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

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Abstract

The recent merger waives in airline markets have received attention by researchers and the general public alike. Most academic studies have analysed the problem using demand/supply or entry models. These contributions assume that airlines' route networks are exogenous, or that airlines' entry decisions are i.i.d. across routes. Instead, we estimate a two-stage model where airlines choose their route networks in the first stage and compete in prices in the second stage. The two-stage framework allows us to account for selection of airlines into interdependent routes. Moreover, it permits us to make counterfactual exercises which robustly predict changes not only in prices and markups, but also in how airlines adjust their route networks. We estimate the model using cross-sectional data on the US airline market and use our results to evaluate a merger between American Airlines and US Airways. We find that after the merger consumer surplus rises by around 7% and that remedies imposed to the merging parties by the Department of Justice at Charlotte Airport were effective in preventing harm to consumers.

1 Introduction

Competition in airline markets has received a lot of attention in the economic literature, sparked by the U.S. Airline Deregulation Act of 1978 which lifted federal control on ticket prices, routes, and market entry, among others. Many contributions analyzing the entry of new airlines, the appearance of airline hubs, and the competition between airlines have been made since. However, a common aspect of these contributions is that either they assume airlines' "route networks" to be exogenous, or they assume airlines' entry decisions to be i.i.d. across routes (also called local manager hypothesis). Such an approach ignores the fact that a service between two airports allows passengers to reach other destinations. Further, it ignores the fact that a wise design of route networks with interdependent arms can lead to significant cost savings for airlines and serve as an anti-competitive tool (Berry, 1990). Therefore, neglecting the formation of route networks may cause bias in the estimation of demand and marginal cost functions, produce misleading counterfactual results, and induce wrong policy recommendations. Recent advances in the field of set identification have made it possible to estimate a stage where airlines choose their route networks. In fact, revealed preference arguments derived from observed equilibrium behaviour can be used to bound the parameters of interest. In this paper we incorporate such a stage into a standard model of demand and supply for the airline sector. In the first stage, airlines form their route networks and in the second stage, they compete in prices. The two-stage framework allows us to account for selection of airlines into interdependent routes. Moreover, it permits us to make counterfactual exercises which robustly predict changes not only in prices and markups, but also in how airlines adjust their route networks. We estimate our model using cross-sectional data on the US airline market and use the results to evaluate a merger between American Airlines and US Airways.

More precisely, we consider a group of airline firms playing a two-stage game. In the first stage, the firms simultaneously choose which routes (or, equivalently, markets) to serve (i.e, offer non-stop flights) and pay the associated fixed costs. On one hand, the firms want to serve multiple routes in order to take advantage of consumers' heterogeneity and increase their expected variable profits from the second stage. On the other hand, serving multiple routes may inflate the firms' fixed costs. Crucially, we allow the fixed cost of serving a route to depend on the decision of serving adjacent routes. In fact, when serving adjacent routes, some airports may become connecting points for one-stop journeys. In those cases, the firms may need to invest additional resources in order to manage the flows of passengers travelling via the connecting airports and minimise the risk of congestion. The firms may also need more facilities and slots at the connecting airports, as well as use larger aircrafts. In the second stage, for each route chosen in the first stage, the firms sell flights to consumers in a simultaneous pricing game. Such flights can be non-stop or one-stop depending on the route networks designed by the firms in the first stage.

We assume that the researcher observes the firms' route networks and several attributes and cost shifters of the products offered. The researcher is interested in exploiting such data to study identification and inference of the parameters entering the above two-stage game. We show identification of the second-stage parameters by following the standard approach for supply and demand models with differentiated products (e.g., Berry and Haile, 2014). In particular, we rely on moments that are expectations of the demand and marginal cost shocks interacted with instruments. Developing identification arguments for the first-stage parameters is more challenging. In fact, the first stage of the game may display multiple equilibria and the equilibrium selection mechanism adopted by the firms is unobserved by the researcher. Therefore, without further assumptions, the researcher cannot write down a well-defined likelihood function for the equilibrium route networks. Further, the researcher observes only one realisation of the route networks, whose components are interdependent. Therefore, it is not possible to implement a many-markets partial identification approach à la Tamer (2003) and Ciliberto and Tamer (2009). We handle these challenges by adopting a revealed preference perspective and bound the first stage parameters through inequalities derived from equilibrium implications, as proposed by Pakes, Porter, Ho, and Ishii (2015) and implemented, e.g., also by Holmes (2011), Ho and Pakes (2014), Eizenberg (2014), Houde, Newberry, and Seim (2017), Kuehn (2018), and Wollmann (2018). The inequalities obtained are also computationally appealing because linear in the first-stage parameters.

To estimate the model we use data from the Airline Origin and Destination Service which consists of a random sample of all the 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. We use the estimated coefficients to simulate the 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. Standard merger analysis do not take into account network endogeneity, assume that the firms' route networks stay fixed, and artificially determine how the product covariates adjust after the merger, hence possibly incurring into serious misspecification. However, after the approval of the merger, the merging firms may react with further entry accommodations in order to respond to competitors' reactions. Our methodology can handle such effects by allowing the firms to re-optimise prices *and* route networks after the merger. There are several findings from the counterfactual experiment. Most importantly, we find that after the merger consumer surplus rises by around 7%. We also find that some of the remedies imposed in 2013 by the Department of Justice to the merging entities (in particular, the maintenance of a hub at the Charlotte International Airport) were indeed effective in preventing harm to consumers.

This paper aims to bridge a gap between two strands of the literature: the literature on empirical models of market entry and the literature estimating demand and marginal cost functions. The literature on empirical models of market entry builds on the work by Bresnahan and Reiss (1990; 1991a; 1991b). Berry (1992) develops a structural model of market entry with heterogeneous firms. He finds that an airline's market presence at an airport is an important determinant of entry into other routes from that airport. Ciliberto and Tamer (2009) extend Berry (1992)'s approach by allowing for heterogeneous competitive effects and do not make assumptions on equilibrium selection, which may lead to set identification. They find substantive heterogeneity in how different airlines affect each other through their entry decisions. Goolsbee and Syverson (2008) study incumbents' reactions to a threat of entry using Southwest Airlines' entry decisions and find that incumbents cut prices significantly when facing the threat of entry by Southwest. Fu, Jin, Liu, Oum, and Yan (2019) analyse the point-to-point network of Southwest Airlines. Based on a Spatial Probit model, they find that network effects arise in the form of market presence and market substitutability. Aguirregabiria and Ho (2012) investigate how demand, costs, and strategic factors affect the adoption of hub-and-spoke networks in a dynamic setting. They find that the sunk cost of entry into a route declines with the number of connections served from its endpoints. Their results also reveal the existence of an entry deterrence effect that explains adoption of hub-and-spoke networks. Berry, Carnall, and Spiller (1996) estimate a discrete-type version of a random coefficient Logit model (Berry, Levinsohn, and Pakes, 1995, BLP henceforth). Studying the post-deregulation market in the US, they find that longer routes admit economics of density. Berry and Jia (2010) use a similar methodology and estimate their model on data from 1999 and 2006. They find evidence that consumers have become more price sensitive and more averse to choosing connecting flights over time.

An important paper combining both entry and pricing into one empirical model is Ciliberto, Murry, and Tamer (2018). There are two main differences with respect to our approach. First, while in their case airlines' entry decisions are i.i.d. across routes, we adopt a network perspective and allow airlines' entry decisions to be interdependent across routes. Second, while they consider a simultaneous static game, we develop a two-stage (hence, sequential) game. Other contributions are Li, Mazur, Park, Roberts, Sweeting, and Zhang (2018) and Yuan (2018).

Our paper also relates to the empirical literature on two-stage models, with demand and supply models in the second stage and entry, location, or product portfolio choices in the first stage. For instance, Eizenberg (2014) looks at upstream innovation in the US Home PC market and endogenises PC configuration choices. Holmes (2011) and Houde et al. (2017) study the rollout of Walmart stores and Amazon fulfilment centers, respectively. Kuehn (2018) estimates spillovers from bank branch networks by allowing banks to enter or exit markets and adjust the number of branches in a given market. Rossetti (2018) examines product variety in the US Yogurt market. Finally, Wollmann (2018) analyzes what the market outcome on the US truck market would have been if government had not bailed out GM and Chrysler. All the cited papers use revealed preference arguments derived from observed equilibrium behaviour to obtain bounds for the parameters of interest.

Our paper also relates to recent advances in the econometrics of network formation (see e.g. Chandrasekhar (2015), De Paula (2017), De Paula (2019), Graham (2015) for reviews).

We have decide to pursue a revealed preference approach rather than applying those methods in our first stage for two main reasons. First, most of the methodologies developed in the econometrics of network formation assume that the linking decisions are taken by the nodes. In our case, this would imply that the linking decisions are taken at the airport level and, hence, would not help us breaking the local manager hypothesis. Second, those methods typically involve computationally serious challenges, which become even deeper when combined with our second stage. Instead, the inequalities that we obtain from equilibrium implications are computationally tractable to calculate because linear in the first stage parameters.

Lastly, our paper also relates to the recent and growing literature analyzing markups over the past 30 years (De Loecker and Eeckhout, 2017). This literature has found rising markups in airline markets. Our method applied to various periods could be used to decompose the effect of market concentration and higher fixed costs on markups over time.

The rest of the paper is organised as follows. Section 2 presents the model. Sections 3 and 4 discuss identification and estimation, respectively. Section 5 describes the data. Section 6 shows our results. Section 7 illustrates some counterfactual experiments. Section 8 concludes.

Notation Capital letters are used for random variables/vectors/matrices and small case letters for their realisations. Given a random variable X, Supp_X denotes its support. Given two sets, $\mathcal{A}$ and $\mathcal{R} \subseteq \mathcal{A}$, $\mathcal{A} \setminus \mathcal{R}$ is the complement of $\mathcal{R}$ in $\mathcal{A}$. 0_2 indicates the 2×1 vector of zeros.

2 The model

We consider N airline firms playing a two-stage game. In the first stage, the firms simultaneously choose which routes to serve (i.e, offer non-stop flights) and pay the associated fixed costs. On one hand, the firms want to serve multiple routes in order to take advantage of consumers' heterogeneity and increase their expected variable profits from the second stage. On the other hand, serving multiple routes may inflate the firms' fixed costs. We allow the fixed cost of serving a route to depend on the decision of serving adjacent routes in order to capture spillover effects from connecting flights. In the second stage, for each route chosen in the first stage, the firms sell flights to consumers in a simultaneous pricing game. Such flights can be non-stop or one-stop depending on the route networks designed by the firms in the first stage.

More precisely, the two-stage game has the following timeline:

1. The firms are aware of the fixed costs incurred to serve each possible route. Further, the firms have beliefs about the demand and marginal cost shocks entering the demand and supply models in the second stage. The firms simultaneously choose which routes to serve in order to maximise the expected profits from the second stage minus the fixed costs from the first stage. At the end of the first stage, the firms pay the fixed costs for each chosen route.

2. At the beginning of the second stage, the firms observe the realisations of the demand and marginal cost shocks entering the demand and supply models, for each route chosen in the first stage. The firms simultaneously set flight prices for each route chosen in the first stage in order to maximise their total profits from participating in the game.

Sections 2.1 and 2.2 describe the two-stage game formally.

2.1 The first stage of the game

Let $\mathcal{N} \equiv \{1, ..., N\}$ be the set of firms. Let $\mathcal{C} \equiv \{1, ..., C\}$ be the set of cities endowed with airport facilities where the firms can decide to be present.[1] Every pair of cities, $h, k \in \mathcal{C}$, defines a segment, $\{h, k\}$. Let $\mathcal{R}$ be the set of all segments, with cardinality $C(C-1)/2$.

Before the game starts, each firm f selects some cities from $\mathcal{C}$ which will act as connection points for one-stop flights (hereafter, firm f's *hubs*). Then, the firms simultaneously choose which segments to serve. In what follows, we consider firms' hubs as exogenously determined and focus on modelling firms' choices of segments to serve.

Let $G_{hk,f}$ be equal to 1 if firm f serves segment $\{h, k\}$, i.e. if it offers *non-stop* service between cities h, k. Further, if city k is a hub for firm f and $G_{hk,f} = G_{kd,f} = 1$, then firm f also offers *one-stop* service between cities h, d via city k. Let G_f be the $C \times C$ matrix with hk-th term equal to $G_{hk,f}$. Note that G_f is symmetric with all entries on the main diagonal equal to zero. Hereafter, we refer to G_f as firm f's *network*. In the first stage of the game, firms choose $G \equiv (G_f \ \forall f \in \mathcal{N})$.

We now move to define firms' objective functions. Every segment $\{h, k\}$ that firm f could serve is associated with a fixed cost determined, e.g., by the number of gates that firm f operates, aircraft financing, scheduling coordination, etc. More precisely, we specify the fixed cost that firm f incurs when serving segment $\{h, k\}$ as

$$FC_{hk,f}(G_f, \eta_f; \gamma) \equiv \gamma_1 \text{NoHub}_{hk,f} + \gamma_{2f} \sum_{d \in \mathcal{C} \setminus \{h,k\}} \mathbb{1}\{\text{Indirect}_{hkd,f} \text{ or Indirect}_{dhk,f}\} + \eta_{hk,f}, \quad (1)$$

where $\eta_{hk,f}$ represents a fixed cost shock, $\eta_f \equiv (\eta_{hk,f} \ \forall \{h, k\} \in \mathcal{R})$, and the vector of parameters $\gamma \equiv (\gamma_1, \gamma_{2f} \ \forall f \in \mathcal{N})$ should be identified by the researcher. $\text{NoHub}_{hk,f}$ is a dummy variable equal to one if neither endpoint is a hub for firm f. $\mathbb{1}\{\text{Indirect}_{hkd,f} \text{ or Indirect}_{dhk,f}\}$ is a dummy variable equal to one if city k is a hub for firm f and $G_{kd,f} = 1$, or if city h is a hub for firm f and $G_{dh,f} = 1$. $\mathbb{1}\{\text{Indirect}_{hkd,f} \text{ or Indirect}_{dhk,f}\}$ captures the fact that the fixed costs of serving segment $\{h, k\}$ could be higher when one-stop service is provided between cities h, d via city k.[2] This is because firm f may need to manage the flows of passengers traveling between cities h, d via hub city k and, thus, invest additional resources to minimise the risk of congestion.

[1] To enhance computational tractability, we do not distinguish among different airports in the same city.

[2] Recall that if $G_{hk,f} = 1$ and city k is a hub for firm f, then firm f also offers one-stop service between cities h, d via city k.

Firm f may also need more facilities and slots at airport k, as well as use larger aircrafts. For similar reasons, the fixed costs of serving segment $\{h, k\}$ could be higher when one-stop service is provided between cites k, d via hub city h.[3] Therefore, γ_1 captures the systematic fixed cost of serving non-hub segments, $\gamma_{2,f}$ captures the systematic fixed the cost of serving hub segments. Note that we allow the systematic fixed cost of serving hub segments to vary across firms.

In turn, the total fixed cost incurred by firm f is

$$TFC_f(G_f, \eta_f; \gamma) \equiv \sum_{\{h,k\}\in\mathcal{R}} G_{hk,f} \times FC_{hk,f}(G_f, \eta_f; \gamma).$$

The firms observe the realisation of $\eta \equiv (\eta_f \ \forall f \in \mathcal{N})$ at the beginning of the first stage. Further, they form expectations on the second stage's profits. To formally define such expectations we need to introduce additional notation. Let M_{hk} be the total measure of consumers in segment $\{h, k\}$ and $M \equiv (M_{hk} \ \forall\{h, k\} \in \mathcal{R})$. For any possible $g \in \text{Supp}_G$ chosen by the firms in the first stage, let X_g and W_g be the matrices of product characteristics and cost-shifters entering the demand and supply models in the second stage, respectively. Let ξ_g and ζ_g be the vectors of demand and marginal cost shocks entering the demand and supply models in the second stage, respectively.[4] Let $X \equiv (X_g \ \forall g \in \text{Supp}_G)$, $W \equiv (W_g \ \forall g \in \text{Supp}_G)$, $\xi \equiv (\xi_g \ \forall g \in \text{Supp}_G)$, and $\zeta \equiv (\zeta_g \ \forall g \in \text{Supp}_G)$. The realisations of X, W, M are observed by the firms at the beginning of the first stage. The realisations of ξ, ζ are not observed by the firms at the beginning of the first stage. Let $f_{\xi,\zeta}(\cdot|G, X, W, M, \eta)$ denote the density of (ξ, ζ) conditional on the first stage information set, (G, X, W, M, η). The objective function that firm f seeks to maximise in the first stage is

$$\mathbb{E}\Big[\Pi^2_f(X_G, W_G, M, \xi_G, \zeta_G; \theta)\Big| G, X, W, M, \eta\Big] - TFC_f(G_f, \eta_f; \gamma), \quad (2)$$

where θ is the vector of parameters entering the demand and supply models in the second stage and $\Pi^2_f(X_G, W_G, M, \xi_G, \zeta_G; \theta)$ is firm f's profit from the second stage. Note that the expectation in (2), "$\mathbb{E}$", is computed using $f_{\xi,\zeta}(\cdot|G, X, W, M, \eta)$.

2.2 The second stage of the game

As anticipated in Section 2.1, if firm f decides to serve segment $\{h, k\}$ in the first stage (i.e., $G_{hk,f} = 1$), then in the second stage firm f offers the following products in segment $\{h, k\}$: (i) a direct flight between cities h, k; (ii) a one-stop flight between cities h, k via each hub city d if $G_{dk,f} = G_{dh,f} = 1$. Therefore, a product is defined as a flight between two cities, run from a particular carrier, and featuring certain connections. Note that we consider tickets featuring

[3] Recall that if $G_{hk,f} = 1$ and city h is a hub for firm f, then firm f also offers one-stop service between cities k, d via city h.

[4] More details on X_g, W_g, ξ_g, ζ_g are in Section 2.2.

the same firm-itinerary combination but different fares as the same product. In the second stage, the firms simultaneously set prices for each product in order to maximise their total profits from participating in the game.

Before describing the second stage in detail, we introduce some useful notation. For simplicity of exposition, we relabel segments using subscript $t \in \mathcal{T} \equiv \{1, ..., C(C-1)/2\}$. The terms "segment" and "market" will be used as synonyms. We denote by $\mathcal{J}_{G,t} \equiv \{1, ..., J_{G,t}\}$ the set of products offered by the firms in segment t. Given that products are defined as firm-itinerary combinations, note that the number and types of products offered by the firms in segment t depend on G. Lastly, $\mathcal{J}^0_{G,t} \equiv \mathcal{J}_{G,t} \cup \{0\}$, where product 0 is the outside option, i.e., the possibility to purchase none of the products in $\mathcal{J}_{G,t}$.

2.2.1 The demand model

On the demand side we use a Nested Logit demand model (Berry, 1994). We first describe the features of the products offered in segment t. Product $j \in \mathcal{J}_{G,t}$ is associated with a vector of characteristics, $(X_{j,t}, P_{j,t}, \xi_{j,t})$. $X_{j,t}$ collects product j's attributes whose realisations are observed by the researcher, such as the number of stops, the maximum number of connections at the segment endpoints, and the distance between the segment endpoints. $\xi_{j,t}$ represents product j's attributes whose realisations are unobserved by the researcher, such as ticket restrictions, time of departure, flight frequency, and online ticket sale. $P_{j,t}$ denotes product j's price and its realisation is observed by the researcher. Given that products are defined as firm-itinerary combinations, $P_{j,t}$ is computed as the weighted average over all fares that we observe in our data for that firm-itinerary combination.[5] Lastly, we define $P_{G,t} \equiv (P_{j,t}\ \forall j \in \mathcal{J}_{G,t})$, $P_G \equiv (P_{G,t}\ \forall t \in \mathcal{T})$, $\xi_{G,t} \equiv (\xi_{j,t}\ \forall j \in \mathcal{J}_{G,t})$, $\xi_G \equiv (\xi_{G,t}\ \forall t \in \mathcal{T})$, $X_{G,t} \equiv (X_{j,t}\ \forall j \in \mathcal{J}_{G,t})$, and $X_G \equiv (X_{G,t}\ \forall t \in \mathcal{T})$. ξ_G is also referred to as the vector of demand shocks.

We now describe the preferences of each consumer i over the products offered in segment t. These preferences depend on $(X_{G,t}, P_{G,t}, \xi_{G,t})$. In addition, they depend on consumer i's tastes represented by the scalar $\nu_{i,t}$ and the vector $(\epsilon_{ij,t}\ \forall j \in \mathcal{J}^0_{G,t})$, whose realisations are unobserved by the researcher. Specifically, when consumer i buys product $j \in \mathcal{J}_{G,t}$, she receives the payoff

$$u_{ij,t}(X_{j,t}, P_{j,t}, \xi_{j,t}, \nu_{i,t}, \epsilon_{ij,t}; \theta_d) \equiv X'_{j,t}\beta - \alpha P_{j,t} + \xi_{j,t} + \nu_{i,t} + \lambda\epsilon_{ij,t},$$

where the vector of parameters $\theta_d \equiv (\alpha, \beta, \lambda)$ should be identified by the researcher. The payoff from purchasing the outside good is $u_{i0,t} \equiv \epsilon_{i0,t}$. The structure assigned to payoffs is based on the Nested Logit framework, where the "inside" goods are separated from the outside good and the payoffs of the inside goods are correlated. We assume that $\{\nu_{i,t}, \epsilon_{ij,t}\}_{i,j \in \mathcal{J}_{G,t}, t \in \mathcal{T}}$ are i.i.d., and independent of (X_G, P_G, ξ_G). Moreover, the probability distribution of $\nu_{i,t} + \lambda\epsilon_{ij,t}$ is chosen to yield the familiar Nested Logit market share function, with $\lambda \in (0, 1)$. Lastly, differently from Berry et al. (1996) and Berry and Reiss (2007), the parameters α and β are

[5] More details on the calculation of $P_{j,t}$ are in Section 5.

nonrandom. In fact, given that products are defined as firm-itinerary combinations and prices are computed by averaging over fares, we do not have sufficient price variation to allow for random coefficients.

Each consumer i in segment t chooses the product from $\mathcal{J}^0_{G,t}$ maximising her payoff.[6] Therefore,

$$\Pr\Big(j = \text{argmax}_{k\in\mathcal{J}^0_{G,t}}\ u_{ik,t}(X_{k,t}, P_{k,t}, \xi_{k,t}, \nu_{i,t}, \epsilon_{ik,t}; \theta_d)\Big| X_G, P_G, \xi_G\Big)$$
$$= \frac{\exp\left(\frac{X'_{j,t}\beta - \alpha P_{j,t} + \xi_{j,t}}{\lambda}\right)}{1 + \sum_{k\in\mathcal{J}_{G,t}} \exp\left(\frac{X'_{k,t}\beta - \alpha P_{k,t} + \xi_{k,t}}{\lambda}\right)} \equiv \sigma^G_{j,t}(X_{G,t}, P_{G,t}, \xi_{G,t}; \theta_d),$$

for every $j \in \mathcal{J}_{G,t}$, where the map

$$\sigma^G_{j,t} : \text{Supp}_{X_{G,t},P_{G,t},\xi_{G,t}} \to (0, 1),$$

is the demand function of product $j \in \mathcal{J}_{G,t}$. Moreover, we define the map

$$\sigma^G_{0,t} : \text{Supp}_{X_{G,t},P_{G,t},\xi_{G,t}} \to (0, 1),$$

such that $\sigma^G_{0,t}(X_{G,t}, P_{G,t}, \xi_{G,t}; \theta_d) = 1 - \sum_{j\in J_{G,t}} \sigma^G_{j,t}(X_{G,t}, P_{G,t}, \xi_{G,t}; \theta_d)$.

Let $S_{j,t}$ denote the market share of product $j \in \mathcal{J}^0_{G,t}$. If the demand model is correctly specified, then

$$S_{j,t} = \sigma^G_{j,t}(X_{G,t}, P_{G,t}, \xi_{G,t}; \theta_d), \tag{3}$$

for every $j \in \mathcal{J}^0_{G,t}$. Lastly, we define $S_{G,t} \equiv (S_{j,t}\ \forall j \in \mathcal{J}_{G,t})$ and $S_G \equiv (S_{G,t}\ \forall t \in \mathcal{T})$. In what follows the realisation of S_G is considered observed by the researcher. For this to be the case, it is sufficient to have a random sampling scheme in which the researcher draws consumers from the continuum of consumers in every segment $t \in \mathcal{T}$ and records their chosen products.

2.2.2 The supply model

We specify the marginal cost function of every product $j \in \mathcal{J}_{G,t}$ in segment t as

$$MC_{j,t} \equiv W_{j,t}\psi + \zeta_{j,t},$$

where $W_{j,t}$ is a vector of exogenous cost-shifters whose realisations are observed by the researcher, such as the number of stops, the average number of connections at each stop (which we call "Presence"), and the distance between the segment endpoints. $\zeta_{j,t}$ collects other determinants of the marginal cost whose realisations are unobserved by the researcher. The vector of parameters ψ should be identified by the researcher. We also define $MC_{G,t} \equiv (MC_{j,t}\ \forall j \in \mathcal{J}_{G,t})$, $MC_G \equiv (MC_{G,t}\ \forall t \in \mathcal{T})$, $\zeta_{G,t} \equiv (\zeta_{j,t}\ \forall j \in \mathcal{J}_{G,t})$, $\zeta_G \equiv (\zeta_{G,t}\ \forall t \in \mathcal{T})$, $W_{G,t} \equiv (W_{j,t}\ \forall j \in \mathcal{J}_{G,t})$,

[6] Note that, since we compute prices by aggregating up individual fares to the firm/itinerary level, we do not face the problem of product availability.

and $W_G \equiv (W_{G,t}\ \forall t \in \mathcal{T})$. ζ_G is also referred to as the vector of marginal cost shocks.

At the beginning of the second stage, the firms observe the realisations of ξ_G and ζ_G. Then, the firms simultaneously set prices for every product $j \in \mathcal{J}_G$ in order to maximise their profits. The profit of firm f is given by

$$\begin{aligned}
&\Pi_f^2(X_G, W_G, M, \xi_G, \zeta_G; \theta) - TFC_f(G_f, \eta_f; \gamma) \\
&\equiv \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{G,t,f}} [P_{j,t} - MC_{j,t}] \times \sigma_{j,t}^G(X_{G,t}, P_{G,t}, \xi_{G,t}; \theta_d) \times M_t - TFC_f(G_f, \eta_f; \gamma),
\end{aligned}$$

where $\theta \equiv (\theta_d, \psi)$ and $\mathcal{J}_{G,t,f} \subseteq \mathcal{J}_{G,t}$ is the set of products offered by firm f in segment t. In what follows, we refer to $\Pi_f^2(X_G, W_G, M, \xi_G, \zeta_G; \theta)$ as firm f's variable profit.

Hence, the equilibrium prices in segment t satisfy the first-order conditions

$$MC_{j,t} = P_{j,t} - b_{j,t}^G(X_{G,t}, P_{G,t}, S_{G,t}; \theta_d), \tag{4}$$

for every $j \in \mathcal{J}_{G,t}$, where $b_{j,t}^G(X_{G,t}, P_{G,t}, S_{G,t}; \theta_d)$ are the markups.

2.3 Equilibrium

Given a realisation of (X, W, M, η), the firms solve the game described above by working backward from the second stage. First, they calculate the equilibrium profits that will likely accrue to them under any possible set of segment choices and realisation of (ξ, ζ). Then, they choose to serve the segments that maximise the expected value of those profits. The researcher solves the problem in the same order but does not observe the realisation of η.

A pure strategy Subgame Perfect Nash Equilibrium consists of segment choices, $g^* \in \text{Supp}_G$, and price functions, $\{p_g^*(\xi, \zeta)\ \forall g \in \text{Supp}_G\}$,[7] which constitute a Nash equilibrium in every subgame. As standard in the literature, we assume existence of such an equilibrium and we assume that the second stage has a unique equilibrium. However, we allow for multiple equilibria in the first stage.

3 Identification

This section discusses identification of the *true* vector of parameters, $(\theta_0, \gamma_0) \in \Theta \times \Gamma \subseteq \mathbb{R}^K \times \mathbb{R}^{N+1}$, where K is the dimension of θ_0 and $N+1$ is the dimension of γ_0. Recall that θ_0 is the true vector of parameters entering the demand and supply models in the second stage, γ_0 is the true vector of parameters entering the fixed cost equation in the first stage. We organise the discussion in two parts: Section 3.1 explains how to identify θ_0, Section 3.2 explains how to identify γ_0.

[7] For every realisations $g \in \text{Supp}_G$ of G and $(\bar{\xi}, \bar{\zeta}) \in \text{Supp}_{\xi,\zeta}$ of (ξ, ζ), $p_g^*(\bar{\xi}, \bar{\zeta})$ is the vector of optimal prices charged by the firms in the second stage.

To formalise our identification arguments, we introduce some new notation. As highlighted in Section 2.3, the first stage can feature multiple equilibria. For this reason, we introduce an auxiliary random variable, V, which represents a public signal that the firms use to coordinate on a specific equilibrium in the first stage. $\mathcal{J}_t^{\text{all}}$ denotes the set of all possible products that the firms would offer in the second stage in segment $t \in \mathcal{T}$, should they choose to serve every segment in the first stage. We also define the set $\mathcal{J}^{\text{all}} \equiv \cup_{t\in\mathcal{T}}\mathcal{J}_t^{\text{all}}$. Lastly, for every segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\text{all}}$, we collect the demand and marginal cost shocks into a 2×1 vector, $\rho_{j,t} \equiv (\xi_{j,t}, \zeta_{j,t})$.

3.1 Identification of the second stage

This section discusses identification of θ_0. We follow the identification arguments developed for supply and demand models with differentiated products (e.g., Berry and Haile, 2014). In particular, we rely on moments that are expectations of the demand and marginal cost shocks interacted with instruments.

More formally, let us first introduce some assumptions and then discuss them.

Assumption 1. (*Data*) Let the number of cities, C, be large. The researcher observes the realisation (g, x, w, m, p_g, s_g) of (G, X, W, M, P_G, S_G), where the pair (g, p_g) is an equilibrium outcome of the two-stage game described in Section 2.

Assumption 2. (*Exogeneity of demand and marginal cost shocks*) For every segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\text{all}}$, $\mathbb{E}(\rho_{j,t}|X, W, M, \eta, V) = 0_2$ a.s. Further, for every segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\text{all}}$, we define the map $z_{j,t} : \text{Supp}_{X,W} \to \mathbb{R}^L$, where $L \geq K$.

Assumption 3. (*i.i.d.ness of demand and marginal cost shocks*) $\{\rho_{j,t}\}_{j\in\mathcal{J}_t^{\text{all}},t\in\mathcal{T}}$ are i.i.d. conditional on (X, W, M, η, V) a.s.

Assumption 1 states which data are considered available to the researcher in order to identify θ_0. Specifically, the researcher observes the entire network, g_f, built by each firm f. Further, the researcher observes the price and market share, $(p_{j,t}, s_{j,t})$, of each product $j \in \mathcal{J}_{g,t}$ and segment $t \in \mathcal{T}$. Finally, the researcher observes the attributes and cost-shifters, $(x_{j,t}, w_{j,t})$, of each product $j \in \mathcal{J}_t^{\text{all}}$ and segment $t \in \mathcal{T}$, hence including also products not chosen for production.

We construct instruments by taking various functions of the products' covariates. For instance, we consider the number of direct flights operated by the competing firms, the number of different itineraries offered by the competing firms, and the number of competing firms. Assumption 2 guarantees that the instruments are valid. Assumption 2 is similar to the exogeneity condition in standard supply and demand models for differentiated products. However, there are two relevant aspects to notice, which relates to the two-stage structure of the game. First, we impose exogeneity also with respects to the products not chosen for production. This is because the firms could invest resources in the first stage to improve their beliefs about the demand and marginal shocks appearing in the second stage. Such a behaviour would cause endogeneity of the covariates of the selected products. Eizenberg (2014) uses an analogous restriction for studying the U.S. personal computer market. Second, we impose exogeneity also with respect to the vector of fixed cost shocks, η, and the public signal followed by the firms to coordinate on an equilibrium in the first stage, V.

Assumption 3 imposes conditional i.i.d.ness of the demand and marginal cost shocks. This ensures that θ_0 can be expressed as a function of identified quantities as the number of products gets large.

The formal identification result follows.

Proposition 1. (*Identification of the second stage*) Consider segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\text{all}}$. Let the associated vector of demand and supply shocks, $\rho_{j,t}$, be rewritten as a function of the observables, $\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta_0)$, via BLP inversion. Lastly, let $q_{j,t}(X, W, M, \eta, V)$ be a function of (X, W, M, η, V) taking value 1 if product j is chosen for production, and zero otherwise. Under Assumptions 1-3, θ_0 is point identified from the L moment conditions

$$\mathbb{E}\Big[\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta_0) \times z_{j,t,l}(X, W)\Big| q_{j,t}(X,W, M, \eta, V) = 1\Big] = 0_2 \quad \forall l = 1, ..., L.$$

for any segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_{g,t}$. $\diamond$

3.2 Identification of the first stage

This section discusses (partial) identification of γ_0. In particular, we construct bounds for γ_0 based on the revealed preference approach proposed by Pakes et al. (2015) and implemented, e.g., also by Holmes (2011), Ho and Pakes (2014), Eizenberg (2014), Houde et al. (2017), Kuehn (2018), and Wollmann (2018).[8]

Studying identification of γ_0 presents several challenges. First, the first stage of the game may display multiple equilibria and the equilibrium selection mechanism adopted by the firms is unobserved by the researcher. Therefore, without further assumptions, the researcher cannot write down a well-defined likelihood function for the equilibrium network, G. Second, the researcher observes only one realisation, g, of G whose components are interdependent. Interdependence is due to the fact that the segments to serve are selected in the first stage on the basis of a prediction of the second stage profits. Crucially, the second stage features as potential products not only direct flights, but also one-stop flights, hence impeding i.i.d.ness across segments. Interdependence is also due to the fact that the fixed cost incurred to serve each segment may depend on the decision of serving other segments through the term

[8] Note that the bounds derived are not sharp because revealed preference-based inequalities represent necessary, and not necessary and sufficient, equilibrium conditions.

$\sum_{d \in \mathcal{C} \setminus \{h,k\}} \mathbb{1}\{\text{Indirect}_{hkd,f} \text{ or Indirect}_{dhk,f}\}$ in (1). Therefore, the researcher cannot adopt a many-markets partial identification approach à la Tamer (2003) and Ciliberto and Tamer (2009).

We handle these challenges by bounding γ_0 through inequalities derived from equilibrium implications. Specifically, if the observed pair (g, p_g) is an equilibrium outcome of the two-stage game, then no firm can increase its expected variable profit net of fixed costs by unilaterally altering its network. Such necessary conditions produce inequalities that, in turn, are exploited to bound γ_0.

More precisely, the identification procedure involves two steps. First, we need to construct some inequalities from equilibrium implications.[9] Consider any unilateral deviation, g_f^{dev}, from the network observed in the data, g_f, that could be implemented by firm f. Given that (g, p_g) is an equilibrium outcome of the two-stage game, the difference between firm f's expected variable profit net of fixed costs under (g_f, g_{-f}) and firm f's expected variable profit net of fixed costs under $(g_f^{\text{dev}}, g_{-f})$ should be positive. That is,

$$\begin{aligned}&\mathbb{E}\Big[\Pi_f^2(X_G, W_G, M, \xi_G, \zeta_G; \theta_0)\Big| G = g, X = x, W = w, M = m, \eta = \eta^{\text{obs}}\Big] - TFC_f(g_f, \eta_f^{\text{obs}}; \gamma_0)\\ &- \mathbb{E}\Big[\Pi_f^2(X_G, W_G, M, \xi_G, \zeta_G; \theta_0)\Big| G = (g_f^{\text{dev}}, g_{-f}), X = x, W = w, M = m, \eta = \eta^{\text{obs}}\Big] + TFC_f(g_f^{\text{dev}}, \eta_f^{\text{obs}}; \gamma_0) \geq 0,\end{aligned} \tag{5}$$

where (g, x, w, m) is the realisation of (G, X, W, M) observed in the data and $\eta^{\text{obs}} \in \text{Supp}_\eta$ is the realisation of η observed by the firms and not observed by the researcher. By repeating such an argument for every unilateral deviation g_f^{dev} and for every firm f, one obtains D inequalities. Let us index each of these inequalities by $d \in \mathcal{D} \equiv \{1, ..., D\}$. Recall from Section 2.1 that the fixed cost incurred by firm f for every segment $\{a, b\}$ is additively separable in the fixed cost shock, $\eta_{ab,f}$, and is linear in γ_0. Further, by Proposition 1, the researcher knows the two expected values in (5). Therefore, each inequality $d \in \mathcal{D}$ can be more simply expressed as

$$K_d(\theta_0) + \gamma_0' A_d + t_d(\eta^{\text{obs}}) \geq 0, \tag{6}$$

where $K_d(\theta_0)$ captures the differences in the expected variable profits and is known by the researcher; $\gamma_0' A_d$ captures the differences in the systematic fixed costs, is known by the researcher up to γ_0, and is linear in γ_0; $t_d(\eta^{\text{obs}})$ captures the differences in the fixed cost shocks, is known by the researcher up to η^{obs}, and is linear in η^{obs}.

Second, we need to approximate the left-hand-side of (6) by using quantities that do not contain η^{obs}. The difficulty here lies in the fact that considering the average of the D inequalities does not help because $\frac{1}{D}\sum_{d=1}^{D} t_d(\eta^{\text{obs}})$ is close to

$$\mathbb{E}[t_d(\eta)|G = g, X = x, W = w, M = m],$$

[9] Let us add some notational remarks. $g \equiv (g_1, ..., g_N)$ is the observed network under Assumption 1. Also, for any firm f, $g \equiv (g_f, g_{-f})$, where g_{-f} denotes g without g_f.

which, in turn, is different from 0 given that the realisation of η is known by the firms when choosing g. This is the selection problem discussed by Pakes et al. (2015). We solve such an issue by following the instrumental variable approach proposed by Pakes et al. (2015) and implemented, e.g., by Wollmann (2018). In particular, we assume to have H instruments, $\{Z_1, ..., Z_H\}$, which allow us to select from $\mathcal{D}$ some deviations that the firms would not have found profitable under any realisation of η. Hence, we expect the firms to have taken the observed decision not because of the particular realisation of η but rather because of the other, observed, factors in their information sets. For example, in our data, we observe that airlines rarely enter segments where none of the endpoints is a hub. Instead, airlines are more likely to serve segments where at least one of the endpoints is a hub. Also, airlines are more likely to serve segments with large market size, all else equal. Further, around the time period considered for our empirical analysis, several airports were operating at maximum capacity or close to it,[10] thus helping airlines to easily anticipate which airports will be capacity constraint. We argue that selecting deviations according to these factors observed both by the firms and the researcher helps us overcoming the selection problem.

Let $\mathcal{D}_h$ be the collection of deviations selected by instrument Z_h. Let $\mathbb{1}_d(Z_h)$ be an indicator function taking value 1 if instrument Z_h selects deviation $d \in \mathcal{D}$ and 0 otherwise. Then, if the fixed cost shocks are conditionally i.i.d., the average of $t_d(\eta^{\text{obs}})$ over the deviations selected by instrument Z_h is close to

$$\frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \mathbb{E}[t_d(\eta) | \mathbb{1}_d(Z_h) = 1, G = g, X = x, W = w, M = m],$$

for D large. Moreover, if instrument Z_h is valid,

$$\mathbb{E}[t_d(\eta) | \mathbb{1}_d(Z_h) = 1, G = g, X = x, W = w, M = m] = \mathbb{E}[t_d(\eta) | \mathbb{1}_d(Z_h) = 1, X = x, W = w, M = m],$$

where the latter expectation can be assumed equal to zero. Therefore,

$$\frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} [K_d(\theta_0) + \gamma_0' A_d] + \frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} t_d(\eta^{\text{obs}}) \geq 0,$$

can be approximated by

$$\frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} [K_d(\theta_0) + \gamma_0' A_d] \geq 0, \tag{7}$$

for D large. Lastly, note that the left-hand-side of (7) is linear in γ_0. This means that projecting the identified set for γ_0 along every dimension simply amounts to solving a linear maximisation and a linear minimisation problem.

The arguments illustrated above can be condensed down to three assumptions. Assumption 4 formalises the idea of having H instruments allowing us to select from $\mathcal{D}$ some deviations

[10] https://www.faa.gov/airports/planning_capacity/media/FACT3-Airport-Capacity-Needs-in-the-NAS.pdf

that the firms would not have been found profitable under any realisation of η. Assumption 5 impose mean independence of η from such instruments. Assumption 6 requires conditional i.i.d.ness of the fixed costs shocks.

Assumption 4. (*First stage instruments*) For some $H \in \mathbb{N}$ and for each $h \in \mathcal{H} \equiv \{1, ..., H\}$, there exists an instrument, Z_h, which allows us to select from the set of all deviations, $\mathcal{D}$, a subset of deviations, $\mathcal{D}_h$, that the firms would not have been found profitable under any realisation of η. Hence,

$$\begin{aligned}\mathbb{E}[t_d(\eta)|\mathbb{1}_d(Z_h) =& 1, G = g, X = x, W = w, M = m] \\ &= \mathbb{E}[t_d(\eta)|\mathbb{1}_d(Z_h) = 1, X = x, W = w, M = m] \ \forall d \in \mathcal{D}_h, \forall h \in \mathcal{H},\end{aligned}$$

where the functions $t_d(\eta)$ and $\mathbb{1}_d(Z_h)$ have been defined earlier, (g, x, w, m) is the realisation of (G, X, W, M) observed in the data under Assumption 1.

Assumption 5. (*Exogeneity of fixed cost shocks*) For each firm $f \in \mathcal{N}$ and for each segment $\{a, b\} \in \mathcal{R}$, $\mathbb{E}(\eta_{ab,f}|Z_1, ..., Z_H, X = x, W = w, M = m) = 0$ a.s., where (x, w, m) is the realisation of (X, W, M) observed in the data under Assumption 1.

Assumption 6. (*i.i.d.ness of fixed cost shocks*) $\{\eta_{ab,f}\}_{\{a,b\}\in\mathcal{R}, f\in\mathcal{N}}$ are i.i.d. conditional on $Z_1, ..., Z_H, G = g, X = x, W = w, M = m$ a.s., where (g, x, w, m) is the realisation of (G, X, W, M) observed in the data under Assumption 1.

The formal identification result follows.

Proposition 2. (*Identification of the first stage*) Under Assumptions 1-6,

$$\gamma_0 \in \left\{\gamma \in \Gamma : \frac{1}{|\mathcal{D}_h|} \sum_{d\in\mathcal{D}_h} [K_d(\theta_0) + \gamma' A_d] \geq 0 \ \forall h \in \mathcal{H}\right\}.$$

◇

4 Estimation

This section discusses estimation of the true vector of parameters, (θ_0, γ_0). We organise the discussion in two parts: Section 4.1 explains how to estimate θ_0, Section 4.2 explains how to estimate the identified set for γ_0.

4.1 Estimation of the second stage

We estimate θ_0 by using a standard GMM approach. In particular, we consider the L moment conditions of Proposition 1 and use their sample analogues to construct our GMM objective function which should be minimised with respect to $\theta \in \Theta$,

$$Q(\theta) = M(\theta)' A M(\theta),$$

where

$$M(\theta) \equiv \begin{pmatrix} \frac{1}{|\mathcal{J}_G|} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{G,t}} [\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta) \times z_{j,t,1}(X, W)] \\ \frac{1}{|\mathcal{J}_G|} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{G,t}} [\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta) \times z_{j,t,2}(X, W)] \\ \vdots \\ \frac{1}{|\mathcal{J}_G|} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{G,t}} [\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta) \times z_{j,t,L}(X, W)] \end{pmatrix},$$

is a $2L \times 1$ vector and A is an appropriate $2L \times 2L$ weighting matrix.

Note that we estimate the demand and supply sides jointly. One 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 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 correlations between demand and supply moments and, hence, obtain more precise estimates (e.g., 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.

4.2 Estimation of the first stage

Let $\hat{\theta}$ be the estimate of θ_0 from the second stage. We estimate the identified set for γ_0 characterised in Proposition 2 by constructing the feasible region of the linear programming

$$\frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} [K_d(\hat{\theta}) + \gamma' A_d] \geq 0 \ \forall h \in \mathcal{H},$$

with respect to $\gamma \in \Gamma$. Further, in order to obtain the projection of the feasible region along each dimension, we simply solve these linear minimisation and maximisation problems

$$\min_{\gamma \in \Gamma} \gamma_k \text{ s.t. } \frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} [K_d(\hat{\theta}) + \gamma' A_d]) \geq 0 \ \forall h \in \mathcal{H},$$
$$\max_{\gamma \in \Gamma} \gamma_k \text{ s.t. } \frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} [K_d(\hat{\theta}) + \gamma' A_d] \geq 0 \ \forall h \in \mathcal{H},$$

for each k-th element of the vector γ.

We have discussed in Section 3.2 our choice of the first stage instruments. In what follows, we add some minor computational remarks. We include in the collection of all feasible deviations, $\mathcal{D}$, only one-segment unilateral deviations. That is, we allow every firm f to add one segment (if not present in the observed network g_f) or to delete one segment (if present in the observed network g_f) at a time, while competitors' networks remain fixed. Moreover, for each deviation d and candidate parameter γ, we compute $[K_d(\hat{\theta}) + \gamma' A_d]$ in a few steps. Suppose that deviation d is implemented by firm f and consists in adding the segment $\{c, c'\}$ to the observed network g_f. First, we update the systematic fixed costs. Second, we update the list of products offered by firm f, by adding a direct flight between cities c, c' and some one-stop flights if city c and/or city c' are hubs for firm f. Third, we update the matrices of product covariates by adding the attributes and cost shifters of the new products. Fourth, we randomly draw 500 vectors from the joint empirical distribution of the demand and marginal cost shocks.[11,12] For each of these draws, we iterate on the firms' first order conditions (4) to find the new prices[13] and we compute the variable profits. Lastly, we average across draws and obtain our simulated expected variable profits. Hence, $[K_d(\hat{\theta}) + \gamma' A_d]$ is obtained as the difference between the systematic fixed costs plus expected variable profits under g and the systematic fixed costs plus expected variable profits under deviation d. A specular algorithm is developed for the case where deviation d consists of deleting the segment $\{c, c'\}$ from the observed network g_f.

5 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. Moreover, we restrict the sample to flights operated between the 85 largest metropolitan statistical areas (hereafter, MSAs) in the United States. If an MSA has more than one airport (such as New York, Chicago, or Los Angeles), we lump them together in our analysis. We refer to MSAs as "cities" throughout the paper. If an airport within a city serves as a hub for a given airline, that city will be a "hub city" for that airline.[14] The major carriers in the sample are United Airlines (hereafter, UA), Delta Airlines (hereafter, DL), American Airlines (hereafter, AA), US Airways (hereafter, US), and Southwest Airlines (hereafter, WN). All the other carriers in the sample are put either in a group called "Low Cost Carriers"

[11]Recall that the joint empirical distribution of the demand and marginal cost shocks can be obtained from the second-stage estimate, $\hat{\theta}$, by applying BLP inversion.

[12]Note that we can draw second-stage shocks from the joint empirical distribution of the demand and marginal cost shocks because of the timing structure of our game that, combined with Assumption 2, guarantees there is no selection on second-stage shocks.

[13]We have decided to use the firms' first order conditions (4) as a contraction mapping because it has shown to have good convergence properties. While we cannot formally prove that such a function is 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.

[14]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.

(hereafter, LCC), or in a group called "Other". This is because we assume these carriers to merely be 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 of entry when estimating the first stage and we assume that they keep their networks unchanged.

Table 1: Summary Statistics

Variable	Mean	St.Dev.
Variables		
Price (100 USD)	4.32	1.20
Number of Stops	0.86	0.34
Connections	20.06	18.56
Distance (1000 km)	1.44	0.68
Squared Distance (1 million km)	2.54	2.19
Presence	55.9	14.77
Product share	4.61e-04	1.48e-03
Observations	17481	
Passengers by Airline (in 1 million)		
American Airlines	3.15	
Delta Airlines	4.85	
United Airlines	3.81	
US Airways	2.21	
Southwest Airline	6.00	
Low Cost Carriers	4.08	
Other Carriers	1.21	
Market-Level Statistics		
Number of Products	5.56	4.43
Number of Firms	3.59	1.81
Direct Passengers (1000)	6.82	23.98
Connecting Passengers (1000)	1.23	1.58
Number of Market Served	3146	

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. As anticipated in Section 2, we consider tickets featuring the same firm-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 all the remaining fares. Another possibility could have been to keep separately several fare bins, as in Berry et al. (1996) and Berry and Jia (2010). Both strategies have advantages and disadvantages. On one hand, proceeding with fare bins allows to capture lots of consumers' heterogeneity with respect to prices through random coefficients. This is not possible when averaging over fares because there is not sufficient price variation left in the data. On the other hand, the researcher has to define bins and decide how many bins a firm makes use of when entering a market, which can be susceptible to misspecification. Further, keeping separately several fare bins would increase substantially the computational burden of our procedure.

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 mentioned in Section 2, for each segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\text{all}}$, $X_{j,t}$ collects the number of stops ("Stops"), the maximum number of connections at the segment endpoints ("Connections"), the distance between the segment endpoints ("Distance"), and such a distance squared ("Distance2"). Similarly, $W_{j,t}$ collects the number of stops ("Stops Short", "Stops Long"), the average number of connections at each stop ("Presence Short", "Presence Long"), and the distance between the segment endpoints ("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 use data from the US Census Bureau on MSA population in order to compute the market sizes. In particular, we compute the market size of each segment $t \in \mathcal{T}$, M_t, as the geometric mean of the populations at the segment endpoints. Table 1 provides summary statistics for the data.

6 Results

Section 6.2 present the second stage results. Section 6.1 present the first stage results.

6.1 Results from the second stage

Table 2: Second Stage Parameters

Variable	Estimate	Standard Error	Variable	Estimate	Standard Error
Demand Variables			**Cost Variables**		
Constant	-5.476	0.213	Constant Short	3.336	0.090
Price	-0.666	0.050	Constant Long	3.920	0.113
Stops	-1.648	0.032	Stops Short	0.030	0.028
Connections	0.898	0.072	Stops Long	-0.19	0.041
Distance	0.355	0.081	Distance Short	0.476	0.036
Distance2	-0.097	0.017	Distance Long	0.667	0.032
Nesting Parameter (λ)	0.563	0.023	Presence Short	-1.243	0.135
			Presence Long	-1.849	0.143
Carrier Dummies					
DL	-0.171	0.024	DL	0.081	0.035
UA	-0.370	0.024	UA	0.049	0.031
US	0.170	0.030	US	0.078	0.031
WN	-0.504	0.030	WN	-0.362	0.029
LCC	-0.391	0.048	LCC	-1.507	0.055
Other	-0.135	0.046	Other	-1.398	0.048
Value of Objective Function	1919.456				
Number of Observations	17,481				

The second stage results are in Table 2. On the demand side, the price coefficient is negative. It lies in between the price coefficients for the two types in Berry and Jia (2010) and in the ballpark compared to other contributions as well. Passengers exhibit a strong disutility for connecting flights. Further, they benefit from having a high number of connections at the segment endpoints and, hence, from airlines' networks being dense. In fact, a high number of connections enhances the value of frequent flyer programs, the number of check-in places and separate lounges, etc. In line with previous findings, utility seems to be an inverted U-shaped function with respect to the distance between the segment endpoints. We estimate the nesting parameter, λ, to be around 0.6. Recall that as λ approaches one, the Nested Logit model collapses into the standard Logit model. We can conclude that there is substitution between the inside goods and the outside option.

On the cost side, a carrier's market presence lowers marginal costs substantially. This highlights that hub-and-spoke networks can induce (marginal) cost savings. The estimated coefficients of all other cost shifters are positive, with the exception of the number of stops for long-haul flights. Such a negative coefficient suggests that, when controlling for the size of an airline's operation at the endpoints, connecting flights are less expensive to provide in the case of long-haul flights. Lastly, as expected, Southwest, low-cost carriers, and medium size carriers have lower marginal costs than the legacy carriers.

Table 3: Breakdown of Profits

	Profits (100k)	Price	Marginal Cost	Markup	Lerner Index
All Flights	1.560	431.740	333.870	97.870	0.240
Direct Flights	9.880	397.390	290.640	106.750	0.300
Connecting Flights	0.250	437.130	340.660	96.480	0.240

Table 4: Profits by Firm

	Profits (100k)	Price	Marginal Cost	Markup	Lerner Index
AA (All)	1.47	453.36	357.21	96.15	0.23
AA (Direct)	11.4	402.37	299.54	102.83	0.27
AA (Indirect)	0.32	459.26	363.88	95.38	0.22
DL (All)	1.18	436.45	332.34	104.1	0.26
DL (Direct)	10.32	463.26	342.88	120.38	0.28
DL (Indirect)	0.27	433.8	331.3	102.5	0.25
UA (All)	1.03	445.56	350.44	95.12	0.23
UA (Direct)	7.53	458.5	357.06	101.44	0.24
UA (Indirect)	0.17	443.85	349.56	94.29	0.23
US (All)	1.07	453.43	358.69	94.74	0.22
US (Direct)	7.47	407.34	297.2	110.14	0.29
US (Indirect)	0.28	459.1	366.25	92.85	0.21
WN (All)	2.33	419.43	321.58	97.85	0.25
WN (Direct)	10.11	365.14	259.23	105.91	0.31
WN (Indirect)	0.18	434.4	338.77	95.63	0.23
LCC	3.96	363.97	270.46	93.51	0.29
Total Number of Passengers (in 1m)	25.33				

Tables 3 and 4 show average profits and firm-level average profits, respectively. Table 3 reveals that the legacy carriers are quite heterogeneous in terms of marginal costs. Whereas

Table 5: Elasticity Estimates

Price Elasticity	-4.690
Aggregate Easticity	-2.380
Connection semi-elasticity	0.870

American Airlines and US Airways have substantially lower marginal costs on direct flights, it is the opposite for Delta Airlines and United Airlines. Further, Southwest and low-cost carriers have significantly lower marginal costs on direct flights than the legacy carriers. Lastly, all carriers make the overwhelming majority of their profits from direct flights.

Table 5 shows various elasticity measures. The price elasticity is relatively high. This may be due to the fact that our model does not capture sufficient consumers' heterogeneity in price sensitivity. The connection semi-elasticity measures the change in the number of passengers when a direct flight becomes a connecting flight, while holding all other characteristics fixed. It is higher than in Berry and Jia and, thus, in line with the trend towards increasingly strong preferences for direct flights acknowledged by the authors in that paper.

6.2 Results from the first stage

The first stage results are in Table 6. In particular, Table 6 reports the projections of the estimated identified set. The intervals for the γ_2's components are substantially heterogeneous across firms. Further, serving hub segments is more costly for Southwest than for the legacy carriers. This may be due to the fact that Southwest does not employ a full-fledged hub-and-spoke network but rather a network with so-called "base cities" with some degree of connectivity.

Table 7 attempts to measure of how well our model fits the data. The second column reports the observed entry probability (computed as the number of segments served over the total number of segments in the sample), the third column reports the predicted entry probability at the midpoints of the projections of the estimated identified set. We fit entry probabilities reasonably well with the exception of Southwest.

Table 6: Projections of Estimated Identified Set

	Lower Bound	Upper Bound
No Hub (γ_1)	1.028	2.679
Hub AA ($\gamma_{2,\text{AA}}$)	0.129	0.224
Hub DL ($\gamma_{2,\text{DL}}$)	0.090	0.164
Hub UA ($\gamma_{2,\text{UA}}$)	0.098	0.151
Hub US ($\gamma_{2,\text{US}}$)	0.115	0.139
Hub WN ($\gamma_{2,\text{WN}}$)	0.263	0.341

Table 7: Predicted Entry Probabilities at Midpoint

Firm	Data	Predicted Midpoint
AA	6.97	6.88
DL	12.5	10.81
UA	13.1	11.20
US	7.03	6.85
WN	19.05	13.19

7 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.[15] At the time they expressed interest to merge in January 2012, American Airlines' holding company (AMR Corporation) was in Chapter 11 bankruptcy. The merger was cleared by a federal court in March 2012. Shortly after, the Department of Justice (hereafter, DOJ), along with several state attorney generals, sought to block the merger. 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".[16] 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.[17] 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.[18]

In what follows, Section 7.1 describes the exercise and the algorithm designed to reach the counterfactual scenarios. Section 7.2 discusses our results. Section 7.3 investigates the impact on consumer welfare of one the remedies imposed by the 2013 settlement. Sometime we will refer to the merged entity as American Airlines because this is the brand name that "survived" the merger.

7.1 Set-up

We consider three counterfactual scenarios:

[15] 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.

[16] 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

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

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

1. *Network Fixed - Base Case.* After the merger, (g, x, w, m) remain at the pre-merger level. The firms play the simultaneous pricing game described in Section 2.2 and a new equilibrium outcome, p^*, arises. In particular, the merging firms choose the prices maximizing their joint profits, i.e., they behave as if they colluded.

2. *Network Fixed - Best Case.* After the merger, $(g, x_{-\text{AA,US}}, w_{-\text{AA,US}}, m)$ remain at the pre-merger level. The covariates of the merged entity's products are constructed by assigning to the merged entity the most favourable features, both on the demand and cost sides. For example, on the demand side, the estimated coefficient of the variable "Connections" is positive. Hence, the merged entity's products will get the highest value of "Connections" between what American Airlines and US Airways had before merging. After such rearrangements, we let the firms play the simultaneous pricing game described in Section 2.2 and a new equilibrium, p^*, arises.

3. *Two-Stage.* 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 2. A new equilibrium outcome, (g^*, p^*), arises. More details on how the firms re-optimise networks and prices are in Section 7.1.1.

The first two scenarios do not take into account network endogeneity, as it is standard in the literature. In such scenarios, the researcher assumes that the firms' networks stay fixed and artificially determines how the product covariates adjust after the merger, hence possibly incurring into serious misspecification. The third scenario considers the entire two-stage game and allows the firms to re-optimise prices *and* networks after the merger, by leveraging on our methodology. In fact, after the approval of the merger, the merging firms may react with further entry accommodations in order to respond to competitors' reactions. Therefore, the counterfactual predictions from the third experiment incorporates general equilibrium considerations and are expected to be more robust.

In all scenarios, we focus on segments in which American Airlines and/or US Airways have a hub at one or both endpoints.[19] These segments 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. Finally, in all scenarios the merged entity takes on the most favourable firm dummies, both on the demand and cost sides.

7.1.1 Experiment "Two-Stage": details

In the third counterfactual experiment of Section 7.1, the firms re-optimise networks and prices. However, given the complexity of the network formation process, it is infeasible to list all

[19] We assume that 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/Baltimore, Phoenix, Miami, and Los Angeles.

possible post-merger equilibria. To circumvent this issue, we design the following sequential approach. First, consider the network observed before the merger, g, and create a new network, g^{merg}, by combining the pre-merger networks of American Airlines and US Airways. For example, if American and US Airways both offer a direct flight in segment t before the merger, we combine them into a single product. Consequently, update the covariates of the merged entity's products. Second, rank segments and firms according to some criteria. Then, start with the first firm in the first segment and compute that firm's best response to competitors' actions with respect to entry/exit and prices. Update the first firm's network and prices and move on to the second firm in the first segment. Repeat the same procedure and update the second firm's network and prices. When all firms have updated their networks and prices, start again from the first firm in the first segment. Once no firm wishes to deviate from their current decisions in the first segment,[20] move to the second segment. When all markets have been completed, start again with the first firm in the first market and repeat the process. If there are no deviations between the first and the second iterations, stop. Otherwise, proceed to a third iteration, and so on, until convergence.

Other steps are worth discussing. First, when calculating a firm's best response in the sequential procedure above, we have to compare the total profits of that firm under its current entry/exit status (say, serving the segment) with the total profits under the deviation (say, not serving the segment). When one endpoint of the segment is a hub, the firm is allowed to offer one-stop flights via that endpoint. In cases where an endpoint is a hub and the firm does not serve the segment, we assume that, when deviating, the firm offers all one-stop flights via the endpoint that the firm can feasibly supply given its current network. In cases where an endpoint is a hub and the firm serves the segment, we assume that, when deviating, the firm deletes all one-stop flights the firm offered via the endpoint.

Second, the parameters of the first stage are partially identified. Hence, we have to pick a value of such parameters at which to run our counterfactual experiments. As discussed earlier, Table 7 suggests that the midpoints of the projections of the estimated identified set fit well the entry probabilities. Hence, we run our counterfactual experiments at these midpoints.

Third, we have to choose a density from where the fixed cost shocks are drawn. In fact, recall that the probability distribution of η has not been parametrically specified. 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 segment, 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). Specifically, given a firm's expected variable profit net of fixed costs, for each (un)served segment, we find the (minimum) maximum possible realisation that the fixed cost shock could have taken for that segment

[20] In our simulations, we typically get convergence within three iterations. It happens rarely that convergence is not attained. In those few cases, we pick the state of the market at the 25th iteration.

Table 8: Firm Outcomes

	Before		Base Case		Best Case		Two-Stage	
	Pax	Market Share	Pax	Market Share	Pax	Market Share	Pax	Market Share
Merged Entity	4.53	29.61	4.86	31.16	10.42	50.34	4.68	28.47
DL	1.71	11.18	1.70	10.90	1.61	7.78	2.64	16.06
UA	2.14	13.99	2.13	13.66	2.01	9.71	2.10	12.78
WN	3.10	20.26	3.09	19.81	2.98	14.40	3.26	19.83

Table 9: Market Outcomes

	Before	**Base case**	**Best Case**	**Two-Stage**
Price	4.30	4.31	4.04	4.27
Marginal Cost	2.74	2.73	2.45	2.67
Consumer Surplus	3256	3319	4417	3480

to remain (un)served. This gives us a vector of “maximum shocks” for served segments and “minimum shocks” for unserved segments. Then, for each served segment, we find the range of values lying between that segment’s “maximum shock” and the 5-th percentile of the vector of “minimum shocks”. Likewise, for each unserved segment, we find the range of values lying between that segment’s “minimum shock” and the 95-th percentile of the vector of “maximum shocks”. We then take the mid-point of those ranges. Such mid-points represent the shock draws.

7.2 Results

Table 8 shows the effects of the merger on firm outcomes.[21] The results differ quite dramatically between the Base Case and the Best Case scenarios. While market shares are not substantially altered in the Base Case scenario, they increase by roughly 70% in the Best Case scenario and gets close to a threshold used by the DOJ to detect monopoly power in the past.[22] In contrast, all other firms’ market shares drop significantly. The counterfactual market shares under the Two-Stage scenario resemble those of the Base Case scenario, except for Delta whose market share rises by almost 5 percentage points.

Table 9 shows the effects of the merger on market outcomes. In the Base Case scenario, prices rise slightly and marginal costs fall slightly. This can be due to the fact that the merged entity takes on the most favourable firm dummies, both on the demand and cost sides. Consumer surplus rises by around 2%. In contrast, in the Best Case scenario, prices and marginal costs fall by much larger amounts. The fall in marginal costs can be due to the fact that the marginal costs for flights between and passing through well-connected airports are lower. Lastly, consumer surplus rises by around 36%. This suggests that, under the Best Case

[21] In Table 8, “Pax” means “Passengers”.

[22] E.g., United States v. Dentsply Int’l, Inc. 2005

Table 10: Segments Served Out of Hubs, AA

	Before	After
Dallas	67	67
Charlotte	60	36
Chicago	58	59
Philadelphia	51	50
New York City	41	39
Washington DC	39	44
Phoenix	41	32
Miami	39	38
Los Angeles	28	27

scenario, the merger should be allowed to go through. In the Two-Stage scenario, prices fall. This can be due to the fact that the merged entity (and also other competitors) saves marginal costs by disposing of a larger network, as likewise indicated by the drop in marginal costs. In terms of welfare, consumer surplus rises by around 7%.

Table 10 shows the number of segments served by American Airlines before and after the merger. Operations stay roughly the same in most hubs. Let us add few comments on Washington DC. Under the 2013 settlement, the new American Airlines was forced to divest slots and gates at Washington Reagan National Airport, in order to facilitate the entry of other airlines, e.g., Southwest. Our result reveals that these divestitures were warranted. In fact, the new American Airlines adds 5 segments at Washington DC, while Southwest- which the DOJ had identified as a potential entrant in many markets- only adds 2 segments to its already existing 60 (not reported here). This is in line with the findings of Ciliberto, Murry, and Tamer (2018).[23]

7.3 Remedies at American Airlines' hub in Charlotte

Under the 2013 settlement, the new American Airlines agreed to maintain hubs at a number of airports, e.g., Charlotte International Airport, "consistent with historical operations for a period of three years".[24] In this section, we use our methodology to study the impact of such a remedy on consumer welfare. On one hand, the new American Airlines faces a trade-off between keeping and expanding operations, which results in marginal cost savings. On the other hand, the fixed cost of serving a segment increases. Both forces are present in our model. Hence, we can exploit our results to make detailed predictions, compared to other frameworks in the literature where instead networks are kept fixed.

We consider two counterfactual scenarios:

1. *After-Free*. This is the Two-Stage scenario above.

[23]Contrary to us, Ciliberto, Murry, and Tamer (2018) keep airports separate. Hence, they are able to isolate the effect at the targeted airport (Reagan National Airport).

[24]https://americanairlines.gcs-web.com/news-releases/news-release-details/amr-corporation-and-us-airways-announce-settlement-us-department

Table 11: Effects of the Merger in Charlotte

	Before	After-Free	After-Restricted
Served by American	60	36	62
Consumer Surplus	156.88	123.89	165.31

2. *After-Restricted.* The merged entity is forced to keep serving each market out of Charlotte it had served before the merger.

The results in Table 11 show that under the After-Free scenario, consumer surplus contracts sharply by around 21%. Under the After-Restricted scenario, consumer surplus increases by around 5%. This suggests that the remedy was warranted to prevent harm to consumers in Charlotte due to the merger. Further, under the After-Restricted scenario, the new American Airlines even adds 2 segments. This mirrors real developments after the merger occurred. In fact, the new American Airlines expanded operations in Charlotte, both domestically and internationally.

8 Conclusion

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. Our model relaxes the assumption of exogeneity of airlines' route networks and of i.i.d.ness of airlines' entry decisions across routes. The two-stage framework allows us to account for selection of airlines into interdependent routes. Moreover, it permits us to make counterfactual exercises which robustly predict changes not only in prices and markups, but also in how airlines adjust their route networks. We show identification of the second-stage parameters by following the standard approach for supply and demand models with differentiated products. We show (partial) 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. 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 consumer surplus increased by around 7%. We then look at the effects of the merger in markets out of Charlotte, where the merged entity had to pledge to keep operations at previous levels, and find that this remedy was indeed warranted to prevent harm to consumers.

One limitation of our model is that 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. We are currently working on inference for the first stage parameters.

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A Proofs

Proof of Proposition 1 The proof builds on Berry and Haile (2014) and Eizenberg (2014).

Step 0 For every segment $t \in \mathcal{T}$ and product $j \in \mathcal{J}_t^{\text{all}}$, let $q_{j,t}(X, W, M, \eta, V)$ be a function of (X, W, M, η, V) taking value 1 if product j is chosen for production, and zero otherwise. Note that such a function does not depend on (ξ, ζ) because the firms do not observe the realisation of (ξ, ζ) when making their first stage choices. Further, note that under Assumption 1 the researcher observes a realisation of $q_{j,t}(X, W, M, \eta, V)$.

Step 1 Assumption 2 implies

$$\mathbb{E}\Big[\rho_{j,t} \times z_{j,t,l}(X, W) \times q_{j,t}(X, W, M, \eta, V)\Big] = 0_2 \quad \forall l = 1, ..., L, \tag{A.1}$$

for each product $j \in \mathcal{J}_t^{\text{all}}$ and segment $t \in \mathcal{T}$, where $z_{j,t,l}(X, W)$ is the l-th element of the $L \times 1$ random vector $z_{j,t}(X, W)$. If $Pr(q_{j,t}(X, W, M, \eta, V; \theta_0, \gamma_0) = 1) > 0$, (A.1) implies

$$\mathbb{E}\Big[\rho_{j,t} \times z_{j,t,l}(X, W)\Big| q_{j,t}(X, W, M, \eta, V) = 1\Big] = 0_2 \quad \forall l = 1, ..., L, \tag{A.2}$$

for each product $j \in \mathcal{J}_t^{\text{all}}$ and segment $t \in \mathcal{T}$.

Step 2 Fix any $g \in \text{Supp}_{\mathcal{G}}$. Note that, for each segment $t \in \mathcal{T}$, there exists only one realisation of $(\xi_{g,t}, \zeta_{g,t})$, denoted by $(\bar{\xi}_{g,t}, \bar{\zeta}_{g,t}) \in \text{Supp}_{\xi_{g,t},\zeta_{g,t}}$, such that

$$\begin{aligned} s_{j,t} &= \sigma^g_{j,t}(x_{g,t}, p_{g,t}, \bar{\xi}_{g,t}; \theta_{0,d}) && \forall j \in \mathcal{J}^0_{g,t}, \\ w_{j,t}\psi_0 + \bar{\zeta}_{j,t} &= p_{j,t} - b^g_{j,t}(x_{g,t}, p_{g,t}, s_{g,t}; \theta_{0,d}) && \forall j \in \mathcal{J}_{g,t}, \end{aligned}$$

from (3) and (4), for every $(x_{g,t}, p_{g,t}, s_{g,t}, w_{g,t}, m_t) \in \text{Supp}_{X_{g,t},P_{g,t},S_{g,t},W_{g,t},M_t}$. In turn, $(\bar{\xi}_t, \bar{\zeta}_t)$ is given by

$$\begin{aligned} \bar{\xi}_{j,t} &= \sigma^{-1,g}_{j,t}(x_{g,t}, p_{g,t}, s_{g,t}; \theta_{0,d}) && \forall j \in \mathcal{J}_{g,t}, \\ \bar{\zeta}_{j,t} &= p_{j,t} - b^g_{j,t}(x_{g,t}, p_{g,t}, s_{g,t}; \theta_{0,d}) - w_{j,t}\psi_0 && \forall j \in \mathcal{J}_{g,t}. \end{aligned}$$

This implies that $\rho_{j,t}$ in (A.2) can be expressed as a function of the observables,

$$\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta_0).$$

Therefore,

$$\mathbb{E}\Big[\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta_0) \times z_{j,t,l}(X, W)\Big| q_{j,t}(X, W, M, \eta, V) = 1\Big] = 0_2 \quad \forall l = 1, ..., L, \tag{A.3}$$

for each product $j \in \mathcal{J}_t^{\text{all}}$ and segment $t \in \mathcal{T}$.

Step 3 For any product $j \in \mathcal{J}_t^{\text{all}}$ and segment $t \in \mathcal{T}$, we can solve the system of equations (A.3) with respect to θ_0 and show that it has a unique solution, under appropriate rank condition.

Step 4 For each $l = 1, ..., L$, under Assumption 3 (plus additional regularity conditions), it holds that

$$\frac{1}{|\mathcal{J}_g|} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{g,t}} \Big[\delta_{j,t}(x_{g,t}, p_{g,t}, s_{g,t}, w_{G,t}, m_t; \theta_0) \times z_{j,t,l}(x, w) \Big],$$

computed with the available data, is close to

$$\mathbb{E}\Big[\delta_{j,t}(X_{G,t}, P_{G,t}, S_{G,t}, W_{G,t}, M_t; \theta_0) \times z_{j,t,l}(X, W) \Big| q_{j,t}(X, W, M, \eta, V) = 1 \Big],$$

for every product $j \in \mathcal{J}_t^{\text{all}}$ and segment $t \in \mathcal{T}$, when $|\mathcal{J}^{\text{all}}|$ is large. Hence, the researcher can rewrite the unique solution, θ_0, of system (A.3) as a function of known quantities. Therefore, θ_0 is point identified.

Proof of Proposition 2 The proof develops identification arguments similar to those in Eizenberg (2014), Houde, Newberry, and Seim (2017), Kuehn (2018), and Wollmann (2018).

Step 0 We introduce some useful notation. Given the realisation (g, x, w, m, p_g, s_g) of (G, X, W, M, P_G, S_G) observed by the researcher under Assumption 1, let $\eta^{\text{obs}} \in \text{Supp}_\eta$ be the corresponding realisation of η observed by the firms and not observed by the researcher. For each firm $f \in \mathcal{N}$, let g_{-f} denote the collection of competitors' networks. Hence, $g \equiv (g_1, ..., g_N) \equiv (g_f, g_{-f})$. Further, for each firm $f \in \mathcal{N}$, take any $g_f^{\text{dev}} \in \text{Supp}_{G_f} \setminus \{g_f\}$ and let $(g_f^{\text{dev}}, g_{-f})$ denote the collection of networks obtained by replacing g_f with g_f^{dev} in g. Lastly, for each firm $f \in \mathcal{N}$, let $\Delta_f(g, (g_f^{\text{dev}}, g_{-f}), x, w, m, \eta^{\text{obs}}; \theta_0, \gamma_0)$ be the difference between firm f's expected variable profit net of fixed costs under g and firm f's expected variable profit net of fixed costs under $(g_f^{\text{dev}}, g_{-f})$. That is,

$$\begin{aligned}
\Delta_f(g, (g_f^{\text{dev}}, g_{-f}), x, w, m, \eta^{\text{obs}}; \theta_0, \gamma_0) \equiv\ & \mathbb{E}\Big[\Pi_f^2(X_G, W_G, M, \xi_G, \zeta_G; \theta_0) \Big| G = g, X = x, W = w, M = m, \eta = \eta^{\text{obs}} \Big] \\
& - TFC_f(g_f, \eta_f^{\text{obs}}; \gamma_0) \\
& - \mathbb{E}\Big[\Pi_f^2(X_G, W_G, M, \xi_G, \zeta_G; \theta_0) \Big| G = (g_f^{\text{dev}}, g_{-f}), X = x, W = w, M = m, \eta = \eta^{\text{obs}} \Big] \\
& + TFC_f(g_f^{\text{dev}}, \eta_f^{\text{obs}}; \gamma_0).
\end{aligned} \tag{A.4}$$

Step 1 Given that the pair (g, p_g) is an equilibrium outcome of the two-stage game by Assumption 1, it should be that

$$\Delta_f(g, (g_f^{\text{dev}}, g_{-f}), x, w, m, \eta^{\text{obs}}; \theta_0, \gamma_0) \geq 0 \qquad \forall g_f^{\text{dev}} \in \text{Supp}_{G_f} \setminus \{g_f\}, \forall f \in \mathcal{N}. \tag{A.5}$$

Step 2 We now rewrite (A.4) in a more useful way. First, note that the researcher knows the two expected values in (A.4) by Proposition 1. Second, recall that the fixed cost of every segment $\{a, b\} \in \mathcal{R}$ is additively separable in the fixed costs shock, $\eta_{ab,f}$, and is linear in γ_0 (see Equation (1)). Therefore, (A.4) can be expressed as the sum of three components,

$$\Delta_f(g, (g_f^{\text{dev}}, g_{-f}), x, w, m, \eta^{\text{obs}}; \theta_0, \gamma_0) = K_{g_f^{\text{dev}}}(\theta_0) + \gamma_0' A_{g_f^{\text{dev}}} + t_{g_f^{\text{dev}}}(\eta^{\text{obs}}), \tag{A.6}$$

where $K_{g_f^{\text{dev}}}(\theta_0)$ captures the differences in the expected variable profits and is known by the researcher; $\gamma_0' A_{g_f^{\text{dev}}}$ captures the differences in the systematic fixed costs, is known by the researcher up to γ_0, and is linear in γ_0; $t_{g_f^{\text{dev}}}(\eta^{\text{obs}})$ captures the differences in the fixed cost shocks, is known by the researcher up to η^{obs}, and is linear in η^{obs}.

To simplify the notation, let us index the inequalities in (A.5) by the integers in $\mathcal{D} \equiv \{1, ..., D\}$, where D is the total number of inequalities. Hence, by using (A.6), (A.5) can be rewritten as

$$K_d(\theta_0) + \gamma_0' A_d + t_d(\eta^{\text{obs}}) \geq 0 \qquad \forall d \in \mathcal{D}.$$

Step 3 For every $h \in \mathcal{H}$, take the subset of deviations, $\mathcal{D}_h$, selected by instrument Z_h. By Assumption 6,

$$\frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} t_d(\eta^{\text{obs}}),$$

is close to

$$\frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \mathbb{E}\Big[t_d(\eta) \Big| \mathbb{1}_d(Z_h) = 1, G = g, X = x, W = w, M = m\Big],$$

for D large. By Assumption 4,

$$\frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \mathbb{E}\Big[t_d(\eta) \Big| \mathbb{1}_d(Z_h) = 1, G = g, X = x, W = w, M = m\Big] = \frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \mathbb{E}\Big[t_d(\eta) \Big| \mathbb{1}_d(Z_h) = 1, X = x, W = w, M = m\Big].$$

Further, by Assumption 5,

$$\frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} \mathbb{E}\Big[t_d(\eta) \Big| \mathbb{1}_d(Z_h) = 1, X = x, W = w, M = m\Big] = 0.$$

Therefore,

$$\frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} [K_d(\theta_0) + \gamma_0' A_d] + \frac{1}{|\mathcal{D}_h|} \sum_{d \in \mathcal{D}_h} t_d(\eta^{\text{obs}}) \geq 0,$$

can be approximated by

$$\frac{1}{|\mathcal{D}_h|}\sum_{d\in\mathcal{D}_h}[K_d(\theta_0)+\gamma_0' A_d]\geq 0, \tag{A.7}$$

for D large. By considering (A.7) for each $h \in \mathcal{H}$, we obtain H inequalities that allow us to partially identify γ_0.