Ex-post evaluation of the American Airlines-US Airways merger: a structural approach

Christian Bontemps * Kevin Remmy. † Jiangyu Wei ‡

October 30, 2021

Abstract

In this paper, we estimate a structural model of the domestic US airline market to analyze the effect of the recent merger between American Airlines and US Airways. Our results show that, between 2011 and 2016, a substantial fuel price drop in conjunction with changes in consumer preferences toward direct flights completely rationalize the observed decrease in prices. However, we estimate that, during the same period, more than half of the consumer welfare increase is due, on top of these environmental changes, to the ex-post optimization of the networks of the new merged airline and of its competitors.

Acknowledgements: We would like to thank the guest editors and two anonymous referees for helpful comments. Special thanks to Sara Crompton Meade and Mariane Bontemps for proof reading.

Keywords: merger, airlines, network, structural model, nested logit, airfare, demand, supply.

*ENAC & Toulouse School of Economics. Email: christian.bontemps@tse-fr.eu

†University of Mannheim. Email: remmy@uni-mannheim.de

‡Compass Lexecon. Email: jwei2@compasslexecon.com

1 Introduction

Over the last 25 years, the US airline industry has faced a drastic reduction in the number of legacy carriers operating on the domestic market through two merger waves; one following the 9/11 crisis and the other due to the global financial crisis of 2008 (see Philippon, 2019). Thus, the six legacy carriers in operation in 2005 have now consolidated into three legacy carriers: American Airlines, Delta Airlines and United Airlines (see Carlton et al., 2019). The last merger occurred between American Airlines and US Airways, who announced their intention to merge in 2013. The announcement followed two years of American Airlines operating under bankruptcy protection. It created one of the world's largest airlines and drew considerable attention from all stakeholders. As a result, the antitrust division of the US Department of Justice (DoJ), along with several state attorneys general, filed a lawsuit in August 2013 seeking to block the merger. The main argument was that the merger would considerably lessen competition and increase fares, resulting in harm to consumers (see Peterman, 2014).

From the theoretical literature, we know that two opposing forces exist in horizontal mergers in oligopolistic markets. On the one hand, the number of competitors decreases and may lead to a monopoly in some specific markets or a quasi-monopoly if the competitors offer products that are not close substitutes (such as a connecting flight versus a direct one). Monopolization was a major concern of the DoJ when filing the lawsuit. On the other hand, a merger may induce some cost reduction through the rationalization of the network (i.e., exploiting the economies of scale or density generated from a more extensive network), or through the reduction in staff or aircraft maintenance to eliminate redundant entities. These cost reductions can impact the prices charged to consumers. Finally, competitors that are more aggressive on prices can react by entering some markets where there is possible room for competition. In addition, a larger network post-merger can be beneficial to consumers who can reach more destinations.

In this paper, we evaluate the effect on prices and consumer surplus of the merger between American Airlines and US Airways through the estimation of a structural model of the US domestic airline industry. In doing so, we propose an ex-post evaluation of this merger. During the period studied (2011 to 2016), the fuel price dropped by almost two-thirds, causing a drop in the marginal cost of more than 10%. Additionally, the different airlines reacted to this new merger by rationalizing their networks. Indeed, the new entity eliminated overlaps and connecting flights when there were direct flights already proposed. Competitors did the same. Furthermore, this period saw the entry of a number of low-cost carriers (LCCs), who took advantage of new slot availabilities and reduced competition due to the merger. Indeed, one merger remedy was for the newly merged entity to sell slots at several airports, mainly at the Ronald Reagan International Airport and LaGuardia Airport. The slot divestiture at LaGuardia allowed Southwest Airlines and JetBlue to buy slots there for the first time.[1] Finally, consumer preferences changed and the willingness to pay for flying directly increased over the period, a shift already noticed by Berry and Jia (2010) during a former period. Accounting for these changes is crucial in an ex-post analysis of a merger, therefore, finding a reference scenario for conducting a difference-in-differences analysis may be somewhat challenging. Estimating a structural model allows us to disentangle effects directly related to the merger from those that occurred independently.

We use pre- and post-merger fares data from the US Department of Transportation from the second quarter of both 2011 and 2016. In our main analysis, we estimate that airfares should have dropped on average by 6.73% and, therefore, consumer surplus should have increased by around 6.67%, had the supply of flights been the same in 2016 as in 2011. This assumption states that there is no merger and no further entry from LCCs or any other airline but allows for changes in fuel price and consumer preferences. When comparing the 2011 and 2016 data directly, we observe an average decrease in prices of 6.59% and an average increase of consumer surplus of 14.35%. As a result, we can overwhelmingly attribute the decrease in prices observed between 2011 and 2016 to changes in marginal costs and preferences. The merger and the entry/exit decisions of both the new entity and its competitors slightly increased prices and considerably increased consumer surplus by proposing more direct flights. However, it is very difficult to predict what would have been the entry/exit decisions between 2011 and 2016 without such a merger.

As detailed below in the literature review, ex-post merger analyses have traditionally been conducted with reduced form models. We employ a structural approach in this paper. There has been a considerable debate about the advantage of estimating a reduced form model rather than a

[1] See also `https://money.cnn.com/2013/11/12/news/companies/us-airways-american-airlines-antitrust/index.html`.

structural model. Both have their advantages and drawbacks and can be seen as complementary. They have their own sets of implicit or explicit assumptions, in terms of the behavior of the economic agents, linearities of the functional forms, and the stationarity of the environment over the period considered. Most of the empirical literature using structural models has focused on simulating the impact of mergers on prices and welfare **before** the merger has occurred. The first step consists of estimating the demand and supply sides of the industry. The second step is to use these estimations to simulate the merger impact (see, among others, Berry and Pakes, 1993; Nevo, 2001; Peters, 2006) using pre-defined scenarios. However, ex-post merger analyses have been receiving increasing attention, both from policymakers and researchers (Buccirossi et al., 2008; Ilzkovitz and Dierx, 2020). We contribute to this literature by decomposing the difference in price and consumer surplus between 2011 and 2016 into different fictitious steps, such as changes in consumer preferences and marginal costs that are not directly caused by the merger, the merger itself, and the entry/exit reactions of both the newly merged entity and the other airlines. To the best of our knowledge, we are the first to employ such a structural decomposition. We also contribute to the literature studying airline mergers by separating price effects from market structure effects ex-post.

Following earlier structural work (Chen and Gayle, 2019; Gayle and Yimga, 2018), we estimate a nested logit model. Then, with estimates in hand, we perform several counterfactual exercises to evaluate the merger between American Airlines and US Airways. First, we simulate the no-merger case, keeping the market structure constant, but letting the demand and supply parameters take on their 2016 values. Doing so allows us to isolate changes in preferences and marginal costs unrelated to the merger. We find substantial heterogeneity in price and consumer surplus changes across market structures. Markets where both merging parties offered direct flights before the merger saw significant increases in consumer surplus. This increase is mainly due to changes in the merging entity's network and the entry of competitors. On the contrary, markets where only one of the merging parties was present saw consumer surplus decrease. This decrease is mainly due to the exit of either the merged entity or competitors. Overall, consumer surplus increased due to the merger and the entry/exit decisions of airlines.

The remaining part of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 introduces the data used and presents a descriptive analysis of the effect of the merger. Section 4 presents the demand and supply model and the estimation method. Section 5 analyzes the estimates using the 2011 and 2016 waves of the DB1B data. Section 6 presents the counterfactual analysis of our merger simulation and Section 7 concludes. We provide, in a supplementary appendix, a robustness check of our results and more details about our GMM estimation method.

2 Literature review

This paper relates and contributes to several strands of literature. First, there exists a vast literature on merger simulation using structural estimations of demand and supply. Hausman et al. (1994) simulate a merger in the beer industry. Nevo (2001) simulates a merger in the ready-to-eat cereal sector, using a random coefficients model à la BLP (1995). Ivaldi and Verboven (2005) simulate a merger between two truck producers, Volvo and Scania, using a nested logit demand estimation. Björnerstedt and Verboven (2016) propose a post-merger comparison of a merger simulation in the Swedish Analgesics Market by comparing simulated prices and actual prices. We contribute to this literature by extending ex-post merger analysis to consider changes in market structure, as well as considering pure price effects.

Second, a large literature studies past mergers in the airline industry, mostly in reduced form. Borenstein (1990) looks into the mergers that occurred in the mid-1980 in an ex-post way and detects anti-competitive effects of the mergers. Similar evidence of price increases is also revealed by Werden et al. (1991), Kim and Singal (1993), and Morrison (1996) when examining other mergers in the same period. Bilotkach (2011) studies the effects of multi-market contact on frequency following the merger between US Airways and America West. Luo (2014) studies the price effects of the Delta/Northwest merger using regression techniques. Building on Bajari et al.'s (2007) approach, Benkard et al. (2020) study the effects of horizontal mergers from a dynamic perspective. Following Nevo's (2001) approach, Peters (2006) conducts merger simulations for five mergers in the airline industry and makes a comparison between the simulated prices and the actual post-merger prices, as in Björnerstedt and Verboven (2016). Some recent studies investigate the effect of a merger on product quality (Mazzeo, 2003; Rupp et al., 2006; Prince and Simon, 2009; Chen and Gayle, 2019; Rupp and Tan, 2019). Bontemps et al. (2021) propose a two-stage model endogenizing carriers' choices of their networks and use it to predict the change post-merger network structures. Several papers investigate the American Airlines-US Airways merger. Using differences-in-differences (DID), Carlton et al. (2019) claim that the recent legacy mergers, including that of American Airlines and US Airways, were pro-competitive. More recently, Das (2019) simulates the merger of American Airlines and US Airways, using ex-ante simulation and estimate the marginal cost reduction necessary to fit the actual 2016 prices. He examines the effects of this merger on product quality and price, using both DID and merger simulation methods. Ciliberto et al. (2020) extend the merger simulation approach by allowing endogenous entry decisions and also examine American Airlines and US Airways merger.

We contribute to this literature in different ways. Contrary to Benkard et al. (2020); Ciliberto et al. (2020); Bontemps et al. (2021) who make ex-ante predictions about post-merger market structures, we provide an ex-post analysis of changes in market structure. Also, we disentangle changes in prices and consumer surplus directly related to the merger from those not related to the merger and caused by exogenous changes in preferences and costs. Then, we contribute to this literature by documenting large changes in preferences and costs between 2011 and 2016. Here, we connect to the work of Berry and Jia (2010).

Finally, our paper connects to the literature on the structural estimation of demand and supply, which is now the reference in the new empirical industrial organization (IO) literature. Since Berry et al. (1995) developed a random coefficients model, many papers have applied the discrete-choice-type demand models to airline markets. Berry et al. (2006) use a random coefficients model to study the role of hubs. Armantier and Richard (2008) measure the welfare outcomes of the code-share agreement. Berry and Jia (2010) investigate the factors that affect airlines' profitability by comparing demand and supply outcomes between 1999 and 2006. Ciliberto and Williams (2014) examine the potential collusive behavior in the US airline industry and find evidence that carriers with little multi-market contact do not cooperate in setting fares. Ruiz-Pérez (2019) considers the underlying common ownership structures of airlines by financial institutions and studies how it affects entry decisions and price competition. Gayle and Yimga (2018) estimate a nested logit for the demand for air transport and evaluate the impact of airlines' on-time performances.

3 Data and descriptive analysis

3.1 Data and summary statistics

The primary data source we use in our paper is the DB1B database provided by the US Department of Transportation, available online.[2] It consists of a 10% random sample of ticket records for the US domestic airline market in a given quarter. Since we are interested in the demand and supply sides before and after the merger, we select two samples from before and after the merger, respectively. The pre-merger sample comes from the second quarter of 2011, more than one year before American Airlines and US Airways officially announced their intent to merge (February 2013). The post-merger sample comes from the second quarter of 2016, more than one year after the Federal Aviation Administration granted a single operating certificate for US Airways and American Airlines (April 2015).[3]

We exploit the tables "Ticket" and "Market" of this database, keeping the tickets corresponding to the trips between the top 49 US metropolitan areas ("cities" hereafter).[4] Both one-way tickets and return tickets are in the final sample. Following the usual treatment of these data (see, for example, Berry and Jia, 2010), the tickets with more than one stop and multiple operating or ticketing carriers are deleted. We deflate the prices in the 2016 data and all prices are in real 2011 US\$. In our work, we define a market $t \in \mathcal{T}$ as a non-directional city pair, with $\mathcal{T}$ collecting all city pairs in our sample. A non-directional market implies that a flight from A to B and a flight from B to A are in the same market. Also, we do not model the competition between the different airports in a given city.

In a given market, different airlines may propose different products. Airlines can choose to offer a direct flight between the origin and destination (OD). Alternatively, they can provide a one-stop flight with a connection at an intermediate airport. We define a product on the itinerary level. Two flights offered by the same airline with the same endpoints but with a different connecting airport are two different products. This product definition explains why we have many more one-stop than

[2]See the website, `https://www.transtats.bts.gov`

[3]Aircraft with the US Airways livery ceased to fly in October 2015.

[4]We keep the metropolitan areas with population over one million inhabitants.

direct products in our sample (see Table 3). A product in a given OD market is therefore a trip by air proposed by a given airline, with or without a connection and, if the flight is connecting, the identity of the connecting city.

Table 1 provides some summary statistics at the product level. The average price decreased by 6.59% from $194.33 in 2011 to $181.52 in 2016. Since we only keep the observations with at most one stop, the number of stops varies between zero and one, and the mean values show that most of the products are direct flights (see also Table 3). *Connections* is the maximum number of cities that an airline offers direct service to out of the two OD cities.[5]

[**Include Table 1**]

We present some market-level statistics in Table 2. Compared to 2011, the number of products per market increased in 2016. As expected, the number of firms per market decreased from 2011 to 2016. Entry by competitors of the merging entities did not compensate for losing one legacy carrier in most of the markets considered in our sample. The trend of having more direct passengers underlined in Berry and Jia (2010) has continued through our sample period.

[**Include Table 2**]

3.2 A descriptive analysis of the merger: impact on the network

First, we propose a descriptive analysis of the network of the main airlines before and after the merger. We consider the major carriers (United Airlines (UA), Delta Airlines (DL), American Airlines (AA), US Airways (US), and Southwest Airlines (WN)) separately. We collect the remaining carriers into a group called LCC.[6] Table 3 displays the main carrier-level statistics in 2011 and 2016.

[5] If an airline offers direct service to five cities out of endpoint A and direct service to 15 cities out of endpoints B, *Connections* is equal to 15.

[6] These low-cost carriers are Alaska Airlines (AS), JetBlue Airways (B6), Allegiant Air (G4), Frontier Airlines (F9), Spirit Airlines (NK), Sun Country Airlines (SY), US 3,000 Airlines (U5), AirTran Airways (FL), and Virgin America (VX). Between 2011 and 2016, AirTrans merged with Southwest Airlines, and US 3,000 Airlines ceased operations, meaning they are no longer part of our sample in 2016.

Before the merger, American Airlines and US Airways were not as large as the two other major airlines, Delta and United Airlines. However, the merger helped AA overtake Delta and United in terms of passengers and markets served. It is also noteworthy that Southwest Airlines was the largest airline in terms of passengers served, despite serving fewer markets. This fact reflects Southwest's different policy, which mostly offers direct flights. Between 2011 and 2016, the share of legacy carriers has continued to decrease, a trend observed during the last 20 years.

[**Include Table 3**]

In Tables 4 and 5, we display some descriptive statistics of the main airlines' networks for 2011 and 2016. For 2011, we also create a fictive entity, "AA + US", by combining all the direct flights of the individual firms, thus eliminating all duplicate products. Here, a city is a node of the network, and a link between two cities exists if an airline operates a direct flight between at least one airport in each of these two cities. The first two lines report the number of cities connected by each airline and the number of links. At first glance, it is clear that the networks are not fully connected, thanks to the (partial) hub and spoke system operated by the major airlines. Southwest, historically a point-to-point operator, has more links than the major airlines. However, we do see a trend in the rationalization of the networks of major airlines. Delta had 326 direct flights from these cities in 2011 and only 287 (around 12% less) in 2016. The fictive entity AA+US in 2011 would have offered 468 direct flights. However, American Airlines only offers 427 direct flights in 2016, connecting all the cities in our sample. This decrease suggests that AA altered its network by cutting some direct routes and making full use of US Airways' former hubs.

Similarly, the average path length (the path length between two cities is the minimum number of links necessary to join these two cities)[7] slightly increased during this period for all airlines. In contrast, the average degree (i.e., the average number of cities directly connected to a given city) for the legacy carriers decreased because some direct routes were cut. Finally, the average closeness, which measures the inverse of the average length to reach any city from a given one) decreased since the average path length increased.

[**Include Tables 4 and 5**]

[7]A direct flight has a path length of one, a connecting flight, through a hub, a path length of two.

Next, we focus on some node-level characteristics. For each merging party, in 2011 and 2016, we calculate the centrality measures (degree and closeness)[8] by city and rank them accordingly. The figures are reported in Table 6. We focus on the top-five nodes for each merging airline in 2011. Unsurprisingly, these top-five nodes coincide with each carrier's hubs. In an airline network, a firm can select some central airports as "hubs" that link to many other airports. In 2011, American Airlines had six hubs: Chicago (ORD), Dallas (DFW), Los Angeles (LAX), New York (JFK, LGA), and Miami (MIA). US Airways had four hubs: Charlotte (CLT), Philadelphia (PHL), Phoenix (PHX), and Washington (DCA). JFK is the fifth most important node in US Airways' network.

The most influential nodes in American Airlines' network in 2016 include the pre-merger hubs of both airlines. Thus, we see that the merged entity fully integrated US Airways' former hubs. From Figure 2 compared to Figure 1, we can see that the network of the merged entity was much more well-connected compared to 2011, thanks to the merger. In particular, the new American Airlines was able to expand its business along the east coast, which was a major reason to seek a merger with US Airways.

Overall, this section shows that there were significant changes to the post-merger network of the merged entity. Thus, it is crucial to take into account these changes in an ex-post analysis of the merger.

[**Include Table 6**]

[**Include Figures 1 and 2**]

3.3 A descriptive analysis of the merger: impact on prices

Table 7 displays the mean price in 2011 and 2016 as a function of the market structure. Overall prices decreased by 6.59%. At first sight, the merger may have led to this price decrease. However, as mentioned before, fuel prices substantially decreased between 2011 and 2016, affecting marginal costs. These marginal cost changes need to be controlled in order to study the merger's price effects. This price change is however heterogeneous among markets. A few markets exhibit a price increase, mainly when only one of the two entities was present. It is often said that US Airways

[8]As for Tables 4 and 5, we do not report the betweenness as it does not provide any noteworthy information.

was behaving more aggressively pre-merger than the other legacy carriers.[9] This behavior may positively affect prices post-merger if the merged entity no longer acts as aggressively. However, these markets concern only around 12% of the passengers of our sample. In the next section, we introduce our structural model to disentangle the direct merger effect on these prices from the changes in preferences and marginal costs.

[**Include Table 7**]

4 Model

To examine consumer and firm behavior in the US airline industry, we build and estimate a structural model of demand and supply for flights. On the demand side, the goal is to identify consumer preferences for different flight characteristics and their price elasticity. On the supply side, the goal is to determine how specific product attributes affect the marginal cost of serving a given flight. Once estimated, the model allows us to perform a rich set of counterfactuals to analyze the effect of mergers.

We make two critical assumptions. First, we assume that airlines take their network of segments to serve as given. Endogenizing network choices poses a burden, both conceptually and computationally, and is outside of the scope of this paper. However, we are evaluating the merger ex-post, so we observe the post-merger network structure and account for it. Second, we refrain from modeling airlines' frequency and capacity choices. The rationale behind this decision is that we are mainly interested in how mergers affect prices and network structure.

4.1 Demand

We model demand using a nested logit demand model (Berry, 1994). In this section, we present the main results, which are known in the empirical IO literature but are reported here to be self-contained. In market t, the consumer can choose to either fly between the two cities by choosing

[9]We have not been able to find strong statistical evidence after the analysis of our estimated results. See subsection 5.3, last paragraph.

one of the inside products (direct and one-stop flights) $j \in \mathcal{J}_t$ or to consume the outside option (product 0), which means traveling by other means or not traveling at all. Following the literature on demand estimation in airline markets, the inside products are grouped into the first nest whereas the second nest is only composed of the outside option. The utility of consumer i in market t from purchasing product $j \in \mathcal{J}_t$ (an inside product) is

$$u_{ijt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \varepsilon_{ijt}(\lambda), \tag{1}$$

where x_{jt} is a vector of observed product attributes, p_{jt} the price of the product, and ξ_{jt} represents product attributes unobserved by the researcher.[10] We normalize the utility of purchasing the outside option (product 0) to $u_{i0t} = \eta_{i0t}$ where η_{i0t} is an identically and independently distributed (across consumers) "logit error" following the terminology of Berry and Jia (2010). $\varepsilon_{ijt}(\lambda)$ is an idiosyncratic taste shock for product j in market t unobserved by the researcher. We assume it follows the distribution necessary to yield the familiar nested logit market share function, i.e., a generalized extreme value distribution. The nesting parameter $\lambda \in (0, 1)$ governs the substitution patterns between the two nests. As λ approaches 0, all substitution occurs within the nests. When λ approaches 1, the model collapses into a simple logit model. We define $\theta_d \equiv (\beta, \alpha, \lambda)$ to be the vector of parameters to be estimated.

When $\lambda \in (0, 1]$, the share of people choosing product $j \in \mathcal{J}_t$ in market t among the set of people consuming an inside product, the within-group share, is given by

$$s_{j|f,t}(x_t, p_t, \xi_t; \theta_d) = \frac{\exp(\delta_{jt}/\lambda)}{\sum_{k \in \mathcal{J}_t} \exp(\delta_{kt}/\lambda)}, \tag{2}$$

with $\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt}$ being the "mean utility" of product j.

The percentage of people flying in market t is

$$s_{ft}(x_t, p_t, \xi_t; \theta_d) = \frac{\left(\sum_{j \in \mathcal{J}_t} \exp(\delta_{jt}/\lambda)\right)^{\lambda}}{1 + \left(\sum_{j \in \mathcal{J}_t} \exp(\delta_{jt}/\lambda)\right)^{\lambda}}, \tag{3}$$

which allows us to define the market share of product $j \neq 0$ proposed in market t as

$$s_{jt}(x_t, p_t, \xi_t; \theta_d) = s_{j|f,t}(x_t, p_t, \xi_t; \theta_d) \times s_{ft}(x_t, p_t, \xi_t; \theta_d). \tag{4}$$

[10] In the following x_t, p_t and ξ_t denote the vector of collected x_{jt}, p_{jt} and ξ_{jt}, across all inside products proposed in market t.

Similarly, the market share of the outside option is equal to

$$s_{0t}(x_t, p_t, \xi_t; \theta_d) = \frac{1}{1 + \left(\sum_{j \in \mathcal{J}_t} \exp\left(\delta_{jt}/\lambda\right)\right)^{\lambda}}. \tag{5}$$

A manipulation of equations (2) to (5) gives us a linear estimating equation (see Berry, 1994):

$$\ln(\frac{s_{jt}}{s_{0t}}) = x_{jt}\beta - \alpha p_{jt} + (1-\lambda)\ln(s_{j|f,t}) + \xi_{jt}. \tag{6}$$

All terms in equation (6) but ξ_{jt} and θ_d being observed, one can estimate $\theta_d \equiv (\beta, \alpha, \lambda)$ by regression techniques, ξ_{jt} playing the role of the error term. However, since the demand-side unobservables, ξ_{jt}, realize before firms choose prices, there is a correlation between prices and these unobservables, and similarly, between ξ_{jt} and the within-group share $s_{j|f,t}$. Typically, a more demanded product (i.e. with a higher value of ξ_{jt}) is priced higher at equilibrium and has a higher market share. Therefore, equation (6) can be estimated by 2SLS. A discussion of the choice of product attributes and instruments is provided in Section 5.

4.2 Supply

We model the static profit-maximizing price decisions of all the airlines in each market t. We assume that they play a Nash-Bertrand pricing game. For each market t, the profit maximization of airline f determines its pricing strategy. Observe that an airline may offer more than one product; for example, a direct flight and one-stop flight through its hub. Therefore, each firm chooses the set of prices p_{ft} of the products they offer in each market t to maximize

$$\max_{p_{ft}} \ \Pi_{ft} \equiv \sum_{j \in \mathcal{J}_{ft}} (p_{jt} - mc_{jt}) s_{jt}(x_t, p_t, \xi_t; \theta_d) M_t, \tag{7}$$

where $\mathcal{J}_{ft}$ collects all products offered by firm f in market t. Obviously, $\cup_{f \in \mathcal{F}} \mathcal{J}_{ft} = \mathcal{J}_t$. Also, mc_{jt} is the marginal cost of offering product j and M_t is the market size of market t (defined here as the geometric mean of the population at the endpoint metropolitan areas). Together, $s_{jt}M_t$ give the number of consumers (passengers) choosing product (flight) j in market t. The first-order condition with respect to the price of product j writes

$$\frac{\partial \Pi_{ft}}{\partial p_{jt}} = s_{jt}(x_t, p_t, \xi_t; \theta_d) + \sum_{k \in \mathcal{J}_{ft}} (p_{kt} - mc_{kt}) \frac{\partial s_{kt}}{\partial p_{jt}}(x_t, p_t, \xi_t; \theta_d) = 0, \tag{8}$$

giving us the standard trade-off between reducing price to gain a higher market share and increasing price to collect a higher markup, while internalizing the effect of product j's price on other products offered by the firm in the same market.

The market shares are observed from the data and their derivatives with respect to prices can be estimated from the estimation of the demand. Therefore, the previous equation allows us to estimate the markups (or equivalently, the marginal costs) for all products proposed by all firms. For counterfactual analysis, we want to explain how markups are dependent on product attributes. Therefore, we specify the marginal cost function for product j as

$$mc_{jt} = w_{jt}\theta_s + \zeta_{jt}, \tag{9}$$

with w_{jt} a vector of observed marginal cost shifters and ζ_{jt} a marginal cost shock not observed by the researcher. The vector of parameters to be estimated is θ_s. The choice of the product attributes in the marginal cost equation is detailed below. Equation (9) can be estimated by OLS.

4.3 Estimation procedure

As explained above, the parameters of the demand side need to be estimated with Instrumental Variables (for both the price and the within-group share), whereas the parameters of the marginal cost specification only require OLS techniques. However, observe that the marginal costs in (9) are estimated from the demand side and not observed. We should take this uncertainty into account while computing the standard errors of the estimated θ_s. Standard econometric procedures are available to correct for this parameter uncertainty.

However, estimating demand and supply jointly allows us to take into account the potential correlation between demand shocks and marginal cost shocks. Therefore, the joint estimation increases efficiency, resulting in shorter confidence intervals for both the demand and marginal cost parameters, θ_d and θ_s. Therefore, we estimate the demand and supply-side jointly using the Generalized Method of Moments (see Hansen, 1982). Since we have linear models for both the demand and the supply, estimating both sides jointly comes at a negligible computational burden. More details are given in Appendix C.2.

5 Results and analysis

5.1 Specification

On the demand side, we let the utility of purchasing a product depend on several attributes. We select them following the literature (Berry and Jia, 2010; Ciliberto and Williams, 2014). The attributes we consider are the mean price, *Price*, which is endogenous, the number of stops (*Stops*) to account for the fact that consumers value direct and one-stop flights differently, and the maximum number of direct connections offered out of the endpoints (*Connections*). An airline serving more destinations out of an airport can enhance the value of frequent flyer programs, for instance. We also include the distance (in thousand miles) between the endpoint cities (*Distance*) and its square (*Distance2*) to allow for distance to affect utility non-linearly. Finally, we include a set of carrier dummies to capture consumer preferences for different airlines.

On the supply side, we let the marginal cost depend on the number of stops (*Stops*), a hub dummy (*Hub*) equal to one if an endpoint or connecting airport is a hub for the airline, zero otherwise, and the distance (in thousand miles) between the endpoint cities (*Distance*). We allow for two sets of parameters: one for short and medium-haul flights (radial distance less than 1,500 miles) and another for long-haul flights (distance higher than 1,500 miles). We do so to account for the fact that airlines use different types of aircraft for these two types of routes. As for the demand side, we also include carrier dummies to pick up systematic marginal cost differences across airlines.

5.2 Instruments

Since the demand-side unobservables, ξ_{jt}, realize before firms choose prices, there is a correlation between prices and these unobservables. Also, the within-group share $s_{j|g,t}$ in equation (2) is a function of price and hence endogenous. We build instruments in the spirit of Berry and Jia (2010), which are a variant of the instruments proposed by Berry et al. (1995). The idea behind these instruments is that close substitutes in the space of products' attributes constrain a product's price. Functions of rival firm product attributes then serve as a proxy for the level of competition a given product faces. Similarly, attributes of other products produced by the same firm will affect pricing behavior (see equation (8)). In this vein, we use the percentage of rival products that are direct flights, the total number of rival products, the percentage of direct flights in a market, the number of competitors, and a dummy indicating whether a market is a monopoly. We also employ exogenous cost shifters, such as dummies, indicating that at least one of the endpoints is a hub and the number of direct connections offered out of the endpoints. Finally, we include interactions between the instruments.

5.3 Results

We present the estimation results for our GMM estimation of the demand side and the supply side in Table 8. Following the standard GMM procedure, we select our instruments, being mindful that including too many instruments may lead to biased estimates but that incorporating a sufficient number of them guarantees the stability of our estimates, provided the overidentification test is not rejected by the data. With our final choice of instruments, the degree of overidentification is equal to 5 for the 2011 data and 4 for the 2016 data. The J-test statistics are equal to 4.43 and 5.69, respectively and, therefore, we do not reject the overidentification test, for the usual test levels (5% or 1%). Also, we report the F-test statistics for the first stage of the 2SLS demand estimation to assess that our instruments are not weak. The values are equal 479 and 683 for the price in 2011 and 2016, and 845 and 1009 for the within-group market share $s_{j|g}$. These results give us strong reasons to believe that we do not face any problems related to weak instruments (see Stock et al., 2002) and that both our estimates and the estimated standard errors are reliable.

[**Include Table 8**]

The nesting parameter λ lies between zero and one, and is statistically significant, suggesting that substitution between the inside and outside products exists. In other words, when the price of a flight increases, passengers may decide to switch to another inside product or to not fly at all. The price coefficients for both years are negative, which aligns with our expectations and standard economic theory. We report the (mean) own price elasticity estimates in Table 9 with their corresponding 95% asymptotic confidence interval.[11] The absolute values of the estimates

[11]The confidence intervals are calculated by simulating 1000 draws of the parameter θ_d from its asymptotic distri-

of own-price elasticities are lower in 2016 than in 2011 though the difference is not statistically significant. Therefore, we can-not reject the assumption that the price elasticity is the same in 2011 and 2016. Berry and Jia (2010) find an increase in price elasticities between 1999 and 2006 and attribute it to the emergence of search engines and online ticketing services. Both factors have increased customers' ability to gather information and compare prices. However, as customers were already accustomed to online service and air travel during the 2010s, a stability in price elasticity is plausible.

The distance estimates imply a U-shape dependence of utility on distance. Most of the literature finds an inverse U-shape. However, most of the products in our dataset have a distance value corresponding to the increasing part of the distance function. This finding is consistent with the estimates of Ciliberto and Williams (2014) who have a similar definition of the products. Most of their observations also lie on the increasing part of the inverse U-shape function. Moreover, in our robustness analysis (see Appendix B), including only the distance does not modify the outcomes of our model. Finally, we still get the U-shape across several other robustness checks that we present in the same appendix.

A negative estimate of the number of stops shows passengers' preference for direct flights. Note that the variable *Stops* is not conditional on distance, so it measures the disutility incurred by a consumer while holding distance constant. We also display the connection semi-elasticity in Table 9, as well as its 95% confidence interval. It measures the percentage change in a product's demand when a direct flight becomes a connecting flight, *ceteris paribus*. We find that consumers have a higher aversion toward indirect flights in 2016, in line with a trend already found by Berry and Jia (2010) who exploit data from 1999 and 2006. It is difficult to directly compare our values (61.5% for 2011 and 70.9% for 2016) with those estimated in Berry and Jia (2010) because we do not have the same definition of products nor the same model. However, we do have the same order of magnitude.

The effect of an airline's network size on consumers' utility, captured by *Connections*, is positive. One reason for this finding is that more flights increase the attraction of loyalty programs to customers. With a larger number of connections at an airport, a carrier can also provide better service and more convenient gate access for customers (Berry and Jia, 2010). The carrier-specific

bution and by reporting the 25th and 975th values.

taste parameters suggest that, in 2011, American Airlines and US Airways were more popular than Delta Airlines. Nonetheless, Delta Airlines became more popular in 2016 than the merged entity American Airlines. Note that the reference group for both years is United Airlines.

We allow for two sets of marginal cost parameters: one for short-distance markets and the other for long-distance markets. There exist two opposite effects of the number of stops on marginal costs. On the one hand, connecting airports could generate economies of scale by transmitting more passengers, which lowers the marginal cost. On the other hand, the extra volume of traffic would cause higher coordination and management costs and lead to additional fuel consumption at landings and takeoffs, which increases the marginal cost. Hence, the coefficient's sign reflects the trade-off between these two effects (Berry et al., 2006; Berry and Jia, 2010). There is no statistical evidence of economies of scale, even for long routes in 2011. The coordination cost effect seems to dominate any economies of scale. The same reasoning can apply to the hub parameters since hubs mostly function as connecting points. Unlike most previous literature, our results suggest that flights involving hubs have a higher cost, which implies the increasing cost of coordination and fuel prevails over the scale economies. Marginal cost also increases with distance, even for the long routes.

Tables 10 and 11 show average profits, prices, marginal costs, and markups at different levels in both years, respectively. These tables reveal that the marginal costs of connecting flights are indeed higher than for direct flights. The marginal cost of operating a direct flight has decreased by 13.4% between 2011 and 2016 (following the fuel price drop), whereas the marginal cost of operating a connecting flight has remained broadly the same. Also, as expected, LCCs have lower marginal costs, which aligns with the supply estimates.

Marginal costs for all airlines decreased substantially except for Southwest and Delta Airlines. The marginal costs of the LCCs decreased more because, without doubt, the share of fuel cost in their operating cost is higher. Airlines were more "profitable" in 2016 than in 2011.

One of the reasons raised by the DoJ in its attempt to block the merger between American Airlines and US Airways was the fear of increasing coordinated effects, such as an increase in tacit collusion. Ciliberto and Williams (2014) give evidence that multimarket contact may facilitate tacit collusion in a Bertrand price setting. Also, the merged entity internalizing its pricing externality becomes less aggressive in its pricing behavior toward its remaining competitors (see Porter, 2020;

Ivaldi and Lagos, 2017), essentially acting as if facing a higher marginal cost. The DoJ argued that US Airways had a more aggressive pricing behavior toward the other legacy carriers when it offered a connecting flight in a market in which one or more legacy carriers were operating directly. After having carefully investigated the mean Lerner Index of the airlines in different market configurations, we have not been able to find any statistical evidence of these differences in behavior, either before or after the merger.[12]

5.4 Analysis of marginal costs

The main argument for allowing a merger often relies on cost savings that counterbalance the upward pressure on pricing due to reduced competition. We take advantage of having marginal cost estimates pre- and post-merger to quantify how the marginal costs of the new American Airlines are related to the two production technologies of the two merging entities.

First, we compare the distributions of marginal costs for American Airlines and US Airways pre- and post-merger. The results are displayed in Figure 3. As illustrated in Tables 10 and 11, we observe a shift toward the left of the distribution mainly driven by the drop in fuel price (see also Figure 4, which displays the distributions for Delta Airlines, United Airlines and SouthWest Airlines).

[**Include Figures 3 and 4**]

Our objective is to compare the distribution of marginal costs for US Airways and American Airlines pre- and post-merger. As illustrated above, directly comparing these distributions would be misleading due to the changes in fuel price between 2011 and 2016. Therefore, for every flight proposed by US Airways or American Airlines in 2011, we need to impute a value for what would have been the marginal cost of the same product, had US Airways and American not merged between these dates.

To do so, we estimate the distribution of marginal costs for flights proposed by Delta Airlines and United Airlines in 2011 and in 2016. We assume that the rank of the marginal cost of a flight proposed by US Airways or American Airlines in 2011 would have stayed constant in 2016. For

[12] These tables are available upon request directly from the authors.

example, if the marginal cost of a flight proposed by US Airways corresponds to the median of the marginal costs of flights proposed by Delta Airlines and United Airlines in 2011, its imputed value for 2016 is the median of the distribution of marginal costs of flights proposed by Delta Airlines and United Airlines in 2016. This scenario appears to be the most plausible to impute the marginal cost values for counterfactuals that are not observed. Berry and Jia (2010) proceed similarly to input the unobserved component ξ_{jt} in their counterfactuals.[13] We apply this procedure for direct and connecting flights separately.

Figure 5 displays the new distributions (direct flights on the left panel, connecting flights on the right panel). The distribution of American Airlines in 2016 seems to be a mix between the two former distributions. To test it formally, we run a Kolmogorov-Smirnov test to decide which distribution fits the distribution of the marginal costs of the new American Airlines in 2016 best. We consider five candidates: the distribution of American in 2011 "translated" to 2016, the distribution of US in 2011 "translated" to 2016, the distribution which corresponds to the maximum of the two previous distributions, the distribution corresponding to the minimum, and the average of these two distributions. Remember that, pre-merger, American Airlines and US Airways were proposing approximately the same number of flights. The average represents a union of the two former technologies without any cost reduction.

[**Include Figure 5**]

The corresponding test statistics are reported in Table 12. The critical value for a 5% level test is 1.35, meaning we reject all tests but the first one and the average for the direct flights, and we reject all tests but the average for the connecting flights. Therefore, it seems plausible under our assumptions that the merger-related efficiency gains take time to materialize. In 2016, claiming that the production technology of the new entity is just the union of the production technologies of the two former entities is not rejected by the data. In fact, the administrative burden of combining two firms, as well as the need to synchronize baggage handling operations, and the decision of the DoJ to force American Airlines to maintain some flights (in particular from/to the former hubs of US Airways) have generated some frictions which have so far prevented the new entity from improving on its production costs.

[13]See section V.C of Berry and Jia (2010), pages 34-35.

[**Include Table 12**]

6 Counterfactuals

As illustrated in Table 7, the mean price of a ticket has decreased in the markets we consider between 2011 and 2016.[14] However, many changes occurred in the meantime. In particular, marginal costs decreased, largely due to the drop in fuel price.[15] We estimate a 13.4% marginal cost decrease for a direct flight. Also, the preferences of consumers have shifted toward direct flights and, in 2016, more than 80% of passengers take direct flights in our sample. In our counterfactual analysis, we aim to disentangle the effects of each change that occurred between 2011 and 2016. Our structural model is ideally suited for carrying out such a decomposition.

6.1 Deriving the change in prices due to changes in marginal costs and demand

First, we would like to estimate what the prices of the flights proposed in 2011 would be had they been proposed in 2016. This is Scenario 1, and our objective is to compare the outcome of this scenario with the reality of 2016. In this scenario, there is no merger between US Airways and American Airlines. Also, all airlines propose the same products as in 2011 (no entry/exit by anybody) and compete as in 2011. However, marginal costs and consumer preferences change.

To do so, we take the estimates θ_d and θ_s of both the demand and marginal cost of 2016 and recompute the utility and marginal cost for each flight proposed in 2011 but evaluated with the 2016 preferences and costs. The natural question that arises is how to impute the new value of the unobserved product attribute ξ_{jt}. Indeed, ξ_{jt} plays a crucial role in determining the utility and, consequently, the market share of the corresponding product. As mentioned in Berry and Jia (2010), the difference between ξ_{jt} in 2016 and ξ_{jt} in 2011 *"is a combination of changes in taste and*

[14] We recall that all prices are expressed in 2011 US$

[15] From 3.3 US$ per gallon to 1.20 US$ per gallon for the USA Daily Spot Prices for Kerosene. Source: USA Energy Information Administration. https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

changes in unobserved product characteristics". We impute the new value of ξ_{jt} in our scenario by keeping its rank constant, as in Berry and Jia (2010).

To be more specific, we estimate the demand for 2011 and 2016 from which we can recover the distribution of the ξ's for both years studied. If $\hat{\xi}$, for a given product, corresponds to the first quartile of the distribution in 2011, the imputed value for Scenario 1 is the first quartile of the distribution estimated in 2016. More generally, if the quantile of $\hat{\xi}$ is γ, the imputed value is the quantile γ of the distribution estimated in 2016. We do the same for imputing the 2016 value of the ζ's, the unobserved cost shocks.[16]

Table 13 displays the percentage changes in sales-weighted prices (weighted by the number of passengers in each market) and consumer surplus. Overall, we see that prices have decreased by around 6.59%, but would have decreased by 6.73% between 2011 and 2016 because of changes in marginal costs and preferences. In terms of prices, the merger (jointly with its impact on airlines strategies) slightly increased prices. However, in the previous section, we provide evidence that the merged entity has not yet realized any cost savings from the merger.[17] On the other hand, consumer surplus has increased by 14.35%. Less than half of this increase can be attributed to the changes in preferences and marginal costs, suggesting that the merger (and the rationalization of airlines' networks) did increase consumer surplus. In the next part, we present additional scenarios to estimate these networks' effects.

6.2 Decomposition of the merger steps

We consider additional scenarios to disentangle the pure merger effect from changes in the networks of the different airlines. However, it would be fair to say that we are not able to distinguish which entries of competitors (LCC in particular) are directly linked to the merger and which would have occurred nevertheless. We consider three scenarios to lead us from the outcome of Scenario 1 to the actual situation in 2016.

[16] See Berry and Jia (2010), Section V.C .

[17] An interesting avenue for future research would be to investigate whether any cost savings have been realized later.

- *Scenario 2: AA and US merge*

  In Scenario 2, we assume joint profit maximization by American Airlines and US Airways, but otherwise keep the set-up of Scenario 1. The only difference between Scenario 1 and Scenario 2 is that the merged entity now internalizes the effects of changing prices on all products proposed by American Airlines and US Airways. This scenario allows us to back out the *pure price effect* of the merger (see Appendix C.1 for further details).

- *Scenario 3: the new American Airlines updates its network*

  In Scenario 3, we update Scenario 2 by allowing the new entity "American Airlines" to reoptimize its network. We do so by updating its product offerings to those actually proposed in 2016. Similarly, we update the error terms of demand and supply, ξ_{jt} and ζ_{jt} , to the actual estimates from 2016 for the products offered by American Airlines. Note that we restrict the product offerings of all other firms to remain as those we observe in 2011. Hence, we have a data set in which we combine the products offered by the new American Airlines in 2016 with those offered by competitors in 2011. Doing so allows us to isolate the impact of the merging firm's post-merger network re-alignment.

- *Scenario 4: Competitors update their network*

  We move from the outcome of Scenario 3 to the actual market situation in 2016 with Scenario 4. Here, we allow competitors to update their networks. We do so by updating their product offerings to those we observe in 2016. We also use their 2016 estimates for the error terms of both demand and supply, which allows us to estimate the effect of the changes in competitors' product offerings. However, it is difficult to know which fraction of this change is actually a pure reaction to the merger and which would have occurred absent the merger. Disentangling these forces would require a model that endogenizes the market structure, which is beyond the scope of this paper.

These scenarios allow us to perform a detailed step-by-step evaluation of the merger. Having pre- and post-merger data means we do not have to rely on ad-hoc assumptions regarding the post-merger network structure. Ciliberto et al. (2020) and Bontemps et al. (2021) both show that such ad-hoc assumptions strongly drive the analysis. Both also provide ways to take into account changes in network structure in an ex-ante analysis where post-merger data is not (yet) available.

Tables 14 and 15 display the percentage changes in sales-weighted prices (weighted by the number of passengers in each market) and consumer surplus across scenarios. Column 2 in the consumer surplus table reports the observed changes between 2011 and 2016. The first line recaps the information across markets. Then, we decompose the changes according to the market situation in 2011, as in Table 13.

Overall, we see that prices did not vary much when the networks were updated. In Scenario 2, mechanically, prices increase because one competitor vanished, but this increase was very small (+0.05%). This is mainly due to the fact that often the merging entities were competing with at least two other big competitors. Also, there was little overlap in the networks of American Airlines and US Airways, especially when considering direct flights. In Scenario 3, when American Airlines is rationalizing its post-merger network, prices increase slightly (+0.12%) and in Scenario 4, they decrease only very slightly. Overall, the merger and the reoptimization of airlines' strategies induced a price increase of +0.15%.

On the other hand, consumer surplus has increased, especially in Scenario 4. We saw in Scenario 1 that less than half of the consumer surplus increase is due to the drop in marginal costs and changes in preferences. Most of the remaining part is due to the competitors of American Airlines adapting to the new situation by entering new markets and increasing competition.

This global analysis hides heterogeneity across different market structures, especially for the consumer surplus. We see that in markets where both American Airlines and US Airways were present before the merger, consumer surplus increased by more than in the no-merger scenario. Again, this finding underlines the fact that competitive pressure and new entries (or threats of entries) kept prices from increasing too much. Also, stronger consumer tastes for a more extensive network and an expanded network post-merger led to higher consumer surplus.

On the other hand, consumer surplus absent the merger would have been higher in markets where only one of the merging parties was present before the merger. Consumers in these markets saw less new entry of competitors, which may explain this result.

Finally, we see that in markets where neither merging party was present, the reoptimization of the competitors' networks harms consumers considerably (-31.23% change in consumer surplus). However, this only concerns 26 markets (0.2% of the passengers), some of which saw airlines leave for reasons that may be unrelated to the merger.

7 Conclusion

In this paper, we study the merger between American Airlines and US Airways and in particular, its impact on the US domestic market connecting the top metropolitan areas. Fuel prices dropped substantially in the period under scrutiny, having a high impact on production costs.

We estimate a structural model of demand for and supply of differentiated products from the US Department of Transportation data collecting a 10% random sample in the second quarters of 2011 and 2016. We find that the mean price has decreased by 6.59% but estimate that, without the merger, the mean price would have dropped by 6.73%. The merger with firms' subsequent reactions and adaptations to the new consumer tastes explain the gap. It is worth noting that, following Berry and Jia (2010), the shift in consumer preferences toward direct flights - which tend to be more expensive - has continued. This trend also explains part of this relative increase in prices. In addition, we do not find evidence of any cost savings in the merging entities.

Breaking down the results by market structure, we find that consumers in markets where both American and US Airways were present in 2011 benefited from the merger, even if prices did not change because of that. This fact is mainly due to the entry of LCCs and to a lesser extent, a more extensive network of the merged entity. On the other hand, consumers in markets where only one of the merging parties was present would have enjoyed a higher consumer surplus without a merger. Overall, these findings suggest that merger remedies, such as slot divestiture at LaGuardia, that gave LCCs and Southwest Airlines slots worked well.

In our simulations, entry of either low-cost or other legacy carriers often offsets the effect of a decrease in the number of legacy carriers. We find this pattern mainly in markets where the two merging entities were both operating before the merger. Modeling the endogeneity of the entry behavior is beyond the scope of this paper. It has been tackled by Ciliberto et al. (2020) and requires the use of moment inequalities to endogenize these decisions. There is, however, the necessity to provide empirical researchers with tools to deal with it while using standard econometric techniques, at the price of adding some assumptions, such as in the entry game literature.

Finally, it is worth noting that doing our simulation ex-post allows us to consider the shifts in both supply and demand. Merger analysis is often conducted ex-ante and rarely done ex-post. Having pre- and post-merger data enables us to decompose the effect of the merger. It also prevents us from having to make ad-hoc assumptions on the post-merger network structure that have been shown to strongly influence the analysis.

References

Armantier, O. and Richard, O. (2008), 'Domestic airline alliances and consumer welfare', *The RAND Journal of Economics* **39**(3), 875–904.

Bajari, P., Benkard, C. L. and Levin, J. (2007), 'Estimating dynamic models of imperfect competition', *Econometrica* **75**(5), 1331–1370.

Benkard, C. L., Bodoh-Creed, A. and Lazarev, J. (2020), Simulating the dynamic effects of horizontal mergers: U.s. airlines, Working paper.

Berry, S., Carnall, M. and Spiller, P. T. (2006), Airline hubs: costs, markups and the implications of customer heterogeneity, NBER Working Papers 5561, National Bureau of Economic Research.

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

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

Berry, S. and Pakes, A. (1993), 'Some Applications and Limitations of Recent Advances in Empirical Industrial Organization: Merger Analysis', *The American Economic Review* **83**(2), 247–252.

Berry, S. T. (1994), 'Estimating discrete-choice models of product differentiation', *The RAND Journal of Economics* pp. 242–262.

Bilotkach, V. (2011), 'Multimarket Contact and Intensity of Competition: Evidence from an Airline Merger', *Review of Industrial Organisation* **38**, 95–115.

Björnerstedt, J. and Verboven, F. (2016), 'Does Merger Simulation Work? Evidence from the Swedish Analgesics Market', *American Economic Journal: Applied Economics* **8**(3), 125–64.

Bontemps, C., Gualdani, C. and Remmy, K. (2021), 'Price Competition and Endogenous Product Choice in Networks: Evidence from the US Airline Industry', *Working Paper TSE* .

Borenstein, S. (1990), 'Airline mergers, airport dominance, and market power', *The American Economic Review* **80**(2), 400–404.

Buccirossi, P., Ciari, L., Duso, T., Fridolfsson, S.-O., Spagnolo, G. and Vitale, C. (2008), 'A short overview of a methodology for the ex-post review of merger control decisions', *De Economist* **156**(4), 453–475.

Carlton, D., Israel, M., MacSwain, I. and Orlov, E. (2019), 'Are legacy airline mergers pro-or anti-competitive? Evidence from recent US airline mergers', *International Journal of Industrial Organization* **62**, 58–95.

Chen, Y. and Gayle, P. G. (2019), 'Mergers and product quality: Evidence from the airline industry', *International Journal of Industrial Organization* **62**, 96–135.

Ciliberto, F., Murry, C. and Tamer, E. T. (2020), 'Market structure and competition in airline markets', *Available at SSRN 2777820* .

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

Das, S. (2019), 'Effect of Merger on Market Price and Product Quality: American and US Airways', *Review of Industrial Organization* **55**(3), 339–374.

Gayle, P. G. and Yimga, J. O. (2018), 'How much do consumers really value air travel on-time performance, and to what extent are airlines motivated to improve their on-time performance?', *Economics of Transportation* **14**, 31–41.

Hansen, L. P. (1982), 'Large Sample Properties of Generalized Method of Moments Estimators', *Econometrica* **50**(4), 1029–1054.

Hausman, J., Leonard, G. and Zona, J. D. (1994), 'Competitive analysis with differenciated products', *Annales d'Economie et de Statistique* pp. 159–180.

Ilzkovitz, F. and Dierx, A. (2020), *Ex Post Economic Evaluation of Competition Policy: The EU Experience*, Kluwer Law International BV.

Ivaldi, M. and Lagos, V. (2017), 'Assessment of post-merger coordinated effects: Characterization by simulations', *International Journal of Industrial Organization* **53**, 267–305.

Ivaldi, M. and Verboven, F. (2005), 'Quantifying the effects from horizontal mergers in european competition policy', *International Journal of Industrial Organization* **23**(9), 669–691.

Kim, E. H. and Singal, V. (1993), 'Mergers and market power: Evidence from the airline industry', *The American Economic Review* pp. 549–569.

Luo, D. (2014), 'The price effects of the delta/northwest airline merger', *Review of Industrial Organization* **44**, 27–48.

Mazzeo, M. J. (2003), 'Competition and service quality in the US airline industry', *Review of Industrial Organization* **22**(4), 275–296.

Morrison, S. A. (1996), 'Airline mergers: A longer view', *Journal of Transport Economics and Policy* pp. 237–250.

Nevo, A. (2001), 'Measuring Market Power in the Ready-to-Eat Cereal Industry', *Econometrica* **69**(2), 307–342.

Peterman, C. A. (2014), 'The Future of Airline Mergers after the US Airways and American Airlines Merger', *Journal of Air Law & Commerce* **79**, 781–817.

Peters, C. (2006), 'Evaluating the performance of merger simulation: Evidence from the US airline industry', *The Journal of Law and Economics* **49**(2), 627–649.

Philippon, T. (2019), *The Great Reversal*, Harvard University Press.

Porter, R. H. (2020), 'Mergers and coordinated effects', *International Journal of Industrial Organization* **73**, 102583.

Prince, J. T. and Simon, D. H. (2009), 'Multimarket contact and service quality: Evidence from on-time performance in the US airline industry', *Academy of Management Journal* **52**(2), 336–354.

Ruiz-Pérez, A. (2019), 'Market Structure and Common Ownership: Evidence from the US Airline Industry', *Working Paper* .

Rupp, N. G. and Tan, K. M. (2019), ‘Mergers and Product Quality: A Silver Lining from De-Hubbing in the US Airline Industry’, *Contemporary Economic Policy* **37**(4), 652–672.

Rupp, N., Owens, D., Plumly, L. et al. (2006), ‘Does competition influence airline on-time performance’, *Advances in airline economics: Competition policy and antitrust* **1**, 251–272.

Stock, J., Yogo, M. and Wright, J. (2002), ‘A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments’, *Journal of Business and Economic Statistics* **20**, 518 – 529.

Werden, G. J., Joskow, A. S. and Johnson, R. L. (1991), ‘The effects of mergers on price and output: Two case studies from the airline industry’, *Managerial and Decision Economics* **12**(5), 341–352.

A Tables and Figures

A.1 Tables

Note that in the following tables, AA stands for American Airlines, UA stands for United Airlines, US stands for US Airways, DL stands for Delta Airlines, WN stands for Southwest and LCC stands for all the other carriers.

Table 1: Product-level descriptive statistics

Variable	Mean (2011)	std dev. (2011)	Mean (2016)	std dev. (2016)
Price (100 USD)	1.94	0.97	1.82	0.91
Number of Stops	0.15	0.34	0.12	0.32
Connections (100)	0.34	0.14	0.36	0.15
Distance (1000 miles)	1.06	0.78	1.09	0.77
Product share	0.37	0.14	0.34	0.13
Observations	17540		19295	

Notes: The mean values for the price and number of stops are weigthed by the number of passengers. Number of stops varies between zero and one due to sample selection. Connections is the maximum number of connections at the segment endpoints (origin and destination). Product share is the market share among the flying options, excluding the outside option.

Table 2: Market-level descriptive statistics

Variable	Mean (2011)	std dev. (2011)	Mean (2016)	std dev. (2016)
Number of Products per market	14.97	9.22	16.44	9.90
Number of Airlines per market	5.43	1.72	4.81	1.51
Direct Passengers (1000)	42.02	96.49	55.47	123.06
Connecting Passengers(1000)	7.14	7.76	7.62	7.86
Number of Markets	1171		1174	

Table 3: Airline-level descriptive statistics

Airline	Market share	No. Mkt served	No. Direct Flights	No. connecting products	Number of Products
Year 2011					
DL	17.7%	1144	326	3360	3686
UA	15.3%	1112	366	3160	3526
US	9.8%	999	316	1850	2166
AA	12.6%	950	245	1715	1960
WN	26.7%	895	673	3622	4295
LCC	17.8%	511	285	969	1254
Year 2016					
AA	21.3%	1157	417	4088	4505
DL	17.1%	1123	287	3338	3625
UA	13.5%	1119	302	3097	3399
WN	27.5%	1080	730	5012	5742
LCC	20.6%	621	506	1518	2024

Table 4: Graph-level descriptive statistics of networks (2011)

	All	AA	US	AA+US	UA	DL	WN	LCC
Number of cities	49	48	48	49	49	49	43	44
Number of Links	968	245	316	468	366	326	673	214
Average path Length	1.18	1.79	1.73	1.6	1.69	1.72	1.25	1.9
Average degree	39.51	10.21	13.17	19.1	14.94	13.31	31.3	9.73
Average Closeness	0.86	0.57	0.59	0.64	0.61	0.6	0.81	0.54

Table 5: Graph-level descriptive statistics of networks (2016)

	All	AA	UA	DL	WN	LCC
Number of cities	49	49	49	49	48	46
Number of Links	912	417	302	287	730	367
Path Length	1.22	1.65	1.74	1.77	1.35	1.67
Average degree	37.22	17.02	12.33	11.71	30.42	15.96
Average closeness	0.84	0.63	0.59	0.58	0.76	0.61

Table 6: Top influential nodes before and after the merger

Airport	Airline	Degree 2011	Closeness 2011	Airport	Degree 2016	Closeness 2016
Year 2011				**Year 2016**		
CLT	US	45	0.96	CLT	47	0.98
ORD	AA	42	0.90	ORD	46	0.96
DFW	AA	45	0.96	DFW	45	0.94
PHL	US	42	0.90	PHL	44	0.92
MIA	AA	35	0.80	MIA	42	0.89
DCA	US	34	0.78	DCA	41	0.87
JFK	AA	32	0.76	JFK	39	0.84
JFK	US	28	0.71			
LAX	AA	25	0.68	LAX	35	0.79
PHX	US	33	0.77	PHX	35	0.79

Table 7: Market prices by market structure in 2011

Market structure 2011	Price 2011	Price 2016	Δ in%	2011 Pax share	No. markets
Overall					
	194.33	181.52	-6.59%	100.00	1171
AA and US present					
2 firms	131.51	114.39	-13.02%	0.64	4
3 firms	211.27	189.73	-10.20%	9.54	162
4 firms	196.04	180.23	-8.06%	77.36	638
AA or US present					
1 firm	232.33	286.68	+23.39%	0.02	7
2 firms	180.93	202.49	+11.92%	0.70	26
3 firms	186.48	188.91	+1.30%	3.02	93
4 firms	168.71	176.83	+4.81%	8.53	215
None present					
1-3 firms	179.25	180.90	+0.92%	0.18	26

Table 8: Structural estimates

Utility			Marginal Cost		
	2011	2016		2011	2016
Mean utility			**Short-haul flights**		
Intercept	-3.332	-2.690	Intercept	1.348	1.112
	(0.187)	(0.188)		(0.032)	(0.031)
Price	-1.723	-1.582	Stops	0.148	0.372
	(0.120)	(0.109)		(0.018)	(0.018)
Stops	-1.397	-1.845	Distance	0.278	0.198
	(0.056)	(0.063)		(0.028)	(0.027)
Connections	3.721	2.111	Hub	0.221	0.203
	(0.289)	(0.200)		(0.019)	(0.017)
Distance	-0.293	-0.463	**Long-haul flights**		
	(0.060)	(0.055)			
Distance2	0.224	0.201	Intercept	0.857	0.641
	(0.024)	(0.021)		(0.055)	(0.050)
Nesting Parameter (λ)	0.711	0.741	Stops	-0.035	0.097
	(0.014)	(0.028)		(0.023)	(0.024)
			Distance	0.685	0.582
				(0.023)	(0.020)
			Hub	0.175	0.278
				(0.023)	(0.018)
Carrier FEs			**Carrier FEs**		
AA	0.356	0.261	AA	-0.024	0.257
	(0.047)	(0.033)		(0.027)	(0.021)
DL	0.150	0.387	DL	-0.116	0.034

Table 9: Average elasticity estimates and 95% confidence intervals

	2011		2016	
	Est.	95%CI	Est.	95%CI
Own-price elasticity	-4.16	(-4.80, -3.56)	-3.49	(-4.16, -2.89)
Connection Semi-elasticity	-0.615	(-0.639, -0.584)	-0.709	(-0.728, -0.686)

Table 10: Profits Breakdown (2011)

	Profits (100k)	Price	Marginal Cost	Markup	Lerner Index
All Flights	42.50	194.33	146.75	47.58	0.27
Direct Flights	49.54	188.53	140.31	48.22	0.28
Connecting Flights	1.03	228.49	184.67	43.82	0.20
AA	33.91	215.15	168.50	46.66	0.23
US	15.78	213.21	166.84	46.38	0.24
UA	30.18	238.51	192.64	45.87	0.21
DL	29.11	213.97	165.55	48.42	0.25
WN	74.64	167.69	117.62	50.07	0.32
LCC	39.82	161.40	115.20	46.21	0.31

Table 11: Profits Breakdown (2016)

	Profits (100k)	Price	Marginal Cost	Markup	Lerner Index
All Flights	52.90	181.52	128.79	52.74	0.33
Direct Flights	60.00	174.60	121.46	53.14	0.35
Connecting Flights	1.20	231.94	182.16	49.78	0.23
AA	45.73	196.30	143.24	53.07	0.29
UA	41.79	217.86	167.16	50.70	0.25
DL	41.20	214.07	161.40	52.68	0.27
WN	76.91	166.04	111.27	54.77	0.35
LCC	45.22	136.29	85.23	51.06	0.46

Table 12: KS Test for the best fit for AA 2016

Distribution	AA	US	Max	Min	Average
Direct flights	1.14	1.38	3.54	3.39	1.32
Connecting flights	1.95	2.20	7.35	8.50	0.89

95% critical value is equal to 1.35

Table 13: Scenario 1 - changes in preferences and marginal costs

Market structure 2011	No of markets	Changes in prices		Changes in CS	
		Changes in preferences and marginal costs	Δ 2011-2016	Changes in preferences and marginal costs	Δ 2011-2016
Overall					
	1171	-6.73%	-6.59%	+6.67%	+14.35%
AA and US present					
3 firms	4	-3.24%	-12.71%	+8.02%	+34.96%
4 firms	162	-0.78%	-9.87%	+8.90%	+24.68%
5 firms	638	-7.05%	-7.73%	+5.08%	+15.86%
AA or US present					
1 firm	7	-7.57%	+23.84%	+35.78%	+18.67%
2 firms	26	+4.14%	+12.33%	+19.64%	+1.40%
3 firms	93	+1.37%	+1.67%	+19.33%	+3.49%
4 firms	215	-1.18%	+5.19%	+11.32%	-2.83%
None present					
None present	26	+7.94%	+1.10%	+17.18%	-16.66%

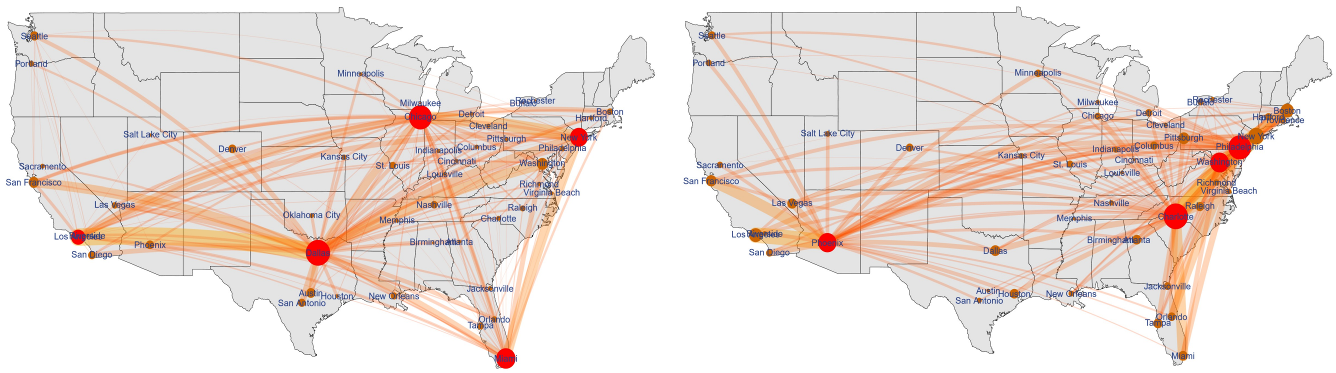
Table 14: Market prices by scenario and market structure in 2011

Market structure 2011	Change 2011-2016	Changes in%			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
		Changes in preferences and marginal costs	AA and US merge	AA updates its network	Competitors update their networks
Overall					
	-6.59%	-6.73%	+0.05%	+0.12%	-0.02%
AA and US present					
3 firms	-12.71%	-3.86%	+0.02%	-3.08%	-6.33%
4 firms	-9.87%	-2.39%	+0.10%	-0.40%	-7.39%
5 firms	-7.73%	-7.94%	+0.06%	-0.04%	+0.21%
AA or US present					
1 firm	23.84%	-8.02%	0.00%	+34.26%	+0.28%
2 firms	12.33%	+1.16%	0.00%	+2.94%	+7.87%
3 firms	1.67%	-1.37%	0.00%	+2.14%	+0.92%
4 firms	5.19%	-3.40%	0.00%	+1.01%	+7.80%
None present					
None present	1.10%	+0.13%	0.00%	+0.61%	+0.36%

Table 15: Market consumer surplus by scenario and market structure in 2011

Market structure 2011	Change 2011-2016	Changes in%			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
		Changes in preferences and marginal costs	AA and US merge	AA updates its network	Competitors update their networks
Overall					
	+14.35%	+6.67%	-0.27%	+1.23%	+6.18%
AA and US present					
3 firms	34.96%	+8.02%	-0.05%	+9.49%	+14.17%
4 firms	24.68%	+8.90%	-0.41%	+4.22%	+10.31%
5 firms	15.86%	+5.08%	-0.31%	+1.14%	+9.35%
AA or US present					
1 firm	18.67%	+35.78%	0.00%	+12.44%	-22.27%
2 firms	1.40%	+19.64%	0.00%	-0.04%	-15.21%
3 firms	3.49%	+19.33%	0.00%	-3.36%	-10.26%
4 firms	-2.83%	+11.32%	0.00%	+0.15%	-12.84%
None present					
None present	-16.66%	+17.18%	0.00%	+3.42%	-31.23%

A.2 List of Figures

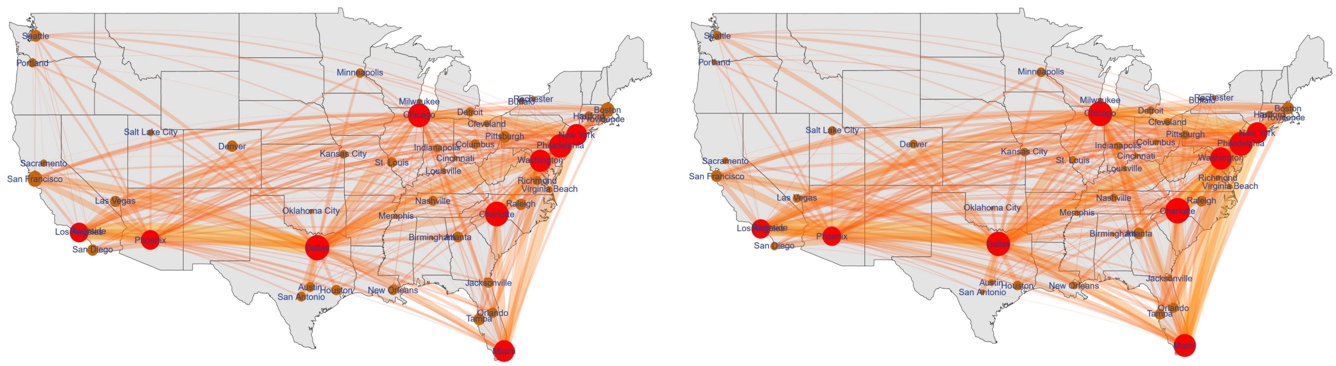


(a) Network of AA (2011)

(b) Network of US (2011)

Notes: In these figures, the size of the node is constructed based on the normalized degree value of each node, and the width of the curve representing a link between two cities is associated the number of passengers traveling through such a route. Red nodes in the graphs indicate the hubs for the airline. Most of the thick curves in the figures involve the hubs, and most large nodes are red suggesting that the hubs indeed undertake a higher volume of traffic. Besides, as the graphs suggest, the hubs of American Airlines were more evenly distributed while US Airways emphasized its business more along the east coast. Overall, Dallas could be the most important node for American Airlines, and Charlotte was the most influential node for US Airways.

Figure 1: Networks of American Airlines (AA) and US Airways (US) (2011)

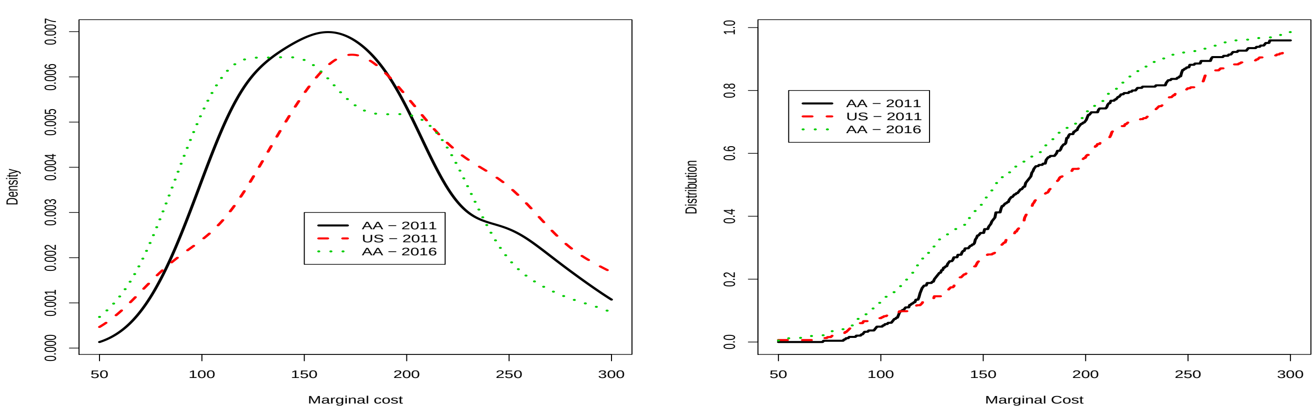


(a) Network of AA + US (2011)

(b) Network of AA (2016)

Notes: see Figure 1 for explanations.

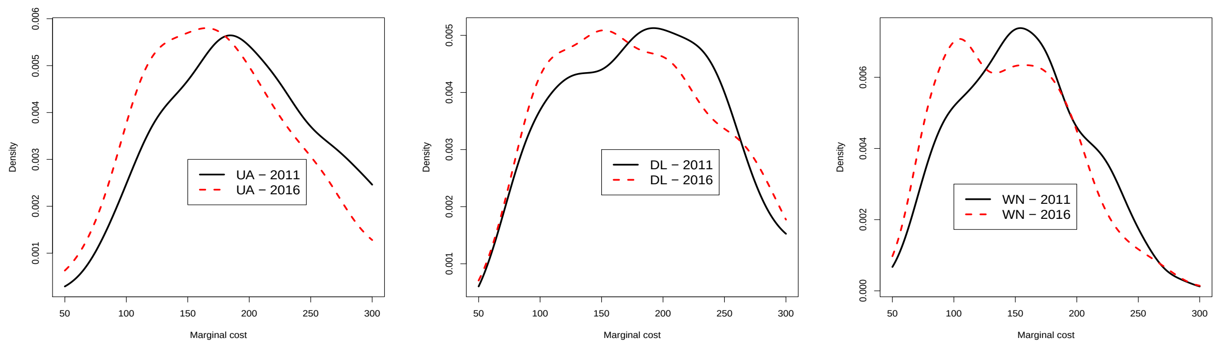
Figure 2: Networks of Merged Entities Before and After Merger



(a) Density

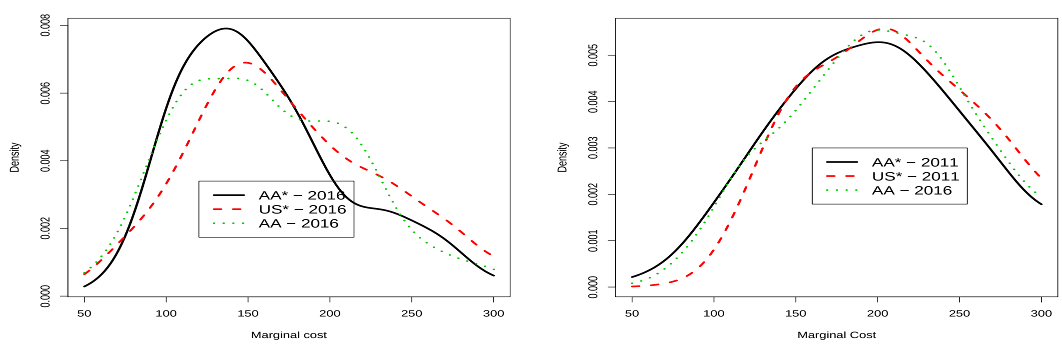
(b) C.d.f.

Figure 3: Distribution of estimated Marginal Costs for direct flights of US and AA pre and post-merger



(a) Distribution for DL (b) Distribution for UA (c) Distribution for WN

Figure 4: Distribution of estimated Marginal Costs for direct flights pre and post-merger



(a) Direct flights (b) Connecting flights

Figure 5: Distribution of estimated Marginal Costs of US and AA pre and post-merger / imputed values.

Supplement to "Ex-post evaluation of the American Airlines-US Airways merger: a structural approach"

by Christian Bontemps, Kevin Remmy and Jiangyu Wei

B Robustness checks

In this section, we document some robustness checks. We discuss the choice of instruments then, the scenario for imputing the values in the counterfactual analysis. In the main text, we have selected our set of instruments in order to have a minimum degree of overidentification to get optimal and stable estimates, while not rejecting the overidentification test. In this robustness analysis, we report the **demand** side estimates and some estimates for other choices of sets of instruments. We use the following sets:

IV 1: Instrument set for 2011 used in the main specification

IV 2: Instrument set for 2011 without interaction variables

IV 3: The three instruments which are used in common for both 2011 and 2016

IV 4: Instrument set for 2016 used in the main specification

IV 5: Instrument set for 2016 without interaction variables

We build these five instrument sets for both year's data. The results are reported in Tables 16 and 17. We also display the estimated elasticities as well as the overall price changes calculated from the counterfactual analysis of Scenario 1.

We also add a column of results where we omit the distance squared in the product attributes, combining this specification with the optimal set of instruments chosen in the paper (IV1 for 2011 and IV4 for 2016). Indeed, we observe that the utility to fly is an increasing function of the distance for most of the products of our sample. It seems natural to check whether introducing the distance linearly in the utility function changes the results.

The first column (OLS) holds estimates from a nested logit model where we do not instrument for price nor the within-group share of products. For these non consistent estimates, we notice that the price coefficient is biased towards zero, which is expected as the true coefficient is negative and the correlation between the unobserved product attribute and the price positive (more demanded products are higher priced).

For 2011, we see that the estimates are relatively robust for the first three columns. Then, the estimates become very unprecise, especially with IV3 (only one degree of overidentification). IV4 is rejected by the J-test. IV5 is not but gives very large confidence intervals for the parameters. Overall, the estimates of elasticities and counterfactual are relatively robust.

For 2016, the estimates are also sensitive to changes in the instrument sets. Note that here, the column "IV 4" is the default specification used in the main part of the paper and provide the more accurate estimates. However, the estimates using the sets "IV 1" and "IV 2" does not seem to be be admissible from an economic point of view. Also, we reject the J test for these two cases.

We see that for 2011 and 2016, we recover a U-shaped dependence of utility on distance and that not including the square slightly changes the estimates but not the outcomes of the model.

C Details on the estimation procedure

C.1 Details on the supply-side + scenario 2

The first-order conditions with respect to the prices of the products offered in market t are given by equation (8), for all $j \in \mathcal{J}_t$. We can stack the first order conditions to get the following matrix/vector equality:

$$s_t + \Delta_t[p_t - mc_t] = 0_{\mathcal{J}_t}, \tag{C.1}$$

where s_t and mc_t are vectors collecting the market shares and marginal costs, respectively, of products offered in market t. The matrix Δ_t is of dimension $\mathcal{J}_t \times \mathcal{J}_t$ and holds own- and cross-price derivatives, with

$$\Delta_{kl,t} = \begin{cases} \frac{\partial s_{lt}}{\partial p_{kt}} \text{ if } k, l \in J_{ft}, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{C.2}$$

Observe that s_t, Δ_t depend on the product attributes of all products proposed in the market, including the prices and the marginal cost of each product depends on its attributes.

When one knows the demand function and the marginal cost, the price can be derived from looking at the fixed point of equation (C.1). For example, assume that in market t, one firm offers products 1 and 2 and another firm offers product 3, the prices of these three products solve the following FOC system (omitting the product attributes):

$$\begin{bmatrix} s_1(p_1,p_2,p_3) \\ s_2(p_1,p_2,p_3) \\ s_3(p_1,p_2,p_3) \end{bmatrix} + \begin{bmatrix} \frac{\partial s_1}{\partial p_1}(p_1,p_2,p_3) & \frac{\partial s_2}{\partial p_1}(p_1,p_2,p_3) & 0 \\ \frac{\partial s_1}{\partial p_2}(p_1,p_2,p_3) & \frac{\partial s_2}{\partial p_2}(p_1,p_2,p_3) & 0 \\ 0 & 0 & \frac{\partial s_3}{\partial p_3}(p_1,p_2,p_3) \end{bmatrix} \begin{bmatrix} p_1 - mc_1 \\ p_2 - mc_2 \\ p_3 - mc_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

When setting the prices of its products, firm 1 takes p_3 as "given" and endogeneizes the impact of a change in p_1 on both s_1 and s_2. It does not take into account the impact of p_1 on s_3. When setting the price of product 3, firm 2 only solves one equation:

$$s_3 + \frac{\partial s_3}{\partial p_3}(p_3 - mc_3) = 0.$$

Table 16: Demand-side variables with different instruments: year 2011

	OLS	IV 1	IV 1	IV 2	IV 3	IV 4	IV 5
Mean utility							
Intercept	-5.137	-3.332	-4.184	-3.306	-3.004	-3.357	-2.597
	(0.037)	(0.187)	(0.117)	(0.190)	(0.685)	(0.196)	(0.320)
Price	-0.299	-1.723	-1.484	-1.742	-1.938	-1.703	-2.203
	(0.008)	(0.120)	(0.094)	(0.121)	(0.469)	(0.124)	(0.211)
Stops	-0.959	-1.397	-1.620	-1.369	-1.218	-1.320	-1.015
	(0.023)	(0.056)	(0.047)	(0.056)	(0.163)	(0.056)	(0.082)
OriginConn	2.206	3.721	3.154	3.807	4.379	3.878	5.152
	(0.062)	(0.289)	(0.238)	(0.292)	(1.024)	(0.296)	(0.478)
Distance	-0.189	-0.293	0.434	-0.291	-0.301	-0.307	-0.315
	(0.028)	(0.060)	(0.048)	(0.060)	(0.069)	(0.059)	(0.072)
Distance2	0.057	0.224		0.226	0.258	0.228	0.300
	(0.007)	(0.024)		(0.024)	(0.069)	(0.024)	(0.037)
Nesting	0.637	0.711	0.734	0.704	0.675	0.686	0.635
Parameter (λ)	(0.003)	(0.014)	(0.012)	(0.014)	(0.071)	(0.024)	(0.035)
Carrier FEs							
AA	0.305	0.356	0.313	0.358	0.383	0.364	0.416
	(0.024)	(0.047)	(0.043)	(0.048)	(0.063)	(0.047)	(0.058)
DL	0.125	0.150	0.144	0.154	0.156	0.154	0.159
	(0.020)	(0.039)	(0.036)	(0.040)	(0.043)	(0.039)	(0.048)
US	0.203	0.620	0.591	0.623	0.661	0.605	0.711
	(0.023)	(0.049)	(0.044)	(0.049)	(0.110)	(0.049)	(0.066)
WN	-0.342	-0.896	-0.802	-0.910	-1.030	-0.917	-1.190
	(0.021)	(0.073)	(0.063)	(0.074)	(0.246)	(0.075)	(0.118)
LCC	0.662	-0.030	0.040	-0.026	-0.058	0.020	-0.098
	(0.026)	(0.056)	(0.049)	(0.056)	(0.141)	(0.058)	(0.084)
Statistics							
J-statistic	N/A	4.433	8.8314	0.410	0.0379	45.480	0.359
Degree of overidentification	N/A	5	5	3	1	4	2
Ftest Price	N/A	54.8	66.8	76.7	105.0	84.7	93.5
Ftest Nest share	N/A	847.12	853.5	1098.8	938.1	505.9	715.5
Elasticities							
Own-price elasticity		4.17	3.510	4.24	4.86	4.22	5.78
95% CI		(3.56,4.80)	(3.07,3.98)	(3.63,4.87)	(2.19,8.42)	(3.45,4.99)	(4.41,7.39)
Con. semi-elasticity		0.615	0.656	0.608	0.573	0.597	0.517
95% CI		(0.584,0.639)	(0.634,0.674)	(0.577,0.634)	(0.472,0.611)	(0.567,0.623)	(0.456,0.558)
Scenario 1							
Δ Price		-6.73%	-6.64%	-6.65%	-5.55%	-7.01%	-4.33%

Table 17: Demand-side variables with different instruments: year 2016

	OLS	IV 1	IV 2	IV 3	IV 4	IV 4	IV 5
Mean utility							
Intercept	-4.605	-1.596	-1.559	-2.725	-2.690	-3.413	-2.692
	(0.036)	(0.250)	(0.255)	(0.259)	(0.188)	(0.126)	(0.260)
Price	-0.421	-2.336	-2.360	-1.558	-1.582	-1.416	-1.580
	(0.008)	(0.154)	(0.156)	(0.156)	(0.109)	(0.092)	(0.157)
Stops	-1.208	-0.505	-0.484	-1.858	-1.845	-2.072	-1.840
	(0.024)	(0.085)	(0.086)	(0.082)	(0.063)	(0.053)	(0.082)
OriginConn	2.301	5.064	5.126	2.069	2.111	1.752	2.119
	(0.058)	(0.286)	(0.288)	(0.273)	(0.200)	(0.176)	(0.273)
Distance	-0.197	-0.603	-0.613	-0.463	-0.463	0.244	-0.465
	(0.028)	(0.073)	(0.074)	(0.058)	(0.055)	(0.037)	(0.059)
Distance2	0.060	0.348	0.354	0.199	0.201		0.202
	(0.007)	(0.030)	(0.031)	(0.027)	(0.021)		(0.027)
Nesting	0.610	0.469	0.467	0.742	0.741	0.75995	0.740
Parameter (λ)	(0.003)	(0.028)	(0.028)	(0.037)	(0.028)	(0.026)	(0.038)
Carrier FEs							
AA	0.001	0.243	0.241	0.257	0.261	0.253	0.259
	(0.019)	(0.044)	(0.044)	(0.035)	(0.033)	(0.032)	(0.036)
DL	0.246	0.434	0.437	0.384	0.387	0.368	0.385
	(0.020)	(0.045)	(0.045)	(0.035)	(0.035)	(0.033)	(0.036)
WN	-0.474	-1.200	-1.212	-0.724	-0.732	-0.698	-0.734
	(0.021)	(0.075)	(0.076)	(0.071)	(0.055)	(0.051)	(0.071)
LCC	0.250	-1.168	-1.178	-1.051	-1.065	-0.973	-1.064
	(0.026)	(0.115)	(0.117)	(0.115)	(0.086)	(0.075)	(0.115)
Statistics							
J-statistic	N/A	58.6	51.9	0.17	5.69	2.04	2.09
Degree of overidentification	N/A	5	3	1	4	4	2
First stage: Price	N/A	173.6	234.5	297.3	161.8	186.7	210.7
First stage: Nest share	N/A	1165.5	1565.7	884.3	469.7	459.5	692.6
Elasticities							
Own-price elasticity	N/A	7.32	7.42	3.43	3.49	3.06	3.49
95% CI		(5.87,9.06)	(5.96,9.13)	(2.58,4.40)	(2.88,4.20)	(2.53,3.61)	(2.56,4.47)
Con. semi-elasticity	N/A	0.327	0.317	0.711	0.709	0.738	0.709
95% CI		(0.240,0.397)	(0.220,0.388)	(0.685,0.731)	(0.688,0.729)	(0.722,0.753)	(0.680,0.729)

However, its market share, s_3, depends on the prices of all the products proposed in the market (here p_1, p_2 and p_3).

In Scenario 2, we simulate the case were both AA and US are merging. Imagine AA is firm 1 in the example above and US is firm 2, the new entity needs to take into account that, when it changes p_1, it impacts s_1, s_2, like before, but, also s_3. The new equilibrium prices satisfy the following system:

$$\begin{bmatrix} s_1(p_1,p_2,p_3) \\ s_2(p_1,p_2,p_3) \\ s_3(p_1,p_2,p_3) \end{bmatrix} + \begin{bmatrix} \frac{\partial s_1}{\partial p_1}(p_1,p_2,p_3) & \frac{\partial s_2}{\partial p_1}(p_1,p_2,p_3) & \frac{\partial s_3}{\partial p_1}(p_1,p_2,p_3) \\ \frac{\partial s_1}{\partial p_2}(p_1,p_2,p_3) & \frac{\partial s_2}{\partial p_2}(p_1,p_2,p_3) & \frac{\partial s_3}{\partial p_2}(p_1,p_2,p_3) \\ \frac{\partial s_1}{\partial p_3}(p_1,p_2,p_3) & \frac{\partial s_2}{\partial p_3}(p_1,p_2,p_3) & \frac{\partial s_3}{\partial p_3}(p_1,p_2,p_3) \end{bmatrix} \begin{bmatrix} p_1 - mc_1 \\ p_2 - mc_2 \\ p_3 - mc_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}.$$

Therefore, for this counterfactual, we need to update the matrices Δ_t for all markets and solve for the new equilibrium prices using fixed-point algorithms.

C.2 Estimation procedure

We estimate the demand and supply-side jointly using the Generalized Method of Moments (see Hansen, 1982). Since we employ a nested logit model on the demand side, estimating both sides jointly comes at a negligible computational burden. We form moments that are interactions of the demand-and supply-side shocks with exogenous instruments introduced above.

On the demand side (see equation (6)), the linearity of the system allows us to express the unobservable ξ_{jt} as a function of the demand parameters θ_d and the explanatory variables. We then obtain the moment conditions by interacting the resulting demand-side unobservables with instruments:

$$E[z^d_{jt}\xi_{jt}] = 0,$$

where z^d_{jt} is a $k_1 \times 1$ vector of instruments. On the supply-side (see equation (9)), the supply-side unobservable ζ_{jt}, is the difference between the implied marginal costs from equation (8) and their deterministic part, $w_{jt}\theta_s$. We can then form moment conditions in the same way we did on the demand side:

$$E[z^s_{jt}\zeta_{jt}] = 0,$$

where z^s_{jt} is a $k_2 \times 1$ vector of instruments, in fact the product attributes.

We build sample analogs of the moment conditions by averaging first across products within a given market and then across markets:

$$\bar{g}(\theta) = \begin{pmatrix} \frac{1}{T}\sum_{t\in\mathcal{T}} \frac{1}{\mathcal{J}_t}\sum_{j=1}^{\mathcal{J}_t} z^d_{jt}\xi_{jt} \\ \frac{1}{T}\sum_{t\in\mathcal{T}} \frac{1}{\mathcal{J}_t}\sum_{j=1}^{\mathcal{J}_t} z^s_{jt}\zeta_{jt} \end{pmatrix},$$

with $\theta = (\theta_d, \theta_s)$. $\bar{g}(\theta)$ is a $(k_1 + k_2) \times 1$ vector of means. The GMM objective function to be minimized (with respect to θ) is a distance of $\bar{g}(\theta)$ to 0, i.e.:

$$f(\theta) = \bar{g}(\theta)^\top \Omega \bar{g}(\theta),$$

with Ω a positive definite weighting matrix.

We employ a two-step procedure in which we obtain a first set of estimates using an initial weighting matrix (the identity) before getting the final set of estimates using an estimate of the optimal GMM weighting matrix.