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

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Abstract

We nest conduct parameters into a standard oligopoly model. The conduct parameters are modeled as functions of multimarket contact. Using data from the US airline industry, we find: i) carriers with little multimarket contact do not cooperate in setting fares, while 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.

JEL Codes: L13.

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1 Introduction

Detecting tacit collusion is a central theme of research in empirical industrial organization (Jaquemin 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]

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

[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).

[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 econo-

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 consider a model of the airline industry where the strategic interaction among firms is measured by conduct parameters that are functions of 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.[8] 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 revealed whether firms competed on prices, competed on quantities, or colluded.[9] 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.

metric 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 type of approach that looks for identifying potential facilitators of collusion in the industry has also been recently advocated by Berry and Haile [2010].

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

The main identification concern is whether multimarket contact is exogenous.[10] In their theoretical analysis, Bernheim and Whinston [1990] think of multimarket contact as an "external factor". However, one might reasonably think that there is some source of unobservable heterogeneity that determines both prices and multimarket contact. For example, in the airline industry the multimarket contact is a variable constructed using information on the markets served by an airline, and an airline might self-select into markets where it has a competitive advantage (Ciliberto and Tamer [2010]). We instrument for the multimarket contact variables using a unique and original dataset on the number of gates controlled by each airline at many airports in the US. The number of gates is naturally correlated with the number of markets served by an airline out of an airport, but is not directly correlated with the pricing decisions.[11]

In our reduced-form analysis, we generally confirm the findings of EK. We find that multimarket contact is associated with higher equilibrium fares using both a fixed-effects and instrumental-variables approach.

In the structural analysis, we directly link multimarket contact to collusion. First, we find that carriers with little multimarket contact (e.g. JetBlue and Frontier served 2 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. Second, we find that the standard assumption that firms behave as Bertrand-Nash competitors leads to marginal cost estimates 30 percent higher than when we use a more flexible behav-

[10] 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 multi-market contact.

[11] While an airline can enter and exit markets quite easily and quickly, it is much more difficult to gain access to an airport. The crucial observation here is that the control of gates is associated with sunk entry costs that affect the entry decision but cannot respond contemporaneously to demand or cost shocks as prices do.

ioral model that allows firms to behave differently depending on the extent of multimarket contact. Finally, we show that cross-price elasticities play an important role in determining the impact of multimarket contact on equilibrium fares. If two goods 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 three dimensions. First, we treat multimarket contact as endogenous and use an instrumental-variable approach to control for its endogeneity. Previous solutions to the endogeneity of 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 propose a structural model nested in the mainstream empirical industrial organization literature to directly link 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 5. Section 6 concludes and discusses possible extensions of our research.

2 Data

We use data from three main sources.[12] First, we use data from the Airline Origin and Destination Survey (DB1B) database, a 10% sample of all domestic itineraries which provides information on the fare paid, connections made in route to the passenger's final destination, and information on the ticketing and operating carriers. Second, we use data from the BEA on the population of Metropolitan Statistical Areas (MSAs). Finally, we use data from a survey that we conducted jointly with the ACI-NA, an airport-trade organization, on carrier-specific access to boarding gates at a large number of airports in 2007.[13]

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. We consider markets in which at least 250 passengers were transported in at least one quarter from 2006 to 2008.[14] Finally, we 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 (FL), Allegiant (G4), Spirit (NK), Northwest (NW), Sun Country (SY), AirTran (TZ), USA3000 (U5), United (UA), USAir (US), Southwest (WN), Midwest (YX). A product is then denoted by a combination jmt, which indicates that product j (e.g. nonstop service by American)

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

[13] A copy of the survey is available from the authors upon request.

[14] We drop any markets where fewer than 100 passengers were served in any quarter from 2006 to 2008.

transports its passengers 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 follow EK in measuring multimarket contact, here denoted by mmc_{kh}^t, where k and h are two distinct carriers and t is a time period. For a particular carrier and one of its competitors, this variable is calculated as the total number of markets that the two airlines serve concomitantly. For example, in the first quarter of 2007, American and Delta concomitantly served 855 markets; therefore mmc_{kh}^t equals 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 market-specific average of multimarket contact,[15]

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

where $1[k \text{ } and \text{ } h \text{ } active]_{mt}$ is an indicator function that 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 the variable mmc_{kh}^t across the firms *actively* serving market m at time t. This variable is summarized in **Table 2**.

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

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

The results are nearly identical.

2.3 Fares

We calculate average fares at the product-carrier-market level, where a product is either nonstop or connecting service.[16] **Table 2** summarizes the average fare, $Fare_{jmt}$.[17] The average of $Fare_{jmt}$ of a one-way ticket across all carriers and markets from 2006 to 2008 is around $223.[18]

To control for price differences in one-way and round-trip tickets we include 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.

2.4 Limited Access to Airport Facilities

Airlines require enplaning/deplaning gates to provide service at an airport. Ciliberto and Williams [2010] show that limited access to gates is an important determinant of equilibrium fares and explains approximately 50% of the hub premium, first documented by Borenstein [1989]. We use information on gates as the source of exogenous variation that identifies the effect of multimarket contact on the ability of firms to coordinate their prices.

Gates are typically allocated to carriers through long-term leasing agreements which give a carrier either exclusive or preferential rights to use the gate, while a small fraction of an airport's gates are usually reserved for common use. Given the importance of access to airport facilities in determining equilibrium fares and the inability of a carrier to contemporaneously respond to demand or cost shocks by altering the number of gates it leases at an airport, the allocation of gates among carriers provides a robust set of instruments. In our empirical analysis, we use data on the total number of gates at the airport, the number leased to each

[16] Like EK and consistent with 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. Fares are then deflated using the consumer price index to 2009 dollars. Like 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.

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

[18] This average, across carriers and markets, is not weighted by the number of passengers traveling under each fare.

carrier on a preferential or exclusive basis, and the number reserved for common use by the airport authority.

We collected these detailed data on carrier-specific leasing agreements from airports as part of a survey conducted jointly with the ACI-NA. We received completed surveys from 107 of the top 200 airports in terms of enplanements in 2007. For the 17 carriers in our sample, we construct the mean of the percentage of gates leased on an exclusive or preferential basis by each carrier at the two market endpoints. For each carrier (e.g. AA_avg_m for American), this variable is summarized in **Table 2**. The significant amount of variation across markets in the fraction of gates leased by each carrier provides a great source of identifying variation. We also construct a variable, $Common\_Avg_m$, as the mean fraction of gates reserved by the airport authority for common-use.

2.5 Control Variables

Carriers can offer both nonstop and connecting service.[19] 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 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 and call this variable $NetworkSize_{jmt}$.

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

[19] 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.

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 on shorter markets, travel as a whole is more attractive, while in very long markets any form of travel is less attractive due to the time spent reaching one's destination. Also, the availability and attractiveness of substitutes to air-travel varies 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.

Finally, 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.[20] The variable Hub_{jm} captures whether flying on the hub airline is more attractive than flying on any other airlines. It also captures potential cost advantages.

3 Reduced-Form Analysis

In this section, we first replicate the work of EK and then motivate the structural model by pointing out the limitations of a reduced-form analysis of this type.

3.1 Replicating Evans and Kessides [1994]

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

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

[20] 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).

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 $\beta_{AvgContact_{mt}}$ is expected to be positive. In addition to the controls discussed below, all specifications also 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. The variables mmc_{kh}^{t} and $AvgContact_{mt}$ are constructed with the data from the small sample. 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.

Figure 1 clearly illustrates the significance of this problem. The figure reports two lines, the predicted values of the regression of prices on multimarket contact when we include monopolies and when we don't. We also include the median spline of prices as a function of multimarket contact. There is clearly a discontinuity in the relationship between average multimarket contact and prices when multimarket contact is equal to zero. Prices are high when multimarket contact is equal to zero (monopoly markets), but immediately drop to their lowest point when multimarket contact is just above zero and then increase monotonically with multimarket contact. As **Column 3** demonstrates, if there are many monopoly markets, this discontinuity significantly alters the reduced-form regression results. As we discuss below, the structural analysis does not rely on the average measure, $AvgContact_{mt}$, but on the pair-specific measures, mmc_{kh}^{t}. Consequently, the structural analysis does not encounter this discontinuity problem. It also has the advantage of using information from the distribution of multimarket contact within a market, rather than just the mean.

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**.

Overall, the effects of multimarket contact on prices range between 1 and 5 percent when we include market fixed effects which uses only within-market variation in multimarket contact and prices to identify the causal effect of the first on the second. This presents a problem, since variation within a market in multimarket contact may be driven by the same factors that drive within-market variation in prices. For example, a negative shock (unobserved to the econometrician) to demand may lead firms to exit the market, potentially resulting in an increase (or decrease depending on who exits) in multimarket contact and an increase in fares. However, it would be incorrect to regard this correlation as evidence of a causal relationship between multimarket contact and fares. In these situations, as Griliches and Mairesse [1995] suggest, fixed-effects will perform poorly and the researcher should search for an instrument-variables solution. We follow this suggestion.

To construct instrumental variables, we use the carrier-specific gate data. Our main identifying assumption is that the control of gates is a determinant of prices through its effect on the entry decisions of firms. That is, gates determine which firms serve a market, which in itself determines the value of $AvgContact_{mt}$. The long-term nature of gate leasing agreements ensures that the allocation of gates among carriers cannot respond to transient shocks driving within-market variation in prices. The instruments we use include the average fraction of gates leased by each carrier at the market endpoints and the average fraction of gates reserved for common use at the market endpoints. Also, for each carrier and market we generate three instruments to capture the level of potential competition a carrier faces in a market from legacy and low-cost carriers as well as Southwest: the sum over carrier-type (legacy, Lcc, Southwest) of the average fraction of gates leased by each carrier at the market endpoints.

Column 5 of **Table 3** presents the results from the instrumental variable regressions with market-specific random effects. We consider the full sample of markets, including monopoly markets. We estimate the coefficient of $AvgContact_{mt}$ equal to 0.520. 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 the entry behavior of firms, the indicators $1[k \text{ and } h \text{ active}]_{mt}$ in Equation 1, which determines the observed level of $AvgContact_{mt}$.

Overall, our results are largely consistent with those of EK. In the section to follow, we explore what can be learned from a more structural approach.

3.2 Motivating a Structural Analysis

There are three clear reasons for exploring a more structural approach.

First, the reduced-form analysis shows that an increase in multimarket contact leads to higher prices. However, we cannot determine the exact degree by which multimarket contact leads to a more collusive behavior, hence to higher prices. In particular, we can only recover the relationship between fares and multimarket contact, not collusion and multimarket contact.

Second, the reduced-form analysis only examines the relationship between average multimarket contact and equilibrium fares. A more structural approach allows one to take into account the full distribution of each carrier's contact with every other carrier in the market. To see why looking at a distribution is important, consider two markets that are identical except for the degree of contact between the incumbent carriers. Suppose at time t, the multimarket contact matrix for the two markets is given by

$$mmc^t = \begin{pmatrix} \cdot & .75 & .75 \\ .75 & \cdot & .75 \\ .75 & .75 & \cdot \end{pmatrix}, \quad mmc^t = \begin{pmatrix} \cdot & .25 & 1 \\ 0.25 & \cdot & 1 \\ 1 & 1 & \cdot \end{pmatrix}.$$

In both markets $AvgContact_{mt}$ is equal to 0.75. However, suppose that 750 markets are enough to support full cooperation between carriers in setting fares, while 250 markets is not. In the first market, there would be full cooperation in setting fares. In the second market, there would be full cooperation between the first carrier and the other two carriers. However, the level of multimarket contact between carriers two and three would result in less cooperation in setting fares. This simple example demonstrates that there is not necessarily a one-to-one mapping between $AvgContact_{mt}$ and equilibrium fares as the reduced-form analysis assumes.

Finally, the structural analysis deals with the sample selection issue related to monopoly markets in a natural way. Monopoly markets are not used to identify the effect of multimarket contact, since there is only one firm in those markets. However, monopoly markets are used to identify all the other parameters of the model. Thus, our structural model of demand and pricing utilizes information from the full sample to identify demand and marginal cost while also providing insight into the relationship between multimarket contact and collusion.

4 Structural Analysis

In this section, we describe our structural approach for identifying the relationship between multimarket contact and collusion.

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 (for simplicity, we abstract from the market, m, subscript), the utility of consumer i of type r, is given by

$$u_{ijt}^{r} = x_{jt}\beta_r + p_{jt}\alpha_r + \xi_{jt} + \upsilon_{it}(\lambda) + \lambda\varepsilon_{ijt}$$

where x_{jt} is a vector of product characteristics, p_{jt} is the price, (β_r, α_r) are the taste parameters for a consumer of type r, and ξ_{jt} are product characteristics unobserved to the econometrician. The term, $\upsilon_{it}(\lambda) + \lambda\varepsilon_{ijt}$, 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 since only differences in utility, not levels, are identified.

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

$$\frac{D_{rt}^{\lambda}}{1+D_{rt}^{\lambda}} \tag{3}$$

where

$$D_{rt} = \sum_{k=1}^{J_t} e^{(x_{jt}\beta_r + p_{jt}\alpha_r + \xi_{jt})/\lambda}.$$

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

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

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

$$s_{jt}(\mathbf{x}_t, \mathbf{p}_t, \boldsymbol{\xi}_t, \gamma_d) = \sum_{r=1}^{2} \kappa_r \frac{e^{(x_{jt}\beta_r + p_{jt}\alpha_r + \xi_{jt})/\lambda}}{D_{rt}} \frac{D_{rt}^{\lambda}}{1+D_{rt}^{\lambda}} \tag{5}$$

where κ_r is the proportion of consumers of type r and γ_d is the collection of demand parameters to be estimated. To control for persistent variation in consumers' tastes across carriers and time, we add carrier and year-quarter fixed effects (d_{jt}) such that

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

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 models predicted shares to observed market shares for each product, conditional on $\gamma_d = \{\lambda, \alpha, \beta, \kappa, \psi\}$. Observed market shares are calculated as

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

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 to generate a set of instruments.

4.2 The Bertrand-Nash Pricing Game

We maintain that airline firms compete on prices and offer differentiated products.[22] We start by assuming that observed equilibrium prices are generated from play of a Bertrand-Nash pricing game (Bresnahan [1987]). This assumption generates the following supply relationship for any product j belonging to the set of products, $l = 1, ..., F_t^k$, produced by firm k in a market at time t,

$$s_{jt} + \sum_{l \in F_t^k} (p_{lt} - mc_{lt}) \frac{\partial s_{lt}}{\partial p_{jt}} = 0.$$

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

For each market, this set of J_t equations implies price-cost margins for each product. Using matrix notation, this set of first-order conditions for market t can be rewritten as

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

where each element of $\mathbf{\Omega}$ can be decomposed into the product of two components, $\Omega_{jl} = \Sigma_{jl}\Theta_{jl}$. The first component is the own or cross-price derivatives of demand, $\Sigma_{jl} = \partial s_{lt}/\partial p_{jt}$, while the second component is an indicator of product ownership. More precisely, if products j and l belong to the same firm, then Θ_{jl} equals 1 while Θ_{jl} equals 0 otherwise. With the

[22] 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, Peters [2006], Berry and Jia [2010]).

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 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 multimarket contact between carriers. In particular, we expect higher levels of multimarket contact between competitors to facilitate collusion. To capture this idea, we depart from differentiated literature and define Θ_{jl} 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_{jl} 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. 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.[23]

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)

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

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.

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 that are 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

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

[23] 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 shifts the incentive of firms to collude.

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

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

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

We specify the conduct parameters as

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

which restricts $f(mmc_{kh})$ between zero and one.[24]

We then use Equation 8 to form the sample counterpart of the moment condition,

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

where γ_s are the conduct and marginal cost parameters and z_{jt} are the vector of instruments discussed in Section 2.4. 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.[25]

5 Multimarket Contact and Collusion

The structural estimates are reported in **Table 4** which is organized into panels. The top panel presents the results for the demand estimation. The middle panel presents the esti-

[24] We find nearly identical results for an alternative specification for the conduct parameters,

$$f(mmc^t_{kh}) = \max\left[0, \min\left\{1, \phi_1 + \phi_2 mmc^t_{kh}\right\}\right].$$

Given the similarity in the results, for conciseness, we only report the results for the first specification.

[25] 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.

mates of the cost parameters. The next panel presents the results for the conduct parameters, ϕ_1 and ϕ_2. The bottom panel describes marginal costs and elasticities of demand.

5.1 Bertrand-Nash Competition

Column 1 of **Table 4** presents the estimates from the model when we assume firms price as Bertrand-Nash competitors.[26] 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 -1.32 for the first type and equal to -0.126 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 -4.31 while only -0.42 for the business-traveler type. The mean own-price elasticity across all markets, products, and types is -3.042, a number consistent with previous work.[27]

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 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

[26] 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.

[27] 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.

equal to -5.692 and for the business-traveler type is equal to -7.626. 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 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 the marginal cost of connecting service is more expensive than nonstop service. The mean of marginal cost across all markets is \$111.[28]

5.2 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 4** shows the results under the assumption that firms fully cooperate in setting fares. First, we find that the price coefficients are now equal to -1.674 for the tourist traveler against the value of -1.32 that we had estimated in **Column 1**. We find that the estimated coefficient of price for the business traveler is now equal to -0.223, twice as large as in **Column 1**. This large differences in the estimated coefficients lead to significantly different estimates of the marginal cost, whose average is now estimated to

[28] 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.

be equal to 53.7 dollars, approximately 50% less than the estimates in **Column 1.** The coefficient estimate of κ_1 is also very different in **Columns 1** and **2.**

The estimates of the cost coefficients are also quite different in **Columns 1** and **2**. The constant term is almost half as big (0.502 against 0.869). Moreover, the cost is now increasing at a slower pace in distance. Finally, we find the marginal cost of connecting service is now less expensive than nonstop service at all distances. This is not a particularly surprising result since longer connections through major hubs often involve the use of larger planes that have a lower cost per passenger.

5.3 A Model with Conduct Parameters

Column 3 of **Table 4** 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. That is, 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** are much closer to those in **Column 1** (Bertrand-Nash behavior) than to those in Column 2 (collusive behavior). For example, the price coefficients for the first type of consumer, the tourist type, are equal to -1.32 in **Column 1** and -1.189 in **Column 3**, but up to -1.674 in **Column 2**. The price coefficient for the business travelers is equal to -0.117 in **Column 3** and equal to -0.126 in **Column 1**. It was estimated equal to -0.223 in **Column 2**.

Now consider the fraction of vacation travelers. This fraction is equal to 68.7 percent in Column 3 and to 67.5 in Column 1, but it is equal to 40.1 percent in Column 2.

The cost estimates in **Column 3** are between those in **Column 2** and **Column 1**. The mean of marginal cost is now equal to \$77, compared to the estimate of \$111 in **Column 1** and \$53.7 in **Column 3**. This suggests that strict assumptions regarding firm behavior, firms behaving as Bertrand-Nash competitors or as a fully-collusive cartel, leads to biased estimates of marginal cost. The intuition for marginal costs now being lower than in **Column 1** is 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.

Consider now the estimates for ϕ_1 and ϕ_2 which shift the conduct parameters. We estimate ϕ_1 equal to -3.145 and ϕ_2 equal to 6.006. **Figure 2** plots the conduct parameters. From **Figure 2** 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 5 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 5** 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 5,** we find that the conduct parameter is equal to 0.880, 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 5** shows that the conduct parameter is equal to 0.067, 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 much 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 ($f(mmc) = 0.398$) 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.[29]

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 3** 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 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 3**. 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 multi-market 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

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

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 4**. The bottom half of **Figure 4** 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 4**, 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 4** are exactly as one would expect given the shape of **Figure 2**. 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 4** 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 5** 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.

6 Conclusion

In this paper, we build on Nevo [1998] to develop a new methodological approach 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. Frontier and Delta) do not cooperate in setting fares, while 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 (Delta and Northwest) and proposed (Continental and United) mergers between legacy carriers should have little consequence for market power while potentially introducing significant cost efficiencies.[30]

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, while one might be interested in learning how the firms get to agree to tacitly collude.[31] This would require that we model the strategic interaction between firms as a dynamic game, which is clearly beyond the scope of this paper.

[30] See Brueckner and Spiller [1994] for a discussion of economies of density.

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

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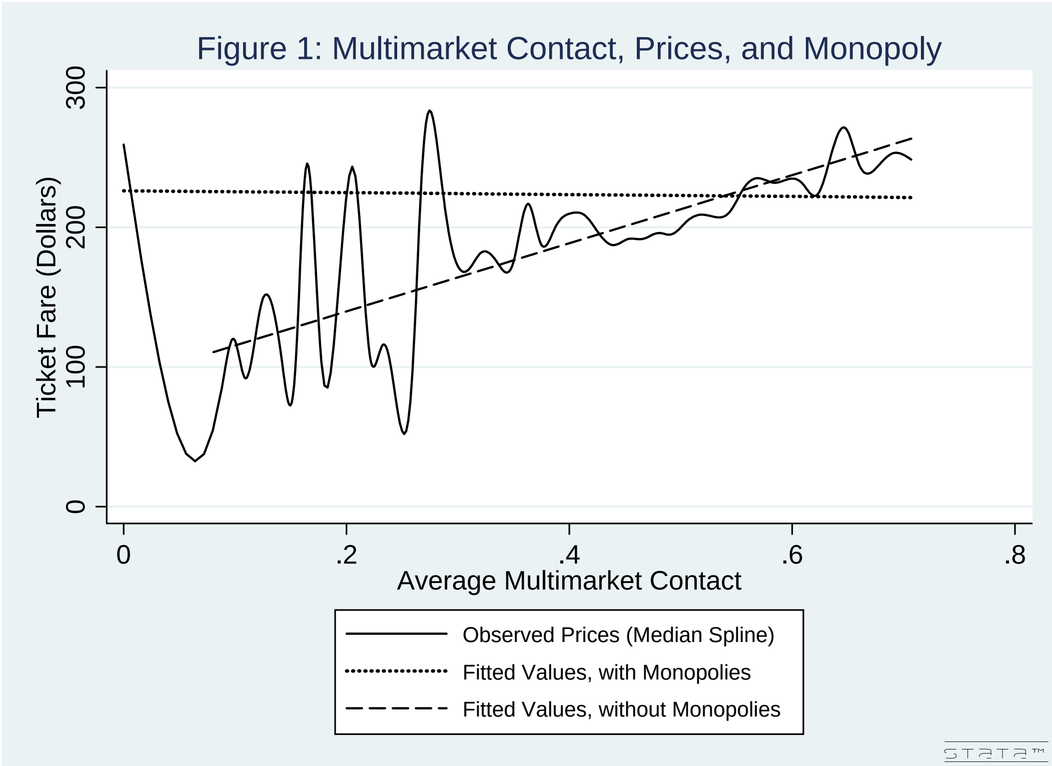
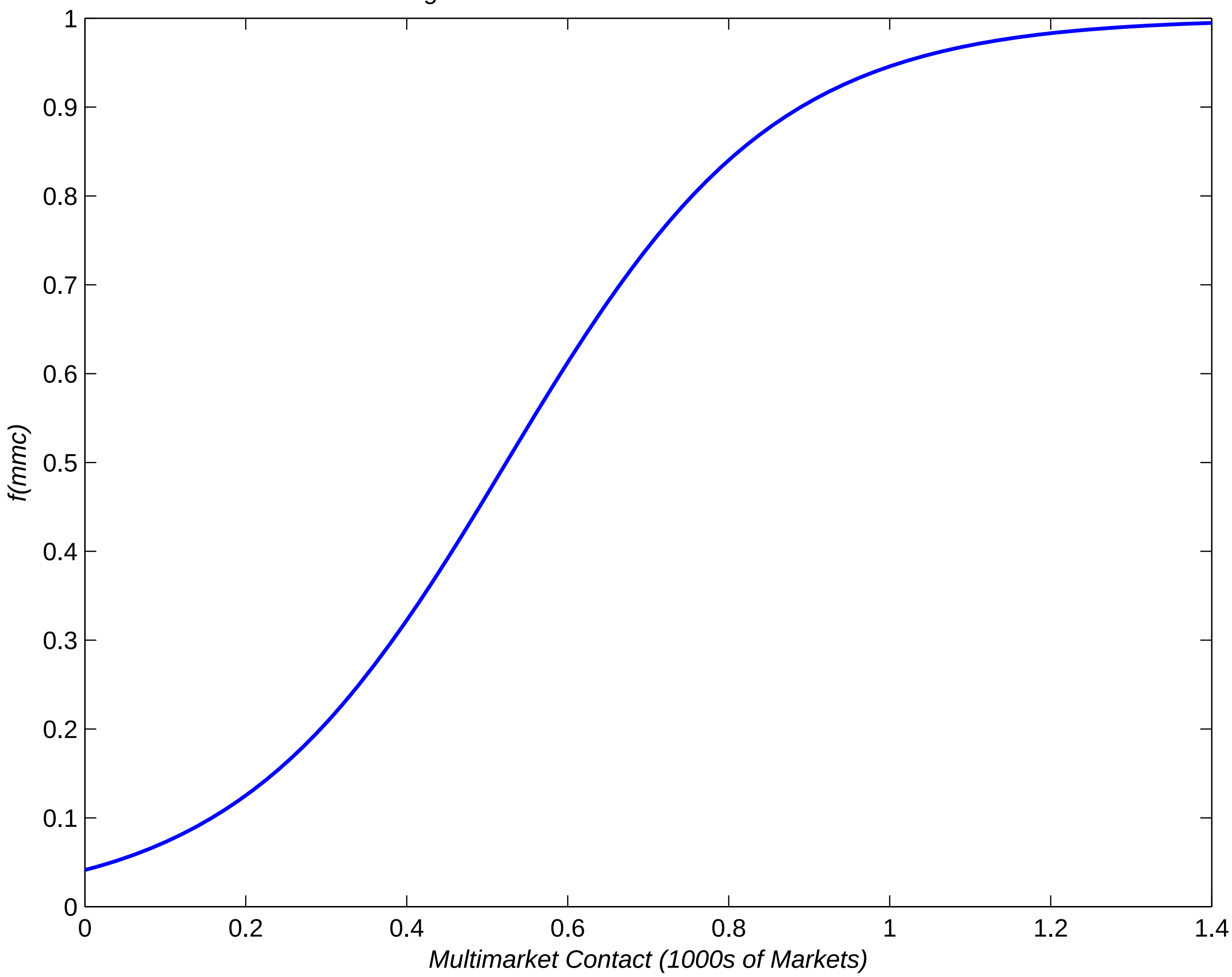


Figure 1: Multimarket Contact, Prices, and Monopoly
Ticket Fare (Dollars)
0
100
200
300
0
.2
.4
.6
.8
Average Multimarket Contact
Observed Prices (Median Spline)
Fitted Values, with Monopolies
Fitted Values, without Monopolies

Figure 2: Collusion and Multimarket Contact



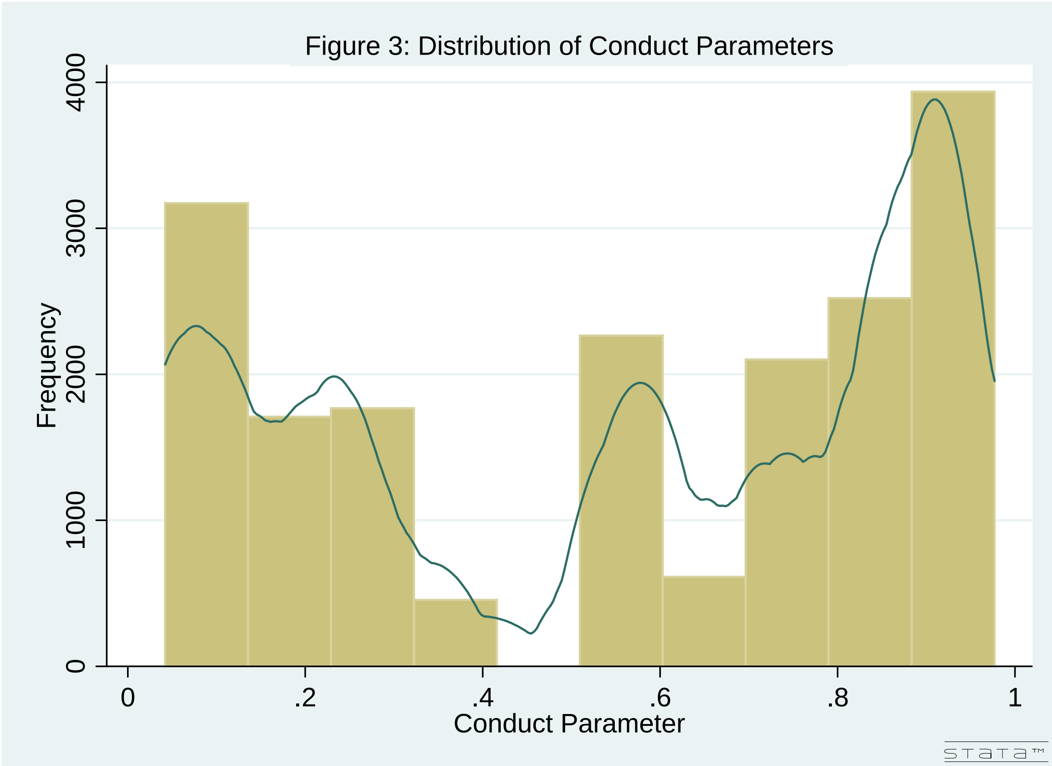


Figure 3: Distribution of Conduct Parameters
Frequency
0
1000
2000
3000
4000
0
.2
.4
.6
.8
1
Conduct Parameter
stata™

Figure 4: Multimarket Contact and Prices

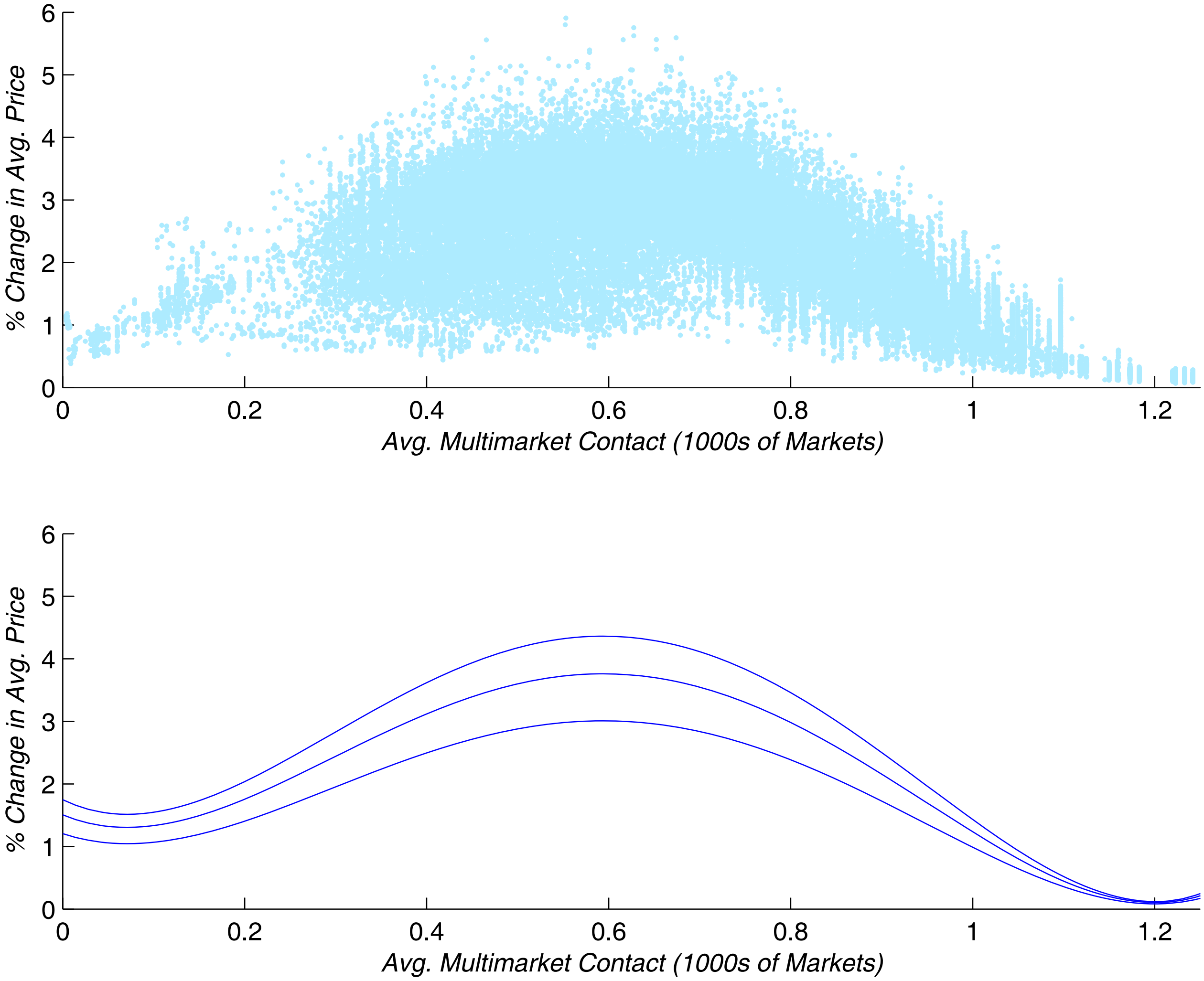


Figure 5: Cross-Price Elasticities, Multimarket Contact, and Prices

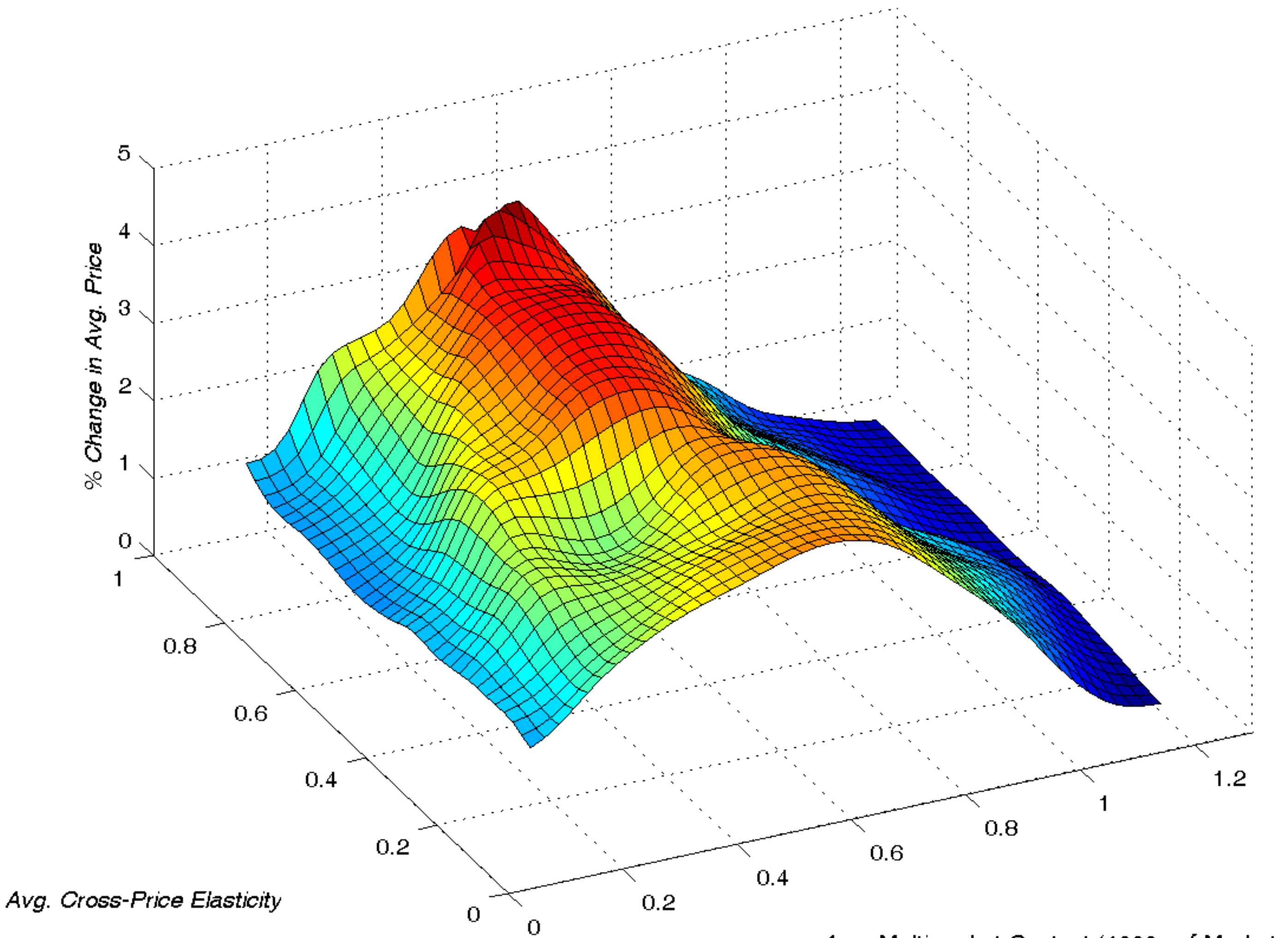


Table 1: Number of Common Markets in 2007-Q1

	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	295674	0.443	0.470	0.174
ExtraMiles	DB1B	Average Distance Flown Between Market Endpoints (equals Distance for Nonstop Service)	268119	1258.628	1121.000	625.219
Average_MMC	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
Common_avg	Survey	Common Mean % Gates at Market Endpoints	268119	0.270	0.226	0.178
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

Table 3: Prices and Multimarket Contact

	Top 1000 Markets		All Markets			
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Average_MMC	0.246***	0.291***	-0.017***	0.054***	0.520***	0.667***
	(0.030)	(0.029)	(0.002)	(0.004)	(0.009)	(0.016)
Hub		0.208***	0.190***	0.191***	0.177***	0.194***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
NetworkSize	0.630***	0.314***	0.224***	0.226***	0.496***	0.207***
	(0.013)	(0.013)	(0.005)	(0.006)	(0.007)	(0.006)
Nonstop	-0.054***	-0.065***	-0.032***	-0.032***	-0.054***	-0.033***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
RoundTrip	-0.548***	-0.576***	-0.533***	-0.539***	-0.443***	-0.548***
	(0.006)	(0.006)	(0.003)	(0.003)	0.004)	(0.004)
HHI	0.014					
	(0.011)					
MktShare	0.063***					
	(0.005)					
Log(Distance)					-1.240***	-0.438***
					(0.024)	(0.058)
Log^2(Distance)					0.105***	0.049***
					0.002	(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	0.167	0.223	0.143	0.171	0.241	0.350
Observations	85,920	85,920	268,119	252,284	268,119	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: BCS Estimation

	(1)		(2)		(3)	
	BCS - No Collusion		**BCS - Full Collusion**		**BCS - CV**	
Demand	estimate	std. error	estimate	std. error	estimate	std. error
$Price_1$	-1.32***	0.017	-1.674***	0.016	-1.189***	0.022
$Price_2$	-0.126***	0.003	-0.223***	0.003	-0.117***	0.004
κ_1 (fraction type 1 consumers)	0.675***	0.337	0.401***	0.204	0.687**	0.417
$Constant_1$	-5.692***	0.526	-4.861***	0.328	-5.954***	0.679
$Constant_2$	-7.626***	1.019	-7.59***	0.618	-7.596***	1.155
$Nonstop_1$	1.194***	0.007	1.119***	0.008	1.144***	0.008
$Nonstop_2$	0.931***	0.009	1.074***	0.009	1.034***	0.009
λ (nesting parameter)	0.571***	0.002	0.540***	0.002	0.564***	0.003
Network Size	0.600***	0.018	0.419***	0.018	0.542***	0.018
Distance	1.93***	0.032	1.814***	0.032	1.848***	0.032
$Distance^2$	-0.482***	0.029	-0.481***	0.011	-0.476***	0.011
Extra-miles	-0.867***	0.029	-0.696***	0.029	-0.775***	0.029
$Extra\text{-}miles^2$	0.131***	0.009	0.107***	0.009	0.115***	0.009
Supply						
Constant	0.869***	0.005	0.502***	0.005	0.549***	0.003
Distance	0.257***	0.013	0.171***	0.013	0.383***	0.008
$Distance^2$	-0.01***	0.005	-0.047***	0.005	-0.072***	0.003
Extra-miles	0.073***	0.013	-0.063***	0.013	-0.063***	0.008
$Extra\text{-}miles^2$	-0.039***	0.004	0.009***	0.005	0.006***	0.003
Contact						
Constant					-3.145***	0.295
MMC					6.006***	2.989
Model Fit						
Median Marginal Cost	1.111		0.537		0.778	
Median Elasticity	-3.042		-2.746		-2.813	
Median Elasticity - Type1	-4.306		-5.701		-3.922	
Medoam Elasticity - Type2	-0.415		-0.763		-0.389	
Function Value	28785.805		27402.381		27176.777	

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: Price Coordination in 2007-Q1

	AA	AS	B6	CO	DL	F9	FL	G4	NK	NW	SY	TZ	U5	UA	US	WN	YX
AA	•	0.047	0.067	0.723	0.880	0.080	0.182	0.043	0.044	0.726	0.044	0.049	0.042	0.855	0.582	0.248	0.081
AS	0.047	•	0.042	0.044	0.050	0.044	0.042	0.041	0.041	0.046	0.041	0.042	0.041	0.055	0.049	0.043	0.042
B6	0.067	0.042	•	0.071	0.087	0.042	0.057	0.041	0.043	0.066	0.041	0.041	0.042	0.083	0.084	0.052	0.042
CO	0.723	0.044	0.071	•	0.779	0.068	0.157	0.042	0.044	0.547	0.042	0.047	0.043	0.572	0.553	0.221	0.067
DL	0.880	0.050	0.087	0.779	•	0.079	0.398	0.042	0.046	0.909	0.043	0.048	0.044	0.948	0.977	0.303	0.079
F9	0.080	0.044	0.042	0.068	0.079	•	0.052	0.041	0.042	0.068	0.042	0.043	0.041	0.091	0.079	0.062	0.046
FL	0.182	0.042	0.057	0.157	0.398	0.052	•	0.041	0.044	0.213	0.042	0.046	0.042	0.197	0.307	0.075	0.056
G4	0.043	0.041	0.041	0.042	0.042	0.041	0.041	•	0.041	0.042	0.042	0.041	0.041	0.044	0.042	0.041	0.042
NK	0.044	0.041	0.043	0.044	0.046	0.042	0.044	0.041	•	0.044	0.041	0.042	0.042	0.045	0.046	0.043	0.042
NW	0.726	0.046	0.066	0.547	0.909	0.068	0.213	0.042	0.044	•	0.045	0.048	0.043	0.890	0.630	0.190	0.106
SY	0.044	0.041	0.041	0.042	0.043	0.042	0.042	0.042	0.041	0.045	•	0.041	0.041	0.044	0.043	0.041	0.042
TZ	0.049	0.042	0.041	0.047	0.048	0.043	0.046	0.041	0.042	0.048	0.041	•	0.041	0.049	0.047	0.048	0.044
U5	0.042	0.041	0.042	0.043	0.044	0.041	0.042	0.041	0.042	0.043	0.041	0.041	•	0.042	0.044	0.043	0.041
UA	0.855	0.055	0.083	0.572	0.948	0.091	0.197	0.044	0.045	0.890	0.044	0.049	0.042	•	0.875	0.237	0.101
US	0.582	0.049	0.084	0.553	0.977	0.079	0.307	0.042	0.046	0.630	0.043	0.047	0.044	0.875	•	0.235	0.063
WN	0.248	0.043	0.052	0.221	0.303	0.062	0.075	0.041	0.043	0.190	0.041	0.048	0.043	0.237	0.235	•	0.052
YX	0.081	0.042	0.042	0.067	0.079	0.046	0.056	0.042	0.042	0.106	0.042	0.044	0.041	0.101	0.063	0.052	•