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On the Reliability of Structural Methods in Merger Review

Evidence from the US Airline Industry

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Abstract

The objective of this study is to provide evidence on the accuracy of merger simulation methods, which have become common instruments to evaluate ex-ante the effects of complex transactions. In particular, I study the price effects of one of the most important mergers in the U.S. airline industry, namely the 2013 American Airlines – US Airways merger. Drawing from the theoretical background of the Empirical Industrial Organization, I perform an empirical investigation in three steps. In the first place, I estimate a nested logit demand system. Secondly, I use the retrieved parameters to predict the effects of the merger under scrutiny. Lastly, the forecast is evaluated ex post using data from the period following the transaction, by means of difference-in-differences techniques. Results show that, in this case, simulation methods underpredicted – although not substantially – the increases in prices.

Contents

1 Introduction **3**
1.1 Literature Review . . . 4
1.2 The AA-US merger . . . 9

2 Structural Methods **13**
2.1 Demand estimation . . . 14
2.2 Supply side . . . 21

3 Empirical analysis **25**
3.1 Sample selection . . . 25
3.2 Demand specification . . . 30
3.3 Simulation . . . 35
3.4 Ex-post analysis . . . 41
3.5 Results and discussion . . . 49

4 Concluding remarks **55**

Bibliography **59**

Chapter 1

Introduction

[I]t seems that the evaluation of merger simulation models by a comparison of predicted and actual outcomes is in its infancy. In view of the extensive use to which these models are put, a careful evaluation of their effectiveness seems long over due.

Ashenfelter and Hosken (2008, p. 36)

From the 1990s, the use of structural methods by antitrust authorities and economic consultancies has become one of the tools used to assess the competitive concerns in merger review, both in the United States (see the US Horizontal Merger Guidelines [37] in § 6.1) and in the European Union (Buettner et al., 2016). In practice, a merger simulation is a prediction which generates the equilibrium prices when the ownership structure in the market changes. In fact, as a result of a concentration, firms will maximize their objective functions taking into account the decreased number of rivals and the combined profits.

Elaborating the prediction is though the last step, as one shall firstly estimate an underlying demand and supply model. In fact, the solution of the new equilibrium is determined according to the assumed behavior of consumers and firms.

The objective of this study is to evaluate whether the predictions of such structural models are correct. More in detail, we will assume a demand system for the US airline market in the early 2010s, recover the corresponding parameters and perform a simulation concerning the 2013 American Airlines – US Airways merger. Lastly, results of this exercise will be compared with the ones obtained using an ex-post reduced form analysis.

The empirical investigation shows that the assumed model underpredicts the observed change as a result of the new equilibrium.

This work thus intends to contribute to a narrow literature which combines the use of ex-ante simulation with retrospective evaluation, in order to shed light on the accuracy of these techniques.

This work is organized as follows. The first Chapter is dedicated to review the relevant literature and to introduce our reader to the merger we consider for the investigation. Chapter 2 presents discrete choice models for the analysis of demand and supply. Chapter 3 illustrates the results of demand estimation, simulation and ex-post analysis. Eventually, Chapter 4 draws final considerations on the applicability of the two methods in merger review.

1.1 Literature Review

In this section, we will review the literature concerning structural estimation (in a broad sense, ex-ante analysis) and ex-post evaluations of mergers using reduced form methods. A third part will illustrate the studies proposing a combination of the two, i.e. ex-post evaluation of merger simulation.

The literature concerning the analysis of the (US) airline markets is particularly rich, thanks to the data made available by the US Department of Transportation. Nonetheless, applications of the discrete choice framework and, in particular, of merger simulation techniques are few, at least in the scientific and academic literature.

1.1.1 Ex-ante analysis: demand and simulation

Ex-ante analysis generally consists in estimating a structural model of demand and supply and predicting a counterfactual scenario, in which a merger took place and firms optimize taking into account the different ownership. As far as this and the next section are concerned, we will only focus on studies in the airline markets.

Berry et al. (2006) use the discrete choice framework, by means of a discrete version of the random coefficients logit model, to estimate demand parameters and analyze the effects of the transition from the "point-to-point" organization to "hub-and-spoke" networks, where airlines set up major airports (hubs) in which they try to collect passengers from different origins and exploit economies of scope and density to reduce costs. They find that hubs let companies reduce costs and profit from higher markups on hub-originating passengers, in particular price-inelastic ones. Their paper is relevant for our purposes due to the formulation of a demand and supply model which could be adapted to our framework.

Berry and Jia (2010) also present a structural model of the US airline industry, analyzing the impact on profitability of demand and supply changes. In fact, the authors try to estimate the impact of some factors contributing to the decrease in profitability in this industry – namely, the decrease in the willingness-to-pay of business travellers, the tightened security regulations in force after 9/11, the new possibility of purchasing tickets on the Internet, the expansion of low-cost carriers (LCC), the developments in aviation technology and the variations in the price of jet fuel. Following Berry et al. (2006), they also use a discrete-type version of the BLP model, though exploiting a nesting structure which differentiates between flying and the outside good. They find that price sensitivity had increased and passengers prefer non-stop flights (which were also favoured due to changes in marginal costs).

Ciliberto et al. (2016) introduce a framework in which entry and pricing decision are taken into account. Their object is to study the strategic decisions of airlines which enter markets and fix prices, in order for market structure to vary as a consequence of new events, such as mergers. In an application, they simulate the American Airlines – US Airways merger, allowing for the market structure to vary in the post-merger period, in contrast to typical simulations based on pre-transaction structure and shares. According to them, self-selection indeed occurs and has an effect on the estimation of elasticities and markups, so that policy instruments such as merger simulation might suffer from biases.

Richard (2003) performs a merger simulation not only capturing the effect on prices but also on flight frequencies, differently from other papers. One of the examples is the American – United Airlines merger and its effect at Chicago O'Hare airport (ORD). He finds that flight frequency has great importance in consumers' utility and that the merger benefited consumers thanks to this aspect.

Benkard et al. (2019) propose a framework to evaluate ex-ante the potential dynamic effects resulting from a merger and apply it to the US airline market. In particular, their method – unlike the discrete choice framework – does not estimate the structural parameters. It estimates the equilibrium of the model from the data and, assuming that the strategy would not change after the merger, simulates the counterfactual outcome. Differently from standard merger simulation tools too, it aims to predict medium and long term outcomes. The application they propose concerns the United Airlines – US Airways merger (which was prohibited), the Delta – Northwest and the United – Continental ones. They find that the latter would have had a more anti-competitive effect than the former. They explain that UA and US had a high degree of overlap but LCCs were expanding on those routes, while this was not true for the other two.

1.1.2 Ex-post analysis

Ex-post analysis is generally performed by means of reduced form equations. Using data for the periods before and after the merger, they do not estimate a structural model. Ex-post analyses are more common in the academic literature than in proceedings of antitrust authorities.

Ashenfelter et al. (2009) advocate the necessity of retrospective analysis in the context of merger review and suggest applications for ex-post studies. They discuss the goodness of reduced form methods – in which price variations are function of costs and demand factors and an indicator of consummated mergers – and difference-in-differences analysis, its most relevant issue being the difficulty in finding a good control group.

Kim and Singal (1993) are interested in the price effects of some airline mergers in the second half of the eighties (some coincide with the ones of Peters, 2006). Using a difference-in-differences approach, the authors compare the routes in which merging firms were present to similar ones in which they did not operate and did not experience reduction in competition. Overall, they detect significant price increases, in particular on longer routes – where competition from other means of transportation was less likely to occur.

Kwoka and Shumilkina (2010) examine the 1987 merger of USAir (until 2013, US Airways) and Piedmont Airlines and aim to provide evidence concerning the price increase as a result of the elimination of potential competition.[1] They find that significantly detectable price increases occurred on routes in which either USAir or Piedmont was already present and the other (merging) company was a potential entrant, as a result of the relaxation of competitive constraints.

Dobson and Piga (2013) focus on the European airline markets, in particular on the behaviour of the LCCs Easyjet and Ryanair after having acquired a competitor (Go Fly and Buzz, respectively). Using original data (prices posted on airlines' websites), they conduct an ex-post study which shows that the mergers had beneficial effects in terms of consumer welfare (lower fares – except for the ones posted few days before departure) and increased capacity and frequency.

Hüschelrath and Müller (2014) conduct an ex-post study of the 2005 America West Airlines – US Airways merger. Exploiting a difference-in-differences technique, they find that the merger led to an increase in prices, though not uniformly across the different market environments (one-stop and overlapping, not overlapping). In general, they conclude that the merger had a negative effect on consumer welfare for about one out of ten passengers, while it was beneficial or neutral for the remaining portion.

Luo (2014) investigates the effect on prices of the 2008 Delta Airlines – Northwest Airlines merger. The author uses a regression specification of price, taking into account non-stop and connecting markets and the competitive environment of legacy and low-cost carriers. In summary, she finds that there has been a small increase in fares, particularly in the connecting and overlapping markets.

Carlton et al. (2019) conduct a retrospective study concerning mergers in the airline market, and in particular the Delta – Northwest merger, the United – Continental and the American Airlines – US Airways ones. Focusing on overlapping routes and using a difference-in-differences regression, they find that – in general – these mergers did not have anti-competitive effects. In fact, price decreased or did not change substantially, while capacity increased.

Zhang and Nozick (2018) present a study similar to Kwoka and Shumilkina (2010) on the analysis of potential competition after the American Airlines – US Airways merger. They find that higher fares are present in more concentrated markets. In particular, fares

[1] This topic is of particular relevance today in the discussion of the so-called "killer acquistions": see Cunningham et al. (2018)

rose after the merger, not only in the markets where the two merging companies were present, but also in the ones in which at least one of them was absent and another legacy carrier was present. On the contrary, LCCs decreased their fares, particularly in the market where at least either AA or US was incumbent.

1.1.3 Ex-post evaluation of merger simulations

Few studies which include an ex-ante and ex-post evaluation are collected in this last section. The authors generally performed a merger simulation and, afterwards, evaluated whether the results were consistent with observed data. The literature in this field is very limited, therefore all the known studies have been examined.

Peters (2006) aims to evaluate the performance of merger simulation techniques by predicting price changes for five airline mergers in the 1980s and estimating the differences between these predictions and the real changes. Similarly, he uses the DB1B data and relies on a discrete choice model, comparing the results of a simple logit model and a more elaborated GEV logit model, in which three nesting categories are used (outside/inside, direct/connecting and airports in the same metropolitan area). Focusing on overlapping markets, he finds that there are "generally significant differences between the average observed price changes and the average predicted price changes" (p. 642). According to him, divergences are due to loss of competition, change in the set of products and non-price observed variables, unobserved changes in demand and in supply. In conclusion, he finds that deviations can be probably attributed to a different model of firm conduct.

Weinberg (2011) estimates a logit and nested logit demand model to predict the price variation resulting from the 1997 acquisition of Tambrands by P&G, in the market for tampons and hygiene pads. He finds that elasticities retrieved from the models are inconsistent with the observed ones and that merger simulation does not perform adequately in predicting the change in price.

Houde (2012) performs a study about the effects of a merger in retail markets for gasoline in Canada, combining the structural approach of simulation techniques and difference-in-differences. However, he extends the model incorporating the behaviour of consumers, taking into account the geographical features of the market. He finds that the estimates of the simulation roughly correspond to the observed changes, thus providing support for simulation methods.

Weinberg and Hosken (2013) investigate the accuracy of merger simulations resulting from different models in the market for passenger car motor oil and breakfast syrup. They use AIDS, linear and logit systems and find that, overall, the simulations performed better in explaining the price variations of the non-merging firms than the merging firms' ones. They argue that bias could arise from four sources: a) the quality of demand estimates, b) the instability of demand primitives when estimating only before the merger and on a longer time period including after it, c) the definition of potential market size and d) limitations in the available data (particularly concerning substitutable products).

Björnerstedt and Verboven (2016) analyze the predictions of a merger simulation in the Swedish market for analgesics, namely the one between AZT and GSK, which was cleared in 2009. By modelling demand both in a nested logit and BLP fashion and supply as a Bertrand-Nash game, they find that the predictions of the model underestimated the observed price increase. When expanding the supply model with package size and accounting for partial coordination, they find results closer to the observed changes.

Eventually, Miller and Weinberg (2017) try to reconcile the empirical evidence of surge in prices after the consummation of the MillerCoors joint venture, in the American brewing industry. They find that data do not support the common hypothesis according to which firms play a Nash-Bertrand game, as the price variation does not match the simulation of the standard model. On the contrary, modeling several counterfactuals, they find that a framework allowing for post-merger coordination does better match the empirical evidence.

1.2 The AA-US merger

The objective of this study is to analyze the 2013 American Airlines - US Airways merger. In this section, further details on this transaction are provided.

American Airlines and US Airways (controlled, respectively, by AMR Corporation and US Airways Group) were two major legacy carriers for domestic and international flights in the United States. It is possible to appreciate the importance of the domestic networks of the two companies in 2012, represented, respectively, in Panel A and B of

Figure 1.1.[2] American mainly operated out of five cities, i.e Dallas/Fort Worth (DFW), Chicago O'Hare, Miami, New York (JFK and LGA) and Los Angeles, while US Airways had the most important bases in Charlotte, Philadelphia, Phoenix and Washington National.

A plan for a merger between US Airways Group and AMR Corporation (American Airlines) was announced in February 2013. After the merger, they would retain the AA brand, while the management of US Airways would oversee the new merged airline.

This merger contributed to further consolidate the airline market in the United States, as a result of subsequent mergers which affected this industry in this first part of the century. More in detail, in the previous years, US Airways merged with America West in 2005, Northwest Airlines merged with Delta in 2008, United Airlines with Continental in 2010 and, eventually, Southwest acquired AirTran in 2011. As a consequence, after the merger, three legacy carriers would remain in the US, namely American, United and Delta.

On August 13, 2013, the Antitrust Division of the U.S. Department of Justice filed a complaint (subsequently revised, see [69]), according to which the merger would have violated Section 7 of the Clayton Act. In particular, the DoJ alleged that the transaction would have resulted in multiple anti-competitive consequences, in terms of both price and non-price effects. Moreover, it would have limited the capacity, end AA's expansion plans and possibly reinforced the opportunity of coordination (see the Complaint [69] and Peterman, 2014).

The litigation ended just prior to the trial, in November 2013, when the DoJ and the two carriers reached a settlement. The Antitrust Division explained that the merger would have been allowed, conditional on certain divestitures. Namely, the airlines must divest 104 slots at Ronald Reagan National Airport DCA in Washington, D.C. (all of American's DCA slots), 34 slots at LaGuardia Airport LGA in New York City and two gates and

[2] In the empirical investigation which will follow, the number of routes might seem to the reader disproportionately high, with respect to the ones in Figure 1.1. It is yet true that a large number of airports is not served by either AA or US. More importantly, it shall be considered that Figure 1.1 only shows direct routes. Therefore, for instance, the map does not report the route San Francisco-New York for US Airways. However, US operates the route San Francisco-Phoenix and the route Phoenix-New York. Therefore, it will be considered active in the market San Francisco-New York, offering an itinerary with a layover.

Figure 1.1: American Airlines (A) and US Airways (B) nonstop domestic routes in 2012

Panel A: American Airlines

Panel B: US Airways

Note: Elaboration on OAG data. Endpoints in Alaska and Hawaii are not mapped.

ground facilities at Boston Logan, Chicago O'Hare, Dallas Love Field, Los Angeles and Miami, key airports in the network of American. These remedies contributed to the largest airline merger divestiture ever (Olley and Town, 2018). The divestiture at DCA was particularly important due to the important presence of AA and US in this airport and the fact that it is severely constrained, up to the point that a single slot[3] may be worth up to two million dollars (Olley and Town 2018, p. 452).

As a result, the new airline would still provide 57% departures at Reagan National, 28% at LaGuardia and occupy 56% gates at Miami, 46% at Chicago O'Hare, 30% at Boston Logan and 21% at Los Angeles (Peterman 2014, p. 803).

The merger was closed on December 9, 2013. Gradually, the company launched the code-sharing and began integrating the operations of the two carriers. It also sold the slots at DCA and LGA (part of the remedy), for 381 million dollars.[4] US Airways also joined American in the Transatlantic Joint Business agreement and code-sharing with British Airways, Iberia, Finnair and AirBerlin. Eventually, the new entity received a single operating certificate from the Federal Aviation Administration (FAA) on April 8, 2015. This was a signal of the completed integration in operations. A unique reservation system was fully implemented starting October 2015.

This completed one of the biggest and most important airline mergers in the world up to this moment.

[3]We can basically define a slot as a permit to land or take off at an airport which usually faces capacity constraints.

[4]This figure underlines the importance and value that are attributed to slots at city airports such as Washington National and New York LaGuardia.

Chapter 2

Structural Methods

Understanding the functioning of markets is at the core of microeconomic applications, common in the Industrial Organization literature. Therefore, it is essential to understand how demand and supply behave to make the correct predictions, to solve policy questions, but also to determine firms' strategies. The diffusion of empirical industrial organization has made it possible to evaluate mergers, quantify damages in antitrust litigation, decide regulatory matters, set prices, design auctions and markets.[1] Structural estimation refers to the fact that the researcher investigates parameters which "describe the consumer preferences, production technology and institutional constraints" (Decarolis, 2018, p. 5). When looking at the equilibrium in a market, researchers try to identify the preferences of consumers and the supply functions of firms. In practice, both the theoretical literature and empirical applications have focused on the estimation of demand systems. On the contrary, supply is often left as a residual, mainly because more data are available for the demand-side and also because it has proved quite difficult to understand firms' costs.

The objective of this chapter is to review some models of demand, focusing on discrete choice methods, and illustrate the common Bertrand multiproduct oligopoly model.

[1] Several applications are illustrated in Einav and Levin (2010).

2.1 Demand estimation: from product space to characteristics space

The problem of modelling demand has been solved in the literature by means of demand systems in product space and demand systems in characteristics space.

In the former, individuals make choices between products. This family includes models such as the linear expenditure system (Stone, 1954), the CES demand system (Spence, 1976; Dixit and Stiglitz, 1977) and the AIDS (Almost Ideal Demand System; Deaton and Muellbauer, 1980). The problems which generally arise from this kind of models are basically five (Nevo, 2011; Decarolis, 2018). In the first place, dimensionality increases substantially: not only there is a problem regarding the number of varieties, but also the amount of observations is generally not enough to perform the estimation. In the second place, a representative consumer is assumed. However, demand models shall incorporate heterogeneity in consumers' tastes, so that ignoring this factor could lead to biases. Moreover, this assumption entails issues regarding the parametrization of specific consumer behaviour. Fourthly, it is almost impossible to predict the demand for goods not yet available in the market: this arises from the estimation of new parameters and insufficient data. Eventually, there is a problem of endogeneity of prices which requires as many instrumental variables as the number of prices.

The family of models which refer to the characteristics space, on the other hand, is distinguished by the fact that each product is considered as a collection (a bundle) of characteristics. For example, in air transportation, relevant characteristics could include price, number of connections, restrictions applied to the ticket, baggage allowance, etc. A consumer would therefore choose a product (in the example, would buy a ticket for a certain flight) by considering these characteristics. The dimensionality problem which we have pointed out to above is less relevant in this context, as the attributes define the parameters to be estimated.

In this setting, it is the utility of consumers which depends on the characteristics of products and individual taste. Thus the aggregation of the choices of individual consumers will determine market-level demand.

Discrete choice models In the discrete choice models, it is not necessary for the researcher to observe the whole set of characteristics of products. The main elements which are necessary are the prices and quantities sold by firms in the market.

Let us denote with $\mathbf{x} = (x_1, x_2, \ldots, x_N)$ the observable characteristics which affect demand, with $\mathbf{w} = (w_1, w_2, \ldots, w_N)$ the ones which affect marginal costs. Moreover, define as $\boldsymbol{\xi} = (\xi_1, \xi_2, \ldots, \xi_N)$ the unobserved demand characteristics and as $\boldsymbol{\omega} = (\omega_1, \omega_2, \ldots, \omega_N)$ the unobserved cost variable. Following Berry's (1994) notation, the utility of each consumer i for product j can be written as

$$U(x_j, \xi_j, p_j, \nu_i, \theta_d) = u_{ij} = x_j\beta_i - \alpha_i p_j + \xi_j + \epsilon_{ij} \tag{2.1}$$

Hence, α measures the marginal valuation relative to the price, while the vector β the impact of all the other observable characteristics.

Nevo (2011) underlines that that the term ξ_j is an important part of the specification. In fact, "[i]n many cases we might doubt the ability of observed characteristics to capture the essence of the product. [...] The unobserved characteristic is meant to address this type of concerns. It captures unobserved attributes of the product, unquantifiable factors (brand equity), systematic shocks to demand, or unobserved promotional activity. [...] [I]t is essential to explain the data" (p. 59). Considering these terms, we define the mean utility of product j as

$$\delta_j \equiv x_j\beta - \alpha p_j + \xi_j \tag{2.2}$$

In particular, in models where consumers' tastes are i.i.d., only the mean utilities δ_j are different from one another. Therefore, δ_j will determine elasticities and market shares. Eventually, the role of ϵ_{ij} is to make utility stochastic for the research, as it cannot account for the fact that, despite being $\delta_{1j} = \delta_{2j}$, individual 1 and individual 2 make different choices. Therefore, while ϵ_{ij} is deterministic for the individuals, it is stochastic for the researcher (as there is a part for which he cannot give an explanation). Hence, in these models ϵ plays the role of an unobserved, product- and consumer-specific characteristic. In the various logit models, it is assumed to follow an Extreme Type I distribution.

In this model, the role of utility is central. In fact, individuals purchase the good for which their utility is the highest. In other words, when facing characteristics $\mathbf{x}$ and $\boldsymbol{\xi}$ and prices $\mathbf{p}$, good j is preferred over any other good k if

$$U(x_j, \xi_j, p_j, \nu_i, \theta_d) > U(x_k, \xi_k, p_k, \nu_i, \theta_d) \qquad \forall k \neq j$$

The choice is thus based on a set of unobservables which can be defined as $A_j(\delta) = \{\nu_i \mid \delta_j + \nu_{ij} > \delta_k + \nu_{ik}\}$ which contributes to define market shares, i.e. the probability that ν_i falls into A_j:

$$\mathfrak{s}_j\left(\boldsymbol{\delta}\left(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}\right), \mathbf{x}, \boldsymbol{\theta}\right) = \int_{A_j(\boldsymbol{\delta})} f(\mathbf{v}, \mathbf{x}, \sigma_v)\, d\mathbf{v}$$

When the dimension of a market is H, we have that that the observed output is

$$q_j = H\mathfrak{s}_j \tag{2.3}$$

Eventually, the system needs to be completed by allowing for the option that a consumer would not buy any good, i.e. will choose the so-called outside option. In this case, the utility is set to zero: $u_{ij} = 0$.

2.1.1 The logit model

The simplest model in the discrete choice framework is the one known as simple logit. In fact, the formula for the choice probabilities takes a closed form (Train, 2009).

Recall from the previous section that the error term ϵ follows an Extreme Value Type I distribution: its density and cumulative functions take the following forms

$$f(\epsilon_j) = \exp(-\epsilon_j)\exp\left(-e^{-\epsilon_j}\right) \qquad F(\epsilon_j) = \exp\left(-e^{-\epsilon_j}\right) \tag{2.4}$$

When ϵ_j and ϵ_i are i.i.d. Extreme Value Type 1, $\epsilon^\star = \epsilon_j - \epsilon_i$ is distributed according to the logistic

$$F(\epsilon^\star) = \frac{\exp(\epsilon^\star)}{1 + \exp(\epsilon^\star)}$$

From above, we have that the probability of consumer i choosing product j is

$$\begin{aligned} Pr_{ij} &= Pr\left(\delta_{ij} + \epsilon_{ij} > \delta_{ik} + \epsilon_{ik}\right) \\ &= Pr\left(\epsilon_{ik} < \delta_{ij} - \delta_{ik} + \epsilon_{ij}\right) \\ &= \exp\left(-e^{-(\delta_{ij} - \delta_{ik} + \epsilon_{ij})}\right) \end{aligned}$$

where the last inequality follows from (2.4). As the ϵ are independent, the cumulative for all $k \neq j$ is the product:

$$Pr_{ij} \mid \epsilon_{ij} = \prod_{k \neq j} \exp\left(-e^{-(\delta_{ij} - \delta_{ik} + \epsilon_{ij})}\right)$$

and, being ϵ_{ij} not given, it is possible to integrate to get rid of it, using the density function of (2.4):

$$Pr_{ij} = \int \left[\prod_{k \neq j} \exp\left(-e^{-(\delta_{ij} - \delta_{ik} + \epsilon_{ij})}\right)\right] \exp\left(-\epsilon_{ij}\right) \exp\left(-e^{-\epsilon_{ij}}\right) \, d\epsilon_{ij}$$

from which it is possible to obtain the formula for probabilities of choices (and thus, market shares):

$$s_j = \frac{\exp\left(\delta_j\right)}{1 + \sum_{n=1}^{N} \exp\left(\delta_n\right)}$$

Outputs can be retrieved using (2.3). Eventually, the own-price elasticity is determined according to the following:

$$\eta_{jj} = \frac{\partial s_j}{\partial p_j} \frac{p_j}{s_j} = -\alpha p_j \left(1 - s_j\right)$$

Problems of the simple logit We briefly examine the problems of this simple logit model, following Train (2009). The first issue concerning simple logit models is the limited possibility to represent taste variation. While variations attributable to systematic and observed characteristics can be incorporated, the ones depending on unobservables or chance cannot. For instance, let us consider a traveller buying a ticket. We could assume that the purposes of the trip (tourist or business) will affect his sensitivity to price. These difference can be included in the logit. However, if we want it to vary with respect to unobservables or purely randomly, then this is not possible in this framework. In the second place, this model is characterized by the property of independence of irrelevant alternatives, that is, the relative odds of choosing a product j over k are the same, independently of other available alternatives or their attributes. This implies that cross-demand elasticities are the same for any product:

$$\eta_{jk} = \frac{\partial s_j}{\partial x_k} \frac{x_k}{s_j} = \beta x_k s_k$$

This assumption might be unrealistic in some contexts. However, when the IIA is valid (this can also be tested), it simplifies a lot the estimation of parameters. Lastly, there is a problem concerning the use of time-series: when unobserved factors influence dynamics, the logit is not adequate to explain the data, as it is assumed that the unobservables are unrelated over choices.

2.1.2 The nested logit model

The nested logit model belongs to a more general class of models known as Generalized Extreme Value (GEV), which is characterized by the fact that the unobserved parts of utility are jointly distributed as a generalized extreme value. Actually, it is possible to show that also the simple logit model belongs to this class. In fact, GEV allows for alternatives to be correlated and, when all correlations are zero, the distribution collapses to the simple logit.

In a nested logit specification, products are divided into mutually exclusives nests $g = 1, \dots, G$. There is also an additional group (let us call it 0) which only contains the outside good. Utility can now be defined as follows (for simplicity, we will consider the case of a single level of nesting):

$$u_{ij} = \delta_j + \zeta_{ig} + \left(1 - \sigma^G\right) \nu_{ij} = \delta_j + \epsilon_{ij}$$

where ϵ_{ij} follows the GEV cumulative distribution

$$F(\epsilon_{ij}) = \exp\left(-\sum_{k=1}^{K}\left(\sum_{j\in g}\exp\left(-\epsilon_{ij}/\left(1-\sigma^G\right)\right)\right)^{1-\sigma^G}\right)$$

The parameter which assumes particular relevance is σ^G.[2] In particular, one can think of it as (although, strictly speaking, it is not) a correlation in unobserved utility, considering the goods in a certain nest. So, when $\sigma^G = 0$, there is not any correlation, i.e. there is complete independence in nest g. If this holds for all nests, then we are back to the logit model explained above.

The probability of choosing good $j \in g$ is

$$s_j = Pr_j = \frac{e^{\delta_j/\left(1-\sigma^G\right)}\left(\sum_{j\in g} e^{\delta_j/\left(1-\sigma^G\right)}\right)^{-\sigma^G}}{\sum_{g\in G}\left(\sum_{j\in g} e^{\delta_j/(1-\sigma^G)}\right)^{(1-\sigma^G)}} = \frac{e^{\delta_j/\left(1-\sigma^G\right)} D_g^{-\sigma^G}}{\sum_{g\in G}\left(D_g^{(1-\sigma^G)}\right)} \tag{2.5}$$

Taking alternatives $j \in a$ and $k \in b$ and the ratio of their probabilities:

$$\frac{Pr_j}{Pr_k} = \frac{e^{\delta_j/\left(1-\sigma^A\right)}\left(\sum_{l\in a} e^{\delta_l/\left(1-\sigma^A\right)}\right)^{-\sigma^A}}{e^{\delta_k/(1-\sigma^B)}\left(\sum_{l\in b} e^{\delta_l/(1-\sigma^B)}\right)^{-\sigma^B}}$$

if $A = B$ (i.e. the goods are in the same nests), only the first part remains (because $1-\sigma^A = 1-\sigma^B$ and the summation is the same):

$$\frac{Pr_j}{Pr_k} = \frac{e^{\delta_j/\left(1-\sigma^A\right)}}{e^{\delta_k/(1-\sigma^B)}}$$

and independence of irrelevant alternatives still holds.

In the foregoing, we have explained that the outside good is part of a so-called group zero, in which it is the unique component. Therefore, by applying formula (2.5), being utility normalized to zero, we have that $\delta_0 = 0$ and $\sum_{k=0}\exp\left(\delta_k/\left(1-\sigma^G\right)\right) = 1$, so that

[2]It is required that the σ^G parameter belongs to the interval $[0, 1)$. In addition to the possibility to test whether $\sigma^G = 0$, indicating that the simple logit is a reasonable specification, when the estimated parameter does not belong to this interval, the model is not consistent with utility maximization. We refer to Train (2009, p. 81) for a more detailed explanation.

its share is

$$s_0 = Pr_0 = \frac{1}{\sum_{g \in G} \left(\sum_{j \in g} e^{\delta_j / (1-\sigma^G)} \right)^{(1-\sigma^G)}} = \frac{1}{\sum_{g \in G} \left(D_g^{(1-\sigma^G)} \right)} \tag{2.6}$$

Taking the difference of the logarithms of (2.5) and (2.6) gives

$$\ln (s_j) - \ln (s_0) = \delta_j / \left(1 - \sigma^G\right) - \sigma^G \ln (D_g) \tag{2.7}$$

At this point, it is possible to invert the formula for group shares:

$$\bar{s}_g (\delta, \sigma) = \frac{D_g^{\left(1-\sigma^G\right)}}{\sum_{g \in G} \left(D_g^{(1-\sigma^G)} \right)} \iff \ln (D_g) = [\ln (\bar{s}_g) - \ln (s_0)] / \left(1 - \sigma^G\right) \tag{2.8}$$

Eventually, combining (2.7) and (2.8) and expressing δ_j as per (2.2) gives:

$$\ln (s_j) - \ln (s_0) = x_j \beta - \alpha p_j + \sigma^G \ln (\bar{s}_{j|g}) + \xi_j$$

so that it is possible to recover the the parameters of interests using a linear regression.[3]

The nested logit relaxes some assumptions of the simple logit model and allows for richer possibilities in substitution patterns, still ensuring relative computational tractability. In fact, while linear estimation is generally possible (although it depends on the exact estimation one would like to perform), it allows for "non-trivial interactions between product and consumer characteristics" (Berry 1994, p. 254). The nested logit model can be interpreted, as Berry (1994) underlines, as "a random coefficient model involving random coefficients ζ_{ig} only on group-specific dummy variables" (p. 252). For this reason, it is often used in applications.

2.1.3 The random coefficients logit model

A further extension is provided by the random coefficients logit model, also known as BLP (Berry, Levinsohn and Pakes; see Berry et al. 1995) or mixed logit. This model is

[3]When extending the model including also a second level of nesting, the regression becomes $\ln (s_j) - \ln (s_0) = x_j \beta - \alpha p_j + \sigma^G \ln (\bar{s}_{h|g}) + \sigma^{HG} \ln (\bar{s}_{j|hg}) + \xi_j$

more complex than the ones presented in the foregoing and – since it will not be used in the present work – only a brief review follows.

The major advantages of such a specification are the fact that it allows random taste variation, substitution patterns which are not restricted and correlation in unobserved factors over time. For instance, if a traveller likes first class, then he is more likely to buy a first-class ticket than the average traveller.

The name of the model comes from the fact that each individual could potentially have different sensitivities for each of the characteristics included in the specification. More specifically, utility can be represented in the usual fashion

$$u_{ij} = -\alpha_i p_j + x_j \beta_i + \xi_j + \epsilon_{ij}$$

where ϵ_{ij} are i.i.d. Extreme Value Type 1. Note that, in this case, the coefficients on the price and the observable characteristics (respectively, α and β) have been represented as consumer-specific (this is specified by the subscript i). In fact, it is possible to say that they are randomly distributed around a mean value, that is

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \nu_i$$

where the ν_i are i.i.d. as a Normal, $N(0, \Sigma)$. In this sense, individuals can be thought having different sensitivities, but each of them averages to a product-specific mean sensitivity. In this model, Independence of Irrelevant Alternatives is not present and elasticities are much more flexible. However, as there is not any closed form to solve for, Berry et al. (1995) propose a fixed point algorithm for the estimation. The computational power required is therefore more relevant in this case.

2.2 Supply side

In the following, we examine the standard behaviour of firms, as per Björnerstedt and Verboven (2014).

The objective of a firm f which produces a variety of products $\{j \mid j \in F_f\}$ is to maximize its combined profits, namely

$$\max \quad \Pi_f(\mathbf{p}) = \sum_{j \in F_f} (p_j - c_j)\, q_j(\mathbf{p}) + \phi \sum_{j \notin F_f} (p_j - c_j)\, q_j(\mathbf{p}) - FC$$

where p_j and c_j represent, respectively, the price and marginal cost of product j, $\phi \in [0,1]$ is a conduct parameter which represents the level of coordination (collusion) of firms and FC is a fixed cost. The first-order condition of the firm's problem, when choosing prices, is

$$\frac{\partial \Pi_f}{\partial p_j} = q_j(\mathbf{p}) + \sum_{k \in F_f} (p_k - c_k) \frac{\partial q_k(\mathbf{p})}{\partial p_j} + \phi \sum_{k \notin F_f} (p_k - c_k) \frac{\partial q_k(\mathbf{p})}{\partial p_j} = 0 \qquad \forall j \in F_f \tag{2.9}$$

When all firms play this strategy, this is a Bertrand-Nash equilibrium. It is useful to rewrite the first-order conditions as shown below. Firstly, define the firms' product-ownership matrix $\Theta_{J \times J}$, whose generic element is

$$\theta\,(j,k) = \begin{cases} 1 & \text{if } j \text{ and } k \text{ are produced by the same firm} \\ \phi & \text{otherwise} \end{cases}$$

There are two basic cases: if $\phi = 0$, Θ is a block diagonal matrix (sorting products by firms); if each firm only produces one good, $\Theta = \mathrm{I}_{J \times J}$. Moreover, define as $\mathbf{q}(\mathbf{p})$ the $J \times 1$ demand vector, $\Delta(\mathbf{p}) = \partial \mathbf{q}(\mathbf{p}) / \partial \mathbf{p}'$ the $J \times J$ Jacobian of first derivatives w.r.t. prices and, eventually, $\mathbf{c}$ the $J \times 1$ marginal cost vector. Accordingly, (2.9) is rewritten as

$$\mathbf{q}(\mathbf{p}) + (\Theta \odot \Delta(\mathbf{p}))\,(\mathbf{p} - \mathbf{c}) = 0$$

or, in a more interesting formulation,

$$\mathbf{p} = \mathbf{c} - (\Theta \odot \Delta(\mathbf{p}))^{-1}\, \mathbf{q}(\mathbf{p}) \tag{2.10}$$

so that we are back with a slight variation of the well-known formula for prices as function of costs and markups. Moreover, it is evident that one could solve for the equilibrium marginal cost by knowing the prices and (estimating) price elasticities. In fact, in practice, marginal costs are very difficult to observe (even from the firms' point of view). In counterfactual simulations, therefore, one typically uses the marginal costs which are consistent or implied in the model.

Merger simulation Using the instruments and the models set up, merger simulation amounts to a change in the ownership matrix Θ. In fact, it is sufficient to change the matrix so that the elements $\theta(j,k)$ will be equal to 1 when they refer to products which are produced by the new merged firm. According to the new system of equations determined by this change, the new firm will maximize its joint profits, taking into account the products of the two merged entities. A final note regards efficiencies, which are usually claimed by merging firms. In fact, absent any efficiency, mergers increase market power and lower consumer surplus and total welfare. However, "it is well established in the economic literature that efficiency gains might offset the enhanced market power of merging firms and result in higher welfare. This is because the merger might cause the insiders to be more efficient and save on their unit costs" (Motta 2004, p. 238). Thus, during the procedures of merger review, firms often claim that they will be able to obtain efficiencies thanks to rationalisation and economies of scale or scope: using counterfactual simulations it is also possible to take into account such efficiencies. In fact, the $\mathbf{c}$ vector in (2.10) can be changed accordingly.

Chapter 3

Empirical analysis

The empirical analysis will be performed using the models illustrated in the foregoing. This chapter presents first the sample used for this work, then reviews the specification and estimation of demand parameters. In the third part, simulation is performed. Lastly, results are evaluated in light of ex-post data using difference-in-differences techniques.

3.1 Sample selection

The investigation is based on market data, collected from the US Department of Transportation Airline Origin and Destination Survey (DB1B).[1] Basically, DB1B is a 10% sample of airline tickets issued by air carriers in the United States, reported quarterly from 1993 until today. In summary, for each ticket issued by an airline, DB1B reports the origin, the destination, connecting airports (if any), ticketing and operating carriers,[2] number of passengers, fare class and (prorated) fare, miles flown.

DB1B contains three different data tables: Coupon, Market and Ticket. The main source for our purposes is DB1BMarket, which summarizes coupon data into single trips.[3]

[1]Available at `https://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=125`

[2]This information is fundamental as there are companies which operate service for other carriers. For example, Republic Airways is a regional airline which operates as American Eagle, Delta Connection and United Express (which are competitors). However, Republic Airways does not issue tickets for its own flights. Tickets are issued and sold by the ticketing carrier for which the flight is operated.

[3]DB1B records one coupon for each single flights. Consequently, if a passenger is travelling from Boston BOS to Washington, D.C. DCA via New York LGA, it would record a coupon BOS-LGA and another one LGA-DCA. DB1BMarket would summarize this information into a single record BOS-LGA-DCA,

However, coupon data are also used to determine the restrictions applied to the ticket. This is one step ahead of related literature, which did not include restrictions and generally relegated it to the unobservable part. Restrictions on single coupons are used to determine a summarised measure for the restrictions applied on the one-way journey. In particular, when different coupons are characterized by different restrictions, the most restricted class is applied to the whole one-way journey. The reason is that if a single leg of the journey is restricted, then it is impossible for the passenger to change or refund the ticket: while he could move the date for one leg, he cannot do that for the other and, as a consequence, the ticket as a whole becomes substantially restricted.[4]

Also, we apply other selection criteria which are standard in the literature (see, e.g., Peters, 2006; Berry et al., 2006; Berry and Jia, 2010). In particular, we use data reported only by US carriers flying over US and US territories. Moreover, we do not include trips which include different ticketing carriers. The reason is that it would be difficult to assume that prices for an itinerary involving a stop and different marketing carriers are set taking into account a market as defined in the present work, i.e. from the origin to the destination airport.[5] Also, we do not include in our data journeys which are characterized by more than one stop (each way) and when ground traffic is included. Eventually, tickets which have very low (less than $ 25) and very high fares (more than $ 9,999) are not considered. In fact, the former are very likely to be employee tickets or purchased using frequent flyer programs, while the latter probably include typing errors. As fares as concerned, in addition, records are aggregated according to progressive fare bins for the purposes of estimating the demand parameters.[6] This is done mainly in order to reduce the computational burden, without losing too much information.

recording BOS as origin, DCA as destination and LGA as connecting airports, respectively.

[4]In fact, determining restrictions is rather straightforward when the entire ticket is issued in a single or comparable fare class. However, it becomes trickier when there is a stop and change of fare class. For instance, using the example above, BOS-LGA might be on an unrestricted economy class, while LGA-DCA on a restricted economy class. In this case, as explained, we apply the most restricted class to the whole journey (one leg is, indeed, not modifiable).

[5]In fact, in this case, passenger flying on carrier A for the BOS-LGA route and on carrier B for the LGA-DCA route, using two different tickets, would pay the price for the BOS-LGA market and for the LGA-DCA market.

[6]We use the same bins as in Berry and Jia (2010): in particular, $ 20 in the $ 25-700 range, $ 50 in the $ 700-1,000 range and $ 100 for tickets above $ 1,000.

In addition, we use data on frequency from the Official Airline Guide (OAG),[7,8] extracting the quarterly frequency on the routes considered. Data from OAG allow to overcome a common problem in the literature, as the BTS T-100 Database does not report the marketing carrier, rather only the operating airline. As explained in footnote 2, the same regional carrier may serve different national airlines on a route, so that it would have been necessary to reconstruct flight frequency proportionally to the number of passengers transported. Thanks to the different reporting system of OAG, this is not needed and the frequency variable is more precise.[9]

Lastly, the size of the market is usually defined in the literature as a function of the population of the endpoint cities of the flights. However, in order to limit the computational burden and focus the attention on the most relevant markets, an additional filter is applied, i.e. routes departing or arriving to airports situated in metropolitan areas with less than 850,000 inhabitants are not considered. This still leaves more than 10,000 markets each quarter in the data. Data concerning the location of airports in the metropolitan areas is from the Intermodal Passenger Connectivity dataset of the US DoT,[10] while population is taken from the Population Change for Metropolitan and Micropolitan Statistical Areas of the US Census Bureau.[11] The sample includes years from 2011 to 2016.

3.1.1 Data Summary

Table 3.1 reports the summary statistics for the sample, divided in three columns: the first for the years observable in the ex-ante analysis (2011-2012), the second for the years afterwards (2013-2016) and the last for all years in the data considered. Respectively, the tickets included in the samples are 70,149,554, 152,244,514 and 222,394,068.

The average fare has increased between the two periods, from 209.7 to 218.7 dollars. It is also possible to appreciate this shift by observing the plotted kernel densities for fares

[7] Available at `https://www.oag.com/`

[8] I am grateful to Paolo Lio and Nicolò Filardo for their help.

[9] Alternatively, one could use the Bureau of Transportation Statistics Airline On-Time Performance Database, available at `https://www.transtats.bts.gov/Tables.asp?DB_ID=120&DB_Name=Airline%20On-Time%20Performance%20Data&DB_Short_Name=On-Time`. Nonetheless, it reports the marketing carrier beginning 2018 only, making it ineffective for this work.

[10] Available at `https://www.transtats.bts.gov/tables.asp?db_id=640&DB_Name=`

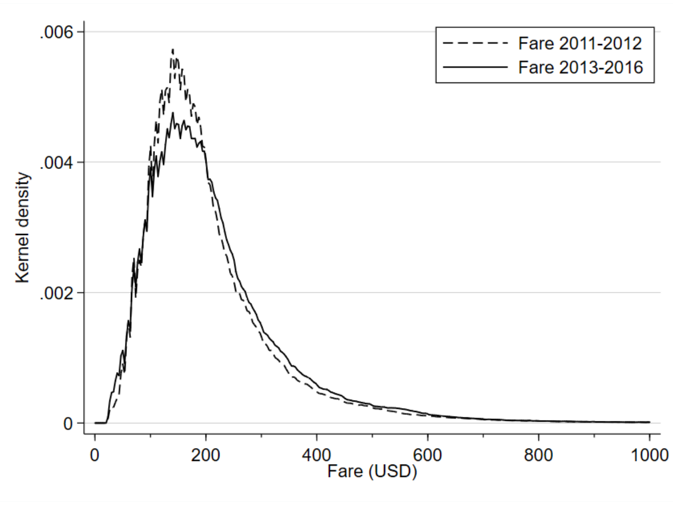
[11] Available at `https://www.census.gov/programs-surveys/metro-micro/data/tables.All.html`

Table 3.1: Summary Statistics for the Sample

	2011-2012		2013-2016		2011-2016	
	Mean	SD	Mean	SD	Mean	SD
Fare (100 USD)	2.097	(1.539)	2.187	(1.624)	2.159	(1.598)
Product share	1.02e-05	(6.01e-05)	9.64e-06	(4.43e-05)	9.82e-06	(4.98e-05)
Inside share	0.003	(0.007)	0.003	(0.006)	0.003	(0.006)
Nr of stops	0.268	(0.443)	0.253	(0.435)	0.258	(0.437)
Daily frequency	3.448	(2.290)	3.255	(2.220)	3.319	(2.246)
Distance (1000 M)	1.128	(0.724)	1.146	(0.720)	1.141	(0.721)
Hub at origin	0.221	(0.415)	0.247	(0.431)	0.239	(0.426)
Hub	0.553	(0.497)	0.565	(0.496)	0.561	(0.496)
Slot-control	0.174	(0.386)	0.182	(0.393)	0.180	(0.391)
American (AA)	0.113	(0.317)	0.152	(0.359)	0.140	(0.347)
Alaska (AS)	0.032	(0.177)	0.040	(0.196)	0.038	(0.190)
JetBlue (B6)	0.054	(0.225)	0.054	(0.226)	0.054	(0.226)
Continental (CO)	0.030	(0.172)			0.010	(0.097)
Delta (DL)	0.185	(0.388)	0.186	(0.389)	0.186	(0.389)
Frontier (F9)	0.025	(0.156)	0.026	(0.158)	0.025	(0.158)
AirTran (FL)	0.044	(0.205)	0.008	(0.087)	0.019	(0.137)
Allegiant (G4)	0.011	(0.104)	0.016	(0.125)	0.014	(0.119)
Hawaiian (HA)	0.009	(0.092)	0.009	(0.093)	0.009	(0.093)
Spirit (NK)	0.016	(0.127)	0.030	(0.171)	0.026	(0.158)
Sun Country (SY)	0.003	(0.055)	0.004	(0.064)	0.004	(0.061)
United (UA)	0.117	(0.322)	0.139	(0.346)	0.132	(0.339)
US Airways (US)	0.104	(0.305)	0.065	(0.247)	0.077	(0.267)
Virgin Am. (VX)	0.015	(0.121)	0.016	(0.126)	0.016	(0.124)
Southwest (WN)	0.241	(0.428)	0.256	(0.436)	0.251	(0.434)
Nr of tickets	70,149,554		152,244,514		222,394,068	

Hub = 1 if either the origin, the connecting or destination airport is a hub for the carrier. Slot-control refers to the number of slot controlled airports aircraft passes in. Values for US Airways (US) are present in the second period as the code was retired only in October, 2015.

Figure 3.1: Fare dispersion (one-way tickets)



Note: the graph is truncated at 1000 dollars.

in Figure 3.1. In fact, the distribution for the second period is less skewed right.

The product share is on average very small as it is considered out of the total market potential, i.e. the geometric average of the population of the endpoint cities.

It is also possible to observe that connecting passengers diminished (from 26.8% to 25.3%), following a trend already present in Berry and Jia (2010, p. 14) determined by the partial dismantling of more traditional hub-and-spoke models towards point-to-point networks. However, it is still true that half of passengers pass through (either originating from, connecting in or arriving to) legacy carriers' hubs.

Low-cost carriers (JetBlue, Frontier, Allegiant, Spirit, Sun Country, Southwest, AirTran, Virgin America and Hawaiian) account for about 41% of the tickets.

The most represented carrier in the years 2011-2012 is Southwest (24%), followed by Delta (19%), United (12%) and American (11%). Afterwards, American becomes the second most relevant, as it accounts for almost 22% of the tickets.

3.2 Demand specification

In this section we are going to illustrate the empirical model used to estimate the demand parameters.

As set out in the foregoing, a discrete choice model will be exploited. Otherwise – as Peters (2006) highlights – a long time series of data would be needed to identify parameters for each market, as they are released on a quarterly level. In addition, while it is true that the markets analyzed are served by the same group of airlines, yet each geographic market is characterized by a unique combination of products. Therefore, differently from other industries, it is particularly unreasonable to impose restrictions concerning elasticities across different markets.

We will therefore exploit a nested logit model. As underlined, indeed, it allows for significant possibilities in substitution patters, still being computationally tractable.

Based on the available data, a market is defined as an ordered airport-pair combination. For instance, New York-Los Angeles and Los Angeles-New York are different markets. A product in the market is defined as a combination of itinerary (sequence of airports),[12] ticketing carrier, restrictions applied to the ticket and fare in bins. As explained, each market also allows for an outside good, i.e. travelling between the cities using other means of transportation or not travelling at all.

The following elements represent the observable characteristics for the demand side:

(i) the fare – expecting that demand decreases as fare increases;

(ii) the average frequency – expecting that more frequent flights impact positively on utility, as travellers will be more likely to find a flight which matches their needs;

(iii) distance – expecting that demand increases with it, as other means of transportation become worse substitutes for longer distances;

(iv) number of stops – expecting that travellers dislike connecting in another airport, being direct flights preferred, both in terms of time and convenience;

[12]In this case, New York-Chicago-Los Angeles is a different product than New York-Dallas-Los Angeles, but they belong to the same New York-Los Angeles market.

(v) restrictions – expecting that it will impact negatively on utility, as the ticket holder cannot change or refund his ticket in case of need.

Moreover, we allow utility to depend on unobservable components: for this reason, time and carrier fixed-effects are included in the model. In fact, airline policies regarding baggage, not to mention frequent flyers programs and on-board service are likely to be taken into account by travellers, when choosing a product. As it is not possible to observe and include these elements, they represent the unobservable (to the researcher) components of product quality (conventionally, ξ_j). We are going to consider fares and frequencies as endogenous, and the other variables as exogenous.

As far as the model is concerned, we allow for a two-level nesting structure. The upper nest separates travelling by plane from the outside option, while the lower level differentiates between non-stop and itineraries with a layover. The structure will be evaluated comparing the values of σ^G and σ^{HG} which approximately represent the level of within-group substitution (respectively, between airline products and between direct flights). The restriction for this model to be valid is, therefore, that $1 > \sigma^{HG} \geq \sigma^G \geq 0$ (in fact, products belonging to the same sub-nest shall be closer substitutes, compared to the ones belonging to the other nest).

Instruments Berry (1994) and Berry et al. (1995) underline that a problem in estimating the structural equation is that prices are correlated with the unobserved characteristics ξ_j. As a consequence, it is necessary to perform an instrumental variable regression. Standard instruments in the literature of demand estimation are the so-called BLP instruments (which include characteristics of other products), Hausman-Nevo instruments (which are based on prices in other markets) and Arellano-Bond instruments (which include lags of prices and market shares). In this setup, the fare and frequency of flights coefficients are endogenous: instrumentation will thus aim to the identification of these parameters.[13] As aforementioned, however, it is not really possible to use instruments which refer to other markets: not only because the combination of products is peculiar for each market, but also because shocks might be spatially correlated. The literature focuses on using route-level characteristics. In addition, factors which affect costs (but not demand) are

[13]In addition, instruments are required for the identification of the σ.

also considered. It is assumed for this reason that the overall network structure of an airline is exogenous (see Peters, 2006).

In this setup, the instrumentation set includes the characteristics regarding rivals' direct flights, number of destination, average distance, number of carriers. The intuition for which these instruments can identify the parameters of interest is that the competitive environment affects price and frequency. For instance, if the number of closer substitutes increases, then it is likely for prices to fall. In addition, the hub status of origin, destination and connecting airports is included, as a result of the claim that economies of scale are present in carriers' hub airports. Whether an airport is slot-controlled by the FAA is taken into account, too, as airlines have higher costs when flights depart from or arrive to these airports since, usually, slots need to be purchased or result from auctions. Eventually, the other regressors of the main equation are included instruments.

3.2.1 Demand parameters

The results of the regression are displayed in Table 3.2. The table provides results for three different periods: 2011-2012, 2013-2016 and all years. In particular, the estimation for the first period includes a sample which would be observed in an ex-ante analysis. The second block, on the other hand, contains the estimated parameters for the years afterwards, while the third spans the whole sample.

Each block is then divided into two columns, in which – respectively – estimates from the one-level nested logit and two-level nested logit models are reported. Observations are around 7.5 million in the first period, 16 in the second and almost 24 million in total. Markets are on average around 11,000 in each group.[14]

As far as the specification of the model is concerned, there is evidence supporting the fact that a two-level nested logit model is more appropriate in explaining the data. In fact, the restriction $1 > \sigma^{HG} \geq \sigma^{G} \geq 0$ is verified in the three periods and the estimation is sufficiently precise. This suggests – as one could expect – that, on the one hand, direct itineraries are closer substitutes for other direct journeys than connecting ones and, on the other, that there is higher correlation among choosing to fly rather than using other means of transportation or even not travelling at all.

[14]The figure in the table differentiates the same geographic market based on year and quarter.

Table 3.2: Results from demand estimation

	2011-2012				2013-2016				All years			
	(1) One-level NL		(2) Two-level NL		(3) One-level NL		(4) Two-level NL		(5) One-level NL		(6) Two-level NL	
Fare (in 100 USD)	-0.572***	(0.0201)	-0.602***	(0.0272)	-0.519***	(0.0198)	-0.522***	(0.0244)	-0.537***	(0.0194)	-0.548***	(0.0245)
Daily frequency	0.176***	(0.0102)	0.178***	(0.0102)	0.144***	(0.0070)	0.144***	(0.0068)	0.154***	(0.0075)	0.155***	(0.0074)
Distance (in 1000 miles)	0.438***	(0.0185)	0.497***	(0.0381)	0.391***	(0.0173)	0.398***	(0.0358)	0.407***	(0.0170)	0.431***	(0.0354)
Nr. of stops	-1.599***	(0.0299)	-1.704***	(0.0607)	-1.588***	(0.0304)	-1.600***	(0.0613)	-1.596***	(0.0296)	-1.639***	(0.0598)
Restricted ticket	0.078***	(0.0088)	0.035**	(0.0107)	0.204***	(0.0070)	0.202***	(0.0107)	0.168***	(0.0057)	0.159***	(0.0144)
σ^G	0.380***	(0.0122)	0.305***	(0.0427)	0.373***	(0.0097)	0.365***	(0.0394)	0.375***	(0.0102)	0.345***	(0.0398)
σ^{HG}			0.435***	(0.0388)			0.380***	(0.0376)			0.399***	(0.0372)
American (AA)	-0.071	(0.0961)	-0.026	(0.0994)	0.110	(0.0750)	0.114	(0.0768)	0.069	(0.0792)	0.085	(0.0815)
Alaska (AS)	0.430***	(0.0936)	0.423***	(0.0967)	0.404***	(0.0706)	0.403***	(0.0710)	0.408***	(0.0754)	0.405***	(0.0767)
JetBlue (B6)	-0.011	(0.0883)	-0.048	(0.0953)	0.303***	(0.0725)	0.303***	(0.0731)	0.215**	(0.0754)	0.209**	(0.0777)
Continental (CO)	-0.061	(0.0926)	-0.015	(0.0967)					0.028	(0.0770)	0.047	(0.0804)
Delta (DL)	0.026	(0.0929)	0.061	(0.0956)	0.169*	(0.0725)	0.172*	(0.0735)	0.133	(0.0766)	0.145	(0.0781)
Frontier (F9)	0.062	(0.0821)	0.081	(0.0842)	0.206**	(0.0635)	0.206**	(0.0637)	0.162*	(0.0674)	0.167*	(0.0681)
AirTran (FL)	0.080	(0.0820)	0.087	(0.0845)	0.103	(0.0654)	0.108	(0.0685)	0.145*	(0.0683)	0.153*	(0.0694)
Allegiant (G4)	0.472***	(0.0915)	0.343*	(0.1340)	0.420***	(0.0742)	0.404***	(0.1140)	0.428***	(0.0772)	0.374**	(0.1170)
Hawaiian (HA)	2.206***	(0.1390)	2.188***	(0.1420)	1.915***	(0.1430)	1.912***	(0.1440)	2.007***	(0.1370)	1.996***	(0.1390)
Spirit (NK)	-0.117	(0.0948)	-0.163	(0.1020)	-0.219***	(0.0651)	-0.223**	(0.0690)	-0.222**	(0.0703)	-0.239**	(0.0756)
United (UA)	0.079	(0.0919)	0.119	(0.0947)	0.237**	(0.0735)	0.242**	(0.0758)	0.191*	(0.0766)	0.207**	(0.0787)
US Airways (US)	0.143	(0.0936)	0.178	(0.0965)	0.165*	(0.0723)	0.168*	(0.0736)	0.177*	(0.0768)	0.189*	(0.0785)
Virgin America (VX)	0.722***	(0.1210)	0.784***	(0.1180)	0.714***	(0.1040)	0.721***	(0.0966)	0.725***	(0.1080)	0.750***	(0.1010)
Southwest (WN)	0.041	(0.0850)	0.061	(0.0871)	0.119	(0.0657)	0.121	(0.0660)	0.103	(0.0699)	0.111	(0.0707)
Observations	7,549,054		7,549,054		16,324,001		16,324,001		23,873,055		23,873,055	
Markets	92,904		92,904		189,238		189,238		282,142		282,142	

Robust standard errors (clustered at route level) in parentheses.

Fixed-effects are not reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Moving now to comment the other results, the coefficient on price has the correct negative sign. Values range from -0.52 to -0.60 across the three different periods (for the two-level NL). The relative elasticity is therefore quite stable, even if it is not possible to claim that coefficients do not differ from one another. One could also notice that the estimates for the one-level NL are (in absolute values) lower. Eventually, the magnitude is in line with the related literature. As far as daily frequency is concerned, it is characterized by a positive coefficient, thus confirming the expectations outlined above. The decrease occurred between the pre-merger period and the years 2013-2016 could suggest that less importance is attributed to the frequency of flights. The transition from the hub-and-spoke model towards a point-to-point network could help to explain this change. In fact, as direct flights become more common, less importance is attributed to frequency, since passengers do not need to connect.[15] The positive sign for distance also confirms the expectations and suggests that travellers like to fly when distance increases, so that other means of transportation become less appealing. The coefficient for a connecting flight is negative: travellers prefer to fly directly to their destination rather than stopping, possibly reducing their total journey time and the risk of missed connections.

In an attempt to interpret the preferences on frequency and connections together, a possible explanation could be that – while people value direct flights – yet to reach some destinations it might be necessary to connect.[16] Thus there is less aversion for connections as they are perceived as necessary, while frequency is slightly less important because of the reasons explained above.

Eventually, the coefficient on restriction does not have the expected negative sign. This might be related to the fact that it captures a marginal positive impact in utility because the price of a restricted ticket is lower. Results show indeed that restrictions have a negative impact on prices. Travellers may value the fact that the price of a ticket is lower if they are not allowed to change flights when sure of their schedules.

[15] In practice, the airline industry has moved towards an organizational model in which passengers can fly point-to-point, without the need to stop in companies' hubs. Smaller aircrafts have been substituting larger ones as density decreases.

[16] As an example, the DCA Perimeter Rule (49 U.S.C. § 49109) is in force at Ronald Reagan Washington National Airport (DCA), prohibiting flights arriving from and departing to airports located more than 1,250 miles away (with exemptions), in an attempt to protect service at Washington Dulles International Airport. For instance, it is not possible to fly non-stop from San Francisco to Washington National.

Of the fifteen carriers in the records, the one excluded from the regression is Sun Country (SY), due to its very limited importance. Results for the pre-merger period highlight that, in relative terms, travellers like flying Hawaiian Airlines, as well as Virgin America, Alaska and Allegiant. On the other hand, the ultra-low cost Spirit Airlines is disliked.[17] Comparing the two periods, JetBlue became more appreciated, as well as Delta and Frontier. It is possible to notice that American Airlines has a positive coefficient in the second period, although not significantly (probably in part absorbing the effect of US Airways after the merger).

3.3 Simulation

As the values of the structural parameters have been recovered, the next step consists in performing the simulation exercise.

The baseline simulation amounts to a change in the ownership matrix Θ so that all the products that were previously sold by AA and US are now sold by a unique entity – American Airlines. Consequently, in the markets where the two merging firms were present, a decrease in the number of active firms occurs. According to standard microeconomic theory, the simulation should predict the unilateral effects of the mergers, i.e. the new merged entity would now take into consideration the previous externality and increase prices, absent any efficiency gain.

This exercise thus is aimed at calculating the new Bertrand price equilibrium under the new ownership matrix and predicting variations arising from reduced within-market competition. The procedure will recover the implied marginal costs and solve for the new prices using a fixed-point iteration. As Berry et al. (2006) note, however, the "assumption of a static Nash equilibrium in prices is obviously a simplification. Airline yield management techniques attempt to allocate seats across different fare classes in a complicated fashion that depends on the sale history of a particular flight. Therefore, the true equilibrium involves more choices than just prices and it has some dynamic component" (p. 194). Yet, it is overly difficult to implement such an extension into

[17] Although the negative coefficient is not significant in the first period, it becomes afterwards. This seems to confirm its notorious reputation of "worst airline in America".

this model, so we will rely on the prediction of a standard static game. Some additional comments about different conducts of firms will be considered in section 3.5. We will therefore obtain an estimate of the gross magnitude of the probable variation, under the assumption of the Bertrand-Nash setting.[18]

We calibrate the model using the estimates for the demand parameter obtained in the previous section for the years before the merger (2011-2012) and apply it to the 2012 data, so that a forecast is produced for all quarters in a year, possibly removing any exceptional variation which may have occurred in a certain period. The overall effect is then quantified computing a weighted average of the original and predicted prices.

3.3.1 General simulation

A first general simulation is performed across all markets included in the selected sample.

Table 3.3: Predicted price changes (all markets)

Predicted price change	No.	Freq.	Cum.
No variation	5683	49.2	49.2
0 to 5 percent	5629	48.7	97.9
5 to 10 p.	202	1.8	99.6
10 to 15 p.	32	0.3	99.9
15 to 20 p.	8	0.1	100.0
more than 20 p.	2	0.0	100.0
Total	11556	100.0	

Results displayed in Table 3.3 show that in slightly less than 50% of the routes (taking into account a route as a directional trip), it is not likely to see any increase in the price.[19] On the other hand, in almost the other half of the routes, there will be an increase in price between 0 and 5%, while about 2% of the 11,566 routes would suffer a variation higher than 5%.

[18]The code for the simulations is from the Stata package `rcl` by Lorincz (2016).

[19]This might seem at odds with the theory. However, recall that we are considering *all* markets: no change is detected since the merging carriers were not active on these routes or only one of them was.

3.3.2 Overlapping markets

However, analyzing all markets is not very interesting nor informative of the effects that are worthwhile to compare. In fact, for instance, if only one of the merging firm is active in a certain market, it could be assumed that the price would remain the same, under this kind of analysis.[20] For this reason, similarly to Peters (2006), we are going to focus on the so-called overlapping markets, i.e. the ones in which both the two carriers were active and in which the transaction – according to the US Horizontal Merger Guidelines (see [37]) – either raised significant competitive concerns (HHI $>$ 2500 and 100 $\leq \Delta$HHI $\leq$ 200) or was presumed to be likely to enhance market power (HHI $>$ 2500 and ΔHHI $>$ 200).

According to these definitions, in the sample considered, it is possible to identify 2,766 directional routes (821 – almost 30% – raising significant concerns and 1,945 – about 70% – presumed to be illegal, i.e. likely for market power to be enhanced). Many of them refer to airports in which American Airlines was required to divest (LaGuardia, Washington National, Chicago O'Hare, Los Angeles, Boston Logan, Miami International and Dallas Love Field).

Table 3.4 reports unweighted averages by firm of fares, model-implied marginal costs and Lerner indexes. The pre-merger Lerner index is estimated to be around 40% for both American Airlines and US Airways. It is necessary to recall that the Lerner index measures the margin which, in this case, would be the difference between the fare of the purchased ticket and the marginal costs, over the price. Given the nature of the industry, it is possible to assume a not so low margin, as a result of the high fixed costs incurred by airlines.[21]

The averaged implied own-price elasticity for the two merging parties is -2.01, while the cross-price one is 0.11. In general, if two firms offer similar services (for instance, in this case, if AA and US offer connections on the same routes) the estimated cross-price elasticity is going to be higher than in other situations and the price increases are predicted to be more pronounced. In fact, there will be fewer options of comparable substitutable goods (holding the market environment constant).

[20] In the baseline case, efficiency gains resulting from the merger are not taken into account. Moreover, this exercise cannot predict entry or exit of carriers in a given market.

[21] It is also possible to notice that some low-cost airlines are estimated to have a significant margin.

Table 3.4: Average fares, implied costs and estimated Lerner index

Carrier	Fare	Implied MC	Lerner (%)
AA	387.0	273.6	42.06
AS	413.9	312.5	35.58
B6	331.4	228.2	41.51
DL	350.8	240.0	43.31
F9	248.9	149.6	53.60
FL	260.7	161.8	45.50
G4	167.6	47.69	87.20
HA	616.6	504.5	24.56
NK	170.3	68.54	81.82
SY	297.9	188.7	48.34
UA	392.6	284.0	40.66
US	376.7	268.9	39.24
VX	416.3	315.1	43.41
WN	293.8	182.9	44.92

Unweighted averages by firm

Table 3.5: Predicted price changes (concentrated markets)

	Degree of concentration								
Price change	$100 \leq \Delta \leq 200$			$\Delta > 200$			**Total**		
	No.	Freq.	Cum.	No.	Freq.	Cum.	No.	Freq.	Cum.
0 to 5 percent	821	100.0	100.0	1701	87.5	87.5	2522	91.2	91.2
5 to 10 p.	0	0.0	100.0	202	10.4	97.8	202	7.3	98.5
10 to 15 p.	0	0.0	100.0	32	1.6	99.5	32	1.2	99.6
15 to 20 p.	0	0.0	100.0	8	0.4	99.9	8	0.3	99.9
more than 20 p.	0	0.0	100.0	2	0.1	100.0	2	0.1	100.0
Total	821	100.0		1945	100.0		2766	100.0	
Avg. change (%)	1.086	(0.578)		3.085	(2.344)		2.491	(2.190)	

The summary results of this simulation are reported in Table 3.5. It is possible to observe, consistently with the theory, that a smaller variation occurs when markets suffer a less pronounced increase in the degree of concentration.[22] On the other hand, markets

[22]The number of routes in which it is likely to observe a change in the range $0-5\%$ does not coincide

in which the merger is presumed to be illegal are also likely to experience increases in price which are between 5 and 10% (202 routes, 10.4%), while for 42 routes the increase is quantified in more than 10%. The average percentage change is, however, 2.5% across all routes (2.55% weighting for passengers). Looking at the different market settings, however, the average change ranges from 1.1% in markets characterized by significant concerns to 3.1% in markets likely to suffer from dominance.

3.3.3 Presumptively illegal markets according to the DoJ

The list of markets used for the estimation in the previous paragraph is obtained calculating the levels and variations in the HHI index as a result of the market definition above. The US Department of Justice also presented a list of presumptively illegal routes (i.e. routes in which the merger was likely to enhance market power, see [69]), which slightly differs from ours as a result that it is elaborated on the basis of city-pairs instead of airports. In any case, the estimate of a variation in price around 3% is also valid when performing the simulation exercise on this list of city pairs. In this case, estimated changes are displayed in Table 3.6. It is possible to notice that the magnitude of the relative frequencies is not very different from the one in Table 3.5.[23]

The dispersion in the estimated price increases is plotted in Figure 3.2 as well. Panel A of Figure 3.2 represents the data corresponding to Table 3.5 and Table 3.6. The graph shows that the dispersion of the estimated variations almost coincides when considering the routes where the merger is presumptively illegal (corresponding to the second main column of Table 3.5) and the routes included in the DoJ complaint, thus confirming the evidence above. Conversely, the variation is more skewed right for the overlapping routes (corresponding to the third main column of Table 3.5), as some of them were characterized by less significant variations in the HHI index. On the contrary, price variations weighted for the number of passengers on a route are plotted in Panel B of Figure 3.2. One could note that the distribution is less regular and that some relatively important routes – in terms of passenger transported – suffer very significant increases.

with the one in Table 3.3 as the latter includes routes in which the post-merger HHI is below 2500 and/or the change in HHI is less than 100.

[23]The reason why the absolute numbers of the total are different is that the list in the DoJ Complaint groups some routes.

Figure 3.2: Dispersion in estimated price variations

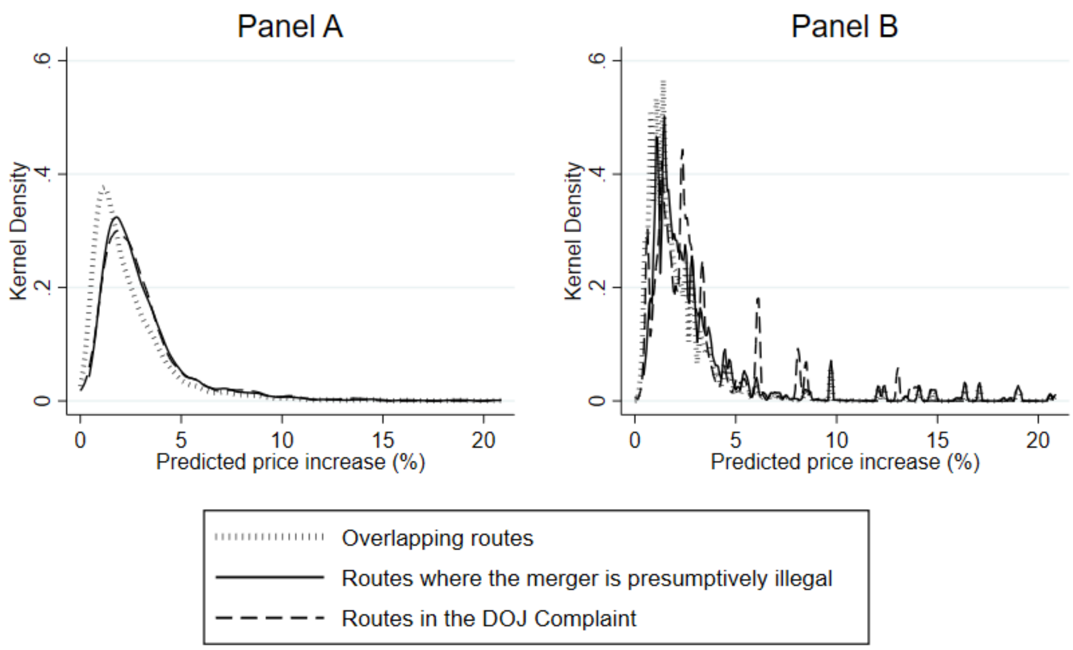


Table 3.6: Predicted price changes (markets of the Amended Complaint)

Price change	No.	Freq.	Cum.
0 to 5 percent	1279	87.2	87.2
5 to 10 p.	156	10.6	97.8
10 to 15 p.	30	2.0	99.9
15 to 20 p.	0	0.0	99.9
more than 20 p.	2	0.1	100.0
Total	1467	100.0	
Avg. change (%)	3.054	(2.282)	

3.4 Ex-post analysis

The purpose of this last section is to evaluate the effective impact of the merger under scrutiny and verify whether the predictions of the simulation exercise are correct. A methodological foreword is needed.

3.4.1 Method

"The goal of a merger retrospective is straightforward: learn if prices changed as the result of a merger. [...] The major issue in estimating the price effect of a merger, as with any evaluation of a change in a market using nonexperimental data, is the method used to control for other confounding factors that may also have changed at the time of the event. Of especial concern in a merger setting is the effect of possible changes in demand or costs unrelated to the merger that may cause prices to change" (Ashenfelter et al., 2009, pp. 5-6).

According to these authors, there are essentially two methods to assess the effects of mergers. Confronting the prices pre- and post-transaction, in fact, is not correct as a series of shocks, completely unrelated to the merger, may influence the level of prices.

The first method specifies a reduced form equation in which prices are functions of time-varying costs and demand characteristics (c_t and γ_t) and a series of indicators for the post-merger period D_t:

$$p_{Mt} = \alpha_{M0} + c_t + \gamma_t + \alpha_{M1} D_{Mt} + \epsilon_{Mt} \tag{3.1}$$

For this method to be valid, it is of crucial importance that all the relevant factors which influence the structure of costs (and, therefore, the pricing rule) and the variability of demand are taken into account. Otherwise, if a variation due to these elements occurs at the time of the merger, the coefficient of interest is distorted due to the bias arising from omitted variables.

The second method is known as difference-in-differences (Ashenfelter, 1978; Angrist and Pischke, 2008) and it is the most common one. The researcher identifies treated and control units and assumes that the dynamics of prices in the two groups are approximately the same, except for the price effect of the merger.

In this case, therefore, it is assumed that prices in the control group can be explained according to the reduced-form equation

$$p_{Ct} = \alpha_{C0} + c_t + \gamma_t + \epsilon_{Ct} \tag{3.2}$$

so that the difference of equations (3.1) and (3.2) is

$$p_{Mt} - p_{Ct} = (\alpha_{M0} - \alpha_{C0}) + \alpha_{M1} D_{Mt} + (\epsilon_{Mt} - \epsilon_{Ct}) \tag{3.3}$$

and the coefficient α_{M1} will yield the effect, provided the hypothesis are satisfied. Among others, it is necessary to make the (admittedly) strong assumption that the transaction is exogenous to market conditions (Hosken et al., 2011; Taylor and Hosken, 2007).

Eventually, while it is straightforward to determine the treated group, defining the control might not be an easy task. In fact, "there is often a tension between finding products that are in different geographic markets and therefore not affected by the transaction, while truly facing similar demand and cost conditions" (Ashenfelter et al., 2009, p. 9).

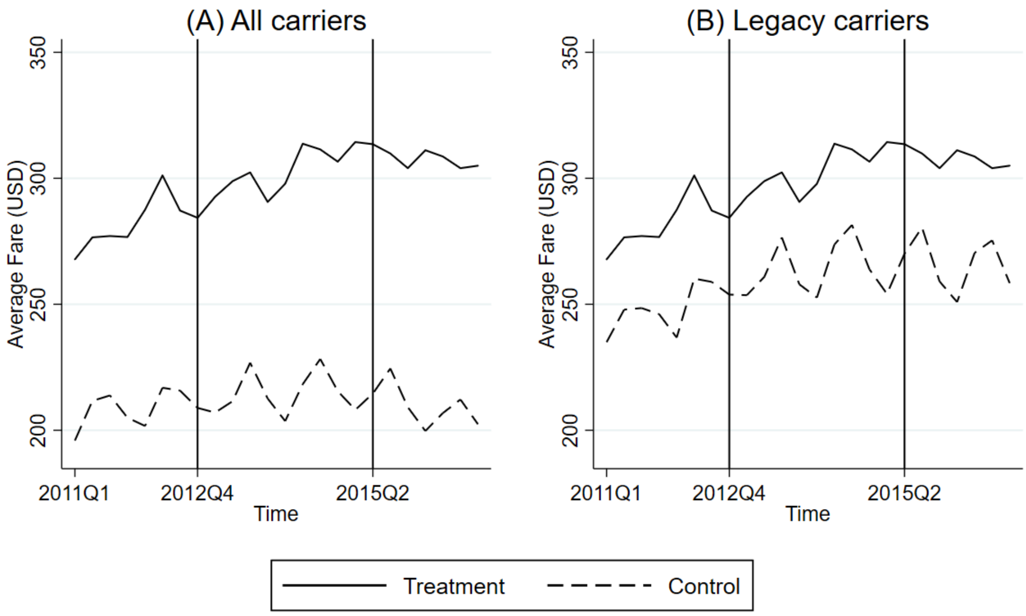
3.4.2 Groups and Time

This exercise will estimate the variation in prices in the overlapping routes. Therefore, the treatment group is represented by the fares set by AA and US for flights in these markets and extracted from the sample described above.

Similarly to Kim and Singal (1993) and as suggested by Greenfield (2015), the control group includes routes which are completely unaffected by the merger, i.e. in which neither of the two merging carrier was present in the years considered. This is done in order to ensure that variations in prices in the control group are not influenced by pricing policies of the merged airline. Some indeed argue that legacy carriers match the fares of other carriers on a certain route, even when their service is poorer (see Olley and Town, 2018). For these reasons, we believe it is important to remove routes in which even one of the two carriers was present.

In order to further exclude possible spillovers, routes connecting airports situated in

Figure 3.3: Evolution of average fares between 2011 and 2016



the same statistical areas as the endpoints of affected routes are not considered, as well.[24]

Given these premises, the resulting trends of the two groups are plotted in Figure 3.3, Panel A. Yet, one could object that the two lines diverge in some points. To identify a more suitable control group, therefore, low-cost carriers have been removed from this latter.[25] This exclusion is not arbitrary: in fact, it is reasonable to claim that the structure of costs and pricing decisions of legacy carriers are quite different from the ones of LCCs.[26] The resulting new trends are plotted in Panel B. It is now possible to appreciate that the lines are much more similar.

The choice of time periods is not an obvious nor objective choice as well. In fact, while formally two companies become one entity at a certain moment, it might take a long time

[24]Inspection of the HHI levels of the two groups suggests that the market environments are broadly similar. This is done in order to avoid biases resulting from the comparison of markets which face substantially different competitive constraints, as Simpson and Schmidt (2008) suggest.

[25]Namely, the LCCs are – adapting from Brueckner et al. (2014) – JetBlue, Frontier, AirTran, Allegiant, Spirit, Sun Country, Southwest, Virgin America and Hawaiian.

[26]This is not only due to the different organization of the networks, the personnel, frequent flyers program and so on, but also in terms of revenue management, i.e. the process and the algorithms used by carriers to post fares. LCCs often aim to earn a fixed amount over costs, while legacy airlines have more complex rules (Vasigh et al., 2008; Lio and Barontini, 2019).

to integrate the two and effects are likely to emerge gradually.

Greenfield (2015) underlines indeed that "[l]ong-term contracts and other real world frictions prevent firms from instantly adjusting prices to reflect the new ownership structure. Moreover, in a differentiated products setting, the merged firm may choose to reposition or combine brands, which inevitably requires some lead time. More generally, capacity changes, capital investments, and integration of physical assets can take years to reach fruition" (p. 63).[27] The author also observes that Kwoka and Shumilkina (2010) drop two intermediate years just after the merger, as well as Tenn (2011): this "enables a clean comparison between baseline premerger fares and post-integration fares when the full competitive effects are most likely to be realized" (p. 63). Zhang and Nozick (2018), in their evaluation of this merger, exclude years 2012, 2013 and 2014.

The graphs in Figure 3.3 exhibit two lines, corresponding to the end of 2012 and the second quarter of 2015. The first line indicates the time period which, in a broad sense, is not interested by the merger. Indeed, the plan for a merger was announced in the first quarter of 2013. As the second line is concerned, it reasonably identifies the post-merger period. In fact, New American was issued a single operating certificate from the Federal Aviation Administration on April 8, 2015. Arguably, this represents the full integration of the activities of the two airlines, while the complete integration of the reservation system and the retirement of the US code and callsign occurred later on.

In conclusion, for the baseline case, the treatment group comprises products sold by the merging carriers in the routes identified as overlapping in the previous section. On the other hand, the control group includes products sold by legacy carriers on US routes in which neither AA or US was present. Pre-merger period includes quarters from the beginning of 2011 to the end of 2012, while post-merger period covers from the second quarter of 2015 to the end of 2016.

[27] In this setting, not only there are the issues of combining the operations of the two carriers and harmonizing the schedules – which both require advanced planning – but also tickets begin being sold far in advance.

3.4.3 Base case

In the base case, the following fixed-effects model is going to be estimated:

$$\log(p_{irt}) = \alpha + \gamma D_{rt} + \sum_r \delta_r Route_r + \sum_t \phi_t Time_t + \epsilon_{irt} \tag{3.4}$$

in which $\log(p_{irt})$ is the log price of product i on route r at time t, D_{rt} is a dummy which takes value 1 for the treated routes and in the post-merger period, while $Route_r$ and $Time_t$ are route- and quarter-level fixed-effects. Eventually, ϵ_{irt} is the error term.

The coefficient of interest in this specification is γ, which will give the (approximate) percentage variation in prices as a result of the merger.[28] Results of the regression are shown in the first column of Table 3.7. It is possible to observe that, using this specification, the price increases implied by the merger are estimated to be slightly below 4% (*Effect* reports the coefficient γ).

Table 3.7: Estimation of the effects of the merger - Base specification

	(1) Log Fare	(2) Log Fare *with LCCs*	(3) Log Fare	(4) Log Fare *with LCCs*
Effect	0.037***	0.062***		
	(0.008)	(0.007)		
Short-term effect			0.024***	0.041***
			(0.007)	(0.006)
Medium-term effect			0.035***	0.061***
			(0.008)	(0.007)
Constant	5.531***	5.471***	5.532***	5.474***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	79,080	89,209	109,841	123,364
Routes	4,076	4,547	4,076	4,547
R^2 adj.	0.619	0.715	0.617	0.715

Robust standard errors (clustered at route level) in parentheses.
Fixed-effects not reported.

To better understand the evolution of prices in time, an additional equation is estimated. In particular, similarly to Aguzzoni et al. (2015), the term γD_{rt} in (3.4) is

[28] For γ sufficiently small, $e^{\gamma} - 1 \approx \gamma$

replaced by two terms, respectively $\gamma_s D^s_{rt}$ and $\gamma_m D^m_{rt}$ (s for short and m for medium). By using this specification, one could disentangle the short-term effects and the medium-term one. In this case, differently from above, only the year 2013 is removed from the sample. The short term includes the period from the first quarter of 2014 to the first quarter of 2015 (included). The medium term covers the rest. In this case, effects are estimated to be significantly positive, respectively 2.4% and 3.5% (column (3) in Table 3.7). In conclusion, the change is more evident in the second period.

As an additional check, the same equations are run including low-cost carriers in the control group, too (columns (2) and (4) in Table 3.7). It appears that, using this control group, the change is estimated to be more marked (6% in the specification with one time period and, respectively, 4% and 6% in the other case).

3.4.4 Trend case

It has been mentioned above that one of the fundamental hypotheses of the difference-in-differences method is that the trend of the outcome variable would have been the same in the two groups, absent the merger.

The problem that arises in this context is that the inclusion of group-specific trends in the model might erroneously confound pre-existing trends with the response to the observed change, thereby possibly biasing the coefficients (Wolfers, 2006).

While it is not possible to test that similar unobservable effects affect the two groups, tests to verify whether the assumption of parallel trend is reasonable have been proposed. In particular, two assessments will be performed. The former replicates the test proposed in Aguzzoni et al. (2015). In particular, the authors estimate a version of equation (3.4) in which D_{rt} is removed and substituted with a dummy for each quarter, taking value 1 only in that quarter and for the treated group. Afterwards, they "compute the slope of a linear trend of the coefficients of these dummies in the pre-merger period and test whether the estimated slope is statistically different from zero" (p. 28). The second assessment is taken from Ashenfelter et al. (2013) and it is, according to the authors, more powerful.

They propose to estimate the following equation (adapted to our case):

$$\begin{aligned}\log(p_{irt}) = \alpha & + & \beta_1 \times t \times Pre_t \\ & + & \beta_2 \times t \times Pre_t \times T_i \\ & + & \beta_3 \times t \times Post_t \\ & + & \beta_4 \times t \times Post_t \times T_i + \epsilon_{irt}\end{aligned}$$

where t is the time trend, Pre_t and $Post_t$ are dummy variables equal to 1 in the pre- and post-merger period, respectively. Eventually, T_i is an indicator for the treated group. The test amounts to verify whether β_2 is different from zero.

While the first test in some specifications does not reject the hypothesis of similar trends at 5% significance level, the second always does. In particular, it shows that in the treated group there is more price variation than in the control group.

Therefore, we also estimate a model incorporating a linear time trend, as a check to the results shown above. In this setting, the underlying hypothesis for a valid identification does not require anymore unobserved effects to impact similarly the two groups in the absence of the merger event. Instead, it is necessary to assume that the evolution of the dependent variable in the treated group follows the same trend as in the pre-merger period.

Namely, the following regression is run:

$$\log(p_{irt}) = \alpha + \sum_{t>t^M} \gamma_t D_{rt} + \sum_g \lambda_g t + \sum_r \delta_r Route_r + \sum_t \phi_t Time_t + \epsilon_{irt}$$

In this specification, there is a dummy (D_{rt}) for each quarter after the merger ($t > t^M$) and the treated group. Therefore, the coefficient γ_t will yield the variation for each unit of time. In this way, the specification can account for a progressive and dynamic response, which is likely to occur in a merger of this kind. To conduct inference – similarly to Aguzzoni et al. (2015) – the γ_t are averaged and the standard error of the averages are calculated.[29] Secondly, a time trend (t) is included for the two groups $g = \{T, C\}$. Ideally,

[29] The averages are computed for two periods: beginning 2014 to the first quarter of 2015 and from the second quarter of 2015 to the end of 2016 (broadly corresponding to the coefficients of columns 3 and 4 in Table 3.7).

one shall include $\lambda_g t$ for all the groups which potentially show different trends. In this setting, we are able to do it for the treatment and control groups.[30]

Table 3.8: Estimation of the effects of the merger - Trend specification

	(1) Log Fare	(2) Log Fare
Short-term effect	0.051*	0.060**
	(0.013)	(0.013)
Medium-term effect	0.088***	0.093***
	(0.009)	(0.009)
Constant	5.529***	5.530***
	(0.003)	(0.003)
Observations	109,841	134,199
Routes	4,076	4,076
R^2 adj.	0.618	0.619

Standard errors in parentheses.
For γ_s and γ_m, s.e. of the averages are used to make inference.
Fixed-effects not reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of this specification are displayed in the first column of Table 3.8. In particular, one could notice that this second regression implies a more pronounced price increase, namely 5% in the short term and 9% in the years 2015-2016. Similar results are also obtained when including the entire time period ranging from 2011 to the end of 2016, as one can appreciate looking at column (2). The main limitation faced in the estimation of the time trend is the impossibility to suitably include a polynomial form, which would have allowed for a more flexible evolution. This is due to the time frame, which is inadvisable to extend in the past to avoid contamination from the 2010 Continental - United Airlines merger.

[30]It is not possible to assign time trends to each route due to collinearity issues.

3.5 Results and discussion

Summary of results The empirical study performed in this chapter comprised three main tasks.

The first one concerned the identification of structural demand parameters, in which the main role is played by the price and nesting factors. We have used, as a result of the estimation, a two-level nested logit demand system, in which the first nest separates the outside option, while the lower nest groups direct flights and the ones with layovers. The estimation of these parameters is fundamental to simulate a new equilibrium in the market, if they are not available from previous studies. The specification used in this work has returned values which are broadly consistent with the literature in the airline markets.

Secondly, the simulation exercise focused on variations emerging from the new competitive structure in markets which, according to merger legislation, may be severely affected by further concentration. Predicted price changes are on average in the order of 1-3%, depending on the increase in HHI levels.

Eventually, the results of the ex-post analysis, performed using two versions of the difference-in-differences technique, shed light on the observed changes in the fares set by New American Airlines. More in detail, different specifications indicate an increase quantifiable in the range 2-6% just after the merger and 3-9% after the complete integration of the two companies. Therefore, it is possible to claim that the average change is more relevant for the subsequent period, as one could expect, given the fact that the gradual integration let the companies harmonize schedule, revise capacity, integrate reservation systems and pricing algorithms. Zhang and Nozick (2018), on the contrary, find that price increases were more significant in 2015 than in 2016, but on average about 8% (compared to 2011). On the other hand, Carlton et al. (2019) detect a decline in prices, although focusing on a very small set of routes.

When confronted with the results from the simulation exercise, it appears that the prediction understated the effect as detected from the ex-post analysis, although not substantially. Some considerations will be presented in the next lines.

Divestitures As discussed above, the merging carriers were required to divest slots at Washington National and New York LaGuardia, in addition to two gates and facilities at each of Boston Logan, Chicago O'Hare, Dallas Love Field, Los Angeles and Miami. It is very difficult, if not impossible, to elaborate a simulation accounting for these divestitures. In fact, in other markets, commitments usually consist in divesting a division of a firm or a production line and it can be assumed, with the necessary caveats, that the purchaser would continue to serve the same market. This is very likely not to be case in this industry. For instance, a carrier buying a slot to land at a certain hour, say, in Washington, might decide not to discontinue the service from the city where the flight departed, but it would also be fairly easy for them to change the origin. Indeed, it needs to be considered that the new carrier shall verify whether it would be able to depart from that origin city airport (what if that airport is constrained as well?), not to mention the fact that it might re-direct it from one of its bases, which could well be another market.[31] In conclusion, it is very difficult in this context to even identify the markets that will be served thanks to these divestitures. Therefore, we have not performed such an estimation. However, it is likely that these divestitures contributed to limit the price increases by the merged carrier, especially for the fact that they affected important airports in the network of AA.[32] In summary, from a qualitative point of view and supported by the theory, it is reasonable to claim that the price increases would have been higher in the absence of divestitures. Yet, we underline again, the quantitative evaluation of this scenario is impossible. More in detail, it is even beyond the possibilities to verify whether the commitments were necessary and even proportionate (see also Aguzzoni et al., 2015). Still, qualitative considerations further support the claim that the simulation underestimates the true effect, as it does not account for the divestitures, especially for the fact that the purchasers were LCCs, which are probable to have decreased prices.[33] In any case, we believe it is unlikely that substantially different effects (in terms of magnitude) would have been observed otherwise.

[31]See, in particular, para. IV.C in [68].

[32]Anyhow, it shall be considered that the most important divestitures occurred in Washington and New York, even if some slots were already leased. In other airports, the divestitures were of less importance.

[33]Notably, slots and gates were required to be sold to LCCs, as there is evidence that the entry of low-cost carriers contributes to bring down fares (see, for instance, Brueckner et al., 2013; Alepin et al., 2013)

Efficiency gains In the quantitative analysis, efficiencies have not been considered. It is reasonable to claim that significant synergies are not likely to occur in such a short time period as the one considered in the ex-post analysis. Consequently, for this work and similarly to other studies, efficiency gains are not examined.[34] In any case, according to standard theory, when present they might offset the negative consequences of the concentration, although depending on the magnitude. In such a situation, incentives of the merged firm might entail a decrease in profits of the other market participants. As far as this merger is concerned, the companies illustrated that, already in 2015, the estimated synergies would have amounted to \$ 1,05 billion. In particular, a large part (\$ 900M) would have come from network revenue synergies, about half a billion from cost synergies, while \$ 400M had to be spent for labor harmonization.[35] Yet, while gains were expected to increase over time, the merging firms estimated that transition-related costs would have amounted to \$ 1,2 billion, to be spread in three years.[36] For our purposes, we need to focus on cost synergies. The firms themselves claimed that cost synergies were estimated to be around 0.4% of the predicted revenues, figure which is lower than the achieved efficiencies of other recent similar mergers (United - Continental, US Airways - America West, Delta - Northwest). Moreover, it needs to be considered that the competitive pressure in the market is crucial in determining if and how much gains are passed on to consumers. As several markets in our analysis might suffer from dominance or become quasi-monopolies, it is unlikely that gains can be passed on.[37] In addition, the realization of typical efficiencies seems to be less probable when networks are large (Moss and Mitchell, 2012).

Looking at financial data,[38] some features can be observed. In the first place, both AA and US operating expenses summed up to a value close to the operating revenues between 2010 and 2013, while in the four years after the merger New American managed to increase operating revenues compared to expenses, so that the operating activity showed to be profitable. It seems indeed that the company was able to generate more revenues without

[34] In addition, the lack of data would have made this further evaluation very difficult.

[35] See p. 16 of the merger presentation [3].

[36] Namely, these costs included expenses to integrate IT operations, standardize livery, aircrafts, airports and lounges, achieve the single operating certificate, relocate personnel and similar fees.

[37] See also para. 84 of the European Merger Guidelines [36].

[38] Available at `https://americanairlines.gcs-web.com/financial-results/financial-aal`

reducing costs. Secondly, the breakdown of costs shows that about 60-70% of operating expenses referred to direct costs (in which fuel, crew costs and maintenance played a large role).[39] On the other hand, the indirect costs of the merged entity were relatively higher, when confronted with the ones above. This could reflect the reorganization of activities.

Eventually, this evidence seems also to be confirmed when looking at the CASM ex-fuel and transport-related, computed by the MIT Airline Data Project.[40] The CASM (Cost per Available Seat Mile) is a common measure of cost performance in the airline industry and refers to the cost (in cents) to operate each seat mile offered. Ex-fuel and transport-related refers to the fact that fuel and transport-related expenses are not considered, therefore including labor and structural costs of the firm only (Belobaba et al., 2009). Data show that, after the merger, the CASM followed an increasing trend. It is likely that this was the case due to higher costs: the two companies had to be integrated and this could have caused their relative performance to be lower.

These comments further support our assertion that cost synergies did not play a significant role in the considered period after the merger.

Other aspects A further remark concerns the predictions regarding dynamic adjustments. As noted, it is not possible to incorporate in the standard multiproduct Bertrand model the entry or exit of market participants. Moreover, we cannot account for progressive changes: the simulation predicts one price for the (near) future.

Eventually, it is clear that this model focuses on price effects only. However, there are several other aspects which influence the customer experience. As an example, these can include punctuality, as well as in-flight amenities. With the creation of new American, US left Star Alliance and joined Oneworld. While it is true that this latter alliance became larger, yet US consumers might have lost the opportunity to choose between the two on the routes previously served by both carriers. Also, as a carrier becomes larger and more important in a market, it can diminish the relative quality of products as consumers might have limited alternative choices. Without claiming to be neither exhaustive nor

[39] The classification of costs reflects the one proposed by the Federal Aviation Administration.

[40] Available at `http://web.mit.edu/airlinedata/www/default.html`. Data are elaborated from US DoT Form 41.

rigorous, inspection of the DoT Air Travel Consumer Reports[41] suggests that the on-time performance of the new carrier resembled the average of the merging firms. On the other hand, new AA better managed denied boardings, but received a higher relative number of complaints. This latter evidence can signal the lowering in quality standards, aspect which would be certainly interesting to analyze in future research.

Explaining the differences It has been mentioned above that the simulation under-predicted the effects of the merger. The differences between the predicted and observed prices could be explained by two main elements, in addition to the dynamics outlined above. In fact, the variations which this exercise accounts for are due to the loss of competition, i.e. the internalization of the profit function of the other firm.

The first element which may contribute to explain the differences concerns the demand side. In fact, it can be that the demand system hypothesized does not incorporate exactly the behavior of consumers and fails to generate an accurate prediction. Namely, this can be related to the low estimated cross-price elasticities, which indicate how well the products of a firm are substitutable with the products of another one. Indeed, the negative effects of a merger will tend to be more significant when closeness of competition between the merging firms is higher, because elimination of the competitor causes more consumers to be attracted to the merged firm. Thus, as the estimates of cross-price elasticities between the products of the two airlines are not high, a very significant increase in price would imply a large loss of customers and profits. The merged airline needs to balance the marginal benefit of higher revenues when increasing prices with the loss of clients switching to other products. In this case, higher values of cross-price elasticities between the two merging firms would have caused greater predicted price increases, more similar to the observed ones. Imposing and testing a slightly different demand system with higher cross-price elasticities is an indication for future examinations of these markets.

From another perspective, it can be that changes occurred in the supply side, as firms modified their behavior or the model implied marginal costs were not so close to the real ones. As far as the behavior of firms is concerned, Miller and Weinberg (2017) – investigating the effects of a joint venture in the US brewing industry – find that the

[41] Available at `https://www.transportation.gov/individuals/aviation-consumer-protection/air-travel-consumer-reports`

predictions of structural methods differed from the observed changes in prices. However, when they simulate other counterfactual scenarios in which the merger took place, they notice that the observed trend could be better explained when taking into account post-merger coordination. In other words, while the standard Bertrand-Nash framework was unable to correctly predict the variation arising from the change in market structure, allowing for coordination made the predicted values to be closer to the actual outcome. This would suggest that the underlying model was not really that of Bertrand-Nash one-shot game, rather it moved towards a collusive equilibrium in the post-merger period. For this reason the observed price increases were higher than the simulated ones. Airline markets do arguably suffer from focal point pricing, as Olley and Town (2018) seem to suggest. There is indeed some evidence apparently supporting the claim that legacy carriers match the fares of competitors on a route, even when their service is poorer. It may be that a similar story concerned the markets under investigation. Consequently, we suggest that future analyses of these markets shall take into account post-merger coordination, especially in cases in which only few players remain in the market.

Conclusions and extensions Overall, the above considerations let us conclude that the simulation performed not so poorly in the prediction of the counterfactual outcome, notwithstanding the observed differences and the unavoidable dynamic responses.

As a concluding remark, we propose possible extensions to the present work. A first suggestion concerns the demand model, in particular further studies could specify it allowing for random coefficients, thus relaxing the assumptions imposed by the nested logit and generating more heterogeneity. In this way, it would be interesting to verify which specification yields results more similar to the observed variation. In the second place, one could perform a similar analysis looking at other mergers (in the airline sector or in other industries), in order to generate more evidence on the appropriateness of the hypotheses and results of structural methods. Also, specifying a model of demand and supply would allow to estimate welfare changes arising from the merger: not only because of price variations, but also looking at other factors (frequency and capacity, for example).

Chapter 4

Concluding remarks

> *Merger simulation is [...] still a very young and innovative instrument of antitrust and, therefore, (i) its "technical" potential is far from being comprehensively exploited and (ii) teething problems in its practical use in antitrust prevail.*
>
> Budzinski and Ruhmer (2009, p. 314)

Ten years have passed since the publication of this paper, in which the authors reviewed the state of the art in merger simulation methods and called for a systematic testing of results produced by these techniques. However, a lot is still to be done, as only a couple of published studies has been added to the (already short) list that they compiled some time ago.

In fact, the need to assess tools which are today employed in antitrust analysis to evaluate changes in the structure of markets and the lack of a sufficient number of studies have inspired the idea for this thesis. In our mind, indeed, the objective was to use the instruments of the New Empirical Industrial Organization and assess whether they could reconcile with the empirical work which is mainly based on actual or quasi- experiments and looks for the so-called treatment effects. The main contribution of this work, in fact, is to have provided evidence regarding the reliability of merger simulation methods. Similarly to other studies, the results of the comparison show that simulations do not generate precise estimates, although our results do not greatly differ from evidence obtained through ex-post analysis.

This difference between results gives the opportunity to briefly introduce the controversy between scholars supporting the two methods. It might not be obscure to our reader, indeed, that a debate filled the pages of the *Journal of Economic Perspectives* in Spring 2010, when Angrist and Pischke (2010) labeled this discipline as "Industrial Disorganization", basically due to the – according to them – elaborate models, lack of foundation in experience and "results which do not match credible design-based" studies (p. 22) (see also the discussion in Keane, 2010). However, the use of methods which aim to evaluate treatment effects seems very difficult in this context, particularly when economists are asked to generate a prevision. In other words, as Nevo and Whinston (2010) say, "[structural modeling, i]n an ideal research environment, would be unnecessary. Whenever we would be called upon to predict the effect of a proposed policy or anticipated change in the economic environment, there would be many prior events where the same change happened exogeneously (whether through actual randomized trials or naturally occurring ones) and we could use these to estimate a treatment effect. That is, as Angrist and Pischke note, past evidence would then be rich enough to provide a *general picture*. Unfortunately, the real world is not always so ideal" (p. 71).

As they correctly note, often there is not enough accurate evidence on past events which economists can rely on to develop a prediction. For instance, in this case, it is very unlikely that the creation of a similar large carrier happened in the past. While, as noted above, consolidation occurred in the US, other mergers were not of this dimension. Therefore, it might be arbitrary to assume that this event would be similar to other ones occurred in the past and use them as comparable outcomes. What is most problematic, moreover, is that selection would occur in this sample. In fact, it would be possible to verify the impact of mergers the antitrust authorities cleared in the end, as they did not raise significant anti-competitive concerns (at least in the recent period). A proposed merger which would substantially lessen competition might not be comparable to other events, just because these did not happen precisely because of similar concerns. Therefore, the lack of analogous episodes might already be a signal of issues, yet it may well be the case that it would prove very difficult, if not impossible, to quantify these effects – at least in a credible manner. In this case, structural methods allow to overcome the issue thanks to the possibility of modeling several different counterfactual scenarios and assessing differences between one another.

In any case, we believe, together with several scholars and enforcers (see, e.g., Kwoka, 2018), that it is important to extend our knowledge using more retrospectives on mergers. While studies of cartels and other conspiracies are more frequent, mainly because to the incentives which affected parties have in claiming damages, this is not the case for mergers. Apart from the incentives argument, in fact, another substantial obstacle hampers the production of this kind of studies, namely the availability of data. Writing this work has been possible thanks to the databases of the Bureau of Transportation Statistics of the DoT, which publishes extensively on this topic. In Europe, for instance, no institution releases information regarding airline tickets and this work would not have been possible using ordinary resources. It is also very difficult to obtain information from the proceedings, since – especially when disputes are settled – much of the analysis is not published at all (for instance, in this case).

Merger retrospectives would not be useful *per se* only, but they will contribute to further assess the reliability of structural methods and generate evidence to ensure a deeper understanding of their limitations and power.

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