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Does Multimarket Contact Facilitate Tacit Collusion? Inference on Conduct Parameters in the Airline Industry.*

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Abstract

We provide empirical evidence to support the hypothesis that multimarket contact facilitates tacit collusion in the US airline industry using two complementary approaches. First, we show that the more extensive is the overlap in the markets that the two firms serve, i) the more firms internalize the effect of their pricing decisions on the profit of their competitors by reducing the discrepancy in their prices, and ii) the greater the rigidity of prices over time.

Next, we develop a flexible model of oligopolistic behavior, where conduct parameters are modeled as functions of multimarket contact. We find i) carriers with little multimarket contact do not cooperate in setting fares, while we cannot reject the hypothesis that 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 collusive behavior and equilibrium fares; iii) marginal changes in multimarket contact matter only at low or moderate levels of contact; iv) assuming that firms behave as Bertrand-Nash competitors leads to biased estimates of marginal costs.

Keywords: Multi-Market Contact, Collusion, Differentiated Products, Airport Facilities, Airline Industry, Screening Test, Price Rigidity.

JEL Codes: L13.

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1 Introduction

Detecting tacit collusion is a central theme of research in empirical industrial organization (Jacquemin and Slade [1989], Porter [2005], Harrington [2008]). In most instances, tacit collusion leads oligopolistic firms to monopolize a market, leading to reduced and inefficient equilibrium output, higher prices, and lower consumer welfare.[1] Not surprisingly, then, detecting collusion is a fundamental objective of antitrust agencies in both Europe and the United States. In the US, collusion is prohibited under the Sherman Act.[2]

Identifying collusive behavior poses difficult econometric challenges. If we see all firms charging the same price, is it because they are colluding and charging the monopoly price, or are they competing aggressively against each other while facing similar costs? If one firm raises its prices and its competitors respond by raising their prices as well, can we conclude that firms in this market are colluding? Or should we be worried about conscious parallelism, whereby it may be rational to follow the anticompetitive lead of one's rival if the firm believes that the rival has better information about market conditions (Porter and Zona [2008])?[3] To our knowledge the antitrust agencies have only succeded in proving collusion with the help of law enforcement agencies. For example, in the case of lysine price-fixing conspiracy (White [2001]), the intervention of the FBI was required to prove (explicit) collusive behavior. The objective of our paper is to introduce a *diagnostic* test of collusive behavior when a potential facilitator of collusion (e.g. multimarket contact) can be identified. Analogously to previous tests of collusion, hard evidence is still crucial to definitely prove collusive behavior.

[1] A notable exception, Fershtman and Pakes [2000] show that collusive pricing can lead to increased entry and welfare-improving product variety.

[2] Under Section 1 of the Sherman Act, any cartel or cartel-like behavior is "per se" illegal. Other practices, where, for example, firms might appear to be tacitly colluding, are examined under a rule of reason analysis. Probably the most famous instance when the antitrust agencies were able to detect collusion is the lysine price-fixing conspiracy. As reported by White [2001], in October 1996 the Archer Daniels Midland Company (ADM) pleaded guilty to criminal price fixing with respect to sales of lysine and agreed to pay a $70 million fine.

[3] More generally, the identification problem that we face when trying to detect collusion is conceptually the same as the one that Manski [1993] called the "reflection" problem. Firms might be charging the same prices because of exogenous (contextual) effects; for example, they offer similar products, or because of correlated effects, for example, they face similar (unobservable to the econometrician) marginal costs, or because they do actually collude (endogenous effects).

Previous work has identified collusive behavior by using variation in costs (Rosse [1970], Panzar and Rosse [1987], Baker and Bresnahan [1988]),[4] rotations of demand (Bresnahan [1982], Lau [1982]), taxes (Ashenfelter and Sullivan [1987]), conduct regimes (Porter [1983]), and product entry and exit (Bresnahan [1987], Nevo [2001]).[5] Here, we propose a different identification strategy.

We identify collusive behavior by using variation in multimarket contact across airline markets. Multimarket contact is defined as the number of markets in which firms encounter each other.[6] 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.[7]

We quantify multimarket contact using the measure first introduced by Evans and Kessides [1994] (EK, from here on). Multimarket contact between any pair of airline carriers is equal to the total number of markets that two airlines serve concomitantly. For example, if American and Delta serve 200 markets in common, then this variable is equal to 200 for the American-Delta pair.

We begin our empirical analysis with a reduced form analysis that replicates and extends EK. 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.[8] Bernheim and Whinston [1990] think of multimarket contact as an "external factor"; however, unobservable heterogeneity likely determines both prices,

[4] 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.

[5] 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.

[6] The definition of multi-market contact is attributed to Corwin Edwards; see Bernheim and Whinston [1990].

[7] If, for example, two firms interact in many markets, then they know that if they deviate from collusive behavior in one market, they will be punished by the other firms in all the markets where they interact.

[8] This is a well-recognized problem in the empirical literature on multimarket contact. Waldfogel and Wulf [2006] use the enactment of the Telecommunication Act of 1996 to identify the effect of multimarket contact.

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 dataset on the number of gates controlled by each airline at airports in the US (Ciliberto and Williams [2010] and 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. EK's main conclusion was that the positive relationship between multi-market contact and prices was consistent with the hypothesis that airlines with a high degree of multi-market contact refrain from initiating aggressive pricing actions in any given market to avoid intense price competition in all the other routes they serve concomitantly. We also find that multimarket contact is associated with higher equilibrium fares using both a fixed-effects and instrumental-variables approach. We also find that the relationship between multimarket contact and prices is stronger when we use the instrumental variable approach, confirming that average multimarket contact is endogenous.

Next, in the spirit of Harrington [2008], we provide two *screening tests* of the null hypothesis that *pair-specific* multimarket contact facilitates implicit collusive behavior among airlines. These tests are based on the theoretical work of Werden and Froeb [1994] and Athey, Bagwell, and Sanchirico [2004]. The test based on Werden and Froeb [2004] examines *differences* in the prices charged by firms in a market with differentiated products, and exploits the notion that colluding firms internalize the effect of their pricing decisions on the profit of their competitors. The test based on Athey, Bagwell, and Sanchirico [2004] examines the variation in the prices that two firms charge over time in a market. It exploits the notion that *rigid prices* can arise to facilitate the enforcement of a collusive agreement. Neither of the two tests leads to the rejection of the hypothesis that an increase in multimarket contact is associated with a collusive behavior.

Finally, in the structural analysis we estimate a flexible model of oligopolistic behavior, where conduct parameters are modeled as functions of *pair-specific* multimarket contact. Our modeling strategy implements an idea first proposed by Nevo [1998], who offers a constructive synthesis of the two main methodological ways to identify collusion.[9] The first line of research (for example, Panzar and Rosse [1987], Bresnahan [1982], Ashenfelter and Sullivan [1987], and Porter [1983]) identifies collusive behavior by estimating conduct parameters, which reveals whether firms compete on prices or on quantities, or whether they collude.[10] 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 modeling framework proposed by the second line of research. The main identification concern in the structural analysis is the usual one, with prices and quantities determined simultaneously. We use the same exogenous variation in the number of gates that airlines control at airports to instrument for prices and market shares.

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 40 percent 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

[9] 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].

[10] See Bresnahan [1987] for a superb review of the early empirical work in industrial organization.

are close substitutes, then cooperation in setting fares will result in a larger change from the competitive outcome than in cases where two goods are not such close substitutes.

Our paper is related to previous research that studies the impact of multimarket contact on the strategic decisions of firms (Feinberg [1985], Jans and Rosenbaum [1997], Singal [1996], Parker and Roller [1997], Fernandez and Marin [1998], Busse [2000], Waldfogel and Wulf [2006], Bilotkach [2010], and Miller [2010]). However, our work differs from these earlier works in four dimensions. First, we treat average multimarket contact as endogenous and use an instrumental-variable approach to control for its endogeneity. Previous solutions to the endogeneity of average multimarket contact included fixed-effects approaches (e.g. EK) and exploiting regulatory changes to identify a causal relationship (Waldfogel and Wulf [2006] and Parker and Roller [1997]). Second, we take a step forward in the reduced form analysis and carry out two simple and intuitive screening tests to investigate the relationship between pair-specific multimarket contact and collusive behavior. While a test analogous to the one based on the rigidity of prices has been used before (e.g. Abrantes-Metz, Froeb, Geweke, Taylor [2006]), the test that uses the relationship between collusive behavior and discrepancy in prices is, to our knowledge, a novel contribution. Third, we propose a structural model nested in the mainstream empirical industrial organization literature that directly links pair-specific multimarket contact to the degree of coordination in firms' decisions. The extant literature has only been able to 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.

The paper 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 4.4. Section 5 concludes and discusses possible extensions of our research.

2 Data

We use data from four main sources.[11] 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. 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 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.

2.1 Market Definition

Like EK, 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. Our final sample contains 268,119 observations at the product-carrier-market level.

In what follows, markets are indexed by $m = 1, ..., M$. There are $6,366$ markets. Year-quarter combinations are denoted by $t = 1, ...T$. We use data from 2006 to 2008, so $T = 12$. The subindex $j = 1, ..., J_{mt}$ 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 dataset is 17 and includes American (AA), Alaska (AS), JetBlue (B6), Continental (CO), Delta (DL), Frontier (F9), ATA (TZ),

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

Allegiant (G4), Spirit (NK), Northwest (NW), Sun Country (SY), AirTran (FL), USA3000 (U5), United (UA), USAir (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).

2.2 Multimarket Contact

We construct a measure of pair-specific multimarket contact from the DB1B data. Let mmc^t_{kh} denote the number of markets that two distinct carriers, k and h, concomitantly serve in time period t. For example, in the first quarter of 2007, American and Delta concomitantly served 855 markets so both mmc^t_{AADL} and mmc^t_{DLAA} equal 855. For each quarter we construct a matrix of these pair-specific variables. **Table 1** 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,[12]

$$AvgContact_{mt} = \frac{1}{\left(\frac{F_{mt}(F_{mt}-1)}{2}\right)} \sum_{k=1}^{F} \sum_{h=k+1}^{F} 1\left[k \text{ and } h \text{ active}\right]_{mt} * mmc^t_{kh}. \tag{1}$$

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^t_{kh} across the firms *actively* serving market m at time t. This variable is summarized in **Table 2**.

[12] Notice that this measure is not firm specific. In work not shown here we have run our reduced-form regressions considering the following average:

$$AvgContact_{jmt} = \frac{1}{(F_{mt}-1)} \sum_{k \neq h}^{F} 1\left[k \text{ and } h \text{ active}\right]_{mt} * mmc^t_{kh}.$$

The results are nearly identical.

2.3 Fares

We use the DB1B data to calculate average fares at the product-carrier-market level, where a product is either nonstop or connecting service. Like EK and consistent with the unidirectional nature of our market definition above, we treat roundtrip tickets as two one-way tickets and divide the fare by two. We also drop exceedingly high and 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-carrier-market specific average fare, $Fare_{jmt}$.[13] The unweighted average of $Fare_{jmt}$, across all carriers and markets from 2006 to 2008, is around $223.

2.4 Limited Access to Airport Facilities

The market-specific measure of multimarket contact, $AvgContact_{mt}$, is 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 at a point in time comes from differences in the set of firms operating in the market since, at a point in time, the contact for any two carriers (mmc^t_{kh}) is fixed. Variation in $AvgContact_{mt}$ over time within a market comes from changes over time in the set of firms operating in a market as well as potentially changes over time in the degree of overlap between a given pair of firms (mmc^t_{kh}). Since 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

[13] All results and conclusions are robust to using the median fare instead of the average.

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 instrument-variables solution.

To address the endogeneity of $AvgContact_{mt}$, as well as that of prices and quantities, we use data on carriers-specific access to boarding gates at each airport to construct instrumental variables. 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 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.

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 endpoints. This variable (e.g. AA_avg_m for American) is summarized for each carrier in **Table 2**. From these variables, we generate 4 additional instruments that vary by carrier within a market. More precisely, 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 endpoints by each type of a carrier's competitors.[14]

The validity of the instruments depends on the gate leases not being correlated with - or anticipating - market and firm unobservables. Since there may be some persistence in these unobservables, if the leases were signed in 2005 or 2006 they could be correlated with factors

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

that affect prices in the years of the sample. However, the Government Accounting Office, GAO [1990], reports that 22 percent of the gates at the 66 largest airports were for $3-10$ years' duration; 25 percent were for $11-20$ years' duration; and 41 percent 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. Thus, it seems unlikely that a transient demand or cost shock that may alter pricing decisions would substantially alter carriers' sunk investments in gates. In addition, Ciliberto and Williams [2010] note that airlines cannot terminate leases unilaterally. 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.[15]

The validity of the instruments also depends on whether the existence of a secondary market for access to gates would allow entry decisions to be more responsive to (time-varying) market level unobservables. This is extremely unlikely since numerous airlines (Southwest, America West, etc.) have reported costs of subleasing gates that are 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 since carriers' incentives to sublease gates to competitors are diminished further.

2.5 Control Variables

Carriers can offer both nonstop and connecting service.[16] Thus, for each product offered by a carrier in a market, we generate a dummy variable, $Nonstop_{jmt}$, that is equal to 1 if the service offered by a carrier is nonstop. **Table 2** shows that approximately 17% of the observations in our dataset 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

[15] 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.

[16] 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.

airport; see Brueckner, Dyer, and Spiller [1992]. In particular, 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 [2006] (BCS, from here on) and Berry and Jia [2010], we follow the industry standard and define the size of a market, $MktSize_{mt}$, as the geometric mean of the population at the market endpoints. Another important determinant of consumers' travel decisions is the nonstop distance between the endpoints of a market, $Distance_m$. One may expect in shorter markets, travel as a whole is more attractive since less time is spent reaching one's destination. Yet, the availability and attractiveness of substitutes to air-travel vary significantly depending on the distance between the market endpoints. Since the relationship between $Distance_m$ and the demand for air-travel may have some nonlinearities due to these countervailing effects, 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}, which is equal to one if one of the two endpoints of market m is a hub airport of carrier j.[17] The variable Hub_{jm} captures whether flying on the hub airline is more attractive than flying on any other airlines, Borenstein [1989]. It

[17] 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).

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 that is 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 limitations of the variable $BusIndex_m$ are that it 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 rather than to derive them.

3 Reduced-Form Analysis

3.1 Replicating Evans and Kessides [1994]

In our reduced-form analysis, we first replicate the work of EK using our sample of data. EK test the hypothesis that multimarket contact facilitates collusion by running the following regression:

$$\ln(p_{jmt}) = AvgContact_{mt} \cdot \beta_{EK} + Controls_{jmt}\beta_{Controls} + \varepsilon_{jmt} \tag{2}$$

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 2.5, 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. We include data for only the 1,000 largest routes, with the ranking constructed after aggregating the number of passengers in each market over all periods. To make the results of our paper directly comparable to those in EK, the variables mmc_{kh}^t and $AvgContact_{mt}$ are constructed with the data from these 1,000 markets. The mean of $AvgContact_{mt}$ is equal to 0.21 in this small sample. This number is very similar to 0.18, the mean value of the $AvgContact_{mt}$ in EK. Following EK, 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 Herfindhal-Hirschman Index of passengers, HHI_{mt}, a measure of market concentration.

We find that the coefficient of multimarket contact is equal to 0.246. This number should be compared to 0.398, the number reported in **Column 3** of Table III in EK. 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 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 3 percent in fares, compared to 5 percent in EK. The results for the control variables, when precisely estimated, are also comparable with those in EK.

Column 2 of **Table 3** presents another regression in the spirit of EK. We again include data for only the 1,000 largest routes. 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 nearly identical. The coefficient of $AvgContact_{mt}$ is equal to 0.291, which implies that a 0.128 change in $AvgContact_{mt}$ would result in an increase in prices of 4 percent.

Column 3 of **Table 3** considers the full sample of markets. The variables mmc_{kl}^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 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 online appendix discusses this in more detail.

In **Column 4** we run the same regressions using only non-monopoly markets. The coefficient of $AvgContact_{mt}$ is now positive and statistically significant. Its effect is smaller than the one we estimated in **Column 3**. Here, the change of 0.128 in $AvgContact_{mt}$ implies an increase in prices of less than 1 percent against the change of 4 percent 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 discussed in Section (2.4). 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 percent. This effect is similar to those from the estimates in **Columns 1** and **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 percent. At the bottom of **Table 3**, in **Columns 5** and **6**, we present the results of an F 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 online Appendix discusses the results of the first stage in more detail.

In **Column 7** we add the variable $BusIndex_{mt}$ to control for the possibility that the positive correlation of prices across airlines with high multimarket contact might be a function of the differential type of demand that carriers face. In particular legacy carriers (with high contact among one another) might concentrate in markets with a larger fraction of business passengers, driving up $AvgContact_{mt}$, in those markets where one would naturally expect higher fares. We find our results to be largely unchanged with the inclusion of $BusIndex_{mt}$.

3.2 Screening for Collusion

Overall, our results in the previous section are largely consistent with those of EK: an increase in multimarket contact is associated with higher fares. However, we cannot conclude that multimarket contact actually facilitates collusive behavior that significantly raises fares, as there are other plausible explanations, such as unobserved correlation in costs or demand shocks among firms with high multimarket contact.

Next, as a first step to assess collusive behavior in the US airline industry, we conduct two *screening tests* for collusive behavior among airlines that serve many markets concomitantly. These tests are motivated by the theoretical insights of Werden and Froeb [1994] and Athey, Bagwell, and Sanchirico [2004].

3.2.1 Cross-Price Elasticities

Werden and Froeb [2004] make the following key observation: two firms that start colluding (in their analysis, they would merge) increase the price of the product with the smaller share by a greater absolute amount than they increase the price for the product with the larger share. A price increase causes the firm to lose sales. However, as Werden and Froeb [2004] point out using a logit model of demand, the firm would rather lose sales from the product with a smaller share than from the product with the larger share, since consumers no longer purchasing the smaller-share product will disproportionately substitute towards the larger-share product. This crucial insight exploits the dependence of colluding carriers' pricing strategies on the cross-price elasticities among their products, which is the same insight that we will use to interpret the results from the structural analysis.

Under the null hypothesis that an increase in multimarket contact leads to more collusive behavior, one can then infer that an increase in multimarket contact will lead to a smaller absolute difference in the prices of two colluding firms. We can then develop a very simple screening test of collusion, which is based on the following regression:

$$\log\left(|p_{htm} - p_{ktm}|\right) = \beta_{diff} \cdot \log\left(mmc_{hk}^{t}\right) + \epsilon_{hktm},$$

where $|p_{htm} - p_{ktm}|$ is the absolute value of the difference in prices of two products, h and k, in market m at time t. We can then test the hypothesis that multimarket contact leads to more collusive behavior, by simply testing whether $\beta_{diff} < 0$ holds. Notice that the *unit of observation is a pair of carriers* in a market. Thus, using our original dataset, we construct a dataset where each firm is paired with each of its competitors. For each pair we use the multimarket contact variable that we constructed, mmc_{hk}^{t}. It is important to note that our measure of multimarket contact in these regressions, mmc_{hk}^{t}, is the contact between the pair of carriers across *all markets*. Thus, in contrast to when $AvgContact_{mt}$ is used, we do not face the problem of an endogenous market structure that requires an instrumental variable approach. Our results are presented in **Columns 1** through **3** of **Table 4**.

Column 1 shows the results when we regress the logarithm of the difference in prices on the logarithm of multimarket and we include both carrier fixed effects and year-quarter fixed effects. The carrier fixed effects capture the heterogeneity in the prices that carriers charge, while the year-quarter fixed effects capture any seasonal changes in the difference in prices. We estimate β_{diff} equal to -0.109 and statistically significant. This estimates implies that a 10 percent increase in multimarket contact is associated with a 1.2 percent decrease in the difference in prices.

The results with the inclusion of the $BusIndex_m$ variable, to control for heterogeneity in the fraction of business travelers across markets, are presented in **Column 2**. This is to address the concern that a negative correlation between the discrepancy in fares and multimarket contact is just a function of the differential type of demand that carriers face. We estimate β_{diff} equal to -0.107, which is essentially the same number as in **Column 1**. Finally, in **Column 3** we include market fixed effects to control for market-specific unobservables that may both drive price dispersion in the market and are correlated with multimarket contact. We estimate β_{diff} to be statistically significant and equal to -0.094, which is again essentially the same result as in **Column 1**.

Collectively, the results in **Columns 1** through **3** of **Table 4** show a negative relationship between pair-specific multimarket contact and the discrepancy in the prices of the firms, supporting the hypothesis that the positive correlation between fares and multimarket contact is a result of collusion.

3.2.2 Price Rigidity

Athey, Bagwell, and Sanchirico [2004] show that for a wide range of settings, the optimal collusive pricing behavior is characterized by a rigid price. The basic intuition, first put forward by Carlton [1989], is that collusive firms do not adjust their prices after shocks in costs or demand because they do not want to disturb existing oligopolistic discipline. In the words of Athey, Bagwell, and Sanchirico [2004], such price rigidity is the extreme solution to the trade-off between the efficiency benefits of reallocating shares after privately observed cost shocks, and the informational costs that colluding firms face to determine whether any of the competitors has cut prices.

Using this insight we develop our second screening test for collusion using the following regression:

$$\log\left(\frac{\sigma_{hkm}}{\mu_{hkm}}\right) = \beta_{std} \cdot \log\left(mmc_{hk}^{t}\right) + \epsilon_{hktm},$$

where σ_{hkm} and μ_{hkm} are constructed from the average of the fares of carriers h an k, in market m. Specifically, we calculate the weighted average of the fares for a pair of carriers, h and k, in each period, t, in market m. The weights used in each period to calculate the average are the number of passengers for carriers, h and k, respectively. σ_{hkm} is the standard deviation of this pair-specific average fare in market m over time, while μ_{hkm} is the mean over time. The dependent variable, $\frac{\sigma_{hkm}}{\mu_{hkm}}$, is then the coefficient of variation for the pair-specific average over time, in market m.[18] If multimarket contact is associated with

[18] We follow Abrantes-Metz, Froeb, Geweke, and Taylor [2006] in using the coefficient of variation since

collusive regimes that balance efficiency and monitoring costs by charging rigid prices, then we would expect $\beta_{std} < 0$.

Our results are presented in **Columns 4** and **5** of **Table 4**. **Column 4** includes carrier fixed effects to control for the heterogeneity in the dispersion in the prices that airlines charge. For example, legacy carriers are likely to price discriminate more than low-cost carriers do. **Column 5** also includes the variable $BusIndex_m$ to control for the fact that price dispersion, maybe related to price discrimination, might be different in markets with a large fraction of business travelers. The results in **Columns 4** and **5** are nearly identical: a 10 percent increase in multimarket contact decreases the coefficient of variation by 1 percent, and the estimates are also statistically significant. Thus, we cannot reject the null hypothesis that an increase pair-specific multimarket contact leads to more rigid prices, which is consistent with collusive behavior on the part of the airlines.

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.[19] With the additional structure and careful controls for determinants of demand and costs, we can unpack the reduced-form 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 play in both identifying collusion and determining the impact of collusion on fares.

4.1 Demand

Our basic demand model is most similar to BCS and Berry and Jia [2010]. We allow for 2 consumer types, $r = \{1, 2\}$. For product j in market t in market m, the utility of consumer

markets with higher average fares may also have a higher standard deviation. Our results are very similar if we instead use the standard deviation.

[19] This stage of our analysis corresponds to what Harrington [2008] refers to as the *verification* process.

i of type r, is given by

$$u^r_{ijtm} = x_{jtm}\beta_r + p_{jtm}\alpha_r + \xi_{jtm} + \upsilon(\lambda)_{itm} + \varepsilon_{ijtm}$$

where x_{mjt} is a vector of product characteristics, p_{jtm} is the price, (β_r, α_r) are the taste parameters for a consumer of type r, and ξ_{mjt} are product characteristics unobserved to the econometrician. The term, $\upsilon(\lambda)_{itm} + \varepsilon_{ijtm}$, 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).[20] The mean utility of the outside good is normalized to zero since 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

$$\frac{D^\lambda_{mrt}}{1 + D^\lambda_{mrt}} \tag{3}$$

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

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

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

$$s_{jmt}(\mathbf{x}_{mt}, \mathbf{p}_{mt}, \boldsymbol{\xi}_{mt}, \boldsymbol{\beta}_r, \boldsymbol{\alpha}_r, \lambda) = \sum_{r=1}^{2} \kappa_{rm} \frac{e^{(x_{jmt}\beta_r + p_{jmt}\alpha_r + \xi_{jmt})/\lambda}}{D_{rmt}} \frac{D^\lambda_{rmt}}{1 + D^\lambda_{rmt}} \tag{5}$$

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

We propose two alternative approaches to deal with the fact that κ_{mr} is not observed, and both are based on the following specification:

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

$$\kappa_{mr} = \frac{\exp\left(\kappa_0 + \kappa_1 BusIndex_m\right)}{1 + \exp\left(\kappa_0 + \kappa_1 BusIndex_m\right)}.$$

First, we estimate it as a parameter of the model as in BCS and Berry and Jia [2010], such that κ_{rm} will be constant across markets ($\kappa_{rm} = \kappa_r \ \forall m$). We implement this by setting $\kappa_1 = 0$. Second, we use the variable $BusIndex_m$ directly as our measure of the proportion of business travelers, thereby assuming that the proportion of passengers that actually decide to travel is equal to the proportion of business passengers in the population. We implement this second approach by estimating κ_1. Using the two approaches is important to show that our results are not sensitive to BCS's 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 exploit a set of moment conditions formed by interacting the structural error term, $\boldsymbol{\Delta\xi}$, with a set of instruments to recover estimates of γ_d. We use a variation of the Berry, Levinsohn, and Pakes [1995] contraction mapping, due to BCS, to invert Equation 5 and solve for the value of the unobservables that 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 $MktSize_{mt}$. To estimate these parameters, we form the sample counterpart of the moment condition

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

where z_t is a vector of instruments. We treat price as an endogenous regressor and use the average percentage of gates leased by each of the carriers (not just those present in market j at time t) at the market's endpoints as instruments, the same instrumental variables that we used in the reduced-form analysis to control for the endogeneity of the average multimarket contact.

4.2 The Bertrand-Nash Pricing Game

We maintain that airlines compete on prices and offer differentiated products.[21] We start by assuming that observed equilibrium prices are generated from play of a Bertrand-Nash pricing game (Bresnahan [1987]). The Bertrand-Nash pricing assumption generates the following supply relationship for any product j belonging to the set of products, $l = 1, ..., F^k_{tm}$, produced by firm k, in a market m, at time t,

$$s_{jt} + \sum_{l \in F^k_t} (p_{lt} - mc_{lt}) \frac{\partial s_{lt}}{\partial p_{jt}} = 0,$$

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

For each market, this set of J_{tm} equations implies price-cost margins for each product. Using matrix notation, this set of first-order conditions for market m can be rewritten as

$$\mathbf{s}_{tm} - \mathbf{\Omega}_{tm}(\mathbf{p}_{tm} - \mathbf{mc}_{tm}) = \mathbf{0} \tag{6}$$

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, $\Sigma_{jlmt} = \partial s_{ltm}/\partial p_{jtm}$, while 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 while Θ_{jlmt} equals 0 otherwise. With the exception of Nevo [2001], the literature has assumed that $\mathbf{\Theta}$ is a diagonal matrix (block-diagonal in the case of multi-product firms), strictly ruling out any coordination between firms in setting prices. In the next section, Section 4.3, we discuss how our model departs from the literature regarding the assumptions made on firm behavior.

4.3 Multimarket Contact and Conduct Parameters

As pointed out by Nevo [1998, 2001], the standard assumptions on the structure of $\mathbf{\Theta}$ rules out a continuum of pricing outcomes between the competitive Bertrand-Nash ($\mathbf{\Theta}$ is diagonal

[21] In assuming that airlines compete in prices and offer differentiated products, we follow a well-established literature on airline competition; see Reiss and Spiller [1989], Berry [1990], BCS [2006], Peters [2006], Berry and Jia [2010]).

or block-diagonal in the case of multi-product firms) and the fully-collusive outcome ($\mathbf{\Theta}$ is a matrix of ones). In the case of homogenous 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, see 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 such shifter of the "market environment" is the degree of pair-specific multimarket contact between carriers. In particular, higher levels of multimarket contact between competitors facilitates collusion. To capture this idea, we depart from the literature and define Θ_{jlmt} as a function of multimarket contact. In particular, if product j is owned by carrier k and product l is owned by carrier h, then Θ_{jlmt} equals $f(mmc_{kh}^t)$. 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, mmc_{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 1, we can conclude that firms collude.[22]

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

[22] This type of modeling 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 whether the firms collude or compete. Our approach, while less ambitious, is still very effective and simple to generalize to any industry where there is a market-specific exogenous variable that may facilitate collusion.

(market and time subscripts are omitted for simplicity)

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

The first-order condition of firm 1 is then

$$\underbrace{s_1 + \frac{\partial s_1}{\partial p_1}\left(p_1 - mc_1\right)}_{\text{Bertrand FOC}} + \underbrace{f\left(mmc_{12}\right) \cdot \frac{\partial s_2}{\partial p_1}\left(p_2 - mc_2\right)}_{\text{Cooperative Effect}} = 0. \tag{7}$$

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 $f\left(mmc_{12}\right)$ determines the degree to which firms cooperate in setting fares. In particular, values of $f\left(mmc_{12}\right)$ 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.

Our goal is to utilize these first-order conditions to estimate both the conduct parameters and the marginal cost functions of each firm. The set of first-order conditions for each market, Equation 6, can be inverted as

$$\mathbf{p}_{tm} - \mathbf{\Omega}_{tm}^{-1}\mathbf{s}_{tm} - \mathbf{mc}_{tm} = \mathbf{0} \tag{8}$$

where we specify the marginal cost for product j in market t as

$$mc_{jtm} = w_{jtm}\pi + d_{jt} + \omega_{jtm}$$

The w_{jt} 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_{jtm}, is the portion of marginal cost unobserved to the econometrician.

We specify the conduct parameters as

$$f(mmc_{kh}^{t}) = \frac{\exp(\phi_1 + \phi_2 mmc_{kh}^{t})}{1 + \exp(\phi_1 + \phi_2 mmc_{kh}^{t})} \tag{9}$$

which restricts $f(mmc_{kh}^{t})$ between zero and one. As a robustness check, we also estimate a flexible alternative specification for the conduct parameters,

$$f(mmc_{kh}^{t}) = \max\left[0, \min\left\{1, \phi_1 + \phi_2 mmc_{kh}^{t}\right\}\right]. \tag{10}$$

In both specifications, we then use Equation 8 to form the sample counterpart of the moment condition,

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

where γ_s are the conduct and marginal cost parameters and z_{jtm} 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]

4.4 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. **Table 6** presents the estimates of the conduct parameters, along with the corresponding estimates of demand and marginal cost. **Column 1** of **Table 6** presents the results with the introduction of the conduct parameters while maintaining the assumption that the proportion of business travelers is constant across markets, $\kappa_{mr} = \kappa_r$ and $\kappa_1 = 0$, as in BCS [2006] and Berry and Jia [2010]. **Columns 2** and **3** of **Table 6** relax this assumption by letting κ_1 free and estimating it from the data.

[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.

4.4.1 Bertrand-Nash Competition

Column 1 of **Table 5** presents the estimates from the model when we assume firms price as Bertrand-Nash competitors.[24] The demand estimates in the top panel are largely consistent with the previous studies of the industry (BCS [2006] and 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, while 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, while 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.[25]

The coefficient estimate of $\kappa_0 = -0.566$ implies $\kappa_{rm} = 0.362$, or there are 36 percent of business travelers in the markets in our dataset. 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

[24] We also estimated a nested-logit model of demand with one consumer type. The qualitative implications are very similar, suggesting that the specific model of demand is not driving the results.

[25] 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. Since 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.

products occurs 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. This means that the business types are less likely to travel, but when traveling they are less price sensitive.

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 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 endpoints. 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 and then decrease in the number of markets served out of an airport. The median of marginal cost across all markets is \$106.2.[26]

4.4.2 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 coefficient 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

[26] This is at the high end of the range of estimates in Berry and Jia (2010), who define costs for roundtrip service while 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.

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, while we now find that connecting service is less expensive than nonstop service. This is not a particularly surprising result since 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.

4.4.3 A Model with Conduct Parameters

Column 1 of **Table 6** 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 1** of **Table 6** 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 1** of **Table 6**, while the price coefficient for the business travelers is equal to -0.139 in **Column 1** of **Table 6**. 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 percent in **Column 1** of **Table 5** and to 32.7 percent in **Column 1** of **Table 6**, but it is equal to 36.2 percent in **Column 2** of **Table 5** So, again the estimated parameter κ_{rm} is in between those in **Column 1** and **Column 2**.

The cost estimates in **Column 1** of **Table 6** 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. The marginal costs are lower than in **Column 1** of of **Table 5** because the presence of the conduct parameters, ϕ_1 and ϕ_2, allows for an alternative to high marginal costs as an explanation for the high fares we observe in some markets, Equation 7.

Columns 2 and **3** of **Table 6** present the results from two robustness checks on the results from **Column 1** of **Table 6**. In particular, **Columns 2** and **3** relax the assumption that the proportion of business travelers is constant across markets, $\kappa_{mr} = \kappa_r$, for two different specifications of the conduct parameters. Relaxing this assumption by allowing the proportion of business travelers to depend on $BusIndex_m$, we find very similar results for the two alternative specifications of the conduct parameters, Equations 9 (**Column 2** of **Table 6**) and 10 (**Column 3** of **Table 6**).

The marginal cost estimates in **Columns 2** and **3** of **Table 6** are nearly identical to those in **Column 1**. In addition, the implications, discussed immediately below, regarding collusion and multimarket contact of the estimated conduct parameters are nearly identical to those of **Column 1**.

Consider now the estimates for ϕ_1 and ϕ_2 which shift the conduct parameters. Due to the similarity of the results, we focus on **Column 1** of **Table 6**. We estimate ϕ_1 equal to -3.167 and ϕ_2 equal to 5.785. **Figure 1** plots the conduct parameters. From **Figure 1** it is clear that carriers with little multimarket contact do not cooperate in setting fares. Carriers with a significant amount of multimarket contact can sustain near-perfect cooperation in setting fares.

Table 7 provides a one-to-one mapping from multimarket contact matrix in **Table 1** to the level of cooperation carriers can sustain in setting fares. In particular, **Table 7** presents $f(mmc)$ evaluated at each element of **Table 1**. As an example, consider the interaction between American and Delta. **Table 1** shows that in the first quarter of 1997 the two firms overlapped in 855 markets. In **Table 7,** we find that the conduct parameter is equal to 0.856, which is essentially saying that American and Delta collude in fares in markets that they concomitantly serve. Consider, instead, the interaction between American and JetBlue. From **Table 1** we know that they overlap in 84 markets. **Table 7** 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 with one another 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 airline firms 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.[27]

One feature of our framework is that the conduct parameters are not exactly equal to 0 and 1, which are the values that correspond, respectively, to the cases of Nash-Bertrand competition and collusion. However, **Figure 2** shows the distribution of the estimated conduct parameters is bimodal, except for a peak at 0.6. Consider first the case of the parameters that are close to 0 and 1. We interpret the fact that they are not exactly equal

[27] The case is Avery v. Delta Air Lines Inc., AirTran Holdings Inc. 09cv1391, U.S. District Court, Northern District of Georgia (Atlanta).

to 0 or 1 as the result of random sampling and possible model specification. Next, we can ask what explains the peak at 0.6. The conduct parameters close to 0.6 describe the strategic interaction between USAir and Northwest, USAir and American, USAir and Continental, and United and Continental. Our interpretation is that the interaction of these pairs is less frequent than the interaction between other legacy pairs, which might suggest that their strategic behavior might be driven by other, more local, factors. For example, USAir and Northwest might be colluding at some airports where they concumitantly provide many markets, but they do not collude in the other markets.

There are two interesting extensions that could address in more detail the findings in **Figure 2**. First, we could allow the conduct parameter to take two values, 0 and 1, and assume the outcome in any particular market is drawn from a binomial distribution where the probability of each value depends on the level of multimarket contact. However, we feel that this approach would impose more structure than is needed for the empirical analysis presented in this paper. Second, we have assumed that the relevant level of multimarket contact is at the national level, which follows EK and previous work. However, one might think that the level of strategic interaction where multimarket contact plays a role is at the airport level. We leave this extension to future work.

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 similar to 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 3**. The bottom half of **Figure 3** 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 3**, 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 3** are exactly as one would expect given the shape of **Figure 1**. 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 7, 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 3** 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. To see why, recall that the cooperative effect is measured by $f\left(mmc_{12}\right) \cdot \frac{\partial s_2}{\partial p_1}\left(p_2 - mc_2\right)$. **Figure 4** 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 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 since firms are already fully colluding.

5 Conclusion

In this paper, 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, while we cannot reject the hypothesis that 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 (Waldfogel and Wulf [2006] and Parker and Roller [1997]) 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 paper 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, while 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 while 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

[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

would require that we model the strategic interaction between firms as a dynamic game, which is clearly beyond the scope of this paper.

Nevo [2006].

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Figure 1: Collusion and Multimarket Contact

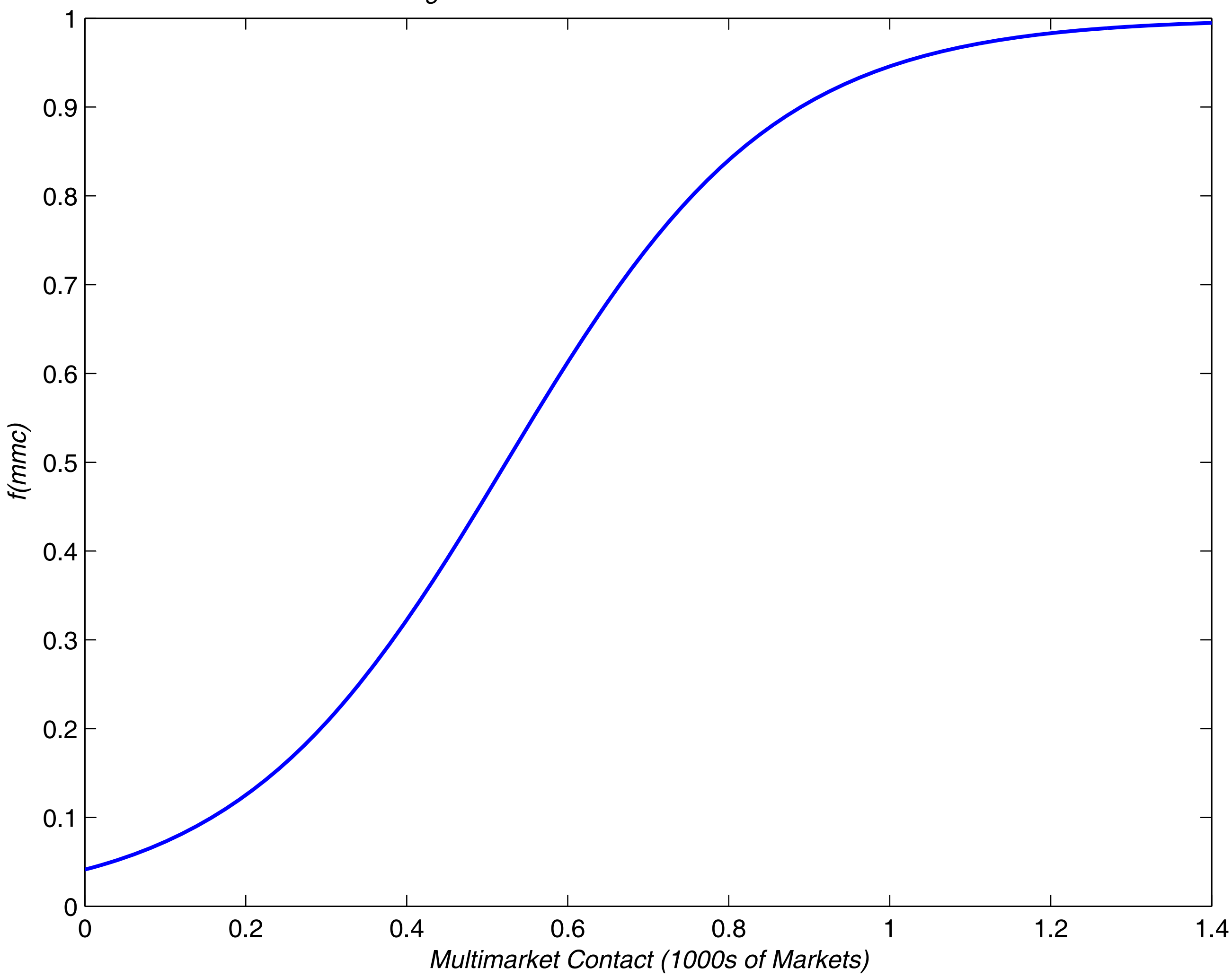

Figure 2: Distribution of Conduct Parameters

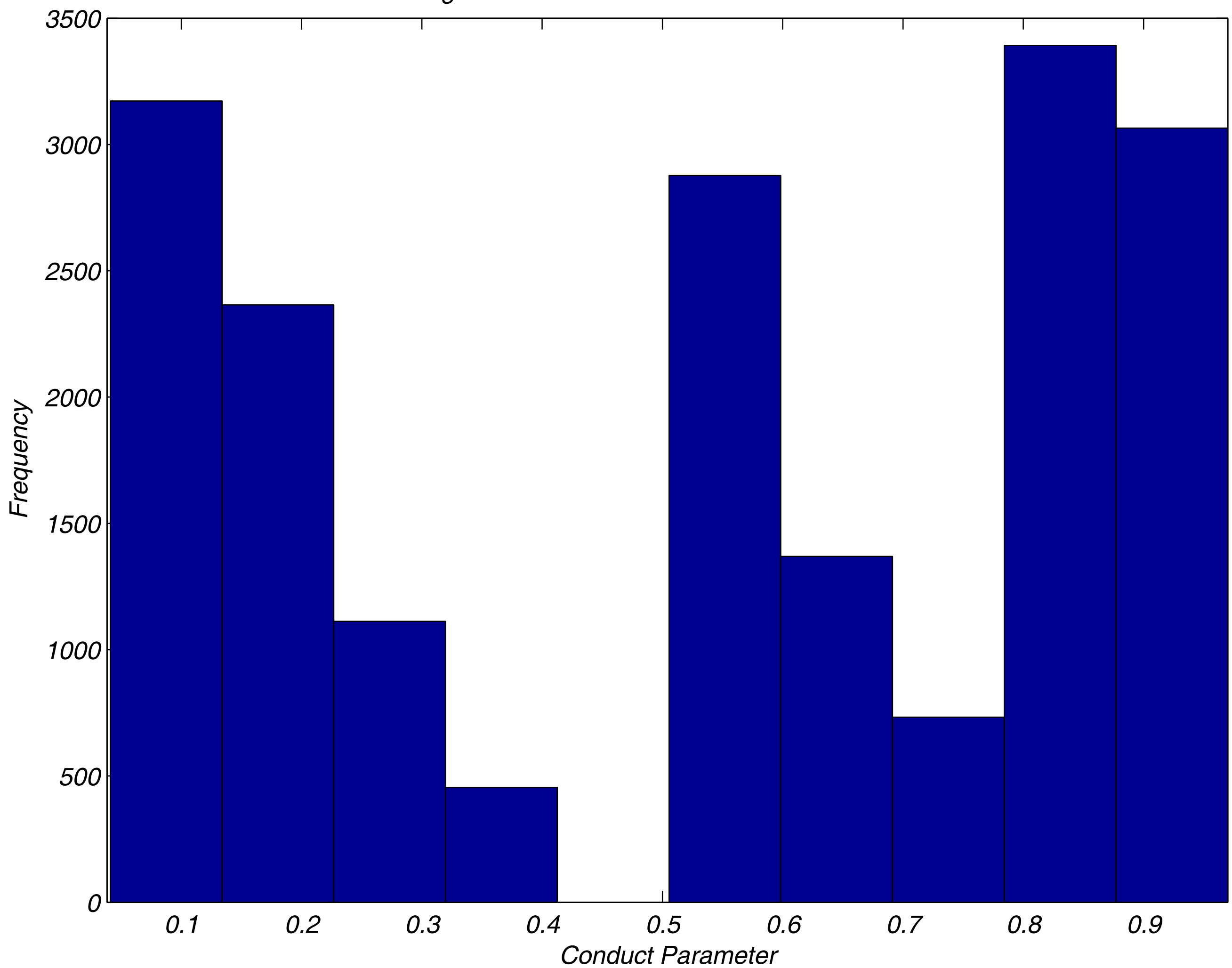

Figure 3: Multimarket Contact and Prices

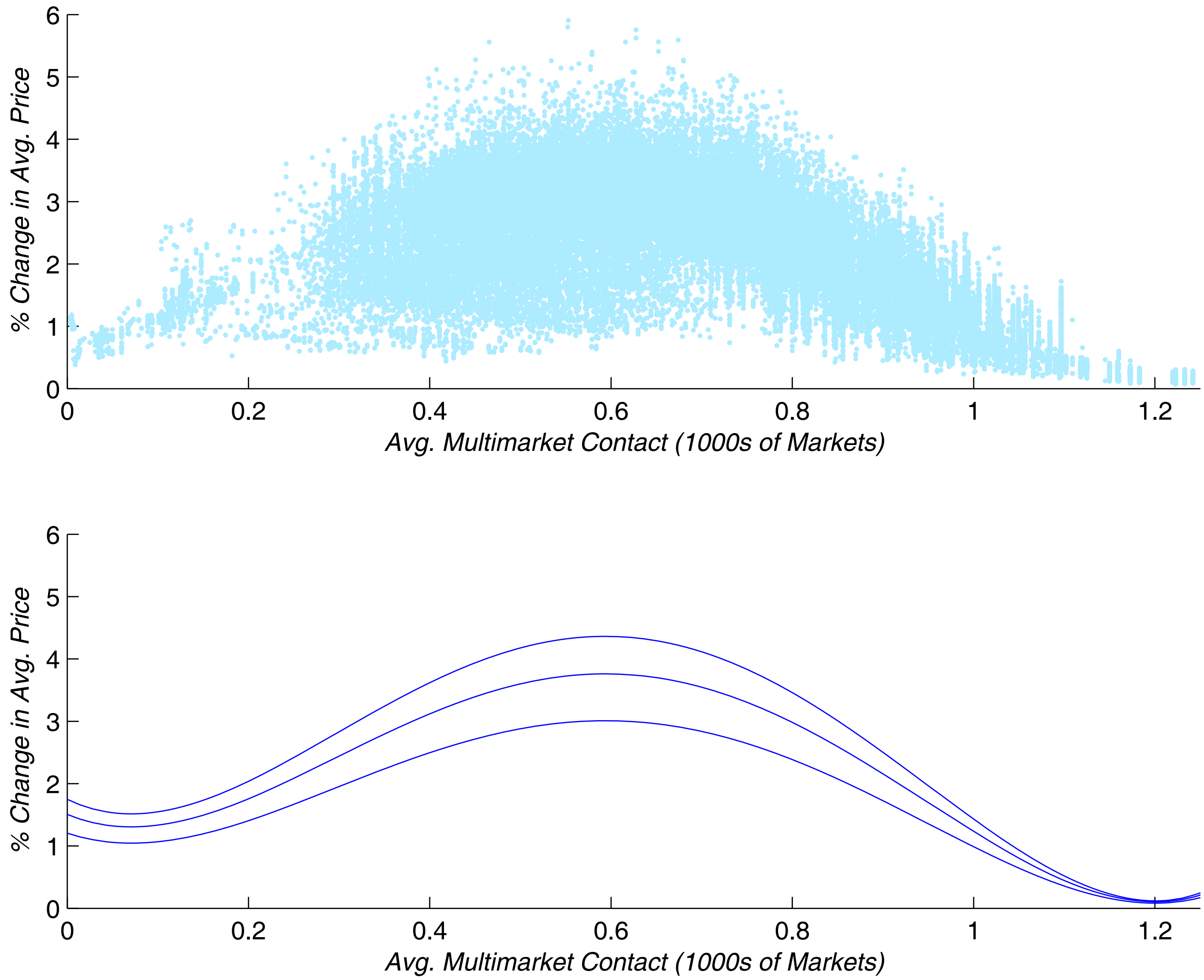

Figure 4: Cross-Price Elasticities, Multimarket Contact, and Fares

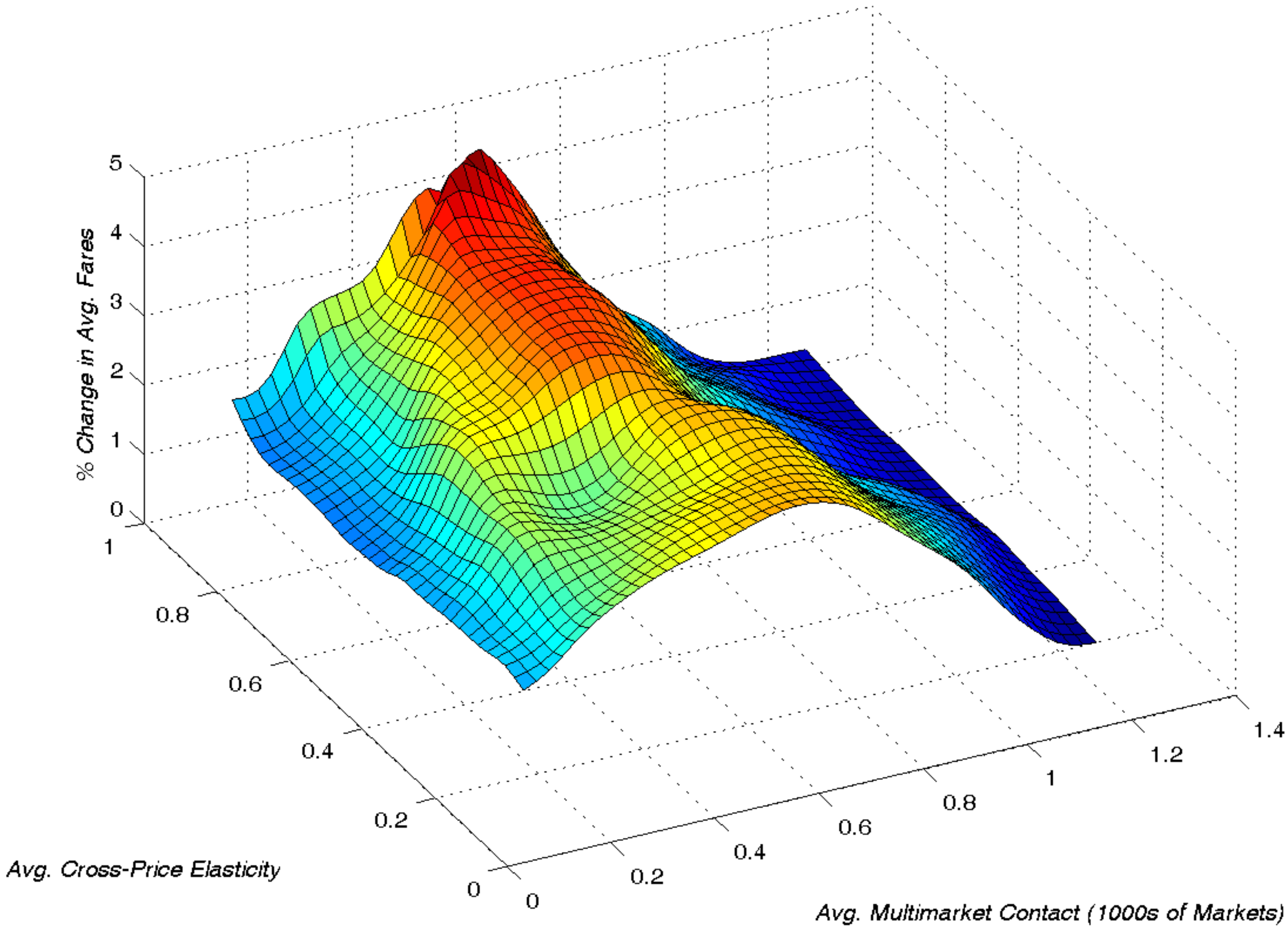

Table 1: Number of Common Markets in 2007-Q1

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

Table 2: Variable Description and Summary Statistics

Variable	Source	Description	Observations	Mean	Median	Std. Dev.
Carrier-Market-Specific Variables						
Fare	DB1B	Carrier-Market-Specific Average Fare	268119	222.692	213.472	66.502
Nonstop	DB1B	Indicator of Nonstop Service	268119	0.173	0.000	0.379
NetworkSize	DB1B	Percentage of All Routes Served by Carrier at Originating Airport	268119	0.443	0.470	0.174
NumMkt	DB1B	Number of Markets Served by Carrier at Originating Airport (1000s)	268119	0.130	0.139	0.050
ExtraMiles	DB1B	Average Distance Flown Between Market Endpoints (equals Distance for Nonstop Service)	268119	1258.628	1121.000	625.219
AvgContact	DB1B	Average Market Contact from mmc Matrix (divided by 1,000)	268119	0.630	0.621	0.265
MktShare	DB1B	Market-Carrier Share of Passengers	268119	0.274	0.168	0.286
HHI	DB1B	Market-Carrier Share of Passengers	268119	0.453	0.404	0.214
Roundtrip	DB1B	Proportion of Roundtrip Passengers	268119	0.827	0.853	0.130
Hub	Author	Indicator for Hub Endpoint	268119	0.104	0.000	0.306
Market-Specific Variables						
Distance	DB1B	Nonstop Distance Between Market Endpoints	268119	1105.694	969.000	596.201
MktSize	BEA	Geometric Mean of Population at Market Endpoints	268119	2409758	1789943	1993143
BusIndex	ATS Survey	Fraction of Business Travelers	268119	0.408	0.411	0.096
AA_avg	Survey	AA Mean % Gates at Market Endpoints	268119	0.097	0.072	0.084
CO_avg	Survey	CO Mean % Gates at Market Endpoints	268119	0.067	0.050	0.075
DL_avg	Survey	DL Mean % Gates at Market Endpoints	268119	0.103	0.084	0.082
NW_avg	Survey	NW Mean % Gates at Market Endpoints	268119	0.085	0.051	0.107
UA_avg	Survey	UA Mean % Gates at Market Endpoints	268119	0.087	0.058	0.081
US_avg	Survey	US Mean % Gates at Market Endpoints	268119	0.126	0.099	0.112
WN_avg	Survey	WN Mean % Gates at Market Endpoints	268119	0.075	0.056	0.075
AS_avg	Survey	AS Mean % Gates at Market Endpoints	268119	0.006	0.000	0.018
B6_avg	Survey	B6 Mean % Gates at Market Endpoints	268119	0.014	0.000	0.018
F9_avg	Survey	F9 Mean % Gates at Market Endpoints	268119	0.012	0.000	0.026
FL_avg	Survey	FL Mean % Gates at Market Endpoints	268119	0.023	0.015	0.027
TZ_avg	Survey	TZ Mean % Gates at Market Endpoints	268119	0.000	0.000	0.001
G4_avg	Survey	G4 Mean % Gates at Market Endpoints	268119	0.006	0.000	0.019
YX_avg	Survey	YX Mean % Gates at Market Endpoints	268119	0.014	0.000	0.042
NK_avg	Survey	NK Mean % Gates at Market Endpoints	268119	0.002	0.000	0.006
U5_avg	Survey	U5 Mean % Gates at Market Endpoints	268119	0.001	0.000	0.003
OwnGates	Survey	Carrier's Own Mean % Gates at Market Endpoints	268119	0.129	0.093	0.129
CompGates	Survey	Total Mean % of Gates at Market Endpoints Held by All *Potential* Competitors	268119	0.587	0.616	0.587
LccGates	Survey	Total Mean % of Gates at Market Endpoints Held by *Potential* Lcc Competitors	268119	0.072	0.063	0.072
WNGates	Survey	Mean % of Gates at Market Endpoints Held by WN, 0 if Carrier is WN	268119	0.064	0.048	0.070

Table 3: Prices and Multimarket Contact

	Top 1000 Markets		All Markets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average_MMC	0.246***	0.291***	-0.017***	0.054***	0.539***	0.667***	0.663***
	(0.030)	(0.029)	(0.002)	(0.004)	(0.009)	(0.016)	(0.016)
Hub		0.208***	0.190***	0.191***	0.177***	0.194***	0.194***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
NetworkSize	0.630***	0.314***	0.224***	0.226***	0.501***	0.207***	0.208***
	(0.013)	(0.013)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Nonstop	-0.054***	-0.065***	-0.032***	-0.032***	-0.053***	-0.033***	-0.033***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RoundTrip	-0.548***	-0.576***	-0.533***	-0.539***	-0.444***	-0.548***	-0.548***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
HHI	0.014						
	(0.011)						
MktShare	0.063***						
	(0.005)						
Log(Distance)					-1.265***	-0.438***	-0.430***
					(0.024)	(0.058)	(0.058)
Log^2(Distance)					0.106***	0.049***	0.048***
					(0.002)	(0.004)	(0.004)
BusinessIndex							-0.029
							(0.021)
Market Fixed Effects	Yes	Yes	Yes	Yes	No	No	No
IV	No	No	No	No	Yes	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	Yes
R^2	0.167	0.223	0.143	0.171	0.241	0.350	
Observations	85,920	85,920	268,119	252,284	268,119	252,284	252,284

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

Note: Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted for sake of brevity.

Table 4: Screening Tests on the Relationship between Multimarket Contact and Collusion

	Differences in Prices			Rigidity of Prices	
	(1)	(2)	(3)	(4)	(5)
MMC	-0.109***	-0.107***	-0.094***	-0.095***	-0.095***
	(0.010)	(0.010)	(0.010)	(0.017)	(0.017)
Log(Distance)	-2.268***	-2.306***		0.122	0.103
	(0.075)	(0.075)		(0.107)	(0.107)
Log^2(Distance)	0.174***	0.177***		-0.012	-0.011
	(0.005)	(0.005)		(0.008)	(0.008)
BusinessIndex		0.243***			0.116***
		(0.020)			(0.028)
Market Fixed Effects	No	No	Yes	No	No
R^2	0.024	0.025	0.012	0.026	0.026
Observations	414,382	414,382	414,382	49,535	49,535

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

Note: Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted for sake of brevity.

Table 5: BCS Estimation

	(1)		(2)	
	BCS - No Collusion		**BCS - Full Collusion**	
Demand	estimate	std. error	estimate	std. error
$Price_1$	-1.333***	(0.007)	-1.315***	(0.004)
$Price_2$	-0.119***	(0.003)	-0.165***	(0.001)
κ^0	-0.662***	(0.065)	-0.723***	(0.034)
$Constant_1$	-5.567***	(0.023)	-5.957***	(0.012)
$Constant_2$	-7.65***	(0.042)	-7.196***	(0.023)
$Nonstop_1$	1.087***	(0.006)	1.103***	(0.006)
$Nonstop_2$	0.954***	(0.006)	1.065***	(0.006)
λ	0.625***	(0.001)	0.622***	(0.002)
Network Size	0.683***	(0.015)	0.578***	(0.015)
Distance	2.223***	(0.026)	2.097***	(0.026)
$Distance^2$	-0.523***	(0.01)	-0.511***	(0.01)
Extra-miles	-1.309***	(0.024)	-1.173***	(0.023)
$Extra\text{-}miles^2$	0.211***	(0.008)	0.182***	(0.008)
Cost				
Constant	0.926***	(0.009)	0.379***	(0.005)
NumMkt	-0.926***	(0.108)	0.344***	(0.056)
$NumMkt^2$	0.432	(0.37)	-1.523***	(0.192)
Distance	0.184***	(0.011)	0.24***	(0.005)
$Distance^2$	-0.008***	(0.004)	-0.055***	(0.002)
Extra-miles	0.157***	(0.011)	-0.104***	(0.005)
$Extra\text{-}miles^2$	-0.052***	(0.004)	0.009***	(0.002)
Model Fit				
Median Marginal Cost	1.062		0.613	
Median Elasticity	-4.320		-4.413	
Median Elasticity - Type1	-6.260		-6.181	
Median Elasticity - Type2	-0.559		-0.769	
Function Value	34766.038		34217.886	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

Note: Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted for sake of brevity.

Table 6: BCS Estimation with Conduct Parameters

	(1)		(2)		(3)	
	BCS - exp CV		**BCS - exp CV - BusIndex**		**BCS - linear CV- BusIndex**	
Demand	estimate	std. error	estimate	std. error	estimate	std. error
$Price_1$	-1.162***	(0.006)	-1.394***	(0.005)	-1.334***	(0.005)
$Price_2$	-0.139***	(0.002)	-0.18***	(0.002)	-0.187***	(0.002)
κ^0	-0.566***	(0.044)	-0.939***	(0.14)	-1.248***	(0.155)
κ^1			0.542***	(0.007)	0.553***	(0.008)
$Constant_1$	-5.954***	(0.017)	-5.794***	(0.049)	-5.902***	(0.044)
$Constant_2$	-7.514***	(0.028)	-7.423***	(0.094)	-7.068***	(0.113)
$Nonstop_1$	1.14***	(0.006)	1.13***	(0.006)	1.119***	(0.006)
$Nonstop_2$	1.03***	(0.006)	1.049***	(0.006)	1.056***	(0.006)
λ	0.601***	(0.002)	0.627***	(0.002)	0.620***	(0.002)
Network Size	0.525***	(0.015)	0.704***	(0.015)	0.637***	(0.015)
Distance	1.997***	(0.026)	2.045***	(0.026)	2.136***	(0.026)
$Distance^2$	-0.497***	(0.01)	-0.504***	(0.01)	-0.516***	(0.01)
Extramiles	-1.039***	(0.023)	-0.999***	(0.023)	-1.2***	(0.023)
$Extramiles^2$	0.163***	(0.008)	0.153***	(0.008)	0.194***	(0.008)
Cost						
Constant	0.541***	(0.006)	0.57***	(0.005)	0.453***	(0.006)
NumMkt	-0.531***	(0.072)	0.036***	(0.061)	0.255***	(0.065)
$NumMkt^2$	1.795***	(0.244)	0.232***	(0.206)	0.411**	(0.219)
Distance	0.249***	(0.007)	0.282***	(0.006)	0.264***	(0.007)
$Distance^2$	-0.039***	(0.003)	-0.059***	(0.002)	-0.059***	(0.002)
Extramiles	0.077***	(0.007)	-0.001	(0.006)	0.069***	(0.006)
$Extramiles^2$	-0.017***	(0.002)	0.004***	(0.002)	-0.003***	(0.002)
Contact						
Constant	-3.167***	(0.058)	-2.44***	(0.047)	-2.571***	(0.027)
MMC	5.785***	(0.085)	6.584***	(0.09)	6.337***	(0.055)
Model Fit						
Median Marginal Cost	0.746		0.780		0.766	
Median Elasticity	-3.519		-4.574		-4.353	
Median Elasticity - Type1	-5.166		-6.578		-6.191	
Median Elasticity - Type2	-0.618		-0.849		-0.868	
Function Value	33900.977		33508.811		33708.790	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

Note: Year-Quarter Dummies, Carrier Dummies included in all regressions. Their coefficient estimates, as well as the constant estimate, are omitted for sake of brevity.

Table 7: 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	•