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

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

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Abstract

We develop a two-stage game in which competing airlines first choose the networks of markets to serve in the first stage before competing in price in the second stage. Spillovers in entry decisions across markets are allowed, which accrue on the demand, marginal cost, and fixed cost sides. We show that the second-stage parameters are point identified, and we design a tractable procedure to set identify the first-stage parameters and to conduct inference. Further, we estimate the model using data from the domestic US airline market and find significant spillovers in entry. In a counterfactual exercise, we evaluate the 2013 merger between American Airlines and US Airways. Our results highlight that spillovers in entry and post-merger network readjustments play an important role in shaping post-merger outcomes.

Keywords: endogenous market structure, networks, airlines, oligopoly, product repositioning, mergers, remedies.

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1 Introduction

When evaluating a merger, antitrust authorities must trade off the costs of an increase in market power and the benefits of merger-induced efficiencies, putting upward and downward pressure on prices, respectively (Williamson, 1968). In network industries, such as the airline industry studied in this paper, post-merger market repositioning can amplify or nullify these effects. The hub-and-spoke system of this industry creates opportunities for the newly merged entity to offer passengers more destination choices, hence increasing the willingness-to-pay on the demand side and reducing costs on the supply side. Driven by such incentives, the merged entity may decide to re-optimise its network of routes.[1] Moreover, rivals may react to the merger by exiting some markets in which the merged entity has become powerful, and entering others where more competitors can remain profitable.

Despite these arguments, traditional merger analyses do not formally incorporate post-merger entry-exit patterns. To address this gap, we build and estimate a structural model of the airline market in which airlines choose their network of markets to transport passengers from one city to another. Our model allows us to conduct an exhaustive evaluation of airline mergers, thus considering the possibility for each airline to redefine the set of destinations offered to passengers. In particular, we quantify the importance of post-merger network re-optimisation in shaping final outcomes using the 2013 merger between American Airlines and US Airways. We also evaluate the global effect of the remedies imposed by antitrust authorities on the merging parties in order to constrain post-merger network readjustments and protect consumer surplus.

Endogenising entry decisions in a model for the airline industry is challenging. The presence of an airline in a given market affects the demand, marginal costs, and fixed costs of the itineraries offered by the same airline in neighboring markets and, hence, spills over into the airline's decision to operate in those neighboring markets. As a result, an airline does not take its entry decisions market-by-market but rather builds the network of served markets on a global basis so as to internalise spillovers in entry. These spillovers arise from the hub-and-spoke system operated by airlines. In addition to flights transporting passengers directly from one city to another, an airline can offer flights connecting cities via a common hub, which acts as a stop-over point towards many final destinations. Such connecting flights can lead to marginal cost savings by activating economies of density and increase demand by boosting the value of loyalty programs in all the markets linked to the same hub. At the same time, they may increase fixed costs due to the risk of congestion at hubs.[2]

[1] Clark (2015) studies airline mergers from the early 2000s and finds that both the America West/US Airways and United/Continental mergers led to network expansions, while the Delta/Northwest merger led to a smaller post-merger network, mainly due to Cincinnati losing its hub status.

[2] For more information on the impact of hub-and-spoke operations on demand, marginal costs, and

We model airlines' decisions as a two-stage game. In the first stage, each airline forms its network by weighting changes in the fixed costs against changes in the expected variable profits. In the second stage, conditional on all the networks, airlines face demand for the offered itineraries, pay the variable costs, and choose the prices to charge while competing in a classic Bertrand-Nash pricing game. The two-stage structure of our model is similar to Eizenberg (2014) and Wollmann (2018), but we face additional methodological and computational challenges: the spillovers in entry break the usual separability across markets of the characteristic space where products are defined.

The timing of the game permits us to identify the supply and demand parameters as in traditional supply-demand models for differentiated products (Berry and Haile, 2014). Identification of the fixed cost parameters is hampered by the possibility of multiple Nash equilibrium networks, which prevents us from writing down a well-defined likelihood function. Further, constructing the set of Nash equilibrium networks for a given value of the fixed cost parameters is computationally burdensome, due to the large number of markets and the presence of spillovers in entry. We circumvent these issues by following the literature on revealed preferences (Pakes, 2010; Pakes et al., 2015), and derive moment inequalities from best-response implications. Namely, if the networks chosen by the airlines constitute a pure strategy Nash equilibrium, then the airlines' profits in these networks are higher than those in counterfactual networks. These moment inequalities are easy to evaluate because they require us to neither impose any ad-hoc equilibrium selection assumption, nor to construct the set of equilibrium networks for each possible value of the fixed cost parameters.

Due to our fixed cost specification, the identified set defined by the moment inequalities is a convex polytope. Convexity has been proven to be a desirable feature in the set identification literature (Beresteanu and Molinari, 2008; Bontemps et al., 2012; Kaido and Santos, 2014). In fact, it often reduces the computational burden of estimation because the analyst can directly estimate the frontier points of the identified set by estimating the support function. This allows us to estimate a set for the fixed cost parameters with an easy-to-implement procedure based on solving linear programs. However, constructing a confidence region for the true parameter vector depends on nuisance parameters that cannot be uniformly estimated, as for most examples of the set identification literature. By exploiting the linearity of the moment inequalities, we design a method to appropriately smooth the identified set. We show that this smoothing step characterises a strictly convex outer set and, hence, guarantees asymptotic normality of the estimated support function with a variance that can be easily computed from the data. In turn, we can con-

fixed costs, see, for instance, Caves et al. (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 et al. (1992), Brueckner and Spiller (1994), Oum et al. (1995), Berry et al. (1996), Nero (1999), Berry and Jia (2010), and Berry et al. (2019). See also Section 3 .

struct confidence intervals for each component (or linear combinations of components) of the vector of fixed cost parameters by solving linear programs with linear and exponential cone constraints.

We estimate our model using US domestic tickets data from the Airline Origin and Destination Survey during the second quarter of 2011. We consider the flights operated by the main airlines between the top 85 US cities. Our empirical findings reveal significant spillovers in entry on the demand, marginal cost, and fixed cost sides. Specifically, on the demand side, consumers benefit from flying with airlines offering many connections out of the itinerary's endpoints due to an increase in the value of loyalty programs. Hence, dense networks increase consumers' willingness-to-pay for an airline's flight. On the supply side, the marginal costs of an itinerary decrease when an airline allows passengers to reach many cities from the itinerary's endpoints and intermediate stops, due to economies of density. Hence, dense networks generate marginal cost savings. At the same time, we find that the denser the networks, the higher the fixed costs of offering direct flights out of hubs due to congestion effects.

Our empirical findings have significant consequences on analysing environmental changes, such as mergers. In particular, we use our estimates to study the merger between American Airlines and US Airways. These two firms merged in 2013, subject to a series of remedies imposed by the Department of Justice (DoJ) to restrict post-merger network readjustments and protect consumer surplus. We highlight three main counterfactual results.

First, without the remedies, the merger leads to a slight increase in consumer surplus by around 0.5%. With the remedies, consumer surplus rises by around 0.8%.

Second, the impact of the merger differs between the markets that the merging parties served pre-merger ("old markets"), on which antitrust authorities typically focus, and the markets where the merged entity enters post-merger ("new markets"), which are usually ignored by antitrust authorities. On the one hand, old markets undergo consumer surplus losses of around 5%. If the merger's effect on consumer surplus in the old markets was the relevant criterion, then the merger should have been blocked. This is in line with the DoJ's initial attempt to stop the merger. On the other hand, new markets experience an increase in consumer surplus by around 45%, driven by the high willingness-to-pay for direct flights. It reveals substantial positive effects of the merger and can be used to legitimise its implementation. Further, the DoJ's remedies, which were tailored for old markets, reduce consumer surplus losses in old markets but, at the same time, weaken consumer surplus gains in new markets. This highlights the need for antitrust authorities to carefully balance these two effects when designing post-merger interventions. To the best of our knowledge, this tension between consumer surplus losses in old markets and consumer surplus gains in new markets is a novel empirical finding that has major implications for policymakers, and clearly shows the inadequacy of the fixed network approach in evaluating mergers.

Third, spillovers in entry substantially shape post-merger outcomes. In particular, the differences between new and old markets are driven by the expansion of the American Airlines' network in an attempt to leverage spillovers on the demand and marginal cost sides, and the reduction of competitors' networks, which are unable to compete with the new powerful player. Importantly, such network changes align with the real entry-exit patterns observed after 2013.

The rest of the paper is organised as follows. Section 2 summarises the literature. Section 3 presents the model. Sections 4 and 5 discuss identification and inference. Section 6 presents the data of our empirical application on the US domestic market. Section 7 displays our estimates of the structural model and Section 8 studies the merger between US Airways and American Airlines. Section 9 concludes. Further details are available in the Online Appendix.

2 Literature review

This paper contributes to a flourishing literature on entry, exit, and product positioning (Mazzeo, 2002; Seim, 2006; Ho, 2009; Holmes, 2011; Fan, 2013; Eizenberg, 2014; Houde et al., 2023; Kuehn, 2018; Rossetti, 2018; Wollmann, 2018; Crawford et al., 2019; Aguirregabiria et al., 2020; Fan and Yang, 2022). Although the two-stage structure of our model is similar to that of Eizenberg (2014) and Wollmann (2018), the spillovers in entry create additional methodological and computational challenges by preventing us from applying a market-by-market analysis. Further, we develop and implement a formal inference procedure for the fixed cost parameters that leverages the convexity of the identified set.

This paper also relates to the recent advances in the econometrics of network formation games (Chandrasekhar, 2016; Graham, 2015; de Paula, 2017; 2020; Graham and de Paula, 2020). The methods proposed in this literature typically require the analyst to construct the set of equilibria for each candidate parameter value. However, this is unfeasible in our setting due to the large dimension of the airlines' networks. Our approach demonstrates that exploiting the necessary conditions for equilibrium, along the lines of Pakes (2010) and Pakes et al. (2015), represents an alternative route for constructing identified sets in large network formation games that offers notable computational advantages. Further, while the network literature typically studies "decentralised" network formation processes, where each node is controlled by a different player, this paper is among the first to consider a "centralised" network formation process, where each airline determines the link decisions of all the nodes.

More broadly, this paper combines two strands of the literature. The first strand is on structural models of demand and supply. This literature estimates demand and supply equations, taking entry decisions as exogenously given (Bresnahan, 1987; Berry, 1994;

Berry et al., 1995; Berry et al., 2004; Berry and Haile, 2014). For applications of these models to airlines, see Berry et al. (1996), Berry and Jia (2010), Ciliberto and Williams (2014), Peters (2006), Israel et al. (2013), and Das (2019). For applications to merger analysis, see Nevo (2000), Bjornerstedt and Verboven (2016), and Miller and Weinberg (2017). The second strand is the literature on entry models. This literature estimates the payoffs from entering markets, assuming that entry decisions are independent across markets, without considering demand and supply equations. See de Paula (2013) for a review. Applications of entry models to airlines can be found, for instance, in Reiss and Spiller (1989), Berry (1992), Goolsbee and Syverson (2008), Ciliberto and Tamer (2009), and Chesher and Rosen (2020).

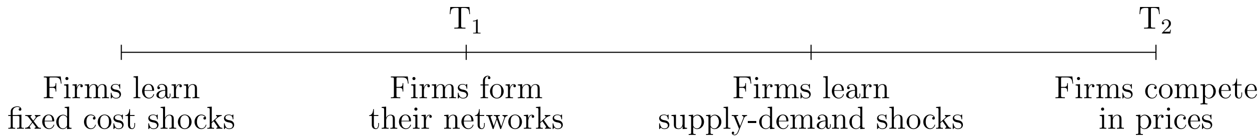
Last, this paper is among the first to model the airlines' entry decisions by taking spillovers in entry into account and combining this step with a supply-demand framework. Ciliberto et al. (2021) and Li et al. (2022) develop methods to estimate models of entry and price decisions, but assume that entry decisions are independent across markets. Aguirregabiria and Ho (2012), Benkard et al. (2020), Park (2020), and Yuan (2020) introduce spillovers in entry in their models for the airline industry. However, differently from our paper, Aguirregabiria and Ho (2012) assume that entry decisions are made by independent local managers to reduce the computational burden. Benkard et al. (2020) investigate the dynamic effects of mergers on the airlines' networks. They focus on medium- to long-run transitions towards the post-merger equilibrium and do not model the demand side. In contrast, our framework includes the demand side and we are interested in the welfare effects emanating from the change between pre- and post-merger equilibrium. Park (2020) endogenises entry and slot choices at the Ronald Reagan Washington National Airport only. Yuan (2020) models entry, capacity, and price decisions, but does not consider spillovers in entry on the fixed cost side and does not formally estimate the fixed cost parameters. Finally, our paper is the first to disentangle and estimate the impact of hub-and-spoke structures, both on the variable profits and fixed costs.

3 The model

There are N airlines, labeled by $f \in \mathcal{N} \coloneqq \{1, \dots, \mathrm{N}\}$, which play a two-stage game. The timing of the game is represented in Figure 1. In the first stage, the airlines design their networks to transfer passengers from one city to another and pay the fixed costs. Cities are connected directly and/or via hubs. Hubs are exogenously pre-determined. In the second stage, given the networks, the airlines face the demand for their products, pay the variable costs, and compete in prices. In the first stage, the airlines observe their own and their competitors' fixed cost shocks. However, they do not observe their own and their competitors' demand and supply shocks, which are discovered before the second stage.

In what follows, we describe the game starting from the second stage.

Figure 1: Timing of the game



3.1 The second stage: demand and supply

In the second stage, the airlines take as given the networks and consequent product choices. Markets are non-directional city-pairs, such as Houston-Boston, which allows the possibility to fly from Boston to Houston or from Houston to Boston. Products are airline-itinerary combinations. For example, in the Houston-Boston market, American Airlines might offer two or more products: a direct flight between Boston and Houston, a one-stop flight between Houston and Boston with an intermediate stop at the Dallas hub, a one-stop flight between Houston and Boston with an intermediate stop at the New York hub, and so on. Each market is indexed by $m \in \mathcal{M}$, where $\mathcal{M}$ is the set of markets. Alternatively, when we need to keep a record of the endpoint cities, the markets whose endpoints are cities a and b are denoted by $\{a, b\} \in \mathcal{M}$. Each product offered in market m is indexed by $j \in \mathcal{J}_m$, where $\mathcal{J}_m$ is the set of products offered in market m.

In every market, the airlines face the demand for their products, pay the variable costs, and simultaneously choose the prices to maximise the variable profits, under complete information. We now present the demand and supply equations.

Demand We consider the nested logit demand with two nests; one for the airline products, and the other for the outside option of not travelling or travelling by other means (Berry, 1994). The utility that individual i receives from buying product j in market m is specified as:

$$U_{i,j,m} = X_{j,m}^{\top}\beta - \alpha p_{j,m} + \xi_{j,m} + \nu_{i,m}(\lambda) + \lambda\epsilon_{i,j,m}. \tag{1}$$

The outside option is denoted by 0 and its utility normalised to $\epsilon_{i,0,m}$. In (1), $X_{j,m}$ is a vector of product characteristics and $p_{j,m}$ is the product price, both observed by the researcher. $\xi_{j,m}$ represents the product characteristics that are unobserved by the researcher and can be arbitrarily correlated with prices. $(\nu_{i,m}(\lambda), \epsilon_{i,j,m}, \epsilon_{i,0,m})$ denote the consumer tastes, unobserved by the researcher, i.i.d. across i, j, m, and independent of all the other variables. The probability distribution of $(\nu_{i,m}(\lambda), \epsilon_{i,j,m}, \epsilon_{i,0,m})$ is chosen to yield the familiar nested logit market share function, with: $\lambda \in (0, 1]$.

We include in $X_{j,m}$ various product characteristics, such as the number of stops and the distance flown, along with carrier and city fixed effects. Further, $X_{j,m}$ contains the number of direct flights offered out of market m's endpoints by the same carrier offering itinerary j (hereafter, "*Nonstop Origin*"). The variable "*Nonstop Origin*" captures the value of frequent flier programs (Berry and Jia, 2010). In fact, the larger the number of destinations for which consumers can redeem frequent flier miles, the higher the value of such loyalty programs, and so the higher the utility consumers can get from flying with a given carrier. Moreover, an airline that flies to many cities is likely to have more convenient parking and gate access and provide better services. See Figure 2 for an example. Note that, due to the variable "*Nonstop Origin*", the demand for product j in market m depends on the entry decisions of an airline in neighbouring markets. This gives rise to spillovers in entry across markets on the demand side.

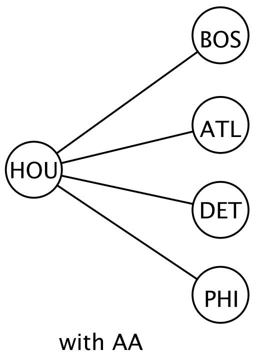


Figure 2: Let market m be Houston-Boston and product j be a direct flight between Houston and Boston offered by American Airlines. The larger the number of direct flights offered by American Airlines to passengers in Houston (for instance, direct flights to Boston as well as Atlanta, Detroit, and Philadelphia, as represented in the image), the higher the value of American Airlines' frequent flier programs, and the more facilities American Airlines will provide to customers at Houston's airport. These mechanisms are expected to increase the utility of buying product j.

From utility maximising behaviour, we obtain the predicted demand in market m.

$$\text{For product } j, \qquad s_{j,m}(X_m, p_m, \xi_m; \theta_d) \times \mathrm{MS}_m = \frac{\exp(\delta_{j,m}/\lambda)}{D_m} \frac{D_m^\lambda}{1 + D_m^\lambda} \times \mathrm{MS}_m.$$

$$\text{For the outside option } 0, \qquad s_{0,t}(X_m, p_m, \xi_m; \theta_d) \times \mathrm{MS}_m = \frac{1}{1 + D_m^\lambda} \times \mathrm{MS}_m, \tag{2}$$

where $X_m := (X_{j,m} : j \in \mathcal{J}_m)$, $p_m := (p_{j,m} : j \in \mathcal{J}_m)$, $\xi_m := (\xi_{j,m} : j \in \mathcal{J}_m)$, $\theta_d := (\beta, \alpha, \lambda)$, $s_{j,m}(X_m, p_m, \xi_m; \theta_d)$ is the product share of product j in market m, MS_m is the market size, $\delta_{j,m} := X_{j,m}^\top \beta - \alpha p_{j,m} + \xi_{j,m}$, and $D_m := \sum_{j=1}^{J_m} \exp(\delta_{j,m}/\lambda)$. The researcher observes the product shares without errors, as is standard in the literature.

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

$$\sum_{m\in\mathcal{M}}\sum_{j\in\mathcal{J}_{f,m}}(p_{j,m}-\mathrm{MC}_{j,m})\times s_{j,m}(X_m,p_m,\xi_m;\theta_d)\times \mathrm{MS}_m, \tag{3}$$

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

$$\mathrm{MC}_{f,m}=p_{f,m}+\Big(\frac{\partial s_{f,m}(X_m,p_m,\xi_m;\theta_d)}{\partial p_{f,m}}\Big)^{-1}s_{f,m}(X_m,p_m,\xi_m;\theta_d), \tag{4}$$

where $\mathrm{MC}_{f,m}$, $p_{f,m}$, and $s_{f,m}(X_m,p_m,\xi_m;\theta_d)$ are the vectors stacking $\mathrm{MC}_{j,m}$, $p_{j,m}$, and $s_{j,m}(X_m,p_m,\xi_m;\theta_d)$, respectively, for each product $j\in\mathcal{J}_{f,m}$. $\frac{\partial s_{f,m}(X_m,p_m,\xi_m;\theta_d)}{\partial p_{f,m}}$ is the matrix collecting the partial derivatives of product shares with respect to prices.

As standard in the literature, we express product j's marginal cost as a function of observed and unobserved cost shifters:

$$\mathrm{MC}_{j,m}=W_{j,m}^{\top}\theta_s+\omega_{j,m}, \tag{5}$$

where $W_{j,m}$ is a vector of marginal cost shifters that are observed by the researcher and $\omega_{j,m}$ represents the marginal cost shifters that are unobserved by the researcher.

As for the demand side, we include in $W_{j,m}$ various product characteristics, such as the number of stops, the distance flown, and whether the itinerary is short-haul or long-haul, along with carrier fixed effects. Further, $W_{j,m}$ contains the number of cities that are reachable from the endpoints and intermediate stops of itinerary j with the same carrier offering itinerary j (variable "*Connections*"). This variable captures economies of density; that is, the fact that more densely traveled markets tend to generate marginal cost savings due to engineering reasons (Berry and Jia, 2010). In particular, the larger the number of final destinations consumers can reach via connecting flights, the more the opportunities for an airline to pool passengers from several itineraries into the same planes, and so the more an airline can efficiently use large aircrafts, which tend to have lower unit costs. Note that, due to the variable "*Connections*", the marginal cost of product j in market m depends on the entry decisions of an airline in neighboring markets. This gives rise to spillovers in entry across markets on the marginal cost side.

3.2 The first stage: entry

In the first stage, the airlines design the networks to transfer passengers from one city to another and pay the fixed costs. Cities are connected directly and/or via hubs with, at most, one intermediate stop. Our data contain very few observations of flights with more than one intermediate stop and flights connecting via non-hubs. 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 that was started by the airlines after the US Airline Deregulation Act of 1978 and was quickly completed by the 1990s, many years before the period considered in our empirical application. Once decided upon, hub locations were not altered in any major way by the airlines, even after mergers and other restructuring events.[3]

We formalise the network formation process as follows. 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 $G_f \coloneqq (G_{ab,f} : \{a, b\} \in \mathcal{M})$ be the network of airline f, where the nodes of the network are the cities and the links of the network are 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 competes in market $\{a, c\}$ by offering one-stop flights between cities a and c via h.

When entering markets, the airlines pay the fixed costs of building and maintaining the physical, technological, and human infrastructures. Examples are the costs of salaries, insurance, scheduling coordination, computer reservation and revenue management systems, and aircraft financing. The fixed costs also include the fees for ticket offices, baggage conveyors, gates, lounges, parking, and hangars at the airports. Further, the literature suggests that hub-and-spoke operations can increase the fixed costs due to the risk of congestion at hubs where many connections must be carefully coordinated. For instance, consider the extra resources needed to invest in order to harmonise flight schedules, the leasing of contiguous gates, and the management of passenger traffic along different parts of the airport, in the case of closely scheduled flights. For a discussion on the impact of hub-and-spoke operations on fixed costs, see Levine (1987), Butler and Houston (1989), Borenstein (1992), Oum et al. (1995), Peterson et al. (1995), Nero (1999), Berry et al. (1996), and Berry et al. (2019).

[3] 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 et al. (2000), and Reynolds-Feighan (2001).

We specify the fixed costs sustained by airline f as:

$$\mathrm{FC}_f(G_f, \eta_f; \gamma) = \sum_{\{a,b\}\in\mathcal{M}} G_{ab,f}(\gamma_{1,f} + \eta_{ab,f}) + \sum_{h\in\mathcal{H}_f} \gamma_{2,f}\Big(\sum_{\substack{a \in \mathcal{C} \\ a \neq h}} G_{ha,f}\Big)^2, \tag{6}$$

where $\mathcal{H}_f$ is the set of airline f's hubs, $\mathcal{C}$ is the set of cities, $\eta_f := (\eta_{ab,f} : \{a,b\} \in \mathcal{M})$ is a vector of mean-zero shocks observed by the airlines but unobserved by the researcher, and $\gamma := (\gamma_{1,f}, \gamma_{2,f} : f \in \mathcal{N})$ collects the parameters to be identified. The fixed cost equation consists of two parts. First, there are market-specific contributions, $\gamma_{1,f} + \eta_{ab,f}$, for each market $\{a,b\}$ served by 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, that 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, that is, the number of markets served out of hub h with direct flights by airline f (also called "spokes"). Due to such quadratic terms, the increase in the fixed costs sustained by airline f when adding a spoke to hub h depends on the number of spokes that hub h already has. This gives rise to spillovers in entry decisions across markets on the fixed cost side.

The assumption that the fixed cost shocks, $\eta := (\eta_f : f \in \mathcal{N})$, are common knowledge among the airlines is deemed appropriate. In fact, in the airline industry, the fixed costs capture fairly standard balance sheet entries that 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 can predict the competitors' fixed cost shocks reasonably well.

In the fixed cost equation, we do not model slot constraints. This is because our framework does not distinguish between airports in the same city, and big cities typically have at least two airports. Importantly, there are no cities in the data where all airports are slot constrained at the time of our empirical application. For the same reason, we do not consider scenarios where the hub airlines may inhibit the competitors' ability to obtain gates, slots, and other facilities necessary for entry or expansion. Nevertheless, our methodology can incorporate such effects, for instance, by introducing in (6) binding upper bounds on the number of links formed by the airlines at specific airports.

We assume that, in the first stage, the airlines know everything about the second stage, except their own and their competitors' demand and marginal costs shocks. This is a natural assumption, because the legacy carriers (which, together with Southwest Airlines, are the main players of our empirical application) typically operate with a time lag between the entry decisions and the sale of flight tickets.

In the first stage, the airlines simultaneously choose the networks $G := (G_f : f \in \mathcal{N})$

that maximise the expected second-stage profits minus the fixed costs:

$$\mathbb{E}[\Pi_f(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \xi^{\oplus}, \omega^{\oplus}, G; \theta) | X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta] - \mathrm{FC}_f(G_f, \eta_f; \gamma), \tag{7}$$

where $\Pi_f(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \xi^{\oplus}, \omega^{\oplus}, G; \theta)$ is the second-stage profit of airline f. Hereafter, we denote by $\mathcal{J}_m^{\oplus}$ the set of *all potential* products in market m, including the products not chosen for production. In turn, $X^{\oplus} := (X_{j,m} : j \in \mathcal{J}_m^{\oplus}, m \in \mathcal{M})$, $W^{\oplus} := (W_{j,m} : j \in \mathcal{J}_m^{\oplus}, m \in \mathcal{M})$, $\xi^{\oplus} := (\xi_{j,m} : j \in \mathcal{J}_m^{\oplus}, m \in \mathcal{M})$, and $\omega^{\oplus} := (\omega_{j,m} : j \in \mathcal{J}_m^{\oplus}, m \in \mathcal{M})$ are the vectors of observed demand shifters, observed marginal cost shifters, demand shocks, and marginal cost shocks of all potential products across all markets.[4] $\mathrm{MS} := (\mathrm{MS}_m : m \in \mathcal{M})$ is the vector of market sizes. $\theta := (\theta_d, \theta_s)$ is the vector of second-stage parameters. Note that the expectation of the second-stage profits is computed by integrating over the demand and supply shocks, $(\xi^{\oplus}, \omega^{\oplus})$, conditional on the variables observed by the airlines in the first stage, $(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta)$. Note also that the second-stage profits depend on the networks formed by the airlines. In fact, these networks determine the offered products and their characteristics, and the equilibrium prices in each market.

3.3 Equilibrium

The airlines solve the game by working backwards 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 that are maximising the expected value of those profits. A subgame perfect pure strategy Nash equilibrium consists of networks and price functions, $\{G^*, (P_m^*(\xi_m^{\oplus}, \omega_m^{\oplus}, G) : m \in \mathcal{M})\}$, constituting a pure strategy Nash equilibrium in every subgame.

The existence and uniqueness of $(P_m^*(\xi_m^{\oplus}, \omega_m^{\oplus}, G) : m \in \mathcal{M})$ 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. As explained in Section B of the Online Appendix, it is difficult to show that at least one G^* exists, due to the presence of spillovers in entry on demand, marginal cost, and fixed cost sides. In what follows, we assume that G^* exists. In Section C of the Online Appendix, we show that the moment inequalities derived in Section 4.2 are robust to the possibility that G^* does not exist for some parameter values and variable realisations.

[4] Analogously, we define the market-specific vectors $X_m^{\oplus} := (X_{j,m} : j \in \mathcal{J}_m^{\oplus})$, $W_m^{\oplus} := (W_{j,m} : j \in \mathcal{J}_m^{\oplus})$, $s_m^{\oplus} := (s_{j,m} : j \in \mathcal{J}_m^{\oplus})$, and $P_m^{\oplus} := (p_{j,m} : j \in \mathcal{J}_m^{\oplus})$. We will also use this notation in Section 4.1.

4 Identification

This section discusses the identification of the vector of parameters, $(\theta, \gamma) \in \Theta \times \Gamma \subseteq \mathbb{R}^{\mathrm{K}} \times \mathbb{R}^{\mathrm{P}}$, where K is the dimension of θ and P is the dimension of γ.

4.1 Identification of the demand and supply parameters

To identify $\theta := (\theta_d, \theta_s) \in \Theta$, we follow the identification arguments for standard supply-demand models with differentiated products (Berry and Haile, 2014). Intuitively, the vector of demand parameters, θ_d, is identified from the distribution of prices, sales, and product covariates. Once θ_d is identified, the markups are also identified from the F.O.C.s in (4). In turn, the marginal costs are identified as the difference between the prices and the markups. Last, the variation in the identified marginal costs and product covariates identifies the vector of marginal cost parameters, θ_s.

More precisely, there are two potential sources of endogeneity to be considered 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 are correlated with the second-stage shocks because the latter are observed by the airlines when playing the second stage. We deal with these two sources of endogeneity by leveraging the timing of choices and information structure of the game, which legitimise us assuming that the second-stage shocks are mean independent of the airlines' information set in the first stage. Formally, we assume that $\mathbb{E}(\xi_{j,m}, \omega_{j,m} | X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) = 0$ a.s., for every product $j \in \mathcal{J}_m^{\oplus}$.

This mean independence assumption is standard in empirical two-stage games (Eizenberg, 2014; Holmes, 2011; Houde et al., 2023; Kuehn, 2018; Rossetti, 2018; Wollmann, 2018) and is similar to the mean independence assumption in classic supply-demand models. This states that the information owned by the airlines in the first stage does not help them to better predict the second-stage shocks.

The mean independence assumption rules out correlation between the second-stage shocks and the fixed cost shocks. Introducing such a correlation is possible in principle, but numerically challenging, because it would break the separation between the two stages in the estimation procedure. We view the absence of correlation as a reasonable simplification. In fact, the selection problem potentially affecting the second-stage estimates is mainly driven by the spillovers in entry. As we explicitly model these spillovers, our fixed cost shocks capture residual factors, which can be safely assumed to be uncorrelated with the supply-demand shocks. For a different approach, see Ciliberto et al. (2021) and Li et al. (2022), which allow for correlation between the fixed cost shocks and the supply-demand shocks without modelling spillovers in entry and given a parametric specification of the distribution of the fixed cost shocks.

From a technical perspective, the mean independence assumption eliminates the first source of endogeneity mentioned above because it implies that $\mathbb{E}(\xi_{j,m}, \omega_{j,m}|G) = 0$ for every product $j \in \mathcal{J}_m^{\oplus}$, that is, the second-stage shocks are mean independent of the list of products offered in the second stage. Further, the mean independence assumption solves the second source of endogeneity because it allows us to instrument the prices and within-group market shares in the usual way. Specifically, θ can be point identified as follows. Let $z_{j,m}(X_m^{\oplus}, W_m^{\oplus})$ be an $\mathrm{L} \times 1$ vector of instruments pertaining to product $j \in \mathcal{J}_m^{\oplus}$, where $\mathrm{L} \geq \mathrm{K}$. Given $\rho_{j,m} \coloneqq (\xi_{j,m}, \omega_{j,m})$, the mean independence assumption implies:

$$\mathbb{E}(\rho_{j,m} \times z_{j,m,l}(X_m^{\oplus}, W_m^{\oplus})|G) = 0 \quad \forall l = 1, \ldots, \mathrm{L}, \tag{8}$$

for every product $j \in \mathcal{J}_m^{\oplus}$. Berry et al. (1995) show that we can uniquely express $\rho_{j,m}$ as a function of the product covariates and θ ("BLP inversion"):

$$\rho_{j,m} = \tau_{j,m}(X_m^{\oplus}, W_m^{\oplus}, \mathrm{MS}_m, s_m^{\oplus}, P_m^{\oplus}, G; \theta).$$

Therefore, we obtain:

$$\mathbb{E}(\tau_{j,m}(X_m^{\oplus}, W_m^{\oplus}, \mathrm{MS}_m, s_m^{\oplus}, P_m^{\oplus}, G; \theta) \times z_{j,m,l}(X_m^{\oplus}, W_m^{\oplus})|G) = 0 \quad \forall l = 1, \ldots, \mathrm{L}, \tag{9}$$

for every product $j \in \mathcal{J}_m^{\oplus}$. The above moment equalities depend only on variables that are observed by the researcher and guarantee point identification of θ under an appropriate rank condition. Following Berry et al. (1995), we use functions of the observed demand shifters as instruments for the price and the within-group market share. See Section H of the Online Appendix for the list of second-stage instruments.

4.2 Identification of the fixed cost parameters

This section shows how $\gamma \in \Gamma$ is set-identified from moment inequalities. We follow the literature on revealed preferences (Pakes, 2010; Pakes et al., 2015) and derive these moment inequalities from best-response implications. Namely, if the networks chosen by the airlines constitute a pure strategy Nash equilibrium (PSNE), then they should lead to higher profits than if the airlines were to deviate from those networks.

This strategy allows us to circumvent two potential difficulties. First, there may be multiple PSNE networks. Second, constructing the set of PSNE networks is computationally burdensome due to the large number of markets and the presence of spillovers in entry. Our moment inequalities do not require us to impose any ad-hoc equilibrium selection assumption and construct the set of PSNE networks for each candidate parameter value.

Best-response implications

Let G_{-f} denote the collections of the networks formed by firm f's competitors and $G \coloneqq (G_f, G_{-f})$. If such networks constitute a PSNE, as we assume, then they should lie on the carriers' best-response curves. In turn, the increase in profits that each airline f would receive if it deviated from G_f and the other firms were mandated to keep G_{-f} is negative. We consider one-link deviations only; that is, each airline f can add/delete direct flights in one market at a time.

For each airline f, take market $\{a, b\}$ that airline f does not serve with direct flights; that is, for which $G_{ab,f} = 0$. Let airline f's counterfactual network be the network in which airline f operates in all markets served under G_f and, additionally, it offers direct flights between cities a an b. We denote it by $G_{(+ab),f}$.

From the revealed preference principle, the difference between the expected variable profits earned by airline f under its counterfactual network and the expected variable profits earned by airline f under its factual network, while the competitors maintain G_{-f}, is less or equal than the extra fixed-cost that airline f pays for the added direct flight:

$$\Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta) \leq \mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma), \tag{10}$$

where Π^e_f is shorthand notation for the expected variable profits in (7). Following (6), the right-hand side of (10) is a linear expression in $\gamma_{1,f}$, $\gamma_{2,f}$ and $\eta_{ab,f}$. Denoting by $\Delta\overline{\mathrm{Q}}_{(+ab),f}$ the difference between the quadratic terms in (6) at $G_{(+ab),f}$ and G_f, we have:

$$\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma) = \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(+ab),f} + \gamma_{1,f} + \eta_{ab,f}.$$

When neither a nor b is a hub of airline f, the difference simplifies to $\gamma_{1,f} + \eta_{ab,f}$. As we expect $\gamma_{1,f}$ and $\gamma_{2,f}$ to be positive, (10) provides a "lower" bound for $\gamma_{1,f}$ and $\gamma_{2,f}$.

Similarly, for each airline f, we consider market $\{a, b\}$ that airline f serves with direct flights; that is, for which $G_{ab,f} = 1$. Let airline f's counterfactual network be the network in which airline f operates in all markets served under G_f, but does no longer offer direct flights between cities a an b. We denote it by $G_{(-ab),f}$. Following the revealed preference principle, we have:

$$\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) \geq \mathrm{FC}_f(G_f, \eta_f; \gamma) - \mathrm{FC}_f(G_{(-ab),f}, \eta_f; \gamma). \tag{11}$$

As above, the right-hand side of (11) can be written as:

$$\mathrm{FC}_f(G_f, \eta_f; \gamma) - \mathrm{FC}_f(G_{-ab,f}, \eta_f; \gamma) = \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} + \gamma_{1,f} + \eta_{ab,f},$$

where $\Delta\overline{\mathrm{Q}}_{(-ab),f}$ is the difference between the quadratic terms in (6) at G_f and $G_{(-ab),f}$.

Again, neither a nor b is a hub of airline f, the difference simplifies to $\gamma_{1,f} + \eta_{ab,f}$. As we expect $\gamma_{1,f}$ and $\gamma_{2,f}$ to be positive, (11) provides an "upper" bound for $\gamma_{1,f}$ and $\gamma_{2,f}$.

Before proceeding, we remark that (10) and (11) are also compatible with equilibrium notions weaker than PSNE. For instance, they resemble the notion of pairwise stability used in network theory, as discussed in Section B of the Online Appendix. Further, Section D of the Online Appendix outlines the steps to calculate (10) and (11) in practice. Note here that, despite considering one-link deviations, (10) and (11) are not computed as if entry decisions were independent across markets. In fact, a one-link deviation creates a "domino effect" in the neighbouring markets, due to the possibility of airline f offering one-stop flights and the presence of spillover effects. This makes our method different from the approaches that assume that entry decisions are independent across markets.

From best-response implications to moment inequalities

In this paragraph, we use (10) and (11) to derive moment inequalities. We take the expectation of (10) and (11) over markets and obtain the following moment inequalities for each airline f:

$$\begin{aligned}&\mathbb{E}\Big[(1-G_{ab,f})\times\Big(\gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(+ab),f}+\gamma_{1,f}+\eta_{ab,f}-\big(\Pi^e_f(G_{(+ab),f},G_{-f};\theta)-\Pi^e_f(G_f,G_{-f};\theta)\big)\Big)\Big]\geq 0,\\&\mathbb{E}\Big[G_{ab,f}\times\Big(\Pi^e_f(G_f,G_{-f};\theta)-\Pi^e_f(G_{-ab,f},G_{-f};\theta)-\Big(\gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f}+\gamma_{1,f}+\eta_{ab,f}\Big)\Big)\Big]\geq 0.\end{aligned}\tag{12}$$

If we could claim that $\mathbb{E}[\eta_{ab,f}\times G_{ab,f}]=0$, then we would delete $\eta_{ab,f}$ from the moment inequalities in (12) and use such moment inequalities for identification. Unfortunately, the expectation is not equal to zero because the fixed cost shocks are structural components observed by the airlines when forming their networks.

Various solutions have been proposed in the literature to handle this selection issue.[5] Eizenberg (2014) assumes that the fixed cost shocks have a bounded support, which is contained within the support of the change in the expected variable profits resulting from one-product deviation at a time. For this approach to generate informative bounds on γ, the support of the change in the expected variable profits should not be too large. This is not the case here, as we consider deviations in fundamentally different markets (that is, small non-hub markets and large hub markets), that face changes in the expected variable profits of significantly different magnitudes. In turn, Eizenberg (2014)'s strategy does not lead to meaningful bounds in our setting. Another approach could be to assume that $\eta_{ab,f}=\eta_{a,f}+\eta_{b,f}$ and take the differences between inequalities that contain the same fixed cost shock, similarly to Kuehn (2018). Alternatively, Ciliberto et al. (2021) parametrically specify the distribution of η and calculate bounds on the probability of observing each possible entry decision. This solution requires enumerating every equilibrium network, which is not feasible in our setting. We do not follow any of these approaches and, instead,

[5]For a thorough discussion on the available strategies, see Kline et al. (2021).

overcome the selection issue by introducing instruments, as in Pakes et al. (2015) and Wollmann (2018). In what follows, we explain how we construct such instruments.

In our data, there are markets that are so profitable for an airline that it would be impossible not to serve them. For instance, airlines tend to always offer direct service in large markets where they have a hub at one or both endpoints. As another example, there are some non-hub markets that airlines have continuously served with direct flights since deregulation in 1978 due to historical reasons. Following these and similar arguments, for every airline f, we characterise R_- groups of markets and assume that airline f almost surely offers direct service in the markets belonging to each of these groups, regardless of the realization of the fixed cost shocks. Formally, for $r = 1, \dots, \mathrm{R}_-$, we introduce a binary variable $Z_{r,(-ab),f}$ (instrument) which is equal to one if market $\{a, b\}$ belongs to group r, and zero otherwise. We assume that $\mathbb{E}(\eta_{ab,f} | Z_{r,(-ab),f} = 1) = 0$ and $\Pr(G_{ab,f} = 1 | Z_{r,(-ab),f} = 1, \eta_{ab,f}) = 1$ almost surely. In turn, we have

$$\mathbb{E}\Big[Z_{r,(-ab),f} \times G_{ab,f} \times \Big(\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{-ab,f}, G_{-f}; \theta) - \Big(\gamma_{2,f} \Delta \overline{\mathrm{Q}}_{(-ab),f} + \gamma_{1,f}\Big)\Big)\Big] \geq 0, \quad r = 1, \dots, \mathrm{R}_-. \tag{13}$$

Conversely, airlines tend to never offer a direct service between one of their hubs and a city that has another of their hubs close by, as this would lead to very low profits. For similar reasons, airlines rarely enter non-hub markets where a competing firm has a hub at one or both endpoints. As above, for every airline f, we characterise R_+ groups of markets and assume that airline f does not offer a direct service in the markets belonging to each of these groups almost surely, regardless of the realization of the fixed cost shocks. Formally, for $r = 1, \dots, \mathrm{R}_+$, we introduce a binary variable $Z_{r,(+ab),f}$ (instrument),which is equal to one if market $\{a, b\}$ belongs to group r, and zero otherwise. We assume that $\mathbb{E}(\eta_{ab,f} | Z_{r,(+ab),f} = 1) = 0$ $\Pr(G_{ab,f} = 0 | Z_{r,(+ab),f} = 1, \eta_{ab,f}) = 1$. In turn, we have:

$$\mathbb{E}\Big[Z_{r,(+ab),f} \times (1 - G_{ab,f}) \times \Big(\gamma_{2,f} \Delta \overline{\mathrm{Q}}_{(+ab),f} + \gamma_{1,f} - \big(\Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta)\big)\Big)\Big] \geq 0, \quad r = 1, \dots, \mathrm{R}_+. \tag{14}$$

The moment inequalities in (13) and (14) now depend only on variables that are observed by the researcher and, hence, can be used to set identify γ. We denote by Γ_I the identified set; that is, the collection of parameters γ that satisfy the two sets of moment inequalities above. We report the list of first-stage instruments in Section H of the Online Appendix.

Γ_I is not sharp; that is, it may be a superset of the set of observationally equivalent parameters. This is due to three reasons. First, the moment inequalities in (13) and (14) are derived from the necessary conditions for PSNE. If the airlines choose G and this is a PSNE, then (10) and (11) should hold. However, as there may be multiple PSNE, one would expect that these moment inequalities do not exploit all the information in the model assumptions. Deriving necessary and sufficient conditions for PSNE requires us to characterize the whole set of possible PSNE, a strategy that is computationally intractable for our specific game. See Beresteanu et al. (2011) for more details on simpler games. Second, our procedure may neglect other valid first-stage instruments. Third, the moment inequalities in (14) and (13) are derived from one-link deviations, but the airlines may also deviate by deleting/adding more than one link at a time. Considering many-link deviations is possible in our framework. It may lead to tighter bounds, however these may be at the cost of increasing the computational burden. We do not account for many-link deviations to maintain a computationally light procedure. Further, we show in Section E of the Online Appendix that many-link deviations do not provide a substantial improvement of the bounds.

Last, in addition to η, Pakes (2010) and Pakes et al. (2015) suggest including in the revealed-preference inequalities some additive perturbations to account for the fact that the model may be mis-specified. We have not included these terms but we check for model mis-specification when conducting inference using the recent work of Stoye (2020).

5 Inference on the fixed cost parameters

Inference on the second-stage parameter, θ, is standard and can be done by GMM. More details are in Section F of the Online Appendix. In this section, we discuss inference on the first-stage parameters, γ. For simplicity of exposition, in what follows, we assume that θ is known. Further, we streamline the notation of (13) and (14) as:

$$\mathbb{E}(Z_{r,m}B_m)^\top \gamma - \mathbb{E}(Z_{r,m}A_m) \leq 0, \quad r = 1, \dots, \mathrm{R}, \tag{15}$$

where r indexes one of the instruments for firm f, m is a market $\{a, b\}$, R is the total number of instruments across all firms, $Z_{r,m}$ is $Z_{r,(-ab),f}$ or $Z_{r,(+ab),f}$, A_m is $G_{ab,f}(\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{-ab,f}, G_{-f}; \theta))$ or $-(1 - G_{ab,f})(\Pi^e_f(G_{+ab,f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta))$, B_m is such that $B_m^\top \gamma$ is equal to $G_{ab,f}(\gamma_{1,f} + \Delta\overline{\mathrm{Q}}_{(-ab),f}\gamma_{2,f})$ or $-(1 - G_{ab,f})(\gamma_{1,f} + \Delta\overline{\mathrm{Q}}_{(+ab),f}\gamma_{2,f})$.

The support function

Γ_I is a convex polyhedron. It is bounded if the differences in the expected variable profits between the realized and counterfactual networks are bounded, and there are enough instruments to select markets that are almost surely served and not served. It is non-empty if the model is correctly specified. In the empirical analysis, we calculate confidence intervals robust to mis-specification.

Convexity has been proven to be a desirable feature in the set identification literature (Beresteanu and Molinari, 2008; Bontemps et al., 2012; Kaido and Santos, 2014). 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, $\delta(\cdot;\Gamma_I)$, in a given direction q, is equal to the (signed) distance between the origin and the supporting hyperplane with outer normal q. The support function gathers all the moment inequalities satisfied by the model because γ belongs to Γ_I if and only if $q^\top\gamma \leq \delta(q;\Gamma_I)$ for each $q \in \mathbb{R}^{\mathrm{P}}$. Moreover, inference on a subvector of γ can be easily performed by considering specific directions. For example, if the chosen direction, q, has its p-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 p-th component of γ.

Due to the linearity of the moment inequalities in γ, the support function of Γ_I in direction q is a linear program:

$$\begin{aligned} \delta(q;\Gamma_I) \coloneqq \sup_{\gamma\in\Gamma} & \, q^\top\gamma, \\ & \text{s.t. } \mathbb{E}(Z_{r,m}B_m)^\top\gamma - \mathbb{E}(Z_{r,m}A_m) \leq 0, \quad r = 1,\dots,\mathrm{R}. \end{aligned} \tag{16}$$

$\delta(q;\Gamma_I)$ can be estimated after replacing the expectations in (16) with sample averages. In particular, let the estimated identified set be defined as:

$$\widehat{\Gamma}_I \coloneqq \left\{\gamma\in\Gamma : \left(\frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}} Z_{r,m}B_m^\top\right)\gamma \leq \frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}} Z_{r,m}A_m \text{ for } r = 1,\dots,\mathrm{R}\right\}. \tag{17}$$

The estimated support function in direction q is the support function of the estimated identified set:

$$\hat{\delta}(q;\Gamma_I) \coloneqq \delta(q;\widehat{\Gamma}_I). \tag{18}$$

Again, $\hat{\delta}(q;\Gamma_I)$ can be calculated from a linear program.

Asymptotic distribution of the estimated support function

We make the simplifying assumption that we have an i.i.d. random sample of observations,

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

where M is the number of markets, and that the Central Limit Theorem applies to all the average of each quantity of interest. The i.i.d. assumption can be relaxed, for example, by implementing the approaches discussed by Leung (2022) and Leung and Moon (2021).

We introduce some notation that is useful for the next arguments. The Lagrangian of (16), rewritten as $-\inf(-q^\top\gamma)$, is equal to:

$$L(\gamma,\lambda_1,\dots,\lambda_{\mathrm{R}}) \coloneqq -q^\top\gamma + \sum_{r=1}^{\mathrm{R}} \lambda_r \left(\mathbb{E}(Z_{r,m}B_m)^\top\gamma - \mathbb{E}(Z_{r,m}A_m)\right), \tag{19}$$

where $\lambda = (\lambda_1, \ldots, \lambda_{\mathrm{R}})^\top$ is the vector of Lagrange multipliers associated with the R inequality constraints. We denote by $\mathcal{G}_0$ the set of optimal solutions γ, and by Λ_0 the set of Lagrange multipliers λ. For every $r = 1, \ldots, \mathrm{R}$, let $W_r(\gamma)$ be the limit in distribution of:

$$\sqrt{\mathrm{M}} \left(\frac{1}{\mathrm{M}} \sum_{m=1}^{\mathrm{M}} (Z_{r,m} B_m^\top \gamma - Z_{r,m} A_m) - (\mathbb{E}(Z_{r,m} B_m)^\top \gamma - \mathbb{E}(Z_{r,m} A_m)) \right).$$

$W_r(\gamma)$ is a univariate centered normal with variance $Var(Z_{r,m} B_m^\top \gamma - Z_{r,m} A_m)$.

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

Theorem 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 in the unit ball:

$$\sqrt{\mathrm{M}} \left(-\hat{\delta}(q; \Gamma_I) + \delta(q; \Gamma_I) \right) \xrightarrow[\mathrm{M} \to \infty]{d} \inf_{\gamma \in \mathcal{G}_0} \sup_{\lambda \in \Lambda_0} \sum_{r=1}^{\mathrm{R}} \lambda_r W_r(\gamma).$$

If $\mathcal{G}_0$ and Λ_0 are singleton, the asymptotic distribution is a Normal distribution. $\diamond$

Theorem 1 shows that the asymptotic distribution of $\hat{\delta}(q; \Gamma_I)$ depends on $\mathcal{G}_0$ and Λ_0. If these sets are singleton, then the estimated support function is asymptotically Normal, with a variance that can be estimated from the data. Unfortunately, this is not always the case. In particular, if the direction q corresponds to the outer normal of an exposed face, then Λ_0 is a singleton while $\mathcal{G}_0$ is not (Bontemps et al., 2012). Further, if more than P moments cross at the same vertex, then $\mathcal{G}_0$ is a singleton while Λ_0 is not. It is generally impossible to know from the sample which case we are facing. Various solutions to this problem have been proposed. Some papers perturb the linear program (Cho and Russell, 2020; Gafarov, 2021; Bontemps et al., 2022). Other papers smooth the identified set (Chandrasekhar et al., 2019). Here, we propose a methodology that follows the second approach. Our methodology permits us to construct confidence regions after having appropriately smoothed the identified set.

Smoothing the identified set

If the identified set is strictly convex, then the support function is differentiable everywhere and $\mathcal{G}_0$ and Λ_0 are singletons. To obtain strict convexity, we consider an approximation of the function $x_+ = \max(x, 0)$. Following Chen and Mangasarian (1995), for any $\alpha > 0$, the function:

$$f_\alpha(x) = x + \frac{1}{\alpha} \log(1 + \exp(-\alpha x)) = \frac{1}{\alpha} \log(1 + \exp(\alpha x)),$$

is strictly convex and lies above x_+. The maximum distance between the two functions is equal to $\log(2)/\alpha$ (at $x = 0$) and it holds that:

$$f_\alpha(x) - \log(2)/\alpha \leq x_+ \leq f_\alpha(x),$$

for each x in $\mathbb{R}$. As a result, f_α converges uniformly to x_+ as α goes to infinity. By using this insight, we replace the original R inequality constraints with:

$$g_\alpha(\gamma) = \sum_{r=1}^{\mathrm{R}} f_\alpha(\mathbb{E}(Z_{r,m}B_m)^\top \gamma - \mathbb{E}(Z_{r,m}A_m)) - \mathrm{R}\log(2)/\alpha \leq 0. \tag{20}$$

Let Γ_I^α be the collection of γs that satisfy (20). Observe that Γ_I^α is strictly convex because g_α is strictly convex. Moreover, the Hausdorff distance between Γ_I^α and Γ_I is bounded above by K/α, where K which depends on Γ_I (Chen and Mangasarian, 1995).

By using (20), we rewrite (16) as:

$$\begin{aligned} \delta(q; \Gamma_I^\alpha) &:= \sup_{\gamma \in \Gamma} q^\top \gamma, \\ &\text{s.t. } g_\alpha(\gamma) \leq 0. \end{aligned} \tag{21}$$

We show in Section G of the Online Appendix that (21) is a linear optimisation problem with exponential cone constraints. This problem can be efficiently solved with any solver used in convex optimisation (RMOSEK in our case).

Let the estimate of Γ_I^α be defined as:

$$\widehat{\Gamma}_I^\alpha := \Big\{\gamma \in \Gamma : \sum_{r=1}^{\mathrm{R}} f_\alpha\Big(\frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}} Z_{r,m}B_m^\top\gamma - \frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}} Z_{r,m}A_m\Big) - \mathrm{R}\log(2)/\alpha \leq 0\Big\},$$

and its support function be:

$$\hat{\delta}(q; \Gamma_I^\alpha) := \delta(q; \widehat{\Gamma}_I^\alpha).$$

Theorem 2 provides the asymptotic distribution of $\hat{\delta}(q; \Gamma_I^\alpha)$ in any direction q.

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

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

(ii) It holds that:

$$\sqrt{\mathrm{M}}\left(\hat{\delta}(q; \Gamma_I^\alpha) - \delta(q; \Gamma_I^\alpha)\right) \xrightarrow[\mathrm{M}\to\infty]{d} Z_\alpha(q),$$

where

$$Z_\alpha(q) = \lambda \left(\sum_{r=1}^{\mathrm{R}} \frac{W_r(\gamma_q)}{1+\exp\left(-\alpha\left(\mathbb{E}(Z_{r,m}B_m)^\top \gamma_q - \mathbb{E}(Z_{r,m}A_m)\right)\right)} \right),$$

γ_q is the unique point of the frontier of Γ_I^α achieving the supremum of $q^\top \gamma$ and λ, the (unique) Lagrange multiplier related to the constraint $g_\alpha(\gamma) \leq 0$.

$\diamond$

As $\delta(q, \Gamma_I^\alpha)$ is differentiable everywhere in q, Theorem 2 shows that the asymptotic distribution of $\hat{\delta}(q; \Gamma_I^\alpha)$ is normally distributed with a variance that can be estimated from the data. Note that if only one constraint, r_0, is binding, then the variance of $\hat{\delta}(q; \Gamma_I^\alpha)$ is equal to the variance of $\lambda W_{r_0}(\gamma_q)/(1+2^{-\mathrm{R}})$.

Theorem 2 allows us to construct a confidence region for the outer set Γ_I^α that is valid for the identified set. In particular, it is straightforward to construct a confidence interval for each component or linear combination of components of γ. It also allows us to draw points from the confidence region for γ. Further details are in Section G of the Online Appendix.

6 Data

Our data are from the Airline Origin and Destination Survey (DB1B) and consist of a 10% random sample of all 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 yet announced their intention to merge. We restrict the sample to the flights operated between the 85 largest metropolitan statistical areas (MSAs) in the United States.[6] Hereafter, we refer to MSAs as cities.

A market is defined as a non-directional pair of two cities, regardless of the actual journey from one city to the other. We delete tickets with multiple operating carriers or multiple ticketing carriers; tickets with different inbound and outbound itineraries; tickets that are not round-trip; connecting tickets via cities that are not hubs; or with more than one stop. Note that we observe very few of these tickets. A product is a combination between an itinerary between two cities with, at most, one stop via a hub and an airline ticketing this trip. We consider tickets featuring the same airline-itinerary combination but with different fares as the same product. We compute the corresponding price as the trimmed average price, weighted by the number of passengers.[7]

[6]We focus on domestic operations because the effects of the merger between American Airlines and US Airways were mainly felt domestically.

[7]We delete tickets with fares in the highest and lowest percentiles and tickets with fares below $25.

We compute the market sizes using data from the US Census Bureau on MSA population. In particular, we calculate the size of a market as the geometric mean of the populations at the endpoints. We compute the share of a product as the total number of passengers buying that product divided by the market size.

The major carriers in the sample are United Airlines (UA), Delta Airlines (DL), American Airlines (AA), US Airways (US), and Southwest Airlines (WN). The four legacy carriers rely on hub-and-spoke operations. Southwest Airlines does not exploit a pure hub-and-spoke business model, but a hybrid system in which a small number of airports are focus cities offering some of the services generally found at hubs. When estimating our model, we treat focus cities as hubs. 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 considered to be fringe competitors, differing only in whether or not they can be classified as low cost. Further, to enhance computational tractability, we do not consider the fixed costs of LCC and Other when estimating the first-stage parameters, and we assume that their networks are exogenously determined before the starting of the game.[8]

The observed demand shifters, $X_{j,m}$, include the number of stops (which is 1 or 0, "*Indirect*"), the maximum number of direct flights offered at the itinerary's endpoints by the same carrier offering itinerary j ("*Nonstop Origin*"), the distance flown in thousands of miles, ("*Distance*"), and its squared value ("*Distance2*"). We also add to $X_{j,m}$ carrier and city fixed effects, in order to capture unobserved brand- and city-specific features. 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. The observed marginal cost shifters, $W_{j,m}$, include the number of stops ("*Indirect*"), the average number of cities that are reachable from the endpoints and intermediate stops of itinerary j with the same carrier offering itinerary j ("*Connections*"). We also add to $W_{j,m}$ carrier fixed effects. We report the list of second-stage instruments in Section H of the Online Appendix.

Table 1 provides some summary statistics. Panel (b) reveals that American Airlines and US Airways are the two smallest carriers among the major airlines. However, if combined, they become the largest airline in terms of pre-merger market shares. From panel (c), we can see that hub cities are much more connected than non-hub cities, as evidenced by the average degree and average density.

[8]See Tables H.1 and H.2 in Section H of the Online Appendix for the list of hubs and focus cities in 2011 and the list of the airlines included in LLC and Other, respectively.

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	
Number of passengers	25.33	
Fraction of direct passengers	0.85	
Fraction of passengers in hub markets	0.57	
Fraction of markets served	0.93	
(b) Market shares by airline		
AA	0.12	
DL	0.19	
UA	0.15	
US	0.09	
WN	0.24	
LCC	0.16	
Other	0.05	
(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 (No hub)	7.21	7.72
Density (No hub)	0.09	0.09
Clustering (No hub)	0.80	0.33
(d) Demand and marginal cost variables	**Mean**	**St.Dev**
Price (100 USD)	4.32	1.20
Indirect	0.86	0.34
Nonstop Origin (100)	0.20	0.19
Connections (100)	0.56	0.15
Distance (1,000 miles)	1.44	0.68
Product share	4.61e-04	1.48e-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: The degree is the number of links out of a node. The density is the ratio between the actual number of links and the total number of potential links. The clustering coefficient is the ratio between the number of closed triplets and the total number of triplets.

7 Results

7.1 Results from the demand and supply

The second-stage results are in Table 2. We find significant spillovers in entry on the demand side. Specifically, passengers benefit from having a large number of direct flights offered by an airline at the itinerary's endpoints ("*Nonstop Origin*"). Hence, denser networks increase consumers' willingness-to-pay for an airline's flights, all the rest being constant. To give an idea of the magnitude of the spillovers, note that, on average, an origin city allows passengers to reach 20 destinations with a given airline. Doubling this number generates an increase in utility equivalent to a decrease in price of around \$30.[9]

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. Passenger utility is an inverted U-shaped function of the distance flown. This means that, as distance increases, air travel becomes more pleasant relative to the outside option. However, as distance increases further, travel becomes less enjoyable and demand starts to decrease. In line with the literature, passengers exhibit a strong disutility for connecting flights. Last, we estimate the nesting parameter, λ, to be around 0.6. Therefore, we can conclude that there is substitution between the inside goods and the outside option.

We also find significant spillovers in entry 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 itinerary's endpoints and intermediate stops ("*Connections*"). This is due to economies of density: 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 so the more an airline can efficiently use larger aircraft that typically have lower unit costs. Hence, denser hub-and-spoke structures lead to marginal cost savings, all the rest being constant. The impact of the variable "*Connections*" is more pronounced for long-haul flights, as the efficiency of large planes is especially evident in long routes. Further, long-haul one-stop flights have lower marginal costs than long-haul direct flights, again by virtue of economies of density. Short-haul one-stop flights are not significantly cheaper or more expensive than short-haul direct flights. This is because economies of density may be offset by the extra take-off and landing, which uses a large volume of fuel. The marginal costs of both long-haul and short-haul flights increase with the distance flown. This is because, as distance increases, more fuel is needed to cover the itinerary. Last, as expected, Southwest Airlines, LCC, and Other have lower marginal costs than the legacy carriers. To provide an illustration of the magnitude of the spillovers, observe that an additional connection reduces marginal

[9]Remember that both "*Nonstop Origin*" and "*Price*" are measured in hundreds.

costs by \$1.2 for short-haul and \$2 for long-haul flights. These magnitudes are comparable to increasing the distance flown by around 30 miles.

Table 3 reports some elasticity estimates. In particular, we call price elasticity the average price elasticity across products. The aggregate elasticity is the percentage change in the inside product share when all products' prices rise by 1%. The price elasticity is consistent with previous findings in the literature.[10]

Section H of the Online Appendix presents the variable profit estimates and a discussion on firm sources of profitability.

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)	Indirect	0.031	(0.028)
Indirect	-1.794	(0.066)	Distance	0.474	(0.037)
Nonstop Origin	0.868	(0.032)	Connections	-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)	Indirect	-0.189	(0.041)
			Distance	0.667	(0.032)
			Connections	-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				
p-value (J-stat)	0.156				
Number of products	17,481				

Note: "*Price*" is in hundreds of USD. "*Connections*" and "*Nonstop Origin*" are in hundreds. "*Distance*" is in thousands of miles. City fixed effects are included in the demand. The number of over-identifying restrictions is 11.

Table 3: Elasticity estimates.

Price elasticity	-3.780	(1.090)
Aggregate elasticity*	-2.100	

Note: Standard deviations across products in parentheses are computed.
*: There is only one estimate for the whole dataset.

[10]See, for example, Ciliberto and Williams (2014) or Li et al. (2022).

7.2 Results from entry

The second and third columns of Table 4 report the projection of the estimated identified set of the first-stage parameters, $\widehat{\Gamma}_I$, from (17) and (18). We see that, in the absence of congestion costs at hubs, the baseline fixed costs, γ_1, of offering a direct service between two endpoints are between \$655, 719 and \$872, 891. In turn, the total baseline fixed costs are obtained by multiplying those numbers by the number of markets an airline serves with direct flights. For example, the total baseline fixed costs of American Airlines are between \$153 and \$204 million.

To interpret the congestion cost parameters, $(\gamma_{2,f} : f \in \mathcal{N})$, consider the second and third columns of Table 5, which report the estimated increase in fixed costs when adding a spoke to a hub with 20 spokes. The results are heterogeneous across firms, although we cannot reject the hypothesis that they are all equal. For instance, US Airways and Southwest Airlines register higher lower bounds than the other airlines. This is because Southwest Airlines uses a business model, which combines hub-and-spoke and point-to-point operations, and US Airways has a small network that is mainly concentrated in the Eastern US. These findings align with the second and third columns of Table 6, which show that US Airways and Southwest Airlines potentially face the highest total fixed costs for a hub with 20 spokes. Such higher fixed costs are counterbalanced by lower marginal costs, as highlighted in Table H.5 of the Online Appendix.

To verify if our fixed cost estimates are reasonable, we compute the estimated share of the variable costs over the "operating costs". The former are obtained as marginal costs times the number of passengers. The latter are defined as the sum of the variable costs and fixed costs, without considering the congestion costs. Table H.6 in Section H of the Online Appendix reports this share for each airline. We compare such shares with the estimates from the FAA for 2018 based on administrative data (Table H.7) and observe similar orders of magnitude.[11]

The other columns of Tables 4, 5, and 6 report the quantities discussed above, but are now corresponding to the estimated smoothed outer set, $\widehat{\Gamma}_I^\alpha$, with $\alpha = 10,000$ and $\alpha = 50,000$. As expected, the projections of $\widehat{\Gamma}_I^\alpha$ get wider as α decreases. Deriving the optimal value of α is beyond the scope of this paper. It depends on the magnitude of the moments $\frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}}(Z_{r,m}B_m^\top\gamma - Z_{r,m}A_m)$, $r = 1, \ldots, \mathrm{R}$ considered. Here, we have chosen α to cover $\widehat{\Gamma}_I$ with a maximum of 1% discrepancy.[12] For our dataset, $\alpha = 50,000$ seems a good compromise. From Table 5 onwards, we report our results based on this choice of α.

Table 7 shows the 95% confidence intervals for each component of γ, obtained from the application of Theorem 2. Implementing the mis-specified adaptive confidence intervals of

[11] See `https://www.faa.gov/regulations_policies/policy_guidance/benefit_cost`, Section 4 of the Benefit-Cost analysis, Table 4-6.

[12] Recall that the identified set can be estimated consistently without smoothing.

Stoye (2020) does not change these confidence intervals, because the estimated difference between upper and lower bounds of each component is large. To further validate our smoothing approach, we consider the test statistic:

$$\xi(\gamma) = \max_{r=1,\ldots,\mathrm{R}} \frac{\sqrt{\mathrm{M}}\left(\frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}} Z_{r,m}B_m^\top\gamma - Z_{r,m}A_m\right)}{\sqrt{W_r(\gamma)}}. \tag{22}$$

In empirical analysis with moment inequalities, researchers often construct a confidence region by testing if the true parameter vector is equal to γ using (22) and the conservative but competitive critical value proposed by Chernozhukov et al. (2018). To be more specific, $\gamma \in \Gamma$ belongs to the confidence region if the test statistic is below the critical value. Here, we compute (22) for each of the 12 vectors γ, such that each component of γ achieves it maximum/minimum within our 95% confidence region. These 12 vectors are the frontier points of the 95% confidence region. Moreover, we calculate the (one-step) Self Normalized critical value with size 5% of Chernozhukov et al. (2018). If (22) is lower (higher) than this critical value, our procedure provides more (less) accurate estimates of the frontier points. Table 8 reports the 12 values of (22) and the critical value. Our procedure performs better in nine of the 12 frontier points considered.

Table 4: First-stage estimates.

	$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}$		$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}^{\boldsymbol{\alpha}}, \boldsymbol{\alpha} = \mathbf{10{,}000}$		$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}^{\boldsymbol{\alpha}}, \boldsymbol{\alpha} = \mathbf{50{,}000}$	
	LB	UB	LB	UB	LB	UB
Baseline fixed costs (γ_1)	655,719	872,891	647,808	1,023,612	655,560	875,906
Congestion costs ($\gamma_{2,f}$)						
AA	8,663	28,152	7,184	32,456	8,633	28,238
DL	6,774	21,906	4,416	24,412	6,727	21,956
UA	4,632	16,708	3,057	18,658	4,600	16,747
US	15,044	34,309	11,450	37,144	14,972	34,366
WN	17,091	31,084	10,173	34,026	16,952	31,143

Note: Quantities are in USD.

Table 5: Estimated increase in fixed costs when adding a spoke to a hub with 20 spokes.

	$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}$		$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}^{\boldsymbol{\alpha}}$	
	LB	UB	LB	UB
AA	1.106	1.960	1.106	1.963
DL	1.027	1.702	1.025	1.705
UA	0.945	1.493	0.945	1.495
US	1.362	2.200	1.359	2.202
WN	1.446	2.086	1.440	2.088

Note: Quantities are in USD 1 million. $\alpha = 50,000$.

Table 6: Estimated fixed costs for a hub with 20 spokes.

	$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}$		$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}^{\boldsymbol{\alpha}}$	
	LB	UB	LB	UB
AA	17.508	28.062	17.503	28.110
DL	16.735	25.551	16.715	25.598
UA	15.938	23.511	15.935	23.559
US	20.009	30.406	19.979	30.451
WN	20.828	29.289	20.770	29.336

Note: Quantities are in USD 1 million. $\alpha = 50,000$.

Table 7: First-stage inference.

	$\widehat{\boldsymbol{\Gamma}}_{\boldsymbol{I}}^{\boldsymbol{\alpha}}$		**95% CI**	
	LB	UB	LB	UB
Baseline fixed costs (γ_1)	655,560	875,906	643,814	1,097,497
Congestion costs ($\gamma_{2,f}$)				
AA	8,633	28,238	6,019	33,102
DL	6,727	21,956	4,043	25,744
UA	4,600	16,747	2,046	18,546
US	14,972	34,366	11,609	38,711
WN	16,952	31,143	13,318	35,751

Note: Quantities are in USD. $\alpha = 50,000$.

Table 8: Test statistic (22) and the (one-step) Self Normalized critical value.

	$\xi(\gamma)$
$\max \gamma_1$	1.672
$\max \gamma_{2,AA}$	1.267
$\max \gamma_{2,DL}$	1.611
$\max \gamma_{2,UA}$	1.030
$\max \gamma_{2,US}$	1.441
$\max \gamma_{2,WN}$	2.918
$\min \gamma_1$	1.580
$\min \gamma_{2,AA}$	3.883
$\min \gamma_{2,DL}$	0.987
$\min \gamma_{2,UA}$	8.711
$\min \gamma_{2,US}$	0.962
$\min \gamma_{2,WN}$	2.177

Note: The Self Normalized 5% critical value is 2.639.

8 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 an interest in merging in January 2012 and officially announced their plans to merge in February 2013. At the time they expressed their interest to merge, American Airlines' holding company (AMR Corporation) was in Chapter 11 bankruptcy.[13] Further, the Department of Justice (DoJ), along with several state attorney generals, sought to block the merger, as they were concerned that it would have substantially lessened competition and hurt consumers. In 2013, a settlement was reached, whereby the merging parties pledged to give up landing slots or gates at seven major airports and to maintain the same level of operations in the hub markets out of Charlotte, New York (Kennedy), Los Angeles, Miami, Chicago (O'Hare), Philadelphia, and Phoenix for a period of three years.[14] Below, we refer to this 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 to generate annual cost savings of around \$1 billion per year.[15] In addition, 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.[16] The merger was the last in a series of mergers between large airlines and reduced the number of legacy carriers to four (Delta Airlines, United Airlines, Southwest Airlines, and the new American Airlines).

8.1 Set-up

When simulating a merger between airlines, the canonical approach consists of relying on demand and supply models, where the firms best respond to competitors by adjusting their prices, while holding the networks fixed. Given that the networks are held fixed, before running the simulation, the researcher needs to take a stand on which network the merged entity will inherit. In turn, this choice determines the list of products offered by the merged entity and their observed characteristics.

In particular, the previous literature has considered a base-case scenario, where the

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

[14] 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.

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

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

merging firms maintain their pre-merger products and behave as if they have colluded. Additionally, a best-case scenario is considered, where the merged entity offers the itineraries that have the most favorable features of the pre-merger products of the merging firms. These are just two possible scenarios, and nothing suggests that they should be taken as extreme reference cases, as there are infinite plausible ways in which the merged entity may revisit its entry decisions. Our methodology eliminates such ambiguity because it allows the merged entity to best respond by adjusting both its network and prices. Depending on the dominating forces, the merged entity may find it convenient to exit some markets in order to downsize the higher total congestion costs from managing a denser network. Alternatively, they may enter new markets so as to exploit the marginal cost savings from denser hub-and-spoke structures and consumers' willingness-to-pay for flying from dense nodes. Further, our methodology allows the competitors to re-optimise both their networks and prices. For example, the competitors may find it opportune to exit markets where the merged firm has acquired excessive market power, or to enter markets where the merger has created space for other companies.

To highlight the advantages of our framework, we compare the counterfactual predictions arising from our model with those obtained using ad-hoc assumptions on the post-merger network. In particular, we consider three ad-hoc scenarios:

1. Networks fixed - base case. After the merger, the merging airlines remain separate entities. All firms maintain the pre-merger networks and products. They play the simultaneous pricing game described in Section 3.1 and new equilibrium prices arise. The merging firms choose the prices that maximise their joint profits; that is, they behave as if they have colluded;

2. Networks fixed - best case. After the merger, all firms, except American Airlines and US Airways, maintain the pre-merger networks and products. The merging firms remain separate entities. They also keep the pre-merger products, but update some of their covariates. In particular, the products of the merging firms get the best firm dummy. Further, if the merging firms offered the same itinerary before the merger, then the two products inherit the most favorable observed demand and marginal cost shifters. For example, on the demand side, the estimated coefficient of the variable "*Nonstop Origin*" is positive. Hence, the two products get the highest value of "*Nonstop Origin*" between the merging airlines. 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;

3. Networks fixed - updated case. After the merger, all firms, except American Airlines and US Airways, maintain the pre-merger networks and products. We treat the merged entity as a new firm that gets the best firm dummy between the merging airlines. We assign the merged entity to 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 demand and supply shocks of the itineraries that were offered both by American Airlines and US Airways before the merger are replaced by their mean values. After such rearrangements, the firms play the simultaneous pricing game described in Section 3.1 and new equilibrium prices arise.

These three ad-hoc scenario are compared with the simulations from our full model. When simulating our full model, we consider three possible scenarios:

1. Networks vary - without remedies. After the merger, we treat the merged entity as a new firm that gets the best firm dummy between the merging airlines. We let the firms play the two-stage game described in Section 3. New equilibrium networks and prices arise. More details on the algorithm used to reach the new set of equilibria are in Section I of the Online Appendix;

2. Networks vary - with remedies. An important advantage of our approach is that it allows us to evaluate the impact on firm and market outcomes of the 2013 settlement. To do so, after the merger, we treat the merged entity as a new firm that gets the best firm dummy between the merging airlines. We let the firms play the two-stage game described in Section 3. New equilibrium networks and prices arise. However, in contrast to the *Networks vary - without remedies* scenario, now we incorporate as binding constraints some of the DoJ's remedies contained in the 2013 settlement. In particular, we force the merged entity to continue serving all the markets that were served by the merging firms before the merger out of Charlotte, New York, Los Angeles, Miami, Chicago, Philadelphia, and Phoenix. Recall that these were the cities signalled by the DoJ, as discussed at the beginning of Section 8.[17,18]

3. Networks vary - PHX dehubbed. In contrast to the *Networks vary - w/o remedies* scenario, we assume that the merged entity removes the hub status of Phoenix and can only offer a direct service from Phoenix to the remaining hubs and no longer to non-hub cities. Later, we clarify why we focus on Phoenix.

8.2 Results

Table 9 shows the impact of the merger on consumer surplus. Before commenting on the results, we clarify that, under the *Networks fixed* column, we report each quantity's median, minimum, and maximum percentage changes across the *Networks fixed - base*

[17]Note that this scenario differs from the *Networks fixed - Updated case* scenario because, first, the competitors of the merged entity are allowed to re-optimise their networks; second, the merged entity is allowed to increase its operations in the markets out of the hubs signalled by the DoJ and to increase/decrease its operations in the markets out of the hubs not signalled by the DoJ (Washington DC and Dallas).

[18]As highlighted at the beginning of Section 8, the 2013 settlement also required the merged airline to give up landing slots or gates at seven major slot constrained airports, in order to facilitate the expansion of low-cost carriers, such as Southwest. This part of the settlement is not incorporated in the simulations, because our framework does not distinguish between airports in the same cities and, hence, does not explicitly model the process of slot assignment. See also Section 3.2 for a discussion on this issue.

case, *best case*, and *updated case* scenarios. Under the *Networks vary* columns, we report each quantity's median, minimum, and maximum percentage changes across different parameter values in the estimated identified set and across different equilibria constructed by the counterfactual algorithms. The minimum and maximum percentage changes are in square brackets. The median percentage change is above the square brackets. The other tables have a similar structure and sometimes replace percentage changes with actual values. For simplicity of exposition, our discussion will be often based on the median values or percentage changes. Hereafter, the merged entity is also referred to as American Airlines. In Section I of the Online Appendix, we present the confidence intervals for our counterfactuals.

The first row of Table 9 reports the impact of the merger on total consumer surplus. Absent any remedies, the merger leads to a modest median increase in consumer surplus by around 0.5%. However, if we look at the minimum percentage changes, our analysis does not rule out a decrease in consumer surplus of up to 7%. With the remedies discussed above, the median increase in consumer surplus is slightly more pronounced and around 0.8%. Importantly, if we look at the minimum percentage changes, the remedies limit consumer surplus losses by more than half. Last, had Phoenix been dehubbed, the merger would have led to a decrease in consumer surplus. These results suggest that the remedies helped prevent consumer surplus losses and that hub closures can cause significant consumer surplus losses.

The second and third rows of Table 9 show the impact of the merger on consumer surplus when we distinguish between two groups of markets. We call "new markets" the markets where the merging parties do not offer direct flights pre-merger. and where the merged entity offers directs flights post-merger. We call "old markets" the markets where the merging parties offer direct flights pre-merger. Old markets are those on which antitrust authorities typically focus their merger analysis. We can see that while the overall impact of the merger on consumer surplus is small, there is an important tension between old and new markets. On the one hand, due to the entry-exit patterns explained below, old markets undergo consumer surplus losses. If the merger's effect on consumer surplus in old markets was the relevant criterion, then the merger should have been blocked. This is in line with the DoJ's initial attempt to stop the merger. On the other hand, new markets experience a considerable increase in consumer surplus, which reveals substantial positive effects of the merger and can be used to legitimise its implementation. Further, the remedies, which were tailored to prevent the exit of American Airlines from the old markets, reduce median consumer surplus losses in the old markets but, at the same time, slightly weaken median consumer surplus gains in new markets. This highlights the need for antitrust authorities to carefully balance these two effects when designing network interventions. To the best of our knowledge, this tension between consumer surplus losses in old markets and consumer surplus gains in

Table 9: Percentage change in consumer surplus across different scenarios.

	Networks fixed	**Networks vary**		
		w/o remedies	w/ remedies	PHX dehubbed
Total consumer surplus	+0.08 [-0.47, +3.40]	+0.46 [-7.13, +3.45]	+0.77 [-2.96, +4.02]	-0.90 [-8.37, +1.71]
New markets		+45.28 [+26.87, +52.06]	+44.78 [+26.9, +53.17]	+42.79 [+21.36, +55.73]
Old markets	+0.08 [-0.47, +3.40]	-5.25 [-9.32, -3.84]	-5.21 [-7.12, -4.03]	-4.65 [-9.31, -2.97]

Note: Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Percentage changes with respect to the pre-merger scenario are reported.

new markets is a novel empirical finding that has major implications for policymakers. Contrary to the fixed network approach, our model is best suited to study such a trade-off.

Table 10 sheds some light on what drives these effects. The last two rows report the number of markets served with direct flights by American Airlines and its competitors before and after the merger out of American Airlines and US Airways' hubs.[19] The merger leads American Airlines to expand its network. Instead, the other major airlines decrease the size of their operations. Taken together, these reactions reduce competition in old markets and generate entry in new markets. On the one hand, American Airlines expands its network to decrease marginal costs via economies of density (recall the variable "*Connections*" in the marginal cost equation) and exploit consumers' willingness-to-pay for flying from dense nodes (recall the variable "*Nonstop Origin*" in the utility function). By doing so, it offsets the higher congestion costs (recall the quadratic term in the fixed cost equation) due to managing a larger number of hubs. On the other hand, post-merger entry by rivals does not happen. This may seem counter-intuitive, as one would expect reduced competition due to the elimination of one firm to free room for competitors. We do not observe this mechanism for two reasons. First, there was relatively little overlap between American Airlines and US Airways, hence there was almost no space created for post-merger entry by the other airlines. Second, as mentioned above, by expanding its network, American Airlines increases consumers' willingness-to-pay for its flights and decreases its marginal costs. This makes it more challenging for the other carriers to compete with such a powerful player and may cause them to exit. As the drop of consumer surplus in the old market suggests, the increased consumer utility from American Ailines' larger network is neutralised by the reduction of competitors' operations. In Section I.3 of the Online Appendix, we show that the expansion of American Airlines' network and the reduction of competitors' networks align with the real entry-exit dynamics observed

[19]Before the merger, we take the sum of the number of markets served with direct flights by US Airways and American Airlines.

Table 10: Outcomes across different scenarios.

	Before	**Merger**			
		Networks fixed	Networks vary		
			w/o remedies	w/ remedies	PHX dehubbed
Total consumer surplus	2807.06	+0.08	+0.46	+0.77	-0.90
		[-0.47, +3.40]	[-7.13, +3.45]	[-2.96, +4.02]	[-8.37, +1.71]
Mean consumer surplus	4.09	+0.08	-0.87	-0.55	-2.18
		[-0.47, +3.40]	[-8.18, +1.82]	[-4.18, +2.38]	[-9.15, +0.39]
Markups: AA/US	119.2	+7.34	+12.77	+12.89	+11.71
		[+5.98, +8.64]	[+7.05, +15.3]	[+9.92, +15.8]	[+6.75, +14.47]
Markups: Other major airlines	116.22	-0.45	-1.28	-1.35	-0.79
		[-0.68, +0.07]	[-1.81, +0.97]	[-2.03, -0.40]	[-1.42, +1.15]
Segments: AA/US	430	430	491	498	457
			[348, 531]	[435, 546]	[335, 497]
Segments: Other major airlines	736	736	686	689	693
			[607, 720]	[606, 710]	[612, 721]

Note: Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Percentage changes with respect to the pre-merger scenario are reported for total consumer surplus, mean consumer surplus, and markups.

after 2013.

Table 10 also reveals that American Airlines' markups increase substantially. This is due to the increase in market power and the necessity of covering the higher fixed costs of serving a larger post-merger network. Table I.3 in Section I of the Online Appendix digs deeper into this effect and shows that American Airlines benefits from considerable marginal cost savings thanks to the merger, with these benefits only partially passed through to consumers.

The entry-exit patterns generated by the merger lead to noticeable heterogeneity across American Airlines' hub markets. Table 11 highlights that while some hub markets experience large consumer surplus gains, others suffer from the merger. The negative effect of the merger is especially pronounced in the markets out of New York, Chicago, Miami, and Phoenix. Table I.2 in Section I of the Online Appendix also reports the hub-level changes in the number of direct flights offered by American Airlines and the other major airlines. It reveals that the consumer surplus decrease in the markets out of New York, Chicago, and Phoenix was driven by the exit of competitors, whereas the consumer surplus decrease in the markets out of Miami was driven by the exit of both American Airlines and competitors. Remember that the 2013 settlement required the merged airline to divest slots at Chicago O'Hare and gates in Miami and at La Guardia Airport in New York. Such remedies, which we do not model, likely prevented the significant rival exit that we predicted in these markets.

Table 11: Percentage change in consumer surplus in the hub markets of AA and US.

	Before	**Merger**			
		Networks fixed	Networks vary		
			w/o remedies	w/ remedies	PHX dehubbed
AA hubs					
DFW	341.22	-1.48	+5.36	+5.36	+4.44
		[-2.94, +7.04]	[+3.24, +8.10]	[+3.45, +8.11]	[+2.11, +7.52]
LAX	520.29	+0.01	-0.81	-0.65	-1.03
		[-0.32, +2.44]	[-6.15, +0.55]	[-2.38, +0.56]	[-6.77, +0.27]
ORD	485.16	+0.46	-11.72	-11.03	-11.95
		[-0.29, +4.07]	[-20.09, -8.01]	[-18.06, -7.01]	[-19.83, -8.86]
MIA	314.55	-0.34	-23.18	-17.62	-23.89
		[-0.51, +4.56]	[-29.23, -16.87]	[-19.34, -15.67]	[-30.51, -17.69]
JFK	631.27	-0.30	-11.86	-11.28	-15.33
		[-0.43, +2.19]	[-21.95, -3.34]	[-17.39, -3.46]	[-24.48, -7.34]
US hubs					
CLT	134.27	-1.52	+11.91	+12.53	+5.85
		[-2.56, +3.27]	[-6.90, +16.80]	[+6.50, +16.80]	[-7.82, +8.61]
PHX	237.55	-0.64	-20.34	-19.92	-32.05
		[-2.48, +3.66]	[-29.42, -18.35]	[-22.26, -18.33]	[-34.78, -30.78]
DCA	428.19	-0.29	+24.88	+22.22	+20.71
		[-0.62, +2.26]	[+4.80, +27.18]	[+4.78, +27.32]	[+1.15, +23.08]
PHL	213.55	-0.91	+13.32	+13.32	+10.78
		[-1.01, +2.98]	[-4.62, +22.06]	[+9.98, +22.06]	[-5.90, +18.45]

Note: Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Percentage changes with respect to the pre-merger scenario are reported.

9 Conclusions

In this paper, we build and estimate a two-stage game model of airline competition in which the airlines choose the networks of markets to serve in the first stage and compete in prices in the second stage. Our model allows for spillovers in entry decisions across markets on the demand, marginal cost, and fixed cost sides. We estimate the model using data from US domestic fares from the second quarter of 2011 and find significant spillovers in entry. We use the estimates to counterfactually evaluate the 2013 merger between American Airlines and US Airways. Our counterfactuals reveal that, absent any remedies, the merger leads to a modest increase in consumer surplus. With the remedies, the increase in consumer surplus is more pronounced. Further, we uncover two important sources of heterogeneity in the merger's impact: first, some hubs enjoy large gains in consumer surplus, while other hubs suffers substantial losses; and second, consumer surplus decreases in markets in which the merging parties served pre-merger and increases substantially in markets where the merged entity enters post-merger. Hence, the decision of whether or not to allow for the merger depends significantly on which markets the antitrust authority focuses on. Last, we show that such differences are driven by the expansion of American Airlines' network in an attempt to leverage spillovers in entry and the exit of rivals. Overall, these findings have important implications for antitrust authorities because they underlie the relevance of endogenising post-merger network readjustments and accounting for spillovers when evaluating mergers.

There are several directions for further research. For instance, it would be interesting to consider whether capacity constraints and intertemporal price discrimination may generate dynamics in the pricing strategies of the airlines. Notably, we also abstract away from frequency choices by airlines. Flight frequency is another margin by which the airlines can respond to a merger and that may have a direct impact on marginal costs and consumer utility. We leave these extensions to future work.

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Online Appendix to "Price Competition and Endogenous Product Choice in Networks: Evidence from the US Airline Industry"

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A Proofs

Proof of Theorem 1 (i) comes from the convergence of $\widehat{\Gamma}_I$ to Γ_I with respect to the Hausdorff distance. (ii) comes from Shapiro et al. (2014), Theorem 5.11, p.193. The uniformity in q for both (i) and (ii) comes from the compactness of the unit ball and the identified set. ■

Proof of Theorem 2 (i) comes from the convergence of $\widehat{\Gamma}_I^\alpha$ to Γ_I^α with respect to the Hausdorff distance. (ii) comes from Shapiro et al. (2014), Theorem 5.11, p.193 combined with the Delta method for the asymptotic variance of the estimated constraints. As a matter of fact, denoting $b_r = \mathbb{E}(Z_{r,m}B_m)$ and $a_r = \mathbb{E}(Z_{r,m}A_m)$, for $r = 1, \ldots, \mathrm{R}$, we have

$$\frac{\partial g_\alpha}{\partial b_r}(\gamma) = \frac{\gamma \exp\left(\alpha\left[b_r^\top \gamma - a_r\right]\right)}{1+\exp\left(\alpha\left[b_r^\top \gamma - a_r\right]\right)} = \frac{\gamma}{1+\exp\left(-\alpha\left[b_r^\top \gamma - a_r\right]\right)},$$
$$\frac{\partial g_\alpha}{\partial a_r}(\gamma) = \frac{-1}{1+\exp\left(-\alpha\left[b_r^\top \gamma - a_r\right]\right)}.$$

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Therefore:

$$\begin{aligned}\sqrt{\mathrm{M}}(\hat{g}_\alpha(\gamma) - g_\alpha(\gamma)) &= \sum_{r=1}^{\mathrm{R}} \frac{\sqrt{\mathrm{M}}\left((\hat{b}_r - b_r)^\top \gamma - (\hat{a}_r - a_r)\right)}{1 + \exp\left(-\alpha\left[b_r^\top \gamma - a_r\right]\right)} + o_P(1),\\ &= \sum_{r=1}^{\mathrm{R}} \frac{W_r(\gamma)}{1 + \exp\left(-\alpha\left[b_r^\top \gamma - a_r\right]\right)} + o_P(1).\end{aligned}$$

The uniformity in q comes from the compactness of the unit ball. ■

B Existence of Nash equilibrium networks

As discussed in Section 3.3 of the main paper, proving the existence of a pure strategy Nash equilibrium (PSNE) $G \coloneqq (G_f : f \in \mathcal{N})$ is difficult due to the presence of spillovers from entry across markets on the demand, marginal cost and fixed cost sides.

Berry (1992)establishes the existence of a PSNE in one of the first empirical models of entry that incorporates strategic interactions between firms in the second-stage pricing game. His proof relies on the assumption that the entry decisions are independent across markets. It is therefore not applicable to our framework. Another approach used in the network formation literature to show the existence of a PSNE is to represent the model as a potential game (Monderer and Shapley, 1996). This is possible if the payoff function is additive separable in the linking decisions and linear in the spillovers (as for example in Mele, 2017), which is not the case here. Alternatively, it is possible to show the existence of a PSNE under the assumption that the game is supermodular, in order to exploit the fixed point theorem for isotone mappings (Topkis, 1979). However, supermodularity does not hold in our setting due to the second-stage competition between airlines. Finally, one could try 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 a PSNE in each local game - which is typically easier to establish - is sufficient for the existence of a PSNE in the original game. However, the classes of spillovers considered in our model do not allow us to implement such a decomposition.

One might also ask whether allowing for private fixed cost shocks could simplify the existence proof. Espín-Sánchez et al. (2021) prove equilibrium existence in an entry model where firms have some private information at the entry stage. However, they do not allow for multi-product firms and they do not allow for spillovers from entry across markets. Moreover, in our setting it is more reasonable to assume that the fixed cost shocks are common knowledge among airlines, as discussed in Section 3.2 of the main paper.

Note that the moment inequalities in Section 4.2 of the main paper are based on necessary conditions for PSNE. Therefore, one could consider a first-stage equilibrium notion that is weaker than PSNE. In particular, given our focus on one-link deviations, inequalities (10) and (11) resemble the notion of pairwise stability used in network theory, according to which no player has profitable deviations by adding or removing a link (Jackson and Wolinsky, 1996). Definition 1 introduces a notion of first-stage equilibrium along the lines of pairwise stability.

Definition 1. (*Pairwise Stability*) The networks $G_1, \ldots, G_{\mathrm{N}}$ represent a pairwise stable outcome if, for each market $\{a, b\} \in \mathcal{M}$ and airline $f \in \mathcal{N}$, it holds that

$$
\begin{aligned}
G_{ab,f} = 0 &\Rightarrow \Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) + \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(+ab),f} + \gamma_{1,f} + \eta_{ab,f} \geq 0, \\
G_{ab,f} = 1 &\Rightarrow \Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) - \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} - \gamma_{1,f} - \eta_{ab,f} \geq 0.
\end{aligned}
$$

◇

In the absence of ties (it is sufficient that the fixed cost shocks have a continuous distribution), Definition 1 can be rewritten as a simultaneous equation model.

Lemma 1. (*Equivalent representation of pairwise stability*) In the absence of ties, the networks $G_1, \ldots, G_{\mathrm{N}}$ represent a pairwise stable outcome if and only if:

$$
\begin{aligned}
G_{ab,f} = \mathbb{1}\{\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) - \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} - \gamma_{1,f} - \eta_{ab,f} \geq 0\}, \\
\forall \{a, b\} \in \mathcal{M}, \forall f \in \mathcal{N}.
\end{aligned}
\tag{B.1}
$$

◇

See Menzel (2017) or Sheng (2020) for a proof of Lemma B.1. Note that although pairwise stability is a weaker equilibrium notion than PSNE, establishing the existence of a pairwise stable outcome does not appear to be easier in our setting. In particular, according to Jackson and Watts (2002), for any payoff function there is either a pairwise stable outcome or a closed cycle.[1] A typical way used in the literature to exclude the presence of closed cycles is to show that the model can be represented as a potential game, as discussed by Jackson and Watts (2001) and Hellmann (2013). As before, however, this is possible if the payoff function is additive separable in the link decisions and linear in the spillovers (as in Sheng, 2020), which is not our case.

C How to deal with incoherence

In Section 4.2 of the main paper, we have constructed the identified set for the first-stage parameters under the assumption that PSNE networks exist for each parameter value and variable realisation. As discussed above, proving the existence of PSNE networks is difficult. Therefore, it is legitimate to wonder whether one should modify the definition

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

of the identified set when non-existence is possible, i.e., when our model is incoherent in the terminology of Tamer (2003) and Lewbel (2007).

To explain how we deal with incoherence, we first report here the moment inequalities predicted by our model as derived in Section 4.2 of the main paper:

$$
\begin{aligned}
&\mathbb{E}_{\Pr}\Big[Z_{r,(-ab),f} \times G_{ab,f} \times \Big(\Pi^e_f(G_f, G_{-f};\theta) - \Pi^e_f(G_{-ab,f}, G_{-f};\theta) - \Big(\gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} + \gamma_{1,f}\Big)\Big)\Big] \geq 0,\\
&r = 1, \ldots, \mathrm{R}_-,\\
&\mathbb{E}_{\Pr}\Big[Z_{r,(+ab),f} \times (1 - G_{ab,f}) \times \Big(\gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(+ab),f} + \gamma_{1,f} - \big(\Pi^e_f(G_{(+ab),f}, G_{-f};\theta) - \Pi^e_f(G_f, G_{-f};\theta)\big)\Big)\Big] \geq 0,\\
&r = 1, \ldots, \mathrm{R}_+,
\end{aligned}
\tag{C.1}
$$

where $\mathbb{E}_{\Pr}$ is the expectation operator based on the probability function Pr associated with the probability space where the random variables of the model are defined. Second, to simplify the exposition, we focus on one moment inequality from (C.1):

$$
\mathbb{E}_{\Pr}\Big[Z_{r,(-ab),f} \times G_{ab,f} \times \Big(\Pi^e_f(G_f, G_{-f};\theta) - \Pi^e_f(G_{-ab,f}, G_{-f};\theta) - \Big(\gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} + \gamma_{1,f}\Big)\Big)\Big] \geq 0. \tag{C.2}
$$

Third, we streamline the notation of (C.2) as:

$$
\mathbb{E}_{\Pr}(G_m\tilde{A}_m) - \mathbb{E}_{\Pr}(G_m\tilde{B}_m^\top)\gamma \geq 0, \tag{C.3}
$$

where the subscripts f and r are omitted, m is a market $\{a, b\}$, $\tilde{A}_m$ is $Z_{r,(-ab),f}(\Pi^e_f(G_f, G_{-f};\theta) - \Pi^e_f(G_{-ab,f}, G_{-f};\theta))$, $\tilde{B}_m$ is such that $\tilde{B}_m^\top\gamma$ is equal to $Z_{r,(-ab),f}(\Delta\overline{\mathrm{Q}}_{(-ab),f}\gamma_{2,f} + \gamma_{1,f})$.

Let $\mathbb{P}$ be the distribution of $(G_m\tilde{A}_m, G_m\tilde{B}_m)$ identified by the sampling process. If the set of PSNE networks is non-empty for each parameter value and variable realisation, then we can replace $\mathbb{E}_{\Pr}$ with $\mathbb{E}_{\mathbb{P}}$ in (C.3) and obtain the identified set for γ associated with $\mathbb{P}$:

$$
\Gamma_I \coloneqq \Big\{\gamma \in \Gamma : \ \mathbb{E}_{\mathbb{P}}(G_m\tilde{A}_m) - \mathbb{E}_{\mathbb{P}}(G_m\tilde{B}_m^\top)\gamma \geq 0\Big\}. \tag{C.4}
$$

If the set of PSNE networks is empty for some parameter values and variable realisations, then the relationship between $\mathbb{P}$ and Pr is not completely defined because our model is silent about the realisations of $(G_m\tilde{A}_m, G_m\tilde{B}_m)$ when the set of PSNE networks is empty. Since non-existence outcomes are never observed in our data, we approach the incoherence problem by assuming that the data are drawn from the subset of the sample space in which the set of PSNE networks is non-empty. That is, $\mathbb{P}$ comes from a truncated version of Pr, as discussed in Section 4.2 of Chesher and Rosen (2020). In what follows, we show that the identified set for γ associated with $\mathbb{P}$ is still defined by (C.4).

For ease of explanation, let us assume that $\tilde{A}_m$ and $\tilde{B}_m$ are discrete random variables. Given $\gamma \in \gamma_I$, our model predicts that

$$
\sum_{a\in\mathcal{A}} a \times \Pr(\tilde{A}_m = a, G_m = 1) - \sum_{b\in\mathcal{B}} b^\top \times \Pr(\tilde{B}_m = b, G_m = 1) \times \gamma \geq 0, \tag{C.5}
$$

where $\mathcal{A}$ and $\mathcal{B}$ are the supports of $\tilde{A}_m$ and $\tilde{B}_m$, respectively. Let $\mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta)$ be the random closed set of PSNE networks.[2] If our model is correctly specified, then the observed realisation of G is associated with realisations of $X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta$ from the truncated support $\{(x^{\oplus}, w^{\oplus}, ms, \bar{\eta}) \in \mathrm{Supp}_{X^{\oplus},W^{\oplus},\mathrm{MS},\eta} : \mathcal{S}_{\theta,\gamma}(x^{\oplus}, w^{\oplus}, ms, \bar{\eta}) \neq \emptyset\}$. Therefore, it holds that:

$$\begin{aligned}&\mathbb{P}(\tilde{A}_m = a, G_m = 1) = \Pr(\tilde{A}_m = a, G_m = 1 | \mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset)\\ &= \frac{\Pr(\tilde{A}_m = a, G_m = 1, \mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset)}{\Pr(\mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset)} = \frac{\Pr(\tilde{A}_m = a, G_m = 1)}{\Pr(\mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset)}.\end{aligned} \tag{C.6}$$

In turn, we can write:

$$\begin{aligned}\Pr(\tilde{A}_m = a, G_m = 1) &= \mathbb{P}(\tilde{A}_m = a, G_m = 1) \times \Pr(\mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset),\\ \Pr(\tilde{B}_m = b, G_m = 1) &= \mathbb{P}(\tilde{B}_m = b, G_m = 1) \times \Pr(\mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset).\end{aligned} \tag{C.7}$$

We plug (C.7) in (C.5) and obtain:

$$\Pr(\mathcal{S}_{\theta,\gamma}(X^{\oplus}, W^{\oplus}, \mathrm{MS}, \eta) \neq \emptyset) \times [\mathbb{E}_{\mathbb{P}}(G_m \tilde{A}_m) - \mathbb{E}_{\mathbb{P}}(G_m \tilde{B}_m^{\top})\gamma] \geq 0, \tag{C.8}$$

which is equivalent to

$$\mathbb{E}_{\mathbb{P}}(G_m \tilde{A}_m) - \mathbb{E}_{\mathbb{P}}(G_m \tilde{B}_m^{\top})\gamma \geq 0. \tag{C.9}$$

Hence, the identified set associated with $\mathbb{P}$ is:

$$\Gamma_I \coloneqq \Big\{\gamma \in \Gamma :\ \mathbb{E}_{\mathbb{P}}(G_m \tilde{A}_m) - \mathbb{E}_{\mathbb{P}}(G_m \tilde{B}_m^{\top})\gamma \geq 0\Big\}, \tag{C.10}$$

as in (C.4).

D Computing the first-stage moment inequalities

We provide some directions on how to compute $\Pi_f^e(G_{(+ab),f}, G_{-f}; \theta) - \Pi_f^e(G_f, G_{-f}; \theta)$ and $\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma)$ entering (10). A similar procedure can be followed to compute (11).

First, we compute $\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma)$. If none of cities a and b are firm f's hubs, then $\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma) = \gamma_{1,f} + \eta_{ab,f}$. If only city a (resp. b) is one of firm f's hubs, then $\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma) = \gamma_{1,f} + \gamma_{2,f} \times ((D_{a,f}+1)^2 - D_{a,f}^2) + \eta_{ab,f}$ (resp. $\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma = \gamma_{1,f} + \gamma_{2,f} \times ((D_{b,f}+1)^2 - D_{b,f}^2) + \eta_{ab,f})$, where $D_{a,f}$ (resp. $D_{b,f}$) is the number of spokes of hub a (resp. b). If both cities a and b are firm f's hubs, then $\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma) =$

[2] For the formal definition of a random closed set, see Molchanov and Molinari (2018) and Molinari (2020).

$\gamma_{1,f} + \gamma_{2,f} \times ((D_{a,f}+1)^2 - D^2_{a,f}) + \gamma_{2,f} \times ((D_{b,f}+1)^2 - D^2_{b,f})$.

Second, we determine the realisations of the second-stage shocks used to evaluate the airlines' expected variable profits. In particular, from the vector of second-stage estimates, $\hat{\theta}$, we compute the second-stage shocks for each product offered using the BLP inversion. For each airline f, we compute the mean and variance of the second-stage shocks just obtained and denote them by μ_f and Σ_f respectively. For each potential product of each airline f, we take 100 random draws from a normal distribution with mean μ_f and variance Σ_f. We store all such draws in a matrix Ξ.

Third, we compute the expected variable profits of airline f under $(G_{(+ab),f}, G_{-f})$. To do so, we update the list of products offered by firm f, by adding direct flights between cities a and b. Further, note that setting $G_{ab,f} = 1$ creates a "domino effect" in neighbouring markets, due to the possibility for airline f to offer one-stop flights and the presence of spillovers in entry across markets. Specifically, 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, then we add one-stop flights, via b, between a and all cities d such that $G_{db,f} = 1$. We update the matrices of product covariates by including the observed demand and marginal cost shifters of the new products. We also update the covariates (namely, "*Nonstop Origin*" and "*Connections*") of the pre-existing products that are affected by the new products. Let $\mathcal{M}_{ab,f}$ be the list of markets containing either new products or products with modified covariates. For each market $m \in \mathcal{M}_{ab,f}$, we let the firms reoptimise their prices by iterating on the F.O.C.s in (4), for every draw of the second-stage shocks stored in the matrix Ξ.[3] We compute the variable profits of airline f, average across draws, and get the simulated expected variable profits of airline f, which we denote by $\sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_{(+ab),f}, G_{-f}; \theta)$. We implement a similar procedure to compute the expected variable profits of airline f in each markets $m \in \mathcal{M}_{ab,f}$ under G, which we denote by $\sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_f, G_{-f}; \theta)$. Lastly, we calculate $\Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta) = \sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_{(+ab),f}, G_{-f}; \theta) - \sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_f, G_{-f}; \theta)$.

E Bounds under many-link deviations

In this section, we show that many-link deviations do not provide a substantial improvement in the bounds. In particular, we show that two-link deviations generate many redundant inequalities compared to those generated by the one-link deviations.

[3] We have decided to use the F.O.C.s in (4) as a contraction mapping. While we do not formally prove that (4) is indeed a contraction mapping, we have found that the resulting price vector does not change when starting from different values and that the mapping converges in all the cases considered.

Adding links to the factual network

Consider markets $\{a, b\}$ and $\{c, d\}$ that are not served by airline f with direct flights (i.e., $G_{ab,f} = G_{cd,f} = 0$). From the revealed preference principle, it holds that

$$\Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta) \leq \text{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma), \tag{E.1}$$

$$\Pi^e_f(G_{(+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta) \leq \text{FC}_f(G_{(+cd),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma), \tag{E.2}$$

$$\Pi^e_f(G_{(+ab,+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta) \leq \text{FC}_f(G_{(+ab,+cd),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma). \tag{E.3}$$

(E.1) and (E.2) are taken into account by our identification methodology, as they refer to one-link deviations. (E.3) is ignored by our identification methodology, as it refers to a two-link deviation. In what follows, we show that if markets $\{a, b\}$ and $\{c, d\}$ are non-hub markets for airline f and have no cities in common, or they share a hub endpoint, then (E.1) and (E.2) imply (E.3). Hence, (E.3) is redundant.

First, consider the case where markets $\{a, b\}$ and $\{c, d\}$ are non-hub markets for airline f and have no cities in common. Given our fixed cost equation, it holds that

$$\text{FC}_f(G_{(+ab,+cd),f}, \eta_f; \gamma) - \text{FC}_f(G_{(+cd),f}, \eta_f; \gamma) = \text{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma).$$

Therefore, the right-hand-side of (E.3) is equal to

$$\begin{aligned} \text{FC}_f(G_{(+ab,+cd),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma) = &\text{FC}_f(G_{(+cd),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma) \\ &+ \text{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \text{FC}_f(G_f, \eta_f; \gamma). \end{aligned} \tag{E.4}$$

Observe that the left-hand-side of (E.3) can be rewritten as

$$\Pi^e_f(G_{(+ab,+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_{(+cd),f}, G_{-f}; \theta) + \Pi^e_f(G_{(+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta).$$

Furthermore, from our second-stage estimates, it generally holds that

$$\Pi^e_f(G_{(+ab,+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_{(+cd),f}, G_{-f}; \theta) \leq \Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta). \tag{E.5}$$

In other words, adding an independent edge $\{a, b\}$ to the counterfactual network $G_{(+cd),f}$ does not tend to generate more expected variable profits than adding it to the actual network G_f. In fact, adding $\{a, b\}$ to $G_{(+cd),f}$ increases expected variable profits due to two effects. First, the demand in market $\{a, b\}$ increases because the passengers of market $\{a, b\}$ can now fly directly between a and b instead of flying through a hub of f which is neither c nor d (recall the variable "*Indirect*" entering the demand function). Second, the demand in markets having a or b as endpoints is increased by adding the direct service between a and b (recall the variable "*Nonstop Origin*" entering the demand function). From Table 2 (demand panel) we can see that the first effect dominates the second: flying direct increases utility by 1.794; adding *one* direct connection increases utility by 0.00868. In turn, through (E.1), (E.2) and (E.5), we see that

$$\begin{aligned}&\Pi^e_f(G_{(+ab,+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_{(+cd),f}, G_{-f}; \theta) + \Pi^e_f(G_{(+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta)\\ &\leq \mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma) + \mathrm{FC}_f(G_{(+cd),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma).\end{aligned} \tag{E.6}$$

Hence, by combining (E.4) and (E.6), (E.3) is verified.

Second, consider the case where markets $\{a, b\}$ and $\{c, d\}$ share a hub endpoint. For instance suppose $a = c$ and a is a hub. Then,

$$\begin{aligned}\mathrm{FC}_f(G_{(+ab,+cd),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma)&\\ =&\mathrm{FC}_f(G_{(+ab),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma)\\ &+\mathrm{FC}_f(G_{(+cd),f}, \eta_f; \gamma) - \mathrm{FC}_f(G_f, \eta_f; \gamma)\\ &+\gamma_2(2D_{a,f} + 3),\end{aligned}$$

where $D_{a,f}$ is the number of hub a's spokes in the factual network G_f (mean 20 in the dataset). Again, given our second-stage estimates, it generally holds that

$$\big(\Pi^e_f(G_{(+ab,+cd),f}, G_{-f}; \theta) - \Pi^e_f(G_{(+cd),f}, G_{-f}; \theta)\big) - \big(\Pi^e_f(G_{(+ab),f}, G_{-f}; \theta) - \Pi^e_f(G_f, G_{-f}; \theta)\big)$$

is small, compared to $\gamma_2(2D_{a,f} + 3)$. (E.5) is not always satisfied because adding $\{a, b\}$ and $\{a, d\}$ creates opportunities to fly from b to d via a. However, in our data, it is always possible to fly from b to d via other hubs in the factual network for the same airline f. As a result, it is reasonable to believe that (E.5) holds for most, if not all, two-link deviations. Therefore, using the same steps as above, we conclude that (E.3) holds.

Removing links from the factual network

Consider the mirror case where markets $\{a, b\}$ and $\{c, d\}$ are served by airline f with direct flights (i.e. $G_{ab,f} = G_{cd,f} = 1$). From the revealed preference principle we can see that

$$\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) \geq \mathrm{FC}_f(G_f, \eta_f; \gamma) - \mathrm{FC}_f(G_{(-ab),f}, \eta_f; \gamma), \tag{E.7}$$

$$\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-cd),f}, G_{-f}; \theta) \geq \mathrm{FC}_f(G_f, \eta_f; \gamma) - \mathrm{FC}_f(G_{(-cd),f}, \eta_f; \gamma), \tag{E.8}$$

$$\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab,-cd),f}, G_{-f}; \theta) \geq \mathrm{FC}_f(G_f, \eta_f; \gamma) - \mathrm{FC}_f(G_{(-ab,-cd),f}, \eta_f; \gamma). \tag{E.9}$$

(E.7) and (E.8) are taken into account by our identification methodology, as they refer to one-link deviations. (E.9) is ignored by our identification methodology, as it refers to a two-link deviation. By following the steps above, it is possible to show that, in most of the cases, (E.9) is redundant.

F Inference on the demand and supply parameters

We conduct inference on θ via GMM 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 $\theta \in \Theta$:

$$Q(\theta) = D(\theta)' A D(\theta), \tag{F.1}$$

where

$$D(\theta) := \begin{pmatrix} \frac{1}{|\mathcal{J}|} \sum_{m \in \mathcal{M}} \sum_{j \in \mathcal{J}_m} [\tau_{j,m}(X_m^{\oplus}, W_m^{\oplus}, \mathrm{MS}_m, s_m^{\oplus}, P_m^{\oplus}, G; \theta) \times z_{j,m,1}(X_m^{\oplus}, W_m^{\oplus})] \\ \frac{1}{|\mathcal{J}|} \sum_{m \in \mathcal{M}} \sum_{j \in \mathcal{J}_m} [\tau_{j,m}(X_m^{\oplus}, W_m^{\oplus}, \mathrm{MS}_m, s_m^{\oplus}, P_m^{\oplus}, G; \theta) \times z_{j,m,2}(X_m^{\oplus}, W_m^{\oplus})] \\ \vdots \\ \frac{1}{|\mathcal{J}|} \sum_{m \in \mathcal{M}} \sum_{j \in \mathcal{J}_m} [\tau_{j,m}(X_m^{\oplus}, W_m^{\oplus}, \mathrm{MS}_m, s_m^{\oplus}, P_m^{\oplus}, G; \theta) \times z_{j,m,\mathrm{L}}(X_m^{\oplus}, W_m^{\oplus})] \end{pmatrix},$$

$\mathcal{J} := \cup_{m \in \mathcal{M}} \mathcal{J}_m$ 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 estimating the demand parameters; then using these estimates to calculate the mark-ups; finally regressing the resulting marginal costs on the observed marginal cost shifts to obtain the supply parameters. We have chosen to estimate the demand and supply sides together because it allows us to take into account the potential correlation between the demand and supply moments and thus obtain more precise estimates, as discussed in Berry et al. (1995). Moreover, since we have a computationally "light" demand specification, the additional cost of estimating the demand and supply sides jointly is negligible.

G Inference on the fixed cost parameters

G.1 Writing (21) as a linear optimisation problem with exponential cone constraints

In what follows, we show that (21) is a linear optimisation problem with exponential cone constraints. First, we simplify the notation of (21) and write it as

$$\begin{aligned}\delta(q, \Gamma_I^\alpha) &:= \sup_{\gamma \in \Gamma} q^\top \gamma, \\ \text{s.t.} &\sum_{r=1}^{\mathrm{R}} f_\alpha(b_r\gamma - a_r) - \mathrm{R}\log(2)/\alpha \leq 0,\end{aligned} \tag{G.1}$$

where b_r stands for $\mathbb{E}(Z_{r,m}B_m)$ and a_r for $\mathbb{E}(Z_{r,m}A_m)$. Both quantities can be estimated consistently from their empirical analogue. Second, observe that

$$\sum_{r=1}^{\mathrm{R}} f_\alpha(b_r\gamma - a_r) - \mathrm{R}\log(2)/\alpha \leq 0 \tag{G.2}$$

$$\Leftrightarrow \log(1 + \exp(\alpha(b_r\gamma - a_r))) \leq t_r \text{ for } r = 1, \dots, \mathrm{R} \text{ and } \sum_{r=1}^{\mathrm{R}} t_r \leq \mathrm{R}\log 2 \tag{G.3}$$

$$\Leftrightarrow \exp(-t_r) + \exp(-t_r + \alpha(b_r\gamma - a_r)) \leq 1 \text{ for } r = 1, \dots, \mathrm{R} \text{ and } \sum_{r=1}^{\mathrm{R}} t_r \leq \mathrm{R}\log 2 \tag{G.4}$$

Therefore, (G.1) is equivalent to

$$\max q^\top \gamma + \sum_{r=1}^{R} 0.t_r + 0.u_r + 0.v_r,$$

under the constraints

$$\begin{aligned}\sum_{r=1}^{\mathrm{R}} t_r &\leq R\log 2, \\ u_r + v_r &\leq 1, \ r = 1, \dots, \mathrm{R}, \\ (v_r, 1, -t_r) &\in K_{\exp} \ r = 1, \dots, \mathrm{R}, \\ (u_r, 1, \alpha(b_r\gamma - a_r) - t_r) &\in K_{\exp} \ r = 1, \dots, \mathrm{R}.\end{aligned}$$

The exponential cone $K_{\exp}$ is a convex subset of $\mathbb{R}^3$ such that

$$K_{\exp} = \{(x_1, x_2, x_3) : \ x_1 \geq x_2 \exp(x_3/x_2); x_2 > 0\} \cup \{(x_1, 0, x_3), \ x_1 \geq 0, x_3 \geq 0\}.$$

The constraints above ensure, in particular, that for any r, $v_r \geq \exp(-t_r)$ and $u_r \geq \exp(-t_r + \alpha(b_r\gamma - a_r))$, and, therefore, ensure (G.4).

See `https://docs.mosek.com/modeling-cookbook/expo.html#softplus-function` for further details.

G.2 Constructing a confidence interval for a component of γ

Suppose we want to construct a confidence interval for a specific linear combination of components of γ, $c^\top\gamma$. Let $q = c/\|c\|$. By Theorem 2,

$$\sqrt{\mathrm{M}}\left(\hat{\delta}(q;\Gamma_I^\alpha) - \delta(q;\Gamma_I^\alpha)\right) \xrightarrow[\mathrm{M}\to\infty]{d} Z_\alpha(q).$$

The optimisation routine detailed in Section G.1 gives us the unique point, γ_q, which achieves the maximum of $c^\top\gamma$ on $\widehat{\Gamma}_I^\alpha$. Let λ_q be the Lagrange multiplier solving

$$\lambda_q \nabla g_\alpha(\gamma_q) = q,$$

where

$$\nabla g_\alpha(\gamma_q) = \sum_{r=1}^{\mathrm{R}} b_r \frac{\exp\left(\alpha\left[b_r^\top\gamma - a_r\right]\right)}{1 + \exp\left(\alpha\left[b_r^\top\gamma - a_r\right]\right)}.$$

Let $W_r(\gamma_q)$ be a random normal variable with variance equal to the asymptotic variance of $\frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}}(Z_{r,m}B_m^\top\gamma_q - Z_{r,m}A_m)$. In turn, we can compute the variance of $Z_\alpha(q)$, which is the variance of a centered normal random variable. We denote it $v_\alpha(q)$. The quantity

$$c^\top\gamma_q + \|c\| n_{1-\beta}\sqrt{v_\alpha(q)},$$

is the upper bound of the $1-\beta$ confidence interval for $c^\top\gamma$, where $n_{1-\beta}$ is the $1-\beta$ quantile of the standard normal distribution.

Similarly, let $-q = -c/\|c\|$ and γ_{-q} be the point which achieves the maximum of $-c^\top\gamma$ on $\widehat{\Gamma}_I^\alpha$. Let λ_{-q} be the Lagrange multiplier solving

$$\lambda_{-q}\nabla g_\alpha(\gamma_{-q}) = -q.$$

As above, we can compute the variance of $Z_\alpha(-q)$ and denote it $v_\alpha(-q)$. The quantity

$$c^\top\gamma_{-q} - \|c\| n_{1-\beta}\sqrt{v_\alpha(-q)},$$

is the lower bound of the $1-\beta$ confidence interval for $c^\top\gamma$.

Note that, following Stoye (2009), we can adapt the choice of the quantile to handle near to point-identified cases.

G.3 Drawing points from the confidence region for γ

In this section, we outline the steps to draw points from the confidence region for the true value γ_0 in order to run our counterfactual analysis.

1. We look for an interior point γ_c in $\widehat{\Gamma}_I^\alpha$. This is known in the convex optimization literature as the Chebyshev center of a polyhedron (Boyd and Vandenberghe, 2004, page 148). Interestingly, it can be solved by linear programming:

$$\begin{aligned}
&\max_{r\geq 0} r, \\
&\text{s.t. } \frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}}(-Z_{r,m}B_m^\top\gamma + Z_{r,m}A_m) + r\|\frac{1}{\mathrm{M}}\sum_{m=1}^{\mathrm{M}} Z_{r,m}B_m\|_2 \leq 0, \\
&r = 1,\ldots,\mathrm{R}.
\end{aligned}$$

2. Draw a random direction q on the unit sphere and find the frontier point $\gamma_q = \gamma_c + r_q q$ of $\widehat{\Gamma}_I^\alpha$ ($r_q \geq 0$). Again, this is a linear program.

3. Calculate the outer normal vector of $\widehat{\Gamma}_I^\alpha$ at γ_q. This is the direction q' such that $\delta(q', \widehat{\Gamma}_I^\alpha) = q'^\top\gamma_q$. It can be done analytically by calculating the gradient of $g_\alpha(\cdot)$ at γ_q.

4. Calculate the variance $V_\alpha(q')$ of $Z_\alpha(q')$ using Theorem 2.

5. The point $f_q = \gamma_q + \sqrt{V_\alpha(q')}n_{1-\beta}q'$ is a frontier point of the (conservative) confidence region $CR_{1-\beta}(\gamma_0)$ (drawn from γ_q in direction q').

6. Draw a norm l uniformly on $[0, 1]$.

7. Pick the point $\gamma_c + lf_q$ which belongs to $CR_{1-\beta}(\gamma_0)$.

Figure G.1 illustrates the sequence.

H Empirical application

H.1 Data

Table H.1 lists the airlines' hubs. Table H.2 reports the airlines belonging to the groups LCC and Other.

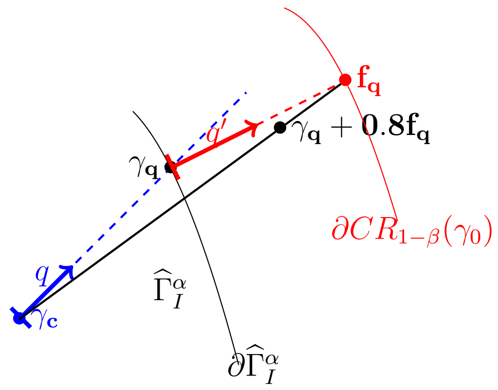

Figure G.1: Drawing from the confidence region

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 H.1: Hubs of the legacy carriers and focus cities of Southwest Airlines in 2011.

LCC	**Other**
Frontier Airlines	AirTran Airways
Alaska Airlines	USA3000 Airlines
Spirit Airlines	
Jetblue Airlines	
Virgin America	
Sun County Airlines	
Allegiant Air	

Table H.2: Airlines in the categories LLC and Other.

H.2 Instruments

Table H.3 lists the instruments we use in the estimation of the fixed cost parameters. Table H.4 lists the instruments we use in the estimation of the demand and supply parameters.

Table H.3: First-stage instruments.

	$Z_{r,(-ab),f} = 1$ if
All firms	$\{a, b\}$ is not a hub market and has been continuously served since 1979 Q1
AA	$\{a, b\}$ is a hub market with size above 6 million
DL	$\{a, b\}$ is a hub market with size above 6 million
UA	$\{a, b\}$ is a hub market with size above 6 million
US	$\{a, b\}$ is a hub market with size above 5 million
WL	$\{a, b\}$ is a hub market with size above 6 million
	$Z_{r,(+ab),f} = 1$ if
All firms	$\{a, b\}$ is not a hub market and a competitor has a hub at a or b
AA	$\{a\}$ is a hub and $\{b\}$ is closer to at least 2 other AA hubs
DL	$\{a\}$ is a capacity constrained hub and $\{b\}$ is closer to all other DL hubs
UA	$\{a\}$ is a hub and $\{b\}$ is closer to at least 2 other UA hubs
US	$\{a\}$ is a capacity constrained hub and $\{b\}$ is closer to all other US hubs
WL	$\{a\}$ is a capacity constrained hub and $\{b\}$ is closer to all other WN hubs

Note: Capacity constrained airports are defined to be airports in need of capacity improvements according to the Federal Aviation Administration's FACT3 report. Note that this definition is not equivalent to an airport being slot constrained.

Table H.4: Second-stage instruments.

Number of firms present in the market
Number of itineraries offered in the market
Number of products offered in the market
Indicator for destination being a hub
Indicator for the market being a monopoly
Number of rival firms offering direct flights in the market
Square of the number of rival firms offering direct flights in the market

H.3 Results from demand and supply

Table H.5 shows the estimated variable profits, prices, marginal costs, and markups at the firm level. For each airline, the first, second, and third rows contain quantities averaged over all products, direct flights and one-stop flights respectively. The fourth and fifth rows contain quantities averaged over direct flights where at least one of the endpoints is a hub, and direct flights where no endpoint is a hub. We can see that airlines charge higher markups on direct flights compared to one-stop flights, which is in line with the fact that consumers prefer to take direct flights (see "*Indirect*" in Table 2, demand panel). The legacy carriers charge higher markups on direct flights where at least one of the endpoints is a hub than on direct flights where no endpoint is a hub, suggesting the existence of a hub premium. This hub premium may be due to the fact that consumers value flying from dense hubs (see "*Nonstop Origin*" in Table 2, demand panel) or to fixed costs due to congestion effects at hubs (see Table 4). While American Airlines, US Airways and Southwest Airlines have lower marginal costs for direct flights, the opposite is true for Delta and United Airlines.[4] The marginal cost of Southwest Airlines is lower than the marginal cost of the legacy carriers. For direct flights, the difference is quite substantial. For one-stop flights, Southwest Airlines' advantage is small, consistent with the fact that Southwest Airlines uses focus cities rather than hubs. Therefore, the marginal cost savings of offering one-stop flights (see "*Connections*" and "*Indirect*" in Table 2, Supply panel) may be less pronounced as not all the features of traditional hubs are used.

H.4 Estimated shares of the variable costs over the operating costs

We compute the estimated share of the variable costs over the operating costs. The former are obtained as marginal costs times number of passengers. The latter are defined as the sum of the variable costs and fixed costs, without considering the congestion costs. Table H.6 reports this share for each airline based on our results. We compare such shares with estimates from the FAA for 2018 based on administrative data (Table H.7) and observe similar orders of magnitude.

I Counterfactuals

I.1 Descriptions of the counterfactual algorithm

The possibility of multiple PSNE networks raises the question of how to obtain counterfactuals when airlines are allowed to reoptimise their networks and prices. Although the data tell us which equilibrium was played in the past, they do not tell us which equilibrium will be chosen by the players once we change the environment. Previous literature has suggested several ways of solving this problem. For example, the analyst could enumerate all possible equilibria and report some summary measures of the resulting range of counterfactuals (Eizenberg, 2014). Alternatively, the analyst could implement a learning algorithm and use it to select a probability distribution of possible equilibria (Lee and

[4] Note that the fact that American Airlines, US Airways and Southwest Airlines have lower marginal costs on direct flights does not contradict the negative sign of the coefficient on "*Connections*" in Table 2. In fact, recall that the results in Table 2 should be interpreted *ceteris paribus*. Instead, the results in Table H.5 are obtained by averaging over all itineraries, including those with different characteristics.

Table H.5: 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

Note: Quantities are in USD.

Table H.6: Estimated shares of the variable costs over the operating costs.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
AA	80.5%	81.5%	82.4%	82.5%	83.7%	84.8%
DL	78.2%	79.3%	80.2%	80.4%	81.7%	82.9%
UA	75.0%	76.2%	77.2%	77.4%	78.8%	80.1%
US	73.9%	75.1%	76.2%	76.4%	77.9%	79.2%
WN	66.3%	67.7%	69.0%	69.3%	71.0%	72.6%

Table H.7: Passenger Air Carriers Filing Schedule P-5.2 Operating and Fixed Costs per Block Hours.

Aircraft Category	Cost per Block Hour								
	Fuel and Oil	Mainte-nance	Crew	Total Variable	Deprec.	Rentals	Other	Total Fixed	Share Variable
Wide-body more than 300 seats	\$5,411	\$1,331	\$2,356	\$9,097	\$845	\$406	\$5	\$1,254	87.9%
Wide-body 300 seats and below	\$4,080	\$1,289	\$1,857	\$7,227	\$685	\$366	\$8	\$1,058	87.2%
Narrow-body more than 160 seats	\$2,054	\$718	\$1,152	\$3,925	\$355	\$217	\$10	\$582	87.1%
Narrow-body 160 seats and below	\$1,741	\$737	\$1,034	\$3,512	\$306	\$215	\$12	\$533	86.8%
RJ more than 60 seats	\$115	\$431	\$444	\$991	\$131	\$252	\$14	\$397	71.4%
RJ 60 seats and below	\$92	\$479	\$470	\$1,041	\$58	\$227	\$8	\$293	78.0%
Turboprop more than 60 seats	\$0	\$880	\$360	\$1,241	\$439	\$103	\$2	\$544	69.5%
All Aircraft	\$1,681	\$727	\$1,012	\$3,420	\$314	\$239	\$11	\$564	85.8%

Source: FAA, `https://www.faa.gov/regulations_policies/policy_guidance/benefit_cost`, Section 4 of the Benefit-Cost analysis, Table 4-6.

Pakes, 2009; Wollmann, 2018). The first approach is not computationally feasible in our setting, due to the large number of markets and the presence of entry spillovers. Therefore, we follow the second approach. We fix an order of markets and firms. For a given value of the parameters, the first firm in the first market best responds to its competitors in terms of entry and pricing decisions. The second firm similarly best responds, taking into account the best response of the first firm. The third company also best responds, taking into account the best responses of the first and second companies. The algorithm cycles through the firms and markets until no airline wishes to deviate. The procedure is repeated for 50 draws of parameter values from the estimated identified set of first-stage parameters. For each parameter value, we consider four market orderings. In the first ordering, we rank the markets according to which hub is involved, whether the market is served by the merged firm, the size of the merged firm's operations at the endpoints, and the market size(ordering A). In the second ordering, we reverse this ranking (ordering B). In the third and fourth orderings, werank markets randomly (orderings C and D). For each of the four market orderings, we consider two firm orderings: AA-DL-UA-WL (ordering 1) and the reverse (ordering 2). This procedure generates a distribution of possible equilibria over 400 (i.e., $50 \times 4 \times 2$) counterfactual runs. In the tables of Section 8.2, we report the minimum, maximum, and median changes in the relevant outcomes under such distribution.

The remainder of the section illustrates the details of the counterfactual algorithm. In particular, we explain the algorithm implemented to simulate the merger under the *Networks vary - w/o remedies* scenario, given an order of markets and firms and a value of the parameters. The algorithm is structured in the following steps:

1. Latent variables. We determine the realisations of the latent variables that are needed to evaluate the airlines' profits. In particular, from the vector of second-stage estimates, $\hat{\theta}$, we compute the second-stage shocks for each product offered by the airlines before the merger, via BLP inversion. For each airline f, we compute the mean and variance of the second-stage shocks and denote them by μ_f and Σ_f, respectively. When computing μ_f and Σ_f for the merged airline, we consider the second-stage shocks associated with all the products offered by the merging firms before the merger. If both American Airlines and US Airways offer a given itinerary before the merger, then we take the mean value of the second-stage shocks of the two pre-merger products. For each potential product of every airline f, we take 100 random draws from a normal distribution with mean μ_f and variance Σ_f. We store all such draws in a matrix Ξ. Further, for each market $\{a, b\}$ and airline f, we impute the fixed cost shock $\eta_{ab,f}$ as explained in Section I.2.

2. Initial state. At the start, all firms except the merged entity are assigned their pre-merger networks and products. The merged entity is assigned the network resulting from combining the pre-merger networks of American Airlines and US Airways. The products initially offered by the merged entity and their observed characteristics are constructed from such merged network. We denote by $G := (G_1, \ldots, G_{\text{N-1}})$ the initial networks of the carriers. We let the firms play the simultaneous pricing game described in Section 3.1, for each draw of the second-stage shocks stored in the matrix Ξ. We save the initial equilibrium prices in a matrix P.

3. Iterations. We take the first firm f in the first market $\{a, b\}$ and let it play its best response as follows. Suppose, for instance, that the initial network G_f is characterised by $G_{ab,f} = 0$. First, we compute airline f's expected variable profits under $(G_{(+ab),f}, G_{-f})$. To do so, we update the list of products offered by firm f, by adding direct flights between cities a and b. Further, note that setting $G_{ab,f} = 1$ creates a "domino effect" in neighbouring markets, due to the possibility for airline f to offer one-stop flights and the presence of spillovers in entry across markets. Hence, 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, then we add one-stop flights, via b, between a and all cities d such that $G_{db,f} = 1$. We update the matrices of product covariates by including the observed demand and marginal cost shifters of the new products. We also update the product covariates (namely, "*Nonstop Origin*" and "*Connections*") of the pre-existing products that are affected by the new products. Let $\mathcal{M}_{ab,f}$ be the list of markets containing either new products or products with modified covariates. For each of these products in every market $m \in \mathcal{M}_{ab,f}$, we let airline f find the best-response price, while holding the other prices in P fixed, for every draw of the second-stage shocks stored in the matrix Ξ. We compute airline f's variable profits, average across draws, and get the simulated airline f's expected variable profits, which we denote by $\sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_{(+ab),f}, G_{-f}; \hat{\theta})$. Next, we implement a similar procedure to compute airline f's expected variable profits in each markets $m \in \mathcal{M}_{ab,f}$ under G, which we denote by $\sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_f, G_{-f}; \hat{\theta})$. We take the difference between airline f's fixed costs under $(G_{(+ab),f}, G_{-f})$ and G, which is $\text{FC}_f(G_{(+ab),f}, \eta_f; \hat{\gamma}) - \text{FC}_f(G_f, \eta_f; \hat{\gamma}) = \hat{\gamma}_{2,f} \Delta\overline{\text{Q}}_{(+ab),f} + \hat{\gamma}_{1,f} + \eta_{ab,f}$, where $\hat{\gamma}$ is the value of the fixed costs parameters drawn from the estimated identified set and $\eta_{ab,f}$ is the imputed value of the fixed cost shock. Lastly, we compute:

$$\sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_{(+ab),f}, G_{-f}; \hat{\theta}) - \sum_{m \in \mathcal{M}_{ab,f}} \Pi^e_{f,m}(G_f, G_{-f}; \hat{\theta}) - (\hat{\gamma}_{2,f} \Delta\overline{\text{Q}}_{(+ab),f} + \hat{\gamma}_{1,f} + \eta_{ab,f}). \tag{I.1}$$

If (I.1) is positive (negative), then the best-response entry of airline f is $G_{ab,f} = 1$ ($G_{ab,f} = 0$). We update G and P and move to the second firm in the first market. We let this firm best respond, while taking into account the first firm's best response. The third firm similarly best responds, while taking into account the first and second firms' best responses, and so on.

4. Stop. We cycle through the firms and markets. When no firm wants to deviate in none of the markets, we stop the procedure. In practice, we have obtained convergence in all the cases considered.

Due to computational costs, the above algorithm does not consider all possible entry deviations by each firm. In fact, it imposes that each firm considers adding/deleting direct flights in one market at a time. Nevertheless, at the rest point of the procedure, the necessary conditions for PSNE that are used in the estimation of the fixed cost parameters hold. Hence, the algorithm provides an equilibrium that is internally consistent with our model. Similar restrictions on the set of admissible deviations are assumed by Eizenberg (2014) and Wollmann (2018).[5]

We also adopt the above algorithm in the merger simulation for the *Networks vary - w/ remedies* and *6. Networks vary - PHX dehubbed* scenarios. However, in scenario *Networks vary - w/ remedies*, we do not allow the merged entity to exit the markets out of Charlotte, New York, Los Angeles, Miami, Chicago, Philadelphia, and Phoenix that were served before the merger by American Airlines or US Airways. In scenario *Networks vary - PHX dehubbed* we delete all flights of the merged entity between Phoenix and non-hub cities and do not allow the merged entity to re-enter those markets.

I.2 Imputation of the fixed cost shocks in the counterfactuals

To perform the 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 shocks generating the observed entry/exit patterns and takes the midpoint. We use a procedure that is similar to Kuehn (2018). We repeat the steps below for each value of γ drawn from the estimated identified set at which we run the counterfactual algorithm. When we observe airline f serving market $\{a, b\}$ with direct flights (i.e., $G_{ab,f} = 1$), we infer that this choice must be profitable, giving us an upper bound for $\eta_{ab,f}$. In fact, let $\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) - \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} - \gamma_{1,f} - \eta_{ab,f}$ be the difference between the factual profits of airline f and the profits that airline f would get if deviating to $G_{ab,f} = 0$. By best-response arguments, it must be that $\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) - \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} - \gamma_{1,f} - \eta_{ab,f} \geq 0$, i.e., $\eta_{ab,f} \leq \Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) - \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} - \gamma_{1,f}$. Thus, $\Pi^e_f(G_f, G_{-f}; \theta) - \Pi^e_f(G_{(-ab),f}, G_{-f}; \theta) - \gamma_{2,f}\Delta\overline{\mathrm{Q}}_{(-ab),f} - \gamma_{1,f}$ represents an upper bound for $\eta_{ab,f}$. Next, we collect all the markets where airline f does not enter, that are hub markets (non-hub markets) if market $\{a, b\}$ is a hub market (is not a hub market) for airline f, and that

[5] The networks at the rest point of our algorithm constitute a pairwise stable outcome, in the sense illustrated by Section B. In fact, our algorithm resembles the tâtonnement dynamics discussed by Jackson and Watts (2002), in which agents form or destroy individual connections, taking the remaining network as given and not anticipating future adjustments. Jackson and Watts (2002) show that pairwise stable networks can be achieved by tâtonnement dynamics.

Table I.1: Comparison of merger prediction with data from 2015-2019.

	2011	**Prediction**	**2015**	**2016**	**2017**	**2018**	**2019**	**Mean 15-19**
Segments: AA/US	430	498 [435, 546]	445	465	464	478	491	468.6
Segments: Other major airlines	736	689 [606, 710]	669	678	698	681	678	680.8

face similar congestion costs. These markets give us a vector of lower bounds for $\eta_{ab,f}$. We take the 2.5th percentile of these lower bounds and use it as a lower bound for $\eta_{ab,f}$. Lastly, we set $\eta_{ab,f}$ equal to the mid-point between the lower and upper bounds. We implement a similar procedure to determine the fixed cost shocks for the markets that are not served by airline f in the data. However, instead of the 2.5th percentile, in that case we take the 97.5th percentile to obtain an upper bound. When simulating the merger, the merged entity gets the mean value of the fixed cost shocks imputed to the merging firms by following the above procedure.

I.3 Comparison with post-merger data

Table I.1 shows a comparison of our *Networks vary - w/ remedies* scenario with post-merger data on the markets served with direct flights by American Airlines and its competitors before and after the merger out of American Airlines and US Airways' hubs. Note that such a comparison is always fraught with difficulties because other changes occurred at the same time the merger was consummated, such as changes in preferences, costs (e.g., a significant drop in the price of kerosene in the 2010s), and other changes in market structure. See, for instance, Bontemps et al. (2022). Nevertheless, our model predicts relatively well the actual entry-exit dynamics. In particular, we correctly predict the post-merger expansion of American Airlines' network and reduction of competitors' networks. In particular, towards 2019, the observed number of markets served with direct flights closely matches the median prediction of our scenarios. Further, the observed number of markets served with direct flights lies within the lower-and upper bounds of our predictions in every year considered.

I.4 Additional tables

Table I.2 shows the hub-level changes in the number of direct flights offered by American Airlines and the other major airlines. The column Av. presence reports the average number of main carriers present across all possible markets out of a given hub. Table I.3 reports the percentage change in prices, marginal costs, and markups of American Airlines and the other major airlines. It distinguishes between direct flights and one-stop flights.

Table I.2: Changes in direct flights offered in the hub markets of AA and US.

	Before			**Merger**								
				w/o remedies			w/ remedies			PHX dehubbed		
	AA/US	Others	Av. presence	AA/US	Others	Av. presence	AA/US	Others	Av. presence	AA/US	Others	Av. presence
AA hubs												
DFW	68	55	1.6	69	57	1.52	68	57	1.52	68	57	1.52
				[66, 73]	[55, 57]	[1.5, 1.59]	[66, 73]	[55, 57]	[1.5, 1.59]	[67, 74]	[54, 57]	[1.49, 1.6]
LAX	28	90	1.51	30	90	1.47	30	90	1.48	34	90	1.52
				[21, 33]	[87, 91]	[1.36, 1.52]	[28, 33]	[87, 91]	[1.44, 1.52]	[22, 35]	[88, 91]	[1.38, 1.56]
ORD	59	129	2.35	63	105	2.05	63	110	2.1	62	108	2.09
				[56, 70]	[73, 116]	[1.68, 2.21]	[60, 71]	[73, 115]	[1.73, 2.23]	[53, 69]	[75, 118]	[1.71, 2.2]
MIA	40	51	1.17	25	52	0.94	42	52	1.13	25	52	0.94
				[15, 44]	[50, 52]	[0.8, 1.16]	[40, 47]	[50, 52]	[1.11, 1.21]	[14, 46]	[50, 52]	[0.79, 1.18]
JFK	41	113	2	58	95	1.85	56	96	1.88	61	97	1.85
				[29, 81]	[49, 113]	[1.55, 2.17]	[43, 81]	[49, 106]	[1.59, 2.16]	[29, 81]	[51, 112]	[1.57, 2.16]
US hubs												
CLT	61	41	1.29	64	41	1.28	65	41	1.29	64	41	1.28
				[43, 69]	[39, 42]	[1.02, 1.35]	[61, 69]	[39, 42]	[1.23, 1.35]	[43, 68]	[39, 42]	[1.04, 1.33]
PHX	41	74	1.49	40	66	1.29	42	65	1.3	8	68	0.93
				[23, 43]	[61, 69]	[1.1, 1.35]	[41, 43]	[59, 68]	[1.22, 1.35]	[8, 8]	[63, 70]	[0.87, 0.95]
DCA	40	130	2.16	81	127	2.52	75	128	2.46	81	127	2.52
				[34, 82]	[123, 133]	[2, 2.6]	[28, 82]	[124, 133]	[1.91, 2.61]	[32, 82]	[124, 133]	[1.98, 2.59]
PHL	52	53	1.33	54	56	1.36	56	55	1.37	55	56	1.37
				[25, 67]	[54, 60]	[1.04, 1.52]	[52, 67]	[54, 56]	[1.32, 1.52]	[28, 66]	[54, 61]	[1.07, 1.49]
Total												
Total	430	736	1.66	491	686	1.6	498	689	1.61	457	693	1.56
				[348, 531]	[607, 720]	[1.43, 1.65]	[435, 546]	[606, 710]	[1.54, 1.67]	[335, 497]	[612, 721]	[1.41, 1.62]

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

I.5 Inference on counterfactuals

In this section, we report the confidence intervals for the counterfactuals presented in Section 8.2 of the main paper. To construct these confidence intervals, we run the counterfactual algorithm discussed in Section I.1 at 50 draws of parameter values from the 95% confidence region for γ. Section G.3 explains how we take such draws. In particular, Table I.4 reports the confidence intervals for Table 9, Table I.5 reports the confidence intervals for Table 10.

Table I.3: Percentage change in prices, marginal cost, and markups.

	Before	Merger		
		w/o remedies	w/ remedies	PHX dehubbed
AA/US: Direct				
Price	406.24	-4.71	-4.68	-4.72
		[-6.73, -3.67]	[-5.36, -3.53]	[-6.71, -3.60]
Marginal cost	276.70	-10.23	-10.05	-10.06
		[-12.62, -9.66]	[-10.87, -9.43]	[-12.52, -9.28]
Markup	129.54	+7.39	+7.04	+7.30
		[+4.6, +9.41]	[+5.64, +9.39]	[+4.22, +9.23]
Others: Direct				
Price	413.19	+0.56	+0.55	+0.78
		[-0.25, +2.50]	[-0.18, +1.43]	[-0.14, +2.65]
Marginal cost	291.60	+1.39	+1.35	+1.38
		[+0.30, +3.40]	[+0.51, +2.26]	[+0.20, +3.23]
Markup	121.59	-1.44	-1.43	-0.64
		[-1.80, +1.16]	[-1.97, -0.21]	[-1.12, +1.50]
AA/US: One-stop				
Price	466.39	-5.69	-5.42	-6.19
		[-8.15, -5.19]	[-5.90, -4.74]	[-7.62, -5.60]
Marginal cost	351.28	-12.67	-12.43	-12.85
		[-14.08, -11.75]	[-12.91, -10.49]	[-13.31, -10.33]
Markup	115.11	+15.27	+15.44	+13.63
		[+8.22, +17.82]	[+12.01, +18.52]	[+8.07, +16.62]
Others: One-stop				
Price	416.12	+4.05	+3.97	+4.13
		[+3.42, +4.97]	[+3.43, +4.52]	[+3.55, +4.98]
Marginal cost	301.18	+6.00	+5.94	+6.03
		[+5.35, +6.63]	[+5.41, +6.49]	[+5.40, +6.58]
Markup	114.94	-1.25	-1.31	-0.84
		[-1.81, +0.99]	[-2.00, -0.44]	[-1.49, +1.07]

Note: Percentage changes with respect to the pre-merger scenario are reported.

Table I.4: Percentage change in consumer surplus across different scenarios.

	Networks fixed	Networks vary		
		w/o remedies	w/ remedies	PHX dehubbed
Total consumer surplus	+0.08	+0.77	+0.91	-0.67
	[-0.47, +3.40]	[-8.92, +3.47]	[-3.92, +3.84]	[-10.01, +1.79]
New markets	0	45.15	45.02	42.87
		[30.77, 52.29]	[29.47, 53.37]	[23.58, 53.02]
Old markets	+0.08	-5.28	-5.12	-4.67
	[-0.47, +3.40]	[-10.67, -3.97]	[-8.18, -3.94]	[-11.23, -3.32]

Note: Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Percentage changes with respect to the pre-merger scenario are reported.

Table I.5: Outcomes across different scenarios

	Before	Merger			
		Networks fixed	Networks vary		
			w/o remedies	w/ remedies	PHX dehubbed
Total	2807.06	+0.08	+0.77	+0.91	-0.67
		[-0.47, +3.40]	[-8.92, +3.47]	[-3.92, +3.84]	[-10.01, +1.79]
Mean	4.09	+0.08	-0.73	-0.44	-1.96
		[-0.47, +3.40]	[-9.58, +1.83]	[-4.76, +2.20]	[-10.67, +0.34]
Markups: AA/US	119.20	+7.34	+12.86	+12.96	+12.36
		[+5.98, +8.64]	[+7.44, +16.30]	[+10.05, +16.37]	[+6.41, +15.50]
Markups: Other major airlines	116.22	-0.45	-1.30	-1.37	-0.93
		[-0.68, +0.07]	[-2.11, +1.10]	[-2.22, -0.40]	[-1.58, +1.17]
Segments: AA/US	430	430	493.5	500	467
			[346, 551]	[434, 559]	[330, 514]
Segments: Other major airlines	736	736	686	688.5	691
			[594, 717]	[596, 710]	[613, 719]

Note: Consumer surplus is computed using the log-sum formula and it is in USD 1 million up to constant of integration. Percentage changes with respect to the pre-merger scenario are reported for total consumer surplus, mean consumer surplus, and markups.

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