

Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry

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We provide empirical evidence that multimarket contact facilitates tacit collusion among airlines using a flexible model of oligopolistic behavior, where conduct parameters are modelled as functions of multimarket contact. We find (i) carriers with little multimarket contact do not cooperate in setting fares, whereas carriers serving many markets simultaneously sustain almost perfect coordination; (ii) cross-price elasticities play a crucial role in determining the impact of multimarket contact on equilibrium fares; (iii) marginal changes in multimarket contact matter only at low or moderate levels of contact; (iv) assuming firms behave as Bertrand-Nash competitors leads to biased estimates of marginal costs.

1. Introduction

■ Firms often compete against one another in many markets. This multiplicity of contact has raised concerns among economists that anticompetitive outcomes are more likely to be realized in the markets in which these firms compete due to “mutual forbearance.” In Bernheim and Whinston’s (1990) words, multimarket contact serves to pool the incentive constraints from all the markets served by the two firms. That is, the more extensive is the overlap in the markets that the two firms serve, the larger are the benefits of collusion and the costs from deviating from a collusive agreement. As collusion can lead to inefficient market outcomes, studying the role of multimarket contact (MMC) as a facilitator of tacit collusion has remained a topic of interest, both theoretically and empirically.¹

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¹ Fershtman and Pakes (2000) demonstrate collusion can increase consumer welfare through a greater variety of higher quality products.

Since Bernheim and Whinston (1990) formalized the intuitive notion of “mutual forbearance” discussed in Edwards (1955), the number of empirical studies on the topic has expanded rapidly. The extant literature spans a variety of industries, including cement (Jans and Rosenbaum, 1997), telecommunications (Parker and Roller, 1997; Busse, 2000), hotels (Fernandez and Marin, 1998), radio (Waldfogel and Wulf, 2006), and airlines (Evans and Kessides, 1994; Singal, 1996; Bilotkach, 2010; Miller, 2010).² The consistent finding in this literature is that multimarket contact is associated with higher prices. Whether the positive correlation between prices and multimarket contact is explained by collusive behavior is still an open and important question. For example, in its civil action to block the proposed merger of American Airlines and US Air, the US Department of Justice has argued that legacy airlines use what they call “cross-market” initiative to coordinate prices across markets.³

This article contributes to this important literature in three ways. First, we demonstrate the usefulness of an instrumental-variable approach for resolving endogeneity issues in the relationship between prices and multimarket contact. Previous solutions to the endogeneity of multimarket contact include fixed-effects approaches (e.g., Evans and Kessides, 1994) and exploiting regulatory changes to identify a causal relationship (e.g., Waldfogel and Wulf, 2006). Second, we propose a structural model nested in the mainstream empirical industrial organization literature that directly links pair-specific multimarket contact, that is, the total number of markets that two firms serve concomitantly, to the degree of coordination in firms’ decisions.⁴ Previous studies have been able to only link multimarket contact to market outcomes, such as prices, providing less information about the degree of coordination that different levels of multimarket contact can support. Finally, we clearly discuss the mechanics by which multimarket contact matters through its links with cross-price elasticities. This is economically important to understand because it allows one to identify markets or industries where collusive behavior will result in significantly higher prices and lower welfare.

We begin our empirical analysis with a reduced-form analysis that uses data from 2006 to 2008 to replicate and extend the analysis conducted by Evans and Kessides (1994) (EK, 1994, from here on). EK demonstrate a positive relationship between multimarket contact measures and prices for the 1984 to 1988 period. We study the correlation between the *average* multimarket contact among firms in a market and their prices. The main identification concern is whether average multimarket contact is exogenous. Bernheim and Whinston (1990) think of multimarket contact as an “external factor”; however, unobservable heterogeneity likely determines prices, entry, and exit decisions (Ciliberto, Murry, and Tamer, 2012) and, consequently, average multimarket contact. We instrument for the average multimarket contact variable using a unique and original data set on the number of gates controlled by each airline at airports in the US (Ciliberto and Williams, 2010; Williams, 2012). The validity of the instrument rests on the fact that the number of gates an airline controls at an airport is naturally correlated with the decision to serve a market by that airline but is not easily adjusted due to the nature of airport-airline leasing agreements.

In our reduced-form analysis, we generally confirm the findings of EK (1994). EK’s (1994) main conclusion was that the positive relationship between multimarket contact and prices was consistent with the hypothesis that airlines with a high degree of multimarket contact refrain from initiating aggressive pricing actions in any given market to avoid intense price competition in all the other routes they serve concomitantly. The relationship between multimarket contact and prices is stronger when we use the instrumental variable approach, consistent with a fixed-effects approach not fully resolving endogeneity concerns.

Next, in the structural analysis we estimate a flexible model of oligopolistic behavior, where conduct parameters are modelled as functions of *pair-specific* multimarket contact. Our modelling strategy implements an idea first proposed by Nevo (1998), which offers a constructive synthesis

² Feinberg (1985) performs a notable early cross-industry study of MMC.

³ www.justice.gov/atr/cases/f299900/299968.pdf.

⁴ The definition of multimarket contact is attributed to Corwin Edwards (1955); see Bernheim and Whinston (1990).

of the two main methodological ways to identify collusion.⁵ The first line of research (e.g., Panzar and Rosse, 1987; Bresnahan, 1982; Ashenfelter and Sullivan, 1987; Porter, 1983) identifies collusive behavior by estimating conduct parameters, which reveals whether firms compete on prices or on quantities, or whether they collude.⁶ The second line of research, which started with Bresnahan (1987), estimates different behavioral models and compares how these models fit the observed data (Gasmi, Laffont, and Vuong, 1992; Nevo, 2001). We take some ingredients from the first line of research (the conduct parameters) and nest them into the modelling framework proposed by the second line of research.

There are two related identification concerns in the structural analysis. The first is the usual one, prices and quantities are determined simultaneously. This requires an instrument for price correlated with both price and market shares, yet uncorrelated with unobserved determinants of demand. The second concerns identification of the conduct parameters and is more subtle. In our model, the conduct parameters enter a firm's pricing equation through interactions of multimarket contact and functions of market shares. As Nevo (1998) points out, if the conduct parameters are not restricted in any way (i.e., each is a free parameter), the required number of instruments, exogenous variables correlated with these interactions but not unobservable determinants of market shares, grows with the square of the number of firms. By modelling the conduct parameters as functions of multimarket contact, we reduce the number of required instruments to just a few, even for flexible functional forms. By doing so, we can then exploit the same exogenous variation in the number of gates that airlines control at airports to jointly identify both price elasticities and the conduct parameters.

We find that carriers with little multimarket contact (e.g., Delta and Alaska served 35 markets concurrently in the second quarter of 2007) do not cooperate in setting fares. Carriers with a significant amount of multimarket contact (e.g., Delta and US Air served 1150 markets concurrently in the second quarter of 2007) can sustain near-perfect cooperation in setting fares. Thus, for very high levels of multimarket contact, where firms are already perfectly coordinating on prices, there is very little impact from an increase in multimarket contact. However, for low or moderate levels of contact, there is a significant increase in fares. We also find that the standard assumption that firms behave as Bertrand-Nash competitors leads to marginal cost estimates 42 % higher than when we use a more flexible behavioral model that allows firms to behave differently depending on the extent of multimarket contact. Finally, we demonstrate the important role that cross-price elasticities play in determining the impact of multimarket contact on equilibrium fares. If two goods are close substitutes, then cooperation in setting fares results in a larger change from the competitive outcome than in cases where two goods are not such close substitutes.

To explore the robustness of the reduced-form and structural results, we consider three alternative definitions of multimarket contact. In contrast to the number of markets that the carriers serve concomitantly, these alternatives allow for asymmetry in the degree of coordination between a pair of carriers as well as variation in the importance of multimarket contact based on the proportion of the carrier's revenue generated in the common markets. Our results are similar both qualitatively and quantitatively for each alternative. In the structural analysis, we also check the sensitivity of our results to assumptions on the functional form of the conduct parameters, which relate the measures of multimarket contact to the degree of coordination in setting fares. For each functional form we find very similar results.

Our article contributes to the broader literature on detecting collusion, a central theme in empirical industrial organization (Jacquemin and Slade, 1989; Porter, 2005; Harrington, 2008). Previous work has identified collusive behavior by using variation in costs (Rosse, 1970; Panzar and Rosse, 1987; Baker and Bresnahan, 1988),⁷ rotations of demand (Bresnahan, 1982; Lau,

⁵ This type of approach that looks for identifying potential facilitators of collusion in the industry has also been recently advocated by Berry and Haile (2010).

⁶ See Bresnahan (1987) for a superb review of the early empirical work in industrial organization.

⁷ See Weyl (2009) for a discussion on the identification of conduct parameters using variation in costs. See Salvo (2010) for a recent work that uses conduct parameters to identify market power under the threat of entry.

1982), taxes (Ashenfelter and Sullivan, 1987), conduct regimes (Porter, 1983), and product entry and exit (Bresnahan, 1987; Nevo, 2001).⁸ Like these studies, our analysis does not move us closer toward proving collusion in a legal sense.⁹ Yet by building on the structural framework of Nevo (1998, 2001), we provide a diagnostic test that can be used to identify potential facilitators of collusion.

The article is organized as follows. The data are described in Section 2. Section 3 presents the reduced-form analysis and results. Our structural econometric approach is discussed in Section 4 and the results in Section 5. Section 6 concludes and discusses possible extensions of our research.

2. Data

■ We use data from four main sources.¹⁰ Data from the Airline Origin and Destination Survey (DB1B) database, a 10% sample of all domestic itineraries, provide information on the fare paid, connections made en route to the passenger's final destination, and information on the ticketing and operating carriers. We use data from January 2006 to December 2008. Information on the population of each Metropolitan Statistical Area (MSA) is collected from the Bureau of Economic Analysis. From a survey that Williams (2012) conducted jointly with the Airports Council International-North America (ACI-NA), North America's largest airport-trade organization, we use information from 2007 to construct measures of carrier-specific access to boarding gates. Our last data source is the 1995 American Travel Survey that we use to construct an airport-specific index measuring the proportion of business passengers.¹¹

□ **Market definition.** Like EK (1994), we define a market as a *unidirectional* trip between two airports in a particular quarter regardless of the number of connections a passenger made in route to his or her final destination. To exclude seasonal markets, we consider markets in which at least 250 passengers were transported in at least one quarter from 2006 to 2008, dropping any markets where fewer than 100 passengers were served in any quarter from 2006 to 2008. We also restrict our sample to airports for which we have information on access to boarding gates.

In what follows, markets are indexed by $m = 1, \dots, M$. There are 6366 markets. Year-quarter combinations are denoted by $t = 1, \dots, T$. We use data from 2006 to 2008, so $T = 12$. The subindex $j = 1, \dots, J_{mt}$ denotes a product j in market m at time t . A product is defined by the carrier (e.g., American) and the type of service, either nonstop or connecting. The total number of carriers in the data set is 17 and includes American (AA), Alaska (AS), JetBlue (B6), Continental (CO), Delta (DL), Frontier (F9), ATA (TZ), Allegiant (G4), Spirit (NK), Northwest (NW), Sun Country (SY), AirTran (FL), USA3000 (U5), United (UA), US Air (US), Southwest (WN), Midwest (YX). The unit of observation is then denoted by a combination, jmt , which indicates a product j (e.g., nonstop service by American), in market m (e.g., Chicago O'Hare to Fort Lauderdale), at time t (e.g., the second quarter of 2007). Our final sample contains 268,119 observations at the product-market-time level.

□ **Fares.** We calculate average fares at the product-market-time level. Like EK (1994) and consistent with the unidirectional nature of our market definition above, we treat round-trip tickets as two one-way tickets and divide the fare by two. We also drop exceedingly high and

⁸ There is also an important literature on detecting collusion in auctions, which presents its own econometric challenges. See Hendricks and Porter (1989) for more on that literature.

⁹ To our knowledge, the antitrust agencies have only succeeded in proving collusion with the help of law-enforcement agencies. For example, in the case of the lysine price-fixing conspiracy (White, 2001), the intervention of the FBI was required to prove (explicit) collusive behavior.

¹⁰ Data on the consumer price index were accessed through the Bureau of Labor Statistics' website at www.bls.gov/cpi/#tables.

¹¹ See Borenstein (2010) for more on this index of business travelers.

TABLE 1a Number of Common Markets in 2007-Q1

	AA	AS	B6	CO	DL	F9	FL	G4	NK	NW	SY	TZ	U5	UA	US	WN	YX
AA	1256	22	84	683	855	116	273	7	11	686	11	29	5	819	579	339	119
AS	22	54	3	13	35	10	3	0	0	18	0	1	0	50	30	9	2
B6	84	3	151	96	132	2	57	0	7	83	0	0	4	124	125	41	2
CO	683	13	96	955	733	88	244	4	12	555	5	24	7	572	559	314	86
DL	855	35	132	733	1915	115	455	5	20	907	7	28	10	1008	1150	385	114
F9	116	10	2	88	115	151	41	0	3	87	5	8	0	140	115	72	18
FL	273	3	57	244	455	41	495	0	13	306	4	17	5	290	388	106	54
G4	7	0	0	4	5	0	0	13	0	5	3	0	0	11	5	0	1
NK	11	0	7	12	20	3	13	0	22	13	0	1	1	14	20	6	1
NW	686	18	83	555	907	87	306	5	13	1327	14	27	7	871	612	282	169
SY	11	0	0	5	7	5	4	3	0	14	14	0	0	13	7	0	3
TZ	29	1	0	24	28	8	17	0	1	27	0	29	0	29	24	28	13
U5	5	0	4	7	10	0	5	0	1	7	0	0	10	5	10	6	0
UA	819	50	124	572	1008	140	290	11	14	871	13	29	5	1556	847	329	159
US	579	30	125	559	1150	115	388	5	20	612	7	24	10	847	1492	327	74
WN	339	9	41	314	385	72	106	0	6	282	0	28	6	329	327	510	39
YX	119	2	2	86	114	18	54	1	1	169	3	13	0	159	74	39	171

Notes: The off-diagonal numbers represent the number of markets served concomitantly by the carrier in the row and the carrier in the column. The numbers on the diagonal are the total number of markets served by a carrier.

low fares (greater than \$2500 and less than \$25) which are likely the result of key-punch errors. Similar to Berry (1992), we drop carriers which do not represent a competitive presence in each market by transporting fewer than 100 passengers in a quarter. This corresponds to dropping those carriers transporting fewer than 10 passengers in the DB1B's sample of itineraries. Fares are then deflated using the consumer price index to 2009 dollars. From this sample, we construct the product-market-time specific average fare, $Fare_{jmt}$.¹² The unweighted average of $Fare_{jmt}$, across all markets from 2006 to 2008, is around \$223.

□ **Multimarket contact.** Let mmc_{kh}^t denote the number of markets that two distinct carriers, k and h , concomitantly serve at time t . For example, in the first quarter of 2007, American and Delta concomitantly served 855 markets, so both mmc_{AADL}^t and mmc_{DLAA}^t equal 855. For each quarter, we construct a matrix of these pair-specific variables. Table 1a shows the matrix, mmc^t , for the 17 carriers in our sample in the first quarter of 2007.

For each quarter, we then use the mmc^t matrix to calculate the same market-specific average of multimarket contact as EK (1994),

$$AvgContact_{mt} = \frac{1}{F_{mt}(F_{mt} - 1)} \sum_{k=1}^F \sum_{h=1, h \neq k}^F 1[k \text{ and } h \text{ active}]_{mt} * mmc_{kh}^t. \quad (1)$$

The indicator, $1[k \text{ and } h \text{ active}]_{mt}$, is equal to 1 if carriers k and h are both in market m at time t , F_{mt} is the number of incumbent firms in market m at time t , and F is the total number of airlines (17). Thus, $AvgContact_{mt}$ is equal to the average of mmc_{kh}^t across the firms actively serving market m at time t . This variable is summarized in Table 2.

To check the robustness of our results, we also consider three other measures of pair-specific multimarket contact. The formula to compute the average contact is the same as in equation (1) for these three alternative definitions.

The first one, called $pct_mmc_{kh}^t$, is equal to mmc_{kh}^t divided by the total number of markets served by firm k . Continuing on the example above, $pct_mmc_{AADL}^t$ equals 0.681 and $pct_mmc_{DLAA}^t$ equals 0.446. Clearly, $pct_mmc_{kh}^t$ is asymmetric as it is larger for the firms that serves fewer

¹² All results and conclusions are robust to using the median fare instead of the average.

TABLE 1b Fraction of Common Markets in 2007-Q1

	AA	AS	B6	CO	DL	F9	FL	G4	NK	NW	SY	TZ	U5	UA	US	WN	YX
AA	1	0.02	0.07	0.54	0.68	0.09	0.22	0.01	0.01	0.55	0.01	0.02	0	0.65	0.46	0.27	0.10
AS	0.41	1	0.06	0.24	0.65	0.19	0.06	0	0	0.33	0	0.02	0	0.93	0.56	0.17	0.04
B6	0.56	0.02	1	0.64	0.87	0.01	0.38	0	0.05	0.55	0	0	0.03	0.82	0.83	0.27	0.01
CO	0.72	0.01	0.10	1	0.77	0.09	0.26	0	0.01	0.58	0.01	0.03	0.01	0.60	0.59	0.33	0.09
DL	0.45	0.02	0.07	0.38	1	0.06	0.24	0	0.01	0.47	0	0.02	0.01	0.53	0.60	0.20	0.06
F9	0.77	0.07	0.01	0.58	0.76	1	0.27	0	0.02	0.58	0.03	0.05	0	0.93	0.76	0.48	0.12
FL	0.55	0.01	0.12	0.49	0.92	0.08	1	0	0.03	0.62	0.01	0.03	0.01	0.59	0.78	0.21	0.11
G4	0.54	0	0	0.31	0.39	0	0	1	0	0.39	0.23	0	0	0.85	0.39	0	0.08
NK	0.50	0	0.32	0.55	0.91	0.14	0.59	0	1	0.59	0	0.05	0.05	0.64	0.91	0.27	0.05
NW	0.52	0.01	0.06	0.42	0.68	0.07	0.23	0	0.01	1	0.01	0.02	0.01	0.66	0.46	0.21	0.13
SY	0.79	0	0	0.36	0.50	0.36	0.29	0.21	0	1	0	0	0	0.93	0.50	0	0.21
TZ	1	0.03	0	0.83	0.97	0.28	0.59	0	0.03	0.93	0	1	0	1	0.83	0.97	0.45
U5	0.50	0	0.40	0.70	1	0	0.5	0	0.10	0.70	0	0	1	0.50	1	0.60	0
UA	0.52	0.03	0.08	0.37	0.64	0.09	0.19	0.01	0.01	0.56	0.01	0.02	0	1	0.54	0.21	0.10
US	0.39	0.02	0.08	0.38	0.77	0.08	0.26	0	0.01	0.41	0.01	0.02	0.01	0.57	1	0.22	0.05
WN	0.67	0.02	0.08	0.62	0.76	0.14	0.21	0	0.01	0.55	0	0.06	0.01	0.65	0.64	1	0.08
YX	0.70	0.01	0.01	0.50	0.67	0.11	0.32	0.01	0.01	0.99	0.02	0.08	0	0.93	0.43	0.23	1

Notes: The table reports the fraction of markets served by a carrier, where the numerator is the off-diagonal number from Table 1a and the denominator is the number on the diagonal in Table 1a.

markets, and thus it captures the idea that the smaller carrier is at risk of losing relatively more by deviating from the collusive agreement than the larger carrier. Table 1b shows the matrix, $pct_mmc_{kh}^t$, for the 17 carriers in our sample in the first quarter of 2007.

The second one, called $max_pct_mmc_{kh}^t$, is defined as the largest one between $pct_mmc_{kh}^t$ and $pct_mmc_{hk}^t$. This measure is symmetric ($max_pct_mmc_{kh}^t = max_pct_mmc_{hk}^t$), allowing for the possibility that the smaller carrier has a stronger incentive to collude, because a larger fraction of its profitability depends on the collusive behavior of the two firms.

Finally, we consider $weighted_pct_mmc_{kh}^{mt}$, which is equal to $pct_mmc_{kh}^t$ times the market share of firm h in all US markets at time t . This last measure of multimarket contact allows for firms with the same number of markets, but different numbers of passengers, to have distinct gains from colluding through multimarket contact.

□ **Control variables.** Carriers can offer both nonstop and connecting service.¹³ Thus, for each product offered by a carrier in a market, we generate a variable, $Nonstop_{jmt}$, equal to 1 if the service offered by a carrier is nonstop. Table 2 shows that approximately 17% of the observations in our data set correspond to nonstop services offered by a carrier. A second source of differentiation among carriers is related to the size of the carrier's network at an airport; see Brueckner, Dyer, and Spiller (1992). Carriers serving a larger number of destinations out of an airport have more attractive frequent flyer programs and other services at the airport (number of ticket counters, customer service desks, lounges, etc.). To capture this idea, we compute the *percentage* of all markets served out of an airport that are served by an airline in the DB1B data and call this variable $NetworkSize_{jmt}$. To control for potential price differences in one-way and round-trip tickets, we construct the variable $Roundtrip_{jmt}$, which measures the fraction of round-trip tickets over the total number of tickets sold by a carrier in a market.

Particular aspects of a market also affect the demand for air travel. One important element of demand is the number of consumers in a market. Like Berry, Carnall, and Spiller

¹³ Even if carriers may "offer" both types of services, one of the two types is either exceedingly inconvenient or prohibitively costly to both the carrier and consumer. Thus, we usually see either nonstop or connecting service, but not both, in the DB1B sample.

TABLE 2 Variable Description and Summary Statistics

Variable	Source	Description	Mean	Median	Standard Deviation
Carrier-Market-Specific Variables					
Fare	DB1B	Carrier-Market-Specific Average Fare	222.692	213.472	66.502
Nonstop	DB1B	Indicator of Nonstop Service	0.173	0.000	0.379
NetworkSize	DB1B	Percentage of All Routes Served by Carrier at Originating Airport	0.443	0.470	0.174
NumMkt	DB1B	Number of Markets Served by Carrier at Originating Airport (1000s)	0.130	0.139	0.050
ExtraMiles	DB1B	Average Distance Flown Divided by the Nonstop Distance	1.18	1.091	0.23
AvgContact	DB1B	Average Market Contact from mmc Matrix (divided by 1000)	0.630	0.621	0.265
MktShare	DB1B	Market-Carrier Share of Passengers	0.274	0.168	0.286
HHI	DB1B	Market Herfindahl – Hirschman Index	0.453	0.404	0.214
Roundtrip	DB1B	Proportion of Round-trip Passengers	0.827	0.853	0.130
Hub	Author	Indicator for Hub End point	0.104	0.000	0.306
Market-Specific Variables					
<i>mmckht</i>	DB1B	EK Multi-market measure	0.63	0.62	0.27
<i>pct_mmckht</i>	DB1B	Multi-market measure with shares	0.5	0.52	0.13
<i>max_pct_mmckht</i>	DB1B	Multi-market measure with shares, using max	0.64	0.66	0.16
<i>weighted_pct_mmckht</i>	DB1B	Multi-market measure with shares weighted with population	0.23	0.23	0.08
Distance	DB1B	Nonstop Distance Between Market End points	1105.694	969.000	596.201
MktSize	BEA	Geometric Mean of Population at Market End points	2409758	1789943	1993143
BusIndex	ATS Survey	Fraction of Business Travelers	0.408	0.411	0.096
OwnGates	Survey	Carrier's Own Mean % Gates at Market End points	0.129	0.093	0.129
CompGates	Survey	Total Mean % of Gates at Market End points Held by All Potential Competitors	0.587	0.616	0.587
LccGates	Survey	Total Mean % of Gates at Market End points Held by Potential Lcc Competitors	0.072	0.063	0.072
WNGates	Survey	Mean % of Gates at Market End points Held by WN, 0 if Carrier is WN	0.064	0.048	0.070

Number of Observations: 268,119.

(2006) (BCS (2006), from here on) and Berry and Jia (2010), we follow the industry standard and define the size of a market, $MktSize_m$, as the geometric mean of the population at the market end points. Another important determinant of consumers' travel decisions is the nonstop distance between the end points of a market, $Distance_m$. As the relationship between $Distance_m$ and the demand for air travel may have some nonlinearities due to countervailing effects, that is, for longer distances air travel becomes relatively more attractive but all forms of travel are less attractive, we include both $Distance_m$ and its square directly in consumers' utility function in our structural analysis. We also construct a variable, $Extramiles_{jmt}$, to measure the indirectness of a carrier's service. More precisely, $Extramiles_{jmt}$ is the

average distance flown by consumers choosing a product relative to the nonstop distance in the market.

Next, we construct an indicator, Hub_{jm} , equal to one if one of the two end points of market m is a hub airport of carrier j .¹⁴ The variable Hub_{jm} captures whether flying on the hub airline is more attractive than flying on any other airlines (Borenstein, 1989). It also captures potential cost advantages. To control for economies of density, we calculate $NumMkt_{jmt}$ as the number of markets served by a carrier out of the origin airport associated with market m .

Finally, we use the index of Borenstein (2010) to measure the share of commercial airline travel to and from cities for business purposes. The index is constructed using data from the 1995 American Travel Survey, a survey of long-distance domestic transportation, which includes 113,842 person-trips on domestic commercial airlines. As Borenstein (2010) explains, the actual airports used for each trip are not reported, but the location of the origin, such as the metropolitan area and the state, is reported. If the origin airport of the unidirectional market, m , is in an MSA, then $BusIndex_m$ is the business travel index of that MSA. In the few cases where an airport is not located in an MSA, then $BusIndex_m$ is equal to the index of the state where the airport is located. The main limitation of $BusIndex_m$ is that it is slightly outdated and that it measures the fraction of travel that is for business purpose among those individuals who chose to travel. For this reason, we use this index only to test the robustness of our main results.

□ **Endogenous variables and exclusion restrictions.** There are three endogenous variables in our empirical analysis: prices, shares (of passengers transported), and multimarket contact among carriers actively serving a market. In the reduced-form analysis we regress prices directly on multimarket contact, and thus we only worry about the endogeneity of *average* multimarket contact. In the structural analysis, we jointly estimate demand and first-order conditions for price, allowing for recovery of preferences, costs, and conduct parameters relating *pair-specific* multimarket contact to the degree of coordination among carriers in setting fares. This requires us to simultaneously address the endogeneity of prices, shares, and *pair-specific* multimarket contact.

The market-specific measures of average multimarket contact are likely endogenous because unobservable heterogeneity can alter the pricing, entry, and exit decisions of a firm (Ciliberto, Murry, and Tamer, 2012). In particular, variation in $AvgContact_{mt}$ across markets comes from differences in the set of firms operating in the market because, at a point in time, the contact for any two carriers (mmc_{kh}^t) is fixed. Variation in $AvgContact_{mt}$ over time within a market comes from changes in the set of carriers operating in a market as well as potentially changes in the degree of overlap between a given pair of carriers (mmc_{kh}^t). As variation in market structure (identity of carriers operating in a market) directly determines the market-specific measure of contact, $AvgContact_{mt}$, and is also likely correlated with unobservables that affect prices, cross-sectional variation cannot be used to infer a causal relationship between fares and multimarket contact. Similarly, a fixed-effects approach that exploits variation over time within a market in $AvgContact_{mt}$ will not be appropriate if market-specific time-varying unobservables drive variation in both fares and market structure. In these situations, as Griliches and Mairesse (1995) suggest, fixed-effects will perform poorly and the researcher should search for an instrumental-variables solution.

We use data on carriers-specific access to boarding gates at each airport to construct instrumental variables that we use both in the reduced-form and structural analysis.¹⁵ We start from the observation that an airline needs access to gates at both the origin and destination airport to serve

¹⁴ The hub airports are Chicago O'Hare (American and United), Dallas/Fort Worth (American), Denver (United), Phoenix (USAir), Philadelphia (USAir), Charlotte (USAir), Minneapolis (Northwest, then Delta), Detroit (Northwest, then Delta), Atlanta (Delta), Cincinnati (Delta), Newark (Continental), Houston (Continental).

¹⁵ These detailed data on carrier-airport leasing agreements were collected as part of a survey conducted jointly with the ACI-NA (Williams, 2012). Williams (2012) contacted executives at the top 200 airports in terms of enplanements in 2007, and 107 of them provided complete information on historical and present gate usage as well as specific terms of

a market. A substantial majority of gates are leased on an exclusive or preferential basis, and for many years. The Government Accounting Office (GAO, 1990) reports that 22% of the gates at the 66 largest airports were for 3 – 10 years' duration; 25% were for 11 – 20 years' duration; and 41% were for more than 20 years' duration (GAO 1990). Our communications with the ACI-NA suggest this pattern was not substantially different during our sample period. Airlines and airports sign long-term leases so that airports can make capital investments while getting lower interest rates on their debt issues; and the airlines can build a network out of an airport, which increases their demand (Berry, 1990).¹⁶

For the 17 carriers in our sample, we calculate the mean of the percentage of gates leased on an exclusive or preferential basis by each carrier at the two market end points. From these variables, we generate four additional instruments that vary by carrier within a market. Specifically, we use a carrier's own gates (*OwnGates_{jm}*) and the level of *potential* competition a carrier faces from all other carriers (*CompGates_{jm}*), just low-cost carriers (*LccGates_{jm}*), and Southwest (*WNGates_{jm}*). The instruments are calculated as the sum, by carrier-type (legacy, low-cost, Southwest), of the average fraction of gates leased at the market end points by each type of a carrier's competitors.¹⁷ These are valid instruments for prices, shares, and multimarket contact for three related reasons.

First, in each step of our analysis, we include control variables that are carrier-specific and airport-specific (e.g., network size), market-specific (e.g., distance), and industry-specific (e.g., year-quarter dummies). These controls remove a substantial amount of persistence from unobservable factors of demand and cost in any given market. The remaining unobserved determinants of demand and costs are then difficult to predict years in advance by the airlines.

Second, it is difficult to adjust access to airport facilities in response to unexpected changes in demand and costs. Ciliberto and Williams (2010) note that airlines cannot terminate leases unilaterally and it is expensive to sublease gates. For example, American Airlines sought to terminate gate leasing agreements with Dallas Love, but the airport declined and American had to pay until 2011, when the lease expired.¹⁸ The existence of a secondary market for access to gates should allow entry decisions to be more responsive to (time-varying) market-specific unobservables. Yet numerous airlines (Southwest, America West, etc.) have reported costs of subleasing gates many times what they would face if they leased the gates directly from the airports (Ciliberto and Williams, 2010; GAO, 1989, 1990). At those airports that impose limits on sublease fees, it's also natural that gates would be unresponsive to changing market conditions, because carriers' incentives to sublease gates to competitors are diminished further.

Finally, it is unlikely that carriers want to change the number of gates they lease in response to market-specific shocks to demand, because a single market typically represents a relatively small proportion of a carrier's revenues out of an airport. Also, because leasing decisions are made at the airport level, fluctuations in one market may be offset by fluctuations in another market, leaving demand out of the airport, and consequently the need for gates, largely unchanged.¹⁹

subleasing agreements. Williams (2012) observed that the response pattern was random based on follow-up calls, ruling out selection bias in the airports which chose to respond to the survey. From the survey, we use information on the total number of gates at the airport, the number leased to each carrier on a preferential or exclusive basis, and the number reserved for common use by the airport authority in 2007.

¹⁶ Signatory carriers often also receive discounts on landing and other fees.

¹⁷ Legacy carriers include AA, CO, DL, NW, UA, and US. The remaining carriers, other than Southwest, are classified as low-cost.

¹⁸ See the February 28, 2005, Letter from Mr. Gwyn, Director of Aviation, City of Dallas, to Ms. Lang, Deputy Director of Airport Planning and Programming, Federal Aviation Administration.

¹⁹ Even if market-specific shocks are correlated within an airport, it still seems unlikely that a carrier could respond by altering gates in a meaningful way. In this situation, demand from potential lessees would also decrease.

TABLE 3 Prices and Multimarket Contact

	Top 1000 Markets		All Markets			
	(1)	(2)	(3)	(4)	(5)	(6)
Average_MMC	0.161*** (0.050)	0.274*** (0.054)	-0.017*** (0.003)	0.054*** (0.007)	0.539*** (0.009)	0.667*** (0.016)
Hub		0.207*** (0.006)	0.190*** (0.004)	0.191*** (0.004)	0.177*** (0.002)	0.194*** (0.002)
NetworkSize	0.284*** (0.032)	0.311*** (0.032)	0.224*** (0.011)	0.226*** (0.011)	0.501*** (0.007)	0.207*** (0.006)
Nonstop	-0.081*** (0.004)	-0.065*** (0.004)	-0.032*** (0.003)	-0.032*** (0.003)	-0.053*** (0.001)	-0.033*** (0.001)
RoundTrip	-0.633*** (0.013)	-0.576*** (0.012)	-0.533*** (0.007)	-0.539*** (0.008)	-0.444*** (0.004)	-0.548*** (0.004)
HHI	-0.023 (0.019)					
MktShare	0.281*** (0.009)					
Log(Distance)					-1.265*** (0.024)	-0.438*** (0.058)
Log2(Distance)					0.106*** (0.002)	0.049*** (0.004)
Market fixed – effects	Yes	Yes	Yes	Yes	No	No
IV	No	No	No	No	Yes	Yes
X ² test static for joint significance of IV					15,314.27***	5,418.90***
Excluding monopolies	No	No	No	Yes	No	Yes
R ²	0.207	0.223	0.143	0.171	0.241	0.350
Observations	85,498	85,498	268,119	252,284	268,119	252,284

Note: Standard errors in parentheses: ***<0.01, **<0.05, *<0.10. Robust standard errors in columns 1 – 4. Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted.

3. Reduced-form analysis

□ **Replicating Evans and Kessides (1994).** We replicate the work of EK (1994) using our data sample. Specifically, their data is drawn from the DB1B database for the 1984 to 1988 time period whereas ours is drawn from the 2006 to 2008 time period. The market for air travel has become more concentrated (the Herfindahl-Hirschman Index [HHI] in their top 1000 markets was 0.41 and is 0.50 in our top 1000 markets) in the intervening years. In particular, our measure of multimarket contact has a mean of 0.21 in our top 1000 markets and 0.18 in their top 1000 ones. We examine whether the relationships in the data identified in the earlier time period remain robust.

EK (1994) test the hypothesis that multimarket contact facilitates collusion by running the following regression:

$$\ln(p_{jmt}) = \text{AvgContact}_{mt} \cdot \beta_{EK} + \text{Controls}_{jmt} \beta_{Controls} + \varepsilon_{jmt}, \quad (2)$$

where j indexes products, m markets, and t time. The dependent variable is the natural logarithm of the average price for product j . The main variable of interest is AvgContact_{mt} , whose coefficient β_{EK} is expected to be positive. In addition to the controls discussed in Section 2, all specifications include carrier and year-quarter fixed effects. In four of the six specifications we also include market fixed effects. We present the results of these regressions in Table 3.

Column 1 of Table 3 replicates the main market-fixed-effects regression in EK (1994). We include data for only the 1000 largest markets, with the ranking constructed after aggregating the number of passengers in each market over all periods. To make the results of our article directly comparable to those in EK (1994), the variables mmc_{kh}^t and AvgContact_{mt} are constructed with

the data from these 1000 markets. The mean of $AvgContact_{mt}$ is equal to 0.21 in this small sample. This number is similar to 0.18, the mean value of the $AvgContact_{mt}$ in EK (1994). Following EK (1994), we include a measure of market share, $MktShare_{jmt}$, the number of passengers transported by a carrier in a market over the total number of passengers transported in that market, as well as the HHI of passengers, HHI_{mt} , a measure of market concentration.

We find that the coefficient of multimarket contact is equal to 0.161. This number should be compared to 0.398, the number reported in Column 3 of Table III in EK (1994). To understand whether the difference between these two numbers is economically meaningful, we can multiply each number by 0.128, which is the change in $AvgContact_{mt}$ that EK (1994) find when moving from the route in their sample with the twenty-fifth percentile in contact to a route with the seventy-fifth percentile. Using our estimates, we find that such a change in multimarket contact corresponds to a change of 2% in fares, compared to 5% in EK (1994). The results for the control variables, when precisely estimated, are also comparable with those in EK (1994).

Column 2 of Table 3 presents another regression in the spirit of EK (1994). We again include data for only the 1000 largest markets. The only difference between Columns 1 and 2 concerns the control variables. Column 2 excludes HHI_{mt} and $MktShare_{jmt}$, which are endogenous, and includes a dummy variable, Hub_{jm} , which is exogenous. The result for the variable of interest, $AvgContact_{mt}$, is similar. The coefficient of $AvgContact_{mt}$ is equal to 0.274, which implies that a 0.128 change in $AvgContact_{mt}$ would result in an increase in prices of 4%.

Column 3 of Table 3 considers the full sample of markets. The variables mmc_{kh}^t and $AvgContact_{mt}$ are constructed using the full sample of markets. The striking result now is that $AvgContact_{mt}$ has a *negative* effect on prices. A crucial limitation of $AvgContact_{mt}$ is that it is not well defined for monopoly markets, for which the denominator $\frac{1}{F_{mt}(F_{mt}-1)}$ is zero. In these cases, we follow EK (1994) and set the variable $AvgContact_{mt}$ equal to zero. The problem with this solution is that, *ceteris paribus*, prices are higher in monopoly markets than in oligopoly markets. Yet we expect prices to increase with multimarket contact. The web Appendix discusses this in more detail.

In Column 4, we run the same regressions using only nonmonopoly markets. The coefficient of $AvgContact_{mt}$ is now positive and statistically significant. Its effect is smaller than the one we estimated in Column 2. Here, the change of 0.128 in $AvgContact_{mt}$ implies an increase in prices of less than 1% against the change of 4% we estimated in Column 2.

Column 5 of Table 3 presents the results from the instrumental variable regressions with market-specific random effects. The instrumental variables are defined and discussed in Section 2. We consider the full sample of markets, including monopoly markets. We estimate the coefficient of $AvgContact_{mt}$ equal to 0.539. This means that the change of 0.128 in $AvgContact_{mt}$ would imply, approximately, an increase in prices of 6.5%. This effect is similar to those from the estimates in Column 2. Column 6 is the same specification as Column 5 but does not include monopoly markets. The results are similar to those in Column 5. The marginal effect is now estimated equal to 8.5%.

At the bottom of Table 3, in Columns 5 and 6, we present the results of an test of the joint significance of our instruments. In both cases, the null is rejected at the 1% level of significance. The intuition behind the success of our instruments is their ability to explain cross-sectional variation in market structure, the indicators $1[k \text{ and } h \text{ active}]_{mt}$ in equation (1), which determines the observed level of $AvgContact_{mt}$. The web Appendix discusses the results of the first stage in more detail.

□ **Robustness analysis.** In this section, we run four specifications to test the robustness of the results in Table 3. In Column 1 of Table 4, we add the variable $BusIndex_{mt}$ to the regression we run in Column 6 of Table 3 to control for the possibility that the positive correlation of prices across airlines with high multimarket contact may be a function of the differential type of demand that carriers face. We find our results to be largely unchanged with the inclusion of $BusIndex_{mt}$.

TABLE 4 Prices and Multimarket Contact, Robustness

	EK (1)	pct (2)	max-pct (3)	wgt-pct (4)
Average_MMC	0.663*** (0.016)	2.725*** (0.054)	2.115*** (0.030)	3.904*** (0.035)
Hub	0.194*** (0.002)	0.195*** (0.018)	0.212*** (0.002)	0.214*** (0.002)
NetworkSize	0.208*** (0.006)	0.167*** (0.006)	0.089*** (0.008)	-0.169*** (0.009)
Nonstop	-0.033*** (0.001)	-0.032*** (0.001)	-0.080*** (0.002)	-0.054*** (0.002)
RoundTrip	-0.548*** (0.004)	-0.551*** (0.004)	-0.404*** (0.005)	-0.511*** (0.005)
Log(Distance)	-0.430*** (0.058)	-0.622*** (0.052)	-0.866*** (0.019)	-0.674*** (0.020)
Log2(Distance)	0.048*** (0.004)	0.064*** (0.004)	0.080*** (0.001)	0.069*** (0.001)
BusinessIndex	-0.029 (0.021)	-0.042** (0.018)	0.110*** (0.006)	0.104*** (0.006)
R ²	0.350	0.346	0.25	0.23

Note: Standard errors in parentheses: ***<0.01, **<0.05, *<0.10.

Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, and that of the constant, are omitted. All regressions use instrumental variables. All columns show instrumental variable regressions and exclude monopolies.

In Columns 2, 3, and 4 of Table 4, we run the same specification as in Column 1 but we use different measures of multimarket contact. Although in Column 1 we used the variable mmc_{kh}^t to construct the variable $AvgContact_{mt}$, in Column 2 we use $pct_mmc_{kh}^t$, in Column 3 we use $max_pct_mmc_{kh}^t$, and in Column 4 we use $weighted_pct_mmc_{kh}^t$. The results for the multimarket variable are all positive and statistically significant. Their magnitude is larger because these are percentages rather than absolute numbers. After we account for the scale of the alternative measures, that is, the smaller standard deviations reported in Table 2 for the alternative measures, the economic implications are similar.

4. Multimarket contact and collusion

■ In this section, we provide a structural analysis of the relationship between multimarket contact and collusion in the airline industry.²⁰ With the additional structure we can unpack the reduced-form analysis and identify the relationship between multimarket contact and the actual degree of cooperation in setting fares, as well as identify those markets where the cooperation has the greatest impact on fares. In particular, we can more clearly demonstrate the important role that cross-price elasticities have in both identifying collusion and determining its impact on fares.

□ **Demand.** Our basic demand model is most similar to BCS (2006) and Berry and Jia (2010). We allow for two consumer types, $r = \{1, 2\}$. For product j at time t in market m , the utility of consumer i of type r , is given by

$$u_{ijmt}^r = x_{jmt}\beta_r + p_{jmt}\alpha_r + \xi_{jmt} + v(\lambda)_{itm} + \varepsilon_{ijmt},$$

where x_{jmt} is a vector of product characteristics, p_{jmt} is the price, (β_r, α_r) are the taste parameters for a consumer of type r , and ξ_{jmt} are product characteristics unobserved to the econometrician.

²⁰ This stage of our analysis corresponds to what Harrington (2008) calls the *verification* process.

The term, $v(\lambda)_{itm} + \varepsilon_{ijmt}$, is the error structure required to generate nested logit choice probabilities for each consumer type. The parameter, $\lambda \in [0, 1]$, governs substitution patterns between the two nests, airline travel and the outside good (not traveling or another form of transportation).²¹ The mean utility of the outside good is normalized to zero because only differences in utility, not levels, are identified.

The proportion of consumers of type r , in market m , choosing to purchase a product from the air-travel nest in market t is then

$$\frac{D_{rmt}^\lambda}{1 + D_{rmt}^\lambda}, \quad (3)$$

where

$$D_{rmt} = \sum_{k=1}^{J_{mt}} e^{(x_{jmt}\beta_r + p_{jmt}\alpha_r + \xi_{jmt})/\lambda}.$$

The probability of a consumer of type r choosing product j , conditional on purchasing a product from the air-travel nest, is

$$\frac{e^{(x_{jmt}\beta_r + p_{jmt}\alpha_r + \xi_{jmt})/\lambda}}{D_{rmt}}. \quad (4)$$

Together, equations (3) and (4) imply that product j 's market share, after aggregating across consumer types, is

$$s_{jmt}(\mathbf{x}_{mt}, \mathbf{p}_{mt}, \xi_{mt}, \beta_r, \alpha_r, \lambda) = \sum_{r=1}^2 \kappa_{rm} \frac{e^{(x_{jmt}\beta_r + p_{jmt}\alpha_r + \xi_{jmt})/\lambda}}{D_{rmt}} \frac{D_{rmt}^\lambda}{1 + D_{rmt}^\lambda}, \quad (5)$$

where κ_{rm} is the proportion of consumers of type r in the full population in market m .

The advantage of this demand specification is that it places no restrictions on the correlation among the taste parameters. This is important, as numerous studies of demand for air travel have identified strong correlations in preferences over fares and other aspects of service like network scope (e.g., Armantier and Richard, 2008). This flexibility results in the number of parameters growing exponentially in the number of types, limiting us to consider only two types.²² However, we can relax the assumption, made by BCS (2006) and Berry and Jia (2010), that κ_{rm} is constant across markets ($\kappa_{rm} = \kappa_r \forall m$). To do so, we specify κ_{rm} as

$$\kappa_{rm} = \frac{\exp(\kappa_0 + \kappa_1 \text{BusIndex}_m)}{1 + \exp(\kappa_0 + \kappa_1 \text{BusIndex}_m)}. \quad (6)$$

If $\kappa_1 = 0$, κ_{rm} is constant across all markets. If $\kappa_1 \neq 0$, the fraction of business travelers fluctuates based on the BusIndex_m variable. We estimate both specifications to show that our results are not sensitive to the assumption that the fraction of business travelers is constant across markets.

To control for persistent variation in consumers' tastes across carriers and time, we add carrier and year-quarter fixed effects (d_{jt}) such that

$$\Delta \xi_{jmt} = \xi_{jmt} - d_{jt}\psi.$$

Following Berry (1994) and Berry, Levinsohn, and Pakes (1995), we then exploit a set of moment conditions formed by interacting the structural error term, $\Delta \xi$, with a set of instruments to recover estimates of γ_d .

We first use a variation of the Berry, Levinsohn, and Pakes (1995) contraction mapping, due to BCS (2006), to invert equation (5) and solve for the value of the unobservables that

²¹ See Goldberg (1995) and Verboven (1996) for models of demand with multiple nests.

²² Alternatives to BCS (2006) and Berry and Jia (2010) that grant greater flexibility are limited in their ability to deal with endogeneity (e.g., Bajari, Fox, and Ryan, 2007; Bajari, Fox, Kim, and Ryan, 2011).

matches the model's predicted shares to observed market shares for each product, conditional on $\gamma_d = \{\lambda, \alpha, \beta, \kappa, \psi\}$. Observed market shares are calculated as the number of passengers transported by a carrier in a market divided by $MktSize_{mt}$. We then estimate these parameters by forming the sample counterpart of the moment condition

$$g_d = E [\Delta \xi_{jmt}(\gamma_d) | z_{jmt}] = \mathbf{0},$$

where z_{jmt} is a vector of instruments. Price is treated as an endogenous regressor and we use the same instrumental variables that we used in the reduced-form analysis to control for the endogeneity of the average multimarket contact.

□ **The Bertrand-Nash pricing game.** We maintain that airlines compete on prices and offer differentiated products. We start by assuming that observed equilibrium prices are generated from play of a Bertrand-Nash pricing game. The Bertrand-Nash pricing assumption generates the following supply relationship for any product j belonging to the set of products, $l = 1, \dots, F_{mt}^k$, produced by firm k , in market m , at time t ,

$$s_{jmt} + \sum_{l \in F_{mt}^k} (p_{lt} - mc_{lt}) \frac{\partial s_{lt}}{\partial p_{jt}} = 0,$$

where mc_{lt} is the marginal cost of product l .

We specify the marginal cost for product j in market m at time t as

$$mc_{jmt} = w_{jmt}\pi + d_{jt} + \omega_{jmt}. \quad (7)$$

The w_{jmt} vector includes $NumMkt$ and its square, $Distance$ and its square, $Extramiles$ and its square, and d_{jt} , a set of carrier and year-quarter dummies. The error term, ω_{jmt} , is the portion of marginal cost unobserved to the econometrician.

For each market, the Bertrand-Nash pricing assumption generates a set of J_{mt} equations, implying price-cost margins for each product. Using matrix notation, this set of first-order conditions for market m can be rewritten as

$$\mathbf{s}_{mt} - \mathbf{\Omega}_{mt}(\mathbf{p}_{mt} - \mathbf{mc}_{mt}) = \mathbf{0}, \quad (8)$$

where each element of $\mathbf{\Omega}$ can be decomposed into the product of two components, $\Omega_{jlmt} = \Sigma_{jlmt}\Theta_{jlmt}$. The first component is the own or cross-price derivatives of demand, $\Sigma_{jlmt} = \partial s_{lmt} / \partial p_{jmt}$, whereas the second component is an indicator of product ownership. More precisely, if products j and l belong to the same firm, then Θ_{jlmt} equals 1 whereas Θ_{jlmt} equals 0 otherwise. With the exception of Nevo (2001), the literature has assumed that Θ is a diagonal matrix (block-diagonal in the case of multiproduct firms), strictly ruling out any coordination between firms in setting prices. In the next section, Section 4, we discuss how our model departs from the literature regarding the assumptions made on firm behavior.

In assuming that airlines compete in prices and offer differentiated products, and modelling the pricing decision for each market separately, we follow a well-established literature on airline competition; (see Reiss and Spiller, 1989; Berry, 1990; BCS, 2006; Peters, 2006; Berry and Jia, 2010). The frontier of the empirical literature on the industry, for example, Benkard et al. (2013), is only now beginning to model the interdependencies across markets in entry decisions of carriers, although ignoring any in pricing. Also, although it would be ideal to model the entire competitive process, that is, entry, exit, and pricing, by which multimarket contact arises and sustains collusive pricing, the thousands of markets most carriers serve make this an intractable problem.

□ **Multimarket contact and conduct parameters.** As pointed out by Nevo (1998, 2001), the standard assumptions on the structure of Θ rules out a continuum of pricing outcomes between the competitive Bertrand-Nash (Θ is diagonal or block-diagonal in the case of multiproduct firms)

and the fully-collusive outcome (Θ is a matrix of ones). In the case of homogeneous products, Bresnahan (1982) and Lau (1982) provide intuitive and technical, respectively, discussions of how “rotations of demand” can be used to distinguish between different models of oligopolistic competition or identify conduct parameters. Recent work by Berry and Haile (2010) formally demonstrates how to extend the intuition of Bresnahan (1981, 1982) to differentiated product markets. Berry and Haile (2010) show that changes in the “market environment” can be used to distinguish between competing models, including variation in the number, product characteristics, and costs of competitors.

In the context of the airline industry, one potential shifter of the “market environment” is the degree of pair-specific multimarket contact between carriers. In particular, higher levels of multimarket contact between competitors may facilitate collusion. To capture this idea, we define Θ_{jlm} as a function of pair-specific multimarket contact. In particular, if product j is owned by carrier k and product l is owned by carrier h , then Θ_{jlm} equals $f(mm c_{kh}^t)$. This function, determining the amount of coordination between carriers k and h in setting fares, is bound between zero and one and dependent on the level of multimarket contact between the two carriers, $mm c_{kh}^t$, the $\{k, h\}$ element of the contact matrix in period t . Thus, the conduct parameters tell us whether price-setting firms compete or collude. If the conduct parameters are estimated to be equal to zero, we can conclude that firms do not cooperate in setting fares. If the conduct parameters are estimated to be equal to one, we can conclude that firms collude.

This type of modelling is admittedly less ambitious than the one proposed by the earlier work on the estimation of conduct parameters (e.g., Brander and Zhang, 1990, 1993). In earlier work, conduct parameters informed the researcher both on the choice variable of the firms (whether firms compete on prices or quantities) and on whether the firms collude or compete. Yet our approach is still very effective and simple to generalize to any industry where there is a market-specific exogenous variable that may facilitate collusion. Note that our approach does not require addressing the critique of Corts’s (1999). Corts (1999) points out inference regarding conduct parameters is invalid if the researcher does not stipulate “the true nature of the behavior underlying the observed equilibrium.” In our analysis, we do explicitly stipulate a Bertrand-Nash pricing model and identify conduct parameters conditional on this behavioral assumption.

The interpretation of these conduct parameters is most easily seen by examining the first-order conditions in the case with two firms. In this case, the first-order conditions are (market and time subscripts are omitted for simplicity)

$$\begin{pmatrix} s_1 \\ s_2 \end{pmatrix} + \begin{bmatrix} \frac{\partial s_1}{\partial p_1} & f(mm c_{12}) \cdot \frac{\partial s_2}{\partial p_1} \\ f(mm c_{21}) \cdot \frac{\partial s_1}{\partial p_2} & \frac{\partial s_2}{\partial p_2} \end{bmatrix} \begin{pmatrix} p_1 - mc_1 \\ p_2 - mc_2 \end{pmatrix} = 0.$$

The first-order condition of firm 1 is then

$$\underbrace{s_1 + \frac{\partial s_1}{\partial p_1} (p_1 - mc_1)}_{\text{Bertrand FOC}} + \underbrace{f(mm c_{12}) \cdot \frac{\partial s_2}{\partial p_1} (p_2 - mc_2)}_{\text{Cooperative Effect}} = 0. \quad (9)$$

The additional cooperative term is what differentiates our model and makes clear how multimarket contact impacts equilibrium pricing behavior through cross-price elasticities.

The impact of this additional term depends on two factors. First, the size of $f(mm c_{12})$ determines the degree to which firms cooperate in setting fares. In particular, values of $f(mm c_{12})$ ranging from zero to one result in equilibrium pricing behavior ranging from the competitive Bertrand-Nash outcome to a fully collusive outcome, respectively. Second, the degree to which cooperation increases prices depends on the cross-price derivatives of demand, $\frac{\partial s_2}{\partial p_1}$ and $\frac{\partial s_1}{\partial p_2}$. This is intuitive: if the products that firms offer are close substitutes ($\frac{\partial s_2}{\partial p_1}$ and $\frac{\partial s_1}{\partial p_2}$ are relatively large), then cooperation will result in fares significantly higher than the competitive Bertrand-Nash outcome.

Equation (9) is very helpful to understand the type of variation in the data that allows us to identify the conduct parameters. Like equation (2) from the reduced-form analysis, equation (9) is a model of the relationship between equilibrium prices and the multimarket contact among carriers serving a market. This relationship has two main determinants, the substitutability of carriers' products (i.e., cross-price elasticities) and the identity of the carriers *actively* serving the market (i.e., pair-specific multimarket contact). Thus, to identify the degree of coordination in setting fares and pair-specific multimarket contact (i.e., the conduct parameters), one must have instruments that explain both the substitutability of carriers' service and which carriers serve the market.

As we discuss in Section 2, there is exogenous, or at least predetermined relative to the unobservable determinants of demand, $\Delta\xi_{jmt}$, and marginal costs ω_{jmt} , variation across firms and markets in access to gates that can be used to identify this relationship. As our reduced-form analysis demonstrates, carrier- and market-specific access to gates do well in identifying this relationship because it can explain both the type of service a carrier can offer (e.g., a determinant of network scope) and consequently the substitutability of carriers' services, as well as the ease of entering a market (i.e., identity of carriers actively serving a market). Also, note that the additional structure of the model allows us to clearly and separately identify coordination in setting fares from other potential stories for higher fares (e.g., marginal cost), as multimarket contact enters only through its interaction with nonlinear functions of market shares ($\frac{\partial s_2}{\partial p_1}$, or more generally, $\Omega_{tm}^{-1}s_{tm}$), whereas determinants of marginal cost do not.

Our goal is to utilize these first-order conditions to estimate both the conduct parameters and marginal cost (specified in equation (7)). We model the conduct parameters as

$$f(mmc_{kh}^t) = \frac{\exp(\phi_1 + \phi_2 mmc_{kh}^t)}{1 + \exp(\phi_1 + \phi_2 mmc_{kh}^t)}, \quad (10)$$

which restricts $f(mmc_{kh}^t)$ between zero and one. Similar to the reduced-form analysis, we estimate this specification of the conduct parameters using each of the three different measures of multimarket contact. These alternative measures allow for asymmetry in the degree of coordination between a pair of carriers and introduce variation in the importance of multimarket contact based on the proportion of the carrier's revenues generated in those markets served concomitantly by each pair of carriers.

We also estimate the model using two alternative, and more flexible, functional forms for the conduct parameters. The first is a cubic specification,

$$f(mmc_{kh}^t) = \max \left[0, \min \left\{ 1, \phi_1 + \phi_2 mmc_{kh}^t + \phi_3 (mmc_{kh}^t)^2 + \phi_4 (mmc_{kh}^t)^3 \right\} \right], \quad (11)$$

which allows for nonmonotonicities in the relationship between multimarket contact and coordination in setting fares, and restricts the conduct parameters to be between zero and one. The second is a dummy-variable specification,

$$f(mmc_{kh}^t) = \sum_{c=1}^5 \phi_c 1[\overline{mmc}_c \leq mmc_{kh}^t < \overline{mmc}_{c+1}], \quad (12)$$

where $\overline{mmc}_1 = 0$, $\overline{mmc}_2 = 0.25$, $\overline{mmc}_3 = 0.50$, $\overline{mmc}_4 = 0.75$, and $\overline{mmc}_5 = \infty$. This specification also allows for nonmonotonicities but does not force the conduct parameters to be between zero and one.

Note that each of these specifications for the conduct parameters allows for imperfect collusion, or outcomes between the competitive and the joint monopoly prices. These outcomes arise when firms collude but cannot sustain the monopoly outcome, that is, there is too much incentive to deviate from the fully collusive agreement.

In each of the specifications, we use equation (8) to form the sample counterpart of the moment condition,

$$g_s = E [\omega_{jmt}(\gamma_d, \gamma_s) | z_{jmt}] = \mathbf{0},$$

where γ_s are the conduct and marginal cost parameters and z_{jmt} is the same vector of instruments used in the demand moments. Following Berry, Levinsohn, and Pakes (1995), we estimate $\gamma = \{\gamma_d, \gamma_s\}$ by minimizing

$$Q(\gamma) = G(\gamma)' W^{-1} G(\gamma),$$

where $G(\gamma)$ is the stacked set of moments, (g_d, g_s) , and W is a consistent estimate of the efficient weighting matrix.²³

5. Results

■ The structural estimates are reported in Tables 5 and 6. Columns 1 and 2 of Table 5 present the estimates of demand and marginal costs when we assume firms compete as Bertrand-Nash competitors and fully cooperate in setting fares, respectively. Column 3 of Table 5 presents the estimates of the conduct parameters, along with the corresponding estimates of demand and marginal cost. Table 6 calculates the degree of coordination in setting fares between each pair of carriers using the estimates from Column 3 of Table 5. Tables 7 and 8 provide the results of our robustness analysis, which we discuss below.

□ **Bertrand-Nash competition.** Column 1 of Table 5 presents the estimates from the model when we assume firms price as Bertrand-Nash competitors. The demand estimates in the top panel are largely consistent with the previous studies of the industry (BCS, 2006; Berry and Jia, 2010).

First, as one would expect, consumers dislike higher fares, *ceteris paribus*. We find the coefficients of price to be equal to -1.333 for the first type and equal to -0.119 for the second type. Not only are these two coefficient estimates significantly different statistically, but their magnitudes are also quite different. We can think of the first type as the tourist type, who is very sensitive to prices, whereas the second type can be thought of as the business-traveler type, who is much less sensitive to prices. The mean own-price elasticity across all markets and products for the tourist type is equal to -6.260 , whereas only -0.559 for the business-traveler type. The mean own-price elasticity across all markets, products, and types is -4.320 , a number consistent with previous work.²⁴

The coefficient estimate of $\kappa_0 = -0.662$ implies $\kappa_{rm} = 0.340$, or there are 34% of business travelers in the markets in our data set. Notice that this number is lower than the average value of *BusIndex_m* in Table 2, which is consistent with the observation we made earlier that the index constructed by Borenstein (2010) overestimates the fraction of business travelers because it is computed only among those who choose to travel and not over the whole population.

Next, we can look at the decision to fly rather than use other means of transportation or simply not traveling at all. This decision is captured by the coefficient estimates of the type-specific constants and by the nesting parameter λ . The nesting parameter is greater than 0.5 in every specification, suggesting much of the substitution by consumers between products occurs

²³ Due to the highly nonlinear nature of the objective function and potential for local minima, we use a stochastic optimization algorithm (simulated annealing) to find a global minimum. In calculating standard errors, we allow for demand and cost errors to be correlated within a market.

²⁴ Our demand is estimated to be slightly more elastic than the estimates of Berry and Jia, (2010). This difference is likely driven by how products are defined. Berry and Jia, (2010) identify each unique fare observed in the data as a different product. As we do not know whether the unique fares observed in the data are in fact a result of variation in unobserved product characteristics or part of an intertemporal pricing strategy of the firm, we chose to aggregate all fares for a carrier in a quarter into one of two groups, nonstop and connecting service.

TABLE 5 BCS Estimation — Pricing Models

Demand	(1) BCS — No Collusion		(2) BCS — Full Collusion		(3) BCS — EK—exp CV	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Price ₁	−1.333***	(0.007)	−1.315***	(0.004)	−1.162***	(0.006)
Price ₂	−0.119***	(0.003)	−0.165***	(0.001)	−0.139***	(0.002)
κ^0	−0.662***	(0.065)	−0.723***	(0.034)	−0.566***	(0.044)
Constant ₁	−5.567***	(0.023)	−5.957***	(0.012)	−5.954***	(0.017)
Constant ₂	−7.650***	(0.042)	−7.196***	(0.023)	−7.514***	(0.028)
Nonstop ₁	1.087***	(0.006)	1.103***	(0.006)	1.140***	(0.006)
Nonstop ₂	0.954***	(0.006)	1.065***	(0.006)	1.030***	(0.006)
λ	0.625***	(0.001)	0.622***	(0.002)	0.601***	(0.002)
Network size	0.683***	(0.015)	0.578***	(0.015)	0.525***	(0.015)
Distance	2.223***	(0.026)	2.097***	(0.026)	1.997***	(0.026)
Distance ²	−0.523***	(0.010)	−0.511***	(0.010)	−0.497***	(0.01)
Extra—miles	−1.309***	(0.024)	−1.173***	(0.023)	−1.039***	(0.023)
Extra—miles ²	0.211***	(0.008)	0.182***	(0.008)	0.163***	(0.008)
Cost						
Constant	0.926***	(0.009)	0.379***	(0.005)	0.541***	(0.006)
NumMkt	−0.926***	(0.108)	0.344***	(0.056)	−0.531***	(0.072)
NumMkt ²	0.432	(0.370)	−1.523***	(0.192)	1.795***	(0.244)
Distance	0.184***	(0.011)	0.240***	(0.005)	0.249***	(0.007)
Distance ²	−0.008***	(0.004)	−0.055***	(0.002)	−0.039***	(0.003)
Extra—miles	0.157***	(0.011)	−0.104***	(0.005)	0.077***	(0.007)
Extra—miles ²	−0.052***	(0.004)	0.009***	(0.002)	−0.017***	(0.002)
Contact						
Constant					−3.167***	(0.058)
MMC					5.785***	(0.085)
Model Fit						
Median marginal cost	1.062		0.613		0.746	
Median elasticity	−4.320		−4.413		−3.519	
Median elast. — type1	−6.260		−6.181		−5.166	
Median elast. — type2	−0.559		−0.769		−0.618	
Function value	34766.038		34217.886		33900.977	

Note: ***<0.01, **<0.05, *<0.10.

Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted.

within the air-travel nest, rather than to the outside option. This means that passengers are more likely to substitute between carriers when prices change rather than deciding not to fly at all. We find that the estimated constant for the tourist type is equal to −5.567 and for the business-traveler type is equal to −7.65.

The results for the other variables are as expected. Both tourist and business travelers prefer nonstop flights and dislike longer connections. Travelers prefer flying with carriers offering a larger network out of the originating airport, which is consistent with previous work; see BCS (2006) and Berry and Jia (2010). The positive coefficient on *Distance* and negative coefficient on *Distance*² show that consumers find air travel more attractive in markets with longer nonstop distances; however, this effect is diminishing as the nonstop distance becomes larger and the outside option becomes relatively more attractive.

On the cost side, we find that the marginal cost of serving a passenger is increasing, although at a decreasing rate, in the nonstop distance between the market end points. We also find that connecting service is more expensive than nonstop service. Finally, we find that there are economies of density in the number of markets served out of an airport as the costs first increase

TABLE 6 Price Coordination in 2007-Q1

	AA	AS	B6	CO	DL	F9	FL	G4	NK	NW	SY	TZ	U5	UA	US	WN	YX
AA	•	0.046	0.064	0.687	0.856	0.076	0.170	0.042	0.043	0.690	0.043	0.047	0.042	0.828	0.546	0.230	0.077
AS	0.046	•	0.041	0.043	0.049	0.043	0.041	0.040	0.040	0.045	0.040	0.041	0.040	0.053	0.048	0.042	0.041
B6	0.064	0.041	•	0.068	0.083	0.041	0.055	0.040	0.042	0.064	0.040	0.040	0.041	0.079	0.080	0.051	0.041
CO	0.687	0.043	0.068	•	0.745	0.066	0.147	0.041	0.043	0.511	0.042	0.046	0.042	0.535	0.517	0.206	0.065
DL	0.856	0.049	0.083	0.745	•	0.076	0.369	0.042	0.045	0.889	0.042	0.047	0.043	0.935	0.970	0.281	0.075
F9	0.076	0.043	0.041	0.066	0.076	•	0.051	0.040	0.041	0.065	0.042	0.042	0.040	0.087	0.076	0.060	0.045
FL	0.170	0.041	0.055	0.147	0.369	0.051	•	0.040	0.043	0.198	0.041	0.044	0.042	0.184	0.284	0.072	0.054
G4	0.042	0.040	0.040	0.041	0.042	0.040	0.040	•	0.040	0.042	0.041	0.040	0.040	0.043	0.042	0.040	0.041
NK	0.043	0.040	0.042	0.043	0.045	0.041	0.043	0.040	•	0.043	0.040	0.041	0.041	0.044	0.045	0.042	0.041
NW	0.690	0.045	0.064	0.511	0.889	0.065	0.198	0.042	0.043	•	0.044	0.047	0.042	0.867	0.592	0.177	0.101
SY	0.043	0.040	0.040	0.042	0.042	0.042	0.041	0.041	0.040	0.044	•	0.040	0.040	0.043	0.042	0.040	0.041
TZ	0.047	0.041	0.040	0.046	0.047	0.042	0.044	0.040	0.041	0.047	0.040	•	0.040	0.047	0.046	0.047	0.043
U5	0.042	0.040	0.041	0.042	0.043	0.040	0.042	0.040	0.041	0.042	0.040	0.040	•	0.042	0.043	0.042	0.040
UA	0.828	0.053	0.079	0.535	0.935	0.087	0.184	0.043	0.044	0.867	0.043	0.047	0.042	•	0.850	0.220	0.096
US	0.546	0.048	0.080	0.517	0.970	0.076	0.284	0.042	0.045	0.592	0.042	0.046	0.043	0.850	•	0.218	0.061
WN	0.230	0.042	0.051	0.206	0.281	0.060	0.072	0.040	0.042	0.177	0.040	0.047	0.042	0.220	0.218	•	0.050
YX	0.077	0.041	0.041	0.065	0.075	0.045	0.054	0.041	0.041	0.101	0.041	0.043	0.040	0.096	0.061	0.050	•

and then decrease in the number of markets served out of an airport. The median of marginal cost across all markets is \$106.2.²⁵

□ **Collusion.** Next, we estimate the model under the assumption that firms fully cooperate in setting fares. In his study of the 1955 price war in the American automobile industry, Bresnahan (1987) shows that one can get dramatically different estimates under different behavioral assumptions. In this section, we set out to test how sensitive the parameter estimates are to the assumed behavioral model.

Column 2 of Table 5 shows the results under the assumption that firms fully cooperate in setting fares. First, we find that the price coefficients are now equal to -1.315 for the tourist traveler against the value of -1.333 that we had estimated in Column 1. We find that the estimated coefficient of price for the business traveler is now equal to -0.165 , about 40% larger than in Column 1. The coefficient estimate of κ_0 is quite similar to the one in Column 1, and it implies that $\kappa_{rm} = 0.32$.

The estimates of the cost coefficients are also quite different in Columns 1 and 2. The constant term is less than half as big (0.379 against 0.926). Cost is still increasing at a decreasing rate in the nonstop market distance, whereas we now find that connecting service is less expensive than nonstop service. This is not a particularly surprising result because longer connections through major hubs often involve larger planes that have a lower cost per passenger.

These differences in the estimated coefficients, along with the assumption that firms cooperate in setting fares, lead to significantly different estimates of the marginal cost, whose median is now estimated to be equal to 61.3 dollars, only 57% of the estimate in Column 1. This is clearly a major difference, which we investigate further below.

□ **Model with conduct parameters.** Column 3 of Table 5 presents the estimates of the model where we allow the degree of price coordination to depend on the level of multimarket contact between each carrier in a market. That is, we now look at a model that allows the firms to behave differently with different competitors. Firm *A* might be colluding with firm *B* but not with a firm *C*.

We start again from the demand estimates. We immediately observe that the coefficient estimates in Column 3 of Table 5 are rather different from Column 1 (Bertrand-Nash behavior) and Column 2 (collusive behavior) of Table 5. For example, the price coefficients for the first type of consumer, the tourist type, are equal to -1.162 in Column 3 of Table 5, whereas the price coefficient for the business travelers is equal to -0.139 in Column 3 of Table 5. These compare to -1.333 and -0.119 (-1.315 and -0.165) when Bertrand-Nash (collusive) pricing behavior is assumed.

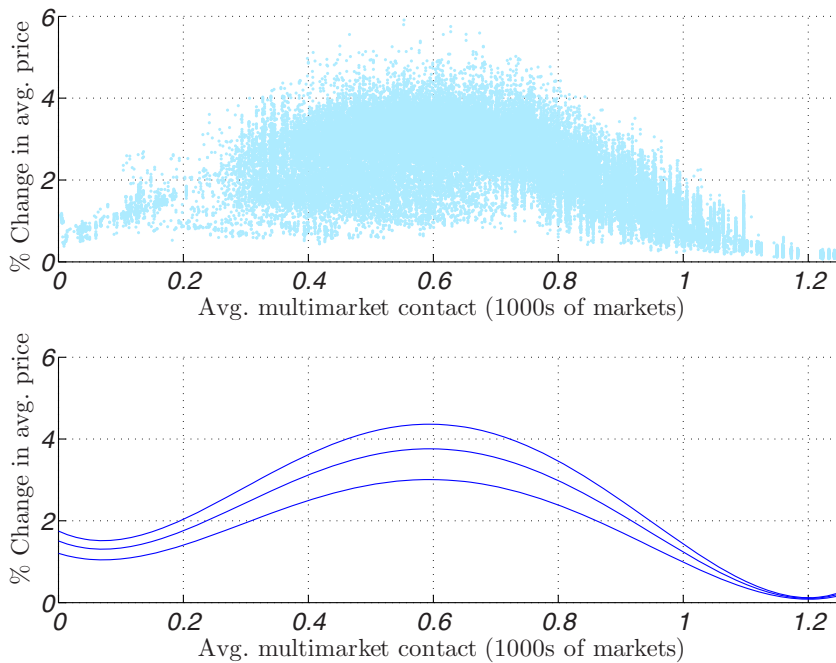
Now consider the fraction of business travelers. This fraction is equal to 34.0 (32.7)% in Column 1 (2) of Table 5, but it is equal to 36.2% in Column 3 of Table 5. So, the estimated parameter κ_{rm} , or the fraction of business travelers, is higher when the conduct parameters are modelled as a function of multimarket contact.

The cost estimates in Column 3 of Table 5 are between those in Columns 1 and 2 of Table 5. The median of marginal cost is now equal to \$74.6, compared to the estimate of \$106.2 in Column 1 and \$61.3 in Column 2 of Table 5. This suggests that strict assumptions regarding firm behavior, firms behaving as Bertrand-Nash competitors or as a fully-collusive cartel, lead to biased estimates of marginal cost. Specifically, the marginal cost estimates are lower than in Column 1 of Table 5 because the presence of the conduct parameters, ϕ_1 and ϕ_2 , allows an alternative to high marginal costs as an explanation for the high fares we observe in some markets, equation (9). If information on actual price-cost margins were available, they could be used to identify the

²⁵ This is at the high end of the range of estimates in Berry and Jia (2010), who define costs for round-trip service whereas we define trips for one-way service. Thus, when comparing the estimates, one should normalize the estimates of Berry and Jia (2010) by dividing by two.

FIGURE 1

MULTIMARKET CONTACT AND PRICES



true model of conduct by comparing them to the implied margins from each column of Table 5. This is precisely the “menu” approach advocated by Nevo (1998, 2001). However, because marginal costs in the airline industry are largely opportunity costs and not directly observable, this approach is difficult to implement.

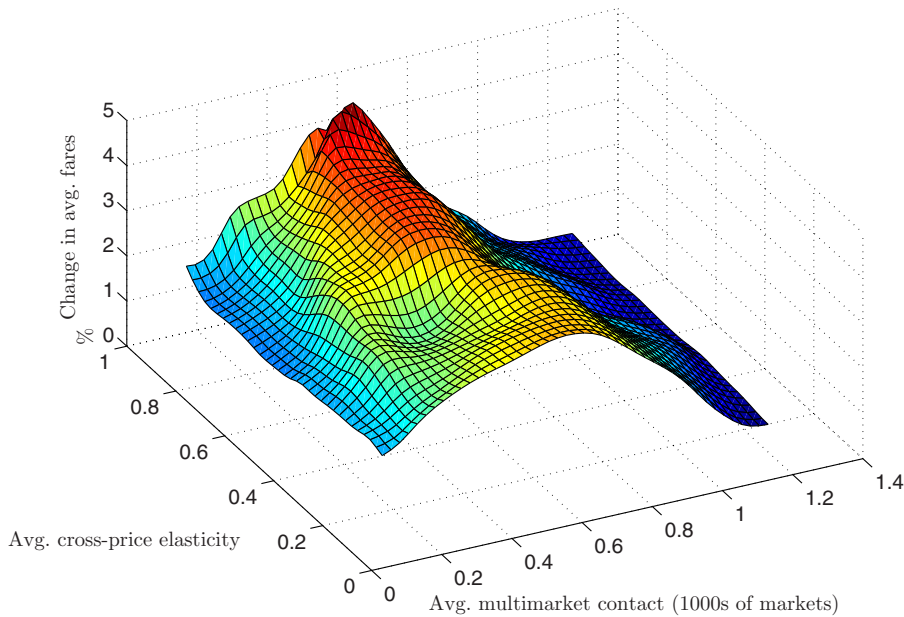
Table 6 provides a one-to-one mapping from multimarket contact matrix in Table 1a to the level of cooperation carriers can sustain in setting fares. In particular, Table 6 presents $f(mmc)$ evaluated at each element of Table 1a. As an example, consider the interaction between American and Delta. Table 1a shows that in the first quarter of 1997, the two firms overlapped in 855 markets. In Table 6, we find that the conduct parameter is equal to 0.856, which is essentially saying that American and Delta collude in markets that they concomitantly serve. Consider, instead, the interaction between American and JetBlue. From Table 1a we know that they overlap in 84 markets. Table 6 shows that the conduct parameter is equal to 0.064, which implies that they do not cooperate in setting fares.

The results suggest that legacy carriers cooperate to a large degree in setting fares. However, there is very little cooperation between most low-cost carriers and legacy carriers. This finding is largely consistent with that of Ciliberto and Tamer (2009), who show that there is heterogeneity in the competitive effects of carriers, and that an additional low-cost competitor has a more significant impact on the level of competition in a market than an additional legacy competitor. There is one notable exception. In recent years, AirTran has rapidly expanded its network out of Delta’s Atlanta-Hartsfield hub. Our results suggest these two carriers can now maintain some level ($f(mmc) = 0.369$) of cooperation in setting fares. Remarkably, Delta and AirTran are currently the target of a civil class-action lawsuit alleging cooperation in introducing and maintaining additional fees on checked bags.²⁶

²⁶ The case is *Avery v. Delta Air Lines Inc., AirTran Holdings Inc.* 09cv1391, US District Court, Northern District of Georgia (Atlanta). Since the time of our data sample, AirTran has been acquired by Southwest Airlines.

FIGURE 2

CROSS-PRICE ELASTICITIES, MULTIMARKET CONTACT, AND FARES



The structural model predicts that different levels of multimarket contact between carriers imply different levels of cooperation in setting fares. However, coordination in setting fares does not necessarily translate to fares significantly different from those that would be realized from a competitive Bertrand-Nash pricing game. To examine the impact of multimarket contact on fares, we perform an exercise like the one used in the reduced-form analysis. In particular, we increase the average multimarket contact in a market by 0.128, increasing each carrier's contact with every other carrier by 0.128, and look at the resulting percentage change in fares. These results are presented in the top half of Figure 1. The bottom half of Figure 1 plots the mean change in fares across all markets for increases in multimarket contact of 0.128, 0.256, and 0.384, respectively.

In both parts of Figure 1, the initial level of average multimarket contact in the market is on the horizontal axis, and the resulting percentage change in the average fare in the market on the vertical axis. The results in the top half of Figure 1 are exactly as one would expect, given that for very high levels of multimarket contact in which firms are already perfectly coordinating on prices, there is very little impact from an increase in multimarket contact. However, for low or moderate levels of contact, there is a significant increase in fares, ranging from 1% to 6%. For these moderate levels of contact, there is also a great deal of dispersion in the change in fares resulting from the increase in multimarket contact. This dispersion can largely be explained by examining equation (9), which shows the important role that cross-price elasticities play in determining the size of the change in fares. The results in the bottom half of Figure 1 are also intuitive; larger increases in multimarket contact result in larger increases in fares, except at very high levels of contact where firms are already perfectly coordinating.

As mentioned above, the impact on fares of a marginal increase in multimarket contact depends on the cross-price elasticity of demand. Figure 2 plots the mean percentage change in fares resulting from the same 0.128 increase in average multimarket contact for different cross-price elasticities. More precisely, we use the average cross-price elasticity across all products in the market. The figure shows that in markets where cross-price elasticities are high, the increase in fares resulting from an increase in multimarket contact is larger. For moderate levels of multimarket contact, the mean percentage change in fares increases from 2% to 5% depending

TABLE 7 BCS Estimation — MMC Measure Robustness

Demand	(1) BCS — pct—CV		(2) BCS — max—pct—CV		(3) BCS — wgt—pct—CV	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Price ₁	−1.162***	(0.006)	−1.198***	(0.006)	−1.302***	(0.006)
Price ₂	−0.139***	(0.002)	−0.128***	(0.002)	−0.123***	(0.002)
κ^0	−0.566***	(0.044)	−0.585***	(0.047)	−0.561***	(0.045)
Constant ₁	−5.954***	(0.017)	−5.590***	(0.016)	−5.802***	(0.016)
Constant ₂	−7.514***	(0.028)	−7.276***	(0.028)	−6.867***	(0.030)
Nonstop ₁	1.140***	(0.006)	1.170***	(0.006)	1.272***	(0.005)
Nonstop ₂	1.030***	(0.006)	1.095***	(0.005)	1.149***	(0.005)
λ	0.601***	(0.002)	0.648***	(0.002)	0.607***	(0.002)
Network Size	0.525***	(0.015)	0.482***	(0.016)	0.509***	(0.002)
Distance	1.997***	(0.026)	2.159***	(0.026)	1.993***	(0.002)
Distance ²	−0.497***	(0.010)	−0.529***	(0.009)	−0.530***	(0.002)
Extramiles	−1.039***	(0.023)	−1.066***	(0.025)	−1.171***	(0.002)
Extramiles ²	0.163***	(0.008)	0.158***	(0.007)	0.143***	(0.002)
Cost						
Constant	0.541***	(0.006)	0.512***	(0.006)	0.504***	(0.005)
NumMkt	−0.531***	(0.072)	−0.572***	(0.078)	−0.565***	(0.085)
NumMkt ²	1.795***	(0.244)	1.714***	(0.246)	1.845***	(0.240)
Distance	0.249***	(0.007)	0.244***	(0.007)	0.247***	(0.007)
Distance ²	−0.039***	(0.003)	−0.038***	(0.003)	−0.040***	(0.003)
Extramiles	0.077***	(0.007)	0.081***	(0.007)	0.074***	(0.006)
Extramiles ²	−0.017***	(0.002)	−0.018***	(0.002)	−0.017***	(0.002)
Contact						
Constant	−3.167***	(0.058)	−2.973***	(0.055)	−2.888***	(0.060)
MMC	5.785***	(0.085)	5.780***	(0.077)	5.208***	(0.075)
Model Fit						
Median marginal cost	0.734		0.722		0.74	
Median elasticity	−3.488		−3.457		−3.46	
Median elast. — type1	−5.001		−5.115		−5.53	
Median elast. — type2	−0.670		−0.636		−0.62	
Function value	33870.916		33815.677		33762.62	

Note: ***<0.01, **<0.05, *<0.10.

Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted.

on the cross-price elasticities in the market. For very high levels of initial multimarket contact, regardless of the cross-price elasticity, there is almost no change in fares because firms are already fully colluding.

□ **Robustness analysis.** To examine the robustness of our estimates and insights from Column 3 of Table 5, we perform two types of robustness analysis. First, we vary the measure of multimarket contact. These results, using the same functional form for the conduct parameters as Column 3 of Table 5, are presented in Table 7. Second, we explore more flexible alternatives for the functional form of both the conduct parameters ($f(mmc)$) and the fraction of business travelers in a market (κ_{mr}). These results are presented in Table 8.

Column 1 of Table 7 presents the results when $pct_mmc_{kh}^t$ is used as the measure of multimarket contact. This allows for asymmetry in the degree to which the carriers cooperate in setting fares, and has the advantage of not being systematically larger for pairs of legacy or national carriers, relative to a legacy and low-cost pair, which relaxes concerns that our estimates in Column 3 of Table 5 simply captured something else specific to legacy carriers

TABLE 8 BCS Estimation—Functional Form Robustness

Demand	(1) BCS— cubic—CP (mmc_{kh}^t)		(2) BCS— dummy—CP (mmc_{kh}^t)		(3) BCS— exp—CP—BusIndex (mmc_{kh}^t)	
	Estimate	Standard Error		Standard Error	Estimate	Standard Error
Price ₁	−1.526***	(0.006)	−1.318***	(0.006)	−1.394***	(0.005)
Price ₂	−0.221***	(0.002)	−0.171***	(0.002)	−0.180***	(0.002)
κ^0	−0.576***	(0.048)	−0.666***	(0.046)	−0.939***	(0.140)
κ^1					0.542***	(0.007)
Constant ₁	−5.817***	(0.016)	−6.086***	(0.016)	−5.794***	(0.049)
Constant ₂	−7.501***	(0.026)	−7.587***	(0.025)	−7.423***	(0.094)
Nonstop ₁	1.124***	(0.006)	1.140***	(0.006)	1.130***	(0.006)
Nonstop ₂	1.030***	(0.006)	1.019***	(0.006)	1.049***	(0.006)
λ	0.665***	(0.002)	0.663***	(0.002)	0.627***	(0.002)
Network size	1.023***	(0.014)	0.953***	(0.014)	0.704***	(0.015)
Distance	2.346***	(0.028)	2.297***	(0.028)	2.045***	(0.026)
Distance ²	−0.546***	(0.010)	−0.538***	(0.009)	−0.504***	(0.010)
Extramiles	−1.353***	(0.024)	−1.329***	(0.021)	−0.999***	(0.023)
Extramiles ²	0.204***	(0.008)	0.200***	(0.007)	0.153***	(0.008)
Cost						
Constant	0.590***	(0.005)	0.503***	(0.006)	0.570***	(0.005)
NumMkt	0.159***	(0.066)	−0.003***	(0.069)	0.036***	(0.061)
NumMkt ²	−0.068***	(0.222)	0.572***	(0.243)	0.232***	(0.206)
Distance	0.164***	(0.006)	0.257***	(0.007)	0.282***	(0.006)
Distance ²	−0.034***	(0.003)	−0.051***	(0.003)	−0.059***	(0.002)
Extramiles	0.118***	(0.007)	0.023***	(0.007)	−0.001	(0.006)
Extramiles ²	−0.015***	(0.002)	−0.007***	(0.002)	0.004***	(0.002)
Contact						
1[0 ≤ MMC < 0.25]			0.127***	(0.059)		
1[0.25 ≤ MMC < 0.50]			0.248***	(0.084)		
1[0.50 ≤ MMC < 0.75]			0.796***	(0.06)		
1[0.75 ≤ MMC]			0.962***	(0.086)		
Constant	−2.894***	(0.052)			−2.44***	(0.047)
MMC	6.205***	(0.092)			6.584***	(0.090)
MMC ²	−0.16	(0.247)				
MMC ³	−0.4***	(0.084)				
Model Fit						
Median marginal cost	0.838		0.701		0.780	
Median elasticity	−4.611		−4.119		−4.574	
Median elast. — type1	−6.471		−5.990		−6.578	
Median elast. — type2	−0.937		−0.885		−0.849	
Function value	33861.400		33770.812		33508.811	

Note: ***<0.01, **<0.05, *<0.10.

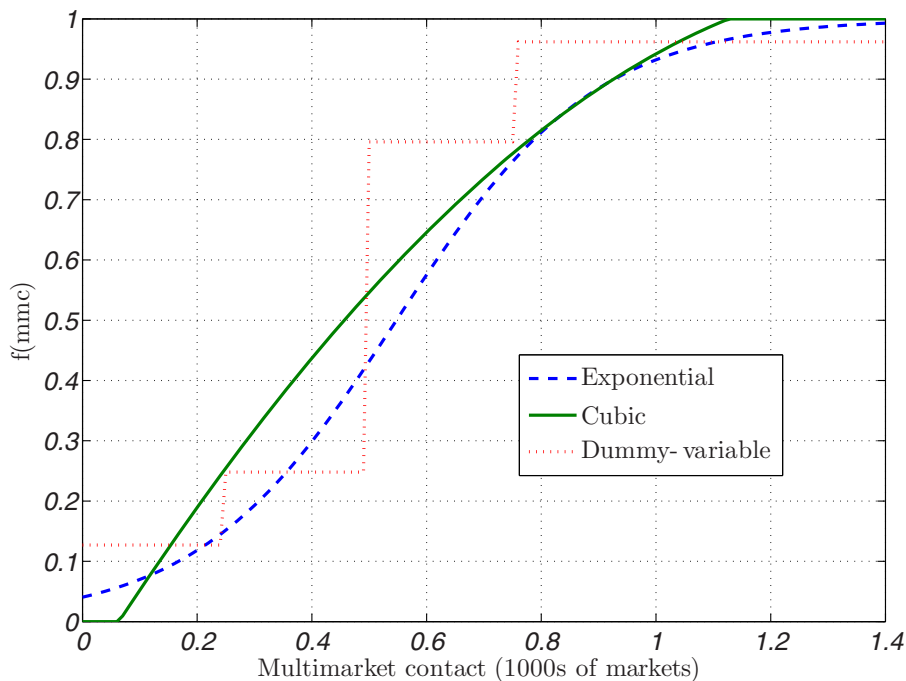
Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted.

(e.g., high costs).²⁷ Columns 2 and 3 of Table 7 present the results when $max_pct_mmc_{kh}^t$ and $weighted_pct_mmc_{kh}^t$ are used, respectively. The max specification has the same advantages as the percentage specification reported in Column 1, but imposes symmetry, whereas the weighted specification allows coordination to be asymmetric and depend upon the importance of the markets, in terms of revenue, concomitantly served by the carriers.

²⁷ Our results are very similar if the smallest carriers (G4, NK, SY, TZ, U5, AS) are eliminated from the analysis, casting further doubt on alternative explanations for our findings.

FIGURE 3

COLLUSION AND MULTIMARKET CONTACT



For each alternative measure of multimarket contact, the taste parameters we estimate are similar to those in Column 3 of Table 5. Most importantly, the estimates of the conduct parameters are very similar. There is a strong positive relationship between multimarket contact and the degree of coordination in setting fares. This results in implied marginal cost estimates within a few dollars of those in Column 3 of Table 5.

Columns 1 and 2 of Table 8 present the results using two alternative functional forms for the conduct parameters, each using the number of markets concomitantly served by a pair of carriers as the measure of multimarket contact. Column 1 presents the results from the cubic specification, equation (11), whereas Column 2 presents the results from the dummy-variable specification, equation (12). Neither of these specifications imposes monotonicity on the relationship between multimarket contact and coordination in setting fares. Even with this flexibility, both specifications give estimates similar to those in Column 3 of Table 5. The only difference of note is that the estimates from the cubic specification yield slightly higher estimates of elasticities and marginal cost. For each specification, we find a strong positive and monotonic relationship, which is quantitatively similar, between multimarket contact and coordination in setting fares. Figure 3 plots the estimates from the three different specifications of the conduct parameters; Column 3 of Table 5 and Columns 1 and 2 of Table 8.

Column 3 of Table 8 presents the results when the assumption that the proportion of business travelers is constant across markets, $\kappa_{mr} = \kappa_r$, is relaxed, and the exponential specification for the conduct parameters is used (equation (10)). When we allow the proportion of business travelers to depend on $BusIndex_m$ (κ_1 not restricted to be zero in equation (6)), we find very similar results. The estimates of the taste parameters imply similar elasticities, and there is a positive and statistically significant relationship between $BusIndex_m$ and the fraction of business travelers in a market. Most importantly, our estimates of the conduct parameters are largely unchanged from Column 3 of Table 5.

6. Conclusion

■ In this article, we build on Nevo (1998) to develop a new test to identify collusive behavior in the US airline industry. In particular, we nest conduct parameters into a standard oligopoly model where firms compete on prices and offer differentiated products. We identify the conduct parameters using variation in multimarket contact across local airline markets. We find that carriers with little multimarket contact (e.g., Alaska and Delta) do not cooperate in setting fares, whereas carriers with a significant amount of multimarket contact (e.g., US Air and Delta) can sustain near-perfect cooperation in setting fares. We also find that cross-price elasticities play a crucial role in determining the impact of multimarket contact on collusive behavior and equilibrium fares.

Our methodology can be applied to any other industry where data from a cross-section of markets are available and where firms encounter each other in many of these markets. More generally, our methodology can be applied to any industry where there is some exogenous shifter of the conduct parameters, such as regulatory changes (Parker and Roller, 1997; Waldfogel and Wulf, 2006) or lawsuits (Miller, 2010). The key step is to express the conduct parameters as functions of these exogenous shifters and nest these functions within a standard empirical oligopoly model.

One interesting extension of this article would be a merger analysis that accounts for the impact of multimarket contact. Our results suggest that mergers between large airlines do not necessarily lead to higher prices. To see why, notice that an increase in multimarket contact between legacy carriers results in almost no change in fares, whereas the same change in multimarket contact between low-cost carriers and legacy carriers will result in large increases in fares. Thus, recently completed mergers (Delta and Northwest and Continental and United) between legacy carriers should have little consequence for market power whereas potentially introducing significant cost efficiencies.²⁸

Our analysis is restrictive in a number of aspects, which constitute themes for future research. First, we have assumed that the functional form that relates conduct parameters to multimarket contact is the same for all carrier pairs. On one hand, this simplifies the analysis considerably and still allows for heterogeneity in the conduct parameters. On the other hand, there might be fundamental differences across different pairs. Second, our model is static, and one might be interested in gaining insight into how firms sustain tacit collusion.²⁹ This would require that we model the strategic interaction between firms as a dynamic game, which is clearly beyond the scope of this article.

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²⁸ See Brueckner and Spiller (1994) for a discussion of economies of density.

²⁹ For a discussion of the importance of accounting for dynamics when estimating demand, see Hendel and Nevo (2006).

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