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# Collusive pricing patterns in the US airline industry☆

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ABSTRACT

We formulate two empirical tests for collusive behavior based on the theoretical insights of Werden and Froeb (1994) and Athey, Bagwell, and Sanchirico (2004). The first predicts that colluding firms will reduce pair-wise differences in prices within a market if demand satisfies certain properties. The second predicts that colluding firms will sacrifice efficiency in production by increasing price rigidity to avoid informational costs. Using panel data from the US airline industry and fixed-effects estimation, we find that greater multimarket contact between carriers leads to pricing patterns consistent with both theoretical predictions, while code-share agreements are consistent with the second prediction.

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## 1. Introduction

Detecting collusion is a central theme of research in empirical industrial organization (Jacquemin and Slade, 1989; Porter, 2005; Harrington, 2008). Collusion can lead oligopolistic firms to achieve monopolistic outcomes, leading to reduced and inefficient equilibrium output, higher prices, and lower consumer welfare.[1] In the US, collusion is prohibited under the Sherman Act. Under Section 1 of the Sherman Act, any cartel or cartel-like behavior is “per se” illegal. Tacit collusion is instead evaluated under the rule of reason. Under this standard, the behavior is illegal only if it results in an unreasonable restraint on trade.[2]

Previous empirical work has identified collusive behavior by using variation in costs (Rosse, 1970; Panzar and Rosse, 1987; Baker and Bresnahan, 1988; Weyl, 2009), 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; Salvo, 2010).[3] In this paper, we propose two empirical tests to identify collusive behavior. We then use panel data from the US airline industry to test whether multimarket contact and code-share agreements are associated with the collusive pricing patterns predicted by the theory underlying the tests.

The idea that relates collusion to multimarket contact originates in Bernheim and Whinston (1990): multimarket contact between firms serves to pool the incentive constraints from all the markets served. 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, which makes collusion easier to sustain. If, for example, two firms interact in many markets, they know that if they deviate from collusive behavior in one market, they will be punished by the other firm in all the markets where they interact. Evans and Kessides (1994) were the first to empirically test this hypothesis using data from the US airline industry, an ideal setting given the relatively small number of airlines that interact in a large number of markets. Like many studies that followed this seminal work, Evans and Kessides (1994) find that average prices in a market increase with the degree of multimarket contact among firms.

Like multimarket contact, government regulators have expressed concern that code-share agreements may facilitate collusion (US Department of Transportation, 2003). These agreements allow each airline to sell seats on a partner’s aircraft as if it were effectively their own. To make such an agreement operational requires substantial communication and coordination that could facilitate explicit or tacit collusion among the partner airlines. To date, there is only limited empirical analysis to support this

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

[2] Probably the most famous instance when the antitrust agencies detected 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] See Hendricks and Porter (1989) for a survey of the literature on the detection of collusion in auctions.

hypothesis. Gayle (2008) studies the Delta-Continental-Northwest code-share agreement but does not find evidence that average prices rise as a result of the agreement.

In the spirit of the methods for distinguishing collusion from competition discussed in Harrington (2008), the two tests we propose focus on more nuanced pricing patterns that can result from collusive behavior. Specifically, the tests examine whether the presence of a potential facilitator of collusion (i.e., greater multimarket contact or a code-share agreement) is associated with smaller price differences between pairs of firms in a market and less variable prices in a market over time, respectively.

The first test is based on the theoretical insight of Werden and Froeb (1994) that mergers will alter the *difference* between prices in a market with differentiated products in particular ways. Specifically, for logistic demand, pair-wise differences between products' prices decrease with the degree that firms internalize the effect of a price change on the profit of competitors (i.e., merge or collude). We show that this pricing pattern associated with collusion extends to other demand models commonly used in academic studies and antitrust enforcement, including variations of the logit model that relax the independence from irrelevant alternatives (IIA) property and linear demand systems. Therefore, if greater multimarket contact between a pair of firms facilitates collusion, one should observe that pair-wise differences in prices decrease in multimarket contact. Similarly, if code-share agreements facilitate collusion, pair-wise differences in prices between partner airlines should be smaller.

The second test is based on the theory developed in Athey et al. (2004), which predicts colluding firms will sacrifice efficiency in production by increasing fare rigidity to avoid informational costs associated with enforcement of a collusive agreement. Specifically, to avoid costly monitoring or price wars, firms' prices cannot respond to firm-specific shocks, resulting in a misallocation of production across firms. Similar to the Werden and Froeb (1994) test, if multimarket contact facilitates collusion between firms, one should observe a reduction in the variation in two products' prices as multimarket contact increases. Similarly, code-share agreements should result in less variable prices over time in a market if the extensive cooperation to operationalize the agreement facilitates collusion.

To conduct the empirical analysis, we use data from the Airline Origin and Destination Survey (DB1B) from 1993–2016. The DB1B is a 10% sample of domestic itineraries, which includes information on the fare paid, connections made, and ticketing carrier. We complement this data with information on code-share agreements from Ciliberto et al. (2018). We organize the data so that the fundamental unit of observation is a pair of airlines in a market. Next, we compute pair-wise measures of the differences in average fares, variability in fares (i.e., coefficient of variation), and multi-market contact. We also create an indicator for whether a code-share agreement exists between pairs of carriers. To ensure the robustness of our results, we consider a variety of controls and fixed effects, and also alternative measures of multimarket contact.

In our baseline analysis, the measure of multimarket contact equals the total number of markets that a pair of airlines serve concomitantly in a given period (i.e., year-quarter). For example, if American and Delta serve 200 markets in common, then this variable is equal to 200 for the American-Delta pair. This is consistent with Ciliberto and Williams (2014), which uses pair-wise counts of markets. It is also similar to studies that aggregate the pair-wise measures to construct market-specific measures of average multimarket contact (e.g., Evans and Kessides, 1994). In addition, we explore alternatives like revenue-weighted measures of multimarket contact that account for the relative importance of certain markets for carriers.

Our analysis consists of two sets of regressions, corresponding to the testable theoretical predictions from Werden and Froeb (1994) and Athey et al. (2004). To test the first, we run the differences in pair-specific prices on the corresponding pair-specific measure of multimarket contact and code-share agreement indicator, for which the unit of observation is the market-year-quarter-carrier pair. To test the second, we use a market-carrier pair unit of observation and regress the coefficient of variation of fares over time on the mean of pair-specific multimarket contact and code-share agreement indicators. For both tests, we include a variety of fixed-effects and time-varying market-level controls.

Regarding multimarket contact, we find the theoretical predictions of both Werden and Froeb (1994) and Athey et al. (2004) are consistent with our data. An increase in pairwise multimarket contact is associated with an economically and statistically significant decrease in the difference between fares and the variability of fares. These results are consistent across all specifications for both tests. We also find evidence that code-share agreements are associated with economically and statistically significant reduction in the variability of fares but no effect on the difference between fares. Taken together, the results provide evidence of collusion among airlines with high levels of multimarket contact, and some support for the hypothesis that code-share agreements may facilitate collusion.

Our findings generally support the recent antitrust efforts by the US Department of Justice (DOJ) to investigate the competitive conduct of airlines,[4] and class-action lawsuits against US carriers alleging that carriers coordinated to restrict capacity and raise prices.[5] Also, the empirical analysis provides a framework for future analyses of industries where a facilitator of collusion, like multimarket contact or code-share agreements, can be identified and data are available to study its relationship with price.

Our work contributes most directly to two literatures. First, we contribute to the empirical literature on collusive behavior in the airline industry, which is fairly sparse, especially when compared to the literature on acquisitions and mergers. Brander and Zhang (1990) estimate a structural model of competition among US airlines that includes a conduct parameter. They find that the cross-sectional data from the 1985 US airline industry are more consistent with a Cournot than either a competitive or cartel model. Brander and Zhang (1993) extend their analysis to a dynamic setting and reach similar conclusions.

[4] See https://www.wsj.com/articles/justice-department-probes-airlines-for-collusion-1435775547.
[5] See http://fortune.com/2018/01/04/southwest-airlines-price-collusion-settlement/.

More recently, Miller (2010) investigates the effects of the Department of Justice's lawsuit against eight major domestic airlines and the Airline Tariff Publishing Company to see how prices and output choices change in response to the investigation. Miller (2010) finds that average prices fell in response to the investigation but increased following the settlement, implying that the airlines likely returned to their collusive behavior after the settlement. Zhang and Round (2011) investigate price wars and collusion in China's airline markets, and find that both tend to occur but are short-lived. Brueckner and Picard (2013) investigate, theoretically, whether antitrust immunity among international airlines facilitates collusive behavior, and demonstrate the dependence of the results on the demand specification and economies of density. Following the DOJ's recent investigation into airlines' conduct, Aryal et al. (2017) examine whether airlines use earnings announcements to coordinate capacity reductions in an effort to increase fares.

Second, we contribute to the growing literature that studies the impact of multimarket contact on the strategic decisions of firms. Feinberg (1985) represents an early empirical study of the role of multimarket contact in sustaining supra-competitive prices, while Feinberg (1985) provides supporting experimental evidence. After these two early studies and the theoretical formalization of the idea in Bernheim and Whinston (1990), numerous empirical studies of the relationship between multimarket contact and collusion followed. In the airline industry, Evans and Kessides (1994); Singal (1996); Bilotkach (2011), and Ciliberto and Williams (2014) represent contributions to this literature. These studies focus on average prices, not the more nuanced pricing patterns in our tests, and Ciliberto and Williams (2014) is the only one to examine pair-wise multimarket contact. Related studies in other industries include cement (Jans and Rosenbaum, 1997), mobile telephones (Parker and Roller, 1997; Busse, 2000), banking (Pilloff, 1999), hotels (Fernandez and Marin, 1998), and radio (Waldfogel and Wulf, 2006).

The remainder of the paper is organized as follows. The data are described in Section 2. Section 3 develops the empirical tests, and presents and discusses the results. Section 4 concludes and discusses possible extensions of our research.

## 2. Data

We use data from the 1993–2016 Airline Origin and Destination Survey (DB1B), which is a 10% sample of domestic tickets. The DB1B contains information on the complete itinerary (origin, destination, and any connecting airports) and fare paid by all passengers in the sample. Following other studies of the industry, those passengers with exceedingly high (likely keypunch errors) and low (likely frequent-flier tickets) fares are removed from the sample.[6] We also remove passengers associated with a carrier in a market that does not represent a competitive presence in that market.[7] We make further restrictions to

[6] Fares greater than $2500 or less than $25 are removed from the sample.

[7] Like Berry (1992), we remove passengers associated with a carrier that transports fewer than 100 passengers in a market during a quarter. This corresponds to dropping those carriers transporting fewer than 10 passengers in the DB1B's sample of itineraries.

the data to include only routes with a significant impact on an airline's profit.[8] Like Borenstein (1989) and Evans and Kessides (1994), we treat roundtrip tickets as two one-way tickets and divide the fare by two. We deflate all fares by the consumer price index to be in 2016 dollars.[9]

We define a market as a *unidirectional* trip between two airports regardless of the number of connections made between origin and destination. Each market is denoted by $m = 1, \ldots, M$. Our sample consists of 4,311 markets. The sample frequency is quarterly, and each year-quarter combination is denoted by $t = 1, \ldots, T$. The sample includes a total of 20 carriers: American (AA), Alaska (AS), JetBlue (B6), Continental (CO), Delta (DL), Frontier (F9), AirTran (FL), Allegiant (G4), Hawaiian Airlines (HA), American West (HP), Midway Airlines (JI), Spirit (NK), Northwest (NW), Sun Country (SY), Trans World (TW), ATA (TZ), United (UA), USAir (US), Southwest (WN), and Midwest (YX). Some of these carriers enter after 1993, exit before 2016, or are part of a merger, so that they are not present in the entire panel.[10]

We use a number of alternative definitions for multimarket contact in our analysis to ensure the robustness of our results. Our baseline, like Evans and Kessides (1994), defines multimarket contact to equal the number of markets that two distinct carriers, $h$ and $k$, concomitantly serve at time $t$. We refer to this variable as $MMC^{EK}_{hk,t}$. For each quarter we construct a matrix of these pair-specific variables. Table 1 shows the lower-triangular portion of the (symmetric) matrix of this multimarket measure for the 16 carriers active in our sample during the third quarter of 2008. For example, in the third quarter of 2008, American and Delta concomitantly served 1,598 markets; therefore $MMC^{EK}_{hk,t}$ equals 1,598. Notice that this definition ensures symmetry, such that $MMC^{EK}_{hk,t} = MMC^{EK}_{kh,t}$.

We also consider another measure of multimarket contact, which we refer to as $MMC^{CW}_{h\to k,t}$. This measure is equal to $MMC^{EK}_{hk,t}$ divided by the total number of markets served by firm $h$ (the first one in the pair). Continuing on the example above, $MMC^{CW}_{AA\to DL,t}$ equals 0.726 and $MMC^{CW}_{DL\to AA,t}$ equals 0.535. $MMC^{CW}_{h\to k,t}$ is asymmetric for any pair of airlines that each serve a different number of markets, and is larger for the firm that serves fewer markets. Thus, it captures the idea that the smaller carrier is at risk of losing relatively more by deviating from the collusive agreement than the larger carrier. Similar to Evans and Kessides (1994) and Ciliberto and Williams (2014), we also consider a revenue-weighted version of the $MMC^{CW}_{h\to k,t}$ measure, which weights each market's relative importance to the carrier in terms of revenue (i.e., fraction of revenue across the carrier's network that a particular market generates). Table 2 provides

[8] We drop all markets in which an airline serves fewer than 1000 passengers per quarter on average and carriers that serve less than 10% of all passengers on a route in a quarter. This amounts to dropping routes that consistently carry few passengers over the sample and carriers that do not represent a significant competitive presence in a market.

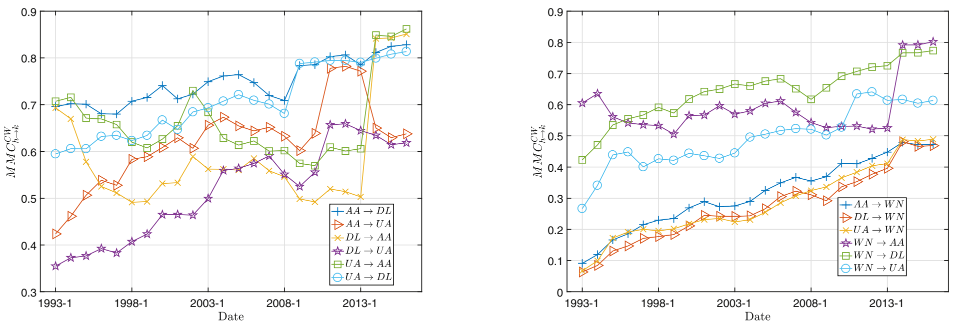
[9] Data on the consumer price index were accessed through the Bureau of Labor Statistics' website at http://www.bls.gov/cpi/#tables.

[10] To construct our sample for merging carriers, we explore alternative definitions for when the merger became effective (i.e., in advance of final approval) and find nearly identical results.

**Table 1**
Pair-wise number of common markets ($MMC^{EK}_{hk,t}$) in 2008-Q3.

| | AA | AS | B6 | CO | DL | F9 | FL | G4 | HA | NK | NW | SY | UA | US | WN | YX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AA** | 2202 | | | | | | | | | | | | | | | |
| **AS** | 56 | 258 | | | | | | | | | | | | | | |
| **B6** | 96 | 6 | 242 | | | | | | | | | | | | | |
| **CO** | 1124 | 29 | 113 | 1589 | | | | | | | | | | | | |
| **DL** | 1598 | 131 | 201 | 1235 | 2989 | | | | | | | | | | | |
| **F9** | 253 | 29 | 0 | 153 | 280 | 404 | | | | | | | | | | |
| **FL** | 357 | 2 | 75 | 250 | 675 | 43 | 706 | | | | | | | | | |
| **G4** | 9 | 6 | 0 | 5 | 18 | 5 | 0 | 87 | | | | | | | | |
| **HA** | 17 | 6 | 0 | 1 | 16 | 0 | 0 | 0 | 52 | | | | | | | |
| **NK** | 34 | 0 | 10 | 13 | 50 | 3 | 21 | 0 | 0 | 66 | | | | | | |
| **NW** | 994 | 46 | 61 | 750 | 1336 | 195 | 302 | 10 | 12 | 11 | 1665 | | | | | |
| **SY** | 7 | 1 | 0 | 0 | 12 | 2 | 2 | 0 | 0 | 0 | 12 | 13 | | | | |
| **UA** | 1375 | 137 | 139 | 1011 | 1637 | 356 | 299 | 24 | 37 | 17 | 1104 | 5 | 2264 | | | |
| **US** | 1062 | 64 | 158 | 937 | 1853 | 203 | 476 | 12 | 9 | 36 | 854 | 6 | 1276 | 2297 | | |
| **WN** | 795 | 65 | 46 | 657 | 882 | 193 | 160 | 0 | 0 | 10 | 490 | 0 | 752 | 734 | 1434 | |
| **YX** | 105 | 0 | 0 | 51 | 102 | 12 | 31 | 2 | 0 | 0 | 135 | 0 | 112 | 24 | 21 | 146 |

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




(a) Legacy-Legacy Pairs (b) Legacy-Southwest Pairs

**Fig. 1.** Figure 1(a) presents variation in the $MMC^{CW}_{h\to k}$ measure of multimarket contact between legacy carriers that are present during the entire panel. Figure 1(b) presents variation in the $MMC^{CW}_{h\to k}$ measure of multimarket contact between Southwest and those legacy carriers that are present during the entire panel.

the complete matrix describing the cross-sectional variation in $MMC^{CW}_{h\to k,t}$ in the third quarter of 2008.[11]

Fig. 1 provides additional detail on the variation in multimarket contact between a subset of the carriers during our sample. Specifically, Fig. 1(a) presents the time series of the $MMC^{CW}_{h\to k}$ measure of multimarket contact for those legacy carriers that were present during the entirety of our sample (i.e., American Airlines, Delta Airlines, and United Airlines). The time-series variation for the pairs of legacy carriers highlights the many

[11] We provide the analogous matrices to Tables 1 and 2 for the third quarter of 1998 in the Appendix.

**Table 2**
Pair-wise fraction of common markets ($MMC^{CW}_{h\to k,t}$) in 2008-Q3.

| | AA | AS | B6 | CO | DL | F9 | FL | G4 | HA | NK | NW | SY | UA | US | WN | YX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AA** | 1 | 0.025 | 0.044 | 0.510 | 0.726 | 0.115 | 0.162 | 0.004 | 0.008 | 0.015 | 0.451 | 0.003 | 0.624 | 0.482 | 0.361 | 0.048 |
| **AS** | 0.217 | 1 | 0.023 | 0.112 | 0.508 | 0.112 | 0.008 | 0.023 | 0.023 | 0 | 0.178 | 0.004 | 0.531 | 0.248 | 0.252 | 0 |
| **B6** | 0.397 | 0.025 | 1 | 0.467 | 0.831 | 0.004 | 0.310 | 0 | 0 | 0.041 | 0.252 | 0 | 0.574 | 0.653 | 0.190 | 0 |
| **CO** | 0.707 | 0.018 | 0.071 | 1 | 0.777 | 0.096 | 0.157 | 0.003 | 0.001 | 0.008 | 0.472 | 0 | 0.636 | 0.590 | 0.413 | 0.032 |
| **DL** | 0.535 | 0.044 | 0.067 | 0.413 | 1 | 0.094 | 0.226 | 0.006 | 0.005 | 0.017 | 0.447 | 0.004 | 0.548 | 0.620 | 0.295 | 0.034 |
| **F9** | 0.626 | 0.072 | 0 | 0.379 | 0.693 | 1 | 0.106 | 0.012 | 0 | 0.007 | 0.483 | 0.005 | 0.881 | 0.502 | 0.478 | 0.030 |
| **FL** | 0.506 | 0.003 | 0.106 | 0.354 | 0.956 | 0.061 | 1 | 0 | 0 | 0.030 | 0.428 | 0.003 | 0.424 | 0.674 | 0.227 | 0.044 |
| **G4** | 0.103 | 0.069 | 0 | 0.057 | 0.207 | 0.057 | 0 | 1 | 0 | 0 | 0.115 | 0 | 0.276 | 0.138 | 0 | 0.023 |
| **HA** | 0.327 | 0.115 | 0 | 0.019 | 0.308 | 0 | 0 | 0 | 1 | 0 | 0.231 | 0 | 0.712 | 0.173 | 0 | 0 |
| **NK** | 0.515 | 0 | 0.152 | 0.197 | 0.758 | 0.045 | 0.318 | 0 | 0 | 1 | 0.167 | 0 | 0.258 | 0.545 | 0.152 | 0 |
| **NW** | 0.597 | 0.028 | 0.037 | 0.450 | 0.802 | 0.117 | 0.181 | 0.006 | 0.007 | 0.007 | 1 | 0.007 | 0.663 | 0.513 | 0.294 | 0.081 |
| **SY** | 0.538 | 0.077 | 0 | 0 | 0.923 | 0.154 | 0.154 | 0 | 0 | 0 | 0.923 | 1 | 0.385 | 0.462 | 0 | 0 |
| **UA** | 0.607 | 0.061 | 0.061 | 0.447 | 0.723 | 0.157 | 0.132 | 0.011 | 0.016 | 0.008 | 0.488 | 0.002 | 1 | 0.564 | 0.332 | 0.049 |
| **US** | 0.462 | 0.028 | 0.069 | 0.408 | 0.807 | 0.088 | 0.207 | 0.005 | 0.004 | 0.016 | 0.372 | 0.003 | 0.556 | 1 | 0.320 | 0.010 |
| **WN** | 0.554 | 0.045 | 0.032 | 0.458 | 0.615 | 0.135 | 0.112 | 0 | 0 | 0.007 | 0.342 | 0 | 0.524 | 0.512 | 1 | 0.015 |
| **YX** | 0.719 | 0 | 0 | 0.349 | 0.699 | 0.082 | 0.212 | 0.014 | 0 | 0 | 0.925 | 0 | 0.767 | 0.164 | 0.144 | 1 |

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

**Table 3**
Descriptive statistics for faresand MMC.

| | # Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *Market-Year-Quarter-Carrier Sample* | | | | | |
| Mean Price | 2,756,657 | 263.66 | 93.77 | 22.79 | 1,149.58 |
| Carrier Passengers | 2,756,657 | 2,799.07 | 7,475.93 | 100 | 203,580 |
| Passenger Share | 2,756,657 | 0.307 | 0.280 | 0.0004 | 1 |
| HHI | 2,756,657 | 0.467 | 0.213 | 0.106 | 1 |
| LCC Indicator | 2,756,657 | 0.227 | 0.419 | 0 | 1 |
| *Pair-wise Price Difference Sample (WF)* | | | | | |
| $\Delta p$ | 8,331,134 | 50.775 | 48.837 | 0 | 848.193 |
| $\mathbb{1}^{code-share}$ | 8,331,134 | 0.076 | 0.265 | 0 | 1 |
| $MMC^{EK}$ | 8,331,134 | 0.99 | 0.63 | 0.001 | 2.99 |
| $MMC^{CW}$ | 8,331,134 | 0.51 | 0.22 | 0.0003 | 1 |
| *Pair-wise Coefficient of Variation Sample (ABS)* | | | | | |
| $CV$ | 249,340 | 0.151 | 0.068 | 0 | 0.694 |
| $\mathbb{1}^{code-share}$ | 249,340 | 0.083 | 0.276 | 0 | 1 |
| $MMC^{EK}$ | 249,340 | 0.868 | 0.651 | 0.001 | 2.989 |
| $MMC^{CW}$ | 249,340 | 0.478 | 0.24 | 0.0004 | 1 |

*Note:* Price and passenger statistics are calculated using a market-year-quarter-carrier unit of observation. Statistics for price differences use a market-year-quarter-carrier pair unit of observation, while those for the coefficient of variation use a market-carrier pair unit of observation. To keep the measures of multimarket contact similar in scale, we divide $MMC^{EK}_{hk,t}$ by 1000.

sources of variation present in the data: expansion of networks, large-scale de-hubbing, bankruptcies, and mergers. In Fig. 1(b), we present the same measure of multimarket contact but for Southwest and the same three legacy carriers. This graph highlights the asymmetry in $MMC^{CW}_{h\to k}$. In particular, the legacy carriers have always had a meaningful presence across most of Southwest's network but only now does Southwest have a similar geographic breadth to its network after two decades of expansion and acquisitions.

Following the standard approach in the airline literature, we aggregate the information from the DB1B database, which is at the individual ticket level, to have one price for each combination of market-carrier-year-quarter. If a carrier offers both nonstop and connecting service in a market, we calculate the fare for the carrier in that market as the weighted average across the two types of services. For comparison to the literature and to demonstrate the representativeness of our sample, the first panel of Table 3 summarizes the average fare at this unit of observation. The average fare equals $264 over the sample of 2,756,657 market-year-quarter-carrier observations. We also provide descriptives for the total number of passengers, passenger shares, Herfindahl-Hirschman Index (HHI), and an indicator for whether a low-cost carrier (LCC) is present in the market.

From this market-year-quarter-carrier sample, we construct a pair-wise sample for which the unit of observation is the market-year-quarter-carrier pair. We use this sample to empirically test the predictions from Werden and Froeb (1994). Descriptive statistics for this sample of 8,331,134 carrier pairs (across markets and time) are presented in the second panel of Table 3. For example, we calculate the absolute difference in the price for each pair of carriers ($h$ and $k$) in market $m$ at time $t$ as $\Delta p_{hk,mt} = |p_{h,mt} - p_{k,mt}|$. The average absolute difference is approximately \$51. We also summarize an indicator, $\mathbb{1}_{hk,t}^{code-share}$, that equals one if a pair of carriers in a given market have a code-share agreement at time $t$ and zero otherwise. Finally, we summarize the measures of multimarket contact, $MMC_{hk,t}^{EK}$ and $MMC_{h\to k,t}^{CW}$. Due to the symmetry of the $MMC_{hk,t}^{EK}$ measure, in the analysis in Section 3, we drop one of the two carriers in each pair so the effective number of observations is half for regressions using that measure.

In the third panel of Table 3, we provide summary statistics for the sample used to test the predictions from Athey et al. (2004). We construct this sample from the market-year-quarter-carrier sample to have a market-carrier pair unit of observation. In particular, we define the market-specific coefficient of variation as $CV_{hk,m} = \frac{\sigma_{hk,m}}{\mu_{hk,m}}$, where $\sigma_{hk,\ m}$ and $\mu_{hk,\ m}$ are constructed from the average of the fares of carriers $h$ and $k$ in market $m$ over time. 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. $\sigma_{hk,\ m}$ is the standard deviation of this pair-specific average fare in market $m$ over time, while $\mu_{hk,\ m}$ is the mean over time. The dependent variable for our analysis, $\frac{\sigma_{hk,m}}{\mu_{hk,m}}$, is then the coefficient of variation for the pair-specific average over time in market $m$. Like Abrantes-Metz et al. (2006), we use the coefficient of variation because markets with higher average fares may also have a higher standard deviation.[12] The average coefficient of variation in our sample of 249,340 market-carrier pair observations equals 0.15. We also provide summary statistics for $\mathbb{1}_{hk,t}^{code-share}$, $MMC_{hk,t}^{EK}$, and $MMC_{h\to k,t}^{CW}$, which we define similarly as the average for each carrier pair over the panel.

## 3. Tests for collusion

To identify facilitators of collusion in the US airline industry we test predictions from two specific models of collusive behavior. Specifically, the theoretical insights of Werden and Froeb (1994) and Athey et al. (2004) provide predictions for how prices should change if firms collude, beyond just an increase in average price.

### 3.1. Price differences

Our first empirical test is based on the theory in Werden and Froeb (1994). Werden and Froeb (1994) make the following key observation: two single-product firms that 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, resulting in more similar prices. This pattern arises because the firm fully internalizes the effect of its price increase on goods it controls, or for goods it refrains from competing against. As Werden and Froeb (1994) point out using a logit model of demand, the firm would

[12] Our results are very similar if we instead use the standard deviation.

rather lose sales from the product with a smaller share than from the product with a larger share, because consumers no longer purchasing the smaller-share product will disproportionately substitute towards the larger-share product. In the Appendix, we show that this intuition extends to some other commonly used models of demand that relax the IIA assumption.

This result for merging firms extends in a natural way to a setting in which firms collude. Collusion allows the firms to internalize the effect of their behavior in a manner similar to merging. In the case of perfect collusion, each firm fully internalizes the effect of its behavior on all other firms, as if they were merged. Thus, the difference in prices between products will be smaller when firms collude in comparison to when they compete. If multimarket contact facilitates collusion, one should observe smaller absolute differences in the prices between firms with greater levels of multimarket contact. Similarly, if code-share agreements facilitate collusion, prices differences between partner firms should be smaller.

This intuition is the basis for our first empirical test for collusion, which, when we use the $MMC^{EK}_{hk,t}$ notion of multimarket contact, is a regression of the following form:

$$\log \Delta p_{hk,mt} = \beta_{diff} \cdot \log\left(MMC^{EK}_{hk,t}\right) + \gamma_{diff} \mathbb{1}^{code-share}_{hk,t} + \alpha X_{mt} + \epsilon_{hk,mt}. \qquad (1)$$

We can then test the hypothesis that multimarket contact leads to more collusive behavior if $\beta_{diff} < 0$, and similarly for codeshare agreements if $\gamma_{diff} < 0$. The $X_{mt}$ vector includes controls for time-varying market-specific factors (i.e., HHI and LCC Indicator).

We model the unobservable in the regression as

$$\epsilon_{hk,mt} = u_{hk,m} + u_t + u_{hk,mt}.$$

To control for unobservables specific to a market and carrier pair, we conduct the analysis with either market and carrier-pair fixed effects, or market-carrier pair fixed effects. For example, if firm $h$ is a legacy carrier and $k$ is a low-cost carrier, then the difference in prices is likely to be larger than if $k$ is another legacy carrier, either due to cost heterogeneity or other market-specific factors. Adding these fixed effects makes the comparison across carriers and markets meaningful. Note that by differencing the fares, any market-specific variable that does not change over time, such as the geographical distance between the airports, is already removed. We also include year-quarter fixed effects in each regression to remove unobservable factors of demand and cost that vary across time. These controls result in identifying variation within a market-carrier pair that is not explained by year-quarter aggregate shocks.[13]

[13] Ciliberto and Williams (2014) use information on airlines' access to gates to serve as instruments for multimarket contact. The authors use a cross-section of data for the analysis, and find that fixed-effects estimation attenuates the estimates of the effect of multimarket contact. We do not have access to this data over time, which would be necessary to instrument in our panel. For this reason, our results are likely conservative estimates of the effect of multimarket contact.

**Table 4**
Price differences and potential facilitators of collusion.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Pair-wise covariates* | | | | | | |
| $\log(MMC^{EK})$ | $-0.035^{***}$ | $-0.051^{***}$ | | | | |
| | (0.0059) | (0.0047) | | | | |
| $\log(MMC^{CW})$ | | | $-0.043^{***}$ | $-0.053^{***}$ | | |
| | | | (0.0054) | (0.0042) | | |
| $\log(\text{Rev-Wgt } MMC^{CW})$ | | | | | $-0.018^{***}$ | $-0.028^{***}$ |
| | | | | | (0.0047) | (0.0034) |
| $\mathbb{1}^{code-share}$ | −0.0055 | 0.0016 | −0.0037 | 0.0030 | −0.0052 | 0.0017 |
| | (0.0047) | (0.0051) | (0.0047) | (0.0036) | (0.0048) | (0.0036) |
| *Fixed effects* | | | | | | |
| Market-carrier pair | No | Yes | No | Yes | No | Yes |
| Year-quarter | Yes | Yes | Yes | Yes | Yes | Yes |
| Market | Yes | No | Yes | No | Yes | No |
| Carrier pair | Yes | No | Yes | No | Yes | No |
| *Market-level controls* | | | | | | |
| HHI | Yes | Yes | Yes | Yes | Yes | Yes |
| LCC Indicator | Yes | Yes | Yes | Yes | Yes | Yes |
| *Sample & fit* | | | | | | |
| # Markets | 4,311 | 4,311 | 4,311 | 4,311 | 4,311 | 4,311 |
| # Carrier pairs | 175 | 175 | 175 | 175 | 175 | 175 |
| # Market-carrier pairs | 129,080 | 129,080 | 258,160 | 258,160 | 258,160 | 258,160 |
| # Observations | 4,165,567 | 4,165,567 | 8,331,134 | 8,331,134 | 8,331,134 | 8,331,134 |
| Within $R$-squared | 0.049 | 0.027 | 0.049 | 0.027 | 0.049 | 0.027 |

*Note:* Standard errors in parentheses: $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}p < 0.10$.

Similarly, we estimate the regression that uses the $MMC^{CW}_{h\to k,t}$ notion of multimarket contact:

$$\log \Delta p_{hk,mt} = \beta_{diff} \cdot \log\left(MMC^{CW}_{h\to k,t}\right) + \gamma_{diff}\mathbb{1}^{code-share}_{hk,t} + \alpha X_{mt} + \epsilon_{h\to k,mt}. \tag{2}$$

As above, we test whether multimarket contact (code-share agreements) lead to more collusive behavior, by testing whether $\beta_{diff} < 0$ ($\gamma_{diff} < 0$). However, the unobservables are now denoted by $\epsilon_{h\to k,\, mt}$ because the measure of multimarket contact is no longer symmetric, resulting in twice as many observations. In this regression, the unobservable is modeled as:

$$\epsilon_{h\to k,mt} = u_{h\to k,m} + u_t + u_{h\to k,mt},$$

so that the market-carrier pair fixed effects $u_{h\to k,\, m}$ are directional.

Table 4 presents the results from alternative specifications of Eqs. (1) and (2). In all specifications, we include the full set of market-specific controls, and use robust standard errors clustered at the market level.[14] Across specifications, we vary the fixed effects and measure of multimarket contact.

Column 1 of Table 4 provides a baseline that uses $MMC^{EK}_{hk,t}$ as the measure of multimarket contact and includes market, carrier-pair, and year-quarter fixed effects. We estimate $\beta_{diff}$ equals −0.035 and is statistically significant. This estimate implies that a 10% increase in multimarket contact is associated with a 3.5% decrease in the difference in prices. This is the first piece of evidence that multimarket contact is negatively associated with differences in prices, consistent with the predictions of Werden and Froeb (1994). In the second column, we include market-carrier pair fixed effects rather than market and carrier-pair fixed effects. This results in a slightly larger estimate of 5.1%. For both specifications, we find the coefficient on the code-share indicator to be insignificant.

Columns 3 and 4 of Table 4 present the results from regressions analogous to Columns 1 and 2, respectively, that use the $MMC^{CW}_{h\to k,t}$ measure of multimarket contact. For both specifications, we find results very similar in magnitude to those using the $MMC^{EK}_{hk,t}$ measure. The estimates of the reduction in the difference in fares for a 10% increase in multimarket contact are now 4.3% and 5.3%, respectively. In the last two columns of Table 4, we consider the revenue-weighted version of $MMC^{CW}_{h\to k,t}$. We find results that are smaller in magnitude, but still economically and statistically significant. These specifications predict between a 1.8% and 2.8% reduction in pair-wise differences in fares if multimarket contact increases by 10%. In the four specifications using the $MMC^{CW}_{h\to k,t}$ measures of multimarket contact, we find no significant relationship between pair-wise differences in fares and the code-share indicator.[15]

Collectively, the results in Table 4 show a negative relationship between pair-specific multimarket contact and differences in fares, providing support for the hypothesis that multimarket contact facilitates collusion between airlines.

### *3.2. Price rigidity*

Our second empirical test is based on the theoretical prediction in Athey et al. (2004). The authors demonstrate 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 et al. (2004), such price rigidity is a 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.

[14] Various block-resampling procedures to account for different forms of dependence result in very similar estimates of standard errors that do not change the level of statistical significance for any of the estimates.
[15] To ensure the robustness of our results, we ran a variety of alternative specifications. We find that using different portions of the panel for the analysis or omitting any subset of the market-specific controls does not substantially impact our findings.

The particular price schedule and degree of rigidity predicted by their model can depend on mitigating factors, like the degree to which firms discount the future, but generally colluding firms increase rigidity. The first empirical test for collusion based on the rigidity of prices was in Abrantes-Metz et al. (2006) using data from the retail gasoline industry. The novelty of our test is that it relates rigidity in prices to potential facilitators of collusion, like multimarket contact and code-share agreements.

To test this prediction using the $MMC_{hk}^{EK}$ measure of multimarket contact, we estimate the following regression:

$$\log CV_{hk,m} = \beta_{std} \cdot \log\left(MMC_{hk}^{EK}\right) + \gamma_{std} \cdot \mathbb{1}_{hk}^{code-share} + \alpha X_m + \epsilon_{hk,m}. \tag{3}$$

The regression relates the market-carrier pair coefficient of variation to the mean of multimarket contact and code-share indicator when the pair of carriers served the market. The controls in this regression include market and carrier-pair fixed effects, and the average values of market-specific controls.

Similarly, when using the $MMC_{h\to k}^{CW}$ measure of multimarket contact, we estimate the following regression:

$$\log CV_{hk,m} = \beta_{std} \cdot \log\left(MMC_{h\to k}^{CW}\right) + \gamma_{std} \cdot \mathbb{1}_{hk}^{code-share} + \alpha X_m + \epsilon_{h\to k,m}, \tag{4}$$

where the controls are the same except that the carrier-pair fixed effects are now directional due to the asymmetry in the multimarket contact measure. We also run an analogous regression for the revenue-weighted version of $MMC_{h\to k}^{CW}$.

In Table 5, we present estimates from three different specifications with the same set of controls and fixed effects but different measures of multimarket contact.[16] Column 1 of Table 5 presents the estimate of $\beta_{std}$ when $MMC_{hk}^{EK}$ is the measure of multimarket contact. We estimate that $\beta_{std}$ equals $-0.073$ and is statistically significant, which implies that a 10% increase in multimarket contact is associated with a 7.3% decrease in the market-specific coefficient of variation of prices. Interestingly, we now also find that code-share agreements are associated with less variable fares. The coefficient of variation is about 1.5% lower if a code-share agreement exists between a pair of carriers.

In Column 2 of Table 5, we present the estimates when $MMC_{h\to k}^{CW}$ is the measure of multimarket contact. We estimate a lesser effect, about a 3.5% reduction, but still statistically and economically significant. The results for the revenue-weighted measure of multimarket contact are presented in Column 3. Again, we find a negative relationship between multimarket contact and fare variability that is statistically and economically significant. For these two specifications, we also find a larger estimate of the effect of code-share agreements, 3.2% and 3.4%, respectively.

The results in Table 5 demonstrate a negative relationship between both pair-specific multimarket contact and code-share agreements, and the variability in fares over time in

[16] Unlike the tests of the Werden and Froeb (1994) predictions, we cannot include market-carrier pair fixed effects because there is one observation per carrier pair in each market.

**Table 5**
Price rigidity and potential facilitators of collusion.

| | (1) | (2) | (3) |
|---|---|---|---|
| *Pair-wise Covariates* | | | |
| $\log(MMC^{EK})$ | $-0.073^{***}$ | | |
| | (0.0046) | | |
| $\log(MMC^{CW})$ | | $-0.034^{***}$ | |
| | | (0.0045) | |
| $\log(\text{Rev-Wgt } MMC^{CW})$ | | | $-0.024^{***}$ |
| | | | (0.0033) |
| $\mathbb{1}^{code-share}$ | $-0.015^{***}$ | $-0.032^{***}$ | $-0.034^{***}$ |
| | (0.0054) | (0.0042) | (0.0042) |
| *Fixed effects* | | | |
| Market | Yes | Yes | Yes |
| Carrier pair | Yes | Yes | Yes |
| *Market-level controls* | | | |
| HHI | Yes | Yes | Yes |
| LCC indicator | Yes | Yes | Yes |
| *Sample & fit* | | | |
| # Markets | 4311 | 4311 | 4311 |
| # Observations | 124,670 | 249,340 | 249,340 |
| Within $R$-squared | 0.183 | 0.182 | 0.182 |

*Note:* Standard errors in parentheses: $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}p < 0.10$.

a market. This provides evidence that increases in multimarket contact and the presence of code-share agreements lead to more collusive behavior. It also suggests that collusion among airlines can result in welfare losses beyond those simply due to higher prices, as firms further distort prices by not responding to cost and demand shocks.

## 4. Conclusion

In this paper, we develop simple empirical tests to identify collusive behavior. The tests are based on the theoretical insights of Werden and Froeb (1994) and Athey et al. (2004). We apply the tests in the airline industry, linking both the amount of multimarket contact and existence of a code-share agreement between each pair of carriers to the difference and rigidity of their prices. We find that an increase in multimarket contact leads to lesser differences between fares and greater rigidity, behavior that is consistent with collusion between airlines. For code-share agreements, we find that the presence of such an agreement results in more rigid fares, but no relationship to the difference between fares.

From a practical point of view, the concept behind our analysis offers a simple tool for antitrust agencies. The test only requires agencies have access to firm-level prices and a measure of the potential facilitator of collusion across markets (e.g., multimarket contact). While defining market boundaries is always an issue in antitrust analysis, our test is not intended as definitive proof of collusion but instead helps highlight where such behavior is more likely. Thus, misspecification of market boundaries is less of a concern at this stage of the analysis. Also, the data requirements on firms are less stringent for our test than what is required for a formal analysis. In our case, we perform the test entirely with publicly-available data. More detailed data can, of course, aid at this stage too. For example, Ciliberto and Williams (2014) utilize gate ownership as a further source of exogenous variation.

The less stringent time and data requirements can also allow more frequent tests for collusion. From a cost-benefit perspective, these tests are a useful tool because they allow the authorities to focus on cases in which the probability of collusion is more likely. This can minimize the amount of “false positive” investigations by antitrust authorities, which is socially valuable. Further, the test can be extended beyond multimarket contact or code-share agreements by relating pricing patterns to other suspected facilitators of collusion, like joint ownership of firms as in Azar et al. (2016) and Azar et al. (2018).

A key insight from our analysis borne out empirically is that the similarity and rigidity of prices, not necessarily the level of price, is what matters for the detection of the collusive behavior we consider. A test based solely on price levels can thus miss anti-competitive behavior in certain markets. For example, if two low-cost carriers serve many markets concomitantly, even if these firms’ price levels are below those of legacy carriers in the same market, similar pricing by the carriers can still be a sign of anti-competitive behavior.

We believe following Harrington (2008) suggestion that development of additional empirical tests provides a promising area for future research. The theoretical literature provides a large set of models from which one can derive testable implications that differ when firms behave competitively versus collusively. Combining these models with detailed studies of industries at risk for monopolistic behavior will provide economists further opportunities to aid in antitrust analysis.

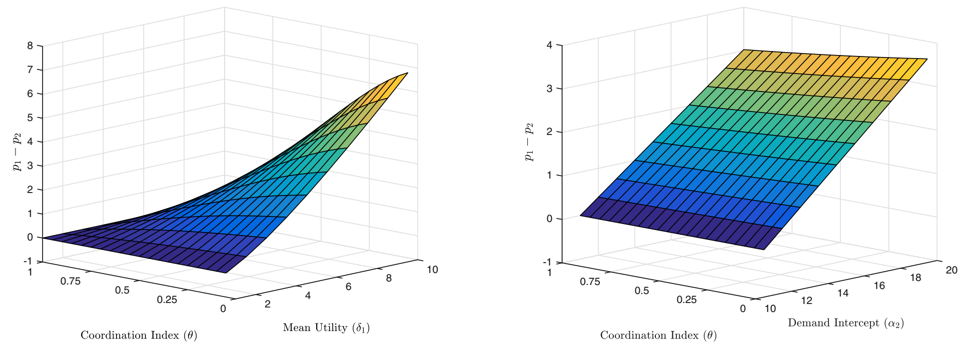
## Appendix A

### *A1. Numerical analysis*

The results in Tables 4 and 5 provide empirical support for the predictions of the two theoretical models of collusion we consider, however, some of the assumptions that generate those predictions merit further discussion.

In particular, the testable prediction from Werden and Froeb (1994) that price differences will decrease when firms merge (or collude), relies on demand being logistic. More general conclusions, without convenient parametric assumptions, are much more difficult. For example, Jaffe and Weyl (2013) derive a formula to approximate the change in prices after a merger:

$$\Delta P = -\left(\frac{\partial f}{\partial P}(P^0) + \frac{\partial g}{\partial P}(P^0)\right)^{-1} g(P^0).$$




(a) Nested Logit

(b) Linear

**Fig. 2.** Comparative statics on equilibrium price differences for nested logit and linear demand models.

Here $P$ is the price vector, $P^0$ is the price vector before the merger, $f(.)$ is the vector of first-order conditions before the merger, and $g(.)$ is the vector that characterizes the generalized pricing pressure. This last term is a combination of the magnitude of substitution towards the newly-acquired good after a price increase and the slope of the residual demand. In the case of a single-product Bertrand duopoly, the first term, $-\frac{\partial f}{\partial P}$, equals

$$-\begin{bmatrix} 2-\frac{Q_i\frac{\partial^2 Q_i}{\partial P_i^2}}{(\frac{\partial Q_i}{\partial P_i})^2} & \frac{\frac{\partial Q_i}{\partial P_j}\frac{\partial Q_i}{\partial P_i}-Q_i\frac{\partial^2 Q_i}{\partial P_i\partial P_j}}{(\frac{\partial Q_i}{\partial P_i})^2} \\ \frac{\frac{\partial Q_j}{\partial P_i}\frac{\partial Q_j}{\partial P_j}-Q_j\frac{\partial^2 Q_j}{\partial P_j\partial P_i}}{(\frac{\partial Q_j}{\partial P_j})^2} & 2-\frac{Q_j\frac{\partial^2 Q_j}{\partial P_j^2}}{(\frac{\partial Q_j}{\partial P_j})^2} \end{bmatrix}.$$

Similarly, $\frac{\partial g}{\partial P}$ is

$$-\begin{bmatrix} -(P_j-c_j)\frac{\frac{\partial^2 Q_j}{\partial P_i^2}\frac{\partial Q_i}{\partial P_i}-\frac{\partial^2 Q_i}{\partial P_i^2}\frac{\partial Q_j}{\partial P_i}}{(\frac{\partial Q_i}{\partial P_i})^2} & -\frac{\frac{\partial Q_j}{\partial P_i}}{\frac{\partial Q_i}{\partial P_i}}-(P_j-c_j)\frac{\frac{\partial^2 Q_j}{\partial P_i\partial P_j}\frac{\partial Q_i}{\partial P_i}-\frac{\partial^2 Q_i}{\partial P_i\partial P_j}\frac{\partial Q_j}{\partial P_i}}{(\frac{\partial Q_i}{\partial P_i})^2} \\ -\frac{\frac{\partial Q_i}{\partial P_j}}{\frac{\partial Q_j}{\partial P_j}}-(P_i-c_i)\frac{\frac{\partial^2 Q_i}{\partial P_j\partial P_i}\frac{\partial Q_j}{\partial P_j}-\frac{\partial^2 Q_j}{\partial P_j\partial P_i}\frac{\partial Q_i}{\partial P_j}}{(\frac{\partial Q_j}{\partial P_j})^2} & -(P_i-c_i)\frac{\frac{\partial^2 Q_i}{\partial P_j^2}\frac{\partial Q_j}{\partial P_j}-\frac{\partial^2 Q_j}{\partial P_j^2}\frac{\partial Q_i}{\partial P_j}}{(\frac{\partial Q_j}{\partial P_j})^2} \end{bmatrix}.$$

The complexity of this equation demonstrates why general conclusions regarding the effects of mergers or collusion on prices is difficult.

In Fig. 2, we provide numerical evidence that other common parametric models of demand, which relax the IIA property, yield similar predictions to those in Werden and Froeb (1994) for logistic demand. Specifically, we consider a price-setting duopoly with constant marginal costs, normalized to zero, and two commonly-used models of demand. Given a model of demand, we calculate equilibrium prices varying the degree to which firms internalize the effect of price changes on competitors' profits. Formally, we assume

**Table 6**
Pair-wise number of common markets ($MMC^{EK}_{h\to k,t}$) in 1998-Q3.

| | AA | AS | CO | DL | F9 | FL | HA | HP | JI | NK | NW | TW | TZ | UA | US | WN | YX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AA** | 2087 | | | | | | | | | | | | | | | | |
| **AS** | 1 | 170 | | | | | | | | | | | | | | | |
| **CO** | 934 | 1 | 1317 | | | | | | | | | | | | | | |
| **DL** | 1503 | 65 | 1054 | 2921 | | | | | | | | | | | | | |
| **F9** | 26 | 0 | 12 | 25 | 45 | | | | | | | | | | | | |
| **FL** | 62 | 0 | 47 | 173 | 0 | 217 | | | | | | | | | | | |
| **HA** | 10 | 0 | 2 | 8 | 0 | 0 | 35 | | | | | | | | | | |
| **HP** | 370 | 6 | 176 | 330 | 16 | 2 | 0 | 536 | | | | | | | | | |
| **JI** | 7 | 0 | 8 | 47 | 0 | 10 | 0 | 0 | 53 | | | | | | | | |
| **NK** | 0 | 0 | 1 | 11 | 0 | 0 | 0 | 0 | 2 | 19 | | | | | | | |
| **NW** | 892 | 1 | 568 | 1122 | 23 | 63 | 10 | 176 | 2 | 4 | 1495 | | | | | | |
| **TW** | 787 | 2 | 399 | 775 | 9 | 22 | 0 | 171 | 0 | 2 | 603 | 1008 | | | | | |
| **TZ** | 66 | 0 | 26 | 62 | 5 | 8 | 5 | 12 | 0 | 0 | 61 | 41 | 103 | | | | |
| **UA** | 1234 | 72 | 666 | 1256 | 31 | 26 | 23 | 410 | 2 | 0 | 931 | 650 | 56 | 1912 | | | |
| **US** | 563 | 0 | 580 | 1296 | 7 | 144 | 0 | 62 | 53 | 10 | 555 | 215 | 28 | 529 | 1632 | | |
| **WN** | 492 | 47 | 315 | 542 | 13 | 12 | 0 | 225 | 2 | 3 | 267 | 248 | 14 | 381 | 135 | 904 | |
| **YX** | 50 | 0 | 10 | 46 | 1 | 0 | 0 | 5 | 0 | 0 | 71 | 23 | 15 | 66 | 13 | 1 | 76 |

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

firm $i \in \{1, 2\}$ chooses price $p_i$ to solve

$$\max_{p_i} \ \pi_i(p_i, p_{-i}) + \theta\pi_{-i}(p_i, p_{-i}).$$

The parameter $\theta \in [0, 1]$ is the degree of coordination in price setting, ranging from Bertrand–Nash ($\theta = 0$) to perfect collusion ($\theta = 1$). For logistic demand, Werden and Froeb (1994) show that the difference in optimal prices, $|p_i - p_{-i}|$, is decreasing in $\theta$.

We first consider a nested-logit model of demand similar to many empirical studies of the airline industry (e.g., Peters, 2006; Berry et al., 2006; Berry and Jia, 2010; Aguirregabiria and Ho, 2012; Ciliberto and Williams, 2014). We fix the mean utility of product 2 to equal 1 (i.e., $\delta_2 = 1$), and we vary the mean utility of product 1 between 1 and 10 (i.e., $\delta_1 \in [1, 10]$) to generate asymmetry in market shares. We set the nesting parameter equal to 0.75 ($\lambda = 0.75$), which is in the middle of the range estimated by Berry and Jia (2010). In Fig. 2(a), we present the results of the equilibrium calculations. The equilibrium price difference ($|p_1 - p_2|$) is on the z-axis for different combinations of the coordination index ($\theta$) and mean utility of product 1 ($\delta_1$). Qualitatively similar to logistic demand, the effect of collusion is increasing in the difference between the mean utility of the two products. That is, the more asymmetric market shares are under competition, the greater the reduction in the price difference with a merger or collusion.

We perform the same calculations for a linear demand system. Specifically, demand for product 1 and 2 are given by $q_1 = a_1 - b_1p_1 + c_1p_2$ and $q_2 = a_2 - b_2p_2 + c_2p_1$, respectively. We set $b_1 = b_2 = 1$, $c_1 = c_2 = 0.5$, and $a_2 = 10$, and vary $a_1 \in [10, 20]$. In Fig. 2(b),

**Table 7**
Pair-wise fraction of common markets ($MMC^{CW}_{h\rightarrow k,t}$) in 1998-Q3.

| | AA | AS | CO | DL | F9 | FL | HA | HP | JI | NK | NW | TW | TZ | UA | US | WN | YX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AA** | 1 | 0 | 0.448 | 0.720 | 0.012 | 0.030 | 0.005 | 0.177 | 0.003 | 0 | 0.427 | 0.377 | 0.032 | 0.591 | 0.270 | 0.236 | 0.024 |
| **AS** | 0.006 | 1 | 0.006 | 0.382 | 0 | 0 | 0 | 0.035 | 0 | 0 | 0.006 | 0.012 | 0 | 0.424 | 0 | 0.276 | 0 |
| **CO** | 0.709 | 0.001 | 1 | 0.800 | 0.009 | 0.036 | 0.002 | 0.134 | 0.006 | 0.001 | 0.431 | 0.303 | 0.020 | 0.506 | 0.440 | 0.239 | 0.008 |
| **DL** | 0.515 | 0.022 | 0.361 | 1 | 0.009 | 0.059 | 0.003 | 0.113 | 0.016 | 0.004 | 0.384 | 0.265 | 0.021 | 0.430 | 0.444 | 0.186 | 0.016 |
| **F9** | 0.578 | 0 | 0.267 | 0.556 | 1 | 0 | 0 | 0.356 | 0 | 0 | 0.511 | 0.200 | 0.111 | 0.689 | 0.156 | 0.289 | 0.022 |
| **FL** | 0.286 | 0 | 0.217 | 0.797 | 0 | 1 | 0 | 0.009 | 0.046 | 0 | 0.290 | 0.101 | 0.037 | 0.120 | 0.664 | 0.055 | 0 |
| **HA** | 0.286 | 0 | 0.057 | 0.229 | 0 | 0 | 1 | 0 | 0 | 0 | 0.286 | 0 | 0.143 | 0.657 | 0 | 0 | 0 |
| **HP** | 0.690 | 0.011 | 0.328 | 0.616 | 0.030 | 0.004 | 0 | 1 | 0 | 0 | 0.328 | 0.319 | 0.022 | 0.765 | 0.116 | 0.420 | 0.009 |
| **JI** | 0.132 | 0 | 0.151 | 0.887 | 0 | 0.189 | 0 | 0 | 1 | 0.038 | 0.038 | 0 | 0 | 0.038 | 1 | 0.038 | 0 |
| **NK** | 0 | 0 | 0.053 | 0.579 | 0 | 0 | 0 | 0 | 0.105 | 1 | 0.211 | 0.105 | 0 | 0 | 0.526 | 0.158 | 0 |
| **NW** | 0.597 | 0.001 | 0.380 | 0.751 | 0.015 | 0.042 | 0.007 | 0.118 | 0.001 | 0.003 | 1 | 0.403 | 0.041 | 0.623 | 0.371 | 0.179 | 0.047 |
| **TW** | 0.781 | 0.002 | 0.396 | 0.769 | 0.009 | 0.022 | 0 | 0.170 | 0 | 0.002 | 0.598 | 1 | 0.041 | 0.645 | 0.213 | 0.246 | 0.023 |
| **TZ** | 0.641 | 0 | 0.252 | 0.602 | 0.049 | 0.078 | 0.049 | 0.117 | 0 | 0 | 0.592 | 0.398 | 1 | 0.544 | 0.272 | 0.136 | 0.146 |
| **UA** | 0.645 | 0.038 | 0.348 | 0.657 | 0.016 | 0.014 | 0.012 | 0.214 | 0.001 | 0 | 0.487 | 0.340 | 0.029 | 1 | 0.277 | 0.199 | 0.035 |
| **US** | 0.345 | 0 | 0.355 | 0.794 | 0.004 | 0.088 | 0 | 0.038 | 0.032 | 0.006 | 0.340 | 0.132 | 0.017 | 0.324 | 1 | 0.083 | 0.008 |
| **WN** | 0.544 | 0.052 | 0.348 | 0.600 | 0.014 | 0.013 | 0 | 0.249 | 0.002 | 0.003 | 0.295 | 0.274 | 0.015 | 0.421 | 0.149 | 1 | 0.001 |
| **YX** | 0.658 | 0 | 0.132 | 0.605 | 0.013 | 0 | 0 | 0 | 0 | 0 | 0.934 | 0.303 | 0.197 | 0.868 | 0.171 | 0.013 | 1 |

*Note:* The table reports the fraction of markets served by a carrier, where the numerator is the off-diagonal number from Table 6 and the denominator is the number on the diagonal in Table 6.

we plot the results from these calculations. Similar to the logit and nested-logit models, the difference between prices is decreasing in the degree of coordination in setting prices.

Thus, for both nested logit and linear demand, the substitution patterns are similar enough to logit to yield the same testable predictions even if a general result is not available.

### *A2. Variation in multimarket contact*

In this portion of the Appendix, we provide additional information on the variation in measures of multimarket contact during our period of study (1993–2016). In Tables 1 and 2 in the main text we present variation in multimarket contact across carriers for the third quarter of 2008. In Tables 6 and 7 below, we present the same measures of multimarket contact for the third quarter of 1998.

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