Tacit Collusion and Price Dispersion in the Presence of Southwest Airlines

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Abstract

We study the impact of tacit collusion on price dispersion in the U.S. airline industry. We find that tacit collusion driven by multimarket contact has a positive effect on prices, but a negative effect on price dispersion. Our empirical results suggest that airfares throughout the price distribution increases, yet the price distribution becomes more compressed since 10th percentile airfares increase by a larger amount than 90th percentile airfares. Moreover, we also find that this pricing phenomenon does not exist if Southwest Airlines is present on the route. Thus, route-level price competition is softened when the same airlines directly compete more frequently, except when Southwest Airlines services that route. As such, our empirical analysis provides evidence that the presence of Southwest Airlines exhibits an anti-collusive effect.

JEL classifications: L13, L24, L93
Keywords: Tacit Collusion, Price Dispersion, Multimarket Contact, Outsourcing

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1 Introduction

The airline industry has been the focus of empirical studies on price discrimination because two important prerequisites for firms to price discriminate are present in this market. First, customers have different demand elasticities since demand from business travelers is less price elastic than that of leisure travelers. Second, airlines are able to distinguish between these two types with certain ticket restrictions, including advance-purchase requirements, nonrefundable tickets, and Saturday night stay-overs.

The existing literature contains contrasting research on the effect of competition on price dispersion. On the one hand, Borenstein and Rose (1994) use cross-sectional data to find a positive effect of airline competition on price dispersion, whereas Gerardi and Shapiro (2009) use panel data to find that price dispersion decreases with competition. More recently, Kim and Shen (2018) reconcile these results by showing that the outcome hinges on product differentiation and market definition. Using panel data from 1993 to 2013, they find that an increase in competition has a positive effect on price dispersion for one-way tickets, but a negative effect for round-trip tickets.

Typically, competition is proxied using the Herfindahl-Hirschman Index (HHI) or the number of firms in a market. However, a decrease in market concentration or an increase in the number of firms might not necessarily result in stronger price competition. One of the market conditions that could facilitate collusion is multimarket contact, in which rival firms compete head-to-head in a multitude of markets. Indeed, Ciliberto and Williams (2014) find evidence of tacit collusion in the airline industry since an increase in average multimarket contact is associated with higher average airfares.

The first main result of this paper is that multimarket contact has a negative effect on price dispersion. Consistent with Ciliberto and Williams (2014), we find that airlines with more multimarket contact are more likely to tacitly collude by raising average prices. We expand on their analysis by showing that price dispersion decreases since airlines raise their 10th percentile airfares (likely paid by leisure travelers) by a relatively higher amount than their 90th percentile airfares (likely paid by business travelers). Our second main result is that the presence of Southwest Airlines mitigates the effect of multimarket contact such that the evidence for tacit collusion occurs in markets that are not serviced by Southwest but disappears in markets operated by Southwest.

This paper contributes to the existing literature in two ways. First, we combine the empirical research on the relationship between price dispersion, competition, and multimarket contact. We achieve this by constructing new instrumental variables for average multimarket contact based on outsourcing agreements between major carriers and regional airlines. Second, we provide evidence that Southwest creates not only a pro-competitive effect on airfares but more interestingly the presence of Southwest also exhibits an anti-collusive effect in the airline industry. To the best of our knowledge, we are the first to document the chilling effect that Southwest has on tacit collusion.

2 Literature Review

Feinberg (1984) and Bernheim and Whinston (1990) serve as seminal papers on the theoretical work on the effect of multimarket contact and price competition. In particular, Feinberg (1984) discusses the mutual forbearance behavior, in which conglomerate firms take each other's actions into consideration when they compete in multiple markets together. Firms choose output independently, yet fear indirect retaliation in another market. In other words, multimarket contact is more likely to induce collusion. Moreover, Bernheim and Whinston (1990) posits that multimarket contact facilitates collusion under certain conditions of repeated competition. Although the mutual forbearance story is typically associated with conglomerates, the theory can be applied to multi-product firms, including companies that produce a single product in multiple geographic markets. They show that a number of factors (e.g. costs, market characteristics, and discount factor) determine whether prices can rise or fall due to multimarket contact.

Several empirical papers have applied the theory from Feinberg (1984) and Bernheim and Whinston (1990) to the airline industry. Evans and Kessides (1994) finds that average one-way airfares are higher in city-pair markets served by carriers with extensive multimarket contact, whereas Zou, Yu, and Dresner (2012) find that airline alliances mitigate the positive relationship between multimarket contact and airfares for transpacific routes. Instead, they find that higher airfares exist when airlines have greater multimarket contact on open-skies routes. Although most applied work examine the effect of multimarket contact on price competition, Prince and Simon (2009) and Bilotkach (2011) find that multimarket contact can also adversely affect flight delays and flight frequency, respectively. Thus, multimarket contact has been shown to facilitate softer price competition and lower product quality in the U.S. airline industry.

There have certainly been considerable empirical work on the effect of multimarket contact on prices in industries other than airlines. For example, Fernandez and Marin (1998) confirm the theory in Bernheim and Whinston (1990) that multimarket contact facilitates collusion using data from the Spanish hotel industry. Interestingly, they find that the omission of variables measuring multimarket contact creates a downward bias on the effect of concentration on prices. Indeed, prices are higher when there is more multimarket contact among firms in the U.S. cement industry (Jans and Rosenbaum, 1996), movie theaters (Feinberg, 2014), and hospitals (Schmitt, 2018). Finally, Pilloff (1999) finds that multimarket contact is positively related to profitability in the banking industry.

3 Data

3.1 Data Sources

We obtain data from two main sources. Our first main data set is the Airline Origin and Destination Survey (DB1B) database, which is a 10% random sample of all domestic air travel and provides information on prices, origin, destination, the number of passengers per ticket, the number of coupons for an itinerary, distance, and a round-trip indicator. Following Gerardi and Shapiro (2009), we focus on domestic, coach-class, and nonstop airline tickets, but we expand the sample time period to 1993:Q1 and 2017:Q4. The second main data set is from the T-100, which provides data on capacity (the number of flights and seats), as well as total enplaned passengers. Both of these data sets are made publicly available by the Bureau of Transportation Statistics.

We identify outsourcing in the DB1B data set when the ticketing carrier is a major airline, while the operating carrier is a regional airline. Major airlines like American Airlines or Delta Air Lines outsource the operation of certain routes to various regional airlines like Air Wisconsin, Chautauqua, Mesa, Republic Airlines, SkyWest Airlines, and Trans State Airlines. Under these agreements, major airlines are responsible for ticket sales and airport operations, whereas regional airlines operate the route with their own aircraft and flight crew.[1]

3.2 Variable Construction

Our variable construction closely follows Gerardi and Shapiro (2009) and Ciliberto and Williams (2014). To calculate average fares for ticketing airline i on route j in year-quarter t ($Fare_{ijt}$), we first treat round-trip tickets as two one-way tickets by dividing the fare by two and deflating fares using the consumer price index to 2017 dollars.[2] As with Ciliberto and Williams (2014), routes

[1] Forbes and Lederman (2009) and Tan (2018) provide detailed information on the relationship between major carriers and regional airlines.

[2] We use data on the Consumer Price Index from the Bureau of Labor Statistics in order to deflate prices.

are defined as a uni-directional airport-pair.[3] We also drop exceedingly low and high fares (less than \$25 and greater than \$2,500). We also calculate the 10th percentile airfare ($Fare10_{ijt}$) and the 90th percentile airfare ($Fare90_{ijt}$). The Gini coefficient ($Gini_{ijt}$) measures price dispersion and is defined as twice the expected absolute difference between two ticket prices drawn randomly from the population. As such, a Gini coefficient equal to 0 implies that every passenger pays the same price, whereas an increase in the Gini coefficient suggests an increase in price dispersion. The log-odds ratio of the Gini coefficient ($Gini\_lodd_{ijt}$) is defined as $ln\left[\frac{Gini}{(1-Gini)}\right]$.

Our key variable of interest is average multimarket contact. We follow Evans and Kessides (1994) and Ciliberto and Williams (2014) to construct multimarket contact for a pair of airlines A and B on a route (MMC^t_{AB}) and average multimarket contact on a route (Avg_MMC_{jt}). First let MMC^t_{AB} denote the number of routes that two distinct carriers, A and B, simultaneously serve at time t. For example, American and Delta directly competed on 855 routes in the first quarter of 2017 so both $MMC^{2017Q1}_{AADL} = MMC^{2017Q1}_{DLAA} = 855$. For each quarter, we construct a matrix of these pair-specific variables. We then use the MMC^t matrix to calculate the route-specific average of multimarket contact for each year-quarter:

$$Avg\_MMC_{jt} = \frac{1}{F_{jt}(F_{jt}-1)} \sum_{A=1}^{F} \sum_{B=1,A\neq B}^{F} I[A \text{ and } B \text{ active}]_{jt} * MMC^t_{AB},$$

where the indicator function, $I[A \text{ and } B \text{ active}]_{jt}$ is equal to 1 if carriers A and B are both on route j at time t, F_{jt} is the number of incumbent firms on route j at time t, and F is the total number of airlines so that $F_{jt}(F_{jt}-1)$ drops diagonal elements in the matrix since those indicate multimarket contacts of themselves. Thus, Avg_MMC_{jt} is equal to the average of MMC^t_{AB} across the firms actively serving route j at time t. As such, variation in average multimarket contact across markets comes from differences in the set of firms operating in the market because the multimarket contact

[3] Following Gerardi and Shapiro (2009), we avoid "double counting" round-trip tickets by dropping one of the directions consistently. For example, suppose a passenger flies Southwest Airlines nonstop between Baltimore-Washington International Airport (BWI) and Boston Logan International Airport (BOS). We drop the return leg (BOS to BWI) in order to avoid double counting the round trip ticket.

of two carriers, MMC^t_{AB}, is fixed for a specific time period. In other words, the numerical value for Avg_MMC_{jt} varies based on changes in the set of airlines operating in the market, as well as potential changes in the degree of overlap between a given pair of carriers.

We use outsourcing agreements between major carriers and independent regional airlines to construct two instruments for Avg_MMC_{jt}. We first separate routes into 10 markets based on deciles of route-level passenger traffic (i.e. 0-10, 10-20, 20-30,…, 90-100 percentiles of route-level enplanements). Next, we calculate two average outsourcing ratios: 1) an outsourcing ticket ratio for a particular airline ($own\_outsourcing_{ijt}$) and 2) an outsourcing ticket ratio for competing firms ($competitor\_outsourcing_{ijt}$) for the relevant market size of each route. To be sure, route j is not included in the construction of the two outsourcing variables in order to avoid the direct correlation between an airline's outsourcing decision made for a given market and our dependent variables (airfares and the Gini coefficient) in that market. For example, suppose American Airlines flies three airport-pair routes (A-B, C-D, and E-F) in one of the market groups. We define $own\_outsourcing_{ijt}$ for American Airlines on the A-B route by taking the average of $own\_outsourcing_{ijt}$ for C-D and E-F routes. Similarly, the average of $own\_outsourcing_{ijt}$ for A-B and E-F routes are used to calculate the value of $own\_outsourcing_{ijt}$ for American Airlines servicing the C-D route.

Regional airlines can be either a wholly owned subsidiary of a major airline or independent from major airlines. Following Tan (2018), we focus our attention on the partnerships between major airlines and independent regional airlines since including wholly owned regionals in our analysis can lead to endogeneity issues if a demand shock can lead to a major both changing its pricing and reallocating flights serviced by its wholly owned regional airlines.[4] Major airlines are

[4]Since each major airline owns multiple regional airlines, we do not include these wholly owned subsidiaries in our outsourcing variables. For example, Envoy Air (formerly, American Eagle) and Executive Airlines have been American Airlines's wholly owned subsidiaries. PSA and Piedmont Airlines were wholly owned subsidiaries of US Airways before the American - US Airways merger in 2015, and subsequently became a wholly owned subsidiary of American. ExpressJet (formerly, Atlantic Southeast Airlines) was a wholly owned subsidiary of Delta Air Lines from 1999 to 2005 before being purchased by SkyWest, while Comair was a wholly owned subsidiary of Delta before Delta shut it down in 2012. Mesaba and Compass Airlines were wholly owned subsidiaries of Northwest Airlines and then became wholly owned subsidiaries of Delta following the Delta - Northwest merger in 2010 before being sold to Pinnacle and Trans States Airlines, respectively. Endeavor Air (formerly, Pinnacle Airlines) emerged from Chapter 11

responsible for the pricing of flights operated by regional airlines, especially in the case of wholly own subsidiaries, so major airlines can change their prices for flights operated by their wholly owned regionals promptly in response to market specific shocks. Thus, we do not include these wholly owned subsidiaries in defining our outsourcing variables and instead only use independent regional airline partners.

Although we do not have access to actual outsourcing contracts between major airlines and their independent regional airline partners, a variety of sources, including the annual report on Form 10-K offered by U.S. Securities and Exchange Commission (SEC), the airlines' official websites, and news articles, show that these contacts are long-term agreements usually with initial terms of at least 10 years and grants major airlines with the option to extend the initial term (Form 10-K, Delta, 2010-12-31).[5] According to the DB1B data, outsourcing contracts last for 36.6 quarters on average during our sample period with the following breakdown by airline: American (36.6 quarters with 9 regional airlines), Alaska (63 quarters with 2 regionals), Continental (30 quarters with 30.2 quarters with 9 regionals), Delta (38.9 quarters with 13 regionals), Northwest (28.6 quarters with 9 regionals), United (44.5 quarters with 15 regionals), US Airways (39.7 with 10 regionals). Given the long-term contracts between major airlines and independent regionals, frequent flight reallocation to endogenize market specific shocks might be hard so our instruments are less likely to be correlated with the error term.

We include several additional control variables in our regressions. Carriers serving a larger number of destinations out of an origin airport can offer more attractive frequent flyer programs and experience stronger demand so $Networksize_{ijt}$ is the percentage of all routes serviced out of an airport by an airline. We construct the variable $Roundtrip_{ijt}$ to be the proportion of round-trip tickets sold by an airline for a particular route in order to control for potential discounting of

reorganization as a wholly owned subsidiary of Delta in 2013. Finally, Continental Micronesia was a wholly owned subsidiary of Continental Airlines prior to the Continental-United merger.

[5]See Gil, Kim, and Zanarone (2019) and Kim and Kim (2019) for more information on the long-term agreements between major airlines and independent regional airlines.

round-trip vs. one-way travel. Hub_{ijt} is a dummy variable that indicates whether at least one of the endpoint airports on a route serves as a hub airport for that airline. Finally, HHI_{jt} is the route-level Herfindahl-Hirschman Index, which is the sum of squared market shares.

Table 1: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
$Fare$	267.375	107.137	41.390	1207.841	242,088
$Fare10$	129.676	47.344	25.740	807.559	242,088
$Fare90$	467.263	236.268	44.558	2050.327	242,088
$Gini$	0.270	0.061	0.000	0.609	242,088
$Gini\_lodd$	-1.017	0.315	-6.142	0.444	241,637
Avg_MMC	232.361	173.331	1.000	1058.000	242,088
$own\_outsourcing$	0.148	0.203	0.000	1.000	242,088
$competitor\_outsourcing$	0.081	0.142	0.000	1.000	242,088
$Networksize$	0.472	0.350	0.008	1.000	242,088
$Roundtrip$	0.727	0.178	0.000	1.000	242,088
Hub	0.649	0.477	0.000	1.000	242,088
HHI	0.620	0.218	0.143	1.000	242,088

Summary statistics are reported in Table 1. Our final data set contains 242,088 observations for 26 airlines, 4,409 routes, and 100 year-quarter time periods. Detailed directions of our data construction are outlined in the data appendix.

4 Empirical Analysis

4.1 Estimation Strategy

Our empirical analysis combines the estimation strategy in Gerardi and Shapiro (2009) and Ciliberto and Williams (2014). We investigate the effect of multimarket contact along different points of the price distribution in order to provide insight on the resulting change in price dispersion. The main econometric specification is

$$y_{ijt} = \alpha + \beta Avg\_MMC/SD_{jt} + \gamma X_{ijt} + \rho_{ij} + \delta_{it} + \varepsilon_{ijt}, \tag{1}$$

where y_{ijt} is either the Gini coefficient ($Gini_{ijt}$ or $Gini\_lodd_{ijt}$) or logged airfare ($lnFaremean_{ijt}$, $lnFare10_{ijt}$, or $lnFare90_{ijt}$) for airline i on route j at time t. Following Ciliberto and Williams (2014), we proxy for tacit collusion using Avg_MMC_{jt}; however, instead of dividing this variable by 1,000 as in their paper, we instead scale our variable by dividing Avg_MMC_{jt} by 173, which is the sample standard deviation as reported in Table 1. As such, the key variable of interest in Equation (1) is Avg_MMC/SD_{jt}. X_{ijt} includes additional control variables: $Networksize_{ijt}$, $Roundtrip_{ijt}$, Hub_{ijt}, and HHI_{jt}.[6] We include carrier-route fixed effects, ρ_{ij}, and carrier-time fixed effects, δ_{it}. We cluster standard errors by route to account for serial correlation and correlation between pricing decisions of carriers on the same route.

Following Gerardi and Shapiro (2009), we include three instruments for HHI in all of our regressions. The first instrument is $lnRoutePass_{jt}$, which is logged route-level passenger traffic in a given time period. The second instrument is $iRouteHHI_{ijt}$, which is a function of the route-level HHI, as well as observed and fitted values of an airline's route-level market shares.[7] Finally, our third instrument is $PassRatio_{ijt}$, which is a ratio based on an airline's airport-level passenger traffic and the overall passenger traffic at that airport.[8]

The effect of Avg_MMC_{jt} on airfares is uncertain. On the one hand, an increase in the number of rival firms in a market should strengthen competition and lead to lower airfares. If this holds, then we anticipate a negative value for β in our price regressions. On the other hand, the mutual forbearance hypothesis suggests that average multimarket contact should facilitate tacit collusion such that weaker price competition results in higher airfares, resulting in a positive sign for β.

[6] As a robustness check, we also include weather-related variables collected from the National Oceanic and Atmospheric Administration (NOAA), such as precipitation, snowfall, and temperature, as well as capacity-related variables obtained from the Bureau of Transportation Statistics, including peaktime and loadfactor. Our results are qualitatively similar and available upon request.

[7] Following both Borenstein and Rose (1994) and Gerardi and Shapiro (2009), *iRouteHHI* is calculated as $\hat{S}^2_{ijt} + \frac{HHI_{jt} - S^2_{ijt}}{(1-\hat{S}_{ijt})^2} * (1-\hat{S}_{ijt})^2$, where $\hat{S}^2_{ijt}$ is the fitted value for market share for carrier i on route j at time t.

[8] As in Gerardi and Shapiro (2009), $PassRatio_{ijt} = \frac{\sqrt{Pass_{i1} * Pass_{i2}}}{\sum_k \sqrt{Pass_{k1} * Pass_{k2}}}$, where i is the observed airline, k indexes all airlines, and $Pass_{k1}$ and $Pass_{k2}$ are quarterly airport-level passenger traffic at the two endpoint airports.

Ciliberto and Williams (2014) suggest that average multimarket contact is endogenous since time-varying and market-specific unobservables may affect price, entry, and exit decisions by airlines. Therefore, we construct two instrumental variables: outsourcing ticket ratio of an airline ($own\_outsourcing_{ijt}$) and outsourcing ticket ratio of competing airlines ($competitor\_outsourcing_{ijt}$). In order to be a valid instrument, these outsourcing ticket ratios must be correlated with average multimarket contact and uncorrelated with the error term in Equation (1). As such, a major airline's outsourcing decision can affect multimarket contact. For example, suppose a route is serviced by two airlines, Delta (DL) and United (US), that also simultaneously compete head-to-head on 500 routes ($MMC_{DLUS} = MMC_{USDL} = 500$) in a given time period. In this case, the average multimarket contact on this route, $Avg\_MMC = \frac{2\times500}{2\times1} = 500$. Then suppose that American (AA) enters this route under an outsourcing contract with SkyWest (OO), an independent regional airline, such that $MMC_{AADL} = MMC_{DLAA} = 1000$ and $MMC_{AAUS} = MMC_{USAA} = 600$, respectively. Thus, AA's entry increases average multimarket contact since $Avg\_MMC = \frac{2\times500+2\times1000+2\times600}{3\times2} = 700$. Therefore, outsourcing can lead to changes in the average multimarket contact.

We expect a positive correlation between average multimarket contact and outsourcing as in the numerical example for two reasons. First, there is a higher level of pair-wise multimarket contact between airlines due to an increase in the set of operating firms when major airlines expand their outsourcing arrangements with independent regional airlines. Second, when a major carrier enters a new route but outsources the flight operations to an independent regional airline partner, the increase in the degree of overlap between a given pair of airlines results in an increase in pair-wise multimarket contact.[9]

One may argue that outsourcing decisions may not be valid if it is correlated with a carrier's entry/exit decisions to endogenize market specific-shocks. However, major airlines and independent regional airlines are typically engaged in long-term business relationships as discussed in Section

[9]It is possible for an independent regional airline to contract with multiple major airlines on a given route. As a robustness check, we drop these cases and the results are qualitatively similar. See Kim and Kim (2019) for more details on this special type of partnership and its direct effect on tacit collusion.

3.2. More importantly, since major airlines are motivated to outsource in order to exploit the independent regional airlines' benefit with respect to cost, economies of scale, and efficient resource allocations from a long-term point of view, unexpected market-specific shocks to demand or cost would not affect a major airline's decision on long-term outsourcing contracts.

Also, it is unlikely that major airlines want to terminate outsourcing contract in response to market-specific shocks to demand because a single route typically represents a relatively small portion of a major airline's revenues out of an airport. For example, SkyWest operated a variety of different routes for Delta in 2017 which connect around 46 different airports.[10] Therefore, shocks in one route may be offset by shocks in another route, which can neutralize a change in demand out of an airport and consequently leave outsourcing decisions unchanged. At the same time, independent regional airlines and major airlines have developed a symbiotic relationship as discussed in Tan (2018) since independent regional airlines depend on their contracts with major carriers for passengers, whereas major carriers rely on independent regional airlines as an important feeder of passengers within their route network. Thus, it appears that major airlines will not unilaterally terminate outsourcing contracts with independent regional airlines unless they are bankrupt.

According to Forbes and Lederman (2009), many contracts between major and regional airlines allocate the rights to decide on schedule adjustments to the major airlines. However, having the rights to order specific schedule changes is not equivalent to having the rights to actually implement those schedule changes. Schedule changes ordered by the major airlines must still be carried out by the regional airlines. The same logic seems reasonable to apply towards the rights to changing prices since airlines consider many aspects in their pricing decisions. Even though major airlines have a right to adjust prices in real time, they may not want to do so without the cooperation of regional airlines given the delays and high adaptation costs in the adjustment process between major and regional airlines.

[10]SkyWest primarily operates Delta-ticketed flights out of Delta's Atlanta (ATL), Detroit (DTW), Minneapolis/St. Paul (MSP), and Salt Lake City (SLC) hubs. SkyWest's route map can be found at `https://www.skywest.com/fly-skywest-airlines/skywest-airlines-route-map/`.

4.2 Multimarket Contact and Price Dispersion

We start with the fixed effects (FE) regression results for Equation (1). Table 2 contains estimation results for all five dependent variables: logged average fare (Column 1), logged 10th percentile airfares (Column 2), logged 90th percentile airfares (Column 3), the Gini coefficient (Column 4), and the log-odds ratio of the Gini coefficient (Column 5). To be sure, there are less observations in the regression results for Column 5 since there were 447 observations in which $Gini = 0$ and therefore the value for *Gini_lodd* for these observations does not exist.

Table 2: Multimarket Contact and Price Dispersion (FE)

VARIABLES	(1) lnFare	(2) lnFare10	(3) lnFare90	(4) Gini	(5) Gini_lodd
Avg_MMC/SD	0.017***	0.026***	0.013***	-0.003***	-0.014***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)
$Networksize$	0.018	-0.022*	0.004	0.003	0.016
	(0.013)	(0.013)	(0.017)	(0.003)	(0.013)
$Roundtrip$	0.003	0.009	0.110***	0.022***	0.102***
	(0.013)	(0.012)	(0.019)	(0.003)	(0.016)
Hub	0.059***	0.015	0.102***	0.016***	0.086***
	(0.012)	(0.012)	(0.016)	(0.003)	(0.014)
$\widehat{HHI}$	0.338***	0.327***	0.334***	-0.009***	-0.045***
	(0.016)	(0.016)	(0.019)	(0.003)	(0.014)
Observations	240,527	240,527	240,527	240,527	240,080

Notes: (i) HHI is instrumented by $lnRoutePass$, *iRouteHHI*, and $PassRatio$. (ii) Carrier-route and carrier-time fixed effects are included in all regressions. (iii) Route-specific clustered standard errors in parentheses. (iv) *** p<0.01, ** p<0.05, * p<0.1.

As in Evans and Kessides (1994) and Ciliberto and Williams (2014), we find a positive and significant coefficient for average multimarket contact (*Avg_MMC*) in Column 1, suggesting that an increase in average multimarket contact increases average fares. Thus, we provide corroborating evidence that tacit collusion leads to weaker price competition in the U.S. airline industry. More importantly, Columns 4 and 5 show that average multimarket contact has a negative and significant impact on price dispersion. Since 10th percentile airfares (Column 2) increase by more than 90th percentile airfares (Column 3), the price distribution becomes more compressed.

Table 3: Multimarket Contact and Price Dispersion (FE 2SLS - Second Stage)

VARIABLES	(1) lnFare	(2) lnFare10	(3) lnFare90	(4) Gini	(5) Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.280***	0.351***	0.272***	-0.024***	-0.132***
	(0.027)	(0.030)	(0.032)	(0.004)	(0.023)
$Networksize$	0.020	-0.019	0.006	0.002	0.015
	(0.017)	(0.018)	(0.021)	(0.003)	(0.014)
$Roundtrip$	-0.046***	-0.052***	0.062***	0.026***	0.124***
	(0.016)	(0.016)	(0.022)	(0.003)	(0.017)
Hub	0.032**	-0.019	0.075***	0.019***	0.098***
	(0.016)	(0.018)	(0.019)	(0.003)	(0.015)
$\widehat{HHI}$	0.091***	0.022	0.091**	0.012**	0.066***
	(0.030)	(0.033)	(0.035)	(0.005)	(0.025)
Observations	240,527	240,527	240,527	240,527	240,080

Notes: (i) Avg_MMC/SD is instrumented by *own_outsourcing* and *competitor_outsourcing*. (ii) HHI is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

The results in Table 2 might be biased given endogeneity concerns so we report the regression results of the two-stage least squares fixed effects (FE 2SLS) estimations in Table 3 using both outsourcing ticket ratio of an airline (*own_outsourcing*) and outsourcing ticket ratio of competing airlines (*competitor_outsourcing*) as instrumental variables for average multimarket contact. As in Table 2, the coefficients for average multimarket contact in the price regressions (Columns 1-3) remain positive and statistically significant, whereas the coefficients for *Avg_MMC* in the price dispersion regressions (Columns 4 and 5) are still negative and statistically significant. Thus, the regression results in Table 3 provide the first main results of the paper, which is that tacit collusion has a negative effect on price dispersion due to higher 10th percentile airfares compared to mean airfares and 90th percentile airfares.

Columns 1-5 in Table 4 shows the first stage regression results for Columns 1-5 in Table 3, respectively. The outsourcing ticket ratio of an airline (*own_outsourcing*) has a positive effect on average multimarket contact, meaning that major carriers that outsource a higher proportion of their own tickets to regional airlines tend to compete head-to-head more frequently against rival carriers. Similarly, the estimated coefficient for the outsourcing ticket ratio of competing airlines (*competitor_outsourcing*) is also positive and significant. Moreover, F-statistics are all greater than 10, implying that our instruments satisfy the relevance assumption for 2SLS. Lastly, Column 6 shows an Hausman test result, confirming that average multimarket contact is indeed endogenous due to correlation with the error term.

Table 4: Multimarket Contact and Price Dispersion (FE 2SLS - First Stage)

VARIABLES	(1) Avg_MMC/SD	(2) Avg_MMC/SD	(3) Avg_MMC/SD	(4) Avg_MMC/SD	(5) Avg_MMC/SD	(6) Gini
own_outsourcing	0.460***	0.460***	0.460***	0.460***	0.459***	
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	
competitor_outsourcing	0.383***	0.383***	0.383***	0.383***	0.382***	
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	
Networksize	0.007	0.007	0.007	0.007	0.007	0.002
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.003)
Roundtrip	0.182***	0.182***	0.182***	0.182***	0.186***	0.026***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.003)
Hub	0.113**	0.113**	0.113**	0.113**	0.109**	0.019***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.003)
$\widehat{HHI}$	0.952***	0.952***	0.952***	0.952***	0.951***	0.012**
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.005)
Avg_MMC/SD						-0.024***
						(0.004)
Residual						0.022***
						(0.004)
F-stat	97.257	97.257	97.257	97.257	97.136	36.986
Observations	240,527	240,527	240,527	240,527	240,080	240,527

Notes: (i) *HHI* is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (ii) Carrier-route and carrier-time fixed effects are included in all regressions. (iii) Route-specific clustered standard errors in parentheses. (iv) *** p<0.01, ** p<0.05, * p<0.1.

As a robustness check, we consider two alternative measures for tacit collusion introduced in Ciliberto and Williams (2014): 1) $Avg\_pct\_MMC_{jt}$ and 2) $Avg\_pct\_weighted\_MMC_{jt}$. Using the notation for Avg_MMC_{jt} in Section 3.2, we construct $pct\_MMC^t_{AB}$ to be equal to MMC^t_{AB} divided by the total number of markets served by airline A such that Avg_MMC_{jt} factors for the potential risk of smaller airlines having more to lose than larger airlines by deviating from the collusive agreement.[11] Feinberg (1985) weights multimarket contact by the sales at stake in the markets in which multimarket contact occur so we define $Avg\_pct\_weighted\_MMC^t_{AB}$ as the weighted

[11] $Avg\_pct\_MMC_{jt} = \frac{1}{F_{jt}(F_{jt}-1)} \sum_{A=1}^{F} \sum_{B=1,A\neq B}^{F} I[A \text{ and } B \text{ active}]_{jt} * pct\_MMC^t_{AB}$.

average of $pct\_MMC^t_{AB}$ based on airline B's market share, which allows for airlines with varying passenger volumes to benefit differently from the collusive agreement.[12]

Table 5: Multimarket Contact and Price Dispersion (Alternative Measures)

VARIABLES	(1) lnFare	(2) lnFare10	(3) lnFare90	(4) Gini	(5) Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.280***	0.351***	0.272***	-0.024***	-0.132***
	(0.027)	(0.030)	(0.032)	(0.004)	(0.023)
$\widehat{Avg\_pct\_MMC}$	8.088***	9.541***	7.522***	-0.701***	-3.749***
	(1.579)	(1.833)	(1.591)	(0.167)	(0.880)
$\widehat{Avg\_pct\_weighted\_MMC}$	2.997***	2.178***	2.008*	-0.268*	-1.172*
	(0.916)	(0.767)	(1.043)	(0.141)	(0.700)
Observations	240,527	240,527	240,527	240,527	240,080

Notes: (i) Each of the three multimarket contact measures is instrumented by *own_outsourcing* and *competitor_outsourcing*. (ii) *HHI* is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

In order to be concise, we truncate the regression results in Table 5 by only presenting the estimated coefficients of the three collusion variables and their standard error for each of the five dependent variables. As such, the regression results for $\widehat{Avg\_MMC/SD}$ are identical to the results presented in Table 3. As in Ciliberto and Williams (2014), our regression results are qualitatively similar for all three measures for tacit collusion.

4.3 Multimarket Contact and Southwest Airlines

Previous papers have studied the so-called Southwest Effect, in which the presence of Southwest Airlines puts downward pressure on airfares. Vowles (2001) documents that rival airlines decrease their airfares when they compete head-to-head with Southwest Airlines, as well as when Southwest services a nearby airport. Morrison (2001) not only documents Southwest's pro-competitive effect on direct and adjacent competition as in Vowles (2001), but also shows that incumbent air-

[12] $Avg\_weighted\_pct\_MMC_{jt} = \frac{1}{F_{jt}(F_{jt}-1)} \sum_{A=1}^{F} \sum_{B=1, A \neq B}^{F} I[A \text{ and } B \text{ active}]_{jt} * pct\_MMC^t_{AB} * Mktshare^t_B$.

lines lower price due to potential competition, which occurs when Southwest services both endpoint airports, but not the direct route itself. Indeed, Goolsbee and Syverson (2008) finds strong evidence of this pro-competitive effect from potential competition with Southwest Airlines and documents that this pricing phenomenon does not exist on routes where Southwest does not service either endpoint. More recently, Brueckner, Lee, and Singer (2013) show that competition against legacy carriers yields weak effects on average airfares, while the presence of low-cost carriers, particularly Southwest, exhibits strong downward pressure on prices. Finally, Tan (2015) find that entry by Southwest Airlines leads to lower price dispersion since incumbent airlines lower their 90th percentile airfares by more than their 10th percentile airfares.

We analyze the effect of Southwest Airlines on the pricing phenomenon addressed in Section 4.2 by splitting our data set into two subsamples: one with only routes served by Southwest and another with routes not served by Southwest. We then run separate regressions based on Equation (1) for each subsample while dropping observations for Southwest. Table 6 breaks down the summary statistics between the two subsamples. Based on the existing literature, it is unsurprising that the mean airfare (*Fare*), 10th percentile airfare ($Fare10$), and 90th percentile airfare ($Fare90$) are all lower, on average, for routes serviced by Southwest than for routes not serviced by Southwest. In addition, price dispersion (*Gini*) is also lower for Southwest markets, which means that the price distribution is more compressed, on average, given the presence of Southwest Airlines. However, there is a higher incidence of multimarket contact (*Avg_MMC*), our key variable of interest, on routes serviced by Southwest Airlines. In Section 4.4, we implement a PSM estimation strategy to account for the possible heterogeneity of market types.

Figure 1 illustrates the relationship between *Avg_MMC* and *Gini* for four routes. The regression results discussed in Section 4.2 pertain to the two markets that are not serviced by Southwest Airlines (top row), whereas the negative correlation between multimarket contact and price dispersion no longer holds for the two markets where Southwest is present (bottom row).[13] This novel

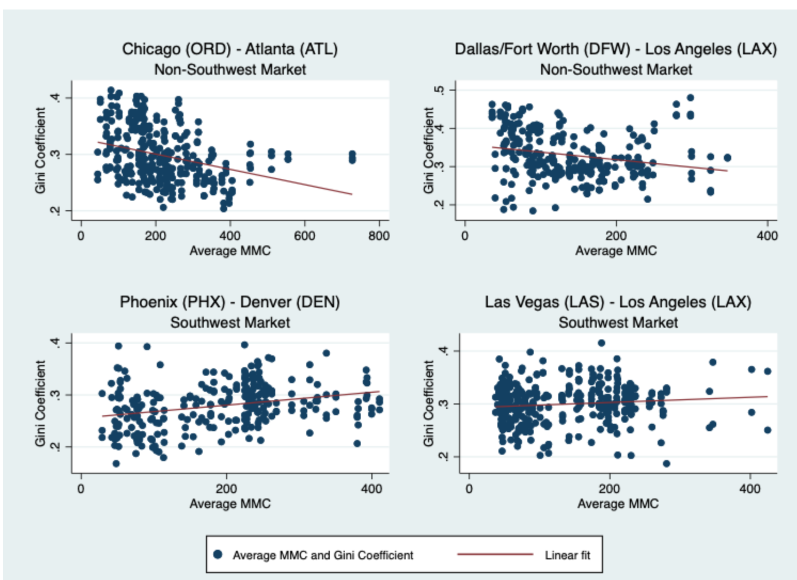
[13] Other popular Southwest routes listed on its official website (`https://www.southwest.com/html/air/`

result motivates the regression analysis presented in the rest of this section.

Table 6: Summary Statistics for Non-Southwest vs. Southwest Markets

	Non-Southwest Markets		**Southwest Markets**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Fare	287.558	109.385	216.715	85.644
*Fare*10	135.208	47.992	113.341	44.719
*Fare*90	511.537	246.244	356.456	166.605
Gini	0.279	0.061	0.255	0.049
Gini_lodd	-0.966	0.309	-1.085	0.261
Avg_MMC	1.256	1.010	1.427	0.887
own_outsourcing	0.155	0.206	0.186	0.203
competitor_outsourcing	0.079	0.142	0.056	0.108
Networksize	0.483	0.364	0.412	0.327
Roundtrip	0.758	0.166	0.672	0.184
Hub	0.685	0.465	0.600	0.490
HHI	0.635	0.217	0.570	0.218
*Airport_cost*1	0.363	0.177	0.166	0.116
*Airport_cost*2	0.363	0.183	0.163	0.118
Observations	177,696		45,002	

Figure 1: Multimarket Contact and Price Dispersion for Non-Southwest vs. Southwest Markets



routes/index.html?clk=GFOOTER-FLY-ROUTES), such as Atlanta (ATL) to Chicago (MDW), Las Vegas (LAS) to Denver (DEN), and Oakland (OAK) to Las Vegas (LAS), are associated with a similar non-negative correlation between multimarket contact and price dispersion. These figures are available upon request.

Table 7: Multimarket Contact and Southwest Airlines (FE 2SLS)

	Non-Southwest Markets					Southwest Markets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	lnFare	lnFare10	lnFare90	Gini	Gini_lodd	lnFare	lnFare10	lnFare90	Gini	Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.192***	0.253***	0.184***	-0.019***	-0.101***	0.044	0.174**	0.040	-0.025	-0.146
	(0.022)	(0.022)	(0.027)	(0.004)	(0.021)	(0.055)	(0.071)	(0.073)	(0.017)	(0.090)
Networksize	0.009	-0.026	-0.010	0.001	0.010	0.032	-0.021	0.051*	0.009	0.045
	(0.017)	(0.017)	(0.022)	(0.003)	(0.015)	(0.023)	(0.028)	(0.031)	(0.007)	(0.036)
Roundtrip	-0.018	-0.051***	0.139***	0.041***	0.190***	-0.028	0.028	-0.044	-0.017***	-0.081**
	(0.017)	(0.017)	(0.023)	(0.004)	(0.019)	(0.024)	(0.026)	(0.035)	(0.006)	(0.034)
Hub	0.029	0.001	0.078**	0.018***	0.086***	0.010	-0.033**	0.047***	0.015***	0.085***
	(0.025)	(0.031)	(0.033)	(0.006)	(0.026)	(0.011)	(0.016)	(0.013)	(0.004)	(0.021)
$\widehat{HHI}$	0.150***	0.032	0.166***	0.021***	0.110***	0.245***	0.145**	0.254***	0.016	0.094
	(0.031)	(0.032)	(0.038)	(0.006)	(0.029)	(0.047)	(0.063)	(0.061)	(0.014)	(0.074)
$lnAirport\_cost1$	0.083***	0.054***	0.099***	0.005***	0.027***	0.004	0.007**	0.004	-0.001	-0.004
	(0.005)	(0.005)	(0.006)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.004)
$lnAirport\_cost2$	0.080***	0.053***	0.095***	0.005***	0.024***	0.004	0.008**	0.004	-0.000	-0.004
	(0.005)	(0.005)	(0.006)	(0.001)	(0.004)	(0.003)	(0.004)	(0.004)	(0.001)	(0.004)
Observations	176,282	176,282	176,282	176,282	175,861	44,383	44,383	44,383	44,383	44,357

Note: (i) Avg_MMC/SD is instrumented by *own_outsourcing* and *competitor_outsourcing*. (ii) HHI is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

Table 7 presents separate regression results based on Equation (1) for the non-Southwest markets subsample and the Southwest markets subsample. In addition to the control variables listed in Section 4.1, we include two additional covariates related to airport costs in order to avoid a possible endogeneity issue associated with Southwest's entry decision and demand or supply shocks in the market. For example, Southwest may choose to enter routes with falling operating costs, and thus incumbents may cut their prices in response to lower operating costs rather than Southwest's entry. Following Goolsbee and Syverson (2008) and Ma (2019), the airport operating cost measure for an origin airport ($lnAirport\_cost1_{ijt}$) is defined as carrier i's average logged airfare divided by distance for routes between the origin airport of route j and airports not serviced by Southwest. Similarly, $lnAirport\_cost2_{ijt}$ is the airport operating cost measure for a destination airport and is calculated as carrier i's average logged airfare divided by distance for routes between the destination airport of route j and airports not serviced by Southwest.

The estimated sign for *Avg_MMC* for routes without a Southwest presence is positive and statistically significant in the three fare regressions (Columns 1-3), whereas the results for *Avg_MMC* for Southwest markets are generally statistically insignificant (Columns 6-8). This provides evidence for tacit collusion on routes where Southwest does not exist; however, the presence of Southwest Airlines precludes this type of collusive behavior. Similar to our key result in Section 4.2, Columns 4 and 5 suggest that price dispersion decreases in non-Southwest markets; however, price dispersion does not change significantly for markets that include Southwest (Columns 9 and 10). In other words, the price distribution shifts to the right and becomes more compressed for routes that Southwest does not service. On the other hand, the price distribution for Southwest markets weakly shifts to the right with no alteration to its standard deviation. Thus, Table 7 presents the second main result of the paper, which is that multimarket contact softens route-level price competition except when Southwest is present on that route.

Table 8: Multimarket Contact and Southwest Airlines (Alternative Measures)

	Non-Southwest Markets					Southwest Markets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	lnFare	lnFare10	lnFare90	Gini	Gini_lodd	lnFare	lnFare10	lnFare90	Gini	Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.192***	0.253***	0.184***	-0.019***	-0.101***	0.044	0.174**	0.040	-0.025	-0.146
	(0.022)	(0.022)	(0.027)	(0.004)	(0.021)	(0.055)	(0.071)	(0.073)	(0.017)	(0.090)
$\widehat{Avg\_pct\_MMC}$	5.305***	6.264***	4.567***	-0.595***	-3.094***	-1.243	-0.913	-1.041	-0.062	-0.644
	(1.068)	(1.197)	(1.088)	(0.137)	(0.696)	(0.780)	(0.804)	(1.077)	(0.193)	(1.008)
$\widehat{Avg\_weighted\_pct\_MMC}$	3.432***	3.337***	2.447**	-0.453***	-2.277***	-3.390*	-4.103*	-2.882	0.140	0.239
	(0.884)	(0.808)	(0.964)	(0.134)	(0.666)	(1.870)	(2.168)	(2.349)	(0.403)	(2.078)
Observations	176,282	176,282	176,282	176,282	175,861	44,383	44,383	44,383	44,383	44,357

Notes: (i) Each of the three multimarket contact measures is instrumented by *own_outsourcing* and *competitor_outsourcing*. (ii) *HHI* is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

As a robustness check, we substitute Avg_MMC/SD with two alternative measures for multimarket contact (Avg_pct_MMC and $Avg\_pct\_weighted\_MMC$) as with Table 5. The results in Table 8 are qualitatively similar to the results presented in Table 7. By construction, the regression results for Avg_MMC/SD are identical in both Tables 7 and 8. More importantly, the estimated coefficients for Avg_pct_MMC and $Avg\_pct\_weighted\_MMC$ are generally statistically insignificant for Southwest markets, further suggesting that the presence of Southwest exhibits anti-collusive behavior in the airline industry.

4.4 Robustness Checks

To mitigate the potential concern that the effect of multimarket contact on the dependent variables between non-Southwest markets and Southwest markets is driven by the systemic differences between the two subsamples, we constructed a sample of non-Southwest markets using propensity score matching (PSM) following Ma (2019), in which we fit a multinomial logistic regression as a function of the set of covariates that we include in our specifications such as HHI, distance, a dummy variable indicating whether there is a low-cost carrier other than Southwest on a route, as well as other carrier-route characteristics. Following Cochran and Rubin (1973) and Austin (2011), we use a Caliper Matching Process with a caliper of width equal to 0.2 of the standard deviation of the logit of the propensity score.

Table 9: Multimarket Contact and Southwest Airlines (PSM Estimation)

	Non-Southwest Markets					Southwest Markets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	lnFare	lnFare10	lnFare90	Gini	Gini_lodd	lnFare	lnFare10	lnFare90	Gini	Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.184***	0.253***	0.163***	-0.021***	-0.114***	0.044	0.174**	0.040	-0.025	-0.146
	(0.029)	(0.031)	(0.035)	(0.005)	(0.027)	(0.055)	(0.071)	(0.073)	(0.017)	(0.090)
Networksize	-0.001	-0.023	-0.018	-0.000	0.001	0.032	-0.021	0.051*	0.009	0.045
	(0.027)	(0.025)	(0.034)	(0.004)	(0.019)	(0.023)	(0.028)	(0.031)	(0.007)	(0.036)
Roundtrip	-0.057***	-0.052**	0.027	0.021***	0.094***	-0.028	0.028	-0.044	-0.017***	-0.081**
	(0.021)	(0.021)	(0.029)	(0.005)	(0.024)	(0.024)	(0.026)	(0.035)	(0.006)	(0.034)
Hub	0.042	0.061	0.065	0.004	0.021	0.010	-0.033**	0.047***	0.015***	0.085***
	(0.039)	(0.040)	(0.048)	(0.007)	(0.032)	(0.011)	(0.016)	(0.013)	(0.004)	(0.021)
$\widehat{HHI}$	0.212***	0.105***	0.244***	0.020***	0.111***	0.245***	0.145**	0.254***	0.016	0.094
	(0.034)	(0.036)	(0.041)	(0.006)	(0.032)	(0.047)	(0.063)	(0.061)	(0.014)	(0.074)
$lnAirport\_cost1$	0.081***	0.056***	0.098***	0.005***	0.027***	0.004	0.007**	0.004	-0.001	-0.004
	(0.006)	(0.006)	(0.007)	(0.001)	(0.006)	(0.003)	(0.003)	(0.003)	(0.001)	(0.004)
$lnAirport\_cost2$	0.070***	0.048***	0.085***	0.004***	0.020***	0.004	0.008**	0.004	-0.000	-0.004
	(0.006)	(0.006)	(0.008)	(0.001)	(0.006)	(0.003)	(0.004)	(0.004)	(0.001)	(0.004)
Observations	87,745	87,745	87,745	87,745	87,229	44,383	44,383	44,383	44,383	44,357

Note: (i) Avg_MMC/SD is instrumented by *own_outsourcing* and *competitor_outsourcing*. (ii) HHI is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

Table 9 presents the regression results using this PSM estimation method.[14] Consistent with Table 7, airfares for non-Southwest markets increase all along the price distribution, while price

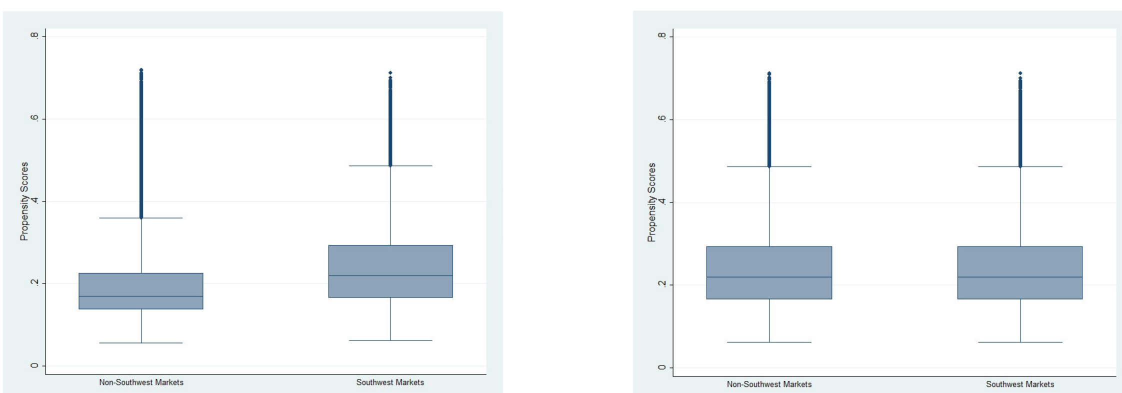
[14] Although we report the results using PSM two times, we obtain qualitatively similar estimates when using PSM either one time or three times. These results are available upon request.

dispersion significantly decreases due to the relatively larger increase on 10th percentile airfares compared to the 90th percentile airfares. In contrast, estimates for Avg_MMC/SD across the five regression specifications for Southwest markets are generally insignificant such that there is no change in airfares or the Gini coefficient. These consistent results imply that our main results in Table 7 neither suffer from heterogeneous market characteristics nor result from spurious effects. Therefore, we conclude that Southwest Airlines exhibits an anti-collusive impact on price competition.

Table 10: Balance Test of Covariates Before and After PSM

	Mean in Treated (Southwest Markets)	Mean in Untreated (Non-Southwest Markets)	Unweighted Standardized Diff.	Weighted Standardized Diff.
Networksize	0.41	0.48	-0.205	0.017
Roundtrip	0.67	0.76	-0.491	0.006
Hub	0.60	0.68	-0.176	0.003
Bankruptcy	0.00	0.01	-0.051	0.002
Legacy	0.77	0.88	-0.289	0.003
Distance	1021.18	979.35	0.067	-0.004
HHI	0.57	0.63	-0.300	-0.015

Figure 2: Overlap Test of Propensity Scores Before and After PSM



(a) Before

(b) After

Table 10 and Figure 2 both provide robustness checks for the results in Table 9. Table 10 reports the standardized mean difference, which is the difference in means divided by the standard deviation. Following Cohen (2013), a standardized mean difference of less than 0.20 is considered "small," 0.40 is considered "moderate," and 0.60 is considered "large." With no established standards for determining substantial overlap of propensity scores, we use a combination of balancing (Table 10) and overlap tests (Figure 2) to assess whether the groups are similar enough to support causal inference. Overall, it appears reasonable to consider the covariates' distributions are balanced between the two different groups after PSM.

Table 11: Multimarket Contact and Low-Cost Carriers

	Non-Low-Cost Carrier Markets					Low-Cost Carrier Markets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	lnFare	lnFare10	lnFare90	Gini	Gini_lodd	lnFare	lnFare10	lnFare90	Gini	Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.224***	0.230***	0.223***	-0.016**	-0.088***	0.170***	0.280***	0.124	-0.037**	-0.178**
	(0.039)	(0.037)	(0.048)	(0.007)	(0.033)	(0.065)	(0.076)	(0.084)	(0.016)	(0.079)
$Networksize$	0.005	-0.034*	-0.021	0.000	0.005	0.012	0.034	-0.014	-0.008	-0.034
	(0.019)	(0.020)	(0.023)	(0.003)	(0.016)	(0.036)	(0.026)	(0.048)	(0.007)	(0.034)
$Roundtrip$	-0.088***	-0.141***	0.150***	0.067***	0.317***	0.028	-0.004	0.090*	0.012*	0.054
	(0.023)	(0.023)	(0.030)	(0.005)	(0.024)	(0.033)	(0.034)	(0.046)	(0.007)	(0.034)
Hub	0.024	-0.023	0.076***	0.022***	0.097***	-0.006	0.004	-0.004	-0.002	0.012
	(0.023)	(0.030)	(0.028)	(0.006)	(0.027)	(0.062)	(0.044)	(0.095)	(0.013)	(0.064)
$\widehat{HHI}$	0.091**	0.034	0.072*	0.007	0.042	0.282***	0.141***	0.374***	0.038***	0.178***
	(0.036)	(0.033)	(0.043)	(0.006)	(0.029)	(0.045)	(0.043)	(0.058)	(0.009)	(0.045)
$lnAirport\_cost1$	0.092***	0.064***	0.107***	0.005***	0.023***	0.078***	0.041***	0.103***	0.008***	0.041***
	(0.007)	(0.006)	(0.008)	(0.001)	(0.005)	(0.008)	(0.007)	(0.010)	(0.002)	(0.009)
$lnAirport\_cost2$	0.093***	0.062***	0.105***	0.005***	0.021***	0.071***	0.044***	0.089***	0.006***	0.029***
	(0.006)	(0.006)	(0.007)	(0.001)	(0.005)	(0.008)	(0.008)	(0.010)	(0.002)	(0.009)
Observations	120,686	120,686	120,686	120,686	120,646	33,919	33,919	33,919	33,919	33,908

Note: (i) Avg_MMC/SD is instrumented by *own_outsourcing* and *competitor_outsourcing*. (ii) HHI is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

It is natural to wonder whether our results pertain only to Southwest Airlines. Indeed, Tan (2015) showed that the Southwest Effect, in which incumbents significantly reduce airfares as a response to entry by Southwest, can loosely be applied to other low-cost carriers. Table 11 reports the regression results when we separate our original data set into two subsamples: markets not serviced by other low-cost carriers and markets serviced by other low-cost carriers.[15] To be sure, we exclude all observations pertaining to Southwest markets so that we can assess whether other low-cost carriers exhibit a similar anti-collusive effect as discussed in Section 4.3. As such, low-cost carrier markets consist of routes serviced by a low-cost carrier other than Southwest Airlines.

[15] A list of low-cost carriers can be found in the Data Appendix at the end of the paper.

As with our analysis for Southwest markets (Table 7), we drop observations pertaining to low-cost carriers in the regressions for low-cost carrier markets so that we are able to compare only the same carrier groups (i.e. major airlines) in both markets.

Unlike with Tables 7 and 9, the estimated coefficients for Avg_MMC/SD in the price regressions presented in Table 11 are positive and significant for both non-low-cost carrier markets (Columns 1-3) and low-cost carrier markets (Columns 6-8). In particular, there is evidence of tacit collusion in other low-cost carrier markets among major airlines, especially on 10th percentile airfares (Column 7), which makes sense given that low-cost carriers' markets are relatively small and more likely serve leisure travelers with lower prices. Moreover, price dispersion significantly decreases in both non-low-cost carrier markets (Columns 4 and 5) and low-cost carrier markets (Columns 9 and 10). Thus, the regression results suggest that there is something special about the presence of Southwest Airlines that precludes tacit collusion. When we turn our attention from Southwest markets to other low-cost carriers' markets, the anti-collusive behavior disappears. Thus, the regression results suggest that Southwest Airlines plays a unique role by exhibiting not only a pro-competitive effect already established in the existing literature but also an anti-collusive effect in the U.S. airline industry.

Although other low-cost carriers like JetBlue or Frontier benefit from low marginal costs like Southwest, Table 11 shows that other low-cost carriers do not have the same effect as Southwest on tacit collusion. According to Kang, Bayus, and Balasubramanian (2010), relative firm size can affect a firm's strategy when faced with high levels of multimarket contact. They find that dominant firms ignore rivals with relatively small market shares and tacitly collude with other dominant firms in markets with intense multimarket contact. According to our sample, Southwest's market share is similar to the market share for major airlines with an average difference of 0.09%. However, other low-cost carriers have a significantly lower market share (19.6%) than major airlines. As such, major airlines still tacitly collude with each other when low-cost carriers other than Southwest are present. Therefore, Southwest is unique compared to other low-cost carriers because of Southwest's similar relative firm size with major airlines along with their lower marginal cost.[16]

Table 12: Multimarket Contact and Price Dispersion (One Year Lag IVs)

VARIABLES	(1) lnFare	(2) lnFare10	(3) lnFare90	(4) Gini	(5) Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.326***	0.485***	0.275***	-0.051***	-0.286***
	(0.072)	(0.087)	(0.081)	(0.012)	(0.065)
Networksize	0.030	-0.001	0.010	-0.001	-0.004
	(0.021)	(0.025)	(0.024)	(0.004)	(0.019)
Roundtrip	-0.056**	-0.077***	0.056**	0.031***	0.145***
	(0.023)	(0.025)	(0.029)	(0.004)	(0.023)
Hub	0.056**	0.027	0.085***	0.010**	0.056**
	(0.025)	(0.030)	(0.029)	(0.004)	(0.023)
$\widehat{HHI}$	0.065	-0.088	0.108	0.037***	0.210***
	(0.069)	(0.083)	(0.078)	(0.012)	(0.063)
Observations	203,634	203,634	203,634	203,634	203,455

Notes: (i) Avg_MMC/SD is instrumented by one year lags of *own_outsourcing* and *competitor_outsourcing*. (ii) HHI is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Multimarket Contact and Southwest Airlines (One Year Lag IVs)

	Non-Southwest Markets					Southwest Markets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	lnFare	lnFare10	lnFare90	Gini	Gini_lodd	lnFare	lnFare10	lnFare90	Gini	Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.172***	0.315***	0.141**	-0.037***	-0.210***	0.076	0.052	0.083	0.006	0.008
	(0.051)	(0.058)	(0.063)	(0.011)	(0.054)	(0.064)	(0.073)	(0.083)	(0.018)	(0.095)
Networksize	0.020	-0.014	-0.004	-0.001	-0.002	0.035	-0.020	0.052	0.009	0.046
	(0.019)	(0.020)	(0.024)	(0.004)	(0.019)	(0.026)	(0.029)	(0.035)	(0.008)	(0.039)
Roundtrip	-0.013	-0.065***	0.147***	0.045***	0.212***	-0.025	0.043	-0.042	-0.019***	-0.101***
	(0.021)	(0.021)	(0.029)	(0.005)	(0.024)	(0.028)	(0.028)	(0.041)	(0.007)	(0.035)
Hub	0.054	0.086*	0.073	-0.002	-0.007	-0.006	-0.023	0.012	0.008*	0.043*
	(0.039)	(0.045)	(0.049)	(0.007)	(0.035)	(0.013)	(0.020)	(0.015)	(0.004)	(0.022)
$\widehat{HHI}$	0.185***	-0.039	0.231***	0.044***	0.241***	0.223***	0.250***	0.227***	-0.008	-0.022
	(0.061)	(0.071)	(0.076)	(0.013)	(0.066)	(0.054)	(0.063)	(0.069)	(0.014)	(0.078)
$lnAirport\_cost1$	0.083***	0.048***	0.099***	0.006***	0.032***	0.003	0.003	0.003	-0.000	-0.002
	(0.006)	(0.006)	(0.007)	(0.001)	(0.005)	(0.003)	(0.004)	(0.004)	(0.001)	(0.004)
$lnAirport\_cost2$	0.080***	0.048***	0.094***	0.005***	0.027***	0.006	0.004	0.007*	0.001	0.002
	(0.006)	(0.006)	(0.007)	(0.001)	(0.005)	(0.003)	(0.004)	(0.004)	(0.001)	(0.004)
Observations	149,477	149,477	149,477	149,477	149,309	38,882	38,882	38,882	38,882	38,872

Note: (i) Avg_MMC/SD is instrumented by one year lags of *own_outsourcing* and *competitor_outsourcing*. (ii) HHI is instrumented by *lnRoutePass*, *iRouteHHI*, and *PassRatio*. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

[16] Demand and marginal cost analysis showing Southwest marginal cost is the lowest compared to major airlines are available in the online appendix.

Although we believe that our instruments are valid, we lag them in order to mitigate concerns about the possible correlation of our instruments with contemporaneous demand shocks. Tables 12 and 13 provide a robustness check for Table 3 in Section 4.2 and Table 7 in Section 4.3, respectively. However, we replace our instruments for Avg_MMC_{jt} with a four quarter lag of airline i's own outsourcing ticket ratio on route j ($own\_outsourcing_{ij,t-4}$) and a four quarter lag of the outsourcing ticket ratio for airline i's competitors servicing route j ($competitor\_outsourcing_{ij,t-4}$).

As with Table 3, the estimated coefficients for $\widehat{Avg\_MMC/SD}$ in the airfare regressions (Columns 1-3) are positive and significant, whereas these coefficients are negative and significant in the price dispersion regressions (Columns 4-5). Moreover, our results in Table 13 are qualitatively similar to the results in Table 7 in Section 4.3. In other words, there is evidence of tacit collusion softening price competition in non-Southwest markets (Columns 1-5); however, the presence of Southwest appears to preclude this type of behavior (Columns 6-10). Thus, our two key results are robust to a one-year lag in our instruments.

In order to further investigate the heterogeneous effects of tacit collusion across markets for different airlines as well as confirm Southwest's unique anti-collusive effect in the airline industry, we include dummy variables that indicate whether the four largest airlines − Southwest ($WNpresence$), American ($AApresence$), Delta ($DLpresence$), or United ($UApresence$) − services a route, as well as the interaction term between these presence dummy variables and the Avg_MMC/SD variable. Table 14 shows that the sign of the coefficients for Southwest are unique compared to the ones for other carriers, especially American and Delta. These results imply that incumbents in Southwest markets raise their prices and lower price dispersion less than in markets for other airlines such that the presence of Southwest Airlines mitigates incumbents' tacit collusion. These results also support our finding that Southwest is unique because of its lower marginal cost compared to other major airlines along with its significant market share.

Table 14: Multimarket Contact and Price Dispersion (MMC-Airline Interaction Terms)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lnFare	lnFare10	lnFare90	Gini	Gini_lodd
Avg_MMC/SD	0.281***	0.310***	0.266***	-0.025***	-0.135***
	(0.045)	(0.044)	(0.053)	(0.007)	(0.033)
$Avg\_MMC/SD \times WNpresence$	-0.140**	-0.233***	-0.144*	0.029***	0.157***
	(0.063)	(0.063)	(0.075)	(0.009)	(0.047)
$WNpresence$	-0.506***	-0.452***	-0.554***	-0.001	-0.001
	(0.033)	(0.031)	(0.039)	(0.005)	(0.026)
$Avg\_MMC/SD \times AApresence$	0.073	0.316***	0.004	-0.060***	-0.308***
	(0.074)	(0.077)	(0.091)	(0.011)	(0.057)
$AApresence$	0.142***	0.154***	0.200***	-0.002	-0.019
	(0.043)	(0.044)	(0.051)	(0.007)	(0.036)
$Avg\_MMC/SD \times DLpresence$	0.416***	0.331**	0.474***	-0.013	-0.072
	(0.127)	(0.129)	(0.146)	(0.020)	(0.102)
$DLpresence$	-0.128***	-0.080**	-0.158***	-0.011*	-0.055*
	(0.031)	(0.031)	(0.039)	(0.006)	(0.028)
$Avg\_MMC/SD \times UApresence$	-0.070*	-0.041	-0.076	0.004	0.016
	(0.041)	(0.040)	(0.048)	(0.006)	(0.031)
$UApresence$	-0.310***	-0.207**	-0.401***	-0.039***	-0.205***
	(0.092)	(0.091)	(0.110)	(0.014)	(0.072)
$Networksize$	-0.002	-0.082***	-0.008	0.013***	0.071***
	(0.022)	(0.022)	(0.027)	(0.004)	(0.018)
$Roundtrip$	-0.104***	-0.117***	0.014	0.033***	0.161***
	(0.021)	(0.019)	(0.026)	(0.004)	(0.019)
Hub	0.106***	0.018	0.172***	0.024***	0.124***
	(0.023)	(0.025)	(0.028)	(0.004)	(0.022)
F-test(H_null: $\alpha^{WN} = \alpha^{AA}$)	139.560	119.953	137.343	0.004	0.165
	(0.000)	(0.000)	(0.000)	(0.948)	(0.684)
F-test(H_null: $\alpha^{WN} = \alpha^{DL}$)	59.176	62.775	44.181	1.198	1.584
	(0.000)	(0.000)	(0.000)	(0.274)	(0.208)
F-test(H_null: $\alpha^{WN} = \alpha^{UA}$)	4.733	7.342	2.106	6.782	7.766
	(0.030)	(0.007)	(0.147)	(0.009)	(0.005)
F-test(H_null: $\alpha^{AA} = \alpha^{DL}$)	19.257	14.121	22.610	0.642	0.423
	(0.000)	(0.000)	(0.000)	(0.423)	(0.515)
F-test(H_null: $\alpha^{AA} = \alpha^{UA}$)	18.854	12.447	22.817	5.255	5.236
	(0.000)	(0.000)	(0.000)	(0.022)	(0.022)
F-test(H_null: $\alpha^{DL} = \alpha^{UA}$)	3.310	1.703	4.087	2.914	3.192
	(0.069)	(0.192)	(0.043)	(0.088)	(0.074)
F-test(H_null: $\beta^{WN} = \beta^{AA}$)	3.065	20.095	1.029	27.027	28.165
	(0.080)	(0.000)	(0.310)	(0.000)	(0.000)
F-test(H_null: $\beta^{WN} = \beta^{DL}$)	9.345	9.494	8.600	2.321	2.663
	(0.002)	(0.002)	(0.003)	(0.128)	(0.103)
F-test(H_null: $\beta^{WN} = \beta^{UA}$)	1.798	13.626	1.247	10.094	11.492
	(0.180)	(0.000)	(0.264)	(0.001)	(0.001)
F-test(H_null: $\beta^{AA} = \beta^{DL}$)	6.534	0.011	8.889	4.262	4.129
	(0.011)	(0.915)	(0.003)	(0.039)	(0.042)
F-test(H_null: $\beta^{AA} = \beta^{UA}$)	1.944	11.566	0.435	20.106	19.944
	(0.163)	(0.001)	(0.510)	(0.000)	(0.000)
F-test(H_null: $\beta^{DL} = \beta^{UA}$)	10.125	5.942	9.500	0.474	0.532
	(0.001)	(0.015)	(0.002)	(0.491)	(0.466)
Observations	207,588	207,588	207,588	207,588	207,146

Note: (i) Each interaction term is $Avg\_MMC/SD*XXpresence$, in which $XXpresence$ is a dummy variable for the presence of airline $XX = \{WN, AA, DL, UA\}$. (ii) We dropped HHI due to severe multicollinearity with the interaction terms and airline presence dummies. (iii) The F-test results for α and β correspond to the coefficients of the airline presence dummy variables and their interaction terms, respectively. (iv) Carrier-route and carrier-time fixed effects are included in all regressions. (v) Route-specific clustered standard errors in parentheses. (vi) *** p<0.01, ** p<0.05, * p<0.1.

Our final robustness check deals with our market definition. An observation in our main data set is at the carrier-route-time level. In other words, a market in our sample is defined as an airport-pair. However, there are cities that are serviced by multiple airports. For example, O'Hare International Airport (ORD) and Midway International Airport (MDW) are both located in Chicago. Brueckner, Lee, and Singer (2014) not only identifies ten multi-airport cities in the United States but also classifies nearby airports as either Primary, Other Core, or Fringe. Based on their methodology, ORD serves as Chicago's primary airport, whereas MDW is the other core airport. Using the airport groupings in Brueckner, Lee, and Singer (2014), we redefine a market as a city-pair in order to test whether our results are sensitive to the airport-pair vs. city-pair definition.

Summary statistics for the city-pair sample is reported in Table 15. To be sure, we re-measured all of the variables in Table 6 for this city-pair market analysis. As such, the mean for *Avg_MMC* is smaller for Non-Southwest markets using the city-pair definition (1.156) vs. the airport-pair definition (1.256); however, the mean for this measure of multimarket contact is larger for Southwest markets using the city-pair definition (1.497) vs. the airport-pair definition (1.427). On the other hand, the mean value of HHI is smaller using the city-pair definition for both non-Southwest markets (0.585) and Southwest markets (0.505) compared to the airport-pair definition (0.635 and 0.570, respectively).

By construction, the ratio of observations pertaining to non-Southwest markets over those for Southwest markets has gotten smaller in Table 15 compared to Table 6 since some non-Southwest markets have been transferred into the Southwest market subsample. In Table 6, observations pertaining to ORD are in the non-Southwest market subsample since Southwest Airlines does not service ORD, whereas observations pertaining to MDW are included in the Southwest market given Southwest's presence at MDW. However, observations pertaining to both ORD and MDW are included in the Southwest market subsample in Table 15 since observations for all airports in a city serviced by Southwest are now identified as a Southwest market.

Table 15: Summary Statistics for Non-Southwest vs. Southwest Markets (City-Pairs)

	Non-Southwest Markets		Southwest Markets	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Fare	282.431	104.513	220.270	86.198
*Fare*10	134.140	47.877	113.300	44.035
*Fare*90	499.275	232.529	366.287	173.220
Gini	0.276	0.061	0.260	0.050
Gini_lodd	-0.980	0.312	-1.064	0.267
Avg_MMC	1.156	0.902	1.497	0.972
own_outsourcing	0.150	0.212	0.203	0.218
competitor_outsourcing	0.080	0.151	0.084	0.125
Networksize	0.487	0.358	0.424	0.325
Roundtrip	0.765	0.161	0.673	0.182
Hub	0.624	0.484	0.602	0.489
HHI	0.585	0.227	0.505	0.214
*Airport_cost*1	0.304	0.193	0.141	0.108
*Airport_cost*2	0.304	0.199	0.137	0.108
Observations	146,784		50,663	

Tables 16 and 17 serve as a robustness check to Tables 3 and 7, respectively. As with Table 3, the estimated coefficient for Avg_MMC/SD in Table 16 is positive and statistically significant for the price regressions (Columns 1-3) and negative and statistically significant for the price dispersion regression (Columns 4 and 5). Moreover, the results in Table 17 suggest that multimarket contact softens price competition in non-Southwest markets but not in Southwest markets, which is consistent with our takeaway from Table 7.[17] Therefore, our results are qualitatively similar when using either an airport-pair definition or a city-pair definition.[18] Ultimately, we elect to use an airport-market definition in order to be consistent with the data cleaning process in Ciliberto and Williams (2014), which uses an airport-pair definition.

[17]Brueckner, Lee, and Singer (2014) mentions that low-cost carriers such as Southwest traditionally relied heavily on secondary airports such as Midway Airport (rather than O'Hare in Chicago), Baltimore-Washington International (rather than Reagan National or Dulles in D.C.) and Oakland (rather than San Francisco in the Bay Area). As such, we alternatively define a city-pair based on whether Southwest services the multi-airport city's primary airport. The results using this narrower market definition yield qualitatively similar results to Table 17.

[18]Brueckner, Lee, and Singer (2014) discuss how Cincinnati and Miami are two multi-airport cities that do not experience competitive spillovers from low-cost carriers. The results omitting Cincinnati and Miami as multi-airport cities are qualitatively similar to the results in Table 17.

Table 16: Multimarket Contact and Price Dispersion (City-Pairs)

VARIABLES	(1) lnFare	(2) lnFare10	(3) lnFare90	(4) Gini	(5) Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.198***	0.226***	0.155***	-0.024***	-0.139***
	(0.044)	(0.042))	(0.055)	(0.008)	(0.039)
Networksize	0.032*	-0.004	0.020	0.001	0.010
	(0.017)	(0.017)	(0.021)	(0.003)	(0.015)
Roundtrip	0.004	0.017	0.102***	0.018***	0.086***
	(0.015)	(0.014)	(0.020)	(0.003)	(0.017)
Hub	0.037**	-0.004	0.082***	0.018***	0.097***
	(0.017)	(0.016)	(0.020)	(0.003)	(0.016)
$\widehat{HHI}$	0.261***	0.195***	0.280***	0.007*	0.031
	(0.024)	(0.024)	(0.028)	(0.004)	(0.021)
Observations	219,596	219,596	219,596	219,596	219,156

Notes: (i) Markets are defined as directional city-pairs following Brueckner, Lee, and Singer (2014). (ii) Avg_MMC/SD is instrumented by $own\_outsourcing$ and $competitor\_outsourcing$. (iii) HHI is instrumented by $lnRoutePass$, $iRouteHHI$, and $PassRatio$. (iv) Carrier-route and carrier-time fixed effects are included in all regressions. (v) Route-specific clustered standard errors in parentheses. (vi) *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Multimarket Contact and Southwest Airlines (City-Pairs)

	Non-Southwest Markets					Southwest Markets				
VARIABLES	(1) lnFare	(2) lnFare10	(3) lnFare90	(4) Gini	(5) Gini_lodd	(6) lnFare	(7) lnFare10	(8) lnFare90	(9) Gini	(10) Gini_lodd
$\widehat{Avg\_MMC/SD}$	0.205***	0.202***	0.163***	-0.019**	-0.106**	0.144	0.268**	0.186	-0.009	-0.069
	(0.048)	(0.046)	(0.060)	(0.009)	(0.045)	(0.098)	(0.106)	(0.128)	(0.021)	(0.111)
Networksize	0.020	-0.005	0.002	0.000	0.003	0.044*	0.007	0.055*	0.007	0.036
	(0.020)	(0.019)	(0.024)	(0.004)	(0.019)	(0.024)	(0.030)	(0.032)	(0.006)	(0.031)
Roundtrip	0.028	-0.003	0.192***	0.039***	0.176***	-0.034	0.027	-0.052	-0.022***	-0.093***
	(0.019)	(0.018)	(0.025)	(0.004)	(0.020)	(0.028)	(0.030)	(0.039)	(0.006)	(0.033)
Hub	0.077***	0.052**	0.124***	0.014***	0.075***	0.001	-0.045**	0.025	0.013***	0.076***
	(0.022)	(0.026)	(0.025)	(0.005)	(0.024)	(0.017)	(0.022)	(0.023)	(0.004)	(0.022)
$\widehat{HHI}$	0.189***	0.109***	0.203***	0.012**	0.064**	0.140***	0.127**	0.170***	0.006	0.011
	(0.029)	(0.029)	(0.034)	(0.005)	(0.027)	(0.040)	(0.051)	(0.048)	(0.008)	(0.039)
$lnAirport\_cost1$	0.045***	0.035***	0.049***	0.000	0.001	0.002	0.007*	0.003	-0.001	-0.005
	(0.004)	(0.004)	(0.004)	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)	(0.001)	(0.004)
$lnAirport\_cost2$	0.046***	0.031***	0.049***	0.001	0.005	0.003	0.006	0.006	0.000	0.000
	(0.004)	(0.004)	(0.005)	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)	(0.001)	(0.004)
Observations	145,752	145,752	145,752	145,752	145,365	49,939	49,939	49,939	49,939	49,893

Notes: (i) Markets are defined as directional city-pairs following Brueckner, Lee, and Singer (2014) such that Southwest Markets include all nearby airports within a city serviced by Southwest Airlines. (ii) Avg_MMC/SD is instrumented by $own\_outsourcing$ and $competitor\_outsourcing$. (iii) HHI is instrumented by $lnRoutePass$, $iRouteHHI$, and $PassRatio$. (iv) Carrier-route and carrier-time fixed effects are included in all regressions. (v) Route-specific clustered standard errors in parentheses. (vi) *** p<0.01, ** p<0.05, * p<0.1.

5 Conclusion

This paper studies how tacit collusion in the U.S. airline industry affects price dispersion for airfares. Our results imply that average multimarket contact increases average fare, 10th percentile airfares, and 90th percentile airfares such that tacit collusion has a negative effect on price dispersion. Given that the mutual forbearance hypothesis implies that multimarket contact softens competition, our results suggest that airlines are tacitly colluding by raising their fares all along the price distribution, on average, when they directly compete more frequently across all routes, but the distribution becomes more compressed since prices on the left tail increase by more than prices on the right tail.

To the best of our knowledge, we are the first to document the role that Southwest Airlines has on limiting the prevalence of tacit collusion. Our results show that multimarket contact leads to softer price competition on routes where Southwest does not exist. More importantly, the presence of Southwest Airlines on a route results in an insignificant impact of multimarket contact on price dispersion and thus no empirical evidence of tacit collusion. The upshot is that Southwest Airlines remarkably inhibits the potential for collusive behavior in the airline industry.

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Appendix A Data Construction

In this appendix, we discuss our methods to construct the sample from DB1B and T-100 Domestic Segment databases. We closely follow the approaches in Gerardi and Shapiro (2009) and Ciliberto and Williams (2014). To construct our panel data of airline-route-time ticket observations, we use only domestic, coach-class and tickets containing direct fights from 1993 to 2017. Here, direct flights encompasses both nonstop flights and flights in which there is a stop but no change of plane. The BTS includes a variable, *DollarCred*, that describes the reliability of each ticket price. Dollar credit is zero if the ticket fare is of questionable magnitude, and one if it is credible. We drop all tickets for which *DollarCred* is equal to zero.

We drop all fares less than \$25 for one-way tickets and \$50 for round-trip tickets. Also, we drop exceedingly high fares greater than \$2500 for one-way tickets, which are likely key punch errors. Fares are then deflated using the consumer price index to 2017 dollars from the Bureau of Labor Statistic. The DB1B also provides information on the fare class of each ticket (coach-class, business-class, or first-class) so we drop all business-class and first-class tickets.

We also drop tickets if the ticketing and operating carriers are different due to code-sharing arrangements among major airlines but not due to outsourcing subcontract between major and regional airlines. Code-sharing occurs when a ticket is sold by a major airline and the flight is operated by a rival major airline, whereas outsourcing occurs when a ticket is sold by a major airline and the flight is operated by a regional airline.

Next, we drop tickets in which the ticketing carrier or operating carrier are not reported. Following Gerardi and Shapiro (2009) and Ciliberto and Williams (2014), we drop airline-route observations that do not have at least 100 passengers in DB1B in order to not only eliminate possible coding errors but also have adequate coverage to calculate reliable price dispersion statistics. We treat round-trip tickets as two one-way tickets, and divide the round-trip fare by two, and drop one of two observations to avoid double-counting.

There is an average of 1.66 ticketing carriers per route, where the minimum is 1 and the maximum is 7 of ticketing carriers. Since major airlines determine the prices for flights operated by regional airlines and airfares are calculated by ticketing airline, regional airlines are not counted as separate competitors and their capacity is merged with that of the major carriers for the purpose of market share computation.

Each airline appears on average for 48.89 quarters (around 12 years). Based on our category of majors and low-cost carriers, major carriers appear on average for 83.88 quarters (around 21 years) and low-cost carriers appear on average for 33.3 quarters (around 8 years). The shorter time span for low-cost carriers is due to the a high incidence of entry and exit. Lastly, we drop monopoly markets since average multimarket contact is undefined for monopoly markets.

Our final unbalanced panel sample contains 242,088 carrier-route-time observations spanning 26 airlines, 4,409 distinct routes, and 100 quarters between 1993:Q1 and 2017:Q4.[19] There have been a decreasing time trend in the number of carriers over the 25 years in our sample with an average of around 13 ticketing carriers operating per year-quarter (the minimum and maximum are 8 in recent years and 19 in the late 1990s). In our sample, the number of routes in our sample is larger than the 2,902 routes in Gerardi and Shapiro (2009) because of entry and exit that occurred in the differing time range. However the number of routes in our sample is smaller than the 6,366 routes in Ciliberto and Williams (2014) since we drop ticketing airline-route-time observations that do not have at least 100 passengers as discussed above.

[19] Following Gerardi and Shapiro (2009), our sample includes 26 airlines. The 8 major carriers are American (AA), Alaska (AS), Continental (CO), Delta (DL), Northwest (NW), Trans World (TW), United (UA), and US Airways (US). The 18 low-cost carriers are JetBlue (B6), Frontier (F9), AirTran (FL), ValuJet (J7), Morris Air (KN), Kiwi (KP), National (N7), Vanguard (NJ), Spirit (NK), Pro Air (P9), Reno (QQ), Sun Country (SY), American Trans Air (TZ), Western Pacific (W7), Eastwind (W9), Southwest (WN), Air South (WV), and Access Air (ZA).

Appendix B Demand and Marginal Cost Analysis

In this online appendix, we investigate why tacit collusion is unlikely to occur in Southwest markets by estimating a demand equation using OLS and 2SLS as in Gayle (2013). Market miles flown and the interaction between jet fuel price and market miles flown are used as instruments for airfare since the price of a product (e.g. a flight) is typically influenced by changes in its marginal cost. Table B.1 presents the regression results for the demand estimations. As expected, the coefficient estimate on *lnFare* is negative, implying that higher prices are associated with lower levels of utility. In other words, passengers prefer cheaper air travel products, all else equal.

Table B.1: Demand Estimation

VARIABLES	(1) OLS	(2) 2SLS
$\widehat{lnFare}$	-0.465***	-3.024***
	(0.014)	(0.281)
$Networksize$	0.776***	0.976***
	(0.052)	(0.071)
$Roundtrip$	2.431***	1.238***
	(0.013)	(0.129)
Hub	0.310***	0.391***
	(0.039)	(0.046)
Under-id		90.734
		(0.000)
Over-id		0.211
		(0.646)
Observations	405,201	405,201

Notes: (i) The Kleibergen-Paap rk LM statistic is used for under-identification test while the Hansen's J statistic is used for over-identification test. (ii) *lnFare* is instrumented by market miles flown and the interaction between jet fuel price and market miles flown. (iii) Carrier-route and carrier-time fixed effects are included in all regressions. (iv) Route-specific clustered standard errors in parentheses. (v) *** p<0.01, ** p<0.05, * p<0.1.

Following Gayle (2013), we then impute the average marginal costs for eight airlines (listed in alphabetical order by IATA code). Table B.2 reports that Southwest has the lowest average marginal cost compared to major airlines. This is consistent with the calculations in the existing literature; for example, Gayle (2013) estimates that Southwest's average marginal cost is $117.95.

Since Scherer (1980) explains that a collusive agreement is more likely to break down if the participating firms have different marginal costs, it makes sense that tacit collusion could occur in non-Southwest markets since the major airlines have similar average marginal costs. However, it would be difficult to maintain tacit collusion in Southwest markets given the stark contrast in Southwest's marginal cost compared to the major airlines.

Table B.2: Average Marginal Costs

Carrier	Code	MC ($)
American Airlines	AA	218.698
Continental Airlines	CO	250.434
Delta Air Lines	DL	209.179
Northwest Airlines	NW	240.825
Trans World Airlines	TW	213.644
US Airways	US	215.254
United Airlines	UA	227.558
Southwest Airlines	WN	137.179