry by a low-cost carrier into a market may induce an incumbent to leave that market resulting in prices returning closer to pre-entry levels.

Given these concerns, our estimates of dynamic pass-through rates are more speculative than the static estimates in Section 4.1. The results are heterogenous by carrier. We first show estimates of dynamic pass-through rates for Southwest, the carrier with the largest first-stage effect on incumbent fares, in Table 10. We find that pass-through rates remain positive even five years after the original entry event.

Table 10: Southwest entry dynamic pass-through

	Change in Indirect Fare ($) $\Delta_y p_{A\to B\to C,i,y,q}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_y p_{A\to B,i,y,q}$	0.106	0.189	0.247	0.079	0.194
	(0.025)	(0.036)	(0.045)	(0.071)	(0.077)
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Carrier	Yes	Yes	Yes	Yes	Yes
Year Quarter	Yes	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV	IV
N	1,259,649	1,110,124	979,439	863,191	760,571
First-stage F statistic	2069.500	901.197	577.999	230.075	187.309

Notes: Estimates of dynamic pass-through rates after Southwest entry events. Column i uses a post-period i years after entry.

Estimates of dynamic pass-through rates are generally statistically insignificant for other carriers, potentially because of the selection and instrument relevance issues discussed above. Table 11 presents estimates of dynamic pass-through rates after Jetblue entry events. We see that pass-through remains positive for two years and then becomes statistically insignificant (and the entry instrument loses power). Results for other carriers are presented in Appendix C.3.

Table 11: Jetblue entry dynamic pass-through

	Change in Indirect Fare ($) $\Delta_y p_{A\to B\to C,i,y,q}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_y p_{A\to B,i,y,q}$	0.311	0.402	-0.231	1.302	36.052
	(0.054)	(0.070)	(0.179)	(0.946)	(406.260)
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Carrier	Yes	Yes	Yes	Yes	Yes
Year Quarter	Yes	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV	IV
N	659,969	545,060	448,947	364,933	297,058
First-stage F statistic	406.862	232.509	36.516	2.805	0.008

Notes: Estimates of dynamic pass-through rates after Jetblue entry events. Column i uses a post-period i years after entry.

4.4 Consumer Surplus

Although previous work has estimated positive welfare effects for direct passengers on routes entered by LCCs, our estimates of positive pass-through to indirect routes suggest that 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 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 that share legs with affected direct routes. We simply take the ratio of indirect fare changes weighted by the number of indirect passengers to direct fare changes weighted by the number of direct passengers. In Equation 6, we can substitute the estimated pass-through rate to obtain Equation 7. Next, we can observe the ratio of connecting travel in the data. Multiplying the two gives the resulting welfare understatement by ignoring spillovers onto indirect routes, summarized in Table 12. We estimate a 13% understatement in the pooled sample that considers entry by all LCCs. Estimates by carrier range from 9% for Southwest up to 50% for Jetblue, suggesting large consumer surplus effects of positive pass-through of shocks from direct to indirect routes.

These are likely underestimates of the understatement in consumer surplus changes since we remove many indirect routes from consideration in our sample creation in order to satisfy the exclusion restriction of the entry instrument (thus reducing the ratio of indirect to direct passengers).[26]

[26] 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.

Table 12: Entry pass-through consumer surplus effect

	Pooled	**Frontier**	**Jetblue**	**Southwest**	**Spirit**
Indirect Welfare Proportion	0.13	0.29	0.50	0.09	0.12

Notes: This table shows the indirect welfare proportion calculated in Equation 7 for the pooled sample and each carrier.

5 Pass-Through after Merger Events

The pass-through of changes in direct fares to indirect fares may also be an important neglected 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. Futhermore, previous airline merger retrospectives often use a difference-in-differences strategy with control routes that did not experience a change in competition. Positive pass-through of shocks on direct to indirect routes suggests that these control routes may be contaminated.

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 merging airlines operated the $A \to B$ leg but at most one operated the $B \to C$ leg. Therefore, at most one of the merging airlines would have operated the $A \to B \to C$ route before the merger.[27]

We estimate the pass-through of fare changes (between approximately one year before and after the date the merger was closed)[28] 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.[29] 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

[27]This sample definition includes two distinct sets of indirect routes: those operated by exactly one of the merging airlines and those operated by competitors of the merging airlines. A price change due to a merger on the direct route predicts both sets of indirect routes experience price changes.

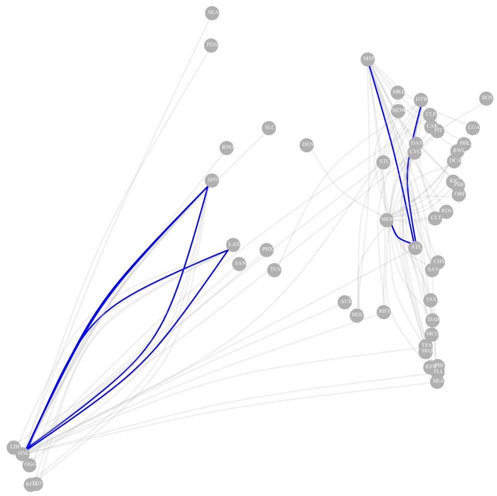
[28]The exact pre- and post- time periods are given in Table 13. For each merger we use quarter 2 fares to avoid capturing changes due to holiday travel.

[29]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.

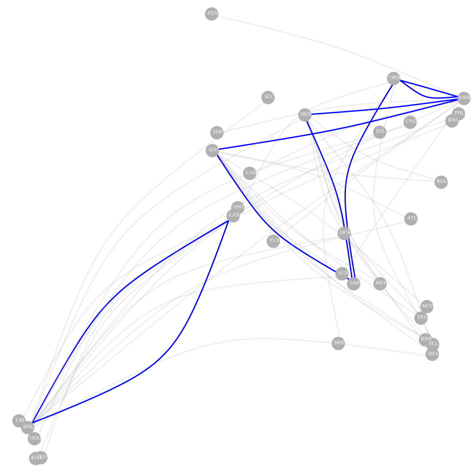
after mergers than just the nonstop routes both airlines operated before the merger. For example, Delta and Northwest simultaneously operated on only five nonstop markets, but an additional 77 indirect routes may have price changes induced by the reduction in competition of the nonstop route experiencing 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 13.

Figure 5 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).

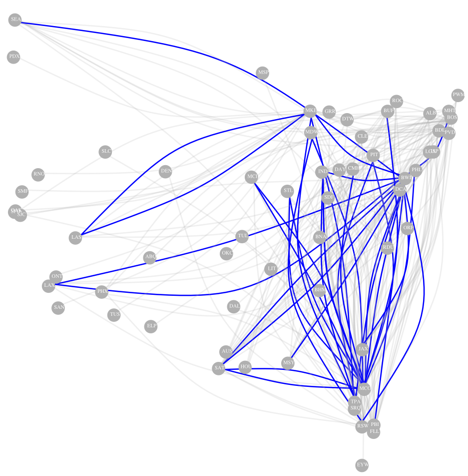
Figure 5: Merger overlap direct routes and affected indirect routes



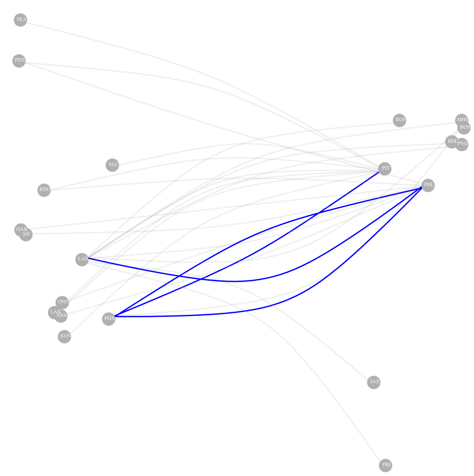
(a) Delta/Northwest



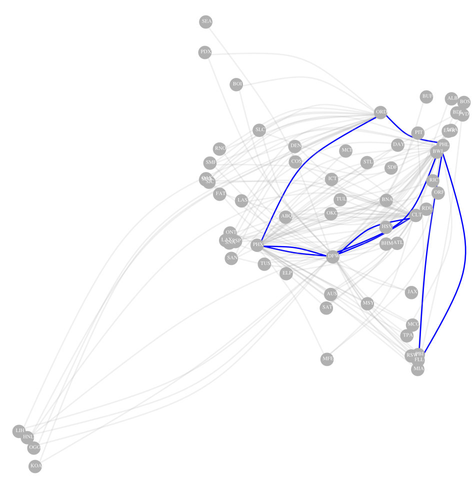
(b) United/Continental



(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 4 to estimate direct fare pass-through after merger events where we instrument for direct fare changes with an indicator for whether a merger reduced competition on that route (i.e., both merging carriers operated that direct route before the merger). We estimate Equations 2 and 3 for each merger, where now the change in prices is 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 (i.e., receive a non-zero value of the instrument) are those that were operated by at most one of merging carriers before the merger (i.e., at most 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 (i.e., receive a zero value of the instrument).

This exclusion of the instrument 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 restriction for the instrument, in this case, may be violated, as it requires that the only reason that indirect fares change after the 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.[30]

[30] As discussed earlier, the exact pass-through rate between direct and indirect fares 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.

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 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 6 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, combining data across all mergers. The intercept of this OLS regression line is near zero, suggesting that when there were no fare changes on direct routes, indirect routes also did not experience price changes.

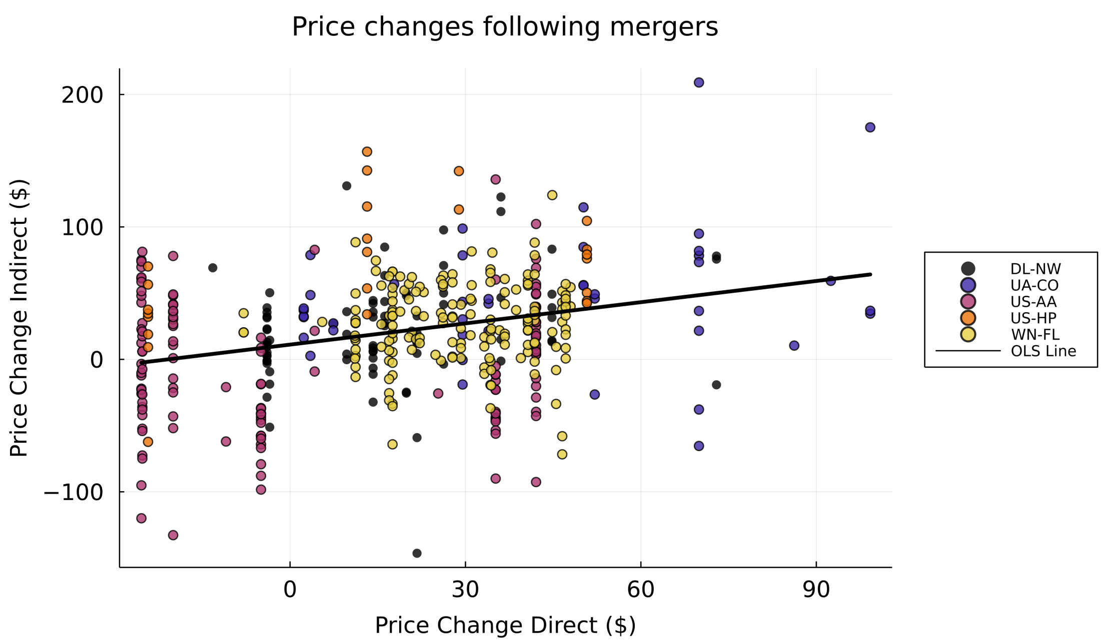


Figure 6: Correlation between direct and indirect fare changes

Table 13 presents descriptive statistics and pass-through rates for the mergers we consider.[31] In the estimation of Equations 2 and 3, we use the following set of instruments in place of the entry instrument:

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

Despite many more indirect routes being affected than direct routes, our sample size is much smaller than the entry application studied above, which considered many years

[31] Additional detail about the overlap routes is given in Table 19 of the Appendix.

of flights. This leads to weaker first-stage estimates. To increase power, we included functions of pre-merger HHI to capture additional variation in fare changes after mergers due to the pre-merger market structure. Additionally, the mergers that are consummated (and hence appear in our sample) are selected because they have few direct overlap routes and purported cost synergies yielding minimal fare changes, which weakens the variation in direct fare changes. Nevertheless, 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 anticompetitive 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.[32] As in Section 4, we can calculate the proportion of welfare changes that are attributable to indirect routes using Equation 7. These estimates are in the row titled "Indirect Welfare Proportion" of Table 13, ranging between .25 and 1.15. Since the ratio between connecting passengers and direct passengers can be arbitrarily large, it is possible to obtain welfare proportions above 1. Our estimate of 1.15 for the United-Continental merger suggests that welfare estimates ignoring positive pass-through to indirect routes may understate the true welfare effects of the merger by nearly 115%.

After a merger, merging airlines may reconfigure their network by adding new routes and ceasing to operate others. We can view $A \to B$ no longer being offered as an increase in that route's price to infinity. The pass-through of this price to indirect $A \to B \to C$ routes is mechanically also infinite since these routes are no longer operated. Importantly, one $A \to B$ 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.[33] As an example, after the Delta-Northwest merger, Delta ceased to offer 236 $A \to B$ routes, which in turn ended 878 $A \to B \to C$ routes.[34] Table 20 in the Appendix provides similar calculations for other mergers.

[32]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.

[33]We do not include $A \to B$ routes that are no longer offered after the merger in our analysis in Table 13 since we do not observe fares in the pre- and post-merger periods.

[34]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 changes in the network structure.

Table 13: Merger pass-through estimates

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

6 Conclusion

In this paper, we demonstrated that considering products related through supply-side factors like capacity constraints (opportunity cost effect) is important for estimating the full consumer surplus effects of changes in competition in addition to considering economies of scale (economies of scale effect). 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 and that the opportunity cost effect stemming from capacity constraints and adjustment costs empirically dominates the economies of scale effect. We document positive pass-through after changes in competition like entry events or mergers, and ignoring price changes on these additional routes can yield severe underestimates of the consumer surplus impacts of these events.

Our work has a number of implications for existing and future research in the airline industry. Existing research studying airline entry events or mergers often estimates treatment effects of these events using differences-in-differences. Our paper suggests that the choice of control routes cannot simply be routes that did not experience a change in competition, as positive pass-through between direct and indirect routes can cause fare changes on routes that did not experience a change in competition. Therefore, existing estimates of the effects of entry or mergers on fares may be subject to control group contamination.

Our finding of positive pass-through also suggests that additional routes must be considered to evaluate the effects of codesharing,[35] vertical integration,[36] or alliances. Finally, the effects documented in this paper need not apply to only airlines, but rather any market with significant capacity adjustment costs.

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[35] 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

[36] 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

Proof of Proposition 1. Recall our assumptions on the revenue, capacity, and adjustment functions imply that first order conditions will characterize the optimal allocation for the firm. For ease of notation, define

$$R_i^t(Q_i) = P_i^t(Q_i)Q_i, \tag{8}$$

as the revenue curve for a given market before or after the shock. Recall, market 2 does not experience a change in demand, so the t superscript is dropped.

Before the shock the relevant first order condition is

$$R_1'(Q_1^*) = R_2'(Q_2^*) = (Q_1^* + Q_2^*)^{\beta-1}. \tag{9}$$

After the shock, the new optima, Q_i^{**} satisfy the following first order condition

$$R_1^{\text{new}\prime}(Q_1^{**}) = R_2'(Q_2^{**}) = (Q_1^{**} + Q_2^{**})^{\beta-1} + \mu f'(Q_1^{**} + Q_2^{**} - Q_1^* - Q_2^*). \tag{10}$$

Part (i) Note that the new solution involves a higher aggregate quantity $Q_1^{**} + Q_2^{**}$ due to the increased demand. Let us begin with the analysis when $\beta = 1$. The two sets of equations above reduce to

$$R_1'(Q_1^*) = R_2'(Q_2^*) = 1, \tag{11}$$
$$R_1^{\text{new}\prime}(Q_1^{**}) = R_2'(Q_2^{**}) = 1 + \mu f'(Q_1^{**} + Q_2^{**} - Q_1^* - Q_2^*). \tag{12}$$

Since the aggregate quantity has increased, we know $1 + \mu f'(Q_1^{**} + Q_2^{**} - Q_1^* - Q_2^*) \geq 1$. Profit maximization post-shock implies $R'(Q_2^{**}) > 1$. Since R' is decreasing this implies $Q_2^{**} < Q_2^*$, which, finally, implies a price increase in the price of product 2.

Continuing with the analysis when $\mu = 0$ we can write analogous first order conditions before and after the shock, respectively.

$$R_1'(Q_1^*) = R_2'(Q_2^*) = (Q_1^* + Q_2^*)^{\beta-1}, \tag{13}$$
$$R_1^{\text{new}\prime}(Q_1^{**}) = R_2'(Q_2^{**}) = (Q_1^{**} + Q_2^{**})^{\beta-1}. \tag{14}$$

Due to the convexity of the problem, gradient descent tells us the direction of the true solution from the original solution. Hence, substituting Q_i^{**} to the first order condition pre-shock yields

$$R_1^{\text{new}\prime}(Q_1^*) > R_2'(Q_2^*) = (Q_1^* + Q_2^*)^{\beta-1}. \tag{15}$$

To equate these expressions, one needs to increase Q_1^* to allow the marginal revenue of product 1 to equalize the marginal cost. However upon doing this, this decreases the marginal cost which necessitates a drop in $R_2'()$, which increases Q_2. Thus the quantity supplied in market two increases which increases the price.

Part (ii) This is where the normalization is required that Q_1^* and Q_2^* be fixed. If β impacts not only the degree of economies of scale but also where on the revenue curve the firms are pricing at before the shock, this muddies the analysis. Hence, as a normalization we fix $Q_1^* + Q_2^* = 1$.

Define

$$f_1 := R_1^{\text{new}\prime}(Q_1^{**}) - (Q_1^{**} + Q_2^{**})^{\beta-1} - \mu f'(Q_1^{**} + Q_2^{**} - 1), \tag{16}$$
$$f_2 := R_2'(Q_2^{**}) - (Q_1^{**} + Q_2^{**})^{\beta-1} - \mu f'(Q_1^{**} + Q_2^{**} - 1). \tag{17}$$

The implicit function theorem then says

$$\begin{bmatrix} \frac{\partial Q_1}{\partial \mu} \\ \frac{\partial Q_2}{\partial \mu} \end{bmatrix} = - \begin{bmatrix} \frac{\partial f_1}{\partial q_1} & \frac{\partial f_1}{\partial q_2} \\ \frac{\partial f_2}{\partial q_1} & \frac{\partial f_2}{\partial q_2} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial f_1}{\partial \mu} \\ \frac{\partial f_2}{\partial \mu} \end{bmatrix} \tag{18}$$

$$= - \begin{bmatrix} R_1^{\text{new}\prime\prime}(Q_1^{**}) - (\beta-1)(Q_1^{**} + Q_2^{**})^{\beta-2} - \mu f''(Q_1^{**} + Q_2^{**} - 1) & -(\beta-1)(Q_1^{**} + Q_2^{**})^{\beta-2} - \mu f''(Q_1^{**} + Q_2^{**} - 1) \\ -(\beta-1)(Q_1^{**} + Q_2^{**})^{\beta-2} - \mu f''(Q_1^{**} + Q_2^{**} - 1) & R_2''(Q_1^{**}) - (\beta-1)(Q_1^{**} + Q_2^{**})^{\beta-2} - \mu f''(Q_1^{**} + Q_2^{**} - 1) \end{bmatrix}^{-1} \begin{bmatrix} -f'(Q_1^{**} + Q_2^{**} - 1) \\ -f'(Q_1^{**} + Q_2^{**} - 1). \end{bmatrix} \tag{19}$$

One can check the determinant of the above matrix is positive. Further, the adjustment cost, $f'(Q_1^{**} + Q_2^{**} - 1)$ is positive. Thus checking the sign of $\frac{\partial Q_2}{\partial \mu}$ is equivalent to checking the sign of

$$\begin{aligned} \frac{\partial Q_2}{\partial \mu} &= R_1^{\text{new}\prime\prime}(Q_1^{**}) - (\beta-1)(Q_1^{**} + Q_2^{**})^{\beta-2} \\ -\mu f''(Q_1^{**} + Q_2^{**} - 1) &- \Big(-(\beta-1)(Q_1^{**} + Q_2^{**})^{\beta-2} - \mu f''(Q_1^{**} + Q_2^{**} - 1) \Big) \\ &= R_1^{\text{new}\prime\prime}(Q_1^{**}) < 0. \end{aligned}$$

Thus, as the adjustment cost increases the quantity supplied in market 1 goes down relative to the pre-period. Hence, the price increases as μ increases.

Further, the analysis for the comparative statics on β are nearly identical. The only difference is noting $\frac{\partial f_1}{\partial \beta} > 0$ and thus the analysis is exactly as before except with the opposite sign.

$\square$

B 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.

C Robustness Checks

C.1 Identifying Pass-through with Regional Demand Variation

An alternative set of instruments for direct fare changes are demand shocks. We present pass-through estimates using demand shocks as instruments as a robustness check to the competition shocks used in Sections 4 and 5. 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.[37] 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,[38] 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.[39] 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:

$$\Delta_q p_{A\to B\to C,i,y,2} = \beta_p \Delta_q p_{A\to B,i,y,2} + \delta_y + \alpha^A + \alpha^C + \alpha^i + \epsilon_{A\to B\to C,i,y,2} \tag{20}$$

$$\Delta_q p_{A\to B,i,y,2} = \gamma Z_{A\to B,y,2} + \delta_y + \alpha^A + \alpha^i + \epsilon_{A\to B,i,y,2} \tag{21}$$

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

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

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

where $Z_{A\rightarrow B,y,2}$ is the set of instruments we include for the direct $A \rightarrow B$ 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.[40] Once we make this restriction, we would not expect demand for the indirect flights to change because of the ski season.[41] 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 $A \rightarrow B$ and $A \rightarrow B \rightarrow C$.[42] 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 14, the squared term is in fact negative.

There are 99 $A \rightarrow$ Denver routes that generate 2345 $A \rightarrow$ Denver $\rightarrow C$ routes.

We estimate Equations 2 and 3 and present results in Table 14. Column (1) estimates

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

[41] 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 14.

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

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 14: 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.[43], Column (2) implies that a one-dollar increase in the fare of a direct leg results in a 19-cent increase in the indirect fare.[44]

[43] 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 .

[44] 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 15, yielding coefficient 0.431 .

C.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:

$$\Delta_q p_{A\to B\to C,i,y,2} = \beta_p \Delta_q p_{A\to B,i,y,2} + \delta_y + \alpha^A + \alpha^C + \alpha^i + \epsilon_{A\to B\to C,i,y,2}, \tag{22}$$

$$\Delta_q p_{A\to B,i,y,2} = \gamma Z_{A\to B,y,2} + \delta_y + \alpha^A + \alpha^i + \epsilon_{A\to B,i,y,2}, \tag{23}$$

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 15.

Table 15: 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.

C.3 Dynamic Pass-through after Entry Events

Table 16: Frontier entry pass-through

	Change in Indirect Fare ($) $\Delta_y p_{A\to B\to C,i,y,q}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_y p_{A\to B,i,y,q}$	0.178	0.101	-0.072	-0.122	0.162
	(0.056)	(0.094)	(0.097)	(0.102)	(0.117)
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Carrier	Yes	Yes	Yes	Yes	Yes
Year Quarter	Yes	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV	IV
N	1,036,162	887,407	755,890	646,067	552,072
First-stage F statistic	398.383	127.820	124.316	113.530	78.408

Estimates of dynamic pass-through rates after Frontier entry events. Column i uses a post-period i years after entry.

Table 17: Spirit entry pass-through

	Change in Indirect Fare ($) $\Delta_y p_{A\to B\to C,i,y,q}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_y p_{A\to B,i,y,q}$	0.174	-0.109	-0.128	0.254	0.144
	(0.073)	(0.065)	(0.056)	(0.106)	(0.187)
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Carrier	Yes	Yes	Yes	Yes	Yes
Year Quarter	Yes	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV	IV
N	1,240,545	1,086,197	951,082	830,396	724,120
First-stage F statistic	229.774	290.611	394.727	99.436	31.210

Estimates of dynamic pass-through rates after Spirit entry events. Column i uses a post-period i years after entry.

Table 18: Pooled entry pass-through

	Change in Indirect Fare ($) $\Delta_y p_{A \to B \to C,i,y,q}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_y p_{A \to B,i,y,q}$	0.136	-0.047	-0.064	-0.029	-0.039
	(0.031)	(0.213)	(0.062)	(0.119)	(0.213)
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Carrier	Yes	Yes	Yes	Yes	Yes
Year Quarter	Yes	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV	IV
N	486,706	192,670	307,685	242,508	190,120
First-stage F statistic	1198.464	25.739	292.263	83.474	25.734

Estimates of dynamic pass-through rates after all LCC (pooled sample) entry events. Column i uses a post-period i years after entry.

C.4 Merger Overlap Route Descriptive Statistics

Table 19 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 19: 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.

C.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 20: Route creation and destruction by merging firms after merger.