The Competitive Effects of Common Ownership: Economic Foundations and Empirical Evidence

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Abstract

A large fraction of US public stock is held by institutional investors that frequently hold shares in multiple firms in the same industry ("common ownership"). Concerns have been raised that common ownership might harm competition if it confers influence over important strategic decisions. Using data from the airline industry, we estimate the effects of common ownership on airline prices using price regressions and a structural oligopoly model consistent with the theory of partial ownership proposed in O'Brien and Salop (2000). Contrary to recent empirical research based on the same data, we find no evidence that common ownership raises airline prices.

Keywords: Price, concentration, common ownership, partial ownership, mergers

JEL Classifications: D43, G23, G34, K21, L13, L41

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I Introduction

Institutional investors (e.g., mutual funds) own a large fraction of publicly-traded stock in the US, on the order of 70-80%.[1] A natural explanation is that such institutions allow individual investors to diversify their portfolios at low cost. In particular, diversification involves obvious economies of scale, as a portfolio of investments by a single institutional investor can diversify the portfolios of millions of retail investors all at once. Because most individuals prefer to spend their time on activities other than managing their own portfolios, or may not believe they have the expertise to do so, the high ownership share of institutional investors is not surprising.

Recently, however, scholars have questioned whether such high ownership by institutions is socially beneficial (Azar, Schmalz, and Tecu, 2017; Azar, Raina and Schmalz, 2016; Posner, Scott-Morton, and Weyl, 2016; Elhauge, 2016). In most industries, each of several institutional investors owns shares in more than one firm in the same industry. The theory of partial ownership advanced by O'Brien and Salop (2000) explains how this can cause problems.[2] If an investor owns shares in two or more competitors ("common ownership") in a concentrated market and has control or influence over one or more of their managers, the investor may direct a manager to compete less aggressively in order to increase the profits of other competitors it owns. This logic is qualitatively the same as that used to explain why a merger between two competitors in a concentrated market could have anticompetitive "unilateral effects."[3] Indeed, a merger is a special case of common ownership in which the same shareholders jointly own and control 100% of two firms that compete against one another prior to the merger. The quantitative difference between these cases turns on differences in the extent of ownership and control.

The concerns expressed about common ownership have drawn proposals to control institutional investing through increased antitrust enforcement (Elhauge, 2016) and regulatory constraints on institutional investors' positions (Posner et al., 2016). The concerns have also drawn the attention of competition authorities in the US and Europe.[4] Yet, given the transaction cost savings and other benefits created by institutional investors, an important question is whether the anticompetitive

[1] Azar, Schmalz, and Tecu (2017); ICI (2015).

[2] O'Brien and Salop's theory builds on the analysis of joint ventures and partial acquisitions in Reynolds and Snapp (1986) and Bresnahan and Salop (1986).

[3] The term "unilateral effects" in merger discussions and the US Horizontal Merger Guidelines refers to effects that arise from internalizing substitution between the merging firms.

[4] Bill Baer, former Assistant Attorney General for Antitrust at the Antitrust Division, testified before the Senate Judiciary Subcommittee on Antitrust that the Antitrust Division "opened investigations in more than one industry." (Senate Judiciary Subcommittee on Antitrust, March 9, 2016). In a recent Statement of Objection for a merger, the European Commission presented an analysis to account for the effects of common shareholding by institutional investors.

concerns justify regulatory action that risks diminishing the benefits.

The analogy between common ownership and merger relies on key assumptions that may or may not hold in a particular circumstance. A critical assumption is that an investor's partial ownership position in at least one of the commonly owned firms gives the investor a degree of "control" or "influence" over managers of the firm(s). This assumption is not obviously satisfied in a given circumstance, particularly if common ownership involves minority positions as in most cases of institutional ownership.[5] A second assumption is that investors with influence have incentives to direct managers to take anticompetitive actions. This assumption could fail if an investor used its control to lower the firm's costs (and the cost reductions outweighed any anticompetitive effects) or if the investor would not benefit from directing anticompetitive actions for other reasons.[6] A third assumption is that any incentives an institutional investor might have to direct management to take anticompetitive actions must work their way into compensation that gives managers an incentive to take the actions. If any of these assumptions are not satisfied, common ownership need not have anticompetitive effects, and whether these assumptions are satisfied is an empirical question.

Much of the recent concern about common ownership traces to two empirical papers that claim to demonstrate that common ownership by institutional investors has raised airline ticket prices (Azar, Schmalz and Tecu, 2017; hereinafter "AST") and banking fees (Azar et al., 2016). The methodology employed in these papers is regression analysis that relates price to a measure of concentration—the modified Herfindahl-Hirschman Index ("MHHI") or its components—and to other variables related to costs and demand.[7] The spirit of the method is reduced-form analysis, but their models are not true reduced forms, as the MHHI depends on both common ownership and market shares, both of which may be endogenous. AST instrument for common ownership, but they do not instrument for the market share component of the MHHI.[8]

More importantly, the price-concentration equations estimated in these papers do not arise as

[5]In the U.S., directors of Delaware corporations have a fiduciary obligation to the corporation and to minority shareholders as to their interest in the corporation (Lafferty et al., 2011). Minority shareholders that do not hold shares in rival companies would like directors to instruct managers to maximize the profits of the company. A strategy that places weight on rivals' profits to reflect the interest of common shareholders appears to violate the directors' fiduciary obligations. Of course, enforcement costs could prevent shareholders from pursuing legal action.

[6]For example, institutional investors compete with each other to attract retail investors. Suppose mutual fund 1 instructs firm A to raise price and this benefits rival firm B. If mutual fund 2 owns a greater share of firm B, then its retail investors may benefit more than the retail investors of mutual fund 1. In this case, mutual fund 1 likely would not have an incentive to issue the instruction.

[7]The MHHI is defined as $\sum_j \sum_k C_{jk} s_j s_k$ where s_j is firm j's market share and C_{jk} is a common ownership term capturing the effects of control over the manager of firm j by investors that own shares in firms j and k. See Section II for details.

[8]See the discussion in footnote 23 below.

either structural or reduced-form equations of any oligopoly theory and therefore have a dubious interpretation. In particular, in the theory of partial ownership that generates the MHHI as a measure of concentration, both price and the MHHI are equilibrium *effects* that depend on cost and demand factors and the structure of ownership and control. Changes in common ownership that either raise or lower price may raise or lower the MHHI; changes in cost or demand factors that either raise or lower price may also raise or lower the MHHI.[9] Thus, the relationship between price and the MHHI (or its components) that these papers estimate does not provide a reliable prediction of the relationship between price and common ownership, and this is true even if steps are taken to correct the endogeneity problem.

In this paper we estimate the effects of common ownership in the airline industry using empirical specifications motivated by oligopoly theory, in particular, the theory of partial ownership due to O'Brien and Salop (2000). Under this theory, the equilibrium effects of common ownership depend on "common ownership incentive terms," which determine the weight that managers place on rival firms in making their strategic decisions. We estimate both linear price regressions in which the choice of the dependent and independent variables is motivated by theory, and a structural oligopoly model that accounts for the interactions among common ownership incentive terms and other market variables in a consistent way. We make an effort to construct the data set used in AST's analysis so we can replicate their regression results and isolate the effects of their choice of empirical specifications on the results they obtain.

In contrast to AST, we find no evidence in our price regressions and structural model estimation that common ownership raises prices. Our price regressions amount to replacing the concentration measures in AST's paper with indices of common ownership incentive terms, which are the relevant primitives from the theory of partial ownership. Because the common ownership indices may not be exogenous, we estimate price regressions using two-stage least squares with instruments that are correlated with the common ownership indices but not correlated with demand and supply factors in the airline industry. BlackRock's acquisition of Barclays Global Investors (BGI) in 2009 provides such an instrument because the transaction affected common ownership but likely was not driven by anything related to the airline industry. [10] We construct another instrument based on airline participation in the Russell 1000 stock market index. This instrument reflects investors' airline shareholdings that are driven by "passive" investment. The two-stage least squares estimates

[9]See O'Brien (2015), O'Brien and Waehrer (2017), and O'Brien (2017) for discussions of the issues.

[10]AST also uses this acquisition to construct instruments for the common ownership term in the concentration measures, although they do not instrument the market share component in the concentration measures.

indicate either no relationship or a negative relationship between price and each common ownership index we construct.[11]

The improvement of our price regressions over those of AST is two-fold. First, the dependent and independent variables are chosen based on a functional relationship consistent with the theory of partial ownership, which is not the case for AST's regressions.[12] In particular, our price regressions do not include concentration as an explanatory variable and therefore avoid the interpretation problems associated with price-concentration regressions. Second, AST did not fully instrument for the MHHI; they instrumented only for the component of the MHHI associated with common ownership (the MHHI delta), but not for the other component (the HHI). Our price regressions fully instrument for common ownership.

A weakness of the price regressions is that they do not fully account for interactions between common ownership and other market variables that are predicted by the theory. Specifically, in a market with N firms, the comparative statics of equilibrium prices generally depend on $N \times (N-1)$ common ownership incentive terms, their interactions with each other, and their interactions with other market variables. Because our sample has thousands of markets, it is not practical to include all important interactions in a price regression.

Our structural-model estimation addresses this limitation of the price regressions. We assume a nested logit demand for airline travel and managers behaving as Bertrand-Nash players with objectives that account for common ownership, as in O'Brien and Salop (2000). The demand model is similar to that of Berry and Jia (2010), who estimate the impact of supply and demand changes on airline profitability, but their supply model does not account for common ownership.[13] We introduce and estimate a single parameter that scales each common ownership incentive term relative to its value under "proportional control" (AST's baseline control assumption), where managers weigh investors' preferences in proportion to their voting shares. Thus, we nest the cases of proportional control and zero control in the same model. We estimate the supply and demand sides of the model jointly using GMM. The estimates reject a null hypothesis of proportional control, but do not reject a null hypothesis of no control. Thus, we do not find evidence that common ownership raises airline prices.

[11]For regressions based on three different indices of common ownership, the Hausman test indicates that the common ownership index is endogenous.

[12]The theory does not yield a function whose arguments are cost variables, demand variables, and concentration. This is discussed further in Section II below.

[13]We also define the product and markets somewhat differently to facilitate comparison with AST. See Sections III and V.

To the best of our knowledge, this is the first paper to estimate a structural model of the effects of common ownership. Miller and Weinberg (2017) test the existence of collusion between Anheuser-Busch InBev (ABI) and MillerCoors in the US beer industry following the Miller-Coors joint venture using a related methodology. In particular, they estimate a parameter that scales the degree of price coordination between ABI and MillerCoors relative to perfect collusion between these firms. However, their estimates do not account for the effects of common ownership.

Another related paper is Gramlich and Grundl (2017), which studies the relationship between price and common ownership in banking. They also use regression analysis to relate price to the common ownership primitives in the theory proposed by O'Brien and Salop (2000), and they find that the sign of the estimated effect of common ownership is sensitive to the specification. However, they do not instrument for common ownership and do not estimate a structural oligopoly model. O'Brien and Waehrer (2017), Rubinfeld and Rock (2017), and Patel (2017) all discuss a broad range of issues relating to the effects of common ownership. The empirical work in this paper was motivated in part by results in O'Brien (2017), which shows that the price-concentration equations estimated in the literature are generally not consistent with oligopoly theory.

The remainder of this paper is organized as follows. Section II describes the theory of common ownership for pricing and the implications for empirical specifications. It also compares these specifications to those in AST and Azar et al. (2016). Section III describes the data. Section IV presents our replication of AST and the implications of replacing the concentration measures with indices of common ownership. Section V presents and estimates a structural model of airline pricing. Section VI concludes the paper.

II Theory of Partial Ownership

Our empirical model is based on the theory of partial ownership developed in O'Brien and Salop (2000). This theory also produces the key variable used to measure common ownership in AST—the MHHI.

Consider an oligopoly market with N firms and I owners. Owner i owns the fraction β_{ij} of firm j's stock, $i = 1, .., .I$, $j = 1, ..., N$. The question arises as to the objective of the manager of firm j (hereinafter, "manager j") given potentially divergent interests of the owners, whose returns arise from potentially different portfolios. Presumably the manager takes into account the owners' financial interests in some way. The assumption in O'Brien and Salop (2000) is that manager j maximizes a weighted sum of returns to firm j's owners, where the weight on owner i's returns is interpreted as the "control" or "influence" owner i has over manager j.

Formally, denote firm j's profit by $\pi_j(y, X)$ where $y = (y_1, ..., y_N)$ is a vector of choice variables (e.g., prices or quantities) and X is a vector of exogenous cost and demand factors. Owner i's total return from stock ownership in the industry is $\pi_i^O(y, X) = \sum_k \beta_{ik}\pi_k(y, X)$.[14] Denote owner i's "control weight" associated with its shares in firm j as γ_{ij}. This is the weight the manager of firm j places on owner i's industry-wide stock returns in its objective. That is, manager j's objective is

$$\pi_j^M(y, X) = \sum_i \gamma_{ij}\pi_i^O(y, X) = \sum_i \gamma_{ij} \sum_k \beta_{ik}\pi_k(y, X)$$

Straightforward algebra shows that manager j's objective can be rewritten as

$$\pi_j^M(y, X) \propto \pi_j(y, x) + \sum_{k \neq j} C_{jk}\pi_k(y, X) \tag{1}$$

where $C_{jk} = \frac{\sum_i \gamma_{ij}\beta_{ik}}{\sum_i \gamma_{ij}\beta_{ij}}$ is a "common ownership incentive term." This term captures the effects of control or influence over manager j by investors that own shares in firms j and k.[15]

Manager j's objective depends on three factors: (1) the vector of choice variables, y; (2) the vector of cost and demand factors, X; and (3) the vector of common ownership incentive terms, $C_j = (C_{j1}, C_{j2}, ..., C_{jN})$ (where $C_{jj} = 1$). The objective does not depend on concentration, which is an equilibrium effect of common ownership and cost and demand factors.

A Structural and Reduced-Form Models from Theory

We assume that manager j chooses y_j to maximize its objective in equation (1).[16] The first order conditions yield structural equations of the form

$$y_j = f_j(y_{-j}, X, C_j), \quad j = 1, ..., N \qquad \text{(Structural equations)} \tag{2}$$

where y_{-j} is the vector of choice variables for firms other than j. Assuming that regularity conditions hold that allow "solving"[17] the system (2) for equilibrium values of the choice variables, the model also yields functional relationships of the form

$$y_j = g_j(X, C), \quad j = 1, ..., N \qquad \text{(``Reduced-form'' equations)} \tag{3}$$

[14]Summations here and elsewhere are take over the entire relevant domain unless otherwise indicated.
[15]See O'Brien and Salop (2000) Appendix C for a detailed discussion of these terms.
[16]We do not consider the possibility that common ownership could facilitate collusion. For a discussion of that issue, see Gilo et al. (2006).
[17]By "solving" we mean applying the implicit function theorem. Closed-form solutions may or may not exist.

where $C = \left(C_{jk}\right)$ is the matrix of common ownership incentive terms. We put "Reduced-form" in quotes because this system is a true reduced-form only if the common ownership incentive terms are exogenous. If investors condition their investments on factors that affect the choice vector y, then common ownership may be endogenous, and the estimation of equation (3) may require a systems estimation technique. We discuss the specific functional forms we employ for the price regressions and structural estimation we pursue in Sections IV and V below.

B Price-Concentration Analysis

The empirical analysis in AST's airline paper and Azar et al.'s (2016) banking paper estimated different relationships than those in equations (2) and (3):

$$y_j = h_j(X, HHI, MHHID) = h_j\Big(X, \sum_k s_k^2, \sum_j \sum_{k \neq j} C_{jk} s_j s_k\Big) \quad \text{(Airline paper)} \tag{4}$$

$$y_j = h_j(X, MHHI) = h_j\Big(X, \sum_j \sum_k C_{jk} s_j s_k\Big) \quad \text{(Banking paper)} \tag{5}$$

where s_j is firm j's market share and the other terms are as follows. The HHI is the Herfindahl-Hirschman index, which is the sum of the squared market shares. The MHHI is the modified Herfindahl-Hirschman index proposed by Bresnahan and Salop (1986) for joint ventures and generalized by O'Brien and Salop (2000) to cover cases where 3rd party investors own shares of multiple firms in the same industry.[18] Given ownership and control matrices $\left(\beta_{jk}\right)$ and $\left(\gamma_{jk}\right)$, O'Brien and Salop (2000) show that $MHHI = HHI + MHHID$ where $MHHID = \sum_j \sum_{k \neq j} C_{jk} s_j s_k$ is the "MHHI delta." This term is a measure of the increase in concentration due to common ownership.

Equations (4) and (5) have two main problems. One problem is that they are not derived from economic theory, so coefficient estimates from empirical specifications of these equations have no clear economic interpretation. More precisely, in any oligopoly model, including the Cournot and differentiated Bertrand models considered in O'Brien and Salop (2000), eliminating quantity from the demand and supply relations allows expressing price as a function of (1) cost variables, (2) demand variables, and (3) the common ownership incentive terms. It does not allow expressing price as a function whose arguments include only cost variables, demand variables, and the MHHI. O'Brien (2017) shows that this function does not exist over typical oligopoly domains.[19]

[18]Cowling and Waterson (1976) showed that the HHI equals the share-weighted sum of the margins times the market demand elasticity under Cournot oligopoly. The MHHI is constructed the same way – i.e., as the share-weighted sum of the margins times the market demand elasticity – but in a Cournot model where managers' take into account common ownership.

[19]In special cases, the first order conditions for optimal quantities do define a specific relationship between price

The reason this is important is that over limited domains in which the functions (4) and (5) exist, they have ambiguous comparative statics. The effect of a higher MHHI (or MHHID) on price, $\partial y_j/\partial MHHI$ (or $\partial y_j/\partial MHHID$), may be positive or negative when common ownership actually increases or decreases price. We illustrate this point for the case of the MHHI with the help of Figure 1, borrowed from O'Brien (2017).

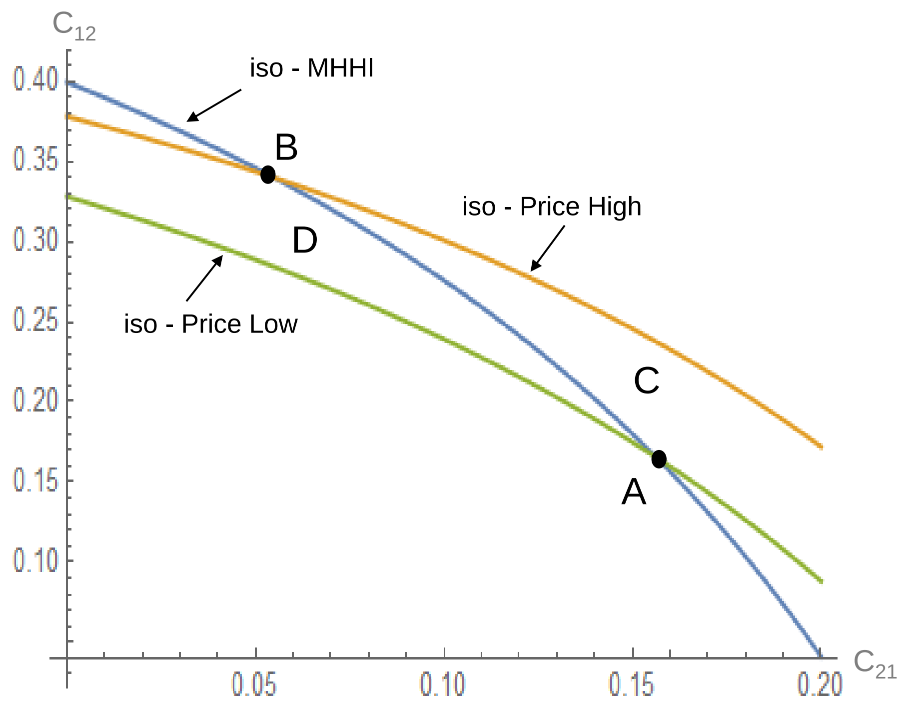

Figure 1: Relation between the MHHI and price.

The curves in the figure are based on a Cournot duopoly example where the inverse demand is $P = 1 - Q$ and the marginal costs of firms 1 and 2 are $v_1 = .1$ and $v_2 = .2$, respectively.[20] The curve iso-MHHI represents pairs of common ownership variables C_{12} and C_{21} such that the MHHI is constant. The MHHI increases as iso-MHHI shifts up and to the right. The iso-Price curves represent pairs of common ownership variables such that the equilibrium price is constant at either a low price (iso-Price Low) or high price (iso-Price High). Observe that the iso-Price curves have a different slope than the iso-MHHI curve. This occurs in the Cournot model when firms have different marginal costs.

and the MHHI. In Cournot oligopoly, for example, it is possible to express price as a function of demand variables, the MHHI, and the *market share-weighted average* marginal cost. However, this is not the relationship in (4) and (5), and the difference is important, as the example in Figure 1 shows.

[20]The example is constructed so that the MHHI=6000 along iso-MHHI, and price is .4670 along iso-Price High and .4620 along iso-price Low.

The common ownership pairs at points A and B in Figure 1 yield the same MHHI, but different prices. This shows immediately that there is no functional relationship between price and the MHHI, as there is no one-to-one mapping from the MHHI to price.[21] Common ownership pairs in region C yield both a higher price and higher MHHI than common ownership at point A, but common ownership pairs in region D yields a higher price and *lower* MHHI than common ownership at point A. Similarly, common ownership pairs in region D yield both a lower price and lower MHHI than common ownership at point B, but common ownership pairs in region C yield a lower price and *higher* MHHI than common ownership at point B.

This example shows that variation in common ownership that raises price (e.g., variation from point A to B, or from point A to region C, or D) may raise or lower the MHHI or leave it unchanged; and variation in common ownership that lowers price (e.g., variation from point B to point A, or from point B to region C, or D) may also raise or lower the MHHI or leave it unchanged. Thus, the relationship between price and the MHHI does not provide information about the relationship between price and common ownership. O'Brien (2017) shows that this problem arises in Cournot and Bertrand oligopoly when firms are asymmetric.

A second problem with (4) and (5) is that the key explanatory variables are concentration measures that depend on market shares and common ownership, both of which may be endogenous. In principle, one could address the endogeneity problem using instrumental variables techniques,[22] but the first problem remains.[23]

III Data

We construct a data set to match the data used by AST as closely as possible. Four data sources are used: (1) the Airline Origin and Destination Survey (DB1B) and (2) the Air Carrier Statistics (T-100) database, both published by the US Department of Transportation (DOT); (3) Equity Ownership Current and Historical Americas provided by Thomson Reuters (TR ownership data);[24]

[21] More precisely, it is not possible to express price as a function whose arguments are cost and demand variables and the MHHI.

[22] AST instrument only for the MHHID (and not the HHI), while Azar et al. (2016) use instruments that depend explicitly on market shares. See O'Brien and Waehrer (2017) for a discussion of the issues.

[23] AST also use a difference-in-difference approach to examine the effects of the one-time change in the MHHI caused by BlackRock's acquisition of Barclays Global Investments in 2009Q4 on airline prices in future periods. In particular, they group markets into terciles according to the size of the one-time implied change in the MHHI caused by the transaction based on shareholdings in 2009Q1. They then regress the change in price between the two periods on the implied change in the MHHI. The key explanatory variable in this analysis – the implied change in the MHHI – depends on market shares and therefore does not resolve the interpretation and endogeneity issues we have raised.

[24] AST use Thomson Reuters's Spectrum product, which provides equity ownership data for institutional investors. Spectrum is no longer available. We understand that TR's Equity Ownership Current and Historical Americas

and (4) the population and income data from the Bureau of Labor Statistics (BLS).

We constructed our data based on our understanding of AST's data construction described in Section 4 and Appendix B of their paper. The data appendix in our paper explains additional modifications that are not specified in AST.

A DB1B and T-100 datasets

The DB1B data contains quarterly information at the itinerary level on the origin and destination, the fare, the marketing and operating carriers,[25] and the number of passengers. The T-100 data provides information on the number of carriers offering non-stop flights between origin and destination airports.

We follow AST closely in constructing ticket prices and market shares. The sample period is 2001Q1-2014Q4. A "product" is defined as a flight between two airports in the United States in a quarter, regardless of the flight direction. An alternative product definition would distinguish flights in different directions as different products, as in Berry and Jia (2010). We chose AST's definition to match their data and isolate the effects of different specifications on the results. Carrier-quarter-level market shares are calculated as the proportion of passengers traveling on a given carrier between an airport pair in a given quarter. Tickets issued by multiple marketing carriers and markets that average fewer than 20 passengers per day are excluded from the analysis.

B Thomson Reuters equity ownership data

The TR ownership data provides quarterly information on the voting and non-voting shareholdings of: (i) institutional investors that manage at least $100 million, who report this information in SEC Form 13F filings; and (ii) non-institutional investors who report their shareholdings via proxy statements.[26] We follow AST in using voting shares to determine control weights for the purposes of calculating the common ownership incentive terms and the MHHI delta. Specifically, we use the sum of "sole" and "shared" voting shares in the TR data as the ownership shares relevant for

product is a re-branded version of Spectrum and that both datasets rely on SEC Form 13F filings, which the Securities and Exchange Commission (SEC) requires from institutional investors that manage at least $100 million. See https://www.sec.gov/divisions/investment/13ffaq.htm for details regarding Form 13F.

[25]The marketing carrier is defined as the airline marketing or selling the ticket, while the operating carrier is the entity that operates the flight.

[26]The TR ownership data provides shareholding information at the "manager" (subsidiary) level with the name of its parent company, and we aggregate managers' holdings up to the parent company level. Because the TR ownership data only provides information on the parent company at the time that data are pulled and does not provide a previous parent company name when there was a ownership change, we use additional data to construct the parent company ownership history. See Appendix Section B.3 for details.

determining control weights.[27]

We combine the TR ownership and voting data with the DB1B data to calculate the MHHI delta for every market-quarter under the assumption that control is proportional to voting shares. In calculating MHHI delta, we count only those investors included in the TR ownership data, and only those with shareholdings of at least 0.5%. We rescale the shareholdings so that they sum up to 100%. This amounts to assuming that the non-institutional shareholders that are missing have infinitesimal shareholdings. For shareholdings during bankruptcy periods, we follow AST and set each investor's holdings during the bankruptcy period to the last value observed in the data prior to the bankruptcy.

In our review of the TR ownership data, we discovered a number of discrepancies (see Appendix). We addressed problems we identified using information from the Securities Exchange Commission (SEC) and other public sources. Because AST use Thomson Reuter's "Spectrum" product while we use its "Equity Ownership Current and Historical Americas" product (which TR indicates is a re-branded version of Spectrum), it is not clear if the discrepancies we found are present in the Spectrum data or how AST may have addressed them if they exist. Despite these questions, we have replicated AST's price regression results quite closely, which suggests that the equity ownership data we use is reasonably close to theirs. The Appendix discusses other adjustments and corrections made to the Thomson Reuters data.

C BLS population and income data

Lastly, we use the population and income data from the BLS for the market characteristics. The data is reported annually and by Metropolitan Statistical Area (MSA). We assign airport pairs to their respective MSAs and use the geometric mean of population and income over the two MSAs as the route characteristics, as in AST. We could not map 190 out of 567 airports to any MSA and dropped the markets that include those unmapped airports from the sample. This reduced the number of observations by 3.9% for the carrier-market-quarter sample and 5.8% for the market-quarter sample.[28]

[27]Thomson Reuters defines "sole" voting shares as shares in which the owner has sole or complete control of the voting rights pertaining to non-routine matters. "Shared" voting shares are those in which the owner has shared control of the voting rights also pertaining to non-routine matters. See question 50a of FAQs about Form 13F at https://www.sec.gov/divisions/investment/13ffaq.htm.

[28]AST likely also made this correction as their sample size falls from 1,312,778 to 1,215,167 observations at the market-carrier level and from 282,333 to 255,385 observations at the market level when income per capita and population are included.

D Comparison of summary statistics

Tables 1 and 2 present summary statistics from our sample and AST's sample. The tables show that we match AST's sample reasonably well. The differences between the means and the standard deviations of the variables are less than 10% in almost all cases. An exception is the non-Southwest low cost carrier dummy (*Other LCC indicator*), where the mean is 23.3% lower in our carrier-market-quarter-level sample than in theirs (0.07 vs. 0.09).[29]

Of particular interest given the issues we identified with the Thomson Reuters ownership data is the comparison of the concentration measures across samples. The difference between the means and standard deviations across samples are less than 8% for the carrier-market-quarter-level data and less than 7% for the market-quarter-level data.

IV Price Regressions

A Replication of AST's panel regressions

AST's panel regressions take the form

$$ln(p_{jmt}) = X_{jmt}\theta + \lambda_1 HHI_{mt} + \lambda_2 MHHID_{mt} + \epsilon_{jmt}$$

where j is the carrier, m is the market, and t is the quarter; X_{jmt} is a vector of covariates;[30] HHI_{mt} is the HHI; and $MHHID_{mt}$ is the MHHI delta. They run both market-carrier-level regressions and market-level regressions that drop the j subscript and replace p_{jmt} with the passenger-weighted average price across carriers in market m and year-quarter t. The market-level regressions include fixed effects for each market and each year-quarter, as well as interactions between the year-quarter fixed effects and average route distance to account for different effects of fuel prices across routes. The market-carrier-level regressions include fixed effects for each market-carrier and each year-quarter, and interactions between the year-quarter fixed effect and average route distance.

Table 3 compares the results from market-carrier-level regressions using our data and AST's. Table 4 compares results from market-level regressions using both data sets. The results are quite similar, although not identical. We consistently find smaller coefficients on the MHHI delta than AST. In the market-carrier-level specification with only time and market-carrier fixed effects, AST report a coefficient of 0.1940, which implies that an increase in the MHHI delta from 0 to 2000

[29]While the means and the standard deviations of the average number of passengers variable (*Passengers*) are close, AST report a much higher minimum (1,800 vs. 10) and a much lower maximum (386,098 vs. 612,390) than we do.

[30]Only the market-carrier fixed effects and the proportion of non-stop flights vary at the market-carrier level.

would increase average fares by 4%. Our replication produces a coefficient of 0.1819, which implies an increase in average fares of 3.7%.[31] The estimates of the other coefficients in our replication have the same sign as ASTs estimates, and the magnitudes are close in all but one case.[32] Given the similarity of these results, it seems likely that the differences between AST's results and those we obtain below are driven largely by differences in specification rather than differences in data, though we cannot be certain about this.

B Price as a function of common ownership primitives

As discussed in Section II, oligopoly theory that accounts for common ownership predicts that equilibrium prices are a function of cost and demand factors and the matrix of common ownership incentive terms, i.e., $p = f(X, C)$ (omitting subscripts and error terms). If the incentive terms are exogenous, this equation is a reduced-form.

For estimation purposes, we consider the linear specification

$$\ln p_{mt} = X_{mt}\theta + \lambda h(C_{mt}) + \epsilon_{mt} \tag{6}$$

where C_{mt} is the matrix of common ownership incentive terms in market m at time t and $h(C_{mt})$ is an index through which common ownership affects price. This is essentially AST's market-level specification with the index $h(C_{mt})$ replacing the components of the MHHI. Unlike the components of the MHHI, $h(C_{mt})$, does not depend on endogenous market shares and therefore does not generate a spurious relationship between price and common ownership due to variation in these shares. However, $h(C_{mt})$ could still be endogenous.

Although equation (6) avoids the noise from variation in markets shares, a shortcoming is that it fails to account for interactions among the common ownership incentive terms and other market variables. However, over 20 airlines in the sample have some degree of common ownership, and this yields over 400 common ownership incentive terms to interact with variables in thousands of airport-pair markets. It is not practical to include all of the terms and interactions. However, the interactions are potentially important – under the theory, the comparative statics with respect to each common ownership incentive term depend on market-specific factors. For this reason, we view our price regressions as a robustness analysis of the results of AST rather than a robust analysis of common ownership effects.

[31] For the specification with the full set of covariates, AST estimate a coefficient of 0.149 which implies and price increase of 3%, while our replication implies a price increase of 2.6%.

[32] The coefficient on the share of connect flights specific to the carrier in a market ("Share Connect MCQ") is lower in our replication than in AST's regression, and it is statistically significant in theirs but not in ours.

We consider three different assumptions for the index $h(C_{mt})$, which amount to different assumptions about the functional form of $f(\cdot)$. Let N_{mt} be the number of carriers in market m in year-quarter t and d_{jkmt} be the average distance flown in market m and year-quarter t by carriers j and k. The three indices are:

$$h^m(C_{mt}) = \sum_j \sum_{k \neq j} \frac{C_{jkmt}}{N_{mt}(N_{mt}-1)} \qquad \text{(Mean)}$$

$$h^g(C_{mt}) = \left(\prod_{j,k \neq j} C_{jkmt} \right)^{1/[N_{mt}(N_{mt}-1)]} \qquad \text{(Geometric mean)}$$

$$h^d(C_{mt}) = \sum_j \sum_{k \neq j} w_{mjkt} C_{jkmt} \qquad \text{(Inverse distance weighted mean)}$$

where sums are taken over carriers in each market for a given quarter and

$$w_{jkmt} = \frac{(1/d_{jkmt})}{\sum_j \sum_{k \neq j} (1/d_{jkmt})}$$

is the "inverse distance weight" for carriers j and k in market m and quarter t. These indices represent different measures of the mean value of common ownership in a given market. The inverse distance-weighted mean applies weights related to a factor—route distance—that has a significant effect on demand in the structural estimation in the next section. Based on those estimates, the demand for airline travel is negatively related to distance, as expected. Weighting by the inverse of distance therefore gives more weight to common ownership involving firms expected to have higher shares, other factors equal.

C Instruments

To correct for potential endogeneity of the common ownership index, we use BlackRock's acquisition of Barclays Global Investments and airline index fund participation as instruments for the common ownership indices. The BlackRock-Barclays instrument is an indicator equal to 1 if common ownership in the market was affected by the merger. The rationale for this instrument is that this acquisition effect should be correlated with common ownership but uncorrelated with other factors that affect airline prices across markets and over time.

We use the number of airlines in each market included in the Russell 1000 index as the other instrument. The rationale for this instrument is that institutional investors frequently take positions that mirror this index. Thus, participation in the index should be correlated with common ownership, but it is unlikely to be correlated with the unobserved component of airline prices across markets and over time.

D Price regression results

Tables 5 reports the results of market-level price regressions using ordinary least squares and our IV approach (two-stage least squares) for each of the three common ownership indices.[33] Table 6 reports the first stage regressions from the two-stage least squares procedure. The weak instrument test is rejected for all three common ownership indices.

The OLS estimates of the common ownership effect are positive and significant, as in AST's baseline specification. However, the IV procedure reverses the sign of the common ownership effect, and the estimates are statistically significant. A Hausman test rejects the hypothesis that the common ownership indices are exogenous. In particular, the results suggest that common ownership is positively correlated with the unobserved (by the researcher) component of price. This could occur for many reasons. One possibility is that institutional investors may tend to invest in airlines that are likely to participate in markets that tend to experience significant price spikes due to demand shocks or other reasons.

Taken at face value, the results from the price regressions suggest that common ownership has a negative effect on airline prices. As we observed earlier, however, we view these results as a robustness analysis more than we do as estimates of the causal effects of common ownership on price. The main reason is that the specification is probably not flexible enough, as it does not capture interactions among common ownership and the other explanatory variables that oligopoly models typically predict. The structural estimation in the next section addresses this issue.

V Structural Estimation

A Structural models of demand and supply

We estimate a structural model of the airline market in which airlines are differentiated Bertrand competitors. The demand model is a random utility discrete-choice model in which consumers first choose whether to travel by air or not between a given pair of airports and then which carrier to use if traveling by air. This is the nested logit model by McFadden (1978) and Cardell (1991) where we assume there are two mutually exclusive nests, traveling by air and the outside option of not traveling by air. As in the previous sections we use "market" to refer to a pair of airports and use the geometric mean of the population of the two MSAs containing the airports as the market size.

For carrier j operating in market m, i.e., flying between two airports, in quarter t, the utility

[33] We present results at the market-level only because the instruments are weak at the market-carrier level.

of consumer r deciding to travel by air and using that carrier is given by

$$u_{rjmt} = X_{jmt}\theta + \alpha p_{jmt} + \xi_{jmt} + \zeta_{rgmt} + (1 - \sigma)\varepsilon_{rjmt}$$

where X_{jmt} is a set of observable product characteristics, including the average distance that carrier j flies, an indicator for offering direct flights, airline fixed effects, market fixed effects, and time fixed effects; θ is a vector of the marginal utility of the observable characteristics; p_{jmt} is the average fare for carrier j in market m at time t; α is the marginal (dis-)utility of price; ξ_{jmt} represents product-level characteristics that consumers observe but the researcher does not; ζ_{rgmt} is consumer utility that is common to traveling by air in market m at time t with g indicating the mutually exclusive nests; and ε_{rjmt} is an idiosyncratic taste variable distributed Type I Extreme Value, with σ determining the degree of the correlation of utility among the carriers operating in market m at time t.

If consumers do not travel by air, they choose the outside option of traveling by another means of transportation or not traveling at all. This outside good, j=0, is assumed to be the only member of group 0 (g=0), and the utility of choosing this outside option is

$$u_{r0mt} = \varepsilon_{r0mt}.$$

Given this utility function, carrier j's share of passengers who decide to travel by air in market m at time t is

$$s_{jmt/g} = \frac{exp((X_{jmt}\theta + \alpha p_{jmt} + \xi_{jmt})/(1 - \sigma))}{D_{gmt}}$$

where

$$D_{gmt} = \sum_k exp((X_{kmt}\theta + \alpha p_{kmt} + \xi_{kmt})/(1 - \sigma)).$$

The share of consumers who are traveling by air is

$$s_{gmt} = \frac{D_{gmt}^{(1-\sigma)}}{\sum_g D_{gmt}^{(1-\sigma)}}.$$

The overall market share of carrier j in market m at time t is

$$s_{jmt} = s_{jmt/g} s_{gmt}.$$

We calculate an empirical counterpart of carrier j's market share by dividing the number of passengers flying with carrier j in a market-quarter by the market size, and we calculate carrier j's within-market share by dividing the number of passengers flying with carrier j in a market-quarter by the total number of passengers traveling by air in that market-quarter.

Our modeling approach for air travel demand is in the same spirit as Berry and Jia (2010), but a difference is that we do not distinguish business and leisure travelers. Distinguishing different types of travelers helps explain the dispersion of air fares for a given carrier in the same market-quarter. Berry and Jia (2010) treat tickets with significantly different fares as distinct products for a given carrier in a market-quarter. We use the average fare to aggregate tickets with different fares, so we interpret a given carrier as selling a single product in any given market-quarter. We use this aggregation mainly for consistency with AST, but it also eases the computational burden in our structural estimation, which uses a 16-quarter panel.

Carrier j's manager sets price to maximize a "scaled" weighted sum of the profits of carriers in which carrier j's owners have partial ownership:

$$\pi_{jmt}(p, X) = (p_{jmt} - mc_{jmt})s_{jmt}M_{mt} + \sum_{k\neq j} \tau C_{jkt}(P_{kmt} - mc_{mkt})s_{kmt}M_{mt}$$

where C_{jkt} is a common ownership incentive term, which is constant across (geographic) markets for carriers j and k but may vary over time, and τ is a scaling factor to be estimated as described below. This is consistent with the theory of partial ownership described in Section II above with the addition of the scaling parameter τ. The first order condition is

$$s_{jmt} + (p_{jmt} - mc_{jmt})\frac{\partial s_{jmt}}{\partial p_{jmt}} + \sum_{k\neq j} \tau C_{jkt}(p_{kmt} - mc_{kmt})\frac{\partial s_{kmt}}{\partial p_{jmt}}.$$

Using the properties of the nested logit model, the system of first order conditions can be written

$$\begin{bmatrix} s_{1mt} \\ s_{2mt} \\ \vdots \\ s_{Jmt} \end{bmatrix} + \begin{bmatrix} p_{1mt} - mc_{1mt} \\ p_{2mt} - mc_{2mt} \\ \vdots \\ p_{Jmt} - mc_{Jmt} \end{bmatrix} \begin{bmatrix} \Delta_{11mt} & \tau C_{12t}\Delta_{12mt} & \dots & \tau C_{1Jt}\Delta_{1Jmt} \\ \tau C_{21t}\Delta_{21mt} & \Delta_{22mt} & \dots & \tau C_{2Jt}\Delta_{2Jmt} \\ \vdots & \vdots & \ddots & \vdots \\ \tau C_{J1t}\Delta_{J1mt} & \tau C_{J2t}\Delta_{J2mt} & \dots & \Delta_{JJmt} \end{bmatrix} = 0 \qquad (7)$$

where $\Delta_{jjmt} = (\frac{\alpha}{1-\sigma})s_{jmt}(1 - \sigma s_{jmt/g} - s_{jmt} + \sigma s_{mtj})$ and $\Delta_{jkmt} = -\alpha s_{kmt}(\frac{\sigma}{1-\sigma}s_{jmt/g} + s_{jmt})$. J is the number of carriers operating in geographic market m, which varies by both m and t but is not indicated to avoid clutter.

The matrix of first order conditions shows that in a market with J competitors, there are $J \times (J-1)$ common ownership incentive terms, C_{jkt}, that affect pricing in each period. Although these terms are constant across markets for any pair of airlines j and k, the terms vary over time. One empirical strategy would be to treat these terms as parameters to be estimated. However, with 20 airlines that are commonly owned in one or more markets, this would mean estimating over 400 common ownership incentive terms for each quarter that enter the first order conditions in a non-linear way. This strategy is not practical. Instead, we adopt a strategy that allows the common ownership incentive terms to vary in proportion to their values under a particular control assumption.

For example, suppose as in AST and the banking paper (Azar et al., 2016) that institutional investors have proportional control. The common ownership incentive terms are then

$$C_{jk} = \frac{\sum_i \gamma_{ij}\beta_{ik}}{\sum_i \gamma_{ij}\beta_{ij}}$$

where γ_{ij} is the control weight, equal to investor i's share of voting stock, and β_{ij} indicates investor i's share of airline j's total shareholdings. We rescale C_{jk} calculated under the proportional control scenario with the parameter τ and estimate it along with other demand- and supply-side parameters. The parameter τ is part of the supply-side parameters. Observe that this nests the assumptions of proportional control ($\tau = 1$) and no control ($\tau = 0$). It also nests intermediate control scenarios for $\tau \neq 0,\ 1$.

B Estimation

As shown in Berry (1994), the nested logit demand model can be written as

$$ln(s_{jmt}) - ln(s_{0mt}) = X_{jmt}\theta + \alpha p_{jmt} + \sigma ln(s_{jmt/g}) + \xi_{jmt}.$$

The price (p_{jmt}) and the within-market share ($s_{jmt/g}$) are endogenous variables that are correlated with the vector of unobserved product characteristics, ξ. We use the average characteristics of rival carriers in a given market as instruments. In particular, for a given market at time t, we use the log of the average flight distance by rival carriers, the number of rival carriers, and the number of rival carriers offering non-stop flights as instruments.

For the supply-side estimation we first solve equation (7) for the vector of marginal costs and then estimate each marginal cost as a linear function of the observed product characteristics, which include the average distance that carrier j flies in a given market, the indicator for offering direct flights in that market, the preference for airline brand, and so forth. The supply-side equation we estimate is

$$mc_{mt} \equiv p_{mt} - b_{mt}(s_{mt}, C_t, \alpha, \sigma) = X_{mt}\omega + u_{mt}$$

where X_{mt} includes the same airline characteristics and fixed effects used for the demand model and $b_{mt}(s_{mt}, C_t, \alpha, \sigma)$ is a vector of carriers' price-cost margins in market m at time t, calculated as

$$b_{mt}(s_{mt}, C_t, \alpha, \sigma) = -\begin{bmatrix} \Delta_{11mt} & \tau C_{12t}\Delta_{12mt} & \dots & \tau C_{1Jt}\Delta_{1Jmt} \\ \tau C_{21t}\Delta_{21mt} & \Delta_{22mt} & \dots & \tau C_{2Jt}\Delta_{2Jmt} \\ \vdots & \vdots & \ddots & \vdots \\ \tau C_{J1t}\Delta_{J1mt} & \tau C_{J2t}\Delta_{J2mt} & \dots & \Delta_{JJmt} \end{bmatrix}^{-1} \begin{bmatrix} s_{1mt} \\ s_{2mt} \\ \vdots \\ s_{Jmt} \end{bmatrix}$$

Because the price coefficient and the nesting parameter enter the supply-side moment conditions through the markup term, we use the same instruments used in the demand model for the supply model, as they help to predict the markup term. In addition, we add two instrument variables created from Russell 1000 index – an indicator of whether a given carrier is part of Russell 1000 index, and the number of carriers in the market that are part of Russell 1000 index – to identify the scaling parameter τ.

We use the generalized method of moments (GMM) to estimate the demand and the supply models jointly. The moment conditions for the demand model are that the unobserved product quality is not correlated with the observed product characteristics and the instruments. These conditions imply

$$E(h(z)\xi) = 0$$

for any function $h(.)$, where z is a vector of all exogenous variables, including the instruments for price and the within share variables. The moment conditions for the supply side are that the cost shock is not correlated with the observed product characteristics and the instruments. These conditions imply

$$E(h(z)u) = 0.$$

C Data for structural estimation

The structural models are estimated using a subset of the data consisting of 16 quarters from 2011Q1 to 2014Q4 and markets with the geometric mean of population no smaller than 2 million in the fourth quarter of 2014. These criteria select 2,017 markets that account for 73% of air travelers during the 16 quarter period. A unit of observation is a carrier-market-quarter combination. There are 137,461 observations used to estimate the structural models.

The reason for using a subset of the sample is computational. Because we estimate the demand and the supply models jointly and each model includes carrier, market, and time fixed effects, the estimation taxes the physical memory capacity of the computer, which limits maximum data size.[34]

[34] The demand and the supply models each include 2,016 dummies for the market fixed effects, 23 dummies for the carrier fixed effects, and 15 dummies for the time fixed effects. Estimation using the limited sample takes approximately two days.

Table 7 reports summary statistics of the variables used in structural estimation. Some variables used in the price regressions are not used in structural estimation. Because we include carrier, market, and time fixed effects, we select variables that represent carrier characteristics that vary across the markets as exogenous demand and supply factors in our structural models. The variables we do not include are *share travel connect*, *population*, *income per capita*, *number of nonstop carriers*, and the dummy variables for *Southwest* and *Other LCC*. The *share travel connect* variable may be endogenous, and all other variables are market characteristics that do not improve model fit significantly when included with market fixed effects.[35] The three concentration measures – *HHI*, *MHHI*, and *MHHI delta* – are not used in structural estimation, but we still report their summary statistics in Table 7 for comparison with the entire sample.

Compared to the entire sample reported in Table 1, the mean of the average fare is $4 higher, and the mean of the distance traveled is about 90 miles shorter. The number of passengers is substantially higher because the sample used in structural estimation is limited to markets with a population of at least 2 million in the fourth quarter of 2014. The mean of the *MHHI* is about 600 points higher and the mean of the *MHHI delta* is about 300 points higher, compared to the whole sample, because the degree of common ownership is higher in the 2011-2014 period.[36] Table 7 also reports summary statistics for the instruments used in structural estimation. On average, a carrier faces 4 competing carriers in a market-quarter, one of which offers a direct flight, and about two thirds of all carriers in a market-quarter are included in Russell1000.

D Results

We report estimation results in Table 8. The instruments pass the weak instrument test for all three endogenous variables—price, within-market share, and common ownership incentive term. In this test, we regress the first derivative of the moment condition with respect to the parameter of each endogenous variable on all exogenous variables, including the excluded instruments. The F-statistic for the joint significance of the instruments is 40.29 for price, 1,607.33 for the within-market share, and 273.42 for the common ownership incentive term.

The parameter that scales each common ownership incentive term relative to its value under proportional control, τ, is estimated to be -0.45 but is not statistically significant, with a p-value greater than 0.20. In other words, the scaling parameter is not statistically different from 0. We

[35]Population is used to calculate carrier market shares so it would be redundant to include it as a demand factor.

[36]The mean of *MHHI* and *MHHI delta* is higher by about 70 and 160 respectively if the sample is not limited to markets with at least 2 million population.

cannot reject the hypothesis that common ownership has no effect on price. We can reject the hypothesis that common ownership raises price as predicted under the assumption of proportional control. These results suggest that it is unlikely that managers' pricing decisions are influenced by investors that have proportional control.

The estimates of most of the other parameters are statistically significant and have the right sign. The price coefficient is -1.20 and the within-group correlation is 0.83. These estimates are close to but slightly higher than (in absolute value) those estimated by Berry and Jia (2010) for leisure travelers in 2006 (-1.05 and 0.72). The passenger-weighted average aggregate price elasticity implied by our estimates is 2.31 in 2011 and 2.43 in 2014.[37]

The coefficient for the direct flight dummy is statistically significant in both the demand and the supply models, and it is positive in the demand model and negative in the supply model, as expected. The positive coefficient in the demand model suggests that consumers prefer the non-stop flights. The negative coefficient in the supply model suggests that it is less costly to operate non-stop flights than connecting flights.

The coefficient for the log of distance is negative and statistically significant in the demand model, suggesting that consumers prefer shorter flying distance. One anomaly is that this coefficient is also negative and statistically significant in the supply model, where it is expected to be positive because flying a longer distance should cost more.

VI Conclusion

Does common ownership by minority shareholders have anticompetitive effects? The theory of how this *could* occur is straightforward – common owners with control or influence over the management of one or more competing firms might direct them to compete less aggressively (a "unilateral effect"), or common owners might facilitate coordination. The focus of this paper is on unilateral effects. As discussed in the introduction and in more detail in O'Brien and Waehrer (2017), it is not obvious that common owners (e.g., institution investors) have either the incentive or the ability to exert influence that would cause anticompetitive unilateral effects.

This paper tests whether common ownership reduces competition in the airline industry using empirical models motivated by the theory of partial ownership. In particular, we estimate price regressions and a structural oligopoly model that relate pricing behavior to the common ownership

[37]The aggregate price elasticity is the percentage change in total air-travel demand (across all markets) when all prices rise by 1% in all markets. We calculated this elasticity for each quarter between 2011 and 2014 and used total passengers as the weight for the annual elasticities.

primitives identified by the theory. We construct our dataset to match as closely as possible that of AST to facilitate a comparison of results from different methodologies. In contrast to AST, we find no evidence that common ownership raises airline prices.

Because the datasets match reasonably well and we largely replicate AST's results when using their method, the difference in results is likely due to differences in methodology. AST's study is based on price regressions that relate airfares to the components of the MHHI. These equations are not derived from economic theory, and they have interpretation problems even if steps are taken to address econometric endogeneity.[38] In particular, the relationship between price and the MHHI may differ from the relationship between price and common ownership, and price and the MHHI are likely to be correlated in data even if common ownership has no effect on incentives. Given these problems, price-concentration regressions are not appropriate for causal inference. By developing our analysis from first principles, we avoid these problems.

Our findings do not support altering antitrust or regulatory policy toward common ownership, and it would be inappropriate to do so based on results from price-concentration analysis. Our results show that empirical specifications grounded in oligopoly theory lead to different conclusions about the effects of common ownership than price-concentration regressions.

The study of common ownership is important not only for antitrust and regulatory policy, but also for the economic theory of the firm. A workhorse assumption in economics is that firms behave to maximize their profits, consistent with the Fisher separation theorem. This assumption is justified when owners have the same objectives, but it has less resonance when owners have divergent interests. How firms behave when this assumption is relaxed is an ongoing area of research that would benefit from a better understanding of how ownership translates into control and ultimately firms' decisions. We hope the methodology we propose here and future extensions helps facilitate this research.

[38] As we explained in Section II, AST's IV estimates do not fully address endogeneity. They instrument for the common ownership component of the MHHI, but they do not instrument for the share component.

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Table 1: Summary statistics at the market and market carrier-level 2001:Q1 through 2014:Q4

Market-carrier level	N	Mean	St. Dev.	Min	Max
Average fare	1,292,689	237.85	102.46	25.16	2,493.02
Log average fare	1,292,689	5.40	0.37	3.23	7.82
HHI	1,292,689	4,585	2,071	1,120	10,000
MHHI	1,292,689	6,605	1,544	2,576	11,009
MHHI delta	1,292,689	2,021	1,092	0	7,364
Number of non-stop carriers	1,292,689	0.78	1.24	0	10
Southwest indicator	1,292,689	0.09	0.29	0	1
Other LCC indicator	1,292,689	0.07	0.26	0	1
Share travel connect (mkt)	1,292,689	0.66	0.39	0	1
Share travel connect (mkt-carrier)	1,292,689	0.85	0.32	0	1
Population	1,242,063	2.39	1.95	0.16	16.32
Income per captia	1,242,063	40.20	6.35	17.71	73.12
Distance	1,292,689	2,719	1,574	27	15,390
Passengers	1,292,689	3,834	12,307	10	336,530
Market level	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Average fare	271,760	227.09	75.75	30.01	1,075.19
Log average fare	271,760	5.37	0.33	3.40	6.98
HHI	271,760	5,176	2,357	1,120	10,000
MHHI	271,760	7,040	1,658	2,576	11,009
MHHI delta	271,760	1,864	1,180	0	7,364
Number of non-stop carriers	27,1760	0.69	1.12	0	10
Southwest indicator	271,760	0.09	0.29	0	1
Other LCC indicator	271,760	0.07	0.25	0	1
Share travel connect (mkt)	271,760	0.64	0.40	0	1
Population	256,129	2.26	1.9	0.16	16.30
Income per capita	256,129	40.21	6.46	17.71	73.12
Distance	271,760	2,369	1,542	27	11,881
Passengers	271,760	18,236	34,790	10	612,390

Table 2: Summary stats reported in Azar, Schmalz, and Tecu (March 2017), 2001:Q1 through 2014:Q4

Market-carrier level	N	Mean	St. Dev.	Min	Max
Average fare	1,312,778	229.16	97.50	25.00	2,498.62
LogAverageFare	1,312,778	5.37	0.36	3.22	7.82
HHI	1,312,778	4,639	2,077	971	10,000
MHHI	1,243,621	6,493	1,655	2,039	10,219
MHHI delta	1,243,621	1,870	1,127	0	5,799
Number of Nonstop Carriers	1,312,778	0.81	1.30	0	11
Southwest Indicator	1,312,778	0.09	0.29	0	1
Other LCC Indicator	1,312,778	0.09	0.28	0	1
Share travel connect (mkt)	1,312,778	0.67	0.39	0	1
Share travel connect (mkt-carrier)	1,312,778	0.86	0.32	0	1
Population	1,215,267	2.42	2.01	0.02	16.32
Income per capita	1,215,267	41.89	4.90	21.53	92.50
Distance	1,312,778	2,687	1,552	27	12,714
Passengers	1,312,778	3,930	11,591	10	23,4146
Market level	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Average fare	282,333	219.31	72.52	29.66	1,045.88
Log average fare	282,333	5.34	0.33	3.39	6.95
HHI	282,333	5,264	2,370	971	10,000
MHHI	262,766	6,976	1,768	2,039	10,219
MHHI delta	262,766	1,731	1,207	0	5,799
Number of Nonstop Carriers	282,333	0.73	1.19	0	11
Southwest Indicator	282,333	0.09	0.29	0	1
Other LCC Indicator	282,333	0.08	0.27	0	1
Share travel connect (mkt)	282,333	0.64	0.41	0	1
Share travel connect (mkt-carrier)	282,333	0.64	0.41	0	1
Population	255,384	2.28	1.97	0.02	16.32
Income per capita	255,384	41.59	5.06	21.53	92.50
Distance	282,333	2,343	1,521	27	11,920
Passengers	282,333	18,429	33,341	1,800	386,098

Table 3: Replication of Azar et al. (2017) – market-carrier-level panel estimates

	Dependent variable: ln(Average Fare)					
	Azar et al. (2017).			*Replication of Azar et al.*		
MHHI delta	0.1940***	0.2190***	0.1490***	0.1819***	0.1800***	0.1292***
	(0.0459)	(0.0387)	(0.0375)	(0.0541)	(0.0477)	(0.0432)
HHI	0.2210***	0.2300***	0.1650***	0.2221***	0.2262***	0.1342***
	(0.0247)	(0.0246)	(0.0209)	(0.0536)	(0.0534)	(0.0361)
Non-stop carriers			-0.00979***			-0.01560***
			(0.00269)			(0.00320)
Non-stop SW			-0.1200***			-0.1299 ***
			(0.00928)			(0.01790)
Non-stop LCC			-0.0618			-0.0699***
			(0.00717)			(0.00980)
Share Connect MQ			0.1240			0.1312***
			(0.0167)			(0.0245)
Share Connect MCQ			0.0986***			0.0133
			(0.0143)			(0.0226)
ln (Population)			0.3060***			0.2839*
			(0.1060)			(0.1555)
ln (Income per capita)			0.3740***			0.3012
			(0.1020)			(0.1907)
Distance x yr-qtr FE		x	x		x	x
Yr-qtr FE	x	x	x	x	x	x
Market-Carrier FE	x	x	x	x	x	x
R-squared	0.8200	0.8250	0.8360	0.8610	0.8646	0.8727

Table 4: Replication of Azar et al. (2017) – market-level panel estimates

	Dependent variable: ln(Average Fare)					
	Azar et al. (2017).			*Replication of Azar et al.*		
MHHI delta	0.3250***	0.3110***	0.2020***	0.2608***	0.2412***	0.1820***
	(0.0446)	(0.0397)	(0.0356)	(0.0350)	(0.0296)	(0.0313)
HHI	0.3650***	0.3570***	0.2550***	0.3663***	0.3694***	0.2540***
	(0.0315)	(0.0313)	(0.0244)	(0.0340)	(0.0319)	(0.0291)
Non-stop carriers			-0.0081***			-0.0148***
			(0.00371)			(0.00270)
Non-stop SW			-0.1490***			-0.1614***
			(0.0135)			(0.0131)
Non-stop LCC			-0.1000***			-0.0955***
			(0.00989)			(0.00940)
Share Connect MQ			0.1580***			0.1625***
			(0.0189)			(0.0183)
ln (Population)			0.3430***			0.2747**
			(0.1220)			(0.1322)
ln (Income per capita)			0.3040***			0.2443**
			(0.1100)			(0.1091)
Distance x yr-qtr FE		x	x		x	x
Yr-qtr FE	x	x	x	x	x	x
Market FE	x	x	x	x	x	x
R-squared	0.8520	0.8610	0.8760	0.8578	0.8626	0.8775

Table 5: Panel regressions with potentially endogenous indices of common ownership incentive terms (Cjk) as covariates and IV regressions with indices of common ownership incentive terms instrumented by (1) the number of airlines present in the Russell 1000 index for each market-quarter, and (2) an indicator for market-quarters affected by the BlackRock Barclays acquisition.

	Dependent variable:					
	ln(Average fare)					
	Not instrumented			*Second stage IV regressions*		
Cjk index	(Mean)	(GMean)	(Inv.Dist.)	(Mean)	(GMean)	(Inv.Dist.)
Cjk index	0.125***	0.041**	0.133***	−2.177***	−1.607***	−2.167***
	(0.027)	(0.017)	(0.027)	(0.489)	(0.322)	(0.487)
Number competitors	−0.012***	−0.012***	−0.012***	−0.036***	−0.061***	−0.035***
	(0.002)	(0.002)	(0.002)	(0.007)	(0.011)	(0.007)
Non-stop carriers	−0.020***	−0.020***	−0.020***	−0.017***	−0.021***	−0.017***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
Non-stop SW	−0.175***	−0.175***	−0.175***	−0.163***	−0.166***	−0.162***
	(0.013)	(0.014)	(0.013)	(0.019)	(0.023)	(0.019)
Non-stop LCC	−0.110***	−0.111***	−0.109***	−0.176***	−0.202***	−0.177***
	(0.009)	(0.009)	(0.009)	(0.019)	(0.025)	(0.019)
Share Connect	0.099***	0.100***	0.098***	0.110***	0.071***	0.113***
	(0.018)	(0.018)	(0.018)	(0.023)	(0.025)	(0.023)
ln (Population)	0.286**	0.282**	0.288**	0.031	−0.118	0.019
	(0.134)	(0.134)	(0.133)	(0.217)	(0.209)	(0.218)
ln (Income per capita)	0.261**	0.269**	0.260**	0.403**	0.266	0.415**
	(0.115)	(0.116)	(0.115)	(0.202)	(0.194)	(0.206)
Distance x yr-qtr FE	x	x	x	x	x	x
Yr-qtr FE	x	x	x	x	x	x
Market FE	x	x	x	x	x	x
Observations	256,129	256,129	256,129	256,129	256,129	256,129
R^2	0.876	0.876	0.876	0.678	0.684	0.676
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 6: First stage regression output for instrumental variables regressions. Dependent variables are the mean, geometric mean, and inverse distance weighted common ownership indices.

	Dependent variable:		
		Cjk Index	
Cjk index	(Mean)	(GMean)	(Inv.Dist.)
Airline presence in Russell 1000	0.018***	0.025***	0.019***
	(0.004)	(0.005)	(0.004)
BlackRock-BGI acquisition	−0.052***	−0.065***	−0.051***
	(0.009)	(0.012)	(0.009)
Number of competitors	−0.014***	−0.035***	−0.014***
	(0.002)	(0.003)	(0.002)
Non-stop carriers	0.001	−0.001	0.001
	(0.002)	(0.002)	(0.002)
Non-stop SW	−0.005	−0.008	−0.004
	(0.005)	(0.010)	(0.005)
Non-stop LCC	−0.028***	−0.055***	−0.029***
	(0.005)	(0.009)	(0.005)
Share Connect	0.003	−0.021**	0.004
	(0.006)	(0.010)	(0.006)
ln (Population)	−0.086	−0.208***	−0.091*
	(0.053)	(0.065)	(0.053)
ln (Income per capita)	0.095	0.044	0.101*
	(0.059)	(0.080)	(0.060)
Distance x yr-qtr FE	x	x	x
Yr-qtr FE	x	x	x
Market FE	x	x	x
Observations	256,129	256,129	256,129
R^2	0.719	0.674	0.717
F-statistic(excl instr.)	28.63	35.13	28.22
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Summary statistics for subsample used in structural estimation

Variables (market-carrier level)	N	Mean	Std. Dev.	Min.	Max.
Airline/market characteristics					
Average fare (in hundred)	137,461	2.42	0.89	0.25	20.60
Dummy for nonstop	137,461	0.28	0.45	0	1
Distance	137,461	2,629.11	1,404.18	122.63	10,788
Log of distance	137,461	7.71	0.61	4.81	9.29
Number of passengers	137,461	7,766.87	17,836.82	10	252,920
Population (in million)	137,461	3.94	2.23	1.87	16.32
Carrier market share	137,461	0.002	0.004	6.13e-07	0.064
Carrier within-market share	137,461	0.23	0.27	1.72e-05	1
Concentration measures					
HHI	137,461	4,874.22	2,054.75	1,513.34	10,000
MHHI	137,461	7,185.22	1,397.79	2,624.15	10,000
MHHI delta	137,461	2,311.00	1,119.80	0	4,884.28
Instruments					
Number of rival carriers	137,461	3.98	1.52	0	10
Log of avg. distance by rival carriers	137,461	7.65	0.82	0	9.21
Number of nonstop rival carriers	137,461	1.07	1.28	0	8
Dummy for being in Russell 1000	137,461	0.66	0.47	0	1
Number of carriers in Russell 1000	137,461	3.14	0.92	0	6

Note: The subsample used is limited to the 2011:Q1-2014:Q4 period and markets with a population of least 2 million in the fourth quarter of 2014. *HHI*, *MHHI*, and *MHHI delta* vary only at the market-quarter level, so all airlines in a given market-quarter have the same value of these variables.

Table 8: Estimation results of the structural models of airline demand and supply

	Demand	Supply
Non-linear parameters		
Scaling parameter (τ)		-0.45
		(0.37)
Price (α)	-1.20**	
	(0.11)	
Nesting parameter (σ)	0.83**	
	(0.01)	
Linear parameters		
Constant	-1.24**	2.94**
	(0.50)	(0.32)
$D_{non-stop}$	0.34**	-0.28**
	(0.02)	(0.02)
ln(distance)	-0.45**	-0.08**
	(0.03)	(0.02)
Carrier FE	Yes	Yes
Yr-qtr FE	Yes	Yes
Geo-market FE	Yes	Yes
No. of obs.	137,461	137,461

$*$ Significant at 10% level, $**$ significant at 5% level.
Note: The models are estimated using a subset of the data that includes the 2011:Q1-2014:Q4 period and markets with at least 2 million population in the fourth quarter of 2014.

Appendix: Data construction

We assembled a data set to match the data used by AST as closely as possible by following the filtering rules described in Section 4 and Appendix B of their paper. Additional filtering rules and data cleaning procedures are described in this appendix.

A Airline name changes resulting from mergers

Airline names in the Department of Transportation's DB1B and T-100 data sets are often not adjusted to reflect ownership changes that result from a merger at the date the merger became effective. For example, United Airlines merged with Continental Airlines in 2010Q4, but Continental is recorded as continuing to operate flights through 2011Q4. We correct for this using information on airline mergers in S&P Capital IQ by assigning a common name to any two airlines that merged from the effective date of the merger. For example, all Continental flights between 2010Q4 and 2011Q4 were assigned to United to reflect the United-Continental merger. Similar changes were made to the following airline mergers:(1) American Airlines and Trans World Airlines in 2001Q2, (2) Republic Airways and Shuttle America Corp. in 2005Q2, (3) US Airways and America West Airlines in 2005Q3, (4) Delta Air Lines and Northwest Airlines in 2008Q4, (5) Republic Airways and Frontier Airlines in 2009Q4, (6) Southwest Airlines and AirTran Airways in 2011Q2, and (7) American Airlines and US Airways in 2013Q4.

B Adjustments made to the TR ownership data

B.1 Voting shares

We identified several discrepancies between Thomson Reuters voting shares (the sum of sole and shared voting shares) and voting shares reported in the underlying SEC 13-F filings by spot-checking the13-F filings. Per our request, Thomson Reuters provided corrections for the following three errors that were identified using this approach: (1) assigning zero voting shares to an airline-investor-quarter where the underlying 13-F reports positive shares, (2) swapping sole with shared voting shares, and (3) assigning total shares to voting shares in cases where the underlying 13-F reports voting shares that are strictly less than total shares.

Three additional discrepancies were not corrected by Thomson Reuters: 1) instances where voting shares were missing (as opposed to zero) while total shares (i.e., voting plus non-voting shares) are populated (this occurs in roughly 2% of airline-quarter-investor observations); instances where the number of voting shares is larger than the number of total shares (this occurs in roughly about 3% of airline-quarter-investor observations); and instances where total shares are missing but voting shares are populated (this occurs in roughly 3% of airline-quarter-investor observations). To correct for the first two cases, we assume that the number of voting shares is equal to the number of total shares. For the third case, we assume that the number of total shares is the same as the number of voting shares.

B.2 Missing shareholding when SEC 13-F filings are present

For some investor-quarters TR does not report shareholdings even though the underlying SEC 13-F filings do report shareholdings. To correct this problem, we imported information directly from 13-F filings. This was done for a subset of investors based on their importance in airline holdings. To identify the subset of investors we summarize investor i's airline holdings in quarter t by

$$H_{it} = \sum_{j \in J_{it}} (holding\_share_{ijt} \times passenger\_share_{jt})$$

where J_{it} indicates a set of airlines investor i owns in quarter t, $holding\_share_{ijt}$ is the share of airline j's shareholdings investor i owns in quarter t, and $passenger\_share_{jt}$ is the national passenger share of airline j in quarter t. We then rank investors by their maximum value of H_{it} and pick the top 300 investors identified by this ranking. The top 300 investors identified by this method covers 90% of TR's airline ownership shares.

We used an algorithm to screen the top 300 investors for quarters where shareholdings are most likely to be missing. The algorithm flags investors that own shares in an airline in one quarter but have zero holdings in the two quarters immediately prior and immediately after. The second filter flags investors that own airline shares in one quarter, sell all airline shares in the following quarter, and then report airline shares in the next quarter. Both of these filters attempt to screen for investor behavior that could indicate Thomson Reuters' failure to record shareholdings. We then examined SEC 13-F filings for the investor quarters that were flagged to determine whether the shareholdings reported in Thomson Reuters was consistent with shareholdings reported in the 13-F.[39] Using this method we identified shareholdings missing from Thomson Reuters in 39 investor-airline-quarters.

AST states in Section 4 of their paper that they added missing filings for "BlackRock in the period 2010 and 2013-2015, Barclays in the period 2003Q4, Northern Trust in the period 2014Q1, BNY Mellon in the period 2013Q3, and JP Morgan in the periods 2003Q4, 2008Q3, 2013Q3-A4"[40] These investor-quarters were not missing from the TR ownership data that we obtained.

[39]Investors were identified by searching via a Central Index Key (CIK). If Thomson Reuters did not provide a CIK, investors were identified by name.

[40]See footnote 7 on page 10 of AST.

Lastly, we make adjustments to the portion of the ownership data that relies upon SEC proxy statements, i.e., non-institutional investor shareholdings. Since non-institutional investors that are required to submit proxy statements do so annually, while the TR ownership data is quarterly, we assume that ownership positions reported via proxy statement are the same throughout all four quarters of the year in which the proxy statement was submitted. Shareholdings by non-institutional investors account for 1.5% of the total.

B.3 Investor parent company

The TR ownership data provides shareholdings at the manager (subsidiary) level. Each manager is mapped to its parent-company at the time that data are pulled.[41] To account for changes in parent company name that occurred through the sample as a result of mergers and acquisitions we needed to modify the TR data. For example, BlackRock acquired Barclays Global Investors in 2009Q4. Thomson Reuters assigns BlackRock Inc. as the parent to all managers that previously belonged to Barclays Global Investors but does not provide the name of the parent company prior to the acquisition. Per our request, Thomson Reuters separately provided a list of "investor-name" changes and the time of changes. However, this list documents name changes at the manager level, but does not provide a mapping from manager to the parent company. Nor does it indicate whether an investor-name change was associated with a change of parent company.

We used publicly available information to determine whether mergers or acquisitions caused changes in investor names. We focused on manager name changes associated with the set of investors that account for 90% of all airline shareholdings. In cases where we could not find information on changes to the parent company we kept the parent company provided by TR. We also searched for mergers and acquisitions that may have affected investor-managers that have names that differ significantly from their parent company name. Our research resulted in adjustments to 124 investors and 54 parent companies in total.

B.4 Multiple security IDs

In the TR ownership data, a given airline is sometimes associated with multiple "security IDs." According to Thomson Reuters, this can occur either to distinguish between different classes of stock – e.g., common, preferred, or fixed income – or to distinguish stocks that existed in pre- versus post-bankruptcy periods. For an investor who owns shares of a given airline across different security IDs, we sum its shares across the different security IDs.

[41]The TR ownership data used in this paper were extracted in the early 2017.