Collusive Capacity Reduction Patterns in the US Airline Industry*

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Abstract

This chapter is an investigation into the possibility that multimarket contacts result in collusion in the setting of capacity in the US domestic airline market. I first provide reduced-form evidence on the effect of multimarket contacts on the possibilities of firms colluding in setting capacity by demonstrating that levels of multimarket contract have significant negative correlations with the quantity of seats that airlines release. Specifically, the effect of multimarket contact is primarily led by the four largest airlines (Southwest, United, Delta, and American); this has a greater effect in smaller markets in comparison to medium-sized and larger ones. Lead by the evidence, I estimate structural model of demand and supply system with conduct parameter which capture the degree of collusion in setting capacity. The conduct parameter is specified as a function of multi market contact; it will be demonstrated that the conduct parameter shows that there is a significant and positive correlation between multimarket contact and collusion, suggesting that the greater the level of multimarket contact, the lower the quantity of seats that will be offered in comparison to non-collusive oligopoly equilibrium.

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Job Market Paper

1 Introduction

In 2015, the U.S. Department of Justice undertook an investigation into 'possible unlawful coordination' by four U.S. airlines (American, Delta, United, and Southwest; hereafter 'the major airlines'), which had been accused of collusion to limit both routes and number of affordable seats ('capacity discipline') available in order to boost prices.[1] Although the inquiry has found no evidence of collusion on either pricing or capacity, it remains ongoing.[2] Findings of previous empirical economic studies across diverse industries indicate that collusive behavior among oligopolistic firms leads to monopolistic output which causes a drop in efficiency across output level and price and is not in the interest of consumers. Detecting collusion has been a mainstream task in the field of industrial organization for so long that a wide range of economists and practitioners have dedicated themselves to identifying the factors indicating and underlying collusive behaviors. Among such factors, market structure stands out and has been the focus of multiple studies in this area. Early studies tended to investigate firms within a single market; however, more recent work has taken account of the fact that as most companies produce more than one product, they also compete across multiple markets.

Previous study in this field has often made reference to Edwards' (1955) 'mutual forbearance hypothesis,' which posits the generation of anti-competitive output when firms compete across several markets. This hypothesis holds that when there is competition in more than one market, competition becomes more aggressive and hence more costly; if, on the other hand, firms choose to collude in such markets, the

[1]https://www.washingtonpost.com/business/economy/doj-investigating-potential-airline-collusion/2015/07/01/42d99102-201c-11e5-aeb9-a411a84c9d55_story.html.

[2]https://www.wsj.com/articles/obama-antitrust-enforcers-wont-bring-action-in-airline-probe-1484130781.

costs are reduced. Bernheim and Whinston's (1990) seminal theoretical study on the association between collusive behaviors and multimarket contact created several formal models, applied Edwards' hypothesis, and found that the incentive constraints which serve to restrict collusion are less strong in a condition of multimarket contact. Economists have empirically extended their work by applying the hypothesis to collusive pricing patterns across a wide range of industrial settings.

Evans and Kessides (1994) investigated the link between multimarket contact and pricing within the U.S. domestic airline industry, finding significantly higher fares where multiple airlines served a single city with higher level of multimarket contact. Several researchers have since investigated the relationship between multimarket contact and collusion in the same sector. The earlier research studies (Singal, 1996; Bilotkach, 2011; Ciliberto and Williams, 2014; Ciliberto et al., 2019) looked exclusively at links between collusive pricing and degree of multimarket contact while the later ones (Mazzeo, 2003; Rupp et al., 2003; Prince and Simon, 2017; Chen and Gayle, 2018) also investigated the impact of market structure on product quality, using the metric of on-time performance.

These studies indicate that a range of market factors can negatively impact product quality in the airline industry, including mergers, monopolies, and dehubbing; however, little work has investigated whether multimarket contact is among these factors. The literature includes only one example of in-depth investigation of collusive behavior: Subsequent to the Department of Justice inquiry in 2015 mentioned above, Aryan et al. (2017) examined the possibility that earnings announcements by U.S. airlines served as a signal to undertake a coordinated campaign of 'capacity discipline', that is, for all players to reduce capacity. Their investigation found that each time the more important players discussed this concept, such capacity was reduced by between 1.14% and 1.48%. To date, while the majority of studies in this area have only investigated the impact of multimarket contact on collusive pricing behavior by using reduced-form analysis, Ciliberto and Williams' (2014) study provides structural analysis of relationship between multimarket contact and collusive pricing behavior.

The empirical examination described in this paper aims to determine whether multimarket contact results rise to collusive capacity setting among U.S. domestic airlines, with a focus on capacity setting competition. Relevant data were gathered from two Department of Transportation (DOT) sources: first, the Airline Origin & Destination Survey (DB1B); and second, the T-100 domestic segment covering both monthly and non-stop routes during the period 2008-2019. Degree of multimarket contact is measured in terms of the number of overlapping markets in which a given carrier competes with at least one other. The robustness of this analysis was verified by the use of two alternative multimarket contact measures (size of airline, and market share on routes operated concomitantly), which allow for any asymmetry in degrees of coordination.

First, a reduced-form analysis is used to reveal whether the two principal variables of airlines in a given market, namely market-level capacity and multimarket contact, correlate. The primary concern in terms of identification is the potential exogeneity of average multimarket contact. While Evans and Kessides (1994) and Bernheim and Whinston (1990), among others, consider multimarket contact an external factor, there is likely to be unobservable heterogeneity that informs decision-making on price, entry and exit, thereby influencing average multimarket contact. Therefore, to resolve these multimarket contact endogeneity concerns, in building the instrumental variables for average multimarket contact, this study uses data on each airline's number of gates at US airports. Although the number of gates controlled by an airline at an airport naturally correlates with that airline's decision to serve a given market, due to the long-term nature of airport-airline leasing agreements, this number cannot be easily adjusted. As a result, these variables represent valid instruments to measure multimarket contact. As the economic and market circumstances influence airlines' capacity decision-making, we incorporate multiple covariates to control for market-specific factors that vary over time. Subsequently, we investigate whether multimarket contact's effect on collusion in terms of capacity-setting strategy varies with the size of the market. As a rule, larger markets imply more competitors and higher demand volatility than small markets, increasing airlines' difficulty in coordinating their capacity-setting measures. Nevertheless, airlines with a higher share of business travelers may be incentivized to coordinate capacity reduction as these passengers are more immune to price changes and are more present in large markets; in such a circumstance, there is more likely to be collusion.

Thereafter, investigation was made of whether the effect of multimarket contact on capacity reduction varies according to carrier type. The four major airlines investigated by the Department of Justice in 2015 were responsible for about 80% of U.S. domestic air travel. Given the allegation that they had colluded to limit routes and the number of affordable seats to boost ticket prices, an investigation is necessary to determine whether these four companies were principally responsible for the effect of multimarket contact on capacity reduction. Therefore, in the current analysis, effect of multimarket contact on capacity reduction is permitted to vary according to first, carrier type and second, whether only the major airlines serve the market or there is a mixture of major airlines and low-cost carriers (LCC). The results of reduced-form analysis suggest that for each one unit increase in average multimarket contact, there is a consequent 1.02% reduction in the number of offered seats. Specifically, the effect of multimarket contact is primarily led by the four largest airlines (Southwest, United, Delta, and American); this has a greater effect in smaller markets in comparison to medium-sized and larger ones.

The next step consists of structural analysis: the formulation of a structural model to estimate inter-airline competition in terms of capacity and price. The demand framework formulated for this analysis built on the work of Berry, Levinsohn, and Pakes (1995), being a random-coefficient discrete-choice model with heterogeneous consumer preferences. In the two-stage supply framework used, airlines first decide capacity per product and then price. Hence, it is possible to determine whether the introduction of first-stage capacity-related decisions taken in light of the degree of multimarket contact has a significant effect on how many seats airlines make available and therefore whether prices change. Conduct parameters built into the model detect whether multimarket contact impacts collusive capacity setting by measuring how far outcomes deviate from a non-collusive oligopoly setup. Following Ciliberto and Williams (2014), the conduct parameters in the model are modelled as a function of multimarket contact. An estimation of conduct parameters enables the relationship between multimarket contact and collusive behavior in capacity setting to be determined. I find that carriers with more multimarket contact, such as the major four airlines, collude when setting capacity, while those with an insignificant multimarket contact do not.

The study makes three major contributions to the literature. First, it expands on the currently meager body of empirical research investigating what facilitates collusion, particularly among airlines. Second, it contributes to the multimarket contact literature, which has focused exclusively on the effect of multimarket contact on collusive pricing behavior rather than on capacity setting. To the best of my knowledge, the latter has not yet been examined. This was achieved in the current research by carrying out a reduced-form analysis using instrumental variable regression. Third, the paper puts forward a structural model linking degree of multimarket contact and degree of collusive behavior in capacity setting. The reduced-form analysis demonstrated only how multimarket relates to market outcomes, but shed less light on how changes to the degree of multimarket contact affects degree of coordination among airlines. The findings of this empirical research are of use to policy makers as they indicate that antitrust enforcement agencies should monitor airlines' capacity-setting behaviors on routes characterized by a high degree of multimarket contact.

The remainder of this paper is structured as follows. Section 2 presents institutional details relating to the antitrust case against the four major airlines, while section 3 explores the data collected, including market definition and MMC measures. Section 4 sets out the reduced-form analysis and results, and section 5 describes the structural analysis and results. Finally, section 6 concludes by presenting the implications of the findings and outlining future research avenues.

2 Background

In July 2015, the U.S. Department of Justice began an investigation into allegations that four major domestic carriers, American, Delta, United and Southwest Airlines, had engaged in collusive behavior. It was reported in the Washington Post and other media outlets that, according to sources close to the inquiry, the Department of Justice was looking into a possible attempt to boost ticket prices through a coordinated reduction of capacity, by limiting seats available on some routes and eliminating other routes altogether.

Although no hard evidence has been submitted to prove this allegation, both consumer advocacy organizations and lawmakers, including Sen. Richard Blumenthal, D-Connecticut, have raised the possibility that the consolidation of market power in the hands of these four airlines may be a breach of antitrust legislation. Their suspicions were further raised by the unprecedently high profits all four had recently posted, along with the fact that ticket prices had risen, despite the rapid drop in jet fuel prices in the 12-month period before the inquiry which should have led to price reductions.[3]

Hence, the DOJ asked the airlines to submit their documented communications with each other concerning flight capacity intentions. In particular, they were asked to produce all documents which might show the necessity or desirability of reducing capacity or limiting their own growth of that of any other airline. Moreover, the airlines were requested to submit regional reports as proof of their monthly capacities as far back as 2010.

Despite sitting for a considerable period, the DoJ inquiry was ultimately unable to find sufficient proof of collusion in regard to capacity and pricing and therefore no antitrust action was brought against the four carriers involved. Nonetheless, the investigation remains officially ongoing.

After reports of the DoJ inquiry first appeared in the Washington Post, lawyers representing consumers filed dozen of lawsuits against the four carriers under investi-

[3]https://www.ctpost.com/news/article/After-Blumenthal-s-call-DOJ-investigates-6361614.php

gation. Consolidated into a single lawsuit, their case is currently being heard in the U.S. District Court for the District of Columbia. One of the defendants, Southwest Airlines, paid out a $15 million settlement in 2018 and agreed to assist the other side's attorneys[4]; another, American Airlines, refused to admit to any wrongdoing but paid a $45 million settlement nonetheless, on the grounds that doing so would be less damaging than engaging in long and costly legal proceedings.[5] The other two carriers, United Airlines and Delta Air Lines, on the other hand, have refused to either admit wrongdoing or come to a financial settlement: Delta insists it has done nothing illegal, and both Delta and United have announced their intention to carry on fighting the allegations in court.[6] This case offers just one example of how difficult it is for government to bring an antitrust action against U.S. airlines. Hence, academic research remains ongoing and important in the area of facilitation and collusive behavior.

3 Data

Four primary sources were used to collect the data for the empirical analysis. The first was the T-100 Domestic Segment, providing the non-stop domestic flight information reported by US carriers, e.g., carrier, seating capacity, load factor, origin, and destination. The second was the Airline Origin and Destination Survey (DB1B) from the US Department of Transportation; this comprises a random 10% sampling of airline tickets as reported by carriers, providing such details as ticketing and operating

[4] https://www.nytimes.com/2018/01/06/business/southwest-airlines-lawsuit-prices.html

[5] https://www.bloomberg.com/news/articles/2018-06-15/american-agrees-to-pay-45-million-to-settle-fare-collusion-suit

[6] https://www.ajc.com/business/settlements-air-fare-collusion-suit-puts-pressure-delta-united/J6bgHDJ4ymc995g1EDAxHI/

carriers, airfare, distance, passenger numbers, and airports (origin, destination, and connecting). [7] The third source was the Bureau of Economic Analysis, from which the populations of the Metropolitan Statistical Areas (MSA) of both origin and destination airports were derived. The data were obtained for the period between January 2005 and December 2015. This period was selected as it saw multiple airlines merging, leading to four major carriers dominating 80% of air traffic and creating a substantial shift in the multimarket contacts among US domestic airlines. The collected data used for the reduced-form and structural analyses are summarized in Table 1.

While general airline data, including pricing and market data, are publicly available, airport gate data remain elusive. To capture gate data, this study constructed a gate leasing dataset derived from information taken from airport competition plans submitted to the Federal Aviation Administration (FAA), combined with information obtained directly from the respective airports. Following the Wendell H. Ford Aviation Investment and Reform Act for the Twenty-First Century (AIR 21), the U.S. Department of Transportation required all major airports to submit such plans to the FAA in return for federal grants. The airports targeted by AIR 21 are commercial airports that account for at least 0.25 percent of the annual total passenger boardings in the United States and have no more than two carriers controlling over 50 percent of passenger boardings. This study used these plans to glean information on airport gate availability, gate and airport facility leasing and subleasing arrangements, and airport-airline agreements. Table 2 reports the observed airports and airlines.

The gathered dataset bears a limitation. As the competition plans are only submitted if there is a change in the conditions, they tend to be only erratically available

[7] The DB1B database contains a sample of 10% of airline tickets supplied by those carriers who report; it is issued every quarter. The DB1B contains a trio of sub components, these being the ticket dataset, coupons, and market. In this research, the ticket dataset and coupon are combined.

and each airport only offers a single observation. To overcome this limitation, this study restricted the sample to the 2008-2018 period, which is suitable as airlines sign long-term gate use contracts with airports. According to the Government Accounting Office (GAO, 1990), at the 66 large and medium-sized airports, almost 88 percent of the 3,129 gates were leased to airlines, and 85 percent of these were for the leasing airline's exclusive use. Furthermore, 87 percent of leased gates at these airports had long-term leases lasting 20 years, and two-thirds of the gates at the large airports had at least 10 years remaining on the lease.

3.1 Market Definition

This study defines a market as any non-directional round trip from the origin airport to the destination airport irrespective of the number of connections, as previously defined by Borenstein (1989) and Evans and Kessides (1994).[8] This study considers only those itineraries that either begin or end within an MSA boundary.[9] Only markets with no less than 250 passengers are included, while those that did not transport 100 passengers during at least one month during the sample period were excluded to factor out charter flights and seasonal travel. Similarly, airlines serving less than 1 percent of a market's passengers were also excluded. As certain regional carriers, e.g., SkyWest, Endeavor and Piedmont Airlines, whether the subsidiaries of network airlines or independent airlines, function as agents for major airlines, these are merged with their network carriers.

[8] In line with other research into airline industry, passengers who have very expensive (over \$1250) or very cheap (under \$25) fares are removed as outliers.

[9] Defined by the Office of Management and Budget in bulletin 18-03 issued on April 10, 2018.

3.2 Market Types

The markets were differentiated in two ways, based on their size or on which carrier type operated them, to assess to what extent the market type affects how multimarket contact impacts on capacity decisions. Specifically, as markets vary in terms of competition, carriers' decision-making in terms of seating capacity may differ between markets, making market size and operating carrier type key factors in evaluating how multimarket contact affects collusive behavior. Following Berry, Carnall, and Spiller (1996), I compute population of the market by using the geometric means of the end-point cities' populations. In addition, Aryal et al. (2018) have defined the concept as being based on the market's population distribution. I ranked market size based on the geometric mean of the population sizes in the end-point cities and defined three variables of market size (i.e., large, medium, and small) based on the population distribution of the market. [10]

This study differentiates between major, mixed, and legacy markets in its empirical analysis. Major markets are those fully serviced by major carriers, referring to the four largest US carriers, i.e. American Airlines, United Airlines, Delta Airlines, and Southwest Airlines. Mixed markets refers to those in which major and LCC carriers operate concurrently, while legacy markets comprise those serviced by American Airlines, United Airlines, and Delta Airlines.

3.3 Multimarket Contact

An empirical examination of the impact of multimarket contact on capacity decision-making first needs multimarket contact to be quantified. While a variety of such

[10] Since the average population is used across the sampling timeframe for the classification of small, medium, and large marketplaces, a fixed classification for market size is used over this timeframe.

measures exist, that of Evans and Kessides (1994) measures in how many overlapping markets an airline faces competition with another, thereby showing the absolute extent of multimarket contact. This study considers it a multimarket contact if airlines i and j both offer non-stop services within the same market; the total number of these markets is the multimarket contact measure for this airline pair. Assuming n airlines with m routes, this number can be calculated by:

$$mmc1_{ij} = \sum_{k=1}^{m} D_{im} D_{jm} \tag{1}$$

where D_{im} is a dummy variable showing 1 if airline i serves market m, and 0 otherwise. $MMC1$ is an $n \times n$ symmetric matrix with the generic element $mmc1_{ij}$ expressing in how many markets airlines i and j compete; $mmc1_{ii}$, on the matrix's diagonal, is the number of markets in which airline i operates. The multimarket contact measures for the 11 airlines found in the study sample for the 2015 fourth quarter are presented in Table 2. Meanwhile, matrix $MMC1$ provides the average multimarket contact measure,$AvgMMC1$, defined as how many markets on average overlap within any given market:

$$AvgMMC1_m = \frac{1}{\left[N_m \left(N_m - 1\right)\right]} \sum_{i=1}^{N_m} \sum_{j=1, j \neq i}^{N_m} mmc1_{ij} D_{im} D_{jm}, \tag{2}$$

where N_m is the number of carriers serving market m.

However, as this multimarket contact measure solely captures the number of overlaps while weighing all carriers and markets the same, any variation in carrier size of market dominance is not taken into account. Hence, to assess the robustness of the results, two alternative multimarket contact measures are used. This first is a second multimarket contact measure, $mmc2_{ij}$, which is determined by dividing the previous measure $mmc1_{ij}$ by the number of markets that airline i serves:

$$mmc2_{ij} = \frac{mmc1_{ij}}{mmc1_{ii}} \tag{3}$$

$MMC2$, presented in Table 3, is an $n \times n$ asymmetric matrix with the generic element $mmc2_{ij}$ expressing that each airline in a pair serves a different number of routes. This allows MMC_2 to capture different airlines sizes, in contrast to MMC_1, which equally weights all multimarket contact pairs. If one airline serves fewer markets than its competitor in any pair, its multimarket contact measure will be larger as the $mmc2_{ij}$ will be asymmetric. This indicates that smaller airlines face a greater cost of deviation from collusive agreements. The following airline size weighted multimarket contact measure for market m is derived from this matrix. From this matrix I create the following airline size weighted measure of average multimarket contact for market m:

$$AvgMMC2_m = \frac{1}{[N_m\,(N_m - 1)]} \sum_{i=1}^{N_m} \sum_{j=1, j \neq i}^{N_m} mmc2_{ij} D_{im} D_{jm}, \tag{4}$$

The other alternative multimarket contact measure, $MMC3$, also considers the market shares of the carriers. Specifically, the MMC_3 matrix has a generic element calculated as $mmc2_{ij}$ multiplied by airline i's US market share:

$$mmc3_{ij} = mmc2_{ij} \cdot \text{market share of airline } i \tag{5}$$

The market share weighted average multimarket contact measure for market m can thus be derived from this matrix:

$$AvgMMC3_m = \frac{1}{[N_m (N_m - 1)]} \sum_{i=1}^{N_m} \sum_{j=1, j \neq i}^{N_m} mmc3_{ij} D_{im} D_{jm}, \tag{6}$$

The time series of the relative extent of the multimarket contact measures emerging during the sample period is depicted in Figure 1, Figure 2, Figure 3 and Figure 4. Figure 1 illustrate a fluctuation in $mmc2_{ij}$ measure of multimarket contact between American Airlines and other airlines and the $mmc2_{ij}$ measure of multimarket contact between Delta and other airlines, United and other airlines, and Southwest and other airlines are illustrated in Figure 2, Figure 3 and Figure 4, respectively. The time-series variation for the pairs of four major airlines highlights the many source of variation present in the data: expansion of networks, de-hubbing and mergers.

3.4 Endogeneity of the Multimarket Contact Variable

As the market-specific measures of average multimarket contact are endogenous, there is a potential for bias in both the reduced form and structural analysis results. As noted by Ciliberto, Murry, and Tamer (2021), market-specific multimarket contact may be endogenous because of unobservables that correlate with the decisions that airlines make on pricing, entry and exit. Specifically, firms choose to enter those markets that offer the best fit for their observable and unobservable characteristics, meaning that they base their market entry decision-making on the profits that they may gain from this entry. Meanwhile, each market contains idiosyncratic time-varying unobservables. For example, additional airlines will enter the market if it is experiencing a positive demand shock. Any change in the airlines operating in a market will lead to a time-dependent variation in that market's $AvgMMC$. As the market structure variation is directly linked to the market-specific measure of average multimarket contact, and is furthermore likely to correlate with price-affecting unobservables, cross-sectional variation cannot be used to determine a causal relationship between multimarket contact and airlines' capacity decision-making. In repeated observations, fixed-effect identification strategies are primarily used to control unobserved and unchanging characteristics related to both the causing variables and their outcomes. As per Griliches and Mairesse (1995), when endogeneity is driven by time-varying unobservables that are market-specific, fixed-effects models are ineffective. Meanwhile, Ciliberto and Williams (2014) propose the use of instrumental variables to mitigate concerns of endogeneity in $AvgMMC$.

Following Ciliberto and Williams (2014), this study constructs the instrumental variables for both the reduced-form and structural analysis based on a dataset comprising individual carriers' access to boarding gates at the respective airports. These data encompass the percentage of gates an airline uses at the origin and destination airports, respectively, as well as the percentage of gates at the respective origin and destination airports used by Southwest Airlines and other low-cost carriers. The long-term nature of airline-airport leasing agreements implies that the number of gates used by a carrier is likely to remain reasonably resistant to shocks. The abovementioned competition plans offer information on the number of gates available, the number of gates in common use, and the number of gates leased to airlines, whether exclusively or preferentially, as reported by the airlines. Thus, we construct $OwnGatesOrigin$ and $OwnGatesDest$, measuring the percentage of gates leased exclusively or preferentially to airline j at the origin and destination endpoints of market r, respectively. Further, we build $LCCGatesOrigin$ and $LCCGatesDest$ for the same information on the low-cost carriers' leases and use $WNGatesOrigin$ and $WNGatesDest$ based on the leases of Southwest Airlines. As airlines have control of their gates while they are using them, exclusive and preferential leases are treated the same. Unlike Ciliberto and Williams (2014), who used the sum of the average fraction of gates leased at a market's endpoints, this study distinguishes between origin gates and destination gates for this measure in order to capture any differences in the effects.

Ciliberto and Williams (2014) provide the following reasoning for why gate information is a valid instrument for multimarket contact. First, airlines have difficulty in adjusting their airport facility access in response to unpredictable demand and cost changes. As noted by GAO (1990), carriers are unable to unilaterally terminate gate leases and subleasing them incurs costs. Second, as individual markets rarely represent a large proportion of an airline's revenue from any given airport, carriers are likely to shy away from changing the number of gates they lease based on market-specific demands. Finally, leasing decision-making is based at the level of airports, and thus fluctuations in a specific market are often offset by those in other markets, meaning that the overall airport demand, i.e. the need for gates, is mostly unaffected.

4 Reduced-form analysis

This study uses reduced-form analysis to evaluate to what extent airlines consider the degree of multimarket contact in deciding on how many seats to offer on a particular route. Ceteris paribus, a higher degree of multimarket contact is expected to relate to a lower number of seats being offered due to the antitrust risk in airlines' capacity decision-making and multimarket contact. Thus, this section examines whether a higher degree of multimarket contact leads to reduced seating capacity based on an airline-airport pair-market fixed-effects model. This model is suitable as most US domestic airlines use hub-and-spoke networks, meaning that the capacity decision-making goes beyond the demands of a specific market to include the numerous spoke markets; the developed model effectively captures such heterogeneities.

However, while the reduced-form analysis uses market-fixed effects for each airline-airport pair, this cannot accommodate the unique heterogeneities of each market. Therefore, the following control variables are used: The geometric mean of the origin and destination cities' populations for market size; the Herfindhal-Hirschmann index (HHI) for route-level passenger numbers to accommodate market concentration; due to the potential for endogeneity, the number of airlines competing at the level of the airport-pair market is also used as an instrument variable; finally, to capture the different market structure of non-monopoly markets, whether a market is served solely by a monopoly carrier is indicated by a dummy variable.

This analysis uses a two-pronged approach. First, a baseline model is specified that will analyze the relationship between the degree of multimarket contact and the natural logarithm of the number of seats. This will enable the extent of the effect of multimarket contact on airlines' capacity decision-making to be determined. Next, as this effect may vary across markets with different sizes, with some characterized by competition between LCCs and legacy carriers and others being served solely by the latter, the second approach considers market size and competing carrier types in estimating the effect of multimarket contact.

4.1 Econometric Models

Base Model

The relationship between the degree of multimarket contact and how many seats airlines offered for the 2005-2015 period is assessed in the following. The following model, describing airline i in market m at time t, was derived from the airline panel data:

$$\begin{aligned} \ln(seats_{imt}) &= \beta_1 AvgMMC1_{mt} + \beta_2 population_{imt} + \beta_3 HHI_{imt} \\ &\quad + \beta_4 monopoly_{imt} + \mu_{i,m} + \mu_{i,t} + \varepsilon_{imt} \qquad , \end{aligned} \tag{7}$$

where the dependent variable is the natural logarithm of the seats that airline i offers in market m at time t. $AvgMMC1$ is the primary variable of interest, whereby the expectation is for its coefficient β_1 to be negative. Multimarket contact indicates that airlines may limit their seating capacity despite sufficient demand, which in turn, can differ over time and across markets. Thus, to control for these intangible factors, this study incorporates carrier-market and carrier-year-quarter fixed effects to accommodate airlines' variations in seating capacity across time and markets.

The Effect of Market Types

The influence of multimarket contact on airlines' capacity decision-making is also analyzed according to the type of carrier. Four major airlines carried 80% of US domestic passengers in 2018. There is a need to identify whether multimarket contact's effect on capacity reduction was driven by the major airlines, particularly in light of the 2015 investigation by the U.S. Department of Justice into potential collusion between them in restricting the number of affordable seats and routes to drive up fares. Therefore, the base model is expanded to examine the variation in the effect of multimarket contact on capacity reduction based on the type of carrier and on whether the market is a mix of major airlines and LCCs or is only served by the major airlines. Hence, the model is as follows:

$$
\begin{aligned}
\ln(seats_{imt}) = {} & \gamma_1^{major} AvgMMC1_{mt} \cdot major_{mt} + \gamma_2^{lcc} AvgMMC1 \cdot lcc \\
& + \gamma_3 population_{mt} + \gamma_4 HHI_{imt} + \beta_4 monopoly_{imt} \\
& + \mu_{i,m} + \mu_{i,t} + \varepsilon_{imt}
\end{aligned} \tag{8}
$$

where $Major$ and lcc respectively indicated whether the operating airline is a major airline or an low-cost carriers. Markets served only by major carriers, also known as major markets, are set at $\gamma_2^{lcc} = 0$.

Based on Stigler (1964), some markets facilitate collusion better than others. For example, all else being equal, larger markets with significant volatility in demand are less able to sustain coordination than smaller markets. Meanwhile, the definition of market size from Berry, Carnall, and Spiller's (1996), i.e. the geometric mean of the origin and destination cities' populations, is drawn upon here to account for the variation in multimarket contact's capacity reduction effect in markets of different sizes. Furthermore, and as mentioned above, three market size variables, namely large, medium and small, are derived from the respective market's population distribution, ranking market size according to the geometric mean of the destination cities' population. In other words, the population of a large market exceeds the 75th percentile of the population distribution, between the 25th and 75th percentiles is classed as a medium market, and beneath the 25th percentile is a small market. Large markets are less likely to offer airlines opportunities to collude on capacity restrictions as they face more volatile demand. Meanwhile, the market size variable also informs on how many airlines serve a large market. As there is more competition in large markets, with the very largest facing fierce competition from LCCs, carriers are more likely to find it difficult to limit the number of seats they offer. Nevertheless, those airlines with a higher share in the business traveler market may be more motivated to coordinate to reduce capacity as such passengers are more frequent in large markets and have less price elasticity. In such a scenario, there is a greater likelihood of coordination to reduce capacity. The following model, incorporating the variation in the multimarket contact effect on market size, is developed to examine the influence of market size on the degree of collusion to reduce capacity:

$$
\begin{aligned}
\ln(seats_{imt}) = {} & \delta_1^{small} AvgMMC1_{mt} \cdot small_{mt} + \delta_2^{medium} AvgMMC1 \cdot medium_{mt} \\
& + \delta_3^{large} AvgMMC1 \cdot large_{mt} + \delta_4 population_{mt} \\
& + \gamma_4 HHI_{imt} + \beta_4 monopoly_{imt} + \mu_{i,m} + \mu_{i,t} + \varepsilon_{imt}
\end{aligned} \tag{9}
$$

where $Small$, $Medium$, and $Large$ are dummy variables that respectively take the value of 1 for small, medium, and large markets.

4.2 Result

The baseline model estimation results are presented in Table 4, Column (1). The coefficient of the average multimarket contact is -0.0102, indicating that for each one-unit increase in average multimarket contact, there is a consequent 1.02% reduction in the number of offered seats. This effect is averaged for all markets, time periods, and carrier types. Robust standard errors are reported, whereby the decrease is significant at the 5% level.

The estimation results of the model incorporating the variations by carrier type and by major market vs mixed market are presented in Table 4, Column (2). The product of the average multimarket contact measure and the market indicator dummies are the main variables of interest. The model indicates that increased multimarket contact relates to a 1.16% reduction in seating capacity in major markets, i.e. those served only by major airlines. This finding suggests that collusion between the major airlines is driving the average multimarket contact effect previously identified in the baseline model. Further insight is obtained from the estimated coefficient on the major airlines and LCCs in mixed markets, where multimarket contact between major airlines leads to their offering 1.29% fewer seats, while no such change is observed for the LCCs.

The results of the model examining the effect of market size on the extent on collusion in capacity decision-making are presented in Table 4, Column (3). The model indicates the increased multimarket contact in small markets causes 2.71% fewer seats to be offered, compared to 1.39% and 0.98% in medium and large markets, respectively, suggesting that the greatest seat reductions by carriers were made in the small markets. The result shows that having more business travelers with less price sensitivity in the market is less of an incentive for collusion than uncertain demand or LCCs entering the market.

Overall, multimarket contact has been shown to effect a reduction in the number of seats available, leading to increased average fares. Reduced-form analysis indicates that the established anti-competitive multimarket contact effect on fares might be aggravated by reduced supply as the latter links directly to passengers' overall travel costs.

4.3 Robustness Check

To assess the results' robustness, the analysis is reiterated with other multimarket contact measures; Table 5 presents the outcomes. Hereby, the average multimarket contact in Column (2) is estimated using $mmc2$; this variable is asymmetric if the members of a carrier pair respectively serve a different number of markets. Meanwhile, Column (3) bases on $mmc3$, or the measure of multimarket contact weighted by the market share. The results are consist with the result of baseline model using $mmc1$ multimarket contact measure and statistically significant; however, the magnitude of the coefficients is not the same because $mmc1$ is the absolute number of contacts while $mmc2$ and $mmc3$ are given as percentages. Thus, multimarket contact is likely to be robust in its definition and have similar implications.

5 Structural Analysis

This section presents the structural analysis, thereby drawing on Ciliberto and Williams (2014), who used structural analysis to examine the relationship between multimarket contact and collusive pricing behavior among the airlines. This facilitates a more in-depth examination of the findings from the reduced-form analysis, showing to what extent multimarket contact affects airlines' degree of collusion in setting capacity.

5.1 Demand Model

The demand model follows Berry, Carnall, and Spiller (BCS, 2006) and Berry and Jia (2010) by extending the nested logit model through heterogeneous preferences for observable and unobservable characteristics of air travel products. There are two types of consumer, $r = \{1, 2\}$. The indirect utility of consumer x having type r and purchasing product j in market m is given by:

$$u_{xjm} = x_{jm}\beta_r - \alpha_r p_{jm} + \xi_{jm} + \nu_{xm}(\lambda) + \lambda\epsilon_{xjm}, \tag{10}$$

where x_{jm} is the vector of product j's observable characteristics; p_{jm} is the price of the product, β_r is a vector of preferences for product characteristics, and α_r is the marginal disutility, which has an increased price for consumers of type r. ξ_{jm} captures product j's unobserved characteristics. v_{im}, which is the nested logit random preference and is constant for all air travel products, distinguishes air travel from the not-flying option. The substitution patterns between the nests of the airline travel and not-flying options are governed by λ, ranging from 0 to 1. ε_{ijm} is a stochastic error term with a mean of 0. Altogether, the error structure $\nu_{im}(\lambda)+\lambda\varepsilon_{ijt}$, is the error structure required to generate nested logit choice probabilities for each consumer type.

The share of type r consumers who purchase air travel products is:

$$s_m^r\left(x_m, p_m, \xi_m, \theta_d\right) = \frac{\left[\sum e^{(x_{jm}\beta_r - \alpha_r p_{jm} + \xi_{jm})/\lambda}\right]^{\lambda}}{1 + \left[\sum_{j=1}^{K} e^{(x_{jm}\beta_r - \alpha_r p_{jm} + \xi_{jm})/\lambda}\right]^{\lambda}} \tag{11}$$

Consumers purchase those air travel products on the market that maximize their indirect utility. This is an optimization problem that results in the following probability of a type r consumer purchasing product j, conditional on the consumer choosing an air travel product:

$$\frac{e^{(x_{jm}\beta_r - \alpha_r p_{jm} + \xi_{jm})/\lambda}}{\sum_{k=1}^{J} e^{(x_{jm}\beta_r - \alpha_r p_{jm} + \xi_{jm})/\lambda}} \tag{12}$$

Thus, market share of product j can be considered as the average purchase probability for all consumers in a given market:

$$s_{jm}\left(x_m, p_m, \xi_m, \theta_d\right) = \sum_r \gamma_r \frac{e^{(x_{jm}\beta_r - \alpha_r p_{km} + \xi_{jm})/\lambda}}{\sum_{j=1}^{K} e^{(x_{jm}\beta_r - \alpha_r p_{jm} + \xi_{jm})/\lambda}} \cdot s_m^r\left(x_m, p_m, \xi_m, \theta_d\right) \tag{13}$$

where γ_r is the percentage in the population of consumers with type r in market m.

5.2 Supply Model

To develop the supply model, airlines' collusion in setting capacity is estimated using Ciliberto and Williams' (2014) framework, which states that the conduct parameter capturing collusive behavior can be modeled as a function of multimarket contact. The extent of deviation from a non-collusive oligopoly outcome is hereby used to measure aggressive or cooperative behavior. As the equally and positively weighting of all competing firms' profits results in full cooperation, firms positively weighting the profits of their competitors will cause the equilibrium outcome to be more cooperative compared to the non-collusive oligopoly equilibrium. Airlines are assumed to compete on prices while offering differentiated products on the market. First, a simple two-stage game is defined: carriers decide on capacity in the first stage, followed by a product-differentiated market game on prices in the second stage[11]. In the first stage,

[11] An assumption is made that the structures of airline networks, e.g., airports used, airport location, routes, and market places, are exogenous. Such an assumption is justifiable because the

firm f makes the capacity decision q^f to maximize profit, thereby considering both the profits for it and its competitor $f\acute{}$. The profit function can be formally specified as:

$$\Pi_f^I = \sum_{j \in J_f} (p_j - MC_j(q_j))\, s_j M + f\,(MMC_{ff'}) \sum_{j' \in J_{f'}} (p_{j'} - MC_{j'}(q_{j'}))\, s_{j'} M - fc(q_j, \mu_j; \tau) \tag{14}$$

where J_f is the set of all the products offered on the market by firm f;[12]. $MMC_{ff'}$ is the level of multimarket contact between firm f and f'; mc_j is the marginal cost of product j, M is a market size, i.e. the geometric mean of the two end-point cities' MSA populations; and fc_j represents the fixed cost function. The level of capacity setting coordination between carriers f and f´ is given by the conduct parameter function $f\,(MMC_{ff'})$.

Following Berry and Jia (2010), the marginal cost function is assumed to be a linear function of the set of cost-related characteristics and given by:

$$mc_{jm} = v_{jm}\varphi + \omega_{jm} \tag{15}$$

where v_{jm} is the vector of the observed marginal cost characteristics, namely frequency, hub, distance of short-haul markets, and distance of long-haul markets; φ is the vector of cost parameters and ω_{jm} indicates unobserved marginal cost shocks.

majority of airlines have extended usage and lease agreements with airports allowing them to use the airport facilities. In addition, because the offer of an airline is a combination of the carrier and route, we may regard it is similar to other environments in which there is an exogenous offer of product quantity.

[12]Following Berry and Jia (2010), I make the assumption of market independence. This means that every profit equation that describes the supply model can be used with all markets without losing generality.

Following Fan (2013), a quadratic function is used to estimate the fixed cost function, whereby the fixed cost slope $fc_j(q_j, \mu_j; \tau)$ regarding carrier capacity choice q_j is assumed to be: [13]

$$\frac{\partial fc_j(q_j, \mu_j; \tau)}{\partial q_j} = \tau_0 + \tau_1 q_j + \nu_j \tag{16}$$

where τ is the vector of parameters and ν_j represent unobservable fixed-cost shock. The capacity choice of a carrier refers to the average number of seats it offers on a route per month. Although airlines can easily adjust prices, capacity is less flexible as changes in seat numbers require changes in aircraft sizes and crew numbers. In addition, agreements with airport authorities are also affected due to the reallocation of gates or landing fee adjustments. Hence, the fixed cost is affected by changes in capacity. ν_j captures other fixed cost shocks, e.g. maintenance. Finally, the conduct parameter $f(mmc)$ is modeled as a linear function of multimarket contact:

$$f\left(MMC_{ff'}\right) = \psi_1 + \psi_2 mmc1_{ff'} \tag{17}$$

The constant term, ψ_1, represents capacity setting behavior that is unrelated to the multimarket contact effect. ψ_2 describes the effect of multimarket contact on collusive capacity setting behavior; a positive conduct parameter indicates that firm f is taking the profit its competitor f' into account in its capacity decision making (cooperative behavior), while a negative parameter implies it aims to minimize the profit of its competitor (aggressive behavior). Following Ciliberto et al. (2019), I divide $mmc1_{ff'}$

[13] The fixed cost slope may be dependent on the capacity behaviors of competitors should market competition be imperfect. Nevertheless, an assumption is made in this study that input price is fixed, and so the slope of fixed costs does not depend on decisions made by competitors regarding capacity.

by 1000 to keep the measure of multimarket contact similar in scale. A simple linear function is used here to model the conduct parameter, unlike Ciliberto and Williams (2014), who restricted $f(mmc_{ff'})$ between zero and one.[14]

Assuming that q^f decided in the first stage, firm f sets the price, p_j, to maximize its profit in the second stage, whereby the profit function is:

$$\Pi_f^{II} = \sum_{j \in J_f} (p_j - mc_j) \cdot M \cdot s_j. \tag{18}$$

The following derives the conditions of optimality for both capacity and prices. Using backward induction, firm f sets the price to maximize its second-stage profit function. Using the derivative of the second-stage profit function Π_f^{II} with respect to price p_j, the following first-order condition is produced:

$$\frac{\partial \Pi_f^{II}}{\partial p_j} = s_j + \sum_{k \in J_f} (p_k - mc_k) \cdot \frac{\partial s_k}{\partial p_j} = 0 \tag{19}$$

Assume that the term of $(p_j - mc_j)$ generates the $J_f \times J_f$ matrix, and define the $J_f \times J_f$ matrix Δ_{s_f, p_f} such that

$$\Delta_{s_f, p_f} = \begin{pmatrix} \dfrac{\partial s_1}{\partial p_1} & \cdots & \dfrac{\partial s_{J_f}}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial s_1}{\partial p_{J_f}} & \cdots & \dfrac{\partial s_{J_f}}{\partial p_{J_f}} \end{pmatrix} \tag{20}$$

and such that the $J_f \times J_f$ matrix of the ownership matrix, Ω_{uv}, is defined by

[14] The conduct parameter restricted model is tested in line with the practice of Ciliberto and Williams (2014). There is no statistical significance in conduct parameter estimates. The objective function value derived from the restricted conduct parameter model was in excess of the final results from the linear model, which implies that the restricted model is not a good fit with the assumptions this study makes related to airlines' behaviors.

$$\Omega_{uv} = \begin{cases} 1 & \text{, if airline offers product } : \{u, v\} \subset J_f \\ 0 & \text{, otherwise} \end{cases} \tag{21}$$

Next, let Ω_{uv} be the product of Δ and Ω, such that

$$\Omega_{uv} = \begin{cases} \dfrac{\partial s_v}{\partial p_u} & \text{, if airline offers product } : \{u, v\} \subset J_f \\ 0 & \text{, otherwise} \end{cases} \tag{22}$$

Subsequently, the first-order condition of firm f's profit function for market m in the second stage can be reformulated as:

$$0 = s_m + \Omega_m \left(p_m - mc_m\right), \tag{23}$$

where $s_m = \left[s_{1m}, \cdots, s_{J_f m}\right]'$, $p_m = \left[p_{1m}, \cdots, p_{J_f m}\right]'$, and $mc_m = \left[mc_{1m}, \cdots, mc_{J_f m}\right]'$. Then the optimal price function of firm f yields

$$p_{jm} = mc_{jm} - \Omega_{jm}^{-1} s_{jm}. \tag{24}$$

Following the determination of the optimal price function, the first stage is addressed. For convenience, the profit function in the first stage can be rewritten as:

$$\Pi_f^I = \Pi_f^{II} + f\left(MMC_{ff'}\right)\Pi_{f'}^{II} - fc(q_j, \mu_j; \tau) \tag{25}$$

The first-stage profit function Π_f^I is differentiated with respect to capacity q_j yielding the first-order condition:

$$\sum_{j\in J_f}\frac{\partial\Pi_f^{II}}{\partial q_j}+\sum_{j\in J_f}\sum_{j'\in J}\frac{\partial\Pi_f^{II}}{\partial p_{k'}}\frac{\partial p_{k'}}{\partial q_j}+f(MMC_{ff'})\sum_{j\in J_f}\sum_{j'\in J}\frac{\partial\Pi_{f'}^{II}}{\partial p_{k'}}\frac{\partial p_{k'}}{\partial q_j}-\frac{\partial fc}{\partial q_j}=0 \quad (26)$$

A cooperative effect is implied by the third term in the first-stage first-order condition. The additional cooperative term indicates to what extent multimarket contact affects a carrier's collusive capacity setting behavior via firm f's capacity decision-making impact on its competitor's profit.

5.3 Estimation

The model parameters are measured by recovering the structural errors in the demand and supply models as a function of the model's parameters and data. Structural errors refers to the unobserved product characteristics (ξ_j), unobserved marginal cost shock (ω_{jm}), and unobserved fixed cost shock (ν_j). The market share function is presented in Equation (13), and can be inverted to derive ξ_j:

$$\xi_{jm}=s_{jm}^{-1}\left(x_m,p_m,\xi_m,\theta_d\right) \quad (27)$$

Following Berry, Levinsohn and Pakes (1995) and Berry and Jia (2010), the equation is solved for ξ_j, equating the estimated market share with the observed market share using contraction mapping with the demand parameters θ_d and data x_m,

$$\xi_{jm}^{H}=\xi_{jm}^{H-1}+\lambda\left[\ln s_{jm}-\ln s_{jm}\left(x_m,p_m,\xi_m,\theta_d\right)\right], \quad (28)$$

where H is the Hth iteration, $s_{jm}$is the observed market share, and $s_{jm}\left(x_m,p_m,\xi_m,\theta_d\right)$ is the estimated market share, as given in Equation (13). This process is reiterated until the difference between ξ_{jm}^{H} and ξ_{jm}^{H-1} is as close as possible to zero.

The first-order condition of firm f's second-stage profit function is used to recover the unobserved marginal cost shock. ω_{jm} is derived as a function of the marginal cost characteristics v_{jm} and parameters φ,

$$\omega_{jm} = p_{jm} - v_{jm}\varphi + \Omega_{jm}^{-1} s_{jm}\left(x_m, p_m, \xi_m, \theta_d\right) \tag{29}$$

Last, the first-order condition of firm f's first-stage profit function can be used to derive the unobserved fixed-cost shock in setting capacity:

$$\nu_j = \sum_{j \in J_f} \frac{\partial \Pi_f^{II}}{\partial q_j} + \sum_{j \in J_f} \sum_{j' \in J} \frac{\partial \Pi_f^{II}}{\partial p_{k'}} \frac{\partial p_{k'}}{\partial q_j} + f(MMC_{ff'}) \sum_{j \in J_f} \sum_{j' \in J} \frac{\partial \Pi_{f'}^{II}}{\partial p_{k'}} \frac{\partial p_{k'}}{\partial q_j} - \tau_0 + \tau_1 q_j \tag{30}$$

To estimate the model parameters, the respective moments representing the expectations for each structural error's interaction with the exogenous instruments are formed. For the demand parameters, this is:

$$E\left(\xi\left(p_m, x_m, s_m, \theta_d\right) \mid Z_{jm}^{d}\right) = 0 \tag{31}$$

For marginal cost parameters:

$$E\left(\omega\left(p_m, x_m, s_m, \theta_d, \varphi\right) \mid Z_{jm}^{mc}\right) = 0, \tag{32}$$

Finally, for the fixed cost and conduct parameters:

$$E\left(\nu_j(p_m, x_m, s_m, \theta_d, \varphi, \psi, \tau) \mid Z_{jm}^{fc}\right) = 0 \tag{33}$$

where Z^{d}_{jm}, Z^{mc}_{jm} and Z^{fc}_{jm} , respectively, the vectors of the instruments for the endogenous variables in the demand, marginal cost, and fixed cost specifications [15]. The generalized method of moments method is used to estimate the nonlinear parameters. $\Phi = [\theta_d \ \delta \ \psi \ \tau]$ is estimated by minimizing

$$Q(\Phi) = G(\Phi)' W^{-1} G(\Phi) \tag{34}$$

where $G(\Phi)$ represents the stacked set of moments conditions and $W$is an optimal weighing matrix.

5.4 Results

Table 5 presents the structural estimations for the demand and supply models. The column (1) presents the estimates for the demand, marginal costs, and fixed costs for the case where there is no capacity setting collusion between two firms in the first stage. In implementing the non-collusion model, the conduct parameter is assumed to be zero. The resulting demand parameters are generally in line with the airline merger study presented in the previous chapter. The estimated coefficients are all statistically significant, with the expected coefficient signs for the product characteristics. Specifically, the negative sign for the airfare coefficient implies that consumers dislike price increases. Moreover, the airfare coefficients for both groups indicate that there are different types of consumers who derive different disutilities from increases

[15] Berry et al (1995) note that there is validity to any instrument that does not involve factors with correlation with ξ_j, ω_j and ν_j. In this study, price, frequency and capacity decisions are and a genius. The exogenous price instrument incorporates how many routes exist in a market and how many competitive rates there are in order to encapsulate the market environment's competitively. The status of the hub shifts costs but does not influence demand, so is employed as a price instrument. Hub status also impacts frequency and airline capacity decisions. The interaction terms have been carefully selected to avoid collinearity.

in price. Meanwhile, direct flights from primarily non-congested airports without slot control are preferred, as are routes that include the hub airport of the carrier. The U-curve in air travel demand in terms of distance is captured by estimating the parameters of demand, namely flight distance and squared flight distance; in other words, demand for short-haul flights first increases and then declines with increasing distance. Those airports with proximity to tourist destinations, including Miami, Las Vegas, and Orlando, also experience higher passenger numbers. Moreover, consumers tend to switch carriers in the event of an airfare increase instead of selecting the no-fly option, as evidenced by the nested logit parameter λ, which gives the substitutability of all the airline products as 0.697. Similarly, the marginal cost coefficients are as expected. As indicated by the negative sign on the coefficient of seating capacity, for each seat added to a given route, the cost of serving the extra passenger declines. An airline routing flights through its hub airport is likely to have a cost advantage, as demonstrated by the estimated parameter for hub status. While the marginal cost rises with distance for both the short- and long-haul markets, the coefficient of distance is greater for the former. [16] Finally, regressing the slope of the fixed costs on the number of seats selected by the carrier estimates the fixed cost parameters, i.e. the marginal effect of adding more capacity is measured by the constant term. The result indicates that by adding more seats, the carrier significantly increases the fixed cost. This is intuitive as increasing capacity on a given route requires more or larger aircraft with the accompanying flight and ground crews.

Subsequently, the column (2) in Table 5 gives the results of the model assuming

[16]Two groups of marginal cost parameters have been incorporated, long and short haul markets, related to connection numbers and distance. I create dummy variable $D_{\text{Short}} = 1$ if distance between origin and destination is below 1,500 miles and $D_{\text{Long}} = 1$ if market distance exceeds 1500. Then the distance variables are computed as $Distance_{\text{Short}} = Distance \cdot D_{\text{Short}}$ and $Distance_{\text{Long}} = Distance \cdot D_{\text{Long}}$.

that the carriers are engaging in capacity setting collusion. In this specification, a single conduct parameter describes the total degree of collusion, disregarding any facilitators. Hereby, a single conduct parameter, ψ_1, is used instead of the function of multimarket contact, $f(mmc_{ff'})$; the positive sign indicates that carriers collude in capacity setting, with a $p-$value of 0.084. The column (1) and column (2) in Table 5 demonstrate that the estimated demand, marginal cost and fixed cost coefficients are different, which is in line with Bresnahan's (1987) study showing that models that base on different assumptions of behavior generate dissimilar estimation results.[17]

Next, the column (3) in Table 5 provides the model estimates assuming that the degree of collusion in capacity setting relates to the degree of multimarket contact between carriers in a given market. In this case, carriers vary their behavior according to their competitors. The estimates for demand, marginal cost and fixed cost are consistent with those of the previous model, while ψ_1, i.e. the constant conduct parameter describing the effect of other factors leading to carriers' capacity collusion behavior, is -0.014 and shows no statistical significance. This indicates that there are no additional factors shaping collusive behavior among carriers in regards to capacity. Meanwhile, ψ_2 is revealed to be statistically significant with a positive sign, implying that increased multimarket contact leads to a greater degree of collusion among carriers, i.e. they set lower capacity levels.

Finally, Table 7 gives $f(mmc_{ff'})$, utilizing the estimated conduct parameters to assess each degree of multimarket contact level presented in Table 2, which numerically presents the airline size weighted measure of multimarket contact for the 11

[17]Bresnahan (1987) undertook empirical research into a price war between manufacturers of automobiles in 1955. This was one of the first empirical study that provided a structural model of consumer demand in an industry in which products were differentiated that ran tests on supply-side competitive hypotheses.

carriers in the sample that operated during the fourth quarter of 2015. Based on the results, it can be concluded that the four major carriers, i.e. American Airlines, Delta, United Airlines, and Southwest Airlines, show collusive behavior when setting capacity; however, no significant collusion is observed between low-cost carriers and the major airlines. This is in line with the results of the reduced-form analysis demonstrating that the multimarket contact effect is being driven by collusive behavior among the major carriers.

6 Conclusion

This chapter explores to what extent multimarket contact affects US airline's capacity setting behavior. According to the reduced-form analysis, a higher degree of multimarket contact leads to fewer seats being made available, driven in particular by the collusion among major carriers with a substantial degree of multimarket contact. Furthermore, this effect is stronger in small markets than in medium or large markets. To conduct the structural-form analysis, Ciliberto and Williams's (2014) framework is adapted to nest the conduct parameters in a two-stage oligopoly model. The degree of collusive behavior in setting capacity is hereby estimated based on the variation in the degree of multimarket contact across air travel markets. The results indicate that carriers with more multimarket contact, such as the major four airlines, collude when setting capacity, while those with an insignificant multimarket contact do not.

The findings bear significant implications for policymakers, highlighting the need to monitor the capacity supply in markets characterized by significant multimarket contact between carriers. Meanwhile, the study's methodology is applicable to not only the air travel sector but also any industry in which there are distinct markets featuring competition between firms.

This study has some limitations that point to promising avenues for future research. First, for simplicity, the linear functional form assumed for the multimarket contact conduct parameters is applied to all carrier pairs, even though these contain the potential for heterogeneity. Thus, future research could use more flexible functional forms to model the conduct parameters, thereby extending the findings of this paper. Second, while the test in this study indicates where collusive behavior may be occurring, there is no definitive proof of collusion between airlines; hence, extending the test beyond multimarket conduct, e.g. by linking capacity setting behavior to alternative potential facilitators of collusion such as code sharing, would provide further insight.

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Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Carrier-Market-Specific Variables				
Airfare	255.01	72.15	25	1,190
Passengers (1,000)	2,900.47	4814.21	100	224,108
Nonstop	0.19	0.37	0	1
No. connection	0.78	1.48	0	3
No. daily departure	2.04	6.12	1	22
Hub	0.14	0.38	0	1
Code shared	0.28	0.12	0	1
HHI	0.41	0.32	0.09	1
Slot-control	0.74	1.00	0	1
Distance	1,217	1,028	210	5,084
Tourist place	0.08	0.15	0	1
American	0.19	0.29	0	1
Continental	0.10	0.15	0	1
Delta	0.17	0.21	0	1
United	0.14	0.19	0	1
US Airways	0.09	0.27	0	1
JetBlue	0.06	0.10	0	1
Southwest	0.14	0.17	0	1
Virgin Atlantic	0.03	0.12	0	1
Market-Specific Variables				
$mmc1$	878	682.54	9	1588
$mmc2$	0.49	0.58	0.002	1
$mmc3$	0.41	0.61	0.001	0.91
Number of Observations	972,159			

Notes: The data were extracted for the period between January 2005 and December 2015.

Table 2: Pair-wise Number of multimarket contacts (2015:Q4)

	AA	UA	DL	AS	B6	F9	G4	HA	NK	SY	WN
AA	1409										
UA	887	1092									
DL	1157	883	1379								
AS	62	74	102	387							
B6	98	37	164	9	304						
F9	122	101	128	10	2	221					
G4	10	0	1	0	0	1	82				
HA	23	39	27	9	0	2	0	112			
NK	79	92	103	15	37	21	0	0	314		
SY	34	11	20	7	0	4	0	0	21	125	
WN	674	558	667	132	122	167	3	5	39	19	841

Notes: The diagonal's number represents the totality of markets a carrier serves. The numbers off the diagonal represent how many markets the carrier serves concomitantly (row) and the carrier (column).

Table 3: Relative measure of multimarket contacts

	AA	UA	DL	AS	B6	F9	G4	HA	NK	SY	WN
AA	1	.630	.821	.044	.071	.087	.007	.016	.056	.024	.478
UA	.812	1	.809	.077	.034	.092	0	.036	.084	.012	.511
DL	.839	.640	1	.074	.119	.093	.001	.020	.075	.015	.484
AS	.160	.217	.264	1	.023	.026	0	.023	.039	.018	.341
B6	.322	.122	.539	.030	1	.007	0	0	.122	0	.401
F9	.552	.457	.549	.045	.009	1	.005	.009	.095	.018	.756
G4	.122	0	.012	0	0	.012	1	0	0	0	.037
HA	.205	.348	.241	.080	0	.018	0	1	0	0	.045
NK	.252	.293	.328	.048	.118	.067	0	0	1	.067	.124
SY	.272	.088	.160	.056	0	.032	0	0	.168	1	.152
WN	.801	.663	.793	.157	.145	.199	.004	.006	.046	.023	1

Notes: This table illustrates the market fraction a carrier serves, with the numerator being the off-diagonal number in Table 2 and the denominator being the number on the diagonal in the same table.

Table 4: The Effect of Multimarket Contacts on Number of Seats

Dependent variable	(1) log($seats$)	(2) log($seats$)	(3) log($seats$)
Average multimarket contact	-0.0102***		
	(0.0027)		
Major market · Avg multimarket contact		-0.0116***	
		(0.0021)	
Mixed market· Avg multimarket contact (Major)		-0.0129***	
		(0.0031)	
Mixed market· Avg multimarket contact (LCC)		-0.0052	
		(0.0049)	
Small market· Avg multimarket contact			-0.0271***
			(0.0104)
Medium market· Avg multimarket contact			-0.0139***
			(0.0062)
Large market· Avg multimarket contact			-0.0098*
			(0.0023)
Log Population	1.5491***		
	(0.0744)		
HHI	0.0022	0.0015	0.0018
	(0.0018)	(0.0011)	(0.0007)
Monopoly	0.0393***	0.0401***	0.0434***
	(0.0021)	(0.0019)	(0.0028)
Adjusted R-squared	0.606	0.651	0.683
Number of observations	972,159	972,159	972,159

Notes: Standard errors in parentheses *** < 0.01, ** < 0.05, * < 0.10.
All regressions include carrier-market and carrier-year-quarter fixed effects.

Table 5: The Effect of Multimarket Contacts on Number of Seats, Robustness Check

Dependent variable	(1) $mmc1$ log($seats$)	(2) $mmc2$ log($seats$)	(3) $mmc3$ log($seats$)
Average multimarket contact	-0.0102***	-0.0527***	-0.0717***
	(0.0027)	(0.0078)	(0.0061)
Log Population	1.5491***	1.5201***	1.6749***
	(0.0744)	(0.0815)	(0.0662)
HHI	0.0022	0.0018	0.0029
	(0.0018)	(0.0010)	(0.0021)
Monopoly	0.0393***	0.0324***	0.0398***
	(0.0021)	(0.0020)	(0.0032)
Adjusted R-squared	0.606	0.558	0.551
Number of	972,159	972,159	972,159

Notes: Standard errors in parentheses *** < 0.01, ** < 0.05, * < 0.10.
All regressions include carrier-market and carrier-year-quarter fixed effects.

Table 6: Model Estimation Results

	(1) No Collusion		(2) Collusion Allowed		(3) Full Model	
	Estimates	Standard Error	Estimates	Standard Error	Estimates	Standard Error
Demand						
$\text{Airfare}_{\text{Business}}$	-0.103**	(0.005)	-0.152**	(0.002)	-0.127**	(0.007)
$\text{Airfare}_{\text{Tourist}}$	-1.014**	(0.009)	-1.009**	(0.010)	-0.981**	(0.017)
$\text{Connection}_{\text{Business}}$	-0.718**	(0.029)	-0.827**	(0.021)	-0.857**	(0.034)
$\text{Connection}_{\text{Tourist}}$	-0.624**	(0.011)	-0.668**	(0.024)	-0.692**	(0.030)
$\text{Constant}_{\text{Business}}$	-5.121**	(0.217)	-5.721**	(0.192)	-5.724**	(0.199)
$\text{Constant}_{\text{Tourist}}$	-8.722**	(0.381)	-8.214**	(0.329)	-8.199**	(0.334)
Code share	-0.081**	(0.001)	-0.097**	(0.007)	-0.101**	(0.005)
Distance	0.381**	(0.008)	0.305**	(0.008)	0.291**	(0.008)
Distance^2	-0.062**	(0.002)	-0.061**	(0.001)	-0.064**	(0.002)
Hub	0.957**	(0.024)	0.814**	(0.011)	0.801**	(0.010)
Slot-control	-0.285**	(0.005)	-0.290**	(0.009)	-0.241**	(0.002)
Tour	0.310**	(0.011)	0.271**	(0.007)	0.216**	(0.005)
λ	0.618**	(0.005)	0.603**	(0.001)	0.595**	(0.003)
Marginal Cost						
Constant	1.621**	(0.022)	1.002**	(0.009)	1.204**	(0.014)
No. seats	-0.030**	(0.005)	-0.027**	(0.002)	-0.025**	(0.003)
Hub	-0.197**	(0.012)	-0.188**	(0.007)	-0.180**	(0.001)
$\text{Distance}_{\text{Short}}$	0.299**	(0.004)	0.240**	(0.010)	0.210**	(0.008)
$\text{Distance}_{\text{Long}}$	0.143**	(0.004)	0.101**	(0.009)	0.095**	(0.005)
Fixed Cost						
Constant	7.405**	(0.044)	5.113**	(0.028)	5.002**	(0.020)
No. seats	0.047**	(0.002)	0.039**	(0.002)	0.032**	(0.001)
Conduct Parameters						
ψ_1			0.797***	(0.304)	-0.014	(1.015)
ψ_2					0.804**	(1.129)
Model Fit						
GMM Objective function	122.797		110.024		106.338	
Observations	972,159		972,159		972,159	

Notes: Standard errors in parentheses *** < 0.01, ** < 0.05, * < 0.10.
All three GMM estimations include Year-Quarter dummies and Carrier dummies.

Table 7: Estimated Degree of Coordination in Setting Capacity

	AA	UA	DL	AS	B6	F9	G4	HA	NK	SY	WN
AA	•										
UA	.699	•									
DL	.916	.696	•								
AS	.036	.045	.068	•							
B6	.065	.016	.118	-.007	•						
F9	-.004	.067	.089	-.006	-.012	•					
G4	-.006	-.014	-.013	-.014	.014	-.013	•				
HA	.004	.017	.008	.007	.014	-.012	-.014	•			
NK	.050	.060	.069	.002	.016	.003	-.014	-.014	•		
SY	.013	.005	.002	.008	.014	.011	-.014	-.014	.003	•	
WN	.528	.435	.522	.092	.084	.120	-.014	-.010	.017	.001	•

Figure 1: $mmc2$ measure of multimarket contact between American Airlines and other airlines (2005-2015)

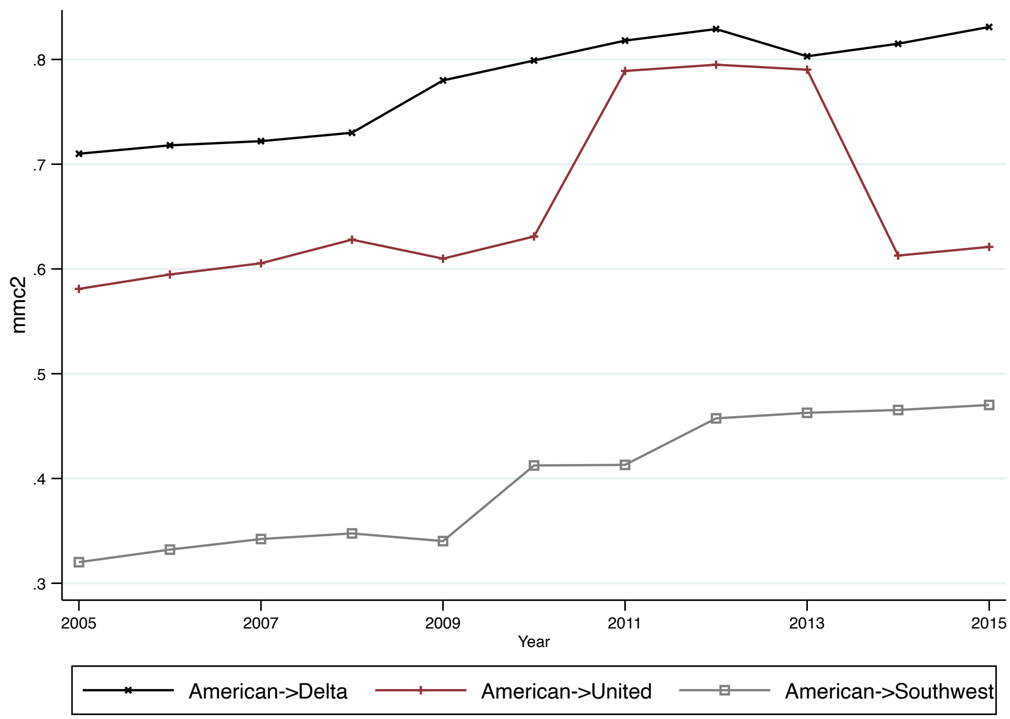

Figure 2: $mmc2$ measure of multimarket contact between Delta Airlines and other airlines (2005-2015)

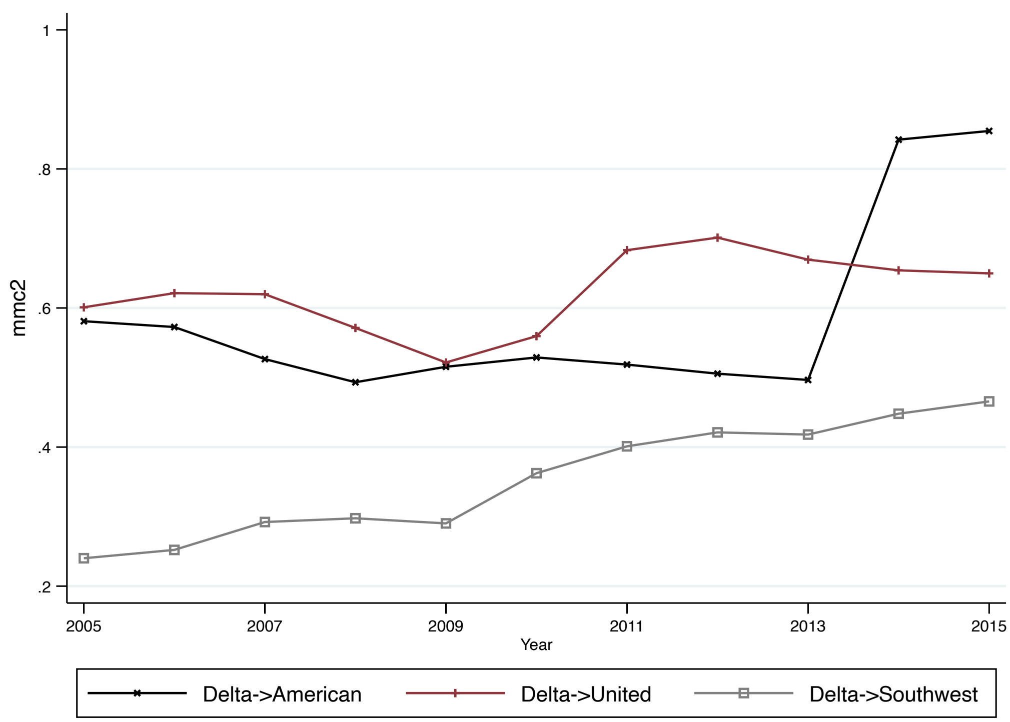

Figure 3: *mmc*2 measure of multimarket contact between United Airlines and other airlines (2005-2015)

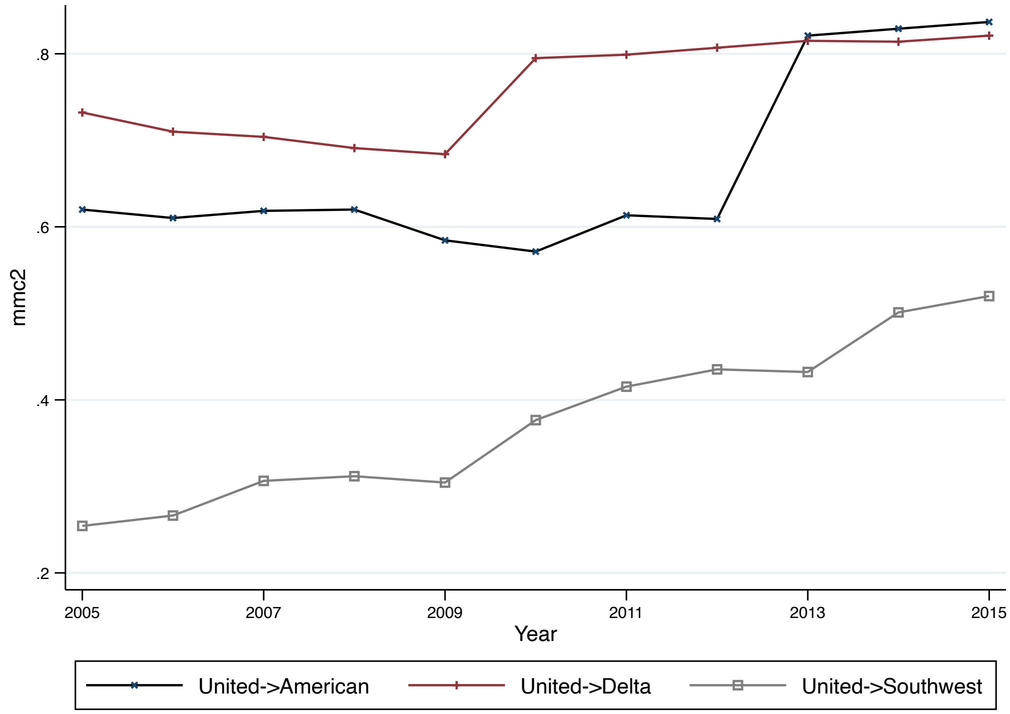

Figure 4: *mmc*2 measure of multimarket contact between Southwest Airlines and other airlines (2005-2015)