Price Competition and Endogenous Product Choice in Networks: Evidence from the US Airline Industry*

Christian Bontemps† Cristina Gualdani‡ Kevin Remmy§

April 2021

Abstract

The recent merger waives in airline markets have received attention from researchers and the general public alike. In this paper, we build and estimate a two-stage model of airline competition in which firms first form the networks of markets to be served and then compete in prices. We estimate our model using fares data from US domestic flights. We show that large hub-and-spoke operations lower marginal costs but increase fixed costs. We evaluate a merger between American Airlines and US Airways and compare it to the bankruptcy and disappearance of American Airlines. We also evaluate remedies imposed by the Department of Justice on the merging parties and find evidence they limited harm to consumers.

Keywords: endogenous market structure, multiple equilibria, oligopoly, product repositioning, mergers, remedies, bankruptcy.

*We would like to thank Dmitry Arkhangelsky, Manuel Arellano, Steven Berry, Jason Blevins, Isis Durrmeyer, Silke Forbes, Panle Jia, Robert de Jong, Pedro Mira, Francesca Molinari, Ariel Pakes, Aureo de Paula, Jörg Stoye, Elie Tamer, and Matthew Weinberg. We would also like to thank the seminar and conference participants at Toulouse School of Economics, The Ohio State University, Cornell University, CEMFI, NYU Abu Dhabi, Sciences Po, EARIE 2018, and ES World Congress 2020. We acknowledge funding from the French National Research Agency (ANR) under the Investments for the Future (Investissements d'Avenir) program, grant ANR-17-EURE-0010. An earlier version of the paper was presented at the EARIE Annual Conference in 2018 under the title "A Two-Stage Model of Airline Competition".

†Email: christian.bontemps@tse-fr.eu, ENAC & Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France.

‡Email: cristina.gualdani@tse-fr.eu, Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France.

§Email: kevin.remmy.001@gmail.com, Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France.

1 Introduction

The airline industry has received a lot of attention in the economic literature, sparked by the wave of mergers and bankruptcies after the U.S. Airline Deregulation Act of 1978.[1] Most of the contributions on merger and bankruptcy evaluations are based on supply-demand models, where the airlines best respond to competitors by adjusting their prices, while holding the entry decisions in markets exogenous and fixed (Bresnahan, 1987; Berry, 1994; Berry, Levinsohn, and Pakes, 1995). More plausibly, such events prompt the airlines to best respond also by repositioning in markets. For example, a merger could generate cost savings for the merged firm which may favour its entry in new markets. Also, after a merger, there might room in some markets for accommodating other entrants. The aim of this paper is to provide a tractable framework for the airline industry which combines entry and pricing decisions and use it to conduct counterfactual exercises where the airlines are allowed to modify prices and market structures.

More broadly, the question about endogenising entry decisions (and, hence, product choices and characteristics) in supply-demand models is of general interest and it was already posed in earlier works. For example, Berry (1994): "*I should emphasize in closing that the techniques of this article rely on a number of restrictive assumptions.* [...] *More importantly, and more difficult to solve, I assume that product characteristics are econometrically exogenous.*" (p.260). Berry et al. (1995): "*The second, and richer, part of the problem is to endogenize the actual choice of the characteristics of the models marketed.*" (p.886). Berry and Jia (2010): "*An implicit assumption of our empirical model is that the network structure and the carriers that serve each market are taken as given. Ideally, we would like to model a three-stage game. First, carriers form their hubs. Second, given the hub structure, each carrier chooses a set of markets to serve. Third, given these entry decisions, carriers compete in prices and the frequency of flight departures.*" (p.20).

Endogenising entry decisions in a supply-demand model for the airline industry is challenging. This is because the entry decisions of an airline are interdependent across markets. Specifically, the literature on the airline industry suggests that hub-and-spoke operations decrease the marginal costs of serving markets out of hubs, via economies of density and scope, and increase the total fixed costs, due to congestion at hubs. Further, customers may find it attractive to fly from dense hubs because this enhances the value of frequent flier programs.[2] Such synergies among markets imply that the entry decision of an airline in market t may *spill over*

[1] See Table C.1 in Appendix C.

[2] See, for example, Caves, Christensen, and Tretheway (1984), Kanafani and Ghobrial (1985), Morrison and Winston (1986), Levine (1987), Butler and Houston (1989), Berry (1990),Borenstein (1989; 1992), Butler and Houston (1989), Morrison and Winston (1989),Berry (1990), Brueckner, Dyer, and Spiller (1992), Brueckner and Spiller (1994), Oum, Zhang, and Zhang (1995), Berry, Carnall, and Spiller (1996), Nero (1999), Berry and Jia (2010), and Berry, Gaynor, and Scott Morton (2019).

its entry decision in market t' by directly affecting the demand, marginal cost, and fixed cost equations (and, in turn, profitability) in market t'. Due to these *spillover effects*, an airline does not take its entry decisions independently across markets. Instead, an airline globally forms the *network* of markets to be served in order to internalise the spillover effects within its optimisation problem.[3]

This paper addresses the above concerns by developing an empirical two-stage game. In the first stage, the airlines form their networks by entering markets and pay the fixed costs. The network an airline consists of a collection of nodes corresponding to the cities (or, airports) and a collection of links between nodes representing the markets served by the airline.[4] In the second stage, the airlines face the demand for their products, pay the variable costs, and choose which prices to charge by competing in a standard Bertrand-Nash pricing game. Thus, in the first stage, the airlines form the networks which maximise the expected second-stage profits net of the fixed costs, while taking into account spillover effects in entry decisions across markets on the demand, marginal cost, and fixed costs sides, as discussed in the previous paragraph.

Identifying the parameters governing our two-stage game is challenging. While identification of the second-stage parameters can be established by following the standard approach for supply-demand models with differentiated products (Berry and Haile, 2014), identification of the first-stage parameters is complicated by the discrete choice nature of the problem. In particular, there are two main issues. First, there may be multiple Nash equilibrium networks. This is because the airlines compete at the entry stage through the second-stage pricing game. In turn, we are not able to write down a well-defined likelihood function. Second, even if one is willing to specify an equilibrium selection mechanism, it remains burdensome to construct the set of Nash equilibrium networks, due to the large number of markets. In turn, we are not able to write down a tractable likelihood function that can be evaluated many times throughout an optimisation routine. Instead of focusing on Nash equilibrium networks, we bypass these two issues by considering *implications* of (i.e., *necessary* conditions for) Nash equilibrium, which are easier to handle from an econometric point of view. More precisely, we implement the revealed preference approach by Pakes (2010) and Pakes, Porter, Ho, and Ishii (2015). This approach consists of two steps. First, we write down inequalities by simply predicting that the observed networks lead to higher profits than the profits would be were the airlines to deviate from the observed networks. Second, we get rid of the structural errors entering the inequalities by taking the expectation of the inequalities over markets and interacting them with appropriate instruments. The resulting moment inequalities characterise a non-sharp identified set that is

[3] The importance of network considerations has been also highlighted in several merger investigations. For example, see the Department of Justice's Competitive Impact statement on the merger between American Airlines and US Airways (`https://www.justice.gov/atr/case-document/file/514516/download`).

[4] For example, Figure C.1 in Appendix C represents the network of markets served by American Airlines, before the merger with US Airways.

a convex polytope, whose projections can be easily obtained by solving linear programming problems.

We estimate the model using data from the US Airline Origin and Destination Service, a 10% random sample of all tickets issued in the United States during the second quarter of 2011. We focus on flights operated between the 85 largest metropolitan statistical areas in the United States, which are served by United Airlines, Delta Airlines, American Airlines, US Airways, Southwest Airlines, low and medium cost carriers. In the first stage, we find that fixed costs increase in the number of destinations reachable from hub airports. On the supply side of the second stage, we find that marginal costs decrease in the number of flights (direct or one-stop) offered out of the endpoints. On the demand side of the second stage, we find that consumer utility increases in the number of direct connections that can be reached from the endpoints. As mentioned above, previous works have suggested that the size of hub-and-spoke networks increase the fixed costs and decrease the marginal cost. To the best of our knowledge, our model is the first to confirm these effects in a structural model of the airline market.

With estimates of the two stages in hand, we simulate the effects of a merger between American Airlines and US Airways and compare the merger, which did occur in 2013, to a bankruptcy and subsequent disappearance of American Airlines.[5] In a first step, we compare the predictions based on our full model to the predictions form a model in which networks do not adjust in response to a merger or bankruptcy. We find that leaving the network unchanged or making ad-hoc assumptions about it can lead to misleading conclusions regarding market outcomes. In a second step, we investigate the merger and, in particular, the effect of remedies that forced the merged entity to not reduce operations at most of its hubs. We find that these remedies turned a slight decrease in consumer surplus into a slight increase. At the most negatively affected hubs, the remedies helped to contain harm to consumers. In a third step, we compare the merger to a scenario in which a bankruptcy of American Airlines leads to its disappearance from the market. Not surprisingly, the bankruptcy induces more rival firm entry than the merger. However, the loss of access to a large network causes substantial loss in consumer surplus at American's hubs. Other firms are not able to fill this void completely. Overall, consumer surplus decreases by more than in the merger case. Our results underline one key advantage of a conditional merger over the bankruptcy of a distressed hub-and-spoke airline: competition authorities can shape post-merger outcomes by imposing remedies.

[5] When the two airlines announced their intention to merge, American Airlines was under Chapter 11 bankruptcy.

2 Literature review

This paper aims to bridge a gap between two strands of the literature. The first strand is the literature on supply-demand models. This literature estimates demand and supply equations, while taking entry decisions as exogenously given (for example, Bresnahan, 1987; Berry, 1994; Berry et al., 1995; Berry, Linton, and Pakes, 2004; Berry and Haile, 2014). Some empirical studies using supply-demand models for the airline industry are Berry et al. (1996), Berry and Jia (2010), Ciliberto and Williams (2014), Peters (2006), Mark, Keating, Rubinfeld, and Willig (2013), and Das (2019). The second strand is the literature on entry models (for example, Reiss and Spiller, 1989; Bresnahan and Reiss, 1990; 1991; Berry, 1992; Goolsbee and Syverson, 2008; Ciliberto and Tamer, 2009). This literature estimates the payoffs from entering markets, under the assumption that entry decisions are independent across markets and without considering demand and supply. In this paper, we model entry decisions, supply, and demand. Moreover, we allow for spillover effects in entry decisions across markets, as discussed in Section 1.

There are other papers which combine entry and pricing decisions for studying the airline industry. The seminal contributions by Li, Mazur, Park, Roberts, Sweeting, and Zhang (2019), and Ciliberto, Murry, and Tamer (2021) acknowledge the network dimension, but treat spillover effects as exogenous product covariates and assume that entry decisions are independent across markets. In turn, when simulating a merger, those approaches require one to focus *separately* on each market and ad-hoc readjust the spillover effects, for example by distinguishing a base-case from a best-case scenarios. This is not needed in our framework because the airlines are allowed to reoptimise their entire networks. In turn, we can offer a *global* view of the overall changes in the networks and other market outcomes. Aguirregabiria and Ho (2012) develop a dynamic game of entry and pricing decisions, but assume that entry decisions are decentralised at the market level (i.e., each market is run by a local manager taking independent entry decisions), which substantially reduces the dimensionality of the strategy space. Here, instead, we model network formation as a process centralised at the level of each airline. Also Benkard, Bodoh-Creed, and Lazarev (2020) consider a dynamic setting, but do not include the demand equation. Hence, differently from our paper, their framework cannot be used to quantify welfare effects. Admittedly, though, our model does not incorporate dynamics, which we leave to future extensions. Park (2020) combine entry and pricing decisions, but entry is endogenised only in the markets out of Ronald Reagan Washington National Airport. Here, instead, we endogenise entry in all markets. Lastly, Yuan (2020) is close in spirit to our approach by developping a three-stage game of entry, frequency, and price choices. However, he obtains point estimates for the first-stage parameters via a calibration strategy and does not consider spillover effects in entry decisions across markets on the fixed cost side.

A number of papers combine entry and pricing decisions for studying other industries (for example, Eizenberg, 2014; Holmes, 2011; Houde, Newberry, and Seim, 2017; Kuehn, 2018; Rossetti, 2018; Wollmann, 2018). As most of these papers, we rely on the revealed preference approach by Pakes (2010) and Pakes et al. (2015) in order to simplify identification of the first-stage parameters. Here, however, we face spillover effects in entry decisions across markets which appear on the demand, marginal cost, and fixed cost sides and create lots of computational challenges.

Finally, our paper broadly connects with the recent advances in the econometrics of network formation (e.g., Chandrasekhar, 2016; Graham, 2015; de Paula, 2017; 2020; Graham and de Paula, 2020). We have decided to pursue the revealed preference approach by Pakes (2010) and Pakes et al. (2015), rather than applying those methods, for two reasons. First, the latter involve computationally serious challenges in the presence of spillover effects, which become even deeper when combined with our second stage. Instead, the moment inequalities that we obtain from the revealed preference approach are computationally easier to handle because linear in the first-stage parameters. Second, the latter typically view network formation as a process decentralised at the level of each node. Here, instead, network formation is centralised at the level of each airline.

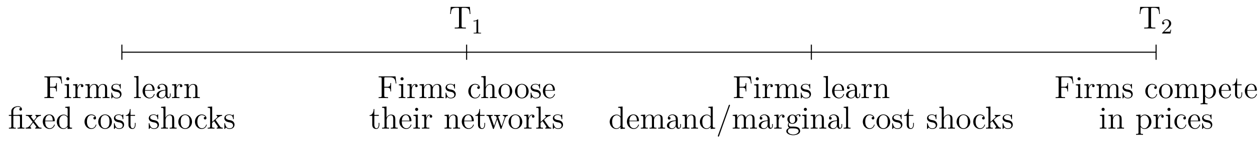
The rest of the paper is organised as follows. Section 3 presents the model. Section 4 discusses identification. Section 5 describes the empirical application. Section 6 concludes. Further details are in the appendices.

3 The model

There are N airlines, labelled by $f \in \mathcal{N} \equiv \{1, \dots, \mathrm{N}\}$, which play a two-stage game. In the first stage, the airlines form their networks by entering markets and pay the fixed costs. In the second stage, the airlines face the demand for their products, pay the variable costs, and choose which prices to charge. In the first stage, the airlines observe their own and the competitors' fixed cost shocks. However, they do not observe their own and the competitors' demand and marginal cost shocks, despite knowing the probability distribution from which such shocks are drawn. Hence, in the first stage, the airlines form expectations about the second-stage profits. The airlines publicly discover the demand and marginal cost shocks just before playing the second stage, where they compete in a standard Bertrand-Nash pricing game. The airlines solve the game by going backward from the second stage and use pure strategy subgame perfect Nash equilibrium as solution concept. In what follows, we describe the game in more details starting from the second stage.[6]

[6]We do not model frequency and capacity choices. This is because we want to preserve tractability, given the many challenges introduced by the network formation stage. Moreover, modelling frequency and capacity choices would require us to collect detailed data on the types of aircrafts used, the flight schedule, and the

Figure 1: Timing of the game



3.1 The second stage

In the second stage, the airlines take as given the entry decisions in markets and the consequent product choices. Markets are undirectional city-pairs (for example, Boston-Houston).[7] Products are airline-itinerary combinations (for example, Boston-Houston via Miami operated by American Airlines).[8] In every market, the airlines face the demand for their products, pay the variable costs, and simultaneously choose the prices maximising the variable profits, under complete information. We use a standard supply-demand framework for differentiated products.

Demand We consider the Nested Logit demand with two nests, one for the airline products, the other for the outside option of not travelling or travelling with other means (Berry, 1994).[9] Each market is indexed by $t \in \mathcal{T}$, where $\mathcal{T}$ is the set of markets. Each product offered in market t is indexed by $j \in \mathcal{J}_t$, where $\mathcal{J}_t$ is the set of products offered in market t. The utility that individual i receives from buying in market t is specified as:

$$\begin{aligned} &\text{product } j: && U_{i,j,t} = X_{j,t}^{\top}\beta - \alpha P_{j,t} + \xi_{j,t} + \nu_{i,t} + \lambda \epsilon_{i,j,t}, \\ &\text{outside option 0:} && U_{i,0,t} = \epsilon_{i,0,t}. \end{aligned} \tag{1}$$

In (1), $X_{j,t}$ is a vector of product characteristics and $P_{j,t}$ is the product price. Both $X_{j,t}$ and $P_{j,t}$ are observed by the researcher. $\xi_{j,t}$ represents the product characteristics that are unobserved by the researcher but are observed by the airlines. $\nu_{i,t}, \epsilon_{i,j,t}, \epsilon_{i,0,t}$ are the consumer tastes, unobserved by the researcher, i.i.d. across i, j, t, and independent of all other variables. The probability distribution of the consumer tastes is chosen to yield the familiar Nested Logit market share function, with $\lambda \in (0, 1]$.

We include in $X_{j,t}$ various product characteristics, such as the number of stops, the distance flown and its squared value, and the number of direct flights offered at the itinerary's origin

number of passengers on each flight. We leave extensions on these aspects to future analysis.

[7] We do not distinguish between airports in the same city. In fact, carriers in nearby airports might compete against each other because customers can choose which airport to fly from. We do not define markets as directional city-pairs because our data contain very few cases of airlines not serving both directions of a given city-pair.

[8] Note that the airlines can be multi-product because, in a given market, an airline may offer direct flights and/or connecting flights. Further, two itineraries offered by an airline with the same endpoints but different connecting cities are treated as two different products.

[9] Also Ciliberto et al. (2021) adopt the Nested Logit demand for studying the airline industry.

by the same carrier offering itinerary j (hereafter, "Connections"[10]). We expect travellers to prefer direct flights. We also expect that, as distance increases, air travel becomes more attractive relative to the outside option. However, as distance increases further, travel becomes less pleasant and demand starts to decrease. The variable Connections captures the value of frequent flier programs. In fact, the larger the number of destinations for which consumers can redeem frequent flier miles, the higher the value of such loyalty programs. Additionally, an airline that flies to many cities is likely to have more convenient parking and gate access and provide better services. For a thorough discussion on the impact of hubbing on costumer utility, see Levine (1987), Borenstein (1989; 1992), Butler and Houston (1989), Morrison and Winston (1989), Berry (1990), Oum et al. (1995), Berry et al. (1996), and Berry and Jia (2010). We include in $X_{j,t}$ carrier fixed effects to control for brand preferences. We also add city fixed effects to catch unobserved heterogeneity at the city level, such as leading economic sectors, climate, and infrastructures.

Note that, due to the variable Connections, the demand for product j in market t depends on the entry decisions of an airline in other markets $t' \neq t$. This gives rise to *spillover effects* in entry decisions across markets on the *demand* side.

We compute $P_{j,t}$ as the average of the fares in the data sharing the same airline-itinerary combination, weighted by the number of passengers.[11] Alternatively, one could introduce a finite number of "fare bins" for each airline-itinerary combination, as in Berry and Jia (2010). We have decided not to do so because, in our two-stage setting, we find more reasonable to consider an average price that the carriers expect or wish to achieve for each offered itinerary. Further, having fare bins would add many methodological and computational challenges. For instance, we would need to carefully examine how to define fare bins in a way that does not make the empirical results excessively sensitive to such a definition. We would also need to deal with the fact that some fare-airline-itinerary combinations may not be available at all time to customers and/or may have zero market shares in the data.[12] Given that our model is already complicated by the network formation stage, we prefer to leave these extensions to future research. In turn, we do not allow for heterogeneity in consumer taste for price. This is because, with average prices, there is not sufficient price variation left in the data.

[10] More precisely, given that markets are defined as undirectional city-pairs, the variable Connections is computed as the maximum between the numbers of direct flights offered at the endpoints of itinerary j by the same carrier offering itinerary j. For example, suppose that market t is Boston-Houston and product j is a direct flight between Boston and Houston operated by American Airlines. Suppose that American Airlines offers direct flights to 3 destinations out of Boston and to 5 destinations out of Houston. Then, the variable Connections is equal to $\max\{3, 5\} = 5$.

[11] See Section 5.1 for more details on the computation of prices.

[12] See, for instance, Abaluck and Adams (2020) and Barseghyan, Coughlin, Molinari, and Teitelbaum (2020) about the identification of discrete choice models with latent choice sets. See Gandhi, Lu, and Shi (2019) about the estimation of the demand for differentiated products with zeroes in market share data.

The demand shock, $\xi_{j,t}$, captures product characteristics that are not in our data and that can be arbitrarily correlated with prices, such as refundable versus non-refundable tickets and the quality of in-flight service. We do not specify any parametric distribution for $\xi_{j,t}$. Instead, to establish point identification of the second-stage parameters, in Section 4.1 we will assume that the demand shocks are uncorrelated with the observed demand shifters, as standard in the literature on supply-demand models. In the same section, we will discuss the pros and cons of this assumption.

From utility maximising behaviour, we obtain the predicted product shares in market t:

$$\begin{aligned} &\text{product } j: && s_{j,t}(X_t, P_t, \xi_t; \theta_d) = \frac{\exp(\delta_{j,t}/\lambda)}{D_t} \frac{D_t^\lambda}{1 + D_t^\lambda}, \\ &\text{outside option } 0: && s_{0,t}(X_t, P_t, \xi_t; \theta_d) = \frac{1}{1 + D_t^\lambda}, \end{aligned} \tag{2}$$

where $D_t \equiv \sum_{j=1}^{J_t} \exp(\delta_{j,t}/\lambda)$, $\delta_{j,t} \equiv X_{j,t}^\top \beta - \alpha P_{j,t} + \xi_{j,t}$, $\theta_d \equiv (\beta, \alpha, \lambda)$, $X_t \equiv (X_{j,t}\ \forall j \in \mathcal{J}_t)$, $P_t \equiv (P_{j,t}\ \forall j \in \mathcal{J}_t)$, and $\xi_t \equiv (\xi_{j,t}\ \forall j \in \mathcal{J}_t)$. In turn, the predicted demand in market t is:

$$\begin{aligned} &\text{product } j: && s_{j,t}(X_t, P_t, \xi_t; \theta_d) \times M_t, \\ &\text{outside option } 0: && s_{0,t}(X_t, P_t, \xi_t; \theta_d) \times M_t, \end{aligned} \tag{3}$$

where M_t is the market size, observed by the researcher. We further assume that the researcher observes the true product shares, as standard in the literature.

Supply In the second stage, the airlines pay the variables costs, such as the costs of fuel, oil, aircraft maintenance, landing fees, and passenger fees. We consider a constant and linear marginal cost specification.[13] In particular, the marginal cost of offering product j in market t is specified as:

$$\text{MC}_{j,t} = W_{j,t}^\top \psi + \omega_{j,t}. \tag{4}$$

In the above expression, $W_{j,t}$ is a vector of marginal cost shifters that are observed by the researcher. $\omega_{j,t}$ represents the marginal cost shifters that are unobserved by the researcher but are observed by the airlines.

We include in $W_{j,t}$ various product characteristics, such as the distance flown and the number of cities that are reachable from the endpoints and intermediate stops of itinerary j with the same carrier offering itinerary j (hereafter, "Presence"[14]). We expect the marginal costs to increase

[13] A constant and linear marginal cost specification is assumed in many other studies of the airline industry, e.g., Berry and Jia (2010), Ciliberto and Williams (2014), Das (2019), Li et al. (2019).

[14] More precisely, the variable Presence is computed as the average number of destinations that are reachable (with direct or connecting flights) from the endpoints and intermediate stops of itinerary j with the same carrier offering itinerary j. For example, suppose that market t is Boston-Houston and product j is a flight between

with distance due to the use of oil and fuel. The variable Presence captures the impact of economies of density on the marginal costs, i.e., the fact that more densely travel segments tend to have lower unit costs due to engineering reasons. In particular, the larger the number of final destinations consumers can reach, the more the opportunities for an airline to pool passengers from several itineraries into the same planes, and the more an airline can efficiently use large aircrafts which generally have lower unit costs. At the same time, many connections may also cause congestion and increase the fixed costs, as discussed in Section 3.2. For a comprehensive analysis on the marginal cost savings induced by hub-and-spoke operations, see Caves et al. (1984), Kanafani and Ghobrial (1985), Morrison and Winston (1986), Butler and Houston (1989), Berry (1990), Brueckner et al. (1992), Brueckner and Spiller (1994), Oum et al. (1995), Berry et al. (1996), Nero (1999), and Berry and Jia (2010). Analogously to the demand side, we also include in $W_{j,t}$ carrier fixed effects and city fixed effects.

Note that, due to the variable Presence, the marginal cost of product j in market t depends on the entry decisions of an airline in other markets $t' \neq t$. This gives rise to *spillover effects* in entry decisions across markets on the *marginal cost* side.

The airlines simultaneously set the prices in each market in order to maximise the variable profits, under complete information:

$$\text{variable profits of airline } f\text{:} \quad \sum_{t\in\mathcal{T}} \sum_{j\in J_{f,t}} (P_{j,t} - \text{MC}_{j,t}) \times s_{j,t}(X_t, P_t, \xi_t; \theta_d) \times M_t, \tag{5}$$

where $\mathcal{J}_{f,t}$ is the set of products offered by airline f in market t. For each airline f and market t, we obtain the Bertrand-Nash F.O.C.s in the usual way:

$$\text{MC}_{f,t} = P_{f,t} + \left(\frac{\partial s_{f,t}(X_t, P_t, \xi_t; \theta_d)}{\partial P_{f,t}}\right)^{-1} s_{f,t}(X_t, P_t, \xi_t; \theta_d), \tag{6}$$

where $\text{MC}_{f,t}$, $P_{f,t}$, and $s_{f,t}(X_t, P_t, \xi_t; \theta_d)$ are the vectors stacking $\text{MC}_{j,t}$, $P_{j,t}$, and $s_{j,t}(X_t, P_t, \xi_t; \theta_d)$, respectively, for each product $j \in \mathcal{J}_{f,t}$. $\frac{\partial s_{f,t}(X_t,P_t,\xi_t;\theta_d)}{\partial P_{f,t}}$ is the matrix collecting the partial derivatives of product shares with respect to prices. Note that, despite the airlines choose the prices market-by-market, the prices in a market indirectly depends on the prices in other markets due to the presence of spillover effects in entry decisions across markets.

3.2 The first stage

In the first stage, the airlines simultaneously form their networks by entering markets and pay the fixed costs. The airlines know everything about the second stage except their own and

Boston and Houston with an intermediate stop at Miami operated by American Airlines. Suppose that American Airlines allows to reach 3 destinations out of Boston, 5 destinations out of Miami, and 4 destinations out of Houston. Then, the variable Presence is equal to $(3 + 5 + 4)/3 = 4$.

the competitors' demand and marginal costs shocks. This is a natural assumption because the legacy carriers - which are the main players of our empirical application - typically operate with a time-lag between the entry decisions and the sale of flight tickets. Nevertheless, the airlines are aware of the probability distribution from which the second-stage shocks are drawn. Therefore, they can compute the expected second-stage profits for any possible entry decisions.

The airlines can enter markets by offering direct flights (for example, American Airlines offering a direct flight between Boston and Houston) and/or connecting flights (for example, American Airlines offering a flight between Boston and Houston with an intermediate stop at Miami). We formalise this as follows. It is useful to re-label each market t by keeping track of the endpoint cities. Specifically, we now denote the market between cities a and b by $\{a, b\}$. Given market $\{a, b\}$, let

$$G_{ab,f} = \begin{cases} 1 & \text{if airline } f \text{ offers direct flights between cities } a \text{ and } b, \\ 0 & \text{otherwise.} \end{cases}$$

Let $G_f \equiv (G_{ab,f} \ \forall \{a, b\} \in \mathcal{T})$ be the network of airline f where the *nodes* of the networks are the cities and the *links* of the network represent the markets served by airline f with direct flights. In the first stage, each airline f chooses its network G_f. In turn, we make this choice automatically determine which markets are served by airline f with connecting flights. In particular, if $G_{ah,f} = G_{hc,f} = 1$ and city h is one of airline f's hubs, then we assume that airline f also enters market $\{a, c\}$ by offering one-stop flights between cities a and c via h.

We assume that hub locations are exogenously determined before the starting of the game. This is because the transition from point-to-point to hub-and-spoke operations was a historical process started by the airlines after the U.S. Airline Deregulation Act of 1978 and quickly completed by the '90s, many years before the sample period of our empirical application. Once decided upon, hub locations were not altered in any major way by the airlines. For detailed studies on the transition to hub-and-spoke operations, see Caves et al. (1984), Kanafani and Ghobrial (1985), Morrison and Winston (1986), Levine (1987), Borenstein (1989; 1992), Butler and Houston (1989), Berry (1990), Brueckner et al. (1992), Evans and Kessides (1993), Brueckner and Spiller (1994), Oum et al. (1995), Berry et al. (1996), Nero (1999), Button, Forsyth, and Nijkamp (2000), and Reynolds-Feighan (2001). We also assume that the airlines can offer connecting flights with one stop only. Moreover, connections are possible at hubs only. This is because in our data we have almost no observations of connecting flights with more than one stop and connecting flights via non-hubs.

When entering markets, the airlines pay the fixed costs of building the physical, technological, and human infrastructures. Examples are the costs of salaries, insurance, scheduling coordination, computer reservation and revenue management system, and aircraft financing. The fixed costs also include the fees for ticket offices, baggage conveyor, gates, lounges, parking, and hangars at the airports. Further, as mentioned earlier, hub-and-spoke operations can increase the fixed costs due to the risk of congestion at hubs where many connections have to be wisely coordinated (for instance, see, Levine, 1987; Butler and Houston, 1989; Borenstein, 1992; Oum et al., 1995; Nero, 1999; Berry et al., 1996; Berry et al., 2019).

We specify the fixed costs sustained by airline f as:

$$\text{FC}_f(G_f, \eta_f; \gamma) = \sum_{\{a,b\} \in \mathcal{T}} G_{ab,f}(\gamma_1 + \eta_{ab,f}) + \sum_{h \in \mathcal{H}_f} \gamma_{2,f} \Big(\sum_{\substack{a \in \mathcal{C} \\ a \neq h}} G_{ha,f} \Big)^2, \tag{7}$$

where $\mathcal{H}_f$ is the set of airline f's hubs, $\mathcal{C}$ is the set of cities, $\eta_f \equiv (\eta_{ab,f} \ \forall \{a,b\} \in \mathcal{T})$ is a vector of market-specific shocks that are observed by the airlines but are unobserved by the researcher, and $\gamma \equiv (\gamma_1, \gamma_{2,f} \ \forall f \in \mathcal{N})$ collects the parameters to be identified.[15] The fixed cost equation consists of two parts. First, there are market-specific contributions, $\gamma_1 + \eta_{ab,f}$, for each market $\{a,b\}$ served by airline f with direct flights. Second, there are quadratic terms, $\gamma_{2,f}(\sum_{\substack{a \in \mathcal{C} \\ a \neq h}} G_{ha,f})^2$, for each hub h of airline f, which account for the risk of congestion at hubs as discussed in the previous paragraph. In particular, $\sum_{\substack{a \in \mathcal{C} \\ a \neq h}} G_{ah,f}$ is the degree of hub h, i.e., the number of markets served out of hub h with direct flights (also called "spokes") by airline f.

Due to the quadratic terms in the fixed cost equation, the fixed costs sustained by airline f when serving a market out of hub h may depend on its decisions to serve other markets out of hub h. This gives rise to *spillover effects* in entry decisions across markets on the *fixed cost* side.

The assumption that the fixed cost shocks, $\eta \equiv (\eta_f \ \forall f \in \mathcal{N})$, are common knowledge among the airlines is deemed appropriate. In fact, in the airline industry, the fixed costs capture fairly standard balance sheet entries which pertain to the long-term side of the business and do not typically involve any industrial or technological secrets. Hence, it is plausible to suppose that the airlines are able to predict the competitors' fixed cost shocks reasonably well.[16]

Importantly, the fixed cost shocks are allowed to be correlated across markets and airlines. This is key because markets and airlines share endpoint cities. To establish point identification of the second-stage parameters, in Section 4.1 we will assume that the fixed cost shocks are uncorrelated with the second-stage shocks. In the same section, we will illustrate the pros and

[15] We could allow γ_1 to be firm-specific. We have not done so to maintain a parsimonious specification.

[16] The assumption that the fixed cost shocks are common knowledge is also imposed, for example, by Ciliberto et al. (2021) and Li et al. (2019).

cons of this restriction. Further, the fact that the airlines observe the fixed cost shocks when choosing their networks creates endogeneity issues which hamper the identification of the first-stage parameters. In Section 4.2, we will explain how to construct appropriate instruments, which are functions of some of the observed demand and marginal cost shifters. Apart from such instruments, the fixed cost shocks are allowed to be correlated with the observed demand and marginal cost shifters.

In the first stage, the airlines simultaneously choose the networks $G \equiv (G_f \ \forall f \in \mathcal{N})$ maximising the expected second-stage profits minus the fixed costs:

$$\text{profits of airline } f\text{:} \quad \mathbb{E}[\Pi_f(X^{\oplus}, W^{\oplus}, M, \xi^{\oplus}, \omega^{\oplus}, G; \theta) | X^{\oplus}, W^{\oplus}, M, \eta] - \text{FC}_f(G_f, \eta_f; \gamma), \tag{8}$$

where $\Pi_f(X^{\oplus}, W^{\oplus}, M, \xi^{\oplus}, \omega^{\oplus}, G; \theta)$ are the second-stage profits. Hereafter, we denote by $\mathcal{J}_t^{\oplus}$ the set of *all potential* products in market t, including the products not chosen for production. In turn, $X^{\oplus} \equiv (X_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus} \ \forall t \in \mathcal{T})$, $W^{\oplus} \equiv (W_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus} \ \forall t \in \mathcal{T})$, $\xi^{\oplus} \equiv (\xi_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus} \ \forall t \in \mathcal{T})$, and $\omega^{\oplus} \equiv (\omega_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus} \ \forall t \in \mathcal{T})$ are the vectors of observed demand shifters, observed marginal cost shifters, demand shocks, and marginal cost shocks of all potential products in every markets.[17] $M \equiv (M_t \ \forall t \in \mathcal{T})$ is the vector of market sizes. $\theta \equiv (\theta_d, \psi)$ is the vector of second-stage parameters. Note that the expectation of the second-stage profits is computed by integrating over the demand and marginal cost shocks, $(\xi^{\oplus}, \omega^{\oplus})$, conditional on the variables observed by the airlines in the first stage, $(X^{\oplus}, W^{\oplus}, M, \eta)$. We highlight that the second-stage profits depend on the networks formed by the airlines. In fact, the networks determine the competing firms, the offered products, the characteristics of the offered product, and the equilibrium prices in each market.

3.3 Equilibrium

The airlines solve the game by working backward from the second stage. First, they calculate the equilibrium profits under any possible networks, demand shocks, and marginal cost shocks. Then, they choose the networks maximising the expected value of those profits. A pure strategy subgame perfect Nash equilibrium consists of networks and price functions, $\{G^*, P_t^*(\xi_t^{\oplus}, \omega_t^{\oplus}, G) \ \forall t \in \mathcal{T}\}$, constituting a pure strategy Nash equilibrium in every subgame.

The existence and uniqueness of $\{P_t^*(\xi_t^{\oplus}, \omega_t^{\oplus}, G) \ \forall t \in \mathcal{T}\}$ is established by Nocke and Schutz (2018) for the case of multi-product Nested Logit, which is what we consider here.

We allow for multiple G^*. Multiple G^* are possible because the airlines compete at the entry stage through the second-stage pricing game. Our methodology does not require the existence

[17] Analogously, we define the market-specific vectors $X_t^{\oplus} \equiv (X_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus})$, $W_t^{\oplus} \equiv (W_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus})$, $s_t^{\oplus} \equiv (s_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus})$, and $P_t^{\oplus} \equiv (P_{j,t} \ \forall j \in \mathcal{J}_t^{\oplus})$. We will use this notation also in Section 4.1.

of G^* for every possible parameterization and realization of the variables. In fact, as discussed in Section 4.2, we will use a collection of revealed-preference inequalities to bound the first-stage parameters, which are *implications* of (i.e., *necessary* conditions for) Nash equilibrium. If a particular parameterisation does not generate Nash equilibrium networks, then the revealed-preference inequalities *may* not be satisfied. In that case, this parameterization would not be included in the identified set. If no parameterization can satisfy the revealed-preference inequalities, then the identified set would be empty. We would conclude that the observed networks cannot be an equilibrium outcome under the model as specified, and so we might reject the model. Thus, our framework can be used even when nonexistence is possible. For further discussion on the existence of Nash equilibrium networks, see Appendix A.[18]

4 Identification

This section discusses identification of the vector of parameters, $(\theta_0, \gamma_0) \in \Theta \times \Gamma \subseteq \mathbb{R}^{\mathrm{K}} \times \mathbb{R}^{\mathrm{N}+1}$, where K is the dimension of θ_0, $\mathrm{N}+1$ is the dimension of γ_0, and the subscript "0" denotes the true parameter values.

4.1 Identification of the second-stage parameters

This section discusses identification of $\theta_0 \equiv (\theta_{d,0}, \psi_0) \in \Theta$. We follow the identification arguments of standard supply-demand models with differentiated products (Berry and Haile, 2014). Intuitively, the vector of demand parameters, $\theta_{d,0}$, is identified from the distribution of prices, sales, and product covariates. Once $\theta_{d,0}$ is identified, the markups are also identified from the F.O.C.s in (6). In turn, the marginal costs are identified as the difference between prices and markups. Finally, the variation in the identified marginal costs and product covariates identifies the vector of marginal cost parameters, ψ_0.

More precisely, there are two potential sources of endogeneity to be faced here. First, the list of products offered in the second stage is selected by the airlines in the first stage and may be correlated with the second-stage shocks. Second, the prices and within-group market shares may be correlated with the second-stage shocks because the latter are observed by the airlines when playing the second stage. We rule out the first source of endogeneity using a classic approach in empirical two-stage games: we assume that the second-stage shocks are mean independent of the airlines' information set in the first stage. The same assumption is imposed by Eizenberg (2014), Holmes (2011), Houde et al. (2017), Kuehn (2018), Rossetti (2018), and Wollmann (2018). We account for the second source of endogeneity by instrumenting the prices

[18]Note here the the revealed-preference inequalities are different, for example, from the identifying bounds in Ciliberto and Tamer (2009). The latter bounds are based on *necessary and sufficient* conditions for Nash equilibrium. Hence, they require the econometrician to explicitly deal with the potential case where the predicted set of Nash equilibria is empty.

and within-group market shares, as usual in supply-demand models. The point-identifying condition for θ_0 is formalised as follows:

Assumption 1. (*Exogeneity of the second-stage shocks*) For every market $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\oplus}$, $\mathbb{E}(\xi_{j,t}, \omega_{j,t} | X^{\oplus}, W^{\oplus}, M, \eta) = 0$. $\diamond$

Assumption 1 essentially states that the information owned by the airlines in the first stage does not help them to predict better the second-stage shocks. It is similar to the mean independence assumption in standard supply-demand models. However, there is a distinguishing aspect to notice, which relates to the two-stage structure of our game: here, we assume that the second-stage shocks are mean independent of the airlines' information set in the first stage, which includes also the covariates of the products not chosen for production and the fixed cost shocks.

Assumption 1 implies that $\mathbb{E}(\xi_{j,t}, \omega_{j,t} | G) = 0$ for every product j and market t, i.e., the second-stage shocks are mean independent of the list of products offered in the second stage. In turn, we can point identify θ_0 via the classic approach. Let $z_{j,t}(X_t^{\oplus}, W_t^{\oplus})$ be an $\mathrm{L} \times 1$ vector of instruments pertaining to product j in market t, where $\mathrm{L} \geq \mathrm{K}$. Given $\rho_{j,t} \equiv (\xi_{j,t}, \omega_{j,t})$, Assumption 2 allows us to write the following moment conditions:

$$\mathbb{E}(\rho_{j,t} \times z_{j,t,l}(X_t^{\oplus}, W_t^{\oplus}) | G) = 0 \quad \forall j \in \mathcal{J}_t^{\oplus}, \quad \forall t \in \mathcal{T}, \tag{9}$$

for every instrument $l = 1, \ldots, \mathrm{L}$. Berry et al. (1995) show that we can uniquely express $\rho_{j,t}$ as a function of the product covariates and θ_0 ("BLP inversion"):

$$\rho_{j,t} = \tau_{j,t}(X_t^{\oplus}, W_t^{\oplus}, M_t, s_t^{\oplus}, P_t^{\oplus}, G; \theta_0) \quad \forall j \in \mathcal{J}_t^{\oplus}, \quad \forall t \in \mathcal{T}. \tag{10}$$

Therefore, we obtain:

$$\mathbb{E}(\tau_{j,t}(X_t^{\oplus}, W_t^{\oplus}, M_t, s_t^{\oplus}, P_t^{\oplus}, G; \theta_0) \times z_{j,t,l}(X_t^{\oplus}, W_t^{\oplus}) | G) = 0 \quad \forall j \in \mathcal{J}_t^{\oplus}, \quad \forall t \in \mathcal{T}, \tag{11}$$

for every instrument $l = 1, \ldots, \mathrm{L}$. The above moment conditions depend only on variables that are observed by the researcher and provide point identification of θ_0. Inference on θ_0 can be conducted via GMM, as illustrated in Appendix B.1. As instruments for the prices and within-group market shares, we use functions of the observed demand shifters, as explained by Berry et al. (1995). For example, we consider the number of competing firms, the number of offered products, and the covariates of the competitors' products. In total, we have 13 instruments for each product.

We conclude the section with a discussion on the pros and cons of Assumption 1. Assumption 1 allows us to apply the classic identification approach to θ_0. Hence, it is key to feasibly nest a network formation step in a supply-demand framework, which is the main objective of our paper. Assumption 1 rules out correlation between the second-stage shocks and the fixed cost shocks. We view this as a reasonable simplification. In fact, the fixed cost shocks capture the residual fixed costs sustained to build the physical, technological, and human infrastructures. Hence, they pertain to the long-term side of the business. Instead, the second-stage shocks represent ticket restrictions and the quality of in-flight service. Hence, they generally relate to operational and short-term activities. Note here that the airline industry is different from the car industry, for instance, where producing a luxury car requires more up-front investment and greater fixed costs to create a single unit.[19] Assumption 1 rules out correlation between the second-stage shocks and the observed product characteristics, as standard in the literature on supply-demand models. Introducing some correlation between the second-stage shocks and the observed product characteristics can be an interesting, albeit difficult, extension for future work. Finally, to further rule out potential sources of correlations, recall that in the utility and marginal cost specifications we include hubbing variables, carrier fixed effects, and city fixed effects.

4.2 Identification of the first-stage parameters

This section discusses identification of $\gamma_0 \in \Gamma$. Identification of γ_0 is hampered by two main issues related to the discrete choice nature of the problem. First, there may be multiple Nash equilibrium networks. This is because the airlines compete at the entry stage through the second-stage pricing game. In turn, we are not able to write down a well-defined likelihood function. Second, even if one is willing to specify an equilibrium selection mechanism, it remains burdensome to construct the set of Nash equilibrium networks due to the large number of markets. In turn, we are not able to write down a tractable likelihood function that can be evaluated many times throughout an optimisation routine. Instead of focusing on Nash equilibrium networks, we bypass these two issues by considering implications of (i.e., necessary conditions for) Nash equilibrium, which are easier to handle from an econometric point of view. More precisely, we implement the revealed preference approach by Pakes (2010) and Pakes et al. (2015). This approach consists of two steps. First, we write down inequalities by simply predicting that the observed networks lead to higher profits than the profits would be were the airlines to deviate from the observed networks. These inequalities do not require that one solves for set of Nash equilibrium networks, do not rule out multiple equilibria, and do not restrict the selection mechanism used when there are multiple equilibria. Second, we get rid of the structural errors entering the inequalities by taking the expectation of the inequalities over markets and interacting them with instruments. The resulting moment inequalities characterise a non-sharp identified set that is a convex polytope, whose projections can be easily obtained

[19] Under the assumption that entry decisions are independent across markets, see Li et al. (2019) and Ciliberto et al. (2021) for possible ways to include correlation between the second-stage shocks and the fixed cost shocks.

by solving linear programming problems. In the remainder of the section, we formally illustrate the procedure.

We construct inequalities by considering *one-link* deviations from the observed networks. More precisely, let $G \equiv (G_f \; \forall f \in \mathcal{N})$ denote the observed networks. For each airline f and market $\{a, b\}$, if $G_{ab,f} = 1$, then we consider airline f deviating from G_f by not offering direct flights between cities a and b (hereafter, class of deviations "$(-ab)$"). Viceversa, if $G_{ab,f} = 0$, then we consider airline f deviating from G_f by offering direct flights between cities a and b (hereafter, class of deviations "$(+ab)$"). Such deviations should lead to lower profits and, hence, produce the following inequalities:

$$\begin{aligned}
&\Delta\Pi_{(+ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(+ab),f}\gamma_0 + \eta_{ab,f} \geq 0 \quad \text{if } G_{ab,f} = 0, \\
&\Delta\Pi_{(-ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(-ab),f}\gamma_0 - \eta_{ab,f} \geq 0 \quad \text{if } G_{ab,f} = 1, \\
&\text{for each } \{a, b\} \in \mathcal{T} \text{ and } f \in \mathcal{N}.
\end{aligned} \tag{12}$$

In (12), $\Delta\Pi_{(+ab),f}$ and $\Delta\Pi_{(-ab),f}$ denote the differences in the expected second-stage profits between the factual and counterfactual scenarios. They contain the second-stage parameters, which are assumed to be already identified. Similarly, $\Delta\overline{\mathrm{FC}}^{\top}_{(+ab),f}\gamma_0$ and $\Delta\overline{\mathrm{FC}}^{\top}_{(-ab),f}\gamma_0$ denote the differences in the systematic fixed costs between the factual and counterfactual scenarios. If $G_{ab,f} = 0$ (resp., $G_{ab,f} = 1$), then the fixed cost shock $\eta_{ab,f}$ should be added to (resp., subtracted from) the profit difference.

We highlight that, despite considering one-link deviations, the left-hand-side of the inequalities in (12) is not computed *as if* entry decisions were independent across markets. In fact, a one-link deviation creates a "domino effect" in the neighbour markets, due to the possibility for airline f to offer one-stop flights and the presence of spillover effects. This makes our method very different from the approaches which assume that entry decisions are independent across markets. As an example, consider the case where airline f deviates from G_f by now setting $G_{ab,f} = 1$. If city a is a hub for airline f and $G_{ac,f} = 1$ in the observed network, then airline f now competes also in market $\{b, c\}$ by offering one-stop flights between cities b and c via a. Similarly, if city b is a hub for airline f and $G_{bd,f} = 1$ in the observed network, then airline f now competes also in market $\{a, d\}$ by offering one-stop flights between cities a and d via b. Further, due to the presence of spillover effects on the demand side, the fact that now airline f offers direct flights between cities a and b could make it more attractive for customers to fly in any markets having cities a or b as origin. Also, due to the presence of spillover effects on the marginal cost side, the fact that now airline f offers direct flights between cities a and b could make it cheaper to offer flights having cities a or b as endpoints or intermediate stops. Finally, if cities a or b are hubs for airline f, then the fixed costs of offering direct flights from such hubs may increase due to congestion effects. Therefore, deviating to $G_{ab,f} = 1$ implies new equilibrium prices and fixed costs in market $\{a, b\}$ *and* in the markets that are in the neighbourhood of market $\{a, b\}$. All such effects are taken into account when computing the left-hand-side of the inequalities in (12). Appendix B.3 discusses in detail how we calculate $\Delta\Pi_{(+ab),f}$, $\Delta\overline{\text{FC}}_{(+ab),f}$, $\Delta\Pi_{(-ab),f}$, and $\Delta\overline{\text{FC}}_{(-ab),f}$.[20]

The inequalities in (12) cannot be used yet for identification because they contain the fixed cost shocks. In order to get of rid of the fixed cost shocks, we take the expectation of the inequalities in (12) over markets:

$$\begin{aligned}
&\mathbb{E}[\Delta\Pi_{(+ab),f} - \Delta\overline{\text{FC}}^{\top}_{(+ab),f}\gamma_0 + \eta_{ab,f}|G_{ab,f} = 0] \geq 0,\\
&\mathbb{E}[\Delta\Pi_{(-ab),f} - \Delta\overline{\text{FC}}^{\top}_{(-ab),f}\gamma_0 - \eta_{ab,f}|G_{ab,f} = 1] \geq 0,\\
&\text{for each } f \in \mathcal{N}.
\end{aligned} \tag{13}$$

If we could claim that $\mathbb{E}[\eta_{ab,f}|G_{ab,f} = 0]$ and $\mathbb{E}[\eta_{ab,f}|G_{ab,f} = 1]$ are equal to zero, then the moment inequalities in (15) could be used for identification. Unfortunately, such conditional expectations are not equal to zero because the fixed cost shocks represent structural components that are observed by the airlines when forming their networks.

We overcome this selection problem by introducing instruments, as discussed by Pakes et al. (2015). More precisely, suppose that for each airline f we have two positive variables, $Z_{(+ab),f}$ and $Z_{(-ab),f}$, such that:

$$\mathbb{E}[Z_{(+ab),f} \times \eta_{ab,f}|G_{ab,f} = 0] = 0 \quad \text{and} \quad \mathbb{E}[Z_{(-ab),f} \times \eta_{ab,f}|G_{ab,f} = 1] = 0. \tag{14}$$

We can interact these instruments with the moment inequalities in (15) and obtain:

$$\begin{aligned}
&\mathbb{E}[Z_{(+ab),f} \times (\Delta\Pi_{(+ab),f} - \Delta\overline{\text{FC}}^{\top}_{(+ab),f}\gamma_0 + \eta_{ab,f})|G_{ab,f} = 0] \geq 0,\\
&\mathbb{E}[Z_{(-ab),f} \times (\Delta\Pi_{(-ab),f} - \Delta\overline{\text{FC}}^{\top}_{(-ab),f}\gamma_0 - \eta_{ab,f})|G_{ab,f} = 1] \geq 0,\\
&\text{for each } f \in \mathcal{N}.
\end{aligned} \tag{15}$$

By the exogeneity restriction in (14), it holds that:

$$\begin{aligned}
&\mathbb{E}[Z_{(+ab),f} \times (\Delta\Pi_{(+ab),f} - \Delta\overline{\text{FC}}^{\top}_{(+ab),f}\gamma_0)|G_{ab,f} = 0] \geq 0,\\
&\mathbb{E}[Z_{(-ab),f} \times (\Delta\Pi_{(-ab),f} - \Delta\overline{\text{FC}}^{\top}_{(-ab),f}\gamma_0)|G_{ab,f} = 1] \geq 0,\\
&\text{for each } f \in \mathcal{N}.
\end{aligned} \tag{16}$$

The moment inequalities in (16) now depend only on variables that are observed by the researcher and, hence, can be exploited for identification. In particular, suppose that one disposes

[20]For the same reasons, the left-hand-side of the inequalities in (12) is not computed as if each market was run by a local manager taking independent entry decisions as assumed in Aguirregabiria and Ho (2012).

of R instruments satisfying the exogeneity restriction in (14). Then, one can use these instruments to obtain R moment inequalities which characterise a non-sharp identified set for γ_0. Further, if the instruments offer sufficient variation in profits relative to the fixed cost shocks, then the identified set is bounded. Note also that the moment inequalities in (16) are linear in γ_0. Therefore, the identified set is a convex polytope.

To construct our first-stage instruments, we follow the approach implemented by Wollmann (2018) in an empirical study of the commercial truck production process. Wollmann (2018) suggests to think about $Z_{(+ab),f}$ as being a function of the information set of firm f in the first stage, taking value 1 if offering direct flights between cities a and b is, *on average*, unoptimal for firm f regardless of $\eta_{ab,f}$, and 0 otherwise. Similarly, $Z_{(-ab),f}$ is a function of the information set of airline f in the first stage, taking value 1 if offering direct flights between cities a and b is, *on average*, optimal for airline f regardless of $\eta_{ab,f}$, and 0 otherwise. For example, we set $Z_{(-ab),f} = 1$ if market $\{a, b\}$ has a very large size and cities a or b are hubs for airline f. In fact, this indicator isolates markets where airline f will tend to always offer direct flights, plausibly unrelated to the fixed cost shocks, due to the expected very high profitability. Viceversa, we set $Z_{(+ab),f} = 1$ if market $\{a, b\}$ has a very small size and cities a and b are hubs for the competitors and not for airline f. In fact, this indicator isolates markets where airline f will tend to never offer direct flights, plausibly unrelated to the fixed cost shocks, due to the expected very low profitability. Along these lines, we construct 10 instruments which are discussed in Appendix B.4.

Instead of introducing instruments, an alternative approach for getting rid of the fixed cost shocks from the inequalities in (12) consists of introducing support restrictions on the fixed cost shocks. For example, in an empirical study of the personal computer industry, Eizenberg (2014) assumes that the fixed cost shocks have a bounded support which is contained within the support of the expected change in the second-stage profits resulting from one-product deviations at a time. We have not pursued this approach because, by construction, it characterises an unbounded identified set when there are spillover effects in entry decisions on the fixed cost side, as explained by Eizenberg (2014) in Appendix A.3.

The identified set that we characterise is not sharp. In principle, one could construct revealed-preference inequalities based on "richer" classes of deviations, for example when an airline adds or deletes two or more links simultaneously. If one was able to find appropriate instruments, the resulting additional moment inequalities would sharpen the identified set. We have not considered simultaneous-link deviations for two reasons. First, finding appropriate instruments for simultaneous-link deviations is challenging. Second, in the empirical application, our strategy delivers sufficiently informative bounds for the first-stage parameters.

We summarise the above discussion with the following assumption:

Assumption 2. (*First-stage instruments*) For each airline f, there exists variables $Z^{r_+}_{(+ab),f}$ for $r_+ = 1, \ldots, \mathrm{R}_+$ and $Z^{r_-}_{(-ab),f}$ for $r_- = 1, \ldots, \mathrm{R}_-$ such that:

$$\mathbb{E}[Z^{r_+}_{(+ab),f} \times \eta_{ab,f} | G_{ab,f} = 0] = 0 \quad \text{for } r_+ = 1, \ldots, \mathrm{R}_+,$$
$$\mathbb{E}[Z^{r_-}_{(-ab),f} \times \eta_{ab,f} | G_{ab,f} = 1] = 0 \quad \text{for } r_- = 1, \ldots, \mathrm{R}_-.$$

◇

In turn, the identified set for γ_0 is:

$$\begin{aligned} \Gamma_I \equiv \Big\{ \gamma \in \Gamma : & \mathbb{E}[Z_{(+ab),f} \times (\Delta\Pi_{(+ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(+ab),f}\gamma_0) | G_{ab,f} = 0] \geq 0, \\ & \mathbb{E}[Z_{(-ab),f} \times (\Delta\Pi_{(-ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(-ab),f}\gamma_0) | G_{ab,f} = 1] \geq 0, \\ & \text{for } r_+ = 1, \ldots, \mathrm{R}_+,\ r_- = 1, \ldots, \mathrm{R}_-,\ f \in \mathcal{N} \Big\}. \end{aligned} \tag{17}$$

In Appendix B.2, we discuss how to conduct inference on Γ_I.

5 Empirical application

5.1 Data

We use data from the Airline Origin and Destination Service (hereafter, DB1D) which consists of a 10% random sample of all the tickets issued in the United States during the second quarter of 2011. By then, the merger between United Airlines and Continental Airlines had been completed and American Airlines and US Airways had not announced their intention to merge yet. We restrict the sample to the flights operated between the 85 largest metropolitan statistical areas (MSAs) in the United States. We refer to MSAs as cities throughout the section. Further, if a city has more than one airport (such as New York, Chicago, and Los Angeles), we combine its airports into one.[21] If an airport within a city serves as a hub for a given airline, then that city is a hub for the airline.[22] The major carriers in the sample are United Airlines (UA), Delta Airlines (DL), American Airlines (AA), US Airways (US), and Southwest Airlines (WN). All the other carriers in the sample are put either in a group called "Low Cost Carriers" (LCC), or in a group called "Other". These carriers are treated as fringe competitors, differing only in whether or not they can be classified as low cost. Also, to enhance computational tractability, we do not consider their fixed costs when estimating

[21] See Footnote 7.

[22] For instance, Dallas/Fort Worth serves as a hub for American Airlines whereas Dallas Love Field does not. Given that we combine both airports into one, the resulting city (Dallas) is a hub for American Airlines.

the first stage parameters and we assume that their networks are exogenously pre-determined before the starting of the game. The legacy carriers use hub-and-spoke operations. Southwest Airlines does not rely on a pure hub-and-spoke business model, but rather on a hybrid system in which some airports are "focus cities" offering some, but not all, of the services generally found at hubs. When estimating our model, we treat "focus cities" as hubs.[23]

We delete tickets with multiple operating carriers or multiple ticketing carriers. Also, we delete tickets with different inbound and outbound itineraries. Further, we delete tickets that are not round-trip. Lastly, to be consistent with our model, we delete connecting tickets via cities that are not hubs. Note that we observe very few of these tickets. As discussed in Section 3, we consider tickets featuring the same airline-itinerary combination but different fares as the same product. We compute the corresponding price as follows. First, we delete tickets with fares in the highest and lowest percentiles and tickets with fares below \$25. Then, we construct the weighted average price over the remaining fares.

We allow the marginal cost parameters to differ between short-haul and long-haul flights, which are defined as flights covering up to 1,500 miles and flights covering more than 1,500 miles, respectively. As anticipated in Section 3, for each market $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\oplus}$, $X_{j,t}$ collects the number of stops ("Stops"), the maximum number of direct flights offered at the itinerary's endpoints by the same carrier offering itinerary j ("Connections"), the distance flown ("Distance"), and its squared value ("Distance2"). Similarly, $W_{j,t}$ collects the number of stops ("Stops Short", "Stops Long"), the average number of cities that are reachable from the endpoints and intermediate stops of itinerary j with the same carrier offering itinerary j ("Presence Short", "Presence Long"), and the distance flown ("Distance Short", "Distance Long"). We include in the demand and supply models firm and city fixed effects in order to capture brand preferences and unobserved city-specific features. Lastly, we compute market sizes using data from the US Census Bureau on MSA population. In particular, we calculate the size of each market $t \in \mathcal{T}$, M_t, as the geometric mean of the populations at the market's endpoints.

Table 1 provides some summary statistics. In panel (a), we see that whereas only around 15% of flights are direct, they account for around 85% of passengers. We can also see the importance of hubs: 57% of passengers travel through, from, or to hubs and 83% of all flights start, land, or connect at a hub. Further, we see in panel c) that airlines serve on average almost 50 direct flights out of hub airports (measured by the "Degree" variable), compared to around 7 for non-hub airports. Looking at panel e), we see that we have on average 5.56 products per market and on average 4.62 hub products.

[23] See Table C.2 in Appendix C for the list of hubs.

Table 1: Summary statistics

(a) Sizes		
Number of firms	7	
Number of products	17,481	
Number of markets	3,146	
Fraction of direct flights	0.14	
Fraction of hub itineraries	0.83	
Fraction of direct passengers	0.85	
Fraction of passengers in hub markets	0.57	
Fraction of markets served	0.93	
(b) Passengers by airline (1 million)		
Total	25.33	
American	3.15	
Delta	4.85	
United	3.81	
US Airways	2.21	
Southwest	6.00	
Low Cost	4.10	
Other	1.21	
(c) Network statistics	**Mean**	**St.Dev**
Degree (Hub)	49.86	13.03
Density (Hub)	0.61	0.16
Clustering (Hub)	0.24	0.14
Degree (Non-hub)	7.21	7.72
Density (Non-hub)	0.09	0.09
Clustering (Non-hub)	0.80	0.33
(d) Demand and marginal cost variables	**Mean**	**St.Dev**
Price (100 USD)	4.32	1.20
Stops	0.86	0.34
Connections (100)	0.20	0.19
Presence (100)	0.56	0.15
Distance (100 km)	1.44	0.68
Product share	4.6083e-04	1.4784e-03
Market size (1 million)	2.55	1.85
(e) Market-level statistics	**Mean**	**St.Dev**
Number of firms	3.59	1.81
Number of products	5.56	4.43
Number of direct flights	0.75	1.20
Number of hub itineraries	4.62	3.43
Number of passengers (1,000)	8.05	24.43
Number of direct passengers (1,000)	6.82	23.98
Number of passengers in hub markets (1,000)	4.60	15.39

Note:
Hub itineraries are itineraries where at least one of the endpoints or intermediate stop is a hub. Hub markets are markets where at least one of the endpoints is a hub. The share of a product is computed as the total number of passengers buying that product divided by the market size, times 10 because we have a 10% random sample. The degree of a (non-)hub is the number of markets served with direct flights out of the (non-)hub by an airline. The density of a (non-)hub is the ratio between the number of markets served with direct flights out of the (non-)hub by an airline and the total number of potential markets out of the (non-)hub. The clustering coefficient of a (non-)hub is the ratio between the number of closed triplets including the (non)-hub served by an airline and the total number of potential triplets including the (non)-hub.

5.2 Results from the second stage

The second-stage results are in Table 2. We find significant spillover effects in entry decisions across markets on the demand side. Specifically, passengers benefit from having a large number of direct flights offered by an airline at the itinerary's endpoints (Connections). That is, dense hubs increase passengers utility, all the rest being constant. This effect captures the value of frequent flier programs. In fact, the larger the number of destinations for which consumers can redeem frequent flier miles, the higher the value of such loyalty programs. Additionally, an airline that flies to many cities is likely to have more convenient parking and gate access and provide better services. The price coefficient is negative. It lies between the price coefficients of the two consumer types considered by Berry and Jia (2010) and within the ballpark of what other contributions have found. Consumer utility is an inverted U-shaped function of the distance flown. This means that, as distance increases, air travel becomes more attractive relative to the outside option. However, as distance increases further, travel becomes less pleasant and demand starts to decrease. In line with the literature, passengers exhibit a strong disutility for connecting flights. Lastly, we estimate the nesting parameter, λ, to be around 0.6. Recall that, as λ approaches one, the Nested Logit model reduces to the standard Logit model. Therefore, we can conclude that there is substitution between the inside goods and the outside option.

We find significant spillover effects in entry decisions across markets also on the marginal cost side. Specifically, the marginal cost of an itinerary decreases with the average number of cities that an airline allows to reach from the endpoints and intermediate stops (Presence). This effects captures the impact of economies of density on the marginal costs, i.e., the fact that more densely travel segments tend to have lower unit costs due to engineering reasons. In particular, the larger the number of final destinations consumers can reach, the more the opportunities for an airline to pool passengers from several itineraries into the same planes, and the more an airline can efficiently use large aircrafts which typically have lower unit costs. This mechanism implies that hub-and-spoke operations provide marginal cost savings, all the rest being constant. The impact of the variable Presence is more pronounced for long-haul flights, as the efficiency of large planes is especially evident in long routes. Further, the number of stops in long-haul flights reduces their marginal cost. Again, this suggests that connecting flights are less expensive to provide for long routes, by virtue of economies of density. The number of stops does not significantly reduce the marginal cost of short-haul flights. This may be because the marginal cost savings induced by economies of density are balanced by the extra take-off and landing, which uses a lot of fuel. The marginal cost of both long-haul and short-haul flights increases with the distance flown. This is because the longer the distance, the more fuel is needed to cover it. Lastly, as expected, Southwest Airline, Low Cost, and Other have lower marginal costs than the legacy carriers.

Table 2: Second-stage estimates

Utility			Marginal Cost		
	Coefficient	SE		Coefficient	SE
Mean utility			**Short-haul flights**		
Intercept	-5.598	(0.262)	Intercept	3.118	(0.090)
Price	-0.587	(0.066)	Stops	0.031	(0.028)
Stops	-1.794	(0.066)	Distance	0.474	(0.037)
Connections	0.868	(0.032)	Presence	-1.245	(0.136)
Distance	0.289	(0.084)	**Long-haul flights**		
Distance2	-0.093	(0.095)	Intercept	3.703	(0.114)
Nesting Parameter (λ)	0.623	(0.025)	Stops	-0.189	(0.041)
			Distance	0.667	(0.032)
			Presence	-2.016	(0.145)
Carrier FEs			**Carrier FEs**		
DL	-0.168	(0.018)	DL	0.082	(0.035)
UA	-0.387	(0.025)	UA	0.050	(0.032)
US	0.142	(0.025)	US	0.079	(0.032)
WN	-0.519	(0.032)	WN	-0.363	(0.029)
LCC	-0.348	(0.032)	LCC	-1.509	(0.055)
Other	-0.074	(0.056)	Other	-1.398	(0.049)
Statistics					
J-statistic	15.627				
Number of observations	17,481				
Price Elasticity	-3.780				
Aggregate Easticity	-2.100				
Connection semi-elasticity	0.880				

Note:
Prices are divided by USD 100. Connections and Presence are divided by 100. City fixed effects are included. The number of over-identifying restrictions is 11.

The bottom part of Table 2 reports some elasticity estimates. In particular, the price elasticity is the average estimated price elasticity across products. The aggregate elasticity is the percentage change in the inside product share when all prices rise by 1%. The connection semi-elasticity is the change in the inside product share if all direct flights became one-stop flights, while holding the other characteristics fixed. The price elasticity is slightly higher than in other contributions in the literature. This may be due to the fact that our model does not capture sufficient consumer heterogeneity in price sensitivity. The connection semi-elasticity is higher than in Berry and Jia (2010). This is in line with the trend towards increasingly strong preferences for direct flights found in their paper.

Table 3: Profits by firms

	Profits (100k)	Price	Marginal cost	Markup	Lerner Index
AA					
All	1.78	453.36	335.20	118.16	0.28
Direct	13.77	402.37	277.42	124.94	0.32
One-stop	0.39	459.26	341.89	117.38	0.27
Direct, hub endpoint	15.06	402.75	276.66	126.09	0.33
Direct, non-hub endpoints	2.00	398.87	284.48	114.40	0.30
DL					
All	1.41	436.45	310.40	126.05	0.31
Direct	12.31	463.26	321.03	142.23	0.33
One-stop	0.33	433.80	309.35	124.45	0.31
Direct, hub endpoint	13.49	482.67	336.83	145.84	0.32
Direct, non-hub endpoints	4.47	334.75	216.44	118.31	0.38
UA					
All	1.25	445.56	328.43	117.13	0.28
Direct	9.17	458.50	334.97	123.53	0.29
One-stop	0.20	443.85	327.56	116.28	0.28
Direct, hub endpoint	11.03	456.82	332.24	124.58	0.29
Direct, non-hub endpoints	2.17	464.88	345.33	119.55	0.29
US					
All	1.30	453.43	336.77	116.67	0.27
Direct	8.99	407.34	275.17	132.17	0.35
One-stop	0.35	459.10	344.34	114.76	0.26
Direct, hub endpoint	10.42	418.96	282.96	136.00	0.35
Direct, non-hub endpoints	3.95	366.22	247.58	118.64	0.36
WN					
All	2.79	419.43	299.51	119.92	0.31
Direct	12.09	365.14	237.09	128.05	0.38
One-stop	0.23	434.40	316.73	117.67	0.29
Direct, hub endpoint	16.49	362.34	233.95	128.39	0.38
Direct, non-hub endpoints	8.88	367.19	239.39	127.80	0.38

Table 3 reports firm-level profits, prices, marginal costs, and markups averaged over different products. For each airline, the first row contains the average across all products, the second line across direct flights, and the third line across one-stop flights. The fourth and fifth rows contain the average across direct flights where at least one of the endpoints is a hub (hub markets) and where no endpoint is a hub (non-hub markets), respectively. We can see that the airlines charge a higher markup on direct flights compared to one-stop flights, which is in line with the fact that consumers value direct flights more. The legacy carriers charge a higher markup on direct flights in hub markets, compared to non-hub markets, suggesting the presence of a hub premium. Charging a high markup on hub markets may be due to high market power at hubs, or to high fixed costs from managing hubs. Whereas American Airlines, US Airways, and Southwest Airlines have substantially lower marginal costs on nonstop flights, it is the opposite for Delta and United Airlines. The marginal cost of Southwest Airlines is lower than the marginal costs of the legacy carriers. For direct flights, the difference is quite substantial. For one-stop flights, Southwest Airlines's advantage is small. The last finding is line with the fact that Southwest Airlines uses focus cities, rather than hubs. Hence, the marginal cost savings from offering connecting flights may be less pronounced since not all features of traditional hubs are exploited.

5.3 Results from the first stage

Table 4: Projections of the estimated identified set

Variable	Lower bound	Upper bound
Intercept	672,624	1,047,511
Congestion costs		
AA	19,216	28,024
DL	12,824	21,776
UA	8,731	16,586
US	27,191	39,044
WL	17,346	30,967

Note:
Entry costs are in $.

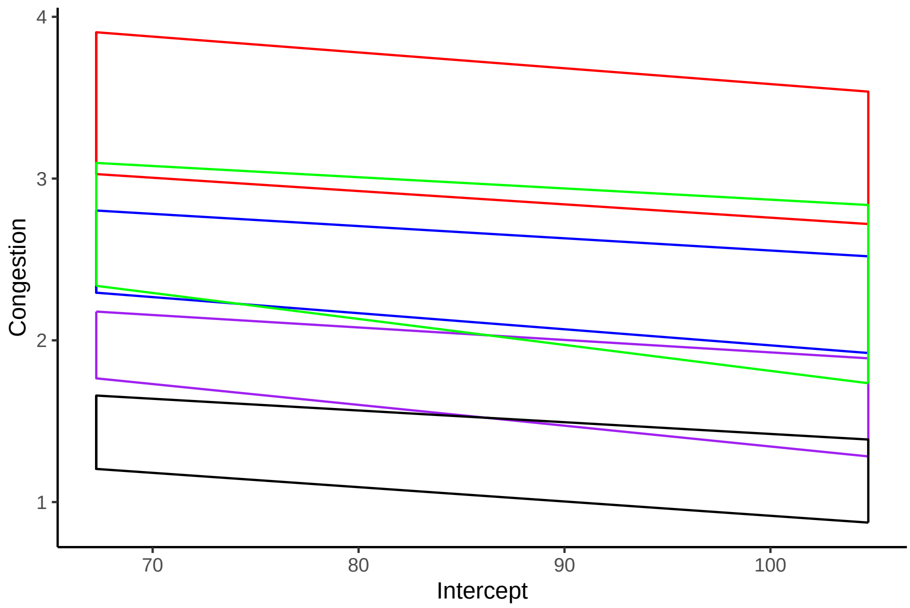
Table 4 reports the projections of the estimated identified set.[24] Estimates are in dollars. We see that, absent congestion costs, offering direct service between two endpoints costs between $\$672,624$ and $\$1,047,511$. To interpret the congestion effect, recall from our specification of the fixed costs (7) that the congestion costs of managing hubs are quadratic in the number of spokes of each hub. For example, American Airlines has a total of 221 spokes, resulting in congestion costs between $214 and $312 million.[25] Their base-line entry costs amount to between $157 and $245 million. The base-line entry cost is just the number of segments served multiplied by the Intercept term. Due to congestion costs, the fixed costs sustained by an airline when serving a market out of a hub depends on its decisions to serve other markets out of the hub. This gives rise to spillover effects in entry decisions across markets on the fixed

[24] We have not implemented the inference methodology yet.

[25] To compute congestion costs, we need to count the number of spokes at each hub, square that number, sum it, and then multiply by the estimated congestion cost. For American, this computation yields, for the lower bound, $19,216 * (68^2 + 29^2 + 26^2 + 39^2 + 59^2)$

cost side. Congestion costs differ substantially across the airlines. US Airways faces larger congestion costs than the other legacy carriers. United Airlines faces lower congestion costs than the other legacy carriers. The heterogeneity in congestion costs is also highlighted by Figure 2 The Figure shows the projections of the estimated identified sets for the 5 airlines. We see that while some sets overlap, there are substantial differences between airlines.

Figure 2: Projections of the estimated identified set



Colors: American (blue), Delta (purple), United (black), US Airways (red), and Southwest (green)

Table 5: Predicted entry probabilities

Firm	Data	Predicted
American	6.89 %	9.74 %
Delta	12.34 %	11.16 %
United	12.96 %	8.41 %
US Airways	6.95 %	11.12 %
Southwest	18.59 %	32.92 %

In Table 5, we report the predicted entry probabilities. To compute the predicted entry probabilities, we construct a grid of admissible parameter values by taking 100,000 draws from the convex polytope defined by our moment inequalities via Gibbs sampling. Then, for each airline, we implement the following procedure. For every parameter value and market, first, we compute the marginal profit from serving the market with direct flights without considering the fixed costs shock; second, we save one if the marginal profit is positive, and zero otherwise. For each parameter value, we sum all the ones and divide the result by the number of markets. Finally, we take the midpoint of these numbers across parameter values. This is the predicted entry probability. Overall, we predict entry patterns reasonably well. The largest discrepancy occurs for Southwest Airlines, which may be due to the fact that Southwest Airlines relies on focus cities, rather than hubs, whose peculiarities are not entirely captured by our framework.

5.4 Counterfactuals

This section studies the impact on firm and market outcomes of a merger between two of the four legacy carriers in our sample, American Airlines and US Airways. These two firms did in fact merge in 2013. They first expressed interest to merge in January 2012 and officially announced their plans to merge in February 2013. At the time they expressed interest to merge, American Airlines' holding company (AMR Corporation) was in Chapter 11 bankruptcy.[26] The Department of Justice (DoJ), along with several state attorney generals, sought to block the merger, concerned that the merger would have substantially lessen competition and hurt consumers. In 2013, a settlement was reached in which the merging parties pledged to give up landing slots or gates at 7 major airports and "*to maintain hubs in Charlotte, New York (Kennedy), Los Angeles, Miami, Chicago (O'Hare), Philadelphia, and Phoenix consistent with historical operations for a period of three years*".[27] Below, we refer to such settlement as the 2013 settlement. According to articles from the time the merger was announced, the parties expected the merger to make the new entity the largest airline in the world in terms of passenger numbers, and annual cost savings of around $1 billion per year.[28] Also, the merger was seen by analysts as an opportunity for American Airlines to expand its footprint in markets along the East Coast, where US Airways had a strong presence.[29]. The merger was the last in a series of large airline mergers and reduced the number of legacy carriers to 4 (Delta Airlines, United Airlines, Southwest Airlines, and the new American Airlines).

We simulate two counterfactual events. In the first event, we assume that American Airlines and US Airways merge. In the second event, we assume that American Airlines goes bankrupt and disappears. We consider the bankruptcy event because, at the time of the merger's announcement, American Airlines was indeed in Chapter 11 bankruptcy, which raises the question of what would have happened had it just disappeared from the market. Note that, throughout the first decade of the new millennium, all the legacy carriers filed for bankruptcy at some point, but were allowed to re-structure or merge in order to recover from financial distress. The debate on the appropriateness of aid to airlines that struggle financially has again become a matter of public concern during the Covid-19 pandemic. Thus, the analysis of the bankruptcy event aims to offer insights on this topic.

[26] Recall that we use data from the second quarter of 2011. This is before the two parties expressed interest to merge and corresponds to the last quarter before AMR filed for Chapter 11 bankruptcy.

[27] https://www.justice.gov/opa/pr/justice-department-requires-us-airways-and-american-airlines-divest-facilities-seven-key, https://americanairlines.gcs-web.com/news-releases/news-release-details/amr-corporation-and-us-airways-announce-settlement-us-department

[28] https://www.reuters.com/article/uk-americanairlines-merger-idUSLNE91D02020130214

[29] https://money.cnn.com/2013/02/14/news/companies/us-airways-american-airlines-merger/index.html

5.4.1 Set-up

When evaluating the merger event, we compare 5 scenarios:

1. *Networks fixed - Base case.* After the merger, the networks remain at the pre-merger levels. The firms maintain the pre-merger products and dummies. If the merging firms offer the same itinerary, then the two products are kept as separate. The firms play the simultaneous pricing game described in Section 3.1 and new equilibrium prices arise. In particular, the merging firms choose the prices maximizing their joint profits, i.e., they behave as if they colluded.

2. *Networks fixed - Best case.* After the merger, the networks remain at the pre-merger levels. All the firms, except American Airlines and US Airways, maintain the pre-merger products and dummies. The merging firms maintain the pre-merger products, but update some of their covariates. In particular, the products of the merging firms inherit the best firm dummies. If the merging firms offer the same itinerary, then the two products are kept as separate. However, differently from the previous scenario, now the two products inherit the most favourable observed demand and marginal cost shifters. For example, on the demand side, the estimated coefficient of the variable Connections is positive. Hence, the two products get the highest value of Connections between what American Airlines and US Airways had before merging. After such rearrangements, the firms play the simultaneous pricing game described in Section 3.1 and new equilibrium prices arise. As in the previous scenario, the merging firms choose the prices maximizing their joint profits, i.e., they behave as if they colluded.

3. *Networks fixed - Updated case.* After the merger, the networks of all the firms, except American Airlines and US Airways, remain at the pre-merger levels. We treat the merged entity as a new firm and assign it the network resulting from merging the pre-merger networks of American Airlines and US Airways. The products of the merged entity and their covariates are constructed from the merged network. The merged entity takes on the most favourable dummies of the merging firms. The demand and marginal cost shocks of the products of the merged entity stay the same as pre-merger, except in markets where both firms were present. There, we use the mean of the pre-merger errors. After such rearrangements, the merged entity and the other firms play the simultaneous pricing game described in Section 3.1 and new equilibrium prices arise.

4. *Networks vary - No remedies.* After the merger, we treat the merged entity as a new firm and we let the firms play the entire two-stage game described in Section 3. New equilibrium networks and prices arise. More details on how the firms reoptimise networks and prices are

in Section 5.4.2.

5. *Networks vary - With remedies.* After the merger, we treat the merged entity as a new firm and we let the firms play the entire two-stage game described in Section 3. New equilibrium networks and prices arise. However, differently from the previous scenario, now we take into account some of the remedies imposed to the merged entity by the 2013 settlement. In particular, recall that the 2013 settlement invited the merged entity "*to maintain hubs in Charlotte, New York (Kennedy), Los Angeles, Miami, Chicago (O'Hare), Philadelphia, and Phoenix consistent with historical operations for a period of three years*". We incorporate these remedies as binding constraints and force the merged entity to keep serving all the markets served pre-merger by the merging firms if one or both endpoints are at one of the hubs mentioned in the 2013 settlement. Note that this scenario differs from the "Networks fixed - Updated case" scenario because, first, the competitors of the merged entity are allowed to reoptimise their networks; second, the merged entity is allowed to enter all markets and exit those markets whose endpoints were not subject to the remedy.

The first three scenarios assume that the airlines do not reoptimise their networks after the merger, as standard in the literature. In turn, the analyst should make ad-hoc assumptions on how the products of the merged entity adjust after the merger, which opens infinite possibilities. The first three scenarios are just some examples and do not obviously exhaust all potential cases, with consequent risk of misspecification. The fourth and fifth scenarios consider the entire two-stage game and allow the firms to reoptimise their prices *and* networks after the merger, by leveraging on our methodology. In fact, after the merger, it is plausible to believe that the merged firm and its competitors will react not only by adjusting their prices, but also by repositioning in markets. For example, after the merger, there might room in some markets for accommodating other entrants. Further, the merger could generate marginal cost savings for the merged firm, by virtue of economies of density triggered by hub-and-spoke operations, which may favour its entry in new markets. The merger could also increase the market power of the merged firm, by disposing of a larger network that enhances consumer willingness to pay. At the same time, the merger might increase the total fixed costs of the merged firm, due to congestion effects at hubs, which may force it to dismiss some operations. All such synergies across markets are taken into account by our procedure.

When evaluating the bankruptcy and disappearance of American Airlines, we consider the following two scenarios:

1. *Networks Fixed.* After the disappearance of American Airlines, the networks of the other firms remain at the pre-merger levels. The firms play the simultaneous pricing game described in Section 3.1 and new equilibrium prices arise.

2. *Networks Vary.* After the disappearance of American Airlines, we let the other firms play the entire two-stage game described in Section 3. New equilibrium networks and prices arise.

The first scenario assumes that the airlines do not reoptimise their networks after the disappearance of American Airlines, as standard in the literature. The second scenario considers the entire two-stage game and allow the firms to reoptimise their prices *and* networks after the disappearance of American Airlines, by leveraging on our methodology. In fact, after the disappearance of American Airlines, it is plausible to believe that its competitors will react not only by adjusting their prices, but also by repositioning in markets. For example, we expect that the disappearance of American Airlines makes it more attractive for other firms to enter markets previously served by American Airlines, in turn alleviating the negative effects of the bankruptcy on consumer surplus. At the same time, replacing the hub-and-spoke operations of the disappearing airline may be infeasible due to the large fixed costs. It is then likely that consumers living in the hub cities of American Airlines will be overall worse off as they will no longer be able to benefit from the services previously offered by American Airlines.

5.4.2 Description of the counterfactual algorithm

In this section, we describe the algorithm implemented to reach a new equilibrium when the airlines reoptimise their prices and networks, in the "Networks vary - No remedies" scenario. In the "Networks vary - With remedies' scenario, we follow the same procedure, but we force the merged entity not to exit all the markets served pre-merger by the merging firms if one or both endpoints are at one of the hubs mentioned in the 2013 settlement.

Recall that there can be multiple equilibrium networks. Hence, in principle, it would be desirable to enumerate all possible equilibrium networks that may arise, as in Eizenberg (2014). However, doing so is infeasible in our setting due to the large number of markets. To make the problem tractable, we build a best-response learning algorithm based on Lee and Pakes (2009) and Wollmann (2018). In particular, we order markets and firms according to some criteria. For a given value of the parameters, firms iteratively best-respond to one another with respect to entry and price decisions sequentially over markets until they reach convergence. We are currently experimenting many different orders of markets and firms in order to obtain a *distribution* of equilibria. For the moment, the results reported below correspond to one specific order of markets and firms. We repeat the procedure for 25 draws of parameter values from the estimated identified set and report the minimum and maximum changes in the networks and market outcomes across such parameter values. In what follows, we provide more details on the steps of the algorithm, for a given value of the parameters and for a given order of firms and markets.

1. We rank markets according to: whether at least one of the market's endpoints are hubs for the merging airlines; whether the merging airlines served the market; the number of markets the merging airlines served out of the endpoints with direct flights; the market size.

2. We rank firms in the following order: American Airlines; Delta Airlines; United Airlines; US Airways; Southwest. When simulating the merger event, we initially assign to the merged entity the network resulting from merging the pre-merger networks of American Airlines and US Airways and let merged entity move first. We also assume that the cities in which either American Airlines or US Airways had a hub prior to the merger will continue to serve as hubs. This means that the merged entity will entertain hubs in Dallas, Chicago, Charlotte, Philadelphia, New York City, Washington DC, Phoenix, Miami, and Los Angeles. Further, the merged entity takes on the most favourable firm dummies of the merging firms.

3. For a given firm in a given market, we let the firm play its best response, holding the firm's network outside of the considered market and the rival networks and prices fixed at the level reached in the previous iteration. In order to find the best response of the firm, we compute the firm's total second-stage profits when serving the market with direct flights, the total second-stage profits when not serving the market with direct flights, and take the difference. Note here that we let the firm to best respond with respect to prices both in the market under consideration and in the neighbour markets due to spillover effects and the possibility of offering one-stop flights. Hence, the simulation is not conducted *as if* entry decisions were independent across markets. We also compute the total fixed costs when the firm serves the market with direct flights and when it does not, and take the difference. If the second-stage profit difference is larger (smaller) than the fixed cost difference, then the best response of the firm is to (not) serve the market with direct flights. We update the network of the firm according to the best response and move to the next firm. We cycle through firms in a given market until no firm wishes to deviate.

4. We cycle through the markets and check how many entry decisions have changed. If that number is larger than some tolerance criterium, we repeat the entire procedure. Once the number of changed decisions is below the criterium, we stop the procedure.

Note that, at the rest point of the procedure described above, the necessary conditions that are used in the estimation of first-stage parameters hold. Hence, the procedure provides an equilibrium that is is internally consistent with our model. Note also that computational costs prohibit to consider all possible entry deviations by each firm, although we believe this results in no meaningful loss of generality. In this respect, the equilibrium reached by the above procedure is a Nash equilibrium within the classes of entry deviations considered. For example, we impose that no firm considers adding/deleting direct flights in more than one market at a time. After extensive experimentation, we concluded that no firm would best respond with more changes than that. However, recall that the airlines offer also one-stop flights and, thus, the total number of product changes at each iteration can be greater than one. Further, we allow the airlines add/delete direct flights only in the hub markets of American Airlines and US Airways. These markets represent around 20% of all segments in our sample and are presumably those where the DoJ would be most worried about potential anti-competitive effects of the merger.

5.4.3 Additional details on how the latent variables are imputed

To perform counterfactuals, we need a measure of the fixed cost shocks. Different approaches have been taken in the literature. For example, Wollmann (2018) draws the fixed cost shocks from a normal distribution with zero mean and variance equal to a fraction of the variance of the systematic fixed costs. Kuehn (2018) finds, for each market, the range of realisations of the fixed cost shock generating either entry or exit and takes the midpoint. We use a procedure that is similar in spirit to Kuehn (2018). In particular, when we observe airline f serving market $\{a, b\}$ with direct flights, we subsume that this choice must be profitable, giving us an upper bound for $\eta_{ab,f}$.[30] Then, we collect all the markets that firms choose not to serve with direct flights and that have a similar change in the congestion costs. These markets give us a vector of lower bounds. We take the 5th percentile of these lower bounds and use it as a lower bound for $\eta_{ab,f}$. Finally, we set $\eta_{ab,f}$ as the mid-point between the lower and upper bounds. A symmetric procedure is implemented when imputing the fixed cost shocks for the markets that are not served by airline f. However, instead of the 5th percentile, we take the 95th percentile. When simulating the merger, the merged entity takes on the mean value of the fixed cost shocks of the merging firms.

To perform counterfactuals, we also need to measure the demand and marginal cost shocks of the products of the merged firm. We draw these from the joint distribution of the merged entity.

[30] Consider market $\{a, b\}$ and airline f. Suppose that $G_{ab,f} = 1$ in the observed network. Let

$$\Delta\Pi_{(-ab),f} - \Delta\overline{\text{FC}}^{\top}_{(-ab),f}\gamma - \eta_{ab,f},$$

be the deviation profits of firm f as discussed in Section 4.2, for any $\gamma \in \Gamma_I$. By revealed preference, it must be that

$$\Delta\Pi_{(-ab),f} - \Delta\overline{\text{FC}}^{\top}_{(-ab),f}\gamma - \eta_{ab,f} \geq 0,$$

or, equivalently,

$$\eta_{f,ab} \leq \Delta\Pi_{(-ab),f} - \Delta\overline{\text{FC}}^{\top}_{(-ab),f}\gamma.$$

5.4.4 Results

We show the impact of the merger and bankruptcy scenarios in Table 6. The first row gives the total consumer surplus, the second row gives the average consumer surplus across hub markets. The second column, under fixed networks, provides the interval between the base-case, the best-case, and the update scenarios and the median value. The other columns, under reoptimised networks, provide the interval across draws of parameter values from the estimated identified set and the median value. In the following, we base our discussion on the median values.

Table 6: Consumer surplus across different scenarios

	Before	**Merger**			**Bankruptcy**	
		Networks fixed	Networks vary, no remedies	Networks varies, with remedies	Networks fixed	Networks vary
Total	2807.06	+0.08	-2.94	+2.15	-12.1	-5.5
		[-0.47, +3.4]	[-8.18, +2.28]	[-3.18, +6.61]		[-9.55, +0.97]
Mean	4.09	+0.08	-4.1	+0.88	-11.84	-5.78
		[-0.47, +3.4]	[-9.11, +0.96]	[-4.57, +5.23]		[-9.55, -0.05]

Note:
Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Mean consumer surplus is total consumer surplus divided by the number of markets out of hubs. Percentage differences with respect to Before are reported.

When comparing the "Networks fixed" to the "Networks vary" scenarios, we see that assuming no changes in networks after a merger or bankruptcy leads to misleading conclusions. In the merger case, the "Networks fixed" scenario predicts little changes in consumer surplus. However, when the firms are allowed to reoptimise their networks, we see that the merger absent any remedies would have led to a drop in total consumer surplus of around 2.94%. When the remedies are further taken into account, we register an increase in consumer surplus of around 2.15%, which highlights that the remedies were warranted. The difference between the "Networks fixed" and the "Networks vary" scenario is even stronger in the bankruptcy case. Here, not allowing for network re-alignment leads to a prediction of a drop in consumer surplus o around 12%, whereas letting networks re-adjust reduces the loss in consumer surplus to around 5.5%. The main reason for the smaller drop in consumer surplus is that firms enter market following the disappearance of American, partially canceling out the negative effects of the bankruptcy.

Comparing the effects of the merger and the bankruptcy across the scenarios in which we make use of our full model, we can see that the bankruptcy would have hurt consumer more than the merger. Two reasons can explain this fact. First, the firm disappearing operates a hub-and-spoke network, so consumers will be hurt a lot in hub airports and other airlines cannot compensate for the loss of access to this network. Second, a merger allows competition authorities to shape market structure and outcomes by imposing remedies. The ability to do so presents a non-negligible advantage of allowing a merger under conditions, compared to the bankruptcy of a large hub-and-spoke carrier. We see that our counterfactual suggests that the merger is less harmful than the bankruptcy absent remedies and even slightly beneficial to consumers with remedies taken into account.

Table 7: Changes in direct flights offered at hub airports of merging firm due to the merger

	Pre-merger			Post-merger					
				Networks vary, no remedies			**Networks vary, remedy**		
	AA/US	Others	Presence	AA/US	Others	Presence	AA/US	Others	Presence
AA hubs									
DFW	68	55	1.6	70	59	1.56	70	59	1.56
				[59, 70]	[53, 89]	[1.48, 1.84]	[60, 70]	[53, 89]	[1.48, 1.83]
LAX	28	90	1.51	27	128	1.9	30	128	1.95
				[24, 29]	[104, 132]	[1.64, 1.98]	[29, 31]	[114, 133]	[1.78, 2]
ORD	59	129	2.35	58	98	1.9	62	144	2.55
				[56, 61]	[90, 161]	[1.82, 2.67]	[61, 66]	[96, 161]	[1.93, 2.71]
MIA	40	51	1.17	18	52	0.84	40	51	1.11
				[13, 22]	[50, 57]	[0.79, 0.95]	[40, 40]	[49, 58]	[1.09, 1.2]
JFK	41	113	2	29	118	1.76	43	118	1.96
				[11, 32]	[113, 159]	[1.57, 2.29]	[43, 44]	[112, 158]	[1.89, 2.46]
US hubs									
CLT	61	41	1.29	63	35	1.2	63	33	1.17
				[61, 64]	[30, 44]	[1.11, 1.32]	[63, 64]	[24, 44]	[1.06, 1.32]
PHX	41	74	1.49	41	64	1.28	41	62	1.26
				[40, 41]	[38, 74]	[0.96, 1.39]	[41, 41]	[38, 73]	[0.96, 1.39]
DCA	40	130	2.16	49	153	2.39	39	141	2.24
				[39, 60]	[133, 161]	[2.2, 2.55]	[10, 51]	[132, 160]	[1.82, 2.48]
PHL	52	53	1.33	50	53	1.27	55	54	1.33
				[43, 52]	[49, 59]	[1.15, 1.36]	[54, 56]	[50, 64]	[1.28, 1.46]
Total									
Total	430	736	1.66	409	797	1.63	444	783	1.67
				[350, 422]	[690, 880]	[1.48, 1.77]	[403, 460]	[696, 906]	[1.54, 1.82]

Note:
Median outcomes reported, with minimum aand maximum outcome in brackets.

Table 8: Changes in direct flights offered at hub airports of American due to the bankruptcy

	Before			After bankruptcy	
	AA	Others	Presence	Others	Presence
AA hubs					
DFW	68	63	1.6	75	0.91
				[75, 110]	[0.91, 1.34]
LAX	26	96	1.51	140	1.73
				[134, 155]	[1.65, 1.91]
ORD	59	134	2.35	168	2.05
				[159, 172]	[1.94, 2.1]
MIA	39	57	1.17	59	0.72
				[56, 72]	[0.68, 0.88]
JFK	29	135	2	149	1.82
				[142, 190]	[1.73, 2.32]
Total					
Total	246	973	1.66	1082	1.47
				[1012, 1224]	[1.38, 1.66]

Tables 7 and 8 show the changes in the number of direct flights offered before and after the merger and bankruptcy, respectively. Looking at the last row in Table 7, we see that the merged entity reduces the operations at the hubs in reaction to the merger, whereas other firms expand at the hubs. The variable Presence in columns 3, 6, and 9 reports the average number of main carriers (American, Delta, United, US, Southwest) present across all possible markets out of a given hub. The value of the variable Presence drops slightly from 1.66 to 1.63 after the merger, suggesting that the merger leads to slightly less competition in hub markets. When looking at what happens in specific cities, we can see that in the "No remedies" scenario, the merged entity reduces operations in Miami (MIA) and New York (JFK) substantially, without substantially entry of the competing airlines. In the "With remedies" scenario, the merged entity serves a larger network compared to both before the merger and to the "No remedies" scenario. The expansion of other carriers is less substantial than in the "No remedies" scenario. However, the value of the variable "Presence" is now 1.67, essentially as before the merger. Overall, Table 7 suggests that the remedies were successful in preventing a large reduction in the post-merger network of the merged entity.

In contrast, Table 8 shows that post-bankruptcy, the level of operations at American's hubs decreases substantially. Even though the remaining firms increase the number of direct flights by more than 100, they are not able to compensate for the disappearance of American (with the exception of Los Angeles). The value of the variable "Presence" confirms this finding, as it drops from 1.66 to 1.47.

Table 9: Change in consumer surplus at hub airports of merging firms

	Pre-merger	Post-merger		
		Networks fixed	Networks vary, no remedies	Networks vary, remedy
AA hubs				
DFW	341.22	-1.48	+6.28	+8.28
		[-2.94, +7.04]	[+1.12, +15.15]	[+3.28, +16.65]
LAX	520.29	+0.01	+6.06	+9.72
		[-0.32, +2.44]	[-2.44, +7.76]	[+3.17, +11.33]
ORD	485.16	+0.46	-16.17	+2.84
		[-0.29, +4.07]	[-18.34, +4.2]	[-14.52, +6.71]
MIA	314.55	-0.34	-29.68	-19.71
		[-0.51, +4.56]	[-31.76, -26.24]	[-20.68, -17.1]
JFK	631.27	-0.3	-21.65	-14.39
		[-0.43, +2.19]	[-26.6, -11.63]	[-15.55, -4.7]
US hubs				
CLT	134.27	-1.52	+10.29	+7.81
		[-2.56, +3.27]	[+3.3, +14.43]	[+1.79, +12.44]
PHX	237.55	-0.64	-20.99	-19.3
		[-2.48, +3.66]	[-33.98, -19.12]	[-32.53, -17]
DCA	428.19	-0.29	+12.68	+12.72
		[-0.62, +2.26]	[+7, +17.07]	[+1.43, +18.49]
PHL	213.55	-0.91	+1.31	+8.48
		[-1.01, +2.98]	[-6.46, +7.43]	[+2.14, +13.58]

Note:
Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Mean consumer surplus is total consumer surplus divided by the number of markets out of hubs. Percentage differences with respect to Before are reported.

Tables 9 and 10 show changes in consumer surplus at the hub level. We see that the impact of the merger is quite heterogeneous across hubs, with consumers in some cities benefiting a lot and others suffering a lot. Not surprisingly, Miami and New York are among the hardest hit, mainly due to reduced operations of the merged entity. Similarly, consumer surplus drops substantially in Chicago (ORD) Phoenix (PHX). All three cities were targeted by the remedies, suggesting the concern of the state Attorney Generals was warranted. When comparing the "No remedies" scenario to the "With remedies" scenario, we see that the drop in consumer surplus in Miami and New York becomes less pronounced and even turns into a gain in Chicago, suggesting that the remedies were helpful in at least mitigating consumer harm.

Table 10: Change in consumer surplus at hub airports of American due to the bankruptcy

	Before	After bankruptcy	
		Networks fixed	Networks vary
AA hubs			
DFW	341.22	-34.37	-16.4
			[-17.37, +0.13]
LAX	520.29	-10.86	+7.1
			[+3.85, +11.8]
ORD	485.16	-16.85	-11.37
			[-16.71, -10.05]
MIA	314.55	-15.33	-30.2
			[-32.61, -25.39]
JFK	631.27	-9.13	-18.36
			[-21.04, -7.68]

Note:
Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Mean consumer surplus is total consumer surplus divided by the number of markets out of hubs. Percentage differences with respect to Before are reported.

In contrast, as Table 10 suggests, the picture is bleaker in the case of American's bankruptcy. With the exception of Los Angeles - where other firms enter a lot- consumer surplus drops substantially. Again, Miami and New York suffer the most. It is also noteworthy that Dallas/Fort Worth (DFW), American's biggest hub, now sees consumer surplus drop by around 16%. Comparing the impact on consumer surplus on hubs between the merger and the bankruptcy of American underlines the negative effects of removing a large hub-and-spoke airline from the market: consumers suffer for no longer having access to a large network and hub amenities and other airlines struggle to fill the void left behind by the bankruptcy.

Finally, Table 11 shows the merger's and bankruptcy's impact on prices, markups, and marginal costs. We observe a drop in prices in response to both the merger and the bankruptcy (with the exception of one-stop flights offered by other airlines). At the same time, marginal cost also falls quite a bit. For the merging entity, the drop in marginal cost is due to a larger network post-merger. Even though their post-merger network is smaller than their combined pre-merger network, the post-merger network is still larger than the individual per-merger networks, allowing for marginal cost savings. Similarly, the other carriers increase their operations substantially both in response to a merger and a bankruptcy, leading to marginal cost savings from a larger network and to lower prices. Interestingly, the remedies reduce the increase in

Table 11: Changes in prices, marginal cost, and markups

	Before	After		
		Merger		**Bankruptcy**
		No remedies	With remedies	
AA: Direct				
Price	406.24	-6.67	-6.56	
		[-6.96, -6.15]	[-7.08, -5.93]	
Marginal Cost	276.7	-11.54	-10.76	
		[-11.82, -11.29]	[-11.19, -9.5]	
Markup	129.54	+3.84	+2.53	
		[+3, +5.31]	[+0.52, +3.71]	
Others: Direct				
Price	413.19	-1.63	-4.01	-2.85
		[-4.18, +0.24]	[-4.98, -0.77]	[-3.9, -1.88]
Marginal Cost	291.6	-4.42	-6.38	-5.68
		[-7.61, -1.14]	[-7.95, -1.77]	[-7.28, -4.37]
Markup	121.59	+3.85	+1.74	+3.73
		[+3.23, +5.06]	[+1.37, +2.69]	[+3.42, +4.1]
AA: One-stop				
Price	466.39	-6.37	-7.06	
		[-7.2, -5.4]	[-7.58, -6.68]	
Marginal Cost	351.28	-10.94	-11.4	
		[-12.15, -9.57]	[-12.05, -10.42]	
Markup	115.11	+8.1	+6.51	
		[+5.51, +9.36]	[+3.28, +7.4]	
Others: One-stop				
Price	416.12	+2.41	+1.75	+1.47
		[+1.32, +3.17]	[+0.97, +2.6]	[+1.13, +1.82]
Marginal Cost	301.18	+2.71	+2.53	+1.24
		[+1.24, +3.81]	[+1.35, +3.65]	[+0.71, +1.66]
Markup	114.94	+1.1	-0.26	+2.18
		[+0.7, +2.75]	[-0.74, +0.82]	[+1.91, +2.62]

markups for all firms and products. The reason may be increased competition, especially since American faces pressure to raise markups as the remedies lead to a larger network with higher fixed costs.

5.4.5 Discussion

Overall, our counterfactual exercise suggests that the merger had a small positive impact on consumer surplus. However, the overall effect hides substantial heterogeneity across cities: consumers in some hub markets saw a large decrease in consumer surplus that was mitigated, but not reversed by the remedies imposed. Further, our results suggest that letting American and US Airways merge was better than the bankruptcy and disappearance of American. Even though the remaining firms enter substantially in response to American disappearing, they cannot completely fill out the void left behind. We also find that the remedies that the merged entity agreed to and put a floor on levels of operation at the majority of hubs helped in mitigating harm to consumers and pushed the overall change in consumer surplus from slightly negative to slightly positive. The positive effect of these remedies shows an advantage of mergers over the disappearance of firms in especially hub-and-spoke networks: competition authorities can shape post-merger outcomes by imposing remedies.

6 Conclusions

We consider a two-stage model of airline competition where airlines design their route networks in the first stage and compete in prices in the second stage. We show identification of the second-stage parameters by following the standard approach for supply and demand models with differentiated products. We show (set) identification of the first-stage parameters by adopting a revealed preference perspective and exploiting inequalities derived from equilibrium implications. We estimate our model using data on the US airline industry from the second quarter of 2011. In the first stage, we find that fixed costs increase in the number of destinations reachable from hub airports. On the supply side of the second stage, we find that marginal costs decrease in the number of flights (direct or one-stop) offered out of the endpoints. On the demand side of the second stage, we find that consumer utility increases in the number of direct connections that can be reached from the endpoints. We then use the results to evaluate the merger between American Airlines and US Airways which did occur at a later date. We find that remedies imposed on the merging parties turned a slight decrease in consumer surplus into a slight increase. At the most negatively affected hubs, the remedies helped to contain consumer harm. We also compare the merger to a hypothetical bankruptcy and disappearance of American Airlines. We find that the bankruptcy leads to more rival firm entry than the merger. However, the loss of access to a large network leads to substantial loss in consumer surplus at American's hubs. Other firms are not able to fill this void completely. Overall, consumer surplus is projected to decrease by more than in the merger case.

Our work leaves several avenues for future research. In our model, we abstract from capacity and frequency choices which are an important point of concern both to consumers as well as antitrust authorities. Extending our framework to include these kind of choices is possible, albeit at the cost of increasing the computational burden. Similarly, endogenising hub decisions would make it possible to analyse deeper changes in network structure, such as the choice between a hub-and-spoke and a point-to-point network. Assuming exogenous hubs prevents firms from creating new hubs, which may be especially interesting to consider in the case where we let American Airlines disappear. However, we believe that the assumption of exogenous hubs is reasonable in our setting for two reasons: First, the other airlines already have large hub-and-spoke networks, making it very costly to create additional hubs. Second, the trend in the US Airline industry has been to reduce the number of hubs, rather than increase them (see also Berry and Jia, 2010). Finally, we do not consider all remedies that were imposed on the new merged entity. For instance, the US Department of Justice ordered the merged entity to give up slots and gates at several airports in order to facilitate the entry of new airlines. Adding capacity and frequency choices to our model would allow for a detailed evaluation of these remedies.

We are currently working on inference for the first-stage parameters and on further robustness checks for the counterfactual part.

References

Jason Abaluck and Abi Adams. What do consumers consider before they choose? Identification from asymmetric demand responses. *Quarterly Journal of Economics (forthcoming)*, 2020.

Victor Aguirregabiria and Chun-Yu Ho. A dynamic oligopoly game of the US airline industry: Estimation and policy experiments. *Journal of Econometrics*, 168(1):156–173, 2012.

Donald WK Andrews and Soonwoo Kwon. Inference in moment inequality models that is robust to spurious precision under model misspecification. Working Paper, 2019.

Isaiah Andrews, Jonathan Roth, and Ariel Pakes. Inference for linear conditional moment inequalities. NBER Working Papers 26374, 2019.

Levon Barseghyan, Maura Coughlin, Francesca Molinari, and Joshua C Teitelbaum. Heterogeneous choice sets and preferences. *Econometrica (forthcoming)*, 2020.

C Lanier Benkard, Aaron Bodoh-Creed, and John Lazarev. Simulating the Dynamic Effects of Horizontal Mergers: U.S. Airlines. Working Paper, 2020.

Arie Beresteanu and Francesca Molinari. Asymptotic properties for a class of partially identified models. *Econometrica*, 76(4):763–814, 2008.

Steven T Berry. Airport presence as product differentiation. *American Economic Review*, 80 (2):394–399, 1990.

Steven T Berry. Estimation of a model of entry in the airline industry. *Econometrica*, 60(4): 889–917, 1992.

Steven T Berry. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262, 1994.

Steven T Berry and Philip A Haile. Identification in differentiated products markets using market level data. *Econometrica*, 82(5):1749–1797, 2014.

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

Steven T Berry and Peter Reiss. Empirical models of entry and market structure. *Handbook of Industrial Organization*, 3:1845–1886, 2007.

Steven T Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890, 1995.

Steven T Berry, Michael Carnall, and Pablo T Spiller. Airline hubs: costs, markups and the implications of customer heterogeneity. NBER Working Papers 5561, 1996.

Steven T Berry, Oliver B Linton, and Ariel Pakes. Limit theorems for estimating the parameters of differentiated product demand systems. *The Review of Economic Studies*, 71(3):613–654, 2004.

Steven T Berry, Martin Gaynor, and Fiona Scott Morton. Do increasing markups matter? Lessons from empirical industrial organization. *Journal of Economic Perspectives*, 33(3): 44–78, 2019.

Christian Bontemps, Thierry Magnac, and Eric Maurin. Set identified linear models. *Econometrica*, 80(3):1129–1155, 2012.

Severin Borenstein. Hubs and high fares: dominance and market power in the U.S. airline industry. *The RAND Journal of Economics*, 20(3):344–365, 1989.

Severin Borenstein. The evolution of U.S. airline competition. *Yale Journal on Regulation*, 4 (2):45–73, 1992.

Timothy F Bresnahan. Competition and collusion in the American automobile industry: The 1955 price war. *The Journal of Industrial Economics*, 35(4):457–482, 1987.

Timothy F Bresnahan and Peter C Reiss. Entry in monopoly market. *The Review of Economic Studies*, 57(4):531–553, 1990.

Timothy F Bresnahan and Peter C Reiss. Empirical models of discrete games. *Journal of Econometrics*, 48(1):57–81, 1991.

Jan K Brueckner and Pablo T Spiller. Economies of traffic density in the deregulated airline industry. *The Journal of Law & Economics*, 37(2):379–415, 1994.

Jan K Brueckner, Nichola J Dyer, and Pablo T Spiller. Fare determination in airline hub-and-spoke networks. *The RAND Journal of Economics*, 23(3):309–333, 1992.

Richard V Butler and John H Houston. How contestable are airline markets. *Atlantic Economic Journal*, 17:27–35, 1989.

Kenneth Button, Peter Forsyth, and Peter Nijkamp. *Air Transport*. Edward Elgar, 2000.

Douglas W Caves, Laurits R Christensen, and Michael W Tretheway. Economies of density versus economies of scale: why trunk and local service airline costs differ. *The RAND Journal of Economics*, 15(4):471–489, 1984.

Arun Chandrasekhar. Econometrics of network formation. In *The Oxford Handbook of the Economics of Networks*, pages 303–357. Oxford University Press Oxford, 2016.

Arun G Chandrasekhar, Victor Chernozhukov, Francesca Molinari, and Paul Schrimpf. Best linear approximations to set identified functions: with an application to the gender wage gap. NBER Working Papers 25593, 2019.

Federico Ciliberto and Elie Tamer. Market structure and multiple equilibria in airline markets. *Econometrica*, 77(6):1791–1828, 2009.

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

Federico Ciliberto, Charles Murry, and Elie Tamer. Market structure and competition in airline markets. *Journal of Political Economy (forthcoming)*, 2021.

Somnath Das. Effect of merger on market price and product quality: American and US Airways. *Review of Industrial Organisation*, 55:339–374, 2019.

Aureo de Paula. Econometrics of network models. In *Advances in Economics and Econometrics: Theory and Applications, Eleventh World Congress*, pages 268–323. Cambridge University Press Cambridge, 2017.

Aureo de Paula. Econometric models of network formation. *Annual Review of Economics*, 12: 775–799, 2020.

Alon Eizenberg. Upstream Innovation and Product Variety in the U.S. Home PC Market. *Review of Economic Studies*, 81(3):1003–1045, 2014.

Joseé-Antonio Espín-Sánchez, Álvaro Parra, and Yuzhou Wang. Equilibrium uniqueness in entry games with private information. Working Paper, 2021.

William N Evans and Ioannis N Kessides. Localized market power in the US airline industry. *The Review of Economics and Statistics*, 75(1):66–75, 1993.

Xiaowen Fu, Huan Jin, Shaoxuan Liu, Tae H Oum, and Jia Yan. Exploring network effects of point-to-point networks: An investigation of the spatial patterns of southwest airlines' network. *Transport Policy*, 76:36–45, 2019.

Bulat Gafarov. Inference in high-dimensional set-identified affine models. arXiv Working Papers 1904.00111, 2019.

Amit Gandhi, Zhentong Lu, and Xiaoxia Shi. Estimating demand for differentiated products with zeroes in market share data. Working Paper, 2019.

Austan Goolsbee and Chad Syverson. How do incumbents respond to the threat of entry? Evidence from the major airlines. *Quarterly Journal of Economics*, 123(4):1611–1633, 2008.

Bryan Graham and Aureo de Paula. *The Econometric Analysis of Network Data*. Academic Press, 2020.

Bryan S Graham. Methods of identification in social networks. *Annual Review of Economics*, 7(1):465–485, 2015.

Cristina Gualdani. An econometric model of network formation with an application to board interlocks between firms. *Journal of Econometrics (forthcoming)*, 2021.

Tim Hellmann. On the existence and uniqueness of pairwise stable networks. *International Journal of Game Theory*, 42:211–237, 2013.

Jean-Baptiste Hiriart-Urruty and Claude Lemaréchal. *Convex Analysis and Minimization Algorithms*. Springer-Verlag, 1996.

Thomas J Holmes. The diffusion of wal-mart and economies of density. *Econometrica*, 79(1): 253–302, 2011.

Jean-François Houde, Peter Newberry, and Katja Seim. Economies of Density in E-Commerce: A Study of Amazon's Fulfillment Center Network. NBER Working Papers 23361, 2017.

Matthew O Jackson and Alison Watts. The existence of pairwise stable networks. *Seul Journal of Economics*, 14(3):299–321, 2001.

Matthew O Jackson and Alison Watts. The evolution of social and economic networks. *Journal of Economic Theory*, 106(2):265–295, 2002.

Matthew O Jackson and Asher Wolinsky. A strategic model of social and economic networks. *Journal of Economic Theory*, 71(1):44–74, 1996.

Hiroaki Kaido and Andres Santos. Asymptotically efficient estimation of models defined by convex moment inequalities. *Econometrica*, 82(1):387–413, 2014.

Adib Kanafani and Atef A Ghobrial. Airline hubbing - Some implications for airport economics. *Transportation Research Part A: General*, 19(1):15–27, 1985.

Joseph Kuehn. Spillovers from entry: the impact of bank branch network expansion. *The RAND Journal of Economics*, 49(4):964–994, 2018.

Robin S Lee and Ariel Pakes. Multiple equilibria and selection by learning in an applied setting. *Economics Letters*, 104(1):13–16, 2009.

Micheal P Leung. Dependence-robust inference using resampled statistics. Working Paper, 2020.

Micheal P Leung. Network cluster-robust inference. Working Paper, 2021.

Michael E Levine. Airline competition in deregulated markets: theory, firm strategy, and public policy. *Journal of Economic Perspective*, 6:393–494, 1987.

Sophia Ying Li, Joe Mazur, Yongjoon Park, James W Roberts, Andrew Sweeting, and Jun Zhang. Repositioning and Market Power After Airline Mergers. Working Paper, 2019.

Israel Mark, Bryan Keating, Daniel L Rubinfeld, and Bobby Willig. Airline network effects and consumer welfare. *Review of Network Economics*, 12(3):287–322, 2013.

Antonio Mele. A structural model of dense network formation. *Econometrica*, 85(3):825–850, 2017.

Yuhei Miyauchi. Structural estimation of pairwise stable networks with nonnegative externality. *Journal of Econometrics*, 195(2):224–235, 2016.

Dov Monderer and Lloyd S Shapley. Potential games. *Games and Economic Behavior*, 14(1): 124–143, 1996.

Steven A Morrison and Clifford Winston. *The economic Effects of Airline Deregulation*. Washington, DC: Brookings Institution, 1986.

Steven A Morrison and Clifford Winston. Enhancing the performance of the deregulated air transport system. *Brookings Papers on Economic Activity. Microeconomics*, 1989:61–123, 1989.

Giovanni Nero. A note on the competitive advantage of large hub-and-spoke networks. *Transportation Research Part E: Logistics and Transportation Review*, 35(4):225–239, 1999.

Volker Nocke and Nicolas Schutz. Multiproduct-firm oligopoly: An aggregative games approach. *Econometrica*, 86(2):523–557, 2018.

Tae Hoon Oum, Anming Zhang, and Yimin Zhang. Airline network rivalry. *Canadian Journal of Economics*, 28(4a):836–857, 1995.

Ariel Pakes. Alternative models for moment inequalities. *Econometrica*, 78(6):1783–1822, 2010.

Ariel Pakes, Jack Porter, Kate Ho, and Joy Ishii. Moment inequalities and their application. *Econometrica*, 83(1):315–334, 2015.

Yongjoon Park. Structural remedies in network industries: An assessment of slot divestitures in the American Airlines/US Airways merger. Working Paper, 2020.

Craig Peters. Evaluating the performance of merger simulation: Evidence from the U.S. airline industry. *The Journal of Law & Economics*, 49(2):627–649, 2006.

Peter C Reiss and Pablo T Spiller. Competition and entry in small airline markets. *The Journal of Law & Economics*, 32(2):S179–S202, 1989.

Aisling Reynolds-Feighan. Traffic distribution in low-cost and full-service carrier networks in the US air transportation market. *Journal of Air Transport Management*, 7(5):265–275, 2001.

Joseph Anthony Rossetti. *Product Variety in the US Yogurt Industry*. PhD thesis, The Ohio State University, 2018.

Alexander Shapiro, Darinka Dentcheva, and Andrzej Ruszczyński. *Lectures on Stochastic Programming: Modelling and Theory*. SIAM, 2014.

Shuyang Sheng. A structural econometric analysis of network formation games through subnetworks. *Econometrica*, 88(5):1829–1858, 2020.

Jörg Stoye. More on confidence intervals for partially identified parameters. *Econometrica*, 77 (4):1299–1315, 2009.

Donald M Topkis. Equilibrium points in nonzero-sum n-person submodular games. *SIAM Journal of Control and Optimization*, 17(6):773–787, 1979.

Thomas G Wollmann. Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review*, 108(6):1364–1406, 2018.

Zhe Yuan. Network competition in the airline industry: A framework for empirical policy analysis. Working Paper, 2020.

A Existence of Nash equilibrium networks

As discussed in Section 3.3, our methodology does not require the existence of Nash equilibrium networks for every possible parameterization and realization of the variables. Formally proving the existence of Nash equilibrium networks is a difficult and open theoretical question, due to the presence of spillover effects in entry decisions across markets on the demand, marginal cost, and fixed cost sides.

Berry (1992) establishes equilibrium existence in one of the first empirical models of entry that accounts for the strategic interactions among the airlines in the second-stage pricing game. His proof relies on the assumption that the entry decisions are independent across markets and, hence, it is not applicable to our case. Another approach that has been used in the literature to show existence of Nash equilibrium networks consists of representing the model as a potential game (Monderer and Shapley, 1996). This seems to be a feasible exercise only when the payoff function is additive separable in the linking decisions and linear in the spillover effects (for example, Mele, 2017), which is not the case here. Alternatively, it is possible to show the existence of Nash equilibrium networks by assuming that the game is supermodular (for example, Miyauchi, 2016; Sheng, 2020), in order to rely on the fixed-point theorem for isotone mappings (Topkis, 1979). However, supermodularity does not hold in our setting due to the second-stage competition among the airlines. Finally, one could attempt to decompose the original game into "local" games such that the original game is in equilibrium if and only if each local game is in equilibrium (Gualdani, 2021). In turn, the existence of an equilibrium in each local game - which is typically easier to be established - is sufficient for the existence of an equilibrium in the original game. However, the classes of spillover effects considered in our model do not allow us to implement such a decomposition.

It should also be noticed that the revealed-preference inequalities, which we use to bound the first-stage parameters, resemble the notion of pairwise stability used in network theory, where no players have profitable deviations by adding or removing a link (Jackson and Wolinsky, 1996). Therefore, we have explored the possibility of establishing an equilibrium in entry decisions weaker than Nash equilibrium, along the lines of pairwise stability. In particular, according to Jackson and Watts (2002), for any payoff function there is either a pairwise stable network or a closed cycle.[31] A typical way used in the literature to exclude the presence of closed cycles consists of showing that the model can be represented as a potential game, as discussed in Jackson and Watts (2001) and Hellmann (2013). As earlier, however, this requires the payoff function to be additive separable in the linking decisions and linear in the spillover effects (for example, Sheng, 2020), which is not our case.[32]

[31] A closed cycle represents a situation in which individuals never reach a stable state and constantly switch between forming and severing links.

[32] One may wonder whether allowing for *private* fixed cost shocks could simplify the existence proof. Espín-

B Inference

B.1 Inference on the second-stage parameters

We conduct inference on θ_0 via GMM and under the assumption that the number of markets goes to infinity. Formally, we consider the moment conditions of Section 4.1 and use their sample analogues to construct a GMM objective function which should be minimised with respect to $\theta \in \Theta$:

$$Q(\theta) = M(\theta)' A M(\theta), \tag{B.1}$$

where

$$M(\theta) \equiv \begin{pmatrix} \frac{1}{|\mathcal{J}|} \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{J}_t} [\tau_{j,t}(X_t^{\oplus}, W_t^{\oplus}, M, s_t^{\oplus}, P_t^{\oplus}, G; \theta_0) \times z_{j,t,1}(X_t^{\oplus}, W_t^{\oplus})] \\ \frac{1}{|\mathcal{J}|} \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{J}_t} [\tau_{j,t}(X_t^{\oplus}, W_t^{\oplus}, M, s_t^{\oplus}, P_t^{\oplus}, G; \theta_0) \times z_{j,t,2}(X_t^{\oplus}, W_t^{\oplus})] \\ \vdots \\ \frac{1}{|\mathcal{J}|} \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{J}_t} [\tau_{j,t}(X_t^{\oplus}, W_t^{\oplus}, M, s_t^{\oplus}, P_t^{\oplus}, G; \theta_0) \times z_{j,t,\mathrm{L}}(X_t^{\oplus}, W_t^{\oplus})] \end{pmatrix},$$

$\mathcal{J} \equiv \cup_{t\in\mathcal{T}} \mathcal{J}_t$ is the set of all offered products, and A is an appropriate $2\mathrm{L} \times 2\mathrm{L}$ weighting matrix. In particular, A is computed via the usual two-step procedure: first, we estimate the parameters using the optimal weighting matrix under conditional homoskedasticity; second, we use the obtained estimates to construct the optimal weighting matrix under conditional heteroskedasticity and re-estimate the parameters.

Note that we estimate the demand and supply sides jointly. We could also estimate the demand and supply sides separately, by following a two-step procedure: first, the demand parameters are estimated; then, these estimates are used to compute the markups; lastly, the resulting marginal costs are regressed on the observed marginal cost shifters to obtain the supply parameters. We have decided to estimate the demand and supply sides jointly because it allows us to take into account the potential correlation between the demand and supply moments and, hence, obtain more precise estimates, as discussed in Berry et al. (1995). Further, given that we have a computationally "light" demand specification, the additional cost of estimating the demand and supply sides jointly is negligible.

Finally, we can account for the non i.i.d.ness of observations across markets by using HAC or cluster-robust standard errors (Leung, 2021).

Sánchez, Parra, and Wang (2021) prove equilibrium existence in a class of entry model where the firms have some private information at the entry stage. However, the class of entry models they consider do not allow for multi-product firms and for spillover effects in entry decisions across markets. Further, in our setting, we view more reasonable to assume that the fixed cost shocks are common knowledge among the airlines, as discussed in Section 3.2.

B.2 Inference on the first-stage parameters

Following Section 4.2, the vector of first-stage parameters, γ_0, is set identified by $\mathrm{N}\times(\mathrm{R}_+ + \mathrm{R}_-)$ moment inequalities, where R_+ is the number of instruments available for the class of deviations "$(+ab)$" for each firm, R_- is the number of instruments available for the class of deviations "$(-ab)$" for each firm, and N is the number of firms. These moment inequalities are

$$\begin{aligned}&\mathbb{E}[Z^{r+}_{(+ab),f} \times (\Delta\Pi_{(+ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(+ab),f}\ \gamma_0)|G_{ab,f} = 0] \geq 0,\\ &\mathbb{E}[Z^{r-}_{(-ab),f} \times (\Delta\Pi_{(-ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(-ab),f}\ \gamma_0)|G_{ab,f} = 1] \geq 0,\\ &r_+ = 1,\dots,\mathrm{R}_+, \quad r_- = 1,\dots,\mathrm{R}_-, \quad f = 1,\dots,\mathrm{N},\end{aligned}$$

where $Z^{r+}_{(+ab),f}, Z^{r-}_{(-ab),f}$ are the instruments, $\Delta\Pi_{(+ab),f}, \Delta\Pi_{(-ab),f}$ are the differences in the expected second-stage profits, and $\Delta\overline{\mathrm{FC}}^{\top}_{(+ab),f}\ \gamma_0, \Delta\overline{\mathrm{FC}}^{\top}_{(-ab),f}\ \gamma_0$ are the differences in the systematic fixed costs. Further, it is useful to rewrite the above moment inequalities as unconditional moment inequalities,

$$\begin{aligned}&\mathbb{E}[(1-G_{ab,f}) \times Z^{r+}_{(+ab),f} \times (\Delta\Pi_{(+ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(+ab),f}\ \gamma_0)] \geq 0,\\ &\mathbb{E}[G_{ab,f} \times Z^{r-}_{(-ab),f} \times (\Delta\Pi_{(-ab),f} - \Delta\overline{\mathrm{FC}}^{\top}_{(-ab),f}\ \gamma_0)] \geq 0,\\ &r_+ = 1,\dots,\mathrm{R}_+, \quad r_- = 1,\dots,\mathrm{R}_-, \quad f = 1,\dots,\mathrm{N}.\end{aligned} \tag{B.2}$$

The moment inequalities in (B.2) are linear in γ_0. Therefore, the identified set for γ_0, Γ_I, is a convex polytope. We assume that Γ_I is nonempty and bounded. The non-emptiness of Γ_I means that our structural model is well-specified and the instruments are valid. Andrews and Kwon (2019) propose a test for misspecification which could be used here. The boundedness of Γ_I means that, within the classes of deviations considered, the instruments capture sufficient variations in profits relative to the support of the first-stage shocks.

Convexity has been proved to be a particularly attractive feature in the set identification literature (Beresteanu and Molinari, 2008; Bontemps, Magnac, and Maurin, 2012; Kaido and Santos, 2014). In fact, it often reduces the computational burden of estimation because the analysts can focus on estimating the support function of the identified set. The support function of Γ_I describes the distances of the supporting hyperplanes of Γ_I in each direction from the origin (Figure B.1). If the chosen direction, q, has its k-th component equal to 1 (resp., -1) and the other components equal to 0, then the support function of Γ_I in direction q is equal to the maximum (resp., minus the minimum) value of the k-th component of $\gamma \in \Gamma_I$.[33] Therefore, constructing a confidence interval for any component (or, any linear combination of components) of $\gamma \in \Gamma_I$ involves the estimation of the support function in two specific directions

[33] In particular, one can easily contruct an outer rectangular set of Γ_I by considering these two directions for each k-th component of $\gamma \in \Gamma_I$.

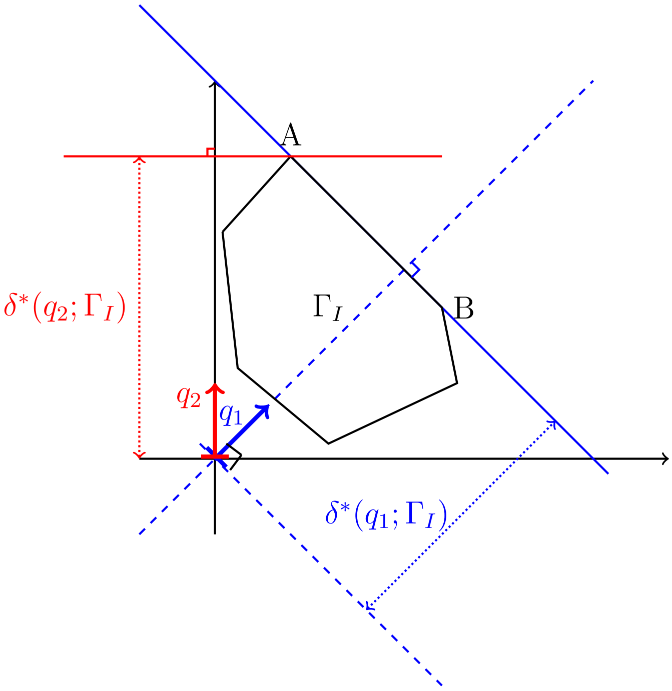


Figure B.1: The support function. A is a vertex. [AB] is an exposed face.

only.

In the next paragraphs, we elaborate on the above discussion. Our exposition is articulated in three steps. First, we argue that the support function of Γ_I can be rewritten as a linear program. Second, we derive the asymptotic distribution of the estimated support function of Γ_I. Third, we show how to use such asymptotic distribution to construct a confidence interval for any component of $\gamma \in \Gamma_I$.[34]

For easiness of exposition, in what follows we focus only on the moment inequalities of firm f and on the class of deviations "$(-ab)$":

$$\mathbb{E}[G_{ab,f} \times Z^{r_-}_{(-ab),f} \times (\Delta\Pi_{(-ab),f} - \Delta\overline{\mathrm{FC}}^\top_{(-ab),f}\ \gamma_0)] \geq 0, \quad r_- = 1, \ldots, \mathrm{R}_-. \tag{B.3}$$

We streamline the notation of (B.3) as

$$\mathbb{E}(Z_{r,m}A_m) - \mathbb{E}(Z_{r,m}B_m^\top)\gamma_0 \geq 0, \quad r = 1, \ldots, \mathrm{R},$$

where the subscript f is omitted; m is the market index and replaces the subscripts ab and $(-ab)$; $Z_{r,m}$ is the instrument and replaces $Z^{r_-}_{(-ab,f)}$; R is the number of instruments and replaces R_-; A_m is the difference in the expected second-stage profits multiplied by $G_{m,f}$ and replaces

[34] Andrews, Roth, and Pakes (2019) develop an inference method for a class of linear conditional moment inequalities. Our approach exploits the convexity of the identified set and allows us to easily incorporate the sampling uncertainty induced by the estimation of θ_0. Comparison with their approach is left to future research.

$G_{ab,f} \times \Delta\Pi_{(-ab),f}$; $B_m^\top \gamma_0$ is the difference in the systematic fixed cost multiplied by $G_{m,f}$ and replaces $G_{ab,f} \times \Delta\overline{\text{FC}}^\top_{(-ab),f}\ \gamma_0$.

Step 1 Following Hiriart-Urruty and Lemaréchal (1996) (p.235), the support function of Γ_I in any direction q can be written as a linear program in the standard form by strong duality:

$$\begin{aligned}\delta(q, \Gamma_I) &\equiv \sup_{\gamma\in\Gamma_I} q^\top \gamma, \\ &= \inf_{t\geq 0} \sum_{r=1}^{\text{R}} t_r \mathbb{E}(Z_{r,m}A_m), \\ &\quad \text{s.t.} \sum_{r=1}^{\text{R}} t_r \mathbb{E}(Z_{r,m}B_m) = q.\end{aligned} \tag{B.4}$$

The Lagrangian of (B.4) is equal to

$$L(t, \mu, \nu) \equiv \sum_{r=1}^{\text{R}} t_r \mathbb{E}(Z_{r,m}A_m) + \mu^\top \left(\sum_{r=1}^{\text{R}} t_r \mathbb{E}(Z_{r,m}B_m) - q \right) - \nu^\top t, \tag{B.5}$$

where $\mu = (\mu_1, \dots, \mu_{\text{N}+1})$ is the vector of Lagrange multipliers for the equality constraints; $\nu = (\nu_1, \dots, \nu_{\text{R}})$ is the vector of Lagrange multipliers for the inequality constraints. We denote by $\mathcal{T}$ and $\mathcal{M}$ the sets of t and μ satisfying the KKT conditions, respectively.

Step 2 We make the simplifying assumption that θ_0 is known by the researcher. In practice, θ_0 is estimated and we explain how to account for the resulting sampling uncertainty at the end of the section. We further make the simplifying assumption that we have an i.i.d. random sample of observations

$$\{Z_{1,m}, \dots, Z_{R,m}, A_m, B_m\}_{m=1}^{\text{M}},$$

where M is the number of sampled markets, and that the Central Limit Theorem applies to all the average of the quantities of interest. In practice, our observations are not i.i.d. across markets and one can account for it, for example, by implementing the resampling approach by Leung (2020).[35]

We introduce some notation that is useful for the next arguments. For every $r = 1, \dots, \text{R}$, let X_r be the limit in distribution of $\sqrt{\text{M}}(\frac{1}{\text{M}} \sum_{m=1}^{\text{M}} Z_{r,m}B_m - \mathbb{E}(Z_{r,m}B_m))$, i.e., a $(\text{N}+1)\times 1$ random normal vector centered with variance-covariance matrix $Var(Z_{r,m}B_m)$. Fix $j = 1, \dots \text{N} + 1$. Select the j-th element from X_r. Repeat this operation for each $r = 1, \dots, \text{R}$. Denote by X_j the resulting $\text{R}\times 1$ vector. Let W_r be the limit in distribution of $\sqrt{\text{M}}(\frac{1}{\text{M}} \sum_{m=1}^{\text{M}} Z_{r,m}A_m - \mathbb{E}(Z_{r,m}A_m))$, i.e., a random normal variable centered with variance $Var(Z_{r,m}A_m)$. As earlier, note that the

[35] Note that our methodology allows for the airlines' networks to be partially observed, provided that we fully observe the portions of the airlines' networks whose nodes are the cities at the endpoints of the sampled markets.

random variables $\{W_r\}_{r=1}^{\mathrm{R}}$ are correlated. Let the estimated identified set be defined as

$$\widehat{\Gamma}_I \equiv \left\{\gamma \in \Gamma : \frac{1}{\mathrm{M}} \sum_{m=1}^{\mathrm{M}} Z_{r,m} B_m^\top \gamma \leq \frac{1}{\mathrm{M}} \sum_{m=1}^{\mathrm{M}} Z_{r,m} A_m \text{ for } r = 1, \dots, \mathrm{R}\right\}.$$

Let the estimated support function in direction q be defined as

$$\hat{\delta}(q; \Gamma_I) \equiv \delta(q; \widehat{\Gamma}_I).$$

Theorem B.1 provides the asymptotic distribution of $\hat{\delta}(q; \Gamma_I)$ in any direction q.

Theorem B.1. Assume that the moments of order $2 + \tau$ of the random variables exist for some $\tau > 0$. Then:

(i) The estimated support function, $\hat{\delta}(q; \Gamma_I)$, tends to the true support function, $\delta(q; \Gamma_I)$, uniformly in q in the unit ball.

(ii) It holds that, uniformly in q,

$$\sqrt{\mathrm{M}} \left(\hat{\delta}(q; \Gamma_I) - \delta(q; \Gamma_I)\right) \xrightarrow[\mathrm{M}\to\infty]{d} \inf_{t \in \mathcal{T}} \sup_{\mu \in \mathcal{M}} \left[\sum_{r=1}^{\mathrm{R}} t_r W_r + \sum_{j=1}^{\mathrm{N}+1} \mu_j t^\top X_j\right].$$

If $\mathcal{T}$ and $\mathcal{M}$ are singleton, then the asymptotic distribution is normal. ◇

Proof. (i) comes from the convergence of $\widehat{\Gamma}_I$ to Γ_I with respect to the Hausdorff distance. (ii) comes from Shapiro, Dentcheva, and Ruszczyński (2014), Theorem 5.11, p.173. □

Step 3 Theorem B.1 provides the asymptotic distribution of the estimated support function in any direction. Hence, as discussed at the beginning of this section, it can be used to derive confidence regions for any component (or, any linear combination of components) of $\gamma \in \Gamma_I$. However, note that such asymptotic distribution depends on $\mathcal{T}$ and $\mathcal{M}$. If these sets are singleton, then the estimated support function is asymptotically normal, with a variance that can be estimated from the data. Unfortunately, these sets are not singleton in all directions q. For instance, consider the directions which correspond to the outer normal of an exposed face of Γ_I (e.g., q_1 in Figure B.1). This is a well-known problem in the set identification literature. One solution consists of smoothing Γ_I. Chandrasekhar, Chernozhukov, Molinari, and Schrimpf (2019) transform the explanatory variables into continuous ones by adding $\varepsilon N(0,1)$ to each discrete explanatory variable. Bontemps et al. (2012) and Gafarov (2019) perturb the support function by adding a penalty term.

Here, we follow Gafarov (2019)'s approach and add the penalty term $\varepsilon||\gamma||_2$ to the support function of Γ_I in any direction q:

$$\delta_\varepsilon(q, \Gamma_I) \equiv \sup_{\gamma \in \Gamma_I} q^\top \gamma - \varepsilon||\gamma||_2, \tag{B.6}$$

with $\epsilon > 0$ but small. Since $\varepsilon||\gamma||_2$ is strictly convex, (B.6) has a unique solution with respect to γ, for any direction q. In turn, by strong duality, it holds that

$$\begin{aligned} \delta_\varepsilon(q, \Gamma_I) = \inf_{t \geq 0} \sum_{r=1}^{\mathrm{R}} t_r \mathbb{E}(Z_{r,m} A_m), \\ \text{s.t.} \quad \left\| \sum_{r=1}^{\mathrm{R}} t_r \mathbb{E}(Z_{r,m} B_m) - q \right\|_2 \leq \varepsilon. \end{aligned} \tag{B.7}$$

The Lagrangian of (B.7) is equal to

$$L(t, \mu, \nu) \equiv \sum_{r=1}^{\mathrm{R}} t_r \mathbb{E}(Z_{r,m} A_m) + \mu^\top \left(\left\| \sum_{r=1}^{\mathrm{R}} t_r \mathbb{E}(Z_{r,m} B_m) - q \right\|_2 - \epsilon \right) - \nu^\top t. \tag{B.8}$$

We denote by $\mathcal{T}_\varepsilon$ and $\mathcal{M}_\varepsilon$ the sets of t and μ satisfying the KKT conditions, respectively.

Note that $\mathcal{M}_\varepsilon$ is a singleton. Further, we impose linear independence constraint qualification on (B.6) so as to ensure that $\mathcal{T}_\epsilon$ is also a singleton. Note also that (B.6) allows us to estimate an outer set of Γ_I and, therefore, makes our confidence intervals slightly conservative. Lastly, note that (B.7) is still relatively easy to calculate because it is a convex quadratic program.

We denote the unique elements of $\mathcal{T}_\varepsilon$ and $\mathcal{M}_\varepsilon$ by t_ε and μ_ε, respectively. If $\{\epsilon_{\mathrm{M}}\}_{\mathrm{M} \in \mathbb{N}}$ is a sequence of penalty terms tending to zero at a speed lower than $\sqrt{\mathrm{M}}$, then the limits of $t_{\varepsilon_{\mathrm{M}}}$ and $\mu_{\varepsilon_{\mathrm{M}}}$ are also unique. We denote such unique limits by t^* and μ^*, respectively.

Under the regularity assumptions above, it holds that

$$\sqrt{\mathrm{M}} \left(\widehat{\delta}_{\varepsilon_{\mathrm{M}}}(q; \Gamma_I) - \delta(q; \Gamma_I) \right) \xrightarrow[\mathrm{M} \to \infty]{d} \sum_{r=1}^{\mathrm{R}} t_r^* W_r + \sum_{j=1}^{\mathrm{N}+1} \mu_j^* {t^*}^\top X_j.$$

In particular, the limiting random variable is a normal random variable, whose variance can estimated from the data.

Therefore, one can derive a 95% confidence interval for any k-th component, γ_k, of $\gamma \in \Gamma_I$ by implementing the following procedure:

1. Take $q = (0, \ldots, 0, 1, 0, \ldots, 0)$, where 1 is in correspondence of the k-th component of q.

2. Take $\varepsilon_{\mathrm{M}} \equiv \log \mathrm{M}$. Compute $\hat{\delta}_{\varepsilon_{\mathrm{M}}}(q; \Gamma_I)$.

3. Compute the standard deviation of $\sum_{r=1}^{\mathrm{R}} t_{r,\epsilon_{\mathrm{M}}} W_r + \sum_{j=1}^{\mathrm{N}+1} \mu_{j,\epsilon_{\mathrm{M}}} t_{\epsilon_{\mathrm{M}}}^{\top} X_j$. Denote such standard deviation by σ_k^u.

4. Repeat Steps 1-3 with $-q$. Denote the standard deviation from Step 3 by σ_k^u.

5. Let z_α be the α-quantile of the standard normal distribution. Then,

$$[-\hat{\delta}_{\varepsilon_{\mathrm{M}}}(-q; \Gamma_I) - z_{1-\alpha/2}\sigma_k^l, \quad \hat{\delta}_{\varepsilon_{\mathrm{M}}}(q; \Gamma_I) + z_{1-\alpha/2}\sigma_k^u],$$

   is a confidence interval for γ_k with limiting coverage probability $1 - \alpha$.

Note that, following Stoye (2009), we can adapt the above procedure to get uniformity with respect to the diameter of the identified set. Lastly, observe that in the previous steps we have assumed that θ_0 is known by the researcher. In practice, θ_0 is estimated and we should account for the resulting sampling uncertainty. θ_0 enters only A_m. Therefore, under the usual smoothness assumption on the behaviour of the function A_m in the neighbourhood of θ_0, we just need to modify the asymptotic distribution of W_r. Specifically, a standard Taylor expansion around θ_0 allows us to incorporate the impact of the sampling uncertainty induced by the estimation of θ_0 in the variance of W_r.

B.3 Computing the first-stage moment inequalities

We provide some directions on how to compute $\Delta\Pi_{(+ab),f}$ and $\Delta\overline{\mathrm{FC}}_{(+ab),f}$ entering the first-stage moment inequalities in (16). First, we update the systematic fixed costs by adding $G_{ab,f} = 1$. Second, we update the list of products offered by firm f, by adding nonstop flights between cities a and b. Further, if a is one of firm f's hubs, then we add one-stop flights via a between b and all cities d such that $G_{da,f} = 1$. Similarly, if b is one of firm f's hubs, we add one-stop flights via b between a and all cities d such that $G_{db,f} = 1$.[36] Third, we update the matrices of product covariates by adding the demand and marginal cost shifters of the new products. Fourth, for each updated market, we randomly draw 500 vectors from a normal distribution with mean and variance equal to the empirical mean and variance of the vector of second-stage shocks that have been computed via BLP inversion. For each of these draws, we iterate on the F.O.C.s in (6) to find the new prices and market shares and we compute the second-stage

[36]We do not add a one-stop flights when the resulting itinerary is unrealistic, such as a flight from Seattle to Denver via Miami. Apart from these extreme cases, we assume that the firm will offer all possible one-stop flights.

variable profits. We have decided to use the F.O.C.s in (6) as a contraction mapping. While we do not formally prove that they are indeed a contraction mapping, we have found that the resulting price vector does not change when using different starting values and that the mapping converges in all the considered cases. We average across draws and get the simulated expected second-stage variable profits. Lastly, we compute $\Delta\Pi_{(+ab),f}$ and $\Delta\overline{\text{FC}}_{(+ab),f}$ as the difference between the expected second-stage profits minus the systematic fixed costs in the factual scenario and the expected second-stage variable profits minus the systematic fixed costs in the counterfactual scenario. An analogous algorithm is developed to compute $\Delta\Pi_{(-ab),f}$ and $\Delta\overline{\text{FC}}_{(-ab),f}$.

B.4 First-stage instruments

Table B.1 reports the instruments used to construct the first-stage moment inequalities. The first section of Table B.1 lists the instruments for the class of deviations "$(-ab)$". The second section of Table B.1 lists the instruments for the class of deviations "$(+ab)$". For example, with regards to American Airlines, we consider 3 instruments for the class of deviations "$(-ab)$":

(1) $Z_{(-ab),\text{AA}} = 1$ if cities a or b are hubs for American Airlines and market $\{a, b\}$ has a size greater than 6 millions.

(2) $Z_{(-ab),\text{AA}} = 1$ if cities a or b are hubs for American Airlines and are not historically classified as having a poor on-time performance of flights, according to the U.S. Department of Transportation.[37]

(3) $Z_{(-ab),\text{AA}} = 1$ if cities a and b are not hubs for any airlines.

American Airlines will tend to always offer direct flights in the above markets, plausibly unrelated to the fixed cost shocks, due to the expected very high profitability. Still with regards to American Airlines, we consider 2 instruments for the class of deviations "$(+ab)$":

(4) $Z_{(+ab),\text{AA}} = 1$ if cities a and b are hubs for the competitors and not for American Airlines.[38]

(5) $Z_{(+ab),\text{AA}} = 1$ cities a or b are hubs for American Airlines and market $\{a, b\}$ has a size smaller than 3 millions.

[37]This can be found at `https://www.transtats.bts.gov/DL_SelectFields.asp?gnoyr_VQ=FGJ&QO_fu146_anzr=b0-gvzr`.

[38]One may wonder whether we should expect the fixed cost shocks of entering non-hub markets to be generally higher because the hub airlines may inhibit potential competitors' abilities to obtain gates, slots, and other facilities necessary for entry or expansion. We do not view this as a systematic tendency taking place at each hub airport. Further, the fact that we do not distinguish between airports in the same city lessens any concern of this type.

American Airlines will tend to never offer direct flights in the above markets, plausibly unrelated to the fixed cost shocks, due to the expected very low profitability.

We construct similar instruments for the other airlines. Note that instruments (1) and (4) are based on lower and upper bounds for the market size that are homogeneous across airlines. The only exception is instrument (4) for AA, where we consider as upper bound 3 millions, while for the other carriers we take 1.5 millions. We do so in order to take account of the different observed segment choice patterns of AA.

Table B.1: First-stage instruments.

Markets that are served with direct flights
American: (1) hub, size > 6 million; (2) hub, no historical constraints; (3) non-hub, no other firm has hub
Delta: (1) hub, size > 6 million; (2) hub, no historical constraints; (3) non-hub, no other firm has hub
United: (1) hub, size > 6 million; (2) hub, no historical constraints; (3) non-hub, no other firm has hub
US Airways: (1) hub, size > 6 million; (2) hub, no historical constraints; (3) non-hub, no other firm has hub
Southwest: (1) hub, size > 6 million; (2) hub, no historical constraints; (3) non-hub, no other firm has hub
Markets that are not served with direct flights
American: (4) hub, size < 3 million; (5) non-hub, other firm has hub
Delta: (4) hub, size < 1.5 million; (5) non-hub, other firm has hub
United: (4) hub, size < 1.5 million; (5) non-hub, other firm has hub
US Airways: (4) hub, size < 1.5 million; (5) non-hub, other firm has hub
Southwest: (4) hub, size < 1.5 million; (5) non-hub, other firm has hub

C Other tables and figures

Table C.1: Mergers and bankruptcies.

Mergers
American Airlines + Trans World Airlines (2001)
US Airways + American West (2005)
Delta Airlines + Northwest Airlines (2008)
United Airlines + Continental Airlines (2010)
Southwest Airlines + AirTran (2010)
American Airlines + US Airways (2013)
Bankruptcies
US Airways (2002-2003)
United Airlines (2002-2006)
US Airways (2004-2005)
Northwest Airlines (2005-2007)
Delta Airlines (2005-2007)
American Airlines (2011-2013)

In the first section of Table C.1, we report the mergers between the major carriers after 2001. As a result of these mergers, the number of legacy carriers has dropped from 11 in 2001 to 4 nowadays. In the second section of Table C.1, we report the airlines which have been under Chapter 11 bankruptcy after 2001. All such bankruptcy events were resolved with a restructuring or a merger.

Figure C.1: American Airlines' network.

Figure C.1 represents the network of markets served by American Airlines, before the merger with US Airways. The nodes of the networks are the cities. There is a link between two nodes if American Airlines offers direct flights between those two cities. The red points represents the hubs of American Airlines (Dallas, New York City, Los Angeles, Miami, and Chicago).

Table C.2: Hubs.

AA	DL	UA	US	WN
Dallas	Atlanta	Washington DC	Charlotte	Washington DC
New York	Cincinnati	Denver	Washington DC	Denver
Los Angeles	Detroit	Houston	Philadelphia	Houston
Miami	New York	New York	Phoenix	Las Vegas
Chicago	Memphis	Los Angeles		Chicago
	Minneapolis-Saint Paul	Chicago		Phoenix
	Salt Lake City	San Francisco		

Table C.2 lists the hubs of the legacy carriers and the focus cities of Southwest Airlines.

References

Jason Abaluck and Abi Adams. What do consumers consider before they choose? Identification from asymmetric demand responses. *Quarterly Journal of Economics (forthcoming)*, 2020.

Victor Aguirregabiria and Chun-Yu Ho. A dynamic oligopoly game of the US airline industry: Estimation and policy experiments. *Journal of Econometrics*, 168(1):156–173, 2012.

Donald WK Andrews and Soonwoo Kwon. Inference in moment inequality models that is robust to spurious precision under model misspecification. Working Paper, 2019.

Isaiah Andrews, Jonathan Roth, and Ariel Pakes. Inference for linear conditional moment inequalities. NBER Working Papers 26374, 2019.

Levon Barseghyan, Maura Coughlin, Francesca Molinari, and Joshua C Teitelbaum. Heterogeneous choice sets and preferences. *Econometrica (forthcoming)*, 2020.

C Lanier Benkard, Aaron Bodoh-Creed, and John Lazarev. Simulating the Dynamic Effects of Horizontal Mergers: U.S. Airlines. Working Paper, 2020.

Arie Beresteanu and Francesca Molinari. Asymptotic properties for a class of partially identified models. *Econometrica*, 76(4):763–814, 2008.

Steven T Berry. Airport presence as product differentiation. *American Economic Review*, 80 (2):394–399, 1990.

Steven T Berry. Estimation of a model of entry in the airline industry. *Econometrica*, 60(4): 889–917, 1992.

Steven T Berry. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262, 1994.

Steven T Berry and Philip A Haile. Identification in differentiated products markets using market level data. *Econometrica*, 82(5):1749–1797, 2014.

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

Steven T Berry and Peter Reiss. Empirical models of entry and market structure. *Handbook of Industrial Organization*, 3:1845–1886, 2007.

Steven T Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890, 1995.

Steven T Berry, Michael Carnall, and Pablo T Spiller. Airline hubs: costs, markups and the implications of customer heterogeneity. NBER Working Papers 5561, 1996.

Steven T Berry, Oliver B Linton, and Ariel Pakes. Limit theorems for estimating the parameters of differentiated product demand systems. *The Review of Economic Studies*, 71(3):613–654, 2004.

Steven T Berry, Martin Gaynor, and Fiona Scott Morton. Do increasing markups matter? Lessons from empirical industrial organization. *Journal of Economic Perspectives*, 33(3): 44–78, 2019.

Christian Bontemps, Thierry Magnac, and Eric Maurin. Set identified linear models. *Econometrica*, 80(3):1129–1155, 2012.

Severin Borenstein. Hubs and high fares: dominance and market power in the U.S. airline industry. *The RAND Journal of Economics*, 20(3):344–365, 1989.

Severin Borenstein. The evolution of U.S. airline competition. *Yale Journal on Regulation*, 4 (2):45–73, 1992.

Timothy F Bresnahan. Competition and collusion in the American automobile industry: The 1955 price war. *The Journal of Industrial Economics*, 35(4):457–482, 1987.

Timothy F Bresnahan and Peter C Reiss. Entry in monopoly market. *The Review of Economic Studies*, 57(4):531–553, 1990.

Timothy F Bresnahan and Peter C Reiss. Empirical models of discrete games. *Journal of Econometrics*, 48(1):57–81, 1991.

Jan K Brueckner and Pablo T Spiller. Economies of traffic density in the deregulated airline industry. *The Journal of Law & Economics*, 37(2):379–415, 1994.

Jan K Brueckner, Nichola J Dyer, and Pablo T Spiller. Fare determination in airline hub-and-spoke networks. *The RAND Journal of Economics*, 23(3):309–333, 1992.

Richard V Butler and John H Houston. How contestable are airline markets. *Atlantic Economic Journal*, 17:27–35, 1989.

Kenneth Button, Peter Forsyth, and Peter Nijkamp. *Air Transport*. Edward Elgar, 2000.

Douglas W Caves, Laurits R Christensen, and Michael W Tretheway. Economies of density versus economies of scale: why trunk and local service airline costs differ. *The RAND Journal of Economics*, 15(4):471–489, 1984.

Arun Chandrasekhar. Econometrics of network formation. In *The Oxford Handbook of the Economics of Networks*, pages 303–357. Oxford University Press Oxford, 2016.

Arun G Chandrasekhar, Victor Chernozhukov, Francesca Molinari, and Paul Schrimpf. Best linear approximations to set identified functions: with an application to the gender wage gap. NBER Working Papers 25593, 2019.

Federico Ciliberto and Elie Tamer. Market structure and multiple equilibria in airline markets. *Econometrica*, 77(6):1791–1828, 2009.

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

Federico Ciliberto, Charles Murry, and Elie Tamer. Market structure and competition in airline markets. *Journal of Political Economy (forthcoming)*, 2021.

Somnath Das. Effect of merger on market price and product quality: American and US Airways. *Review of Industrial Organisation*, 55:339–374, 2019.

Aureo de Paula. Econometrics of network models. In *Advances in Economics and Econometrics: Theory and Applications, Eleventh World Congress*, pages 268–323. Cambridge University Press Cambridge, 2017.

Aureo de Paula. Econometric models of network formation. *Annual Review of Economics*, 12: 775–799, 2020.

Alon Eizenberg. Upstream Innovation and Product Variety in the U.S. Home PC Market. *Review of Economic Studies*, 81(3):1003–1045, 2014.

Joseé-Antonio Espín-Sánchez, Álvaro Parra, and Yuzhou Wang. Equilibrium uniqueness in entry games with private information. Working Paper, 2021.

William N Evans and Ioannis N Kessides. Localized market power in the US airline industry. *The Review of Economics and Statistics*, 75(1):66–75, 1993.

Xiaowen Fu, Huan Jin, Shaoxuan Liu, Tae H Oum, and Jia Yan. Exploring network effects of point-to-point networks: An investigation of the spatial patterns of southwest airlines' network. *Transport Policy*, 76:36–45, 2019.

Bulat Gafarov. Inference in high-dimensional set-identified affine models. arXiv Working Papers 1904.00111, 2019.

Amit Gandhi, Zhentong Lu, and Xiaoxia Shi. Estimating demand for differentiated products with zeroes in market share data. Working Paper, 2019.

Austan Goolsbee and Chad Syverson. How do incumbents respond to the threat of entry? Evidence from the major airlines. *Quarterly Journal of Economics*, 123(4):1611–1633, 2008.

Bryan Graham and Aureo de Paula. *The Econometric Analysis of Network Data*. Academic Press, 2020.

Bryan S Graham. Methods of identification in social networks. *Annual Review of Economics*, 7(1):465–485, 2015.

Cristina Gualdani. An econometric model of network formation with an application to board interlocks between firms. *Journal of Econometrics (forthcoming)*, 2021.

Tim Hellmann. On the existence and uniqueness of pairwise stable networks. *International Journal of Game Theory*, 42:211–237, 2013.

Jean-Baptiste Hiriart-Urruty and Claude Lemaréchal. *Convex Analysis and Minimization Algorithms*. Springer-Verlag, 1996.

Thomas J Holmes. The diffusion of wal-mart and economies of density. *Econometrica*, 79(1): 253–302, 2011.

Jean-François Houde, Peter Newberry, and Katja Seim. Economies of Density in E-Commerce: A Study of Amazon's Fulfillment Center Network. NBER Working Papers 23361, 2017.

Matthew O Jackson and Alison Watts. The existence of pairwise stable networks. *Seul Journal of Economics*, 14(3):299–321, 2001.

Matthew O Jackson and Alison Watts. The evolution of social and economic networks. *Journal of Economic Theory*, 106(2):265–295, 2002.

Matthew O Jackson and Asher Wolinsky. A strategic model of social and economic networks. *Journal of Economic Theory*, 71(1):44–74, 1996.

Hiroaki Kaido and Andres Santos. Asymptotically efficient estimation of models defined by convex moment inequalities. *Econometrica*, 82(1):387–413, 2014.

Adib Kanafani and Atef A Ghobrial. Airline hubbing - Some implications for airport economics. *Transportation Research Part A: General*, 19(1):15–27, 1985.

Joseph Kuehn. Spillovers from entry: the impact of bank branch network expansion. *The RAND Journal of Economics*, 49(4):964–994, 2018.

Robin S Lee and Ariel Pakes. Multiple equilibria and selection by learning in an applied setting. *Economics Letters*, 104(1):13–16, 2009.

Micheal P Leung. Dependence-robust inference using resampled statistics. Working Paper, 2020.

Micheal P Leung. Network cluster-robust inference. Working Paper, 2021.

Michael E Levine. Airline competition in deregulated markets: theory, firm strategy, and public policy. *Journal of Economic Perspective*, 6:393–494, 1987.

Sophia Ying Li, Joe Mazur, Yongjoon Park, James W Roberts, Andrew Sweeting, and Jun Zhang. Repositioning and Market Power After Airline Mergers. Working Paper, 2019.

Israel Mark, Bryan Keating, Daniel L Rubinfeld, and Bobby Willig. Airline network effects and consumer welfare. *Review of Network Economics*, 12(3):287–322, 2013.

Antonio Mele. A structural model of dense network formation. *Econometrica*, 85(3):825–850, 2017.

Yuhei Miyauchi. Structural estimation of pairwise stable networks with nonnegative externality. *Journal of Econometrics*, 195(2):224–235, 2016.

Dov Monderer and Lloyd S Shapley. Potential games. *Games and Economic Behavior*, 14(1): 124–143, 1996.

Steven A Morrison and Clifford Winston. *The economic Effects of Airline Deregulation*. Washington, DC: Brookings Institution, 1986.

Steven A Morrison and Clifford Winston. Enhancing the performance of the deregulated air transport system. *Brookings Papers on Economic Activity. Microeconomics*, 1989:61–123, 1989.

Giovanni Nero. A note on the competitive advantage of large hub-and-spoke networks. *Transportation Research Part E: Logistics and Transportation Review*, 35(4):225–239, 1999.

Volker Nocke and Nicolas Schutz. Multiproduct-firm oligopoly: An aggregative games approach. *Econometrica*, 86(2):523–557, 2018.

Tae Hoon Oum, Anming Zhang, and Yimin Zhang. Airline network rivalry. *Canadian Journal of Economics*, 28(4a):836–857, 1995.

Ariel Pakes. Alternative models for moment inequalities. *Econometrica*, 78(6):1783–1822, 2010.

Ariel Pakes, Jack Porter, Kate Ho, and Joy Ishii. Moment inequalities and their application. *Econometrica*, 83(1):315–334, 2015.

Yongjoon Park. Structural remedies in network industries: An assessment of slot divestitures in the American Airlines/US Airways merger. Working Paper, 2020.

Craig Peters. Evaluating the performance of merger simulation: Evidence from the U.S. airline industry. *The Journal of Law & Economics*, 49(2):627–649, 2006.

Peter C Reiss and Pablo T Spiller. Competition and entry in small airline markets. *The Journal of Law & Economics*, 32(2):S179–S202, 1989.

Aisling Reynolds-Feighan. Traffic distribution in low-cost and full-service carrier networks in the US air transportation market. *Journal of Air Transport Management*, 7(5):265–275, 2001.

Joseph Anthony Rossetti. *Product Variety in the US Yogurt Industry.* PhD thesis, The Ohio State University, 2018.

Alexander Shapiro, Darinka Dentcheva, and Andrzej Ruszczyński. *Lectures on Stochastic Programming: Modelling and Theory.* SIAM, 2014.

Shuyang Sheng. A structural econometric analysis of network formation games through subnetworks. *Econometrica*, 88(5):1829–1858, 2020.

Jörg Stoye. More on confidence intervals for partially identified parameters. *Econometrica*, 77 (4):1299–1315, 2009.

Donald M Topkis. Equilibrium points in nonzero-sum n-person submodular games. *SIAM Journal of Control and Optimization*, 17(6):773–787, 1979.

Thomas G Wollmann. Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review*, 108(6):1364–1406, 2018.

Zhe Yuan. Network competition in the airline industry: A framework for empirical policy analysis. Working Paper, 2020.