Estimating Oligopoly with Shareholder Voting Models*

José Azar

University of Navarra, School of Economics and Business
IESE Business School, Spain and CEPR, UK

Ricardo Ribeiro

Universidade Católica Portuguesa, Católica Porto Business School
Research Centre in Management and Economics, Portugal

March 2024

Abstract

We develop an empirical model of overlapping ownership conduct. The model (i) links firm conduct parameters to deep parameters of the firm's process of shareholder preference aggregation through voting; (ii) can cope with ownership settings involving both intra- and inter-industry overlapping ownership; and (iii) yields an equilibrium flexible formulation for the management's objective function that allows for no internalization, partial internalization and full internalization of shareholder objectives by managers. Using data for the U.S. airline industry in the 2015-2017 period, we find evidence for a partial internalization formulation in which managers put significant weight on shareholder objectives, but substantially less than in the full-internalization limiting case. We find also that inter-industry overlapping ownership is associated to lower inferred marginal costs, and that omitting inter-industry overlapping ownership leads to substantial bias towards zero in the parameters that drive how much intra-industry overlapping ownership is internalized by the firms. Finally, we find, focusing on the 2017Q4 period, that overlapping ownership overall (both intra- and inter-industry) seems to increase the average airline fare by 4.0%, increase industry profit by 24.4% and decrease consumer surplus by 1.8%, and that these effects are mostly due to overlapping ownership by shareholders other than the "Big Three" asset managers.

JEL Classification: D12, D22, L13, L21, L93

Keywords: Market Power, Overlapping Ownership, Structural Estimation, Antitrust Policy, Managerial Entrenchment, Airline Industry

---

* We would like to thank Martin Schmalz, Isabel Tecu and Frank Verboven, as well as seminar and conference participants at the CEPR/JIE Conference on Applied Industrial Organisation, MaCCI Annual Conference, Oxford University Common Ownership Mini-Conference, Bocconi University, Düsseldorf Institute for Competition Economics, University of Bonn, and University of Naples Federico II for helpful comments and suggestions. Ricardo Ribeiro gratefully acknowledges financial support from Fundação para a Ciência e a Tecnologia (UIDB/00731/2020, https://doi.org/10.54499/UIDB/00731/2020). José Azar is with the School of Economics and Business, University of Navarra, IESE Business School, and CEPR, Av Pearson, 21, 08034 Barcelona, Spain. Email address: jazar@iese.edu. Ricardo Ribeiro is with Universidade Católica Portuguesa, Católica Porto Business School and CEGE, Rua de Diogo Botelho 1327, 4169-005 Porto, Portugal. Email address: rribeiro@ucp.pt. All remaining errors are of course our own.

1 Introduction

The implications of growing overlapping ownership of publicly traded firms for antitrust policy are subject of intense debate (see, for example, Elhauge, 2015; Posner et al., 2017; Scott Morton and Hovenkamp, 2017; Tzanaki, 2017; Rock and Rubinfeld, 2018; Phillips, 2018; Delrahim, 2019; BlackRock, 2019; Posner, 2021). However, causal inference on this question presents a formidable challenge. The price-concentration regression approach of Azar et al. (2018) has well-known limitations, as was acknowledged in that paper, and as was also pointed out by O'Brien and Waehrer (2017) and Kennedy et al. (2017). Although the theory of O'Brien and Salop (2000) implies an equilibrium relationship between the Modified Herfindahl-Hirschman delta (or MHHI delta) and markups, the MHHI delta formula involves market shares, which are a function of prices and, therefore, endogenous.

In order to address the endogeneity of price-concentration regressions, the literature that empirically examines the impact of overlapping ownership on market outcomes has evolved towards the estimation of structural empirical models of overlapping ownership conduct, which provide an economically sound causal interpretation of the effect of ownership changes on market outcomes. This literature started with Kennedy et al. (2017) for airlines over the period 2011-2014, and includes contributions by Backus et al. (2021) for the ready-to-eat cereal industry, Ruiz-Pérez (2019) and Park and Seo (2019) also for airlines.[1] However, most of this literature (i) examines firm conduct under intra-industry overlapping ownership by introducing a (non-structural) internalization parameter to capture the degree of internalization of shareholder objectives by managers; and (ii) without accounting for inter-industry overlapping ownership, which Azar and Vives (2021b) show to be associated with lower prices in product markets.

This paper contributes to this existing literature by estimating a structural empirical model of overlapping ownership conduct for the U.S. domestic airline industry which addresses these two issues. To do so, we consider that airlines play an oligopoly game of multiproduct Bertrand competition involving three types of agents: consumers, shareholders and managers. Consumers are assumed to care about the utility obtained from their purchase (or no purchase) decisions, which are modelled using a random-coefficients nested

[1] The move of the empirical overlapping ownership literature towards the estimation of structural empirical models mimics the paradigm-shift in the industrial organization literature as a whole, which - to address the longstanding criticism of the endogeneity of concentration measures (see, for example, Schmalensee, 1989; Bresnahan, 1989) - mostly abandoned the price-concentration regression approach (generally known as the structure-conduct-performance paradigm) in favor of structural empirical models of product differentiation and oligopolistic competition (e.g. Berry, 1994; Berry et al., 1995), an approach that became known in the 1990s as the "New Empirical Industrial Organization". For a review of this methodological approach and recent advances, see Einav and Levin (2010).

logit demand model (as in, for example, Berry et al., 1996; Berry and Jia, 2010; Ciliberto and Williams, 2014). Shareholders can hold shares in multiple airlines (and so engage in intra-industry overlapping ownership) and also in multiple other firms (outside the airline industry and so engage in inter-industry overlapping ownership), and are assumed to care about the utility obtained from their financial holdings. Finally, the managers of airlines are assumed to hold shares in the firm and so, absence any influence from shareholders, would decide the pricing strategy of airlines to maximize own-profit.

Shareholders, due to intra-industry overlapping shareholding, may not, however, unanimously agree on own-firm profit maximization and may, to some extent, influence the pricing strategy proposed by the management. We microfound the aggregation of shareholders (heterogeneous) preferences into the management's objective function through a model of shareholder voting as in Azar (2012), Azar (2017), Brito et al. (2018), Azar (2020) and Moskalev (2019). In particular, we follow Azar (2020) in allowing shareholder dissent to impose a negative cost to managers. This yields a flexible formulation for the management's objective function that (i) allows for no internalization (i.e., profit maximization), partial internalization and full internalization of shareholder objectives by managers; and (ii) predicts that the degree of internalization of shareholder objectives by managers should increase with the level of shareholder concentration within the firm. This gives us a microfounded model of firm conduct, which is more flexible and in which the parameters that determine how much intra-industry overlapping ownership is internalized have a clearer structural interpretation. Explicitly modeling the process of preference aggregation through voting is, not only, a step forward relative to the existing structural overlapping ownership literature, but also constitutes, to the best of our knowledge, a first attempt to develop and estimate a structural model of oligopoly with agency frictions.[2]

Azar and Vives (2021a) show that, from the point of view of airlines, there can be inter-industry positive pecuniary externalities from expanding output. Taking as given output in other industries, increasing output in the airline industry implies that the relative prices (and profits) in industries outside the airline industry are higher. If shareholders engage in inter-industry overlapping ownership, they internalize this increase in profits. In order to incorporate this effect, we allow inter-industry overlapping ownership to influence the marginal cost of airlines. We do so because more inter-industry overlapping ownership leads to more internalization of these pecuniary externalities, and therefore can be thought of as reducing the effective marginal cost of airlines. This reduced-form approach tries to

[2] While there is a theoretical literature on oligopoly models with agency frictions (e.g. Brander and Lewis, 1986; Fershtman and Judd, 1987; Antón et al., 2020), none of these papers attempt to structurally estimate their models.

address the limitations of partial equilibrium oligopoly theory in the context of overlapping ownership, which we hope can be seen as a stepping stone in the direction of a more general equilibrium perspective.

We estimate the model using a period of estimation (2015-2017) that was not affected by (major) airline bankruptcies. The presence of bankruptcies is a major complicating factor and was the main criticism of Azar et al. (2018) by BlackRock (2019) as there is no agreement over how to model control of a firm during bankruptcy.[3] We find that the no and full internalization limiting cases are rejected by the data, which instead favors a partial internalization of shareholder objectives by managers. In other words, the evidence suggests that managers put significant weight on shareholder objectives, but substantially less than in the full-internalization limiting case. Moreover, our conduct parameter estimates indicate that the internalization of shareholder objectives by the management is, in fact, higher when the firm's shareholders are more concentrated.

We find also that inter-industry overlapping ownership has a negative effect on the inferred marginal cost of airlines. Moreover, we show that omitting inter-industry overlapping ownership from the supply side model leads to substantial downward bias in the estimated conduct parameters that drive the internalization of shareholder objectives by the management. In particular, when we assume that the parameters driving this internalization are constant across airlines as in Kennedy et al. (2017), Park and Seo (2019) and Backus et al. (2021), omitting inter-industry overlapping ownership would even lead us not to reject a profit maximization conduct, when profit maximization is clearly rejected by the data once inter-industry overlapping ownership is taken into account.

Using a structural model allows us to perform counterfactuals and do welfare analysis. Focusing on the 2017Q4 period, we examine distinct counterfactual overlapping ownership settings to evaluate the impact of intra-industry overlapping ownership (solely), inter-industry overlapping ownership (solely) and both. We find that intra-industry overlapping ownership does soften competition substantially, despite mitigation of the internalization of shareholders preferences by the manager. In particular, we show that intra-industry overlapping ownership seems to increase the average airline fare by 10.7%, which is near the upper end of the range of pricing impact estimates in Azar et al. (2018), decrease the average number of passengers by 15.6%, increase industry profit by 16.3% and decrease consumer surplus by 7.5%.

We find also that the negative effect of inter-industry overlapping ownership on the

[3]One could, for example, assume that the firm is controlled by its bondholders during bankruptcy. However, data on bondholders (who may also hold shares in competitors) is less readily available than data on stock ownership.

marginal cost of airlines is passed through to prices. This is consistent with Azar and Vives (2021b), who show, using reduced-form regressions, that increases in inter-industry overlapping ownership are associated with lower prices. In particular, we show that inter-industry overlapping ownership seems to decrease the average airline fare by 6.3%, which is near the lower end of the range of pricing impact estimates in Azar and Vives (2021b), increase the average number of passengers by 8.5%, increase industry profit by 7.4% and increase consumer surplus by 6.1%. Combining the two effects suggests that overlapping ownership overall (both intra- and inter) seems to increase the average airline fare by 4.0%, decrease the average number of passengers by 8.2%, increase industry profit by 24.4% and decrease consumer surplus by 1.8%.

Finally, we evaluate the fraction of the impact of overlapping ownership that is due to the "Big Three" asset managers (BlackRock, Vanguard and State Street). To do so, we assume that the ownership structure of the different airlines is such that solely the "Big Three" asset managers engage in overlapping ownership. We find that the intra-industry overlapping ownership of the Big Three seems to increase the average airline fare by 2.7%, decrease the average number of passengers by 4.6%, increase industry profit by 5.1% and decrease consumer surplus by 2.2%. In turn, the inter-industry overlapping ownership of the Big Three seems to decrease the average airline fare by 4.6%, increase the average number of passengers by 6.0%, increase industry profit by 5.4% and increase consumer surplus by 4.3%. Because the inter-industry effect of overlapping ownership is so high, this implies that overall (both intra- and inter) overlapping ownership by the Big Three seems to decrease the average airline fare by 1.9%, increase the average number of passengers by 0.8%, increase industry profit by 10.7% and increase consumer surplus by 2.0%. Thus, the impact of overlapping ownership seems to be due to overlapping ownership by shareholders other than the "Big Three" asset managers.

The remainder of the paper is organized as follows. Section 2 describes the theoretical framework. Section 3 describes the estimation procedure. Section 4 describes the data, the estimation results and the counterfactuals. Section 5 concludes.

2 Theoretical Framework

2.1 Setup

There are K shareholders, indexed by k, who can engage in overlapping ownership and hold shares in multiple firms, index by f. Let Θ_s denote the set of shareholders, Θ_a denote the set of firms in the airline industry and Θ_o denote the set of firms outside of the airline industry.

Let also υ_{kf} denote the fraction of voting shares of shareholder k in firm f and ϕ_{kf} denote the financial interest share of shareholder k in firm f.

Airlines can operate in M markets, indexed by m. Let M_f denote the subset of markets in which airline f operates. In each market, airlines compete for N_m potential consumers, indexed by i, by offering J_m airline ticket products. Let $\mathcal{F}_{fm}$ denote the subset of the J_m products available in market m that are offered by airline f.

The N_m potential consumers in each market m are assumed to choose one option among J_m+1 alternatives, indexed by j: the J_m inside options $j=1,\ldots,J_m$ offered by airlines and an outside option $j=0$, defined as not purchasing an airline ticket product.

2.2 Supply Model

In this subsection, we develop a new, more flexible, objective function for airlines that allows for partial managerial entrenchment. This new objective function nests the objective functions typically used in the corporate finance and industrial organization literatures and allow us to assess competing hypotheses about the degree of internalization of shareholder objectives by the management. To do so, we begin by describing the profit of each airline f, as follows:

$$\pi_f\left(\mathbf{p}_f,\mathbf{p}_{-f}\right) = \sum_{m\in M_f}\left(\sum_{j\in\mathcal{F}_{fm}}\left(p_{jm}-c_{jm}\right)s_{jm}\left(\mathbf{p}_m\right)N_m - C_{fm}\right), \tag{1}$$

where p_{jm} denotes the fare of product j in market m, c_{jm} denotes the (assumed constant) marginal cost of product j in market m, $s_{jm}\left(\mathbf{p}_m\right)$ denotes the market share of product j in market m, which depends on the vector $\mathbf{p}_m$ of fares for all the products available in market m, and C_{fm} denotes the fixed cost of airline f operating in market m. This establishes that the profit of each airline can be written as a function of the full vector $\mathbf{p}$ of fares across the set of M markets, which we decompose between those produced by firm f, denoted $\mathbf{p}_f$ and those produced by all other firms, denoted $\mathbf{p}_{-f}$.

2.2.1 Management's Objective Function

The Fisher Separation Theorem ensures, under perfect competition and complete markets, that all shareholders agree unanimously on profit maximization (Ekern and Wilson, 1974; Radner, 1974; Leland, 1974; Hart, 1979; DeAngelo, 1981). However, this is not the case when shareholders engage in overlapping ownership. In this case, shareholders may not unanimously agree on own-firm profit maximization.

The dominant formulation of the objective function of management in the presence of overlapping shareholders is due to O'Brien and Salop (2000). Incorporating features from Rotemberg (1984) and Bresnahan and Salop (1986), they assume that the management of a firm with overlapping shareholders would decide the strategy of the firm to maximize a weighted sum of the preferences of its shareholders. Azar (2012), Azar (2017), Brito et al. (2018) and Moskalev (2019) show that this formulation can be microfounded through a probabilistic voting model in which shareholders vote to express whether they approve or not of a managerial change in the firm's status quo strategic plan.[4]

The dominant formulation, although heavily used in the literature, has also been critiqued for yielding counter-intuitive implications, particularly when ownership is highly dispersed (see, for example, Gramlich and Grundl (2017); O'Brien and Waehrer 2017; Crawford et al. (2018)). As an illustration, consider the following example. Suppose that an industry has four symmetric firms. Moreover, suppose that the four firms have 1,000 shareholders, each with 0.1% ownership of the whole industry. The dominant formulation implies that the outcome in this industry is the same as in a monopoly in which one shareholder held 100% of the four firms. This seems unlikely, and the reason is that, with such dispersed ownership, why should the firms act in the interest of their shareholders?

We propose to address this issue by developing a new, more flexible, objective function for airlines that allows for partial managerial entrenchment.[5] In particular, we follow Berry and Jia (2010), Ciliberto and Williams (2014), Kennedy et al. (2017) and Park and Seo (2019) in assuming that the airlines compete in fares and follow Azar (2020) in assuming the following behavior for managers and shareholders. The management of each airline f can propose any pricing strategy $\mathbf{p}_f$, which may or may not be the same as the existing strategy of the airline $\tilde{\mathbf{p}}_f$. They do so conditional on the expectation regarding the other airlines' strategies $\mathbf{p}_{-f}$. We assume that the management has, however, its own preferences over strategies, which are increasing in the profits of the airline that they manage, because they hold shares in the firm. The fraction of shares they hold is infinitesimal relative to the total number of shares in the airline, but substantial from the point of view of the managers. Absence any influence from shareholders, managers would therefore maximize profits, and would not take into account any shareholder objectives beyond profit maximization.

Shareholders, due to intra-industry overlapping shareholding, may not, however, unanimously agree on own-firm profit maximization and may, to some extent, influence the strategy

[4]Or, equivalently, through a probabilistic voting model in which shareholders vote to elect the manager from two potential candidates with conceivably differing strategy proposals to the firm.

[5]Brito et al. (2021) develop an alternative objective function for the management to address the same issue. However, their formulation would not allow us to (structurally) assess competing hypotheses about the degree of internalization of shareholder objectives by managers.

proposed by the management. We consider that shareholder dissent imposes a negative cost to managers. This cost can be a higher probability of being replaced, or a lower pay package, or both.[6] Dissent can be expressed through voting against management, or through engagement; what matters is that the cost for managers of dissent is increasing in the number of votes held by the dissenting shareholders. For simplicity, we assume that the cost of dissent is proportional to the number of dissenting votes. Thus, if we denote the probability that shareholder k does not dissent at firm f as χ_{kf}, then the objective function of the management of airline f, captured by their expected utility, is given by:

$$u_f(\mathbf{p}_f, \mathbf{p}_{-f}) = \pi_f(\mathbf{p}_f, \mathbf{p}_{-f}) - \kappa \sum_{k \in \Theta_s} \upsilon_{kf}(1 - \chi_{kf}), \tag{2}$$

where the parameter $\kappa \geq 0$ captures the cost (per dissenting vote) of shareholder dissent.

In order to model the probability that each shareholder k does not dissent at airline f, we have to address the objective function of shareholders. We assume that the objective function of shareholder k is given by the utility she obtains from her intra-industry financial holdings:

$$u_k(\mathbf{p}_f, \mathbf{p}_{-f}) = \sum_{g \in \Theta_a} \phi_{kg} \pi_g(\mathbf{p}_f, \mathbf{p}_{-f}). \tag{3}$$

Further, we assume that the probability that shareholder k does not dissent is uniformly distributed over the difference in the utility she would obtain under the management's proposed strategy $\mathbf{p}_f$ and the existing strategy $\tilde{\mathbf{p}}_f$, as follows:

$$\chi_{kf} = H(u_k(\mathbf{p}_f, \mathbf{p}_{-f}) - u_k(\tilde{\mathbf{p}}_f, \mathbf{p}_{-f})), \tag{4}$$

where $H(\cdot)$ is the cumulative distribution function of an uniform over the interval $[-1/2\psi, 1/2\psi]$, with the parameter $\psi > 0$ controlling the responsiveness of shareholders to managerial behavior. This implies that the objective function of the management of airline f can be rewritten as follows:

$$\begin{aligned} u_f(\mathbf{p}_f; \tilde{\mathbf{p}}_f; \mathbf{p}_{-f}) &= \pi_f(\mathbf{p}_f, \mathbf{p}_{-f}) \\ &- \kappa \sum_{k \in \Theta_s} \upsilon_{kf} \left(1 - H\left(\sum_{g \in \Theta_a} \phi_{kg}(\pi_g(\mathbf{p}_f, \mathbf{p}_{-f}) - \pi_g(\tilde{\mathbf{p}}_f, \mathbf{p}_{-f}))\right)\right). \end{aligned} \tag{5}$$

[6] Aggarwal et al. (2019) show that, even in uncontested elections, directors that get voted against face negative consequences, including a higher probability of leaving the board, a lower probability of taking important positions in the board, and reduced opportunities in the market for directors. Antón et al. (2020) also develop a model of agency with common ownership, in which agency is generated by asymmetric information as opposed to entrenchment. They show that ownership structure affects managerial compensation. This constitutes another way in which shareholders can impose costs on managers.

Conditional on the strategies of the rival airlines $\mathbf{p}_{-f}$, strategy $\mathbf{p}_f$ chosen by the management of airline f is *stable* if and only if it maximizes $u_f(\mathbf{p}_f;\tilde{\mathbf{p}}_f;\mathbf{p}_{-f})$ when $\tilde{\mathbf{p}}_f=\mathbf{p}_f$. That is, an airline's strategy is stable (conditional on the strategies of the rivals) when, if it is the existing strategy, management has no incentive to deviate from it.

The first-order condition for this maximization problem is given by:

$$\frac{\partial\pi_f(\mathbf{p}_f,\mathbf{p}_{-f})}{\partial\mathbf{p}_f}+\kappa\psi\left(\sum_{k\in\Theta_s}\upsilon_{kf}\left(\sum_{g\in\Theta_a}\phi_{kg}\frac{\partial\pi_g(\mathbf{p}_f,\mathbf{p}_{-f})}{\partial\mathbf{p}_f}\right)\right)=\mathbf{0}, \tag{6}$$

which implies that the stable strategy for airline f (again, as a function of the rival airlines' strategies) is entirely equivalent to the one which would result from maximizing the following objective function:

$$\max_{\mathbf{p}_f}\pi_f(\mathbf{p}_f,\mathbf{p}_{-f})+\kappa\psi\left(\sum_{k\in\Theta_s}\upsilon_{kf}\left(\sum_{g\in\Theta_s}\phi_{kg}\pi_g(\mathbf{p}_f,\mathbf{p}_{-f})\right)\right), \tag{7}$$

which, in turn, can be rewritten as a weighted sum of the profits of (potentially) all the airlines in the industry:

$$\max_{\mathbf{p}_f}\pi_f(\mathbf{p}_f,\mathbf{p}_{-f})+\sum_{g\in\Theta_a\setminus f}\lambda_{fg}^{intra,m}\pi_g(\mathbf{p}_f,\mathbf{p}_{-f}). \tag{8}$$

where

$$0\leq\lambda_{fg}^{intra,m}\equiv\underbrace{\frac{\kappa\psi\sum_{k\in\Theta_s}\upsilon_{kf}\phi_{kf}}{1+\kappa\psi\sum_{k\in\Theta_s}\upsilon_{kf}\phi_{kf}}}_{\tau_f}\underbrace{\frac{\sum_{k\in\Theta_s}\upsilon_{kf}\phi_{kg}}{\sum_{k\in\Theta_s}\upsilon_{kf}\phi_{kf}}}_{\lambda_{fg}^{intra}}\leq\lambda_{fg}^{intra} \tag{9}$$

is the intra-industry *managerial* Edgeworth sympathy coefficient, that is, the weight that the management of airline f places on the profit of airline g relative to airline f's profit. This objective function establishes that the management of an airline will, in equilibrium, weigh its preference (own-profit maximization) and the preferences of its shareholders, which may include the profits of other airlines due to intra-industry overlapping ownership. In other words, shareholder dissent may induce the management to internalize (to some degree) the externalities their strategies impose on other airlines.

The intra-industry managerial Edgeworth sympathy coefficient $\lambda_{fg}^{intra,m}$ involves two components. One component coincides with the intra-industry standard Edgeworth sympathy coefficient λ_{fg}^{intra} . This component quantifies the full internalization of shareholder objectives by the management as established in the dominant formulation. The numerator of λ_{fg}^{intra} is a vote-weighted average of the financial interest share of airline f's shareholders in airline g, and the denominator is a vote-weighted average of the financial interest share of airline f's shareholders in airline f. Thus, the ratio indicates the holdings of the average shareholder of airline f in airline g relative to airline f. The other component, in line with Azar (2020), and consistent with the ideas of Phillips (2018) and Bebchuk and Hirst (2018), captures the mitigation of the full internalization λ_{fg}^{intra} due to managerial entrenchment. The mitigation factor τ_f, established to between zero and one, depends on the parameters controlling the cost of shareholder dissent and the responsiveness of shareholders to managerial behavior, κ and ψ, respectively, and also on the vote-weighted average financial interest share of the shareholders in the airline $\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}$.[7,8] This weighted average constitutes a measure of shareholder concentration within the firm and implies that in airlines with less concentrated shareholders, managers are more entrenched, as shareholders with low stakes in airlines are less likely to respond to changes in pricing by voting against management.

The objective function outlined above nests various specifications used in the corporate finance and industrial organization literatures to address intra-industry overlapping ownership, which allows us to assess the following different hypotheses about the degree of internalization of shareholder objectives by the management.

No Internalization. No internalization of shareholder objectives by the management or, in other words, profit maximization, arises as a special case when the cost of shareholder dissent κ is zero and the responsiveness of shareholders to managerial behavior ψ is not infinite. In this case, we have that $\kappa\psi = 0$, which implies that $\tau_f = 0$ for all $f \in \Theta_a$ and, therefore, that all the intra-industry managerial Edgeworth sympathy coefficients are null. Intuitively, if there is no cost of shareholder dissent, or shareholders do not change their behavior in response to managerial behavior, then the preferences of the management determine the objective of the firm. In this case, the management of each airline f will choose the pricing strategy $\mathbf{p}_f$ to maximize $\pi_f(\mathbf{p}_f, \mathbf{p}_{-f})$.

Partial Internalization. Partial internalization of shareholder objectives by the management arises when both the cost of shareholder dissent κ and the responsiveness of shareholders to managerial behavior ψ are strictly positive and finite. In this case, we have that $0 < \kappa\psi < \infty$, which implies that $0 < \tau_f < 1$ for all $f \in \Theta_a$ and, therefore, that all the intra-industry managerial Edgeworth sympathy coefficients are strictly greater than zero and smaller than the intra-industry standard Edgeworth sympathy coefficients. Intuitively,

[7]Under an one-share-one-vote rule, the vote-weighted average financial interest share of the shareholders in the airline reduces to the Herfindahl-Hirschman index of shareholders ownership.

[8]If we consider τ_f to be constant across airlines, it provides a microfoundation for the objective function of the firm in Kennedy et al. (2017) and Backus et al. (2021).

if the cost of shareholder dissent is strictly positive and finite, and shareholders, to some extent, change their behavior in response to managerial behavior, then the preferences of the both management and shareholders determine (partly) the objective of the firm. In this case, the management of each airline f will choose the pricing strategy $\mathbf{p}_f$ to maximize $\pi_f\left(\mathbf{p}_f, \mathbf{p}_{-f}\right) + \sum_{g\in\Theta_a\setminus f} \lambda_{fg}^{intra,m} \pi_g\left(\mathbf{p}_f, \mathbf{p}_{-f}\right)$, where $0 < \lambda_{fg}^{intra,m} < \lambda_{fg}^{intra}$ for all airlines.

Full Internalization. Full internalization of shareholder objectives by the management, as established in the dominant formulation, arises as a special case when either the cost of shareholder dissent κ or the responsiveness of shareholders to managerial behavior ψ are infinite (and neither is zero). In this case, we have that $\kappa\psi = \infty$, which implies that $\tau_f = 1$ for all $f \in \Theta_a$ and, therefore, that all the intra-industry managerial Edgeworth sympathy coefficients coincide with the intra-industry standard Edgeworth sympathy coefficients. This implies that there is no managerial entrenchment and thus intra-industry overlapping ownership is fully internalized by the management. Intuitively, if the cost of shareholder dissent is infinite, or shareholders change their behavior very much in response to managerial behavior, then the preferences of the shareholders determine the objective of the firm. In this case, the management of each airline f will choose the pricing strategy $\mathbf{p}_f$ to maximize $\pi_f\left(\mathbf{p}_f, \mathbf{p}_{-f}\right) + \sum_{g\in\Theta_a\setminus f} \lambda_{fg}^{intra} \pi_g\left(\mathbf{p}_f, \mathbf{p}_{-f}\right)$.

2.2.2 Cost Structure

We follow Berry et al. (1995) in modelling the marginal cost of airline products as a function of observable and unobservable cost-shifters. Further, we also model the marginal cost of airline products as a function of inter-industry overlapping ownership. We do so because, as shown by Azar and Vives (2021b), from the point of view of an airline, there can be inter-industry positive pecuniary externalities from expanding output. Taking as given output in other industries, increasing output in the airline industry implies that the relative prices (and profits) in industries outside the airline industry are higher. If the shareholders of an airline also hold financial interest shares in firms outside of the airline industry, they internalize this increase in profits. More inter-industry overlapping ownership leads to more internalization of these pecuniary externalities and, therefore, can be thought of as reducing the effective marginal cost of the airlines. As such, the marginal cost of product j (offered by airline f) in market m is assumed to be given by:

$$c_{jm} = \gamma\lambda_{fo}^{inter} + \mathbf{w}_{jm}\mathbf{\Gamma} + \omega_{jm}, \tag{10}$$

where

$$\lambda_{fo}^{inter} = \sum_{g \in \Theta_o} \eta_g \frac{\sum_{k \in \Theta_s} \upsilon_{kf} \phi_{kg}}{\sum_{k \in \Theta_s} \upsilon_{kf} \phi_{kf}} \tag{11}$$

is the inter-industry average (standard) Edgeworth sympathy coefficient, that is, the average weight that the management of airline f places on the profit of firms outside of the airline industry (with η_g denoting the weight associated to non-airline firm g in this average) relative to airline f's profit. $\mathbf{w}_{jm}$ denotes a vector of observed cost-shifters of product j in market m, and ω_{jm} denotes the unobserved cost shock of product j in market m.

2.3 Demand Model

In this subsection, we describe the demand model. We use a random coefficients nested logit demand model of consumer preferences in the lines of Grigolon and Verboven (2014), jointly with a Cobb-Douglas specification for the indirect utility as in Berry et al. (1995), Grigolon and Verboven (2014), Grigolon et al. (2018) and Bourreau et al. (2021). As such, the indirect utility obtained by consumer i in market m is assumed to be given by:

$$u_{ijm} = \alpha \log \left(y_{im} - p_{jm} \right) + \mathbf{x}_{jm} \boldsymbol{\beta} + \xi_{jm} + \bar{\varepsilon}_{ijm}, \tag{12}$$

if she chooses an inside option and purchases product $j \in \{1, \ldots, J_m\}$ and by:

$$u_{iom} = \alpha \log \left(y_{im} \right) + \bar{\varepsilon}_{iom}, \tag{13}$$

if she chooses the outside option $j = 0$ and not purchases an airline ticket. y_{im} denotes the income of consumer i in market m, $\mathbf{x}_{jm}$ denotes a vector of observed characteristics of product j in market m, and ξ_{jm} denotes the mean utility obtained from characteristics of product j in market m that are unobserved by the researcher but observed by consumers and airlines. Finally, $\bar{\varepsilon}_{ijm}$ and $\bar{\varepsilon}_{iom}$ denote the remaining consumer i' specific valuations for product j and the outside option, respectively, in market m. These consumer-specific valuations are assumed to follow the distributional assumptions of the nested logit demand model (Berry, 1994; Cardell, 1997):

$$\bar{\varepsilon}_{ijm} = \zeta_{im} + (1 - \rho) \varepsilon_{ijm}, \tag{14}$$

where ζ_{im} is a consumer-specific valuation that is constant across products and differentiates the inside options from the outside option, and ε_{ijm} is independent and identically distributed across products and consumers with the type I extreme value distribution. ζ_{im} is assumed to follow the (unique) distribution such that, for $0 \leq \rho < 1$, $\bar{\varepsilon}_{ijm}$ also has an extreme value distribution. As $\rho \to 1$, we have that $\bar{\varepsilon}_{ijm} \to \zeta_{igm}$, which implies that the consumer-specific valuations for inside options reflect perfect substitutability. In turn, as $\rho \to 0$, the consumer-specific valuations are independent and identically distributed across products and consumers.

Each consumer i in market m chooses the option j that maximizes her (indirect) utility. The distributional assumptions above allow us to integrate the consumer-specific valuations analytically. As such, the mean utility obtained from unobserved characteristics, ξ_{jm}, constitutes the only source of sampling error. This gives an explicit structural interpretation to the error term and, thereby, circumvents the critique provided by Brown and Walker (1989) related to the addition of ad-hoc errors and their induced correlations. In particular, conditional on purchasing some airline ticket product, the probability that consumer i in market m chooses product j is given by:

$$s_{ijm} = s_{ijm|J_m} s_{im}, \tag{15}$$

where

$$\begin{aligned}
s_{ijm|J_m} &= \frac{\exp\left(\frac{\alpha \log(y_{im} - p_{jm}) + \delta_{jm}}{1-\rho}\right)}{\exp\left(\frac{I_{im}}{1-\rho}\right)} \\
s_{im} &= \frac{\exp(I_{im})}{1 + \exp(I_{im})} \\
\delta_{jm} &= \mathbf{x}_{jm}\boldsymbol{\beta} + \xi_{jm} \\
I_{im} &= (1-\rho)\log\left(\sum_{k=1}^{J_m} \exp\left(\frac{\alpha \log(y_{im} - p_{km}) + \delta_{km}}{1-\rho}\right)\right),
\end{aligned}$$

with $s_{ijm|J_m}$ denoting the probability that consumer i in market m chooses product j within the set of J_m available inside options, s_{im} denoting the probability that consumer i in market m chooses an inside option, δ_{jm} denoting the valuation of product j common to all consumers of market m, and I_{im} denoting McFadden (1978)'s inclusive value that consumer i associates to the inside options of market m. In turn, the unconditional choice probability (or aggregate market share) of product j in market m is, thus, given by:

$$s_{jm}(\mathbf{p}_m) = \int s_{ijm} dF(\mathbf{y}_m), \tag{16}$$

where $F(\mathbf{y}_m)$ denotes the population distribution function of consumers income in market m.

2.4 Industry Equilibrium

The stable strategy for airline f as a function of the strategies of the rival airlines constitutes a best-response function for airline f. If we stack the best-response functions in a vector $B(\mathbf{p})$, the industry equilibrium fares $\mathbf{p}$ is defined as a fixed point of the best-response functions: $\mathbf{p} = B(\mathbf{p})$. In particular, the equilibrium fare p_{jm} of product j (offered by airline f) in market m satisfies the following first-order condition, implied by the management's objective function:

$$s_{jm}(\mathbf{p}_m) + \sum_{r \in \mathcal{F}_{fm}} (p_{rm} - c_{rm}) \frac{\partial s_{rm}(\mathbf{p}_m)}{\partial p_{jm}} + \sum_{g \neq f} \lambda_{fg}^{intra,m} \sum_{l \in \mathcal{F}_{gm}} (p_{lm} - c_{lm}) \frac{\partial s_{lm}(\mathbf{p}_m)}{\partial p_{jm}} = 0. \quad (17)$$

We can rewrite the system of J_m first-order conditions for market m in matrix notation as follows:

$$\mathbf{s}(\mathbf{p}_m) - (\mathbf{\Omega}_m \circ \mathbf{\Delta}(\mathbf{p}_m))(\mathbf{p}_m - \mathbf{c}_m) = \mathbf{0}, \quad (18)$$

where the symbol $\circ$ represents element-by-element multiplication, while $\mathbf{s}(\mathbf{p}_m)$, $\mathbf{p}_m$ and $\mathbf{c}_m$ denote the vectors of market shares, fares and marginal costs, respectively, for all the products available in market m. Matrix $\mathbf{\Omega}_m$ is the ownership matrix associated to market m. The diagonal elements of $\mathbf{\Omega}_m$, as well as the off-diagonal elements corresponding to product pairs that belong to the same airline, are equal to 1. The elements of $\mathbf{\Omega}_m$ corresponding to pairs of different airlines are equal to the intra-industry managerial Edgeworth sympathy coefficients $\lambda_{fg}^{intra,m}$. Further, matrix $\mathbf{\Delta}(\mathbf{p}_m)$ contains the slopes of market shares with respect to the prices of the products in market m, with the element jr, with j and r denoting inside options, given by:

$$\mathbf{\Delta}_{jr}(\mathbf{p}_m) = -\frac{\partial s_{rm}(\mathbf{p}_m)}{\partial p_{jm}} \quad (19)$$

where

$$\frac{\partial s_{rm}(\mathbf{p}_m)}{\partial p_{jm}} = \begin{cases} \int \frac{\alpha}{y_{im} - p_{jm}} \left(\frac{1}{1-\rho} - \frac{\rho}{1-\rho} s_{ijm|J_m} - s_{ijm} \right) s_{ijm} dF(\mathbf{y}_m) & \text{for } r = j \\ \int \frac{\alpha}{y_{im} - p_{jm}} \left(-\frac{\rho}{1-\rho} s_{ijm|J_m} - s_{ijm} \right) s_{irm} dF(\mathbf{y}_m) & \text{for } r \neq j. \end{cases}$$

3 Estimation Procedure

3.1 Demand Model

The pricing strategy for each product j is expected to take into account all of the product's characteristics. This introduces correlation between fares and product characteristics and, in particular, between fares and the unobserved product characteristics that constitute the structural error term of the demand model. As a consequence, instrumental variable techniques are required for consistent estimation.

We estimate the fare coefficient, α, the vector of valuations for the observed product characteristics, $\boldsymbol{\beta}$, and the demand nesting parameter, ρ, by exploiting a set of moment conditions formed under the identifying assumption that the structural error term, ξ_{jm}, is mean independent of a set of instruments:

$$E\left(\xi_{jm}\mathbf{z}_{jm}^{D}\right) = \mathbf{0}, \tag{20}$$

where $\mathbf{z}_{jm}^{D}$ denotes a vector of exogenous demand instruments associated to product j in market m. To do so, we use a two-step efficient generalized method of moments estimator to find the estimates of α, $\boldsymbol{\beta}$ and ρ that make the sample analogue of those moment conditions as close to zero as possible.

This procedure requires that we compute an estimate of ξ_{jm}. Let $s_{jm}\left(\mathbf{p}_m, \boldsymbol{\delta}_m; \alpha, \rho\right)$ denote the explicit dependence of the market share of each product j in market m on the vector of common valuations $\boldsymbol{\delta}_m$, the fare coefficient, α, and the demand nesting parameter, ρ, which, for ease of exposition, we have been omitting. Let also $\hat{\alpha}$, $\hat{\rho}$ and $\hat{\boldsymbol{\delta}}_m^0$ denote candidate estimates of α, ρ and $\boldsymbol{\delta}_m$, respectively. We begin to compute an estimate of ξ_{jm} by first using $\hat{\alpha}$ and $\hat{\rho}$ to invert the market share function (16) so to obtain an estimate of the common valuation δ_{jm} for each product j in market m. We do so using the contraction mapping of Grigolon and Verboven (2014):

$$\hat{\delta}_{jm}^{h+1} = \hat{\delta}_{jm}^{h} + (1-\rho)\left(\log\left(s_{jm}^{obs}\right) - \log\left(\hat{s}_{jm}\left(\mathbf{p}_m, \hat{\boldsymbol{\delta}}_m^h; \hat{\alpha}, \hat{\rho}\right)\right)\right), \tag{21}$$

where s_{jm}^{obs} denotes the observed market share of product j in market m, $\hat{\boldsymbol{\delta}}_m^h$ denotes iteration $h \geq 0$ of the vector of candidate estimates for the common valuation of each product j in market m, and $\hat{s}_{jm}\left(\mathbf{p}_m, \hat{\boldsymbol{\delta}}_m^h; \hat{\alpha}, \hat{\rho}\right)$ denotes the predicted market share of product j in market m using the candidate estimates $\hat{\alpha}$, $\hat{\rho}$ and $\hat{\boldsymbol{\delta}}_m^h$. We set a tight tolerance of $1e-13$ for this contraction expressed in terms of the log difference in market shares and, to increase computational speed, implement the SQUAREM algorithm developed by Varadhan and Roland (2008) in parallel over the different markets.[9]

In order to compute the predicted market shares, we approximate the integral in the market share function (16) through ns Monte Carlo income draws from the empirical population distribution function of the income of consumers in each market m. Further, in the spirit of Conlon and Gortmaker (2019), we use a protected version of the market share function (16) to deal with eventual overflow and underflow in this computation. As such the predicted market share $\hat{s}_{jm}\left(\mathbf{p}_m, \hat{\boldsymbol{\delta}}^h_m; \hat{\alpha}, \hat{\rho}\right)$ of product j in market m is approximated as follows:

$$\hat{s}_{jm}\left(\mathbf{p}_m, \hat{\boldsymbol{\delta}}^h_m; \hat{\alpha}, \hat{\rho}\right) \approx \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp\left(\frac{\hat{\alpha}\log(y_{im}-p_{jm})+\hat{\delta}^h_{jm}}{1-\hat{\rho}} - a_m\right)}{\exp\left(\frac{\hat{I}_{im}}{1-\hat{\rho}}\right)} \frac{1}{1+\exp\left(-\hat{I}_{im}\right)}, \tag{22}$$

where

$$\begin{aligned}
\hat{I}_{im} &= (1-\hat{\rho})\left(a_m + \log\left(b_m\right)\right) \\
a_m &= \max_{k\in\{1,\ldots,J_m\}} \left\{0, \frac{\hat{\alpha}\log\left(y_{im}-p_{jm}\right)+\hat{\delta}^h_{jm}}{1-\hat{\rho}}\right\} \\
b_m &= \max_{k\in\{1,\ldots,J_m\}} \left\{5e-324, \sum_{k=1}^{J_m}\exp\left(\frac{\hat{\alpha}\log\left(y_{im}-p_{km}\right)+\hat{\delta}^h_{km}}{1-\hat{\rho}} - a_m\right)\right\},
\end{aligned}$$

with a_m and b_m helping ensure overflow and underflow safety, respectively.

Having an estimate of δ_{jm}, we then obtain an estimate of $\boldsymbol{\beta}$ by running the following linear regression: $\hat{\delta}_{jm} = \mathbf{x}_{jm}\boldsymbol{\beta} + \xi_{jm}$ using linear IV-GMM. Finally, we use the estimates of $\boldsymbol{\beta}$ to obtain an estimate of ξ_{jm}, which we then use to form the sample analogue of the moment conditions. In order to find the estimates $\hat{\alpha}$ and $\hat{\rho}$ that make the sample analogue of the moment conditions as close to zero as possible, we use a limited-memory BFGS optimization algorithm with analytical derivatives and a strict tolerance level of $1e-8$.

3.2 Supply Model

We use the estimates of the demand model and the intra-industry managerial Edgeworth sympathy coefficients to infer the unobserved marginal costs of airlines in each market m. We do so, by solving the system of J_m first-order conditions (18) of each market m for the

[9] Conlon and Gortmaker (2019) show how to use the SQUAREM algorithm to speed computation in the context of random coefficient demand models.

vector of marginal costs $\mathbf{c}_m$, as follows:

$$\mathbf{c}_m = \mathbf{p}_m - \underbrace{\left(\boldsymbol{\Omega}_m \circ \boldsymbol{\Delta}\left(\mathbf{p}_m\right)\right)^{-1} \mathbf{s}\left(\mathbf{p}_m\right)}_{\text{markup vector } \boldsymbol{\mu}_m}. \tag{23}$$

We then use the inferred marginal costs to estimate the parameter associated to the inter-industry average (standard) Edgeworth sympathy coefficient, γ, the vector of cost parameters associated to the observed cost-shifters, $\boldsymbol{\Gamma}$, and, as we cannot identify them separately, the product of the parameters controlling the cost of shareholder dissent and the responsiveness of shareholders to managerial behavior, $\kappa\psi$. Because the inferred markups are endogenous (as the unobserved cost shocks enter implicitly through price), we do so by exploiting a set of moment conditions formed under the identifying assumption that the unobserved cost shocks, ω_{jm}, are mean independent of a set of instruments:

$$E\left(\omega_{jm}\mathbf{z}_{jm}^{S}\right) \;\; = \;\; \mathbf{0}, \tag{24}$$

where $\mathbf{z}_{jm}^{S}$ denotes a vector of exogenous supply instruments associated to product j in market m. To do so, we use a two-step efficient generalized method of moments estimator to find the estimates of γ, $\boldsymbol{\Gamma}$ and $\kappa\psi$ that make the sample analogue of the moment conditions as close to zero as possible.

This procedure requires we compute an estimate of ω_{jm}. Let $\hat{\boldsymbol{\Delta}}\left(\mathbf{p}_m\right)$ denote the matrix that contains the estimates of the slopes of market shares with respect to the prices of the products available in market m, computed using the estimates of the demand model. Let also $\hat{\kappa\psi}$ denote a candidate estimate of $\kappa\psi$. We begin to compute an estimate of ω_{jm} by first using $\hat{\kappa\psi}$ to compute an estimate of the ownership matrix $\hat{\boldsymbol{\Omega}}_m$ associated to market m and, in turn, infer the vector of marginal costs in the market, as follows:

$$\hat{\mathbf{c}}_m \;\; = \;\; \mathbf{p}_m - \left(\hat{\boldsymbol{\Omega}}_m \circ \hat{\boldsymbol{\Delta}}\left(\mathbf{p}_m\right)\right)^{-1} \mathbf{s}\left(\mathbf{p}_m\right), \tag{25}$$

where $\hat{\mathbf{c}}_m$ denotes the vector of the inferred marginal costs for all the products available in market m, which we then use to obtain an estimate of γ and $\boldsymbol{\Gamma}$ by running the following linear regression: $\hat{c}_{jm} = \gamma\lambda_{fo}^{inter} + \mathbf{w}_{jm}\boldsymbol{\Gamma} + \omega_{jm}$ using linear IV-GMM. Finally, we use the estimates of γ and $\boldsymbol{\phi}$ to obtain an estimate of ω_{jm}, which we use to form the sample analogue of the moment conditions. In order to find the estimate $\hat{\kappa\psi}$ that makes the sample analogue of the moment conditions as close to zero as possible, we use a limited-memory BFGS optimization algorithm with analytical derivatives and a strict tolerance level of $1e-8$.

4 Empirical Application

4.1 Data Sources and Variable Definition

We use five sources of data: U.S. Bureau of Transportation Statistics, DataHub.io, U.S. Bureau of Economic Analysis, Institute for Social Research and Data Innovation at the University of Minnesota, and Refinitiv.

On the demand side, we use the airline origin and destination survey (DB1B), which contains a 10% subsample of all airline tickets sold in the U.S., from the U.S. Bureau of Transportation Statistics, to obtain information on airline ticket data. Following Berry et al. (1996) and Berry and Jia (2010), we define a market as directional round-trips between an origin and destination airport in a particular quarter. That is, a round-trip with Chicago as the origin and Los Angeles as the destination is different from a round-trip with Los Angeles as the origin and Chicago as the destination, and a round-trip with Chicago as the origin and Los Angeles as the destination in 2015Q1 is different from a round-trip with Chicago as the origin and Los Angeles as the destination in 2015Q3. Further, we assign tickets to the marketing airline (as opposed to the operating airline, which is often different), and treat nonstop and connecting flights as different products, even if they are offered by the same airline. The DB1B dataset allows us to compute, for each product in each market, information on fare (measured as the product's average fare, in 2015 CPI adjusted thousand dollars, paid), number of passengers, and two important product characteristics: distance (measured by the product's actual miles) and network (measured by the ratio between the number of routes out of the origin airport served by the airline offering the product and the total number of routes out of the origin airport). We complement this information with data from DataHub.io and the U.S. Bureau of Economic Analysis. From the former, we obtain airport latitude and longitude coordinates, which we use to compute the geographic distance between origin and destination airports (according to the vincenty formula), so to obtain an additional (potentially relevant) product characteristic, not included in the DB1B dataset: extra miles (measured by the product's ratio between actual miles flown and the geographic distance). From the latter, we obtain population information by core-based statistical area (CBSA) and year, which we use to define the potential number of consumers of each market (and, as we discuss below, exclude least travelled routes). In particular, we compute market shares as a function of the origin airport population in each year. Finally, we use the American community survey of the integrated public use microdata series (IPUMS) from the Institute for Social Research and Data Innovation at the University of Minnesota to obtain data on the distribution of income (in 2015 CPI adjusted thousand dollars) at the consumer (individual) level by CBSA and year, which we use to approximate the integral in the market share function (16).

On the supply side, we use the Eikon dataset from Refinitiv, which includes historical data on ownership of publicly traded companies, to obtain information on airline ownership and compute the intra-industry standard Edgeworth sympathy coefficient for each airline pair, as well as the within-airline shareholder concentration, in each quarter. For the latter, we follow the literature in assuming an one-share-one-vote rule.[10] Importantly, this dataset includes both institutional and non-institutional shareholders, which is an advantage relative to the 13- F fillings used in Azar et al. (2018) and most of the literature. The Refinitiv Eikon dataset is also to a large extent aggregated by asset manager, therefore requiring less processing than the 13-F fillings (although it still had several separate entries for BlackRock and State Street, which report some of their subsidiary holdings separately, that needed to be combined). Another advantage of the Refinitiv Eikon database is that it has historical data on delisted companies, unlike the ThomsonOne.com dataset used by Lewis and Chugh (2019).[11] This is a significant problem with the ThomsonOne.com dataset, because it means that it has less firms as one goes back in time. In summary, the Refinitiv Eikon dataset avoids many issues with the 13- F fillings as well as even more significant problems with the ThomsonOne.com data. Finally, we use the 13-F filings from Refinitiv, to obtain information on ownership of each airline's shareholders on non-airline S&P 500 firms and compute the inter-industry average (standard) Edgeworth sympathy coefficient for each airline in each quarter, using the S&P 500 firms' sales as weights.

4.2 Data Selection and Description

We focus on the period 2015Q1-2017Q4, a period in which no major airline experienced bankruptcy, which would constitute a major complicating factor, as there is no agreement over how to model control of a firm during bankruptcy. This was the main criticism of Azar et al. (2018) by BlackRock (2019) and also of Kennedy et al. (2017). One could, for example, assume that the firm is controlled by its bondholders during bankruptcy. However, data on bondholders (who may also hold shares in competitors) is less readily available than data on stock ownership.

We focus also on the following airlines: American Airlines, Alaska Airlines, JetBlue

[10] Under this assumption, shareholder concentration is captured by the Herfindahl-Hirschman index of shareholders ownership.

[11] Consistent with the quality of ThomsonOne declining as one goes back in time, Lewis and Chugh (2019) find that the MHHI deltas using ThomsoneOne are much noisier to those using the Thomson 13F data, and that the correlation between the MHHI deltas from both datasets declines as one goes back in time.

Airlines, Delta Airlines, Allegiant Air, Hawaiian Airlines, Spirit Airlines, United Airlines, Virgin America, and Southwest Airlines. They are all publicly listed in every quarter and account for about between 95.2% and 96.5% of the total number of passengers (and between 95.8% and 98.0% of total revenues) in each quarter.[12] Moreover, we focus on routes for which (i) CBSA information for the origin airport is available; (ii) population information for the origin airport CBSA is available in the U.S. Bureau of Economic Analysis; (iii) income information for the origin airport CBSA is available in IPUMS; (iv) airport latitude and longitude coordinates are available in DataHub.io; and (v) more than one flight option exists. The remaining routes account for about between 85.9% and 89.1% of the total number of passengers (and between 86.7% and 89.3% of total revenues) in each quarter. Finally, we eliminate (i) the least travelled routes by focusing on routes in which the population of the origin airport CBSA is at least 850,000 people in 2015Q1; and (ii) seasonal routes by focusing on routes with at least 100 passengers in each quarter of the year. The remaining routes account for about between 78.2% and 81.2% of the total number of passengers (and between 78.0% and 78.2% of total revenues) in each quarter, which is in line with Berry and Jia (2010), who considered airlines and routes that account for about 80% of the total number of passengers, and Kennedy et al. (2017), who considered airlines and routes that account for about 73% of the total number of passengers. The (final) selected sample contains 105,417 markets, encompassing 9,816 origin-destination airport pair routes and 12 year-quarters.

Table 1 shows summary statistics for our selected sample. Panel A presents summary statistics for variables at the route-quarter-product level. The median product in the selected sample has 180 passengers, capturing 0.01% of the population of the origin airport and 17.86% of the total number of passengers travelled in that route and quarter. This median product has an average fare of 4.801 hundreds of 2015 dollars and corresponds to a connecting flight over a distance of approximately 2,517 miles. In contrast to the actual miles flown, the geographic distance between origin and destination airports for the product's route (according to the vincenty formula), was approximately 1,086 miles, which corresponds to a ratio between actual miles flown and geographic distance (extra miles) of 1.0884. The number of routes served by the product's airline from the origin airport was 102, which corresponds to 86.86% of the total number routes out of the origin airport (network).

Panel B presents summary statistics for variables at the origin airport's CSBA-year level. The median origin airport's CSBA has a population of 2.8 million potential consumers, who

[12] Virgin America and Alaska Airlines merged during our sample period. The merger was announced in April 2016 and shareholders approved it on July 2016. In the data, however, we have flights using Virgin America's brand until 2017Q1. As such, for those flights, we use the intra-industry standard Edgeworth sympathy coefficient, the Herfindahl-Hirschman index of shareholders ownership, and the inter-industry average (standard) Edgeworth sympathy coefficient of Alaska Airlines.

Table 1. Summary Statistics

	Mean	Median	Std. Dev.	Minimum	Maximum
Panel A: route-quarter-product level					
Number of Passengers	994.2800	180.0000	3027.4762	10.0000	73400.0000
Market Share	0.0003	0.0001	0.0010	0.0000	0.0742
Within Market Share	0.2653	0.1786	0.2579	0.0001	0.9998
Fare	4.9947	4.8010	1.7670	0.2591	24.9351
Connect	0.8349	1.0000	0.3712	0.0000	1.0000
Distance	2953.7576	2516.5303	1687.6952	200.0000	13098.5000
Vincenty	1305.7393	1086.2432	811.1480	100.7370	5888.7551
Extra Miles	1.1786	1.0884	0.2323	0.9927	2.7903
Nº Routes Out Origin Airport	100.0811	102.0000	41.1466	1.0000	174.0000
Network	0.7643	0.8686	0.2363	0.0054	1.0000
Panel B: origin airport CSBA-year level					
Population	4.5923	2.8000	4.7041	0.8604	20.3000
Income	395.1327	286.0528	424.8830	0.0033	12984.8857
Panel C: quarter-airline pair level					
λ^{intra}	0.5207	0.5315	0.2424	0.0253	1.1631
Panel D: quarter-airline level					
Shareholder HHI	0.0388	0.0321	0.0216	0.0142	0.1188
λ^{inter}	0.4798	0.5184	0.1935	0.0304	0.7505

* The statistics presented in Panels A, B, C and D are computed across 397330, 26896, 1026 and 117, respectively, observations. Market share denotes the number of passengers travelled as a fraction of the population of the origin airport. Within market share denotes the market share as a fraction of the total number of passengers travelled. Fare denotes the average price in hundreds of 2015 USD. Population denotes the origin population in millions. Income denotes the consumer (individual) annual income in hundreds of 2015 USD. Shareholder HHI denotes the Herfindahl-Hirschman index of shareholders ownership.

have a median annual income of 286.053 hundreds of 2015 dollars.

Panel C presents summary statistics for variables at the quarter-airline pair level. The intra-industry standard Edgeworth sympathy coefficient for the median airline pair is 0.53. This implies that, under full internalization of shareholder objectives by the management, the median airline would place a weight on the profit of rival airlines relative to their own profit of 0.53.

Finally, Panel D presents summary statistics for variables at the quarter-airline level. The ownership concentration of the shareholders of the median airline, measured by the Herfindahl-Hirschman index of shareholders ownership (as we assume an one-share-one-vote rule), is 0.03, which is equivalent to having about 30 symmetric shareholders, or to having one shareholder with 17% and the rest being completely dispersed. The inter-industry average (standard) Edgeworth sympathy coefficient for the median airline is 0.52. This implies that this median airline places an average weight on the profit of other (non-airline) S&P500 firms relative to their own profit of 0.52.

4.3 Demand Model Estimation Results

We now address the estimation of the demand model. We follow Grigolon and Verboven (2014), Grigolon et al. (2018), and Bourreau et al. (2021) in expanding the log price term in u_{ijm} for the inside options as follows: $\alpha \log(y_{im} - p_{jm}) \approx \alpha \log(y_{im}) - \alpha_{im} p_{jm}$, where the consumer-specific fare coefficient is given by $\alpha_{im} = \alpha / y_{im}$. Then, without loss of generality, $\alpha \log(y_{im})$ can be dropped everywhere as it is common to all options in each market m.

We include as observed characteristics (in our preferred specification) a connect indicator, extra miles, extra miles squared, and network, as well as (so to reduce the requirements on the instruments) airline, year-quarter and route fixed effects.[13] In order to address the endogeneity of fares, we follow Bresnahan et al. (1997) in instrumenting fare by Berry et al. (1995)-type instruments within the set of closest available options. The identifying assumptions are that (i) changes in the mean utility obtained from unobserved characteristics are mean independent of the observed characteristics and (ii) the correlation of price with those instruments, as established in the system of first-order conditions (29), will be higher among more similar products. In particular, we use sums of the observed characteristics of other products in the market within the set of available options with the same connect indicator. We also follow Berry and Jia (2010) in including squares of the sums of characteristics and their interactions (as long as they are not highly collinear). Finally, in order to identify the demand nesting parameter, we follow Miller and Weinberg (2017) and Park and Seo (2019)

[13]In order to increase computational speed, we absorb the route fixed effects.

in using the number of products in the market.

Table 2 presents the demand model estimation results, with the different columns reporting distinct specifications that vary on the demand model assumed and on the covariates included. Specification NL reports the results of a standard nested logit demand model. This specification uses average income to model the fare coefficient, as follows: $\alpha_{im} = \alpha/\bar{y}_m$, where $\bar{y}_m$ denotes the average income in market m, and includes airline, year-quarter and origin airport fixed effects. The coefficient on fare is negative and highly significant suggesting that consumers are price sensitive. The coefficient on the connect indicator is also negative and highly significant, indicating a preference for direct flights. The coefficients on distance suggest a preference for air-travel (compared to other alternatives like travel by car or train) when involving pairs of airports that are more distant from each other, with this preference increasing with the distance, which indicates a U-shaped pattern. The coefficients on extra miles suggest a preference for shorter flights between a given pair of airports, with the distaste for extra miles decreasing as the flight becomes longer. The coefficient on network is positive and highly significant, indicating that passengers prefer to fly with airlines that have a large network of flights originating at the airport. Finally, the nesting parameter is positive and highly significant, but close to zero, which suggests that consumer-specific valuations are close to independent and identically distributed across products and consumers.

The remaining specifications correspond to random coefficients nested logit demand models, which use $ns = 1000$ income draws per market. Specification RCNL 1 includes airline, year-quarter and origin airport fixed effects, whereas specification RCNL 2 adds destination airport fixed effects and specification RCNL 3 replaces the airport fixed effects with route fixed effects. The qualitative results of the different specifications are very similar to those described above for the standard nested logit demand model. With one important exception. The results suggest that the additional controls in specifications RCNL 2 and RCNL 3 increase the magnitude of the nesting parameter, suggesting that as we control for both origin and destination airport fixed effects (specification RCNL 2) or route fixed effects (specification RCNL 3), products become (as expected) closer substitutes. Ciliberto and Williams (2014) show that price elasticities (and in particular, cross-price elasticities) play a crucial role in the estimation of the supply-side and the policy counterfactuals. As such, we consider specification RCNL 3 to be our preferred specification. The median own-price elasticity in this specification is -6.4. This is in line with the elasticities reported in Berry and Jia (2010), Ciliberto and Williams (2014) and Park and Seo (2019) for tourist-traveller types and with the elasticities reported in Ciliberto et al. (2021) for an exogenous market structure. The median cross-price elasticity in this specification is 0.8 while the median aggregate price elasticity is -1.4, which is close to that reported in Berry and Jia (2010).

Table 2. Demand Model Estimation Results

	NL	RCNL 1	RCNL 2	RCNL 3
Fare/Income Parameter α	-465.0574***	-896.7479***	-372.0425***	-177.8162***
	(15.5546)	(164.1998)	(50.1045)	(16.1852)
Connect	-1.1642***	-1.5436***	-0.5731***	-0.1483***
	(0.0392)	(0.0268)	(0.0217)	(0.0098)
Distance	0.3019***	0.2039***	0.0944***	
	(0.0202)	(0.0195)	(0.0171)	
Distance Squared	0.0393***	0.0006	-0.0204***	
	(0.0031)	(0.0018)	(0.0015)	
Extra Miles	-7.4635***	-5.7364***	-2.6978***	-1.3929***
	(0.2595)	(0.2110)	(0.1447)	(0.0753)
Extra Miles Squared	1.7977***	1.2496***	0.5615***	0.3208***
	(0.0882)	(0.0687)	(0.0446)	(0.0233)
Network	4.3071***	3.5651***	2.1967***	1.0443**
	(0.0777)	(0.0784)	(0.0546)	(0.0366)
Alaska Airlines	1.4143***	1.3781***	0.8288***	0.2673***
	(0.0601)	(0.0523)	(0.0348)	(0.0178)
JetBlue Airlines	1.4439***	1.5688***	1.1030***	0.3908***
	(0.0686)	(0.0563)	(0.0392)	(0.0201)
Delta Airlines	0.3495***	0.1848***	0.1225***	0.0592***
	(0.0171)	(0.0137)	(0.0076)	(0.0039)
Allegiant Air	-1.7846***	-1.0634***	-0.7874***	-0.9242***
	(0.1621)	(0.1579)	(0.1314)	(0.0704)
Hawaiian Airlines	4.7963	3.9923***	2.0423	0.9721***
	(0.2013)	(0.1707)	(0.0979)	(0.0450)
Spirit Airlines	-0.3561***	0.3398***	-0.1744**	-0.4764***
	(0.1057)	(0.1092)	(0.0857)	(0.0444)
United Airlines	-0.0953***	-0.2114***	-0.0971***	-0.0420***
	(0.0196)	(0.0152)	(0.0090)	(0.0043)
Virgin America	2.1960***	2.2256***	1.3645***	0.5441***
	(0.1124)	(0.0927)	(0.0599)	(0.0299)
Southwest Airlines	0.9251***	1.1436***	0.6176***	0.2162***
	(0.0377)	(0.0269)	(0.0205)	(0.0100)
Nesting Parameter ρ	0.0790***	0.0000	0.5217***	0.8499***
	(0.0173)	(0.0091)	(0.0114)	(0.0063)
Origin/Destination Airport FE	Yes/No	Yes/No	Yes/Yes	
Route FE				Yes
Fit and Predictions				
Objective Function	0.0024	0.0050	0.0016	0.0011
Median Own-Price Elasticity	-6.0535	-2.5053	-3.4561	-6.4024
Median Cross-Price Elasticity	0.0578	0.0036	0.2449	0.7967
Median Aggregate-Price Elasticity	-5.9546	-2.4861	-1.9434	-1.4281

* Based on 397,330 observations. All specifications include Year-Quarter FE. The NL model assumes average income (per origin airport CSBA and year) while the RCNL models assume heterogenous income. Standard errors clustered by route. *** denote p-values <0.01, ** denote p-values <0.05, and * denote p-values <0.10.

4.4 Supply Model Estimation Results

We now address the supply model, which we estimate taking the demand results from Table 2, Specification RCNL 3 as given. We include as observed cost-shifters a non-stop indicator, extra miles, extra miles squared, and network, as well as (so to reduce the requirements on the instruments) airline, year-quarter and route fixed effects.[14] In order to address the endogeneity of the inferred markups, we follow Miller and Weinberg (2017) in instrumenting markups with ownership changes. The identification assumption is that changes in unobserved costs, which are route-specific, are mean independent of intra-industry overlapping shareholding, which is airline-specific. In particular, we use simple-averages of the intra-industry standard Edgeworth sympathy coefficients of (i) all other airlines, whether they operate in the same route or not; and (ii) all other airlines in the same route. We also follow Berry and Jia (2010) in including squares of the these instruments and their interactions (as long as they are not highly collinear).

Tables 3 and 4 present the supply estimation results. Table 3 presents our baseline results, with the different columns reporting distinct specifications for the mitigating factor, which determines the degree of internalization of shareholder objectives by the management. We begin by discussing the results regarding this parameter. In specification CON, which constitutes a benchmark specification, the mitigating factor is constant across airlines and does not depend on the concentration of shareholders ownership within the firm. This replicates the objective of the firm in Kennedy et al. (2017), Park and Seo (2019) and Backus et al. (2021). We find that the mitigating factor is equal to 0.38 and statistically significantly different from zero, which implies a median markup (across markets and airlines) of 1.1076 hundreds of 2015 dollars.

In specification STR, which constitutes our structural formulation, the mitigation factor is airline-specific as derived from our partial managerial entrenchment model. In this formulation, the mitigation factor of airline f is given by:

$$\tau_f = \frac{\kappa\psi \sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}}{1 + \kappa\psi \sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}} = \frac{\exp\left(\theta_0 + \log\left(\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}\right)\right)}{1 + \exp\left(\theta_0 + \log\left(\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}\right)\right)}. \tag{26}$$

where the second equality just makes clear that it implies a logistic form which is increasing in the log of the concentration of shareholders ownership, with a coefficient restricted to be equal to one. We find that the $\theta_0 = \log(\kappa\psi)$ is positive and highly significant, which implies a median mitigating factor (across airlines and markets) of 0.42 and a median markup of 1.1330 hundreds of 2015 dollars.

[14] As with the demand estimation, we absorb the route fixed effects to increase computational speed.

Table 3. Supply Model Estimation Results

	CON	STR	LOG	LIN
Conduct Parameters				
τ	0.3771***			
	(0.0266)			
θ_0		3.2454***	1.6981***	1.0758***
		(0.0990)	(0.4627)	(0.1144)
θ_1		1.0000	0.5760***	0.1951***
			(0.1302)	(0.0321)
Marginal Cost Parameters				
λ^{inter}	-0.5615***	-0.4100***	-0.5032***	-0.4325***
	(0.0344)	(0.0306)	(0.0465)	(0.0440)
Connect	0.3004***	0.2948***	0.2950***	0.3009***
	(0.0095)	(0.0092)	(0.0093)	(0.0093)
Extra Miles	0.9866***	0.9891***	0.9919***	1.0177***
	(0.1231)	(0.1234)	(0.1230)	(0.1232)
Extra Miles Squared	-0.1347***	-0.1440***	-0.1418***	-0.1464***
	(0.0427)	(0.0428)	(0.0427)	(0.0427)
Network	-0.1298***	-0.1123***	-0.1078**	-0.1477***
	(0.0450)	(0.0426)	(0.0438)	(0.0444)
Alaska Airlines	-0.4401***	-0.4065***	-0.4111***	-0.4318***
	(0.0375)	(0.0369)	(0.0370)	(0.0374)
JetBlue Airlines	-0.5266***	-0.4922***	-0.4964***	-0.5202***
	(0.0364)	(0.0353)	(0.0356)	(0.0361)
Delta Airlines	0.0490***	0.1424***	0.1082***	0.1406***
	(0.0117)	(0.0093)	(0.0168)	(0.0169)
Allegiant Air	-3.1077***	-2.9999***	-3.0440***	-3.0520***
	(0.0636)	(0.0633)	(0.0644)	(0.0645)
Hawaiian Airlines	-0.1358	-0.0803	-0.0835	-0.1199
	(0.0826)	(0.0814)	(0.0820)	(0.0824)
Spirit Airlines	-2.0455***	-1.9759***	-1.9966***	-2.0222***
	(0.0440)	(0.0424)	(0.0430)	(0.0436)
United Airlines	-0.1194***	-0.1022***	-0.1102***	-0.1017***
	(0.0091)	(0.0089)	(0.0096)	(0.0094)
Virgin America	-0.6083***	-0.5368***	-0.5706***	-0.5909***
	(0.0555)	(0.0544)	(0.0551)	(0.0555)
Southwest Airlines	-0.5393***	-0.5340***	-0.5246***	-0.5481***
	(0.0217)	(0.0201)	(0.0213)	(0.0216)
Fit and Predictions				
Objective Function	0.0004	0.0010	0.0010	0.0009
Median τ	0.3771	0.4209	0.4121	0.3803
Median Marginal Cost	3.6346	3.6067	3.6112	3.6392
Median Markup	1.1076	1.1330	1.1298	1.0969

* Based on 397,330 observations. Year-Quarter and Route FE included in all specifications. Standard errors clustered by route. *** denote p-values <0.01, ** denote p-values <0.05, and * denote p-values <0.10.

In specifications LOG and LIN, we do not constrain the coefficient of the log of the concentration of shareholders ownership to be one (as in the structural specification), but instead we allow it to be different from one. We do so, to empirically examine the implication imposed by the structural mitigating factor that in airlines with less concentrated shareholders, managers are more entrenched, as shareholders with low stakes in airlines are less likely to respond to changes in pricing by voting against management (and so, shareholder objectives are less internalized). Specification LOG continues to assume a logistic form for the mitigation factor of airline f, as follows:

$$\tau_f = \frac{\exp\left(\theta_0 + \theta_1 \log\left(\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}\right)\right)}{1+\exp\left(\theta_0 + \theta_1 \log\left(\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}\right)\right)}, \tag{27}$$

whereas specification LIN assumes a linear form, as follows:

$$\tau_f = \theta_0 + \theta_1 \log\left(\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}\right). \tag{28}$$

In both specifications, θ_0 and θ_1 are positive and highly significant. And although θ_1 is found to be statistically smaller than one, it empirically confirms the main implication that shareholder objectives are less internalized in airlines with less concentrated shareholders. This could be interpreted as consistent with managerial entrenchment mitigating the anti-competitive effects of intra-industry overlapping ownership, as managers are more powerful when shareholders are dispersed, and do not have to take into account shareholder preferences as much. In specification LOG, the results imply a median mitigating factor (across airlines and markets) of 0.4121 and a median markup of 1.1298 hundreds of 2015 dollars, whereas in specification LIN, they imply a median mitigating factor of 0.3803 and a median markup of 1.0969 hundreds of 2015 dollars.

We now address the marginal cost parameters. In all specifications, we find the following. The coefficient on the inter-industry average (standard) Edgeworth sympathy coefficient is negative and highly significant, suggesting that more inter-industry overlapping ownership leads to more internalization of the airlines inter-industry positive pecuniary externalities from expanding output and, therefore, can be thought of as reducing the effective marginal cost of airlines. The coefficient on the connect indicator is positive and highly significant, suggesting that the marginal cost of nonstop flights is lower than that of connecting flights (however, offering nonstop service in a route may involve higher fixed costs, which we do not address). The coefficients on extra miles suggest the marginal cost of serving a route increases with each extra mile above the crow-fly distance between airports, with decreasing marginal increases as the flight becomes longer. Finally, the coefficient on network is negative and highly significant suggesting that routes from which an airline serves a large number of markets have lower costs, all else equal, reflecting economies of scale of using hubs.

Table 4 shows analogous results, but omitting the inter-industry average (standard) Edgeworth sympathy coefficient from the marginal cost equation. As we can see, in all cases the median mitigating factor is substantially lower than when controlling for inter-industry overlapping ownership. In particular, in specification CON, the mitigating factor is not significantly different from zero. Thus, not controlling for inter-industry overlapping ownership would lead us to conclude that we have failed to reject a profit maximization conduct. However, as we could see in Table 3, a profit maximization conduct is clearly rejected when controlling for inter-industry overlapping ownership.

4.5 Policy Counterfactuals

Using a structural model allows us to run policy counterfactuals and do welfare analysis. To do so, we use the demand results from Table 2, Specification RCNL 3 and the supply results from Table 3, Specification STR. We begin by computing the vector $\mathbf{p}_m^c$ of counterfactual fares for all the products available in each market m that would arise in equilibrium for different intra- and inter-industry overlapping ownership settings. We do so by solving the following system of J_m first-order conditions:

$$\mathbf{p}_m^c - \hat{\mathbf{c}}_m^c - \left(\hat{\boldsymbol{\Omega}}_m^c \circ \hat{\boldsymbol{\Delta}}\left(\mathbf{p}_m^c\right)\right)^{-1} \hat{\mathbf{s}}\left(\mathbf{p}_m^c\right) \quad = \quad \mathbf{0}, \tag{29}$$

where $\hat{\mathbf{c}}_m^c$ denotes the vector of the counterfactual inferred marginal costs for all the products available in market m, $\hat{\boldsymbol{\Omega}}^c$ denotes the counterfactual ownership matrix associated to market m, $\hat{\boldsymbol{\Delta}}\left(\mathbf{p}_m^c\right)$ denotes the matrix that contains the estimates of the slopes of market shares with respect to the prices of the products available in market m, and $\hat{\mathbf{s}}\left(\mathbf{p}_m^c\right)$ denotes the vector of the counterfactual predicted market shares for all the products available in market m.

We solve this system of J_m first-order conditions using a limited-memory BFGS optimization algorithm with numeric derivatives and a strict tolerance level of $1e-8$. Further, in order to increase computational speed, we prevent the optimization algorithm from evaluating vectors $\mathbf{p}_m^c$ involving negative counterfactual fares. Finally, as the number of markets in the data is substantial, we focus on the 2017Q4 period to reduce the computational burden.[15]

We then use the counterfactual fares (and inferred marginal costs) to compute (i) the

[15] Despite restricting the counterfactuals to the 2017Q4 period, the analysis involved the computation of a considerable number of counterfactual fares: 33,769.

Table 4. Supply Model Estimation Results w/ No Inter-Industry Overlapping Ownership

	CON	STR	LOG	LIN
Conduct Parameters				
τ	0.0310			
	(0.0289)			
θ_0		2.6844***	4.2357***	1.6825***
		(0.1081)	(0.3958)	(0.0990)
θ_1		1.0000	1.4020***	0.4051***
			(0.1028)	(0.0248)
Marginal Cost Parameters				
Connect	0.3585***	0.3166***	0.3124***	0.3277***
	(0.0100)	(0.0095)	(0.0093)	(0.0097)
Extra Miles	1.1632***	1.0401***	1.0404***	1.1127***
	(0.1288)	(0.1258)	(0.1256)	(0.1271)
Extra Miles Squared	-0.1616***	-0.1457***	-0.1478***	-0.1614***
	(0.0445)	(0.0436)	(0.0436)	(0.0440)
Network	-0.4373***	-0.2130***	-0.1991**	-0.3096***
	(0.0496)	(0.0447)	(0.0433)	(0.0464)
Alaska Airlines	-0.6549***	-0.5061***	-0.4808***	-0.5334***
	(0.0398)	(0.0381)	(0.0377)	(0.0391)
JetBlue Airlines	-0.7562***	-0.5819***	-0.5602***	-0.6274***
	(0.0395)	(0.0369)	(0.0361)	(0.0380)
Delta Airlines	0.0864***	0.1002***	0.1365***	0.2295***
	(0.0127)	(0.0078)	(0.0122)	(0.0151)
Allegiant Air	-3.2233***	-2.9791***	-2.9495***	-3.0393***
	(0.0668)	(0.0655)	(0.0648)	(0.0661)
Hawaiian Airlines	-0.4319***	-0.1737**	-0.1574*	-0.2594***
	(0.0881)	(0.0838)	(0.0830)	(0.0849)
Spirit Airlines	-2.3038***	-2.0574***	-2.0263***	-2.1168***
	(0.0471)	(0.0448)	(0.0435)	(0.0460)
United Airlines	-0.0767***	-0.0854***	-0.0790***	-0.0673***
	(0.0093)	(0.0089)	(0.0091)	(0.0091)
Virgin America	-0.7393***	-0.4871***	-0.4711***	-0.5954***
	(0.0610)	(0.0572)	(0.0558)	(0.0583)
Southwest Airlines	-0.7623***	-0.6527***	-0.6363***	-0.6731***
	(0.0213)	(0.0195)	(0.0190)	(0.0203)
Fit and Predictions				
Objective Function	0.0009	0.0014	0.0013	0.0010
Median τ	0.0310	0.2931	0.3183	0.2386
Median Marginal Cost	3.8623	3.7010	3.6833	3.7510
Median Markup	0.8476	1.0271	1.0466	0.9721

* Based on 397,330 observations. Route and Year-Quarter FE included in all regressions. Standard errors clustered by route. *** denote p-values <0.01, ** denote p-values <0.05, and * denote p-values <0.10.

Table 5. Overlapping Ownership on 2017Q4

	AA	AS	B6	DL	G4	HA	NK	UA	WN
Panel A: Intra-Industry Standard Edgeworth Sympathy Coefficients									
AA	1.0000	0.5281	0.4274	0.4670	0.3551	0.3657	0.2544	0.7117	0.6425
AS	0.9770	1.0000	0.7943	0.5697	0.6512	0.8845	0.6153	0.8145	0.6920
B6	0.5285	0.5310	1.0000	0.3976	0.6486	0.6493	0.7329	0.5788	0.5696
DL	1.1494	0.7579	0.7912	1.0000	0.6780	0.8569	0.5476	1.1631	1.0045
G4	0.2099	0.2081	0.3100	0.1629	1.0000	0.3128	0.2710	0.2147	0.1997
HA	0.4423	0.5782	0.6349	0.4210	0.6399	1.0000	0.4520	0.5237	0.4428
NK	0.3033	0.3965	0.7064	0.2652	0.5464	0.4456	1.0000	0.3446	0.3216
UA	0.9496	0.5875	0.6245	0.6306	0.4845	0.5778	0.3857	1.0000	0.8133
WN	1.0032	0.5841	0.7192	0.6373	0.5275	0.5718	0.4213	0.9518	1.0000
Panel B: Intra-Industry Managerial Edgeworth Sympathy Coefficients									
AA	1.0000	0.2991	0.2420	0.2645	0.2011	0.2071	0.1441	0.4031	0.3638
AS	0.4043	1.0000	0.3287	0.2357	0.2695	0.3660	0.2546	0.3370	0.2864
B6	0.2715	0.2727	1.0000	0.2042	0.3331	0.3335	0.3764	0.2973	0.2926
DL	0.3984	0.2627	0.2743	1.0000	0.2350	0.2970	0.1898	0.4032	0.3482
G4	0.1445	0.1432	0.2134	0.1121	1.0000	0.2153	0.1865	0.1478	0.1375
HA	0.2296	0.3002	0.3297	0.2186	0.3322	1.0000	0.2347	0.2719	0.2299
NK	0.1586	0.2073	0.3693	0.1387	0.2857	0.2329	1.0000	0.1801	0.1681
UA	0.4697	0.2906	0.3089	0.3119	0.2396	0.2858	0.1908	1.0000	0.4023
WN	0.4569	0.2660	0.3275	0.2902	0.2402	0.2604	0.1919	0.4335	1.0000
Panel C: Intra-Industry Average (Standard) Edgeworth Sympathy Coefficients									
S&P500	0.4160	0.6356	0.4183	0.7292	0.1539	0.5000	0.4316	0.5108	0.7505

* AA: American Airlines; AS: Alaska Airlines; B6: JetBlue Airlines; DL: Delta Airlines; G4: Allegiant Air; HA: Hawaiian Airlines; NK: Spirit Airlines; UA: United Airlines; WN: Southwest Airlines; S&P500: non-airline S&P500 firms. Cell entries f, g in Panels A and B, where f indexes row and g indexes column, give the weight that the management of airline f places on the profit of airline g relative to airline f's profit. Cell entries S&P500, f in Panel C give the average weight that the management of airline f places on the profit non-airline S&P500 firms relative to airline f's profit.

Table 6. Impact of Overlapping Ownership on 2017Q4

	Total			Big 3		
	Intra	Inter	Intra Inter	Intra	Inter	Intra Inter
Panel A: Full Internalization						
Fare	45.0817	-6.3417	36.7995	7.2906	-4.5565	2.5837
Number of Passengers	-40.8514	8.5413	-36.8293	-10.9343	5.9654	-6.0334
Industry Profit	40.6514	7.3819	49.7880	12.2571	5.3969	18.1346
Consumer Surplus	-23.1059	6.0518	-18.1902	-5.5364	4.2915	-1.4982
Panel B: Partial Internalization						
Fare	10.6548	-6.3417	3.9645	2.7413	-4.5565	-1.8624
Number of Passengers	-15.5619	8.5413	-8.2075	-4.6289	5.9654	0.7602
Industry Profit	16.3350	7.3819	24.3970	5.1488	5.3969	10.7394
Consumer Surplus	-7.4663	6.0518	-1.7800	-2.1724	4.2915	2.0174

* The impact denotes the percentage change in fares, number of passengers, industry profit and consumer surplus, is computed using the structural profit weights. The impact on fares and number of passengers denotes the mean across the 33,769 products in 2017Q4. The impact on industry profit and consumer surplus denotes the aggregation across the different product and routes in 2017Q4, respectively.

vector of counterfactual predicted number of passengers $\hat{\mathbf{s}}\left(\mathbf{p}_m^c\right) N_m$ for all the products available in market m; (ii) the counterfactual industry variable profit $I\hat{V}P_m$ in market m, defined as the sum across airlines of the variable profit in the market:

$$I\hat{V}P_m = \sum_{f\in\Theta_a}\sum_{j\in\mathcal{F}_{fm}}\left(p_{jm}^c - \hat{c}_{jm}^c\right)\hat{s}_{jm}\left(\mathbf{p}_m^c\right)N_m, \tag{30}$$

and (iii) the counterfactual consumer surplus CS_m in market m, defined as the expected maximum utility normalized by the marginal utility of income, which we approximate through ns Monte Carlo income draws from the empirical population distribution function of the income of consumers in the market:

$$C\hat{S}_m = \frac{1}{ns}\sum_{i=1}^{ns}\frac{1}{\hat{\alpha}_{im}}\log\left(1+\exp\left(\left(1-\hat{\rho}\right)\log\left(\hat{I}_{im}^c\right)\right)\right)N_m, \tag{31}$$

where $\hat{\alpha}_{im}$ and $\hat{\rho}$ denote the estimates of α_{im} and ρ, respectively, and $\hat{I}_{im}^c$ denotes the counterfactual McFadden (1978)'s inclusive value. Finally, we aggregate the counterfactual number of passengers, total variable profit and consumer surplus across the M markets.

Table 5 presents the Edgeworth sympathy coefficients we use to perform the policy counterfactuals, which are reported in Table 6, with the different columns referring to distinct counterfactual intra- and inter-industry overlapping ownership settings. As can be seen from

Table 5, Panels A and B, the managerial Edgeworth sympathy coefficients in our best specification are much lower than the standard Edgeworth sympathy coefficients. For example, the standard sympathy coefficient for the weight that United Airlines placed on the profits of American Airlines relative to its own profits was 0.9496, that is, United valued a dollar of profits by American Airline almost as much as a dollar of its own profits. However, the managerial sympathy coefficient was 0.4697, implying that, while United placed substantially more weight on a dollar of American Airline's profits than implied by the traditional profit maximization problem, it placed substantially less than implied by the O'Brien and Salop (2000) model.

We begin the policy counterfactual analysis by computing the counterfactual outcomes that would arise in the absence of both intra-industry and inter-industry overlapping ownership. To do so, we solve the system of first-order conditions (29) for each market m (i) considering that the elements of $\hat{\mathbf{\Omega}}_m^c$ corresponding to pairs of different airlines are equal to zero ($\lambda_{fg}^{intra,m} = 0$); and (ii) using the counterfactual inferred marginal costs $\hat{\mathbf{c}}_m^c$ that would arise considering that the inter-industry average (standard) Edgeworth sympathy coefficients for all airlines are equal to zero ($\lambda_{fo}^{inter} = 0$). We then solved the system of first-order conditions (29) for each market m introducing intra-industry overlapping ownership (solely), inter-industry overlapping ownership (solely) and both.

Table 6, Panel A presents the results considering that there is no managerial entrenchment and, thus, shareholder objectives are full internalized by the management, as established in the dominant formulation. We begin by evaluating the impact of intra-industry overlapping ownership (solely). To do so, we solve the system of first-order conditions (29) for each market m (i) considering that the elements of $\hat{\mathbf{\Omega}}_m^c$ corresponding to pairs of different airlines are equal to the intra-industry standard Edgeworth sympathy coefficients ($\lambda_{fg}^{intra,m} = \lambda_{fg}^{intra}$), which are depicted in Table 5, Panel A; and (ii) using the counterfactual inferred marginal costs $\hat{\mathbf{c}}_m^c$ that would arise considering that the inter-industry average (standard) Edgeworth sympathy coefficients for all airlines are equal to zero ($\lambda_{fo}^{inter} = 0$). The results suggest that if shareholder objectives were full internalized by the management, the intra-industry effect would be extremely large, implying fares (and number of passengers) that would be, on average, 45.1% higher (40.9% lower) than in a world without intra-industry overlapping ownership, which would give rise to an increase in industry profit of 40.7% and a decrease in consumer surplus of 23.1%. These price effects seem implausibly high, and are much higher than the effects estimated by Azar et al. (2018).

We then evaluate the impact of inter-industry overlapping ownership (solely). To do so, we solve the system of first-order conditions (29) for each market m (i) considering that the elements of $\hat{\mathbf{\Omega}}_m^c$ corresponding to pairs of different airlines are equal to zero ($\lambda_{fg}^{intra,m} = 0$);

and (ii) using counterfactual inferred marginal costs $\hat{\mathbf{c}}_m^c$ that would arise considering the observed inter-industry average (standard) Edgeworth sympathy coefficients λ_{fo}^{inter} for all airlines, which are depicted in Table 5, Panel C. The results suggest that the inter-industry overlapping ownership effect is negative, implying fares (and number of passengers) that would be, on average, 6.3% lower (8.5% higher) than in a world without inter-industry ownership, which would give rise to an increase in industry profit and in consumer surplus of 7.4% and 6.1%, respectively.

We then combine the two effects. The results suggest that the overall effect of overlapping ownership on fares (and number of passengers) with full internalization of shareholder objectives by the management would be 36.8% (-36.8%), which would give rise to an increase in industry profit of 49.8% and a decrease in consumer surplus of 18.2%. Again, these price effects seem implausibly high, and are much higher than the effects estimated by Azar and Vives (2021b).

Table 6, Panel B presents the results considering that there is managerial entrenchment and, thus, shareholder objectives are solely partially internalized by the management (which is, in fact, the conduct preferred by the data). Again, we begin by evaluating the impact of intra-industry overlapping ownership (solely). To do so, we solve the system of first-order conditions (29) for each market m (i) considering that the elements of $\hat{\mathbf{\Omega}}_m^c$ corresponding to pairs of different airlines are equal to the intra-industry managerial Edgeworth sympathy coefficients $\lambda_{fg}^{intra,m}$, which are depicted in Table 5, Panel B; and (ii) using the the counterfactual inferred marginal costs $\hat{\mathbf{c}}_m^c$ that would arise considering that the inter-industry average (standard) Edgeworth sympathy coefficients for all airlines are equal to zero ($\lambda_{fo}^{inter} = 0$). The results suggest much smaller price effects of intra-industry overlapping ownership. In particular, the average effect on fares (and number of passengers) is 10.7% (-15.6%), which is near the upper end of the range of pricing impact estimates in Azar et al. (2018), and would give rise to an increase in industry profit of 16.3% and a decrease in consumer surplus of 7.5%. Combining this with the negative effect of inter-industry overlapping ownership,[16] we have that the total effect of overlapping ownership on fares (and number of passengers) of 4.0% (-8.2%), which is closer to the lower end of the range of pricing impact estimates in Azar and Vives (2021b), and would give rise to an increase in industry profit of 24.4% and a decrease in consumer surplus of 1.8%, the latter of which is ten times lower than in the full-internalization case.

Finally, we evaluate the fraction of these effects that is due to overlapping ownership

[16]The impact of inter-industry overlapping ownership does not depend on whether we allow for managerial entrenchment or not as, in this case, we consider that the elements of $\hat{\mathbf{\Omega}}_m^c$ corresponding to pairs of different airlines are equal to zero.

by the "Big Three" asset managers (BlackRock, Vanguard and State Street). To do so, we assume that the ownership structure of the different airlines is such that solely the "Big Three" asset managers engage in overlapping ownership. This yields the following counterfactual intra-industry standard Edgeworth sympathy coefficient and inter-industry average (standard) Edgeworth sympathy coefficient, respectively:

$$
\begin{aligned}
\lambda_{fg}^{intra} &= \frac{\sum_{k\in\Theta_s^{b3}} \upsilon_{kf}\phi_{kg}}{\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}} \\
\lambda_{fo}^{inter} &= \sum_{g\in\Theta_o} \eta_g \frac{\sum_{k\in\Theta_s^{b3}} \upsilon_{kf}\phi_{kg}}{\sum_{k\in\Theta_s} \upsilon_{kf}\phi_{kf}},
\end{aligned}
$$

where $\Theta_s^{b3} \subset \Theta_s$ denote the subset of Big Three shareholders. The results suggest that if shareholder objectives are solely partially internalized by the management, the intra-industry effect of the Big Three on fares (and number of passengers) is 2.7% (-4.6%), which would give rise to an increase in industry profit of 5.1% and a decrease in consumer surplus of 2.2%. In turn, the inter-industry effect on fares (and number of passengers) is -4.6% (6.0%), with the total effect being -1.9% (0.8%), giving rise to an increase in industry profit of 10.7% and a decrease in consumer surplus of 2.0%. Because the inter-industry effect of overlapping ownership is so high, we find that the effect of the Big Three on fares (and number of passengers) is actually negative (positive) and that the overall effect on consumers surplus is positive. This implies that the anticompetitive effect of overlapping ownership in airlines is coming from other, non-Big Three shareholders.

5 Conclusion

We develop a supply model of overlapping ownership conduct which links firm conduct parameters to deep parameters of the firm's process of shareholder preference aggregation through voting and can cope with ownership settings involving both intra- and inter-industry overlapping ownership. The model yields an equilibrium flexible formulation for the management's objective function that allows for no internalization, partial internalization and full internalization of shareholder objectives by managers and predicts that the degree of internalization of shareholder interests should increase with the level of shareholder dispersion within the firm.

We couple this proposed supply model with a flexible random-coefficients nested logit demand model and estimate both using data for the U.S. airline industry in the 2015-2017 period. We find evidence for a partial internalization formulation in which managers put significant weight on shareholder objectives, but substantially less than in the full-internalization limiting case. Further, we find evidence that the internalization of shareholder objectives by the management is, in fact, higher when its shareholders are more concentrated. This could be interpreted as consistent with managerial entrenchment mitigating the anti-competitive effects of intra-industry overlapping ownership, as managers are more powerful when shareholders are dispersed, and do not have to take into account shareholder preferences as much.

Furthermore, the estimation results are also consistent with the theory that more inter-industry overlapping ownership leads to more internalization of the positive pecuniary externalities from expanding output. We find that inter-industry overlapping ownership has a negative effect on the inferred marginal cost of airlines. Moreover, we show that omitting inter-industry overlapping ownership from the supply side model leads to substantial downward bias in the estimated conduct parameters that drive the internalization of shareholder objectives by the management. In particular, when we assume that the parameters driving this internalization are constant across airlines as in Kennedy et al. (2017), Park and Seo (2019) and Backus et al. (2021), omitting inter-industry overlapping ownership would even lead us not to reject a profit maximization conduct, when profit maximization is clearly rejected by the data once inter-industry overlapping ownership is taken into account.

Finally, we find, focusing on the 2017Q4 period, that assuming full internalization of shareholder objectives by the management implies implausibly large price increases from overlapping ownership relative to a counterfactual world without overlapping ownership. In turn, assuming the partial internalization supported by the data implies more modest price increases from overlapping ownership, which are more in line with the effects estimated in the literature so far. In particular, we find that overlapping ownership overall (both intra- and interindustry) seems to increase the average airline fare by 4.0%, increase industry profit by 24.4% and decrease consumer surplus by 1.8%, and that these effects are mostly due to overlapping ownership by shareholders other than the "Big Three" asset managers.

References

Aggarwal, R., Dahiya, S., and Prabhala, N. R. (2019). The power of shareholder votes: Evidence from uncontested director elections. *Journal of Financial Economics*, 133(1):134–153.

Antón, M., Ederer, F., Giné, M., and Schmalz, M. C. (2020). Common ownership, competition, and top management incentives. *Working Paper*, (1328).

Azar, J. (2012). A new look at oligopoly: Implicit collusion through portfolio diversification. *Ph.D. Thesis, Princeton University.*

Azar, J. (2017). Portfolio diversification, market power, and the theory of the firm. *Working Paper.*

Azar, J. (2020). The common ownership trilemma. *The University of Chicago Law Review*, 87(2):263–296.

Azar, J., Schmalz, M. C., and Tecu, I. (2018). Anticompetitive effects of common ownership. *The Journal of Finance*, 73(4):1513–1565.

Azar, J. and Vives, X. (2021a). General equilibrium oligopoly and ownership structure. *Econometrica*, 89(3):999–1048.

Azar, J. and Vives, X. (2021b). Revisiting the anticompetitive effects of common ownership. *Working Paper.*

Backus, M., Conlon, C., and Sinkinson, M. (2021). Common ownership and competition in the ready-to-eat cereal industry. *Working Paper.*

Bebchuk, L. and Hirst, S. (2018). Index funds and the future of corporate governance: Theory, evidence, and policy. *Working Paper.*

Berry, S., Carnall, M., and Spiller, P. T. (1996). Airline hubs: costs, markups and the implications of customer heterogeneity. *Working Paper.*

Berry, S. and Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics*, 2(3):1–43.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 63(4):841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 25(2):242–262.

BlackRock (2019). Common ownership data is incorrect. *Policy Spotlight.*

Bourreau, M., Sun, Y., and Verboven, F. (2021). Market entry, fighting brands, and tacit collusion: Evidence from the French mobile telecommunications market. *American Economic Review*, 111:3459–3499.

Brander, J. A. and Lewis, T. R. (1986). Oligopoly and financial structure: The limited liability effect. *The American Economic Review*, pages 956–970.

Bresnahan, T. F. (1989). Empirical studies of industries with market power. *Handbook of Industrial Organization*, 2:1011–1057.

Bresnahan, T. F. and Salop, S. C. (1986). Quantifying the competitive effects of production joint ventures. *International Journal of Industrial Organization*, 42:155–175.

Bresnahan, T. F., Stern, S., and Trajtenberg, M. (1997). Market segmentation and the sources of rents from innovation: Personal computers in the late 1980s. *The RAND Journal of Economics*, 28:S17–S44.

Brito, D., Elhauge, E., Ribeiro, R., and Vasconcelos, H. (2021). Modelling the objective function of managers in the presence of overlapping shareholding. *Working Paper*.

Brito, D., Osório, A., Ribeiro, R., and Vasconcelos, H. (2018). Unilateral effects screens for partial horizontal acquisitions: The generalized HHI and GUPPI. *International Journal of Industrial Organization*, 59:127–189.

Brown, B. W. and Walker, M. B. (1989). The random utility hypothesis and inference in demand systems. *Econometrica*, 57:815–829.

Cardell, S. N. (1997). Variance components structures for the extreme-value and logistic distributions with application to models of heterogeneity. *Econometric Theory*, 13:185–213.

Ciliberto, F., Murry, C., and Tamer, E. (2021). Market structure and competition in airline markets. *Journal of Political Economy*, 129:2995–3038.

Ciliberto, F. and Williams, J. W. (2014). Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. *The RAND Journal of Economics*, 45(4):764–791.

Conlon, C. and Gortmaker, J. (2019). Best practices for differentiated products demand estimation with pyblp. *Working paper*.

Crawford, G. S., Lee, R. S., Whinston, M. D., and yurukoglu, A. (2018). The welfare effects of vertical integration in multichannel television markets. *Econometrica*, 86:891–954.

DeAngelo, H. (1981). Competition and unanimity. *The American Economic Review*, 71(1):18–27.

Delrahim, M. (2019). Don't "take the money and run": Antitrust in the financial sector. *Presentation, Fordham University School of Law.*

Einav, L. and Levin, J. (2010). Empirical industrial organization: A progress report. *Journal of Economic Perspectives*, 24(2):145–62.

Ekern, S. and Wilson, R. (1974). On the theory of the firm in an economy with incomplete markets. *Bell Journal of Economics*, 5(1):171–180.

Elhauge, E. (2015). Horizontal shareholding. *Harv. L. Rev.*, 129:1267.

Fershtman, C. and Judd, K. L. (1987). Equilibrium incentives in oligopoly. *The American Economic Review*, pages 927–940.

Gramlich, J. and Grundl, S. (2017). Estimating the competitive effects of common ownership. *Working Paper.*

Grigolon, L., Reynaert, M., and Verboven, F. (2018). Consumer valuation of fuel costs and tax policy: Evidence from the european car market. *American Economic Journal: Economic Policy*, 10:193–225.

Grigolon, L. and Verboven, F. (2014). Nested logit or random coefficients logit? a comparison of alternative discrete choice models of product differentiation. *Review of Economics and Statistics*, 96(5):916–935.

Hart, O. (1979). On shareholder unanimity in large stock market economies. *Econometrica*, 47:1057–1083.

Kennedy, P., O'Brien, D. P., Song, M., and Waehrer, K. (2017). The competitive effects of common ownership: Economic foundations and empirical evidence. *Working Paper.*

Leland, H. E. (1974). Production theory and the stock market. *The Bell Journal of Economics and Management Science*, pages 125–144.

Lewis, E. and Chugh, R. (2019). Common ownership and airlines: Evaluating an alternate ownership data source. *Working Paper.*

McFadden, D. (1978). Modeling the choice of residential location. *Transportation Research Record*, 673:72–77.

Miller, N. H. and Weinberg, M. C. (2017). Understanding the price effects of the millercoors joint venture. *Econometrica*, 85(6):1763–1791.

Moskalev, A. (2019). Objective function of a non-price-taking firm with heterogeneous shareholders. *Working Paper*.

O'Brien, D. P. and Salop, S. C. (2000). Competitive effects of partial ownership: Financial interest and corporate control. *Antitrust Law Journal*, 67:559.

O'Brien, D. P. and Waehrer, K. (2017). The competitive effects of common ownership: We know less than we think. *Antitrust Law Journal*, 81(3):729–776.

Park, A. H. and Seo, K. (2019). Common ownership and product market competition: Evidence from the US airline industry. *Korean Journal of Financial Studies*, 48(5):617–640.

Phillips, N. (2018). Taking stock: Assessing common ownership. *Presentation, The Global Antitrust Economics Conference*.

Posner, E. A. (2021). Policy implications of the common ownership debate. *The Antitrust Bulletin*, 66(1):140–149.

Posner, E. A., Scott Morton, F. M., and Weyl, E. G. (2017). A proposal to limit the anti-competitive power of institutional investors. *Antitrust Law Journal*, 81(3):669–728.

Radner, R. (1974). A note on unanimity of stockholders' preferences among alternative production plans: a reformulation of the ekern-wilson model. *The Bell Journal of Economics and Management Science*, 5(1):181–184.

Rock, E. B. and Rubinfeld, D. L. (2018). Common ownership and coordinated effects. *Working Paper*.

Rotemberg, J. J. (1984). Financial transaction costs and industrial performance. *Working Paper*.

Ruiz-Pérez, A. (2019). Market structure and common ownership: Evidence from the US airline industry. *Working Paper*.

Schmalensee, R. (1989). Inter-industry studies of structure and performance. *Handbook of Industrial Organization*, 2:951–1009.

Scott Morton, F. and Hovenkamp, H. (2017). Horizontal shareholding and antitrust policy. *Yale LJ*, 127:2026.

Tzanaki, A. (2017). The regulation of minority shareholdings and other structural links between competing undertakings: a law & economics analysis. *Ph.D. Thesis, University College London*.

Varadhan, R. and Roland, C. (2008). Simple and globally convergent methods for accelerating the convergence of any em algorithm. *Scandinavian Journal of Statistics*, 35(2):335–353.