Market Structure and Common Ownership: Evidence from the US Airline Industry *

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Abstract

The last two decades have seen a rapid increase in institutional investors' shareholdings of publicly traded firms. This has drawn the attention of scholars and antitrust agencies for its potential effects on economic and corporate governance outcomes. One of the main concerns is that common ownership, which refers to the increased ownership overlap in firms that are in the same sector, can cause lack of incentives to compete. Previous studies have focused on its impact on pricing, but the effects on market structure are less understood. This paper focuses on market entry. I study the airline industry, one of the industries in which common ownership is more pervasive, and find evidence that common ownership can affect airlines' strategies to serve different routes in reduced form regressions. Then, I build a structural model of market entry and price competition with common ownership and I compare it with a standard model of oligopolistic competition. I find that common ownership matters for entry decisions but does not matter for pricing behavior.

JEL Codes: L13, G34, L41, D43, C35, L93
Keywords: Competition, Common Ownership, Antitrust, Entry, Market structure, Airline Industry, Estimation of Entry Games

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1 Introduction

Are institutional investors threatening competition within large industries? A recent number of studies in the economics and finance literature raises the concern that a high degree of overlapping ownership by a small number of investors in publicly traded companies is affecting how they compete. The rationale of this proposition is that, when the proprietors of firms that are supposed to be rivals are the same, maximizing shareholder value does not mean maximizing firm value anymore. This might imply that managers become tempted to avoid aggresive competition by pushing prices up or refraining to compete altogether.

Common ownership (CO) is defined as the situation, described above, in which a large fraction of the shares of firms within the same industry are in hands of the same owners, who are typically big[1]. Azar, Schmalz and Tecu (2018) are the first authors to empirically highlight the pernicious effects that this investment environment might induce in competition in the US domestic airline industry. First, they challenge the notion that common ownership levels are low and they use the US airline domestic market as the object of study. Using a market concentration measure that takes into account shareholder linkages[2], they use route-time variation to show that the higher the concentration due to common ownership, the higher the prices in the route.

These findings have been criticized by later studies due to the measurement issues. Market concentration measures are functions of quantities, which suffer from the classic endogeneity problem of simultaneity. Moreover, as O'Brien and Waehrer (2017) and Kennedy et al. (2017) show, the relationship between a measure of market concentration that accounts for common ownership and prices can deliver multiple outcomes. For these reasons, these studies propose a measure of *profit weights* that reflects how much the profits of a given firm matter for the utility of another firm. This measure, which varies at firm pair level instead of market level,

[1] Some authors prefer to refer to the specific phenomenon of *horizontal shareholding* (Elhauge, 2016, 2019*b*,*a*), which reinforces the idea of natural competitors being jointly held by a set of individuals. I stick to common ownership given the higher prevalence of the term in the literature.

[2] The authors use a Modified Herfindahl-Hirschman Index (MHHI) developed in Reynolds and Snapp (1986), Bresnahan and Salop (2016) and Salop and O'Brien (2000).

$$MHHI = HHI + \sum_j \sum_{k \neq j} \frac{\sum_i \gamma_{ij} \beta_{ik}}{\sum_i \gamma_{ij} \beta_{ij}} s_k s_j$$

This index is the sum of the old Herfindahl-Hirschman Index plus a component named HHI delta, which is the sum of the product of market share pairs and a fraction which relates the importance of firm k to firm j. Here γ_{ij} is the control fraction that shareholder i has over firm j and β_{ij} is the ownership fraction that i has over j.

is a function of the primitives that refers to shareholder control, and thus is free of the above mentioned critique. However, studies that use this variable (Dennis, Gerardi and Schenone, 2019; Gramlich and Grundl, 2018; Kennedy et al., 2017) find no effect of common ownership on airline ticket prices.

Instead, I focus on another aspect of competition and study the relationship between common ownership and market structure in the context of the US domestic airline market. By market structure in this study I refer to the number and identity of entrants into a market. In particular, I hypothesize that common ownership has an effect in the incentives of competitors to enter a market. In the presence of fixed costs, two firms that are commonly owned might prefer to avoid each other in order to prevent harming the profits of the competitor. In addition, if common ownership shapes entry, it might provide a rationale for why market concentration measures affect prices. If firms with less common ownership are more likely to enter and also more likely to compete fiercely on prices, then there would be a positive relation between concentration and pricing.

In order to empirically assess these mechanisms I merge data from various sources. First, I obtain data on ownership from the Securities and Exchange Commision's Edgar database. I scrape all the institutional investors' portfolios for the years 2013 to 2017 which yield information at the security level. This allows me to obtain the number of shares each investor has in each airline. I also obtain quarterly firm reports for all airlines that operate during those years and extract the total outstanding shares in each of the periods to be able to compute the proportion of shareholdings that each investor has.

Second, I use data from the US Department of Transportation on prices and quantities. These data consist in a 10% random sample of all tickets sold in a given quarter by all firms that sell domestic flights, including origin and destination airports, prices, number of passengers and intermediate stops. I define a market as a non-directional airport pair in a given quarter, as in Azar, Schmalz and Tecu (2018), Ciliberto and Tamer (2009) or Kennedy et al. (2017). In order to complement information on the markets, I get population and income per capita data from the census.

In this paper I combine both reduced form evidence and a structural model to test for the

importance of common ownership to shape competition. As an empirical exercise to first explore the data, I select routes in which there is only one airline operating and I look at the common ownership of all potential entrants. I find that the higher the common ownership (that is, the higher the importance of the incumbent's profits for a potential entrant) the lower the likelihood of entry in subsequent periods. This is consistent with my hypothesis that firms tend to avoid each other if common ownership is high, to minimize any damage in profits.

This type of reduced form evidence is not enough to understand the role of common ownership in market structure. This is the case because entry decisions depend on the strategies of all potential players and ignoring strategic interactions can provide misleading results. Therefore, the second part of my analysis consists in building a structural model in which there are two stages: entry and pricing. To the best of my knowledge, this is the first model in which entry and pricing are modelled jointly with common ownership. The structure of the game is as follows. First, firms simultaneously choose whether to enter a market or not, subject to a private information shock. Players form beliefs about the probability of entry of others, and choose to enter if the net value of entering is positive. Here the net value takes into account the profits they would obtain and also how much profits other competitors would be losing. Once all entry decisions have been taken, then a Bertrand Nash pricing game with differentiated goods takes place. Just before choosing a price, a shock to marginal costs and demand occurs which is common knowledge for all players. Then all firms set prices simultaneously, where the demand follows a nested logit specification with two nests: travelling with a carrier or choosing an outside option.

I estimate the parameters of the game in three steps. First, I start with the demand side of the game and I recover the nesting parameter that governs the substitution between groups of products and the semielasticity with respect to price. These parameters allow me to use first order conditions to obtain values for the marginal costs of the firms, which I use to get the remaining parameters of the pricing game. Second, I use the structure of the game to predict all counterfactual profits for any given market structure. Finally, I insert these objects in the equations that determine the entry condition and I estimate the parameters that determine fixed costs using an estimator based on Aguirregabiria and Mira (2002, 2007). I start with an initial

guess for the beliefs of players entering the market and I estimate the parameters given those beliefs. Then, I use the probabilities predicted by the model to iterate again on this process until convergence is reached in both beliefs and parameters.

Next, I reestimate the model shutting down the common ownership channel, that is, I estimate it as a standard oligopolistic model with entry and pricing. I test the null hypothesis that both models are equally close to the true data generating process against the alternative that a model of common ownership has a better fit. I use a statistic developed in Vuong (1989). This paper presents a test based on likelihood ratio statistics for non-nested models which has an asymptotically normal distribution. Once I apply the test to the competing models, I don't reject the null hypothesis that both perform equal in explaining the data. To further explore this result, I estimate alternative games that I compare with a standard oligopolistic model. In particular I estimate a game with common ownership in the entry stage and no common ownership in the pricing stage and the opposite configuration. I find that allowing for common ownership only in entry leads to strongly rejecting the null that common ownership does not matter. However, if I allow for common ownership only in pricing, then the two models are equally close to the truth, indicating that entry considerations might be more important than pricing.

Contributions to the literature. This paper contributes to various strands of the literature. First it contributes to the literature on common ownership, as it closes a gap on the outcomes that have been studied. The closest paper to this one is Newham, Seldeslachts and Banal-Estanol (2018). In the context of the pharmaceutical industry, they study the likelihood of introducing a generic drug after a patent expires. They find that common ownership matters for the introduction of a generic drug, reducing the likelihood of entering up to 10% for a one standard deviation increase. However, they don't take into account strategic interactions and thus findings about market structure are limited. Other papers have studied pricing (Dennis, Gerardi and Schenone, 2019; Gramlich and Grundl, 2018; Kennedy et al., 2017), innovation Antón et al. (2018*b*), or auctions (Asai and Charoenwong, 2019).

Moreover, this paper contributes to a large number of industry studies dedicated to the

airline industry and specifically to entry games and oligopolistic competition, such as Berry (1994), Berry and Jia (2010), Ciliberto and Tamer (2009) or Aguirregabiria and Ho (2012). Differently from other papers, I introduce profit weights in a two-stage static model with entry and pricing and I show that some parameters of the cost structure of firms can be greatly affected with respect to standard models.

The paper is organized as follows. Section 2 presents the measure of common ownership I use, the data and some facts about the US airline market. Section 3 shows some motivating reduced form evidence on the importance of common ownership in entry. Section 4 explains in detail the model of entry and pricing with common ownership. Section 5 develops the estimation of the model. Section 6 presents the estimation results. Section 7 shows how I test the importance of common ownership and its results. Section 8 concludes.

2 Institutional setting and data

2.1 Common ownership terms

The framework that the common ownership literature uses comes from the theory of joint ventures and partial ownership, developed by Bresnahan and Salop (2016) and Salop and O'Brien (2000), which has been later microfounded in a model of managerial elections (Azar, 2012). The fundamental relation is shown in Equation (1).

$$U_j^M(y) = \underbrace{\sum_i \gamma_{ij} u_i^O(y)}_{\text{Weighted shareholders' value}} = \sum_i \gamma_{ij} \sum_k \beta_{ik} \pi_k(y) \propto \underbrace{\pi_j(y) + \sum_{k \neq j} C_{jk} \pi_k(y)}_{\text{Weighted firms' value}} \tag{1}$$

Equation (1) represents the objective function for a manager (M) who works in firm j. Here, y refers to a vector of actions. They could be prices, quantities, entry decisions or any other dimension of interest. This objective function, under this theory, can be expressed as the weighted sum of the utilities of all owners (O) of the firm, which are indexed by i. The weights in this expression are the γ_{ij} parameters, which represent the control that investor i exerts over firm j. For example, a shareholder that holds more than 50% of the shares would have a control of one and the remaining minority ones would have no impact at all. The utility of any given owner is the sum of the profits of the firms in her portfolio, π_k, in proportion to the financial

rights (shares) that they hold (β_{ik}). Therefore, one can collect all the terms that refer to firm j ($\sum_i \gamma_{ij}\beta_{ij}$) and divide the whole expression by them. In this manner, one gets that the objective function of a manager working in j is the sum of the profits in j (π_j) and all the other profits of the competitors weighted by *profit weights* C_{jk}, which are defined as:

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

C_{jk} expresses the importance that has firm k for firm j. It is not symmetric, so C_{jk} does not need to be equal to C_{kj}, and it is only bounded from below by 0, but it can take values above 1. These objects are functions of two sets of parameters, γ and β. The latter have a clear and measurable empirical counterpart, which is the ratio of shares that each shareholder has in each firm. However, it is harder to assign a value to γ. Fortunately, Azar (2012) provides some guidance into this issue. In his microfounded model, the control that an investor exerts might be proportional to her votes $\gamma_{ij} = \beta_{ij}$ or it can be the probability that the shareholder is pivotal (thus having the form of a Banzhaf Power Index). I follow the first form, which is the one that the literature typically uses[3]. Therefore, C_{jk} can be computed alone with data on shareholdings.

2.2 The US airline market

The airline sector in the US has undergone a great transformation during the 2000s and part of the 2010s. On the one hand, common ownership is very prevalent and has been on the rise since the late 1980s, with the average firm having more than 80% in the hands of instutional investors. On the other hand, a wave of mergers and bankruptcies has completely reshaped the industry, going from 24 airlines in the year 2000 to 12 in 2017.

In my empirical analysis I use the years 2014 to 2017 for three reasons. The first one is that the last big merger, the one of US Airways and American Airlines, took place in the last quarter of 2013 and from that moment onwards the industry structure has been more or less stable. The second reason is that, derived from this process of concentration, the number of big players has been reduced to four: American Airlines, Delta, United and Southwest (in the low cost segment

[3]Even if both assumptions can differ greatly, for this application the values that they yield are similar. This is the case because there is no great heterogeneity between pivotality among large shareholders.

of the market). The third reason, of a practical nature, is that ownership data quality from the SEC improved and became more standardized in 2013.

2.3 Data

I gather ownership data from the SEC filings. In particular, I use Form 13F data, which are quarterly reports filled out by institutional investment funds that hold more than $100 million in securities in a given period. These filings give information about the security identification number (CUSIP), the amount of securities, their market value, and their voting rights. I combine this information with 10K and 10Q filings for each of the airline companies, which include the total shares outstanding in each quarter, to compute the proportion of shares that each significant shareholder has. In order to compute the control weights that each shareholder possesses, I follow the literature and use only the shares with voting rights.

In terms of airline data I use the well known Airline Origin and Destination Survey (DB1B), which is managed by the Office of Airline Information of the Bureau of Transportation Statistics. The DB1B survey is a 10% random sample of all the airline tickets sold in the US domestic market by quarter. It contains information on the total fare, the number of passengers, the number of coupons, the origin and destination airports in the itinerary, and the ticketing, operating and reporting carriers[4]. On top of ticket data, I use the T-100 Domestic Non-stop Segment database, which also comes from the same source. The T-100 yields information about all flights scheduled or departed in each month. This allows me to determine whether an airline has a non-stop option for a route.

Finally, I add information on demographics from standard sources. I get population for each Metropolitan Statistical Area (MSA) from the Census Bureau and income per capita from the Bureau of Economic Analysis.

2.4 Market definition and sample selection

I define a market as a nondirectional trip between two airports disregarding intermediate destinations. This means that I use non-stop, direct or connecting flights indistinctly, as long as

[4]Whereas the operating carrier refers to the airline that actually performs the flight, meaning that it provides the plane, the crew and the handling services, the ticketing (or sometimes called marketing) carrier sells the ticket to the client. Often they are the same, but sometimes they are not. This is particularly the case in codeshare agreements or in contracts with regional airlines, for instance.

all the flights are sold by the same carrier[5]. This is the same approach that Kennedy et al. (2017), Azar, Schmalz and Tecu (2018) or Ciliberto and Tamer (2009) take. I use the potential origin-destination pairs of the top 70 most populous MSAs, except for those potential markets that are served less than 50% of the time after 2000 (the whole sample of airline data). This amounts to 3143 routes and 16 quarters of data for 12 carriers. I get the population and income by market by computing the geometric average of the cities in each of the endpoints.

For the structural estimation I use the four largest airlines and pool the remaining eight in a single one due to computational reasons. However, this is not a problem for two reasons. First, the biggest airlines hold about 74% of the overall volume of passengers, indicating a substantial concentration in the market. Second, the minor airlines are mostly regional and any two of them appear together less than 4.7% of the time.

In Table 1 I show some features of the data. I pool all routes in all periods and I show the distribution of competitors in each of the observations. There is substantial variation, with very few units showing zero entry and a substantial mass of observations in four competitors. Moreover, as the literature shows, demographics alone don't explain the variation in number of competitors. Only income seems to explain a shift to more competitors, as those above the median income have 22% of observations in which there are 5 competitors or more against 11% in the case of those below the median.

Table 1: Descriptive statistics of market structures (%)

	Distribution of the number of competitors by airport-pairs					
	0	1	2	3	4	5 or more
Total	3.47	12.03	17.55	20.53	29.39	17.02
Above median population	3.43	11.39	17.10	21.35	29.76	16.95
Below median population	3.51	12.67	18.01	19.72	29.01	17.06
Above median income	3.62	11.88	16.40	19.02	26.91	22.15
Below median income	3.31	12.19	18.69	22.05	31.87	11.87

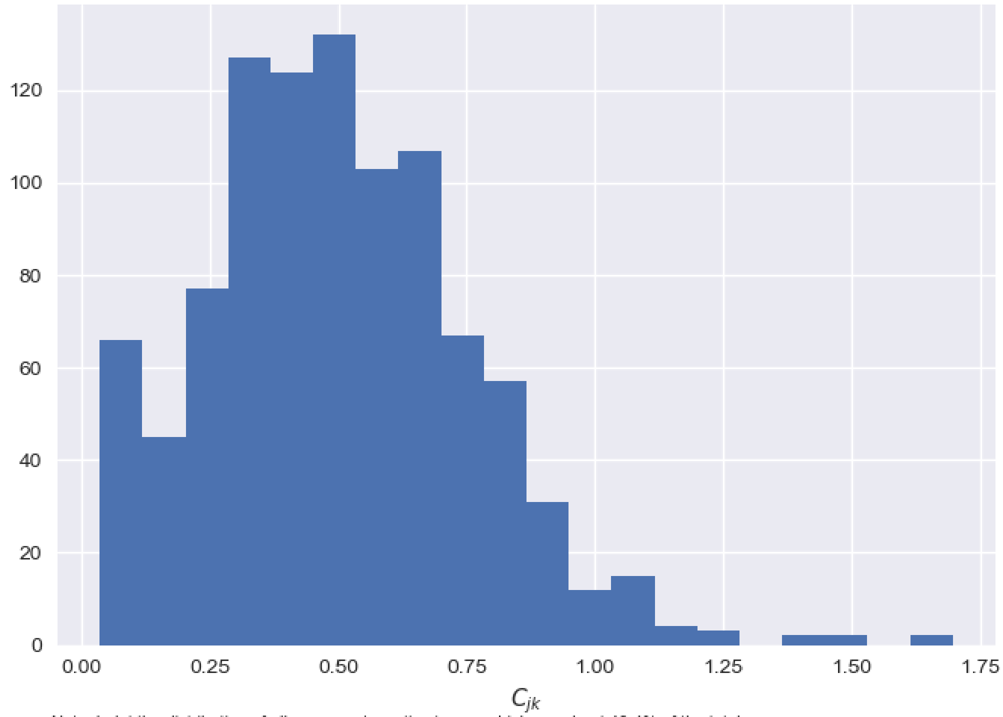
Note: 3143 airport-pairs for 16 quarters (2014-2017) and 12 carriers.

[5]Flights that go from origin to destination without any intermediate stops are called non-stop. The difference between those and direct flights is that the latter might have stops, but they don't imply any change of planes in any case. If there are intermediate change of planes, then the flight is called connecting. For more information about how the data is constructed, please refer to the Data Appendix.

I also construct important covariates that I use for the estimation of the structural model based in Ciliberto and Tamer (2009). First, I construct a variable called *distance to the hub* which measures of how far the nearest hub is relative to the distance of the route. It is computed as the sum of the distances to the nearest hub from both airports minus the distance of the route, which is divided by the distance of the route. Therefore it takes values from zero to infinity. This can explain part of the fixed costs of operating a route. The second covariate is called *market presence*. For each of the endpoints of a route I compute the proportion of routes that an airline serves over the total number of routes that are served from that airport. This affects both costs, as airlines might be able to share resources across routes, and demand, as a higher share of routes served might be beneficial for example for loyalty-gaining purposes. I also construct a third covariate, called *number of connections*, which is the total number of routes served in each of the endpoints.

In Figure 1 I plot the distribution of profit weights C_{jk} conditional on having a positive weight, which comprise about 52% of the total. Given that profit weights only vary over time, I pool all observations for the 16 quarters. This amounts to 2112 observations. The plot shows that there is a wide range of variation, from those that have a weight close to zero to those that have a weight close to one.

Figure 1: Distribution of C_{jk}

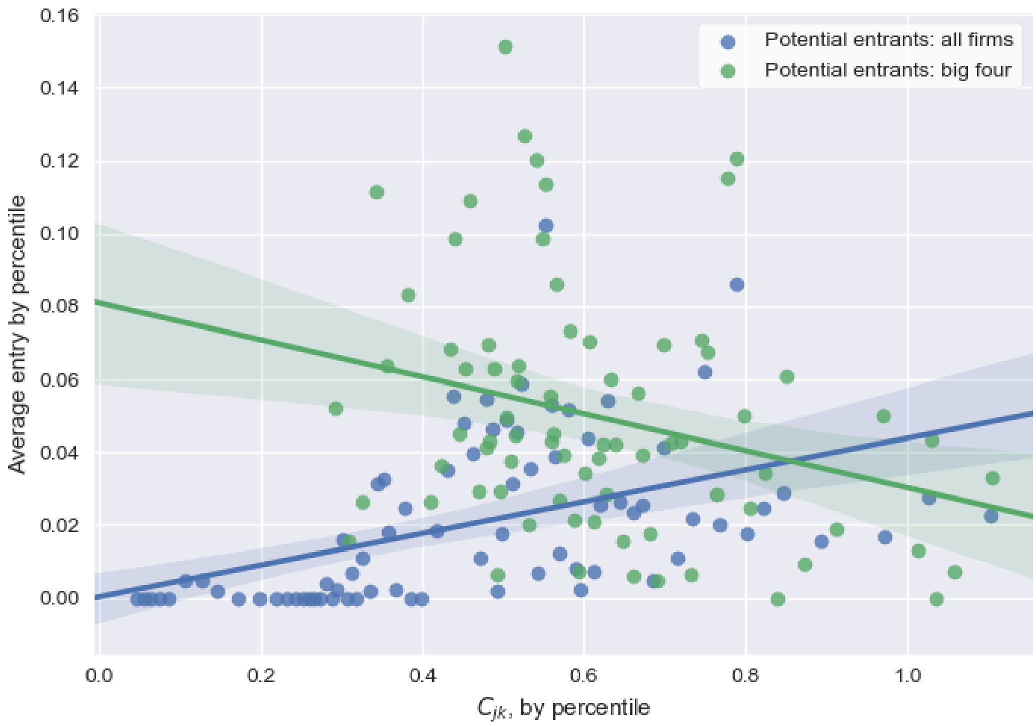


Note: I plot the distribution of all non-zero incentive terms, which are about 48.4% of the total.

3 Motivating evidence

In order to have some reduced form evidence of the effect of common ownership in entry I construct a sample of markets in which there is only one monopolist. Then, I look at the following period and see if any of the other airlines enters. I then correlate entry decisions to the C_{jk} of the pair, with j being the potential entrant and k the incumbent. To show this relation, I split the C_{jk} in bins by percentiles and then I average entry within each bin. The result is shown in Figure 2. If I use all 12 carriers as potential entrants, the relation seems to be positive, given that many of these carriers are smaller, with lower capacity to operate, and they also tend to have less overlapping owners. Once I take into account only the largest four airlines, the slope becomes negative, as expected. If in the lowest range of the C_{jk} variable, around 0.4, the average entry is about 6%, it drops to around 2% in the high range of the variable.

Figure 2: Entry in markets with one incumbent



Note: the proportion of big four observations is 0.41.

I confirm these relations in regression tables. I estimate a number of binary models that explain entry as a function of C_{jk} and covariates. In particular I estimate probit and linear probability models (LPM) controlling for market characteristics, such as distance, income per capita and population. In the case of the linear probability models, I saturate the regressions with route and time fixed effects to be able to absorb only the variation coming from ownership. I summarize the results in Table 2. In columns (1) to (4) I regress entry on C_{jk} in levels, mimicking Figure 2, and in columns (5) to (8) I use ΔC_{jk} instead, which is the change from one period to the next. As seen in columns (1) and (3), raw specifications show a positive association of C_{jk} and entry. However, including the interaction of C_{jk} with a dummy variable for the Big Four airlines reverses the relation (columns (2) and (4)). Given that the average entry is 2%, the results are sizable. Using only the variation coming from the change in C_{jk} is noisier, but it also tends to show a negative effect.

Table 2: Dependent variable: entry

	Probit		LPM		Probit		LPM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C_{jk}	0.04*** (0.003)	0.024*** (0.009)	0.05*** (0.01)	-0.001 (0.006)				
Big 4 $\times C_{jk}$		-0.04*** (0.008)		-0.077*** (0.015)				
ΔC_{jk}					-0.017** (0.007)	-0.068*** (0.026)	-0.006 (0.01)	0.009 (0.008)
Big 4 $\times \Delta C_{jk}$						0.069** (0.01)		-0.07** (0.03)
Dist. Hub		-0.03*** (0.002)		0.001*** (0.0004)		-0.02*** (0.002)		0.001*** (0.0005)
Presence		0.14*** (0.005)		0.21*** (0.04)		0.13*** (0.005)		0.138*** (0.02)
Mkt. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
N. Obs	35047	35047	35047	35047	35047	35047	35047	35047
R^2	0.03	0.35	0.009	0.08	0.003	0.35	0.0002	0.07

Clustering is done at the carrier pair (jk) level. Average derivative effects are reported for probit. Mean dep. var is 0.02.

4 A model of entry with common ownership

In order to shed light on the effect of common ownership on entry and subsequently in competition I propose a model in which ownership naturally interacts with both strategic dimensions. I follow Aguirregabiria and Ho (2012) or Gayle and Xie (2008) and assume that by the time of the entry decision, players do not have any information on unobservables related to demand and marginal costs.

I build a simple static, imperfect information model in which agents are privately informed about a firm-market shock ϵ and, when all entry decisions have been taken, demand and supply shocks η and u are realized (which are common information) and agents compete simultaneously in pricing. The model of pricing is a standard Bertrand Nash game with differentiated goods that follow a nested logit. It is closely related to Kennedy et al. (2017), which follows a similar structure in the pricing game.

4.1 The pricing stage

Once all firms have taken their entry decisions, those that are present in the market compete in prices à la Bertrand-Nash with differentiated goods, where all information is common for all players.

I specify the demand side of the model as a simple discrete-choice problem similar to the one in McFadden (1978). In a market m at time t there is a continuum of consumers indexed by c that make a single consumption decision, with an indirect utility of consuming product j characterized as:

$$u_{cjmt} = \begin{cases} X_{jmt}^D \theta^D + \alpha p_{jmt} + \xi_{jmt} + \zeta_{cgmt} + (1-\sigma)\varepsilon_{cjmt} & \text{if j = 1, ... J} \\ \varepsilon_{c0mt} & \text{if j = 0} \end{cases}$$

It is assumed that the unobservables ε and ζ are drawn so as to generate a nested logit form (Berry and Jia, 2010; Aguirregabiria and Ho, 2012). Here the nests are either travelling by plane (g) or an outside option which might correspond to choosing any other means of transportation or not travelling at all. Therefore, σ controls the substitutability of the different options within the nest of travelling by plane. In an extreme case, when $\sigma = 1$, the shocks are perfectly correlated and all consumers buy the same option. The utility of consumer c when she decides to consume j also includes an unobserved (for the researcher, not for the players) quality shock that is common for all consumers, ξ, observed characteristics, X, and the price, p, where α controls the marginal (dis)utility of a price increase and is common for all consumers.

With the appropriate distributional assumption mentioned before, the share (or probability of choice) of option j conditional on nest g is:

$$s_{jmt/g} = \frac{\exp\left(\left(X_{jmt}^D \theta^D + \alpha p_{jmt} + \xi_{jmt}\right)/(1-\sigma)\right)}{D_{gmt}} \tag{2}$$

With D_{gmt} being:

$$D_{gmt} = \sum_k \exp\left(\left(X_{kmt}\theta + \alpha p_{kmt} + \xi_{kmt}\right)/(1-\sigma)\right) \tag{3}$$

Moreover, the share of the nest g has also a very simple form:

$$s_{gmt} = \frac{D_{gmt}^{(1-\sigma)}}{1 + D_{gmt}^{(1-\sigma)}} \tag{4}$$

To conclude, the unconditional share of product j is:

$$s_{jmt} = s_{jmt/g} s_{gmt} \tag{5}$$

Competitors in this model take demand as given and maximize their objective function choosing a price p_{jmt} for their firm. A manager in firm j maximizes an utility function that

takes into account not only the profit of j but also the profit of other firms (k) present in the market mediated by an incentive term C_{jk}:

$$\max_{p_{jmt}} U_j^M(p_{mt}, X_{jmt}) = \pi_j(p_{mt}, X_{jmt}) + \sum_{k \neq j} C_{jkt} \pi_k(p_{mt}, X_{kmt}) \tag{6}$$

With the profit function of firm j being:

$$\pi_j(p_{jmt}, X_{jmt}) = (p_{jmt} - mc_{jmt})\, s_{jmt} M_{mt} \tag{7}$$

where mc_{jmt} is the marginal cost and M_{mt} is the market size. The first order condition of this problem becomes:

$$s_{jmt} + \frac{\partial s_{jmt}}{\partial p_{jmt}} (p_{jmt} - mc_{jmt}) + \sum_{k \neq j} C_{jk} \frac{\partial s_{kmt}}{\partial p_{jmt}} (p_{kmt} - mc_{kmt}) = 0 \tag{8}$$

The first two terms of the first order condition appear in the standard oligopolistic problem: when a firm marginally increases the price of its product it increase their revenues for units sold (s_{jmt}) but it loses the markup on the quantity that is diverted away ($\frac{\partial s_{jmt}}{\partial p_{jmt}} (p_{jmt} - mc_{jmt})$). When there are many players this tradeoff might prevent the price from rising too much. However, common ownership has the potential to alleviate this tradeoff by internalizing the (positive) effect of an increase of p_{jmt} on the markup of firm k ($\frac{\partial s_{kmt}}{\partial p_{jmt}} (p_{kmt} - mc_{kmt})$). If common ownership is important, this effect could push average prices towards monopolistic outcomes and reduce welfare for consumers.

Stacking all FOCs we get the following system of linear equations in which markups are part of all conditions:

$$\begin{bmatrix} s_{1mt} \\ s_{2mt} \\ \vdots \\ s_{Jmt} \end{bmatrix} + \begin{bmatrix} \frac{\partial s_{1mt}}{\partial p_{1mt}} & C_{12t} \frac{\partial s_{2mt}}{\partial p_{1mt}} & \cdots & C_{1Jt} \frac{\partial s_{Jmt}}{\partial p_{1mt}} \\ C_{21t} \frac{\partial s_{1mt}}{\partial p_{2mt}} & \frac{\partial s_{2mt}}{\partial p_{2mt}} & \cdots & C_{2Jt} \frac{\partial s_{Jmt}}{\partial p_{2mt}} \\ \vdots & \vdots & \ddots & \vdots \\ C_{J1t} \frac{\partial s_{1mt}}{\partial p_{Jmt}} & C_{J2t} \frac{\partial s_{2mt}}{\partial p_{Jmt}} & \cdots & \frac{\partial s_{Jmt}}{\partial p_{Jmt}} \end{bmatrix} \begin{bmatrix} p_{1mt} - mc_{1mt} \\ p_{2mt} - mc_{2mt} \\ \vdots \\ p_{Jmt} - mc_{Jmt} \end{bmatrix} = 0 \tag{9}$$

Here the derivatives have the simple forms $\frac{\partial s_{jmt}}{\partial p_{jmt}} = \left(\frac{\alpha}{1-\sigma}\right) s_{jmt} \left(1 - \sigma s_{jmt/g} - (1-\sigma) s_{jmt}\right)$ and $\frac{\partial s_{kmt}}{\partial p_{jmt}} = -\alpha s_{kmt} \left(\frac{\sigma}{1-\sigma} s_{jmt/g} + s_{jmt}\right) = \frac{\partial s_{jmt}}{\partial p_{kmt}}$.

Assume also that $mc_{jmt} = f(X^S_{jmt}; \theta^S) + u_{jmt}$, that is, marginal costs in market m at time t for firm j is a function of known variables and a shock that is revealed (for all players) after entry[6]. This implies that players cannot fully predict their marginal costs at the time of entry.

4.2 The entry stage

When firms decide whether to serve a market or not they form expectations about how much profits everybody will make. This expectation has two parts: conditional on a given market structure, what profits they will make (that is, the outcome of the pricing game after the realization of u and η) and the probability of each market structure. Each player has a private information shock at the entry stage ϵ and she forms beliefs about the probability of entry of other players, which determines their choice. The entry condition becomes:

$$
\begin{aligned}
&E[\pi^*_j(e_j = 1, e_{-j}, X_{mt}, C_t) - F_{jmt} - \epsilon_{jmt} + \\
&\qquad + \sum_{k \neq j} C_{jk} \left(\pi^*_k(e_j = 1, e_{-j}, X_m, C_t) - \pi^*_k(e_j = 0, e_{-j}, X_k, C_t) \right) |X_{mt}, C_t, \epsilon_{jmt}] > 0 \quad (10)
\end{aligned}
$$

Here e_j is the entry decision of player j and π^*_j is the expected profit of player j conditional on a given market structure (e), covariates (X) and common ownership terms (C). This condition states that a firm enters if the expected net gain (conditional on covariates, common ownership and the private information shock) is positive.

The expected net gain is composed of several terms. First, there is the direct profit that firm j makes (in expected terms), $\pi^*_j(e_j = 1, e_{-j}, X_{mt}, C_t)$. Second, there are the fixed costs, $F_{jmt} + \epsilon$, which have a private information component. These fixed costs can accomodate also for entry costs by using past information on entry (e_{jt-1}). Finally, for each $k \neq j$, player j weighs how much profits she destroys, $\pi^*_k(e_j = 1, e_{-j}, X_m, C_t) - \pi^*_k(e_j = 0, e_{-j}, X_k, C_t)$, by the incentive term C_{jk}.

[6] In particular, I am going to assume that the function is linear, $mc_{jmt} = X^S_{jmt}\theta^S + u_{jmt}$, for the estimation part of the game.

5 Estimation and identification

5.1 Pricing game

Given the assumptions that yield logistic functions in Equations (2) and (4), I transform the equations appropriately to have a linear function of the structural parameters.

$$\ln\left(s_{jmt}\right) - \ln\left(s_{0mt}\right) = X^{D}_{jmt}\theta^{D} + \alpha p_{jmt} + \sigma \ln\left(s_{jmt/g}\right) + \xi_{jmt} \tag{11}$$

Moreover, I recover marginal costs using equation 9. Call b_{mt} the following expression:

$$b_{mt}\left(s_{mt}, C_t, \alpha, \sigma\right) = -\begin{bmatrix} \frac{\partial s_{1mt}}{\partial p_{1mt}} & C_{12t}\frac{\partial s_{2mt}}{\partial p_{1mt}} & \cdots & C_{1Jt}\frac{\partial s_{Jmt}}{\partial p_{1mt}} \\ C_{21t}\frac{\partial s_{1mt}}{\partial p_{2mt}} & \frac{\partial s_{2mt}}{\partial p_{2mt}} & \cdots & C_{2Jt}\frac{\partial s_{Jmt}}{\partial p_{2mt}} \\ \vdots & \vdots & \ddots & \vdots \\ C_{J1t}\frac{\partial s_{1mt}}{\partial p_{Jmt}} & C_{J2t}\frac{\partial s_{2mt}}{\partial p_{Jmt}} & \cdots & \frac{\partial s_{Jmt}}{\partial p_{Jmt}} \end{bmatrix}^{-1} \begin{bmatrix} s_{1mt} \\ s_{2mt} \\ \vdots \\ s_{Jmt} \end{bmatrix} \tag{12}$$

then:

$$mc_{mt} \equiv p_{mt} - b_{mt}\left(s_{mt}, C_t, \alpha, \sigma\right) = f(X^{S}_{jmt}; \theta^{S}) + u_{jmt} \tag{13}$$

For my main results I estimate both types of equations sequentially[7]. First I obtain the structural parameters of demand by using 2SLS and then I use my estimates of α and σ to recover predicted marginal costs ($\hat{mc}_{mt}$), which allows to estimate Equation (13).

In my main specification, X^D and X^S include route and carrier-market characteristics and carrier-period and city fixed effects. Given that I define a market as a non-directional airport pair, the latter consists on one dummy for each endpoint of the route. I include fixed effects in both equations in order to absorb unobserved heterogeneity that might be related to the carrier in marginal costs and aggregate preferences.

The characteristics that I use are (log) distance, market presence and the distance to the closest hub of the carrier. Distance might shift both the demand for the route (especially if longer routes make outside options, such as trains or cars, less attractive) and the costs of serving an extra passenger (for example due to fuel usage). Market presence can shift demand towards some carriers (by offering a higher number of connections for example) and it can also affect marginal costs (possibly via shared resources). The distance to the closest hub can have an impact on demand as well. If any of the endpoints of the route is the hub of a given airline

[7] I do it sequentially for practicality. Joint estimation methods have been tested and yield similar results.

or it is within the same area, passengers might be more willing to choose that option to have the possibility of using a larger network or to have access to more facilities that ease the travel experience.

Given that p_{jmt} and $\ln\left(s_{jmt/g}\right)$ are both endogenous variables, as they are functions of the unobservables ξ, I instrument them using average characteristics of the other price competitors and the number of competitors in the market. The number of competitors is exogenous according to the structure of the game I pose, because there is no dependence between entry-stage and pricing-stage shocks. However, it is plausibly correlated with the price and the share of the nest variables. My main specification is overidentified as I use more moments than parameters. In particular I use average distance to the hub and average market presence of the other competitors as instruments.

After I obtain the demand estimates I plug them in $b_{mt}(s_{mt}, C_t, \hat{\alpha}, \hat{\sigma})$ to predict $\hat{mc}_{mt}$. Then I estimate Equation (14). Here I only include covariates that help approximate marginal costs, such as airline-period fixed effects, city fixed effects, distance and market presence.

$$\hat{mc}_{mt} = X^S_{jmt}\theta^S + u_{mt} \tag{14}$$

5.2 Entry game

Once I recover all the pricing stage parameters, I predict for each market all potential profits under all the possible 2^J configurations, which increase exponentially with the number of players. For each configuration, I solve the game 100 times under the empirical distribution of the errors (u and ξ) and then calculate the average, which approximates the $\pi^*_j(e_j, e_{-j}, X_{mt}, C_t)$ object in Equation (10). In order to finish recovering the structural parameters of the game, I need to estimate the fixed costs of entering, which I parametrize as follows:

$$F_{jmt} = X_{jmt}\theta^F + \gamma^{FC}_{jt} + \gamma^{FC}_{m} + (1 - e_{imt-1})\left(\gamma^{EC}_{jt} + \gamma^{EC}_{m}\right) \tag{15}$$

In X I include distance to the hub and γ are city and airline-period fixed effects, also interacted with incumbent status to better capture heterogeneity in sunk costs. Moreover, Equation (10) allows me to identify the scale of the shocks. Assume $\epsilon_{jmt} = \frac{1}{\eta}\upsilon_{jmt}$. Then it is easy to

rewrite the entry condition as:

$$E[\eta\pi_j^*(e_j = 1, e_{-j}, X_{mt}, C_t) - \eta F_{jmt} - \upsilon_{jmt} + \\ + \eta \sum_{k \neq j} C_{jk} \left(\pi_k^*(e_j = 1, e_{-j}, X_m, C_t) - \pi_k^*(e_j = 0, e_{-j}, X_k, C_t)\right) |X_{mt}, C_t, \epsilon_{jmt}] > 0 \quad (16)$$

In terms of the asymptotics, I assume that the number of routes goes to infinity while keeping the number of airlines and the time periods constant[8]. I postulate that the private information shocks (υ) are logistically distributed, which implies that I can construct a likelihood function that for any given specification of the beliefs follows a standard logit formula. Let me call $\mathbf{P}$ an arbitrary set of beliefs and let me synthesize $E[\pi_j^*(e_j = 1, e_{-j}, X_{mt}, C_t) + \sum_{k \neq j} C_{jk} \left(\pi_k^*(e_j = 1, e_{-j}, X_m, C_t) - \pi_k^*(e_j = 0, e_{-j}, X_k, C_t)\right) |X_{mt}, C_t, \epsilon_{jmt}] \equiv \mathbf{\Pi}_j(X_{mt}, C_t, \mathbf{P})$. This whole expression is a function of covariates that enter in the pricing stage, common ownership and beliefs of a given player. The likelihood function is simply written as:

$$Q(\Theta^E, \mathbf{P}) \equiv \sum_{jmt} e_{jmt} \log\left(\Lambda\left(\eta \mathbf{\Pi}_j(X_{mt}, C_t, \mathbf{P}) - \eta F_{jmt}\right)\right) \\ + (1 - e_{jmt}) \log\left(\Lambda\left(-\eta \mathbf{\Pi}_j(X_{mt}, C_t, \mathbf{P}) + \eta F_{jmt}\right)\right) \quad (17)$$

With Λ the logistic function.

In order to estimate the game I use the Nested Pseudo Likelihood (NPL) estimator, based on Aguirregabiria and Mira (2002, 2007). The advantage of NPL is that initial consistent estimates of the beliefs are not needed. It overcomes this condition by obtaining a fixed point in the beliefs. The NPL mapping $\phi(\cdot)$ is the composition of the best response function $\Psi\left(\Theta^E, \mathbf{P}\right)$ and the solution to the maximum likelihood problem $\hat{\Theta}^E$, so that $\phi(\mathbf{P}) = \Psi\left(\hat{\Theta}^E(\mathbf{P}), \mathbf{P}\right)$. Therefore we look for $\hat{\mathbf{P}} = \phi(\hat{\mathbf{P}})$.

Computing the fixed point can be done with a simple algorithm. First, start with an initial guess of the beliefs $\mathbf{P}^0$. Then, for every $k \geq 1$ estimate the corresponding parameters using maximum likelihood $\hat{\Theta}_k^E = \hat{\Theta}^E(\mathbf{P}^{k-1})$. With estimated beliefs and parameters one can update $\mathbf{P}$ using the NPL iteration $\hat{\mathbf{P}}^k = \phi(\hat{\mathbf{P}}^{k-1}) \equiv \Psi\left(\hat{\Theta}_k^E, \mathbf{P}^{k-1}\right)$. When convergence in beliefs (and, as a consequence, in parameters) has been reached, the algorithm stops.

[8] Even if we include city fixed effects, there is no incidental parameter problem in this application. The number of routes or airport-pairs, which is larger than the number of city-pairs, is A(A-1) with A being the number of airports in the sample. It is clear that the ratio of airports to routes $\frac{A}{A(A-1)} = \frac{1}{A-1}$ goes to zero as the sample increases or $A \to \infty$. Thus, one would get consistency and asymptotic normality in the limit.

6 Estimation results

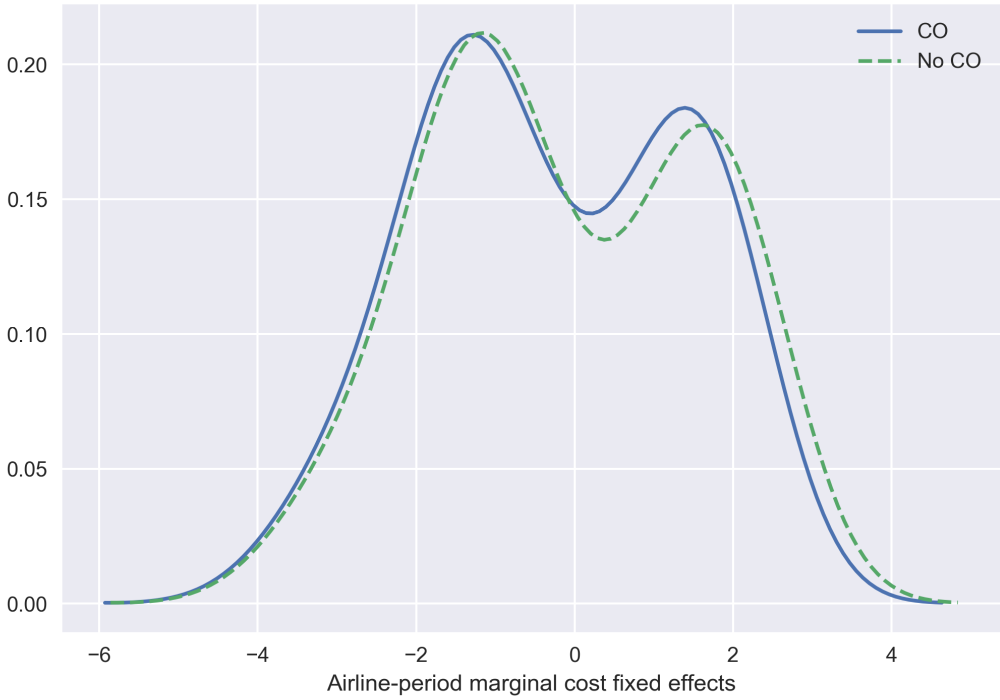
The results on the parameters of demand and marginal costs that appear in the pricing game are presented in Table 3. The nesting parameter σ and the price disutility α are in line with other papers that study the case of the airline industry (Berry and Jia, 2010; Aguirregabiria and Ho, 2012) even if the sample is quite different. Distance has a large positive impact on demand given that it varies at the route level, which shows that when distances are larger the outside option, which might include travelling by another means of transport, shrinks. Marginal cost covariates are similar under common ownership and no common ownership. However, the distribution of airline-period fixed effects is slightly different, as can be seen in Figure 3. In particular, for the subgroup that has higher marginal costs, the assumption that common ownership plays a role shifts the distribution to the left, indicating that if we do not take this into account we might be overestimating the costs.

Table 3: Estimates of the pricing game parameters

		Confidence interval	
Demand	Coefficient	1%	99%
α	-0.1192	[-0.4788,	-0.0402]
σ	0.4595	[0.4220,	0.5212]
Distance	0.8054	[0.1133,	4.3717]
Mkt. Presence	3.5320	[3.0011,	4.0018]
Dist to hub	-0.1773	[-0.2490,	-0.0485]
Marginal costs (CO)		1%	99%
Distance	3.8173	[3.4358,	4.1010]
Mkt. Presence	5.6585	[5.0048,	6.0014]
Marginal costs (No CO)		1%	99%
Distance	3.8239	[3.1747,	4.1360]
Mkt. Presence	5.6690	[5.0544,	6.2744]

Note: Bootstrapped confidence intervals: 1000 subsamples.
Sargan statistic of overidentifying restricion: p-val = 0.74

Figure 3: Distribution of marginal costs fixed effects



In Table 4 I show the results of the entry game estimation. The scale of the shocks is larger with common ownership, indicating that there might be more unexplained elements that determine entry. In terms of fixed costs parameters, the results are similar, including as covariates market presence and a dummy that takes value of one if the airline had a nonstop service in the previous period, thus reducing the fixed costs of operating. Market presence greatly reduces greatly the fixed cost that an airline has to pay. One standard deviation increase in market presence supposes approximately a reduction of \$230,000. This number is high but is comparable to other magnitudes in Aguirregabiria and Ho (2012), even though there the model is fully dynamic.

Table 4: Estimates of the entry game parameters

C.O.	Coefficient	Confidence interval 1%	99%
(Inverse) scale η	0.0101	[0.0052,	0.0151]
Distance	-0.9252	[-1.2432,	-0.5677]
Mkt. Presence	-10.9744	[-12.8001,	-8.5760]
Nonstop (t - 1)	-1.009	[-1.588,	-0.5203]
No C.O.		1%	99%
(Inverse) scale η	0.0422	[0.0023,	0.0865]
Distance	-0.9204	[-1.3450,	-0.5445]
Mkt. Presence	-10.8800	[-12.8021,	-8.3402]
Nonstop (t - 1)	-1.0070	[-1.6020,	-0.5502]

Magnitude of variables: hundreds of thousands of dollars.

7 Hypothesis testing and counterfactuals

7.1 A test of common ownership

To understand if a model of common ownership is able to explain the data better than a standard oligopolistic model of entry and pricing, I take a statistic developed by Vuong (1989), based on likelihood ratios, that is suitable for non-nested hypothesis. The null hypothesis is that a model of common ownership is as close to the true data generating process as a model without common ownership, versus the alternative that the former is closer. The statistic has an asymptotic normal distribution, which makes it easy to interpret.

Let me use a superscript if a model has common ownership in the entry stage and a subscript if the model has common ownership in the pricing stage. For example, a model labeled as M_{NoCO}^{CO} means that it has common ownership in the pricing but not in the entry stage of the game. Then, apart of comparing M_{CO}^{CO} to M_{NoCO}^{NoCO}, I compare intermediate models to understand which dimensions of competition are more affected by ownership.

Table 5: Results of hypothesis testing of non-nested models

$H_0 : M_{CO}^{CO} = M_{NoCO}^{NoCO}$	$H_0 : M_{NoCO}^{CO} = M_{NoCO}^{NoCO}$	$H_0 : M_{CO}^{NoCO} = M_{NoCO}^{NoCO}$
0.777 (0.218)	1.986 (0.0234)	-0.72 (0.7670)

Note: p-value in brackets.

Results in Table 5 indicate that a model of common ownership in both entry and pricing does as well as an oligopolistic model. However, a model with common ownership only in entry

actually performs substantially better than a model with no common ownership, indicating that in reality pricing is a bad dimension to look at how common ownership operates. Indeed, if we were only to look at the pricing dimension, the result would tend to be negative, as shown in the last column.

8 Conclusion

In this paper I study market structure under common ownership. Previous literature has shown mixed results of a high degree of overlapping owners in firms that are supposed to be competitors in pricing, but the potential incentives on market entry has not been studied. I fill this gap by proposing a structural model of market entry and pricing with common ownership and compare it with a standard oligopolistic model that does not take into account the ownership structure of firms.

In my model common ownership decrease the incentives to compete in prices and it also affects how players decide to enter. When a firm makes a choice, the decision is influenced not only by how much profits it would make if it serves a route, but also by how much its action would hurt others' profits. This is done in a static model with private information in the entry stage and a standard Bertrand Nash pricing game with common knowledge in the second stage.

I test the null hypothesis that both types of models are equally close to the true data generating process against the alternative that a common ownership model fares better. I cannot reject the null hypothesis of equality. However, I find that if I separate the effects from entry and from pricing separately, the entry dimension seems to interact much more strongly with common ownership that the pricing dimension, indicating that entry might be more important to study common ownership issues.

Given that common ownership might affect competition beyond pricing, understanding more precisely how the ownership structure interacts with firm decision-making or what would be the effect of banning or limiting overlapping shareholdings are interesting topics for future research.

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A Appendix

A.1 Data Construction

I obtain data on entry, prices and market shares from the Airline Origin and Destination Survey (DB1B) database which is managed by the Department of Transportation. This database consists in a 10% random sample of all tickets sold in the domestic market in a quarterly basis. Each observation includes the origin and destination airports, plus the number of passengers and the price paid for the ticket. A ticket is composed of a collection of coupons, where each coupon is each of the flights that a passenger takes. The data also tells us when there's a directional break in the itinerary. For example, in a roundtrip ticket with one-stop in each direction, there would be a break after the second coupon and a final break after the fourth. This way we can identify the part that corresponds to the inbound segment and the one of the outbound segment (if any).

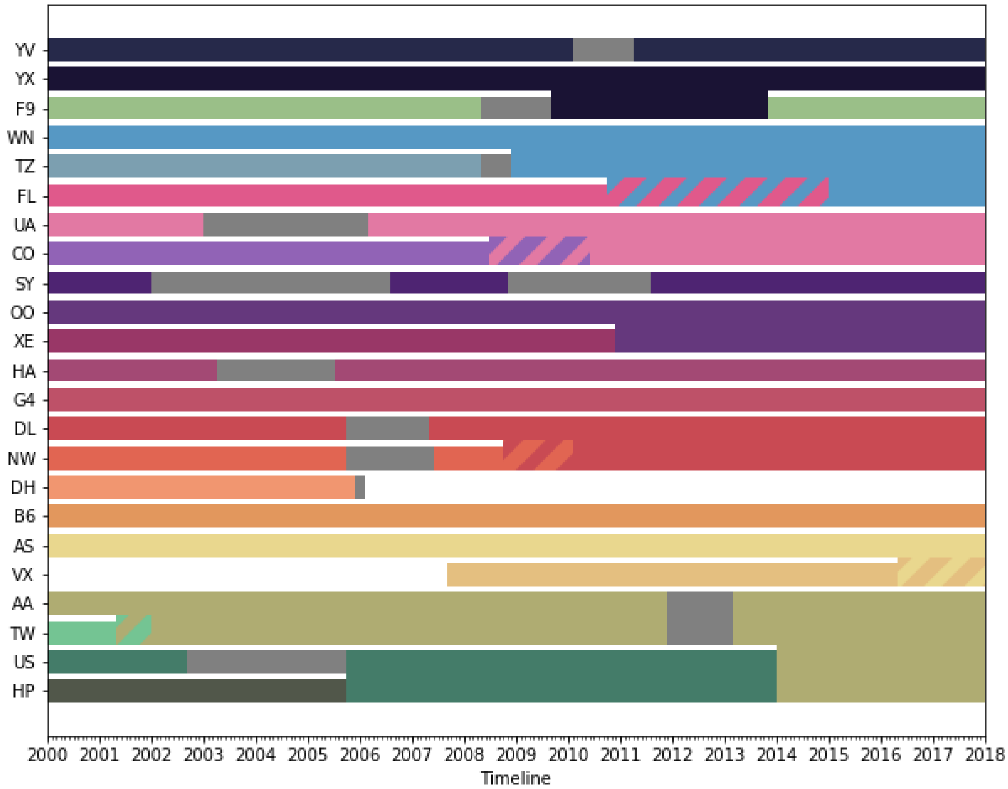
For each coupon we have the operating carrier and the marketing carrier, which is the one that sells the product and the one I use as object of study, given that frequently operating carriers are regional affiliates that don't compete for market share directly. In terms of selecting tickets I follow Azar, Schmalz and Tecu (2018) as close as possible. As stated in the main text, I define a market as a non-directional trip between two airports disregarding intermediate destinations. I select airports that belong to the top 70 metropolitan statistical areas (MSA), as measured in the year 2013.

I exclude tickets that have: more than six coupons, more than three coupons in one direction, more than one marketing carrier, no fare credibility (as indicated by the own database), a non-US marketing carrier and more than two breaks. I also exclude open jaw tickets (roundtrip tickets that do not return to the origin airport) and domestic portions of international flights. I split roundtrip tickets in the inbound and outbound trips and I treat them as separate oneway tickets. I also prorate the price accordingly for each of the parts. After getting a sample of oneway or oneway-equivalent tickets, I exclude fares that are below $25 or above $2,500 (in 2008 dollars).

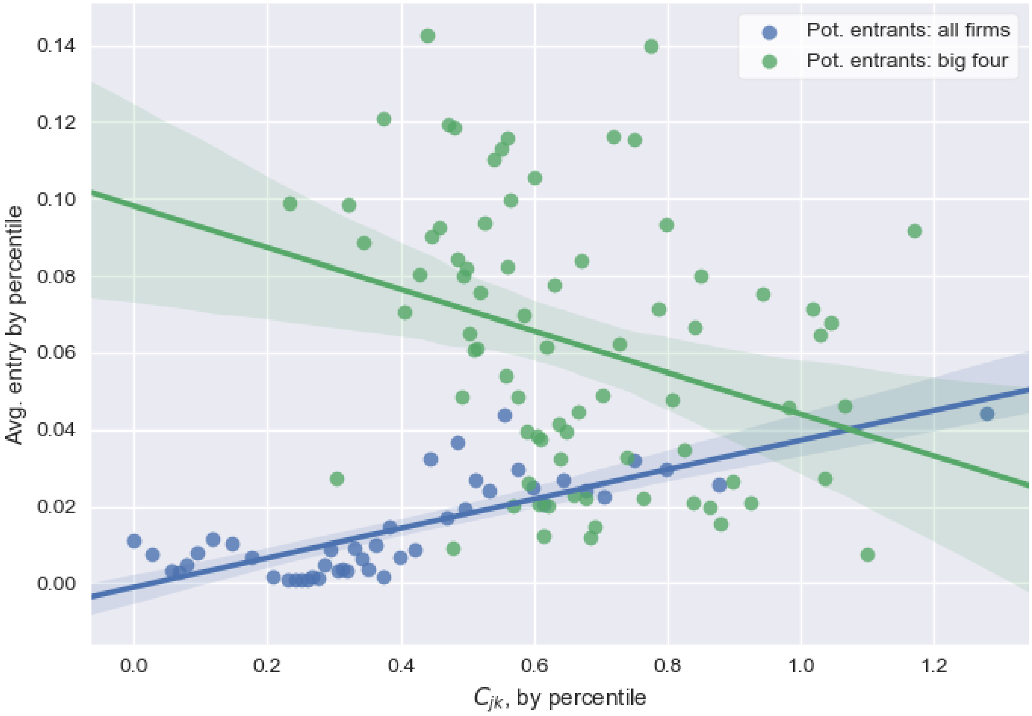
To determine whether a marketing carrier is serving a route nonstop or not, I get information from the T100 database. This database contains information on scheduled and performed flights

by operating carrier. I observe if marketing carriers are selling tickets for which the operating carrier is flying nonstop. If the operating carrier performs more than 60 flights during the quarter I consider it as serving the route nonstop.

A.2 Mergers in the Airline Industry

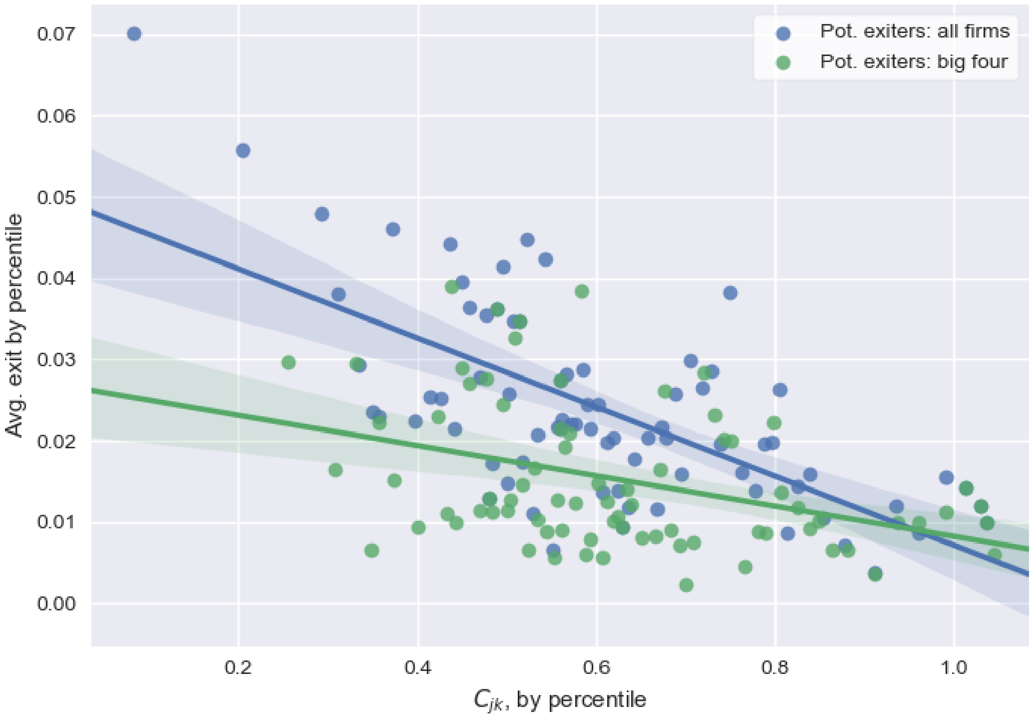


A.3 Entries in all markets

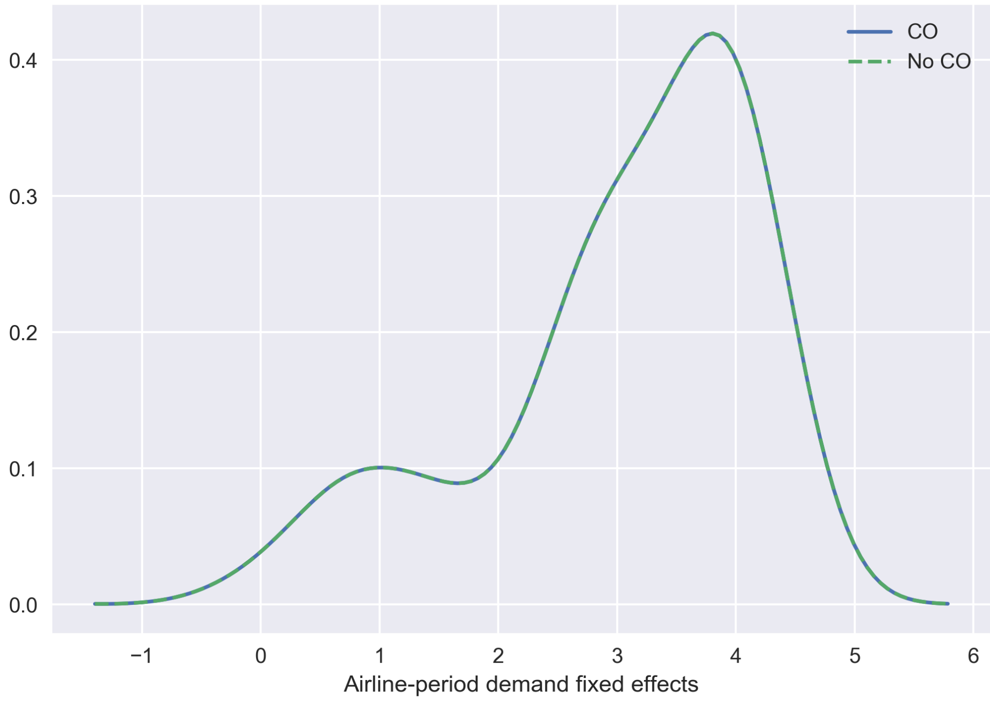


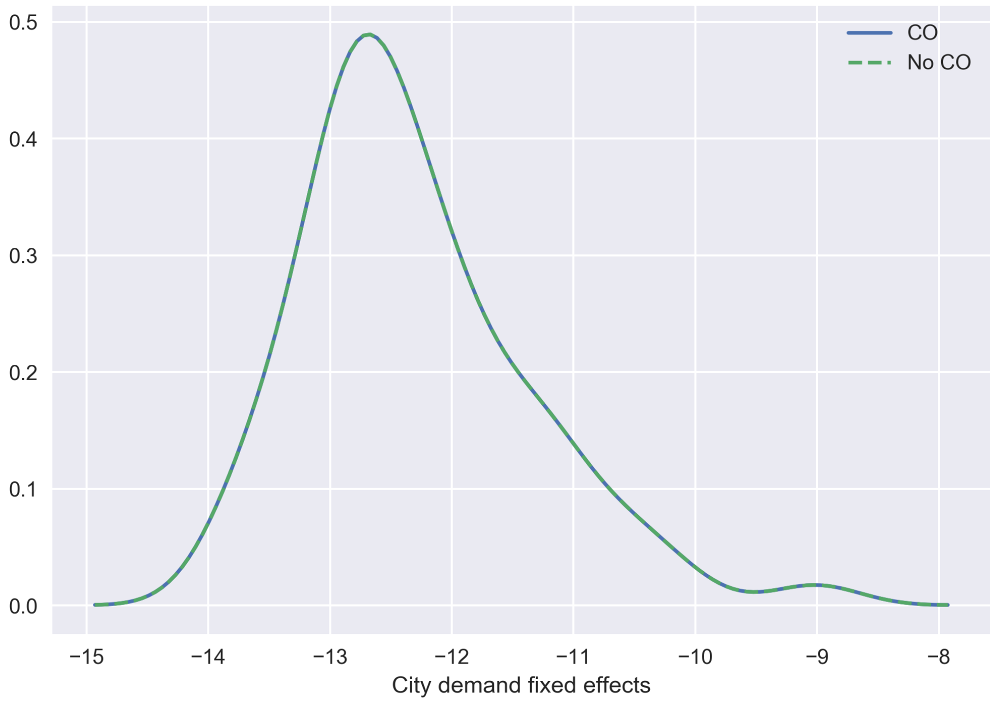
Note: the proportion of big four observations is 0.29.

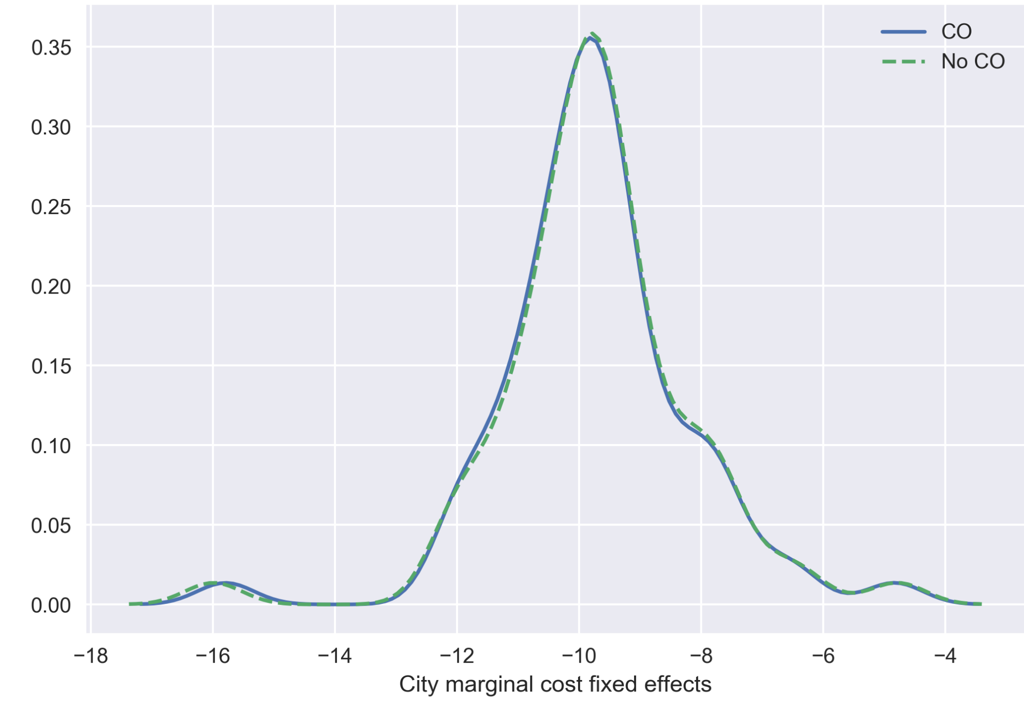
A.4 Distribution of fixed effects

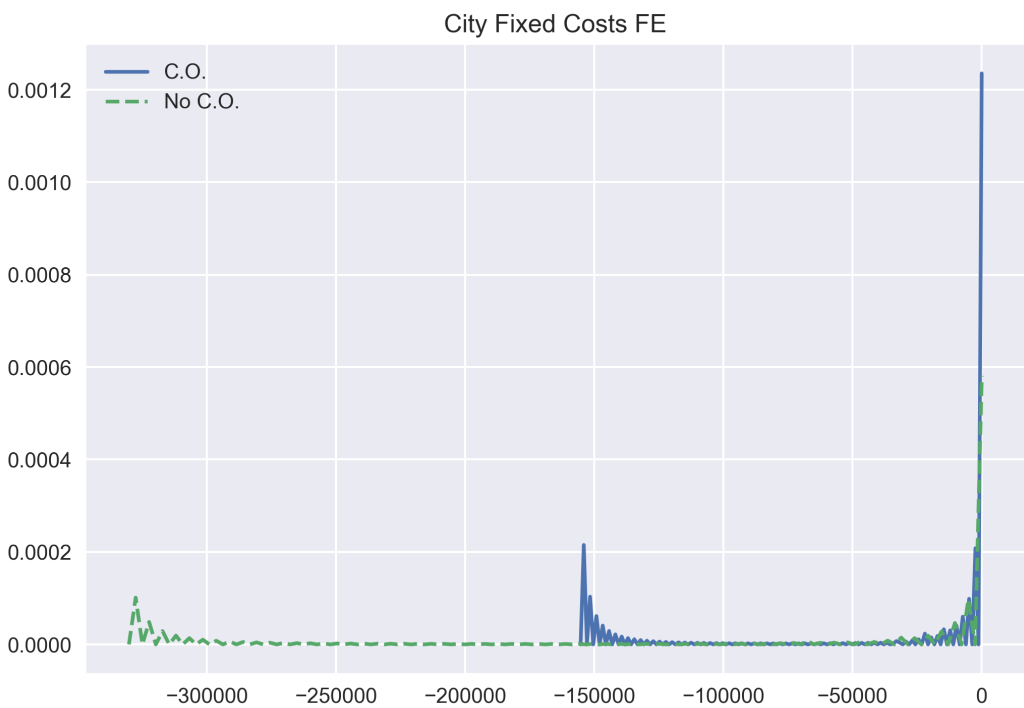


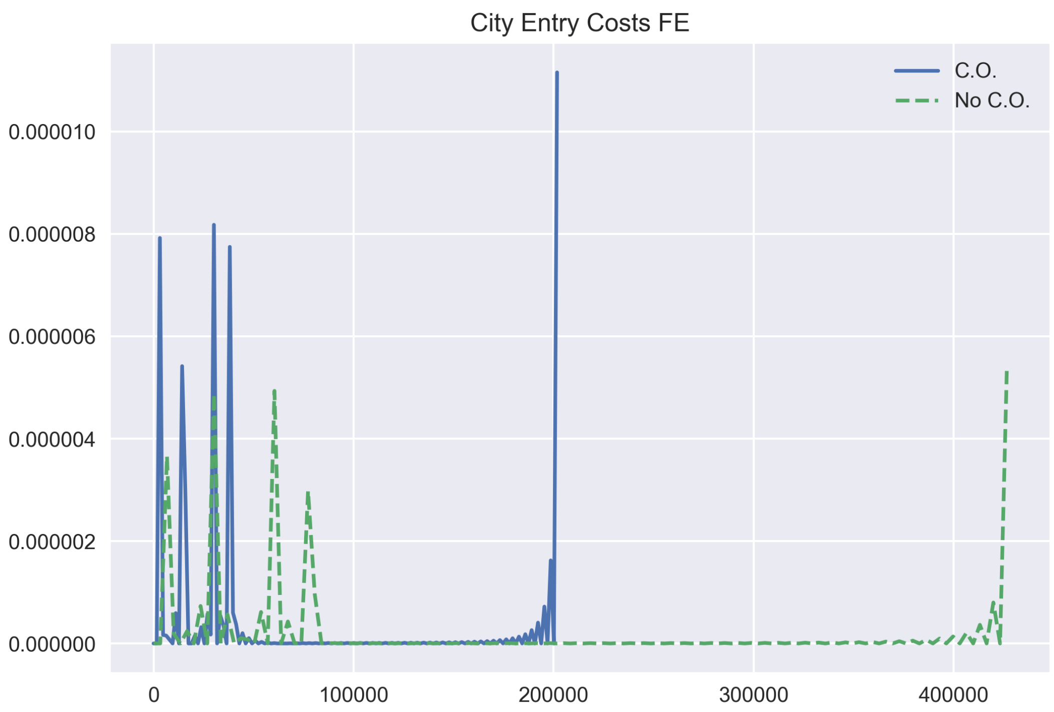
Note: the proportion of big four observations is 0.98.


CO
No CO
0.4
0.3
0.2
0.1
0.0
−1
0
1
2
3
4
5
6
Airline-period demand fixed effects


CO
No CO
0.5
0.4
0.3
0.2
0.1
0.0
−15
−14
−13
−12
−11
−10
−9
−8
City demand fixed effects


CO
No CO
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−18
−16
−14
−12
−10
−8
−6
−4
City marginal cost fixed effects


City Fixed Costs FE
C.O.
No C.O.
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
−300000
−250000
−200000
−150000
−100000
−50000
0


City Entry Costs FE
C.O.
No C.O.
0.000010
0.000008
0.000006
0.000004
0.000002
0.000000
0
100000
200000
300000
400000