EMPIRICAL ESSAYS ON THE U.S. AIRLINE INDUSTRY

A Dissertation

by

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ABSTRACT

This dissertation studies the effects of firm's collaborative strategy on both demand and supply, and equilibrium to derive various welfare implications. I explain both horizontal mergers and vertical relationships, focusing on the U.S. airline industry.

In the first study, I address significant limitations of traditional merger simulations which have focused solely on price changes while constraining the set of product characteristics to be identical pre- and post-merger. To overcome the limitations, I endogenize both prices and product characteristics by specifying a two-stage oligopoly game. After estimating demand and supply system, I simulate the effect of the Delta and Northwest Airlines merger on prices, product characteristics, and welfare. The simulation results show that the merged firm tends to increase product differentiation post-merger, the higher product differentiation reduces the firm's incentive to raise prices, and the changes in characteristics and prices increase not only the merged firm's profit but also consumer welfare. I also compare the predicted to actual post-merger outcome and find that endogenizing product characteristics is essential to better predict the actual outcome.

The second study investigates the impact of contractual agreements regarding gates between airports and carriers on major carrier's market power. Competition Plans reported by thirty one hub airports provide information on a carrier's gate-occupancy, sublease agreement, and Majority-In-Interest clauses at an airport. I estimate the effects of these contractual practices on passengers' utility and carriers' marginal costs. The main results show that a carrier's gate dominance has a positive effect on the demand side through passengers' utility, and business travelers have a higher willingness to pay for gates than tourists. On the supply side, a carrier's gate dominance decreases its own marginal cost, especially when the airport is congested. Furthermore, the existence of sublease agreement at an airport is likely to increase non-signatory carriers' marginal costs, whereas the provision of Majority-In-Interest clauses increases signatory carriers' marginal costs. Based on the estimates, I execute a counterfactual analysis and find that regulatory limits on gate occupancy can reduce the differentials in costs and profits between signatory and non-signatory airlines.

DEDICATION

To my mother, Sujin, and Junwon

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CHAPTER I

INTRODUCTION

This dissertation studies the effects of firm's collaborative strategy on both demand and supply, and equilibrium to derive various welfare implications. I examine both horizontal mergers and vertical relationships, focusing on the U.S. airline industry.

Regarding the horizontal merger, Chapter II addresses significant limitations of traditional merger simulations. The traditional simulations have focused primarily on change in prices, while holding set of characteristics fixed at pre-merger level. According to this setting, a merged firm is assumed to produce identical products pre- and post-merger and to change only prices. However, literature including Peters (2006) and Mazzeo (2003) showed that airlines have adjusted product characteristics facing changes in market structure such as entry, exit, or a merger. Ignoring this aspect can lead to a significant bias in predicted prices in several aspects, thus I aim to overcome this problem by endogenizing not only prices but product characteristics in merger analysis.

To simulate merger effects, I set up an empirical structural model of demand and supply in differentiated product markets. Especially in the supply model, I set up a two-stage oligopoly game where firms decide optimal product characteristics at the first stage, and then choose optimal prices at the second stage. Specifying the sequential choice model causes technical burden, but it is more realistic frame for airline industry where adjusting product characteristics requires a long time.

After estimating demand and supply system, I examine the Delta and Northwest Airlines merger, which created the largest commercial airline in the world as of 2008. For that case, I predict post-merger equilibrium of price and product characteristics, and analyze welfare effect. The simulation results show that (i) the merged firm tends to increase product differentiation post-merger by raising the quality of primary products but largely decreasing that of secondary products. (*ii*) The higher product differentiation reduces the firm's ability of raising prices especially of the primary products. (*iii*) Consumer and producer welfare changes substantially differ from those of standard merger analyses. Specifically, I find that overall consumer surplus increases mainly because the business travelers get welfare gains due to the quality improvement of the primary goods. (*iv*) Finally, I compare the predicted to actual post-merger outcome focusing on flight frequency, and find that endogenizing product characteristics is essential to better predict the actual outcome. In summary, the results highlight that analysts need to endogenize product characteristics along with prices when simulating the effects of proposed mergers.

Chapter III addresses the second issue of vertical relationships, investigating the role of contractual agreement on gates as a determinant of major carrier's market power. Vertical contracts between airlines and airports are widely used and can benefit both parties. From an airport's point of view, long-term contracts can increase revenues by encouraging airlines to concentrate their traffics and to attract more passengers at the airport. From a carrier's perspective, performing a large-scale operations contributes to increasing own market share by providing frequent flight schedules on various routes.

Among various forms of vertical contracts, this study focuses on the case of "signatory carriers", referring to a setting where airlines have fully executed Use-and-Lease Agreements with an airport authority. Under the agreements, the airport grants three special rights to signatory airlines. First, the carriers are able to solely occupy certain airport facilities such as departing/arriving gates, ticket counters, and baggage claim areas for extended periods (e.g. twenty years). Second, the airline can sublease any under-utilized facilities to other carriers possibly at premium prices.

Finally, most large and medium sized airports allow Majority-In-Interest (MII) power wherein signatory carriers can delay or prevent airport capital-development projects.

Several governmental reports (e.g. Department of Transportation, 1999; General Accounting Office, 1990) point out that these contractual practices can be anti-competitive because they can effectively limit competitors' access to gates and other key facilities. More recent work, Ciliberto and Williams (2010) found that the limited access to airport facilities is a critical source of the well known hub premium.

Ciliberto and Williams (2010) uses the contractual practices as measures of the barriers to entry and estimates a linear specification of the reduced-form pricing equation. With this approach, the paper clarifies to what extent the operating practices explain the hub premium. However the practices, especially a carrier's gate control can affect not only consumer utility but also its marginal cost. In this respect, the estimates from the reduced-form regression represent the net effect of the gate control on both sides. Motivated by this aspect, I aim to extend Ciliberto and Williams (2010) by providing more structural descriptions. The primary goal of this paper is to identify the effects of the contractual arrangements on demand and supply separately.

Competition Plans reported by thirty one hub airports provide information on a carrier's gate-occupancy, sublease agreement, and Majority-In-Interest clauses at an airport. I estimate the effects of these contractual practices on passengers' utility and carriers' marginal costs.

The main results show that a carrier's gate dominance has a positive effect on the demand side through passengers' utility, and business travelers have a higher willingness to pay for gates than tourists. On the supply side, a carrier's gate dominance decreases its own marginal cost, especially when the airport is congested. Furthermore, the existence of sublease agreement at an airport is likely to increase non-signatory carriers' marginal costs, whereas the provision of Majority-In-Interest clauses increases signatory carriers' marginal costs. Based on the estimates, I execute a counterfactual analysis and find that regulatory limits on gate occupancy can reduce the differentials in costs and profits between signatory and non-signatory airlines.

CHAPTER II

ENDOGENOUS PRODUCT CHARACTERISTICS IN MERGER SIMULATION: A STUDY OF THE U.S. AIRLINE INDUSTRY

II.1 Introduction

Until recently, standard merger simulations have focused solely on price changes while implicitly constraining the set of product characteristics to be identical pre- and post-merger.[1] However, when an industry experiences a change in market structure such as entry, exit, or a merger, firms are likely to adjust product characteristics. As examples of the airline industry, Peters (2006) shows that a merged airline tends to reduce flight frequency on segments where the merging carriers were competing with each other, and Mazzeo (2003) finds that carriers are likely to deteriorate on-time performance when markets become less competitive.[2]

Ignoring this aspect can lead to a significant bias in predicted prices in several aspects. On the demand side, the set of characteristics is an important part from which consumers derive utility. Then, it is very natural that the post-merger changes in characteristics affect consumers' choices and the resulting market shares of products. On the supply side, merging firms consolidate their production facilities and change the way of conducting operations. This induces the combined firm to search a new set of optimal characteristics based on changes in marginal and fixed cost. Further, the product repositioning influences the extent of cross-price effect merged

[1]Throughout this paper, standard merger analysis refers to the simulation method based on differentiated product demand and firm conduct in oligopolistic markets. This empirical model is widely used since Berry and Pakes (1993), Berry (1994), Werden and Froeb (1994), and Berry et al. (1995).

[2]Merger effect is not the primary focus of Mazzeo (2003), but the finding on the link between market competition and product quality is closely related to this study.

firm internalizes. Suppose that a merged firm's products become more differentiated than before, then cross-price elasticity between them becomes weaker so that the firm has less ability to increase prices than standard simulations predict. However, traditional simulations do not consider these three channels through which optimal prices are affected. Besides the predicted prices, subsequent welfare assessments can be biased in this sense.[3]

To overcome the limitations, I endogenize not only prices but also product characteristics to analyze merger effects in the U.S. airline industry. To be specific, I aim to answer the following four questions: *(i) How does merged firm adjust product characteristics?* A few studies has addressed this issue by comparing 'actual' pre- and post-merger data. Unlike the literature, I 'simulate' post-merger characteristics based on pre-merger data and structural model, assuming that actual outcomes are not available. *(ii) How and to what extent does the product repositioning affect post-merger prices?* After simulating price changes, the paper analyzes how much of the changes is caused through each of three channels (described above). Especially by separating the magnitude of cross-price elasticity, I attempt to see a change in the firm's ability of raising prices. *(iii) How does post-merger equilibrium affect welfare?* I introduce consumer heterogeneity in preferences for the characteristics in the demand specification. Given heterogeneous consumers, merged firm can reposition various subsets of products differently. I assess welfare changes of each type of consumers as well as profit changes by each group of products. *(iv) Does endogenizing product characteristics contribute to better predicting post-merger outcome?* Although a large body of literature has displayed interests in merger simulation, there has been very little studies testing this matter. With a focus on flight frequency, I

[3] Besides the intuitive understanding of limits, Crawford (2012) discusses potential econometric problems associated with exogenous product characteristics.

evaluate the predictive performance of my simulation.

The U.S. air travel market in the late 2000's offers an ideal environment to this research. Above all, the industry has experienced at least nine completed or on-going mergers between 2008 and 2013, including the recently approved the American and US Airways merger.[4] Second, airline mergers involve very complicated integration procedures on various levels. In terms of overall operations, they reform engineering, maintenance, crew training, network design, flight schedule, and allocation of fleets. Also production facilities such as aircraft, gates, and ticket offices are consolidated. Regarding customer service, they create single reservation system and harmonize frequent flier program. All these consolidations can impact operational characteristics of the airline's products. Third, a comprehensive and latest dataset is publicly available from the U.S. Department of Transportation (DOT). The data used include Origin and Destination survey, Air Travel Consumer Report, On-Time Performance, T-100 Domestic Segment, and other sources from the U.S. Bureau of Transportation Statistics.

To simulate merger effects, I set up a structural model of demand and supply in differentiated product markets. The demand model uses discrete choice setting (McFadden, 1981; Berry et al., 1995) and particularly adopts random coefficient logit model with finite consumer types (Berry et al., 2006; Berry and Jia, 2010) to see whether the tourists and the business passengers exhibit heterogeneous preferences for price and characteristics. In the supply model, I set up a two-stage oligopoly game where firms decide optimal product characteristics - flight frequency, on-time performance, mishandled baggage rate, and denied boarding rate - at the first stage,

[4] Since the U.S. airline market was deregulated in 1979, there have been more than thirty merger cases. They exhibit a variation in merging entity types such as legacy, regional, low cost carriers (LCCs). The comprehensive list of U.S. airline mergers is available at http://www.airlines.org/Pages/U.S.-Airline-Mergers-and-Acquisitions.aspx.

and then choose optimal prices at the second stage. Even though the sequential choice model involves technical difficulties, it is more realistic for industries where adjusting product characteristics requires a long time.[5]

After estimating the model parameters, I predict post-merger equilibrium by using three different games: traditional model with endogenous price (Price model, G^P), a new model with endogenous characteristics and endogenous price (Full model, G^{FL}), and a hypothetical model where firms can choose only prices under pre-merger situation, and product characteristics are given by post-merger characteristics of the full model. (Hypothetical model, G^H). Since the hypothetical model does not consider the ownership consolidation, price changes in the game arise from the adjustment of characteristics rather than from the cross-price effect. I compare price changes from the three simulations, and then identify two different cross-price effects, respectively, from the price model and the full model.

This study examines the Delta and Northwest Airlines merger, which created the largest commercial airline in the world as of 2008. Importantly, they competed in more than 450 markets with each other. Based on its greater scale of overlapped markets than other recent merger cases, we can expect the merger effect to be considerable. Further, the integration process had been completed early enough (December 2009) for the actual post-merger data to be available. This enables an evaluation of the simulation performance.

From the simulation results, I find that (i) the merged firm tends to increase product differentiation post-merger. I measure a product quality by taking an inner product of the set of endogenous characteristics and their respective parameters, and

[5]For example, Fan (2013) studied the U.S. Daily Newspaper Market by using a sequential choice model. Endogenous newspaper characteristics include non-advertising space, the number of staff for opinion sections, the number of reporters, and other measures. All these are not quite changeable in a short period of time.

then compute a change in quality of each product. The result shows that the merged firm raises the quality of primary products, but largely decreases that of secondary products.[6] (*ii*) The higher product differentiation reduces the firm's incentive to raise prices especially of the primary products. On the contrary, the firm increases prices of the secondary products substantially with intent to move passengers from secondary to more profitable primary goods. (*iii*) Consumer and producer welfare changes substantially differ from those of standard merger analyses. While the price model predicts decrease in consumer surplus for both types of passengers, the full model predicts that the business travelers get welfare gains due to the quality improvement of the primary goods, and this leads to an overall increase in consumer surplus. Regarding producer surplus, both models show that merged firm earns higher profit and competitors have less profits, but the additional gain to the merged firm is much bigger in full model. (*iv*) Finally, endogenizing characteristics is essential to better predict the actual outcome. Based on the comparison between the pre-merger, the simulated, and actual post-merger frequency, I find that the simulated frequency becomes closer to actual post-merger frequency. In summary, the results highlight that the analysts need to endogenize product characteristics as well, when simulating the effects of a proposed merger.

This paper contributes to the existing literature in three ways. First, it extends merger literature. Focusing on airline merger studies, one group of papers adopts comparative analysis or reduced form model to examine changes in price, output, or welfare. Borenstein (1990), Werden et al. (1991), Kim and Singal (1993), Morrison (1996), Kwoka and Shumilkina (2010), and Luo (2011) belong to this group. Another group takes a more structural approach to simulate post-merger outcomes. Peters

[6] A primary product refers to a major route where passenger traffic is large, and a secondary product indicates a route where small number of passengers travel.

(2006) applies the discrete-choice demand and oligopolistic pricing game and suggests that merger simulation can better perform when it considers the changes in product characteristics. But he updates the characteristics by using actual post-merger data rather than endogenizes them in the model. Richard (2003) endogenizes flight frequency decision as well as quantity decision. However, the model is restricted to a single-firm optimization so that merged firm's decision is not affected by competitors, and the choice variables are decided simultaneously (a one-stage monopoly game). My research belongs to the latter group, but endogenizes both the set of product characteristics and prices in a sequential fashion in oligopolistic markets (a two-stage oligopoly game).

Second, this study contributes to the on-going literature on endogenous product choice (or quality). Starting from Mazzeo (2002), the issue has been continuously addressed by Crawford and Shum (2006), Gandhi et al. (2008), Draganska et al. (2009), Chu (2010), Byrne (2012), and Fan (2013).[7] Endogenizing product characteristics involves serious computational burden, especially when supply model adopts a two-stage oligopoly game with continuous characteristics. This is because one needs to compute derivatives of prices with respect to product characteristics for all products in a market. The literature avoids the complicated matrix by assuming reduced-form profit function without demand-driven market share (Mazzeo, 2002) or by adopting a one-stage game (Gandhi et al., 2008; Chu, 2010) or by analyzing monopoly market (Crawford and Shum, 2006; Byrne, 2012). The closest paper to mine is Fan (2013) in terms of specifying a two-stage oligopoly game. She derives the matrix by taking the total derivative of the second-stage optimality condition as an application of the implicit function theorem. I empirically solve it in a more explicit way in which the

[7]Crawford (2012) well summarizes this on-going literature. Also, Cho (2012) provides a great review by categorizing the literature according by types of product differentiation and consumer heterogeneity.

optimal price function is derived from the second-stage optimality condition, and then I differentiate it with respect to product characteristics to solve the first-stage optimality condition. Since my approach directly computes the derivatives, it can be applied to more complicated optimization problems where multiple choice variables are correlated and decided sequentially (e.g. a three-stage oligopoly game).

Finally, looking at the overlap between above two subjects, this paper adds an empirical evidence on how a merger influences 'product positioning' or 'product variety'. This issue still remains controversial. A series of papers including Berry and Waldfogel (2001), Gandhi et al. (2008), and Sweeting (2010) shows that merged firm tends to increase product differentiation to avoid market cannibalization. On the other hand, Gotz and Gugler (2006) finds that higher concentration in retail gasoline market reduces product variety. This matter is critical because the consumer welfare is largely depending on how products are repositioned post-merger (Mazzeo et al., 2013). To provide a new evidence from the airline industry, I introduce two quality-distance measures: *within-firm distance* and *within-market distance* and analyze post-merger changes in the extent of product differentiation.

The remainder of the paper is organized as follows: Section 2 provides the structural model of air travel market and derives necessary optimality conditions. Section 3 describes the dataset. Section 4 presents an estimation procedure and reports model parameters. Section 5 simulates post-merger product characteristics and price, and analyzes welfare changes. The comparison analysis between the simulated and actual post-merger outcome is also addressed here. Section 6 concludes with a brief summary.

II.2 The Model

This section presents demand and supply model in the air travel market. In each market, carriers provide the set of differentiated products, and each consumer either purchases one product or takes the outside option of not flying. Importantly, the endogenous product characteristics are assumed to affect both consumers' utility and firms' cost.

II.2.1 Demand

The demand model follows discrete choice framework with heterogeneous consumer preferences (Berry et al., 1995, henceforth, BLP). In particular, I allow the consumer heterogeneity to be represented by discrete distribution with only two types of consumers (Berry and Jia, 2010). As Borenstein and Rose (1994), Gerardi and Shapiro (2009), and several airline studies suggest, we can regard them as the business passengers and the tourists ($r = 1$ or 2).

A 'market' is a directional round trip between origin and destination city (see figure 1).[8] A 'product' is a unique combination of carrier-itinerary.[9] In other words, given an itinerary, all tickets sold by a carrier are aggregated to form a representative product.[10] This market and product definitions allow us to distinguish direct and connecting flights and to use information on characteristics for each airport.

Each consumer derives utility from price, observed product characteristics, and unobserved components. The conditional indirect utility of a passenger i who is of

[8] A city is a Metropolitan Statistical Area. In general, one city has one airport, but a few big cities have multiple airports. For example, Chicago has ORD (O'Hare) and MDW (Midway) airport as described in figure 1.

[9] An itinerary is an ordered sequence of airports for a round-trip.

[10] The product definition is based on two considerations. First, the data on mishandled baggage rate and denied boarding rate are available only at carrier-level. Second, if each ticket is considered as a product, the estimation time tends to seriously increase, mainly because product shares need to be inverted at each iteration to derive unobserved product quality.

type r from choosing product j in market t is assumed to be

$$
\begin{aligned}
u_{ijt} &= p_{jt}\alpha_r + y_{jt}\psi_r + z_{jt}\varphi + \xi_{jt} + \nu_{it}(\lambda) + \lambda\epsilon_{ijt} \\
&= x_{jt}\beta_r + \xi_{jt} + \nu_{it}(\lambda) + \lambda\epsilon_{ijt}, \qquad (1)
\end{aligned}
$$

where p_{jt} is a passenger-weighted average ticket price of product j. y_{jt} is a two-dimensional vector including $Ontime15$ and $Layovers$. $Ontime15$ represents on-time performance of a product. A flight is counted as 'on-time' if it arrives at a gate less than 15 minutes after the scheduled arrival time. Since the original data contain a flight's scheduled arrival and actual arrival time on each non-stop segment, I measure $Ontime15$ as the geometric mean of percentage of flights that arrive on-time on each segment. $Layovers$ is the number of connections per round-trip: 0 for direct flights and 2 for connecting flights.[11] I allow p_{jt} and y_{jt} to have random coefficients α_r and ψ_r, respectively, to see whether the business passengers and the tourists exhibit heterogeneous tastes for price, on-time arrival, and direct flight.

The vector z_{jt} includes several other characteristics for which both types of passengers are assumed to have same level of marginal utility (φ). It contains $Frequency$, the number of average daily departures, to capture the benefits from convenient flight schedule with multiple departure times. $Frequency$ is computed as the geometric mean of a flight frequency on each segment for a similar reason to $Ontime15$. $Mishandled\ baggage$ is the number of mishandled baggages per 1,000 passengers. If a passenger's baggage is lost, damaged, or delayed, it is considered mishandled. z_{jt} also includes *Denied boarding* measured by the number of involun-

[11]In the sample, passengers on direct flights have two coupons with no connection, and passengers on connecting flights have four coupons with two connections. Technically, 'direct' means that passengers do not change a plane between origin and destination, whereas 'non-stop' means that the flight does not stop between origin and destination. In this paper, I use both terms to refer to flights that do not stop between origin and destination.

tary denied boardings per 10,000 passengers. Even though consumers hold confirmed reservations, they may be denied boarding from a flight due to airline overbooking.

In this research, the four characteristics - *Ontime*15, *Frequency*, *Mishandled baggage*, and *Denied boarding* - are modeled as endogenous variables (along with endogenous price). In previous studies, the characteristics are assumed to be exogenous based on the notion that firms cannot adjust them at least in the short run. However, this paper aims to simulate the merger effect. Since airline integration process takes a long time to be completed and the consolidation influences the overall operational characteristics of airline products, I reasonably set the characteristics to be a firm's choice variables.[12]

As additional controls, z_{jt} includes $HubDM$, the number of a carrier's hub airports on itinerary. This variable controls consumer valuation for frequent flier program and convenient gate access generated by a carrier's hub operation. I also expect that passengers' utility depend on *Constant*, *Distance* (the total round-trip distance), $Slot - control$ (the number of slot-controlled airports on itinerary), and $Tour$ (1 if a destination airport is located in either California, Florida, or Nevada).[13] Finally, I include several carrier dummies to control the brand-specific effect. Major airlines are Continental (CO), Delta (DL), Northwest (NW), United (UA), US Airways (US), and American (AA, the base carrier). Two low cost carriers are Southwest (WN) and AirTran (FL). The remaining carriers are defined as Other Carriers (OT).

ξ_{jt} is an unobserved (to the econometrician) product quality which is not captured by the dataset. It represents ticket- or flight-level characteristics such as Saturday

[12] The integration process for the Delta and Northwest Airlines merger continued for twenty one months after the initial announcement in April 2008.

[13] In this study, slot-controlled airports include Chicago O'Hare (ORD), John F. Kennedy (JFK), LaGuardia (LGA), Reagan National (DCA) airport.

night stay-over, advance purchase, non-refundability, minimum or maximum stay restriction, and in-flight meal service quality.[14] ν_{it} is the nested logit disturbance. It is constant across all airline products (inside goods) in market t, but differentiates air travels from the outside option of not flying. λ is the nested logit parameter which represents the degree of product differentiation between inside goods. It varies between 0 and 1. If $\lambda = 1$ (then $\nu_{it} = 0$), each airline product is perfectly differentiated. In this case, there will be no need to set outside option, and demand specification becomes a multinomial logit model. If $\lambda = 0$, all airline services are perfectly substitutable. ϵ_{ijt} is an *i.i.d.* (across consumers, products, and markets) logit error. The error structure $\nu_{it}(\lambda) + \lambda\epsilon_{ijt}$ follows the Type I extreme value distribution to derive closed-form market share equation.

The indirect utility from the outside good (e.g. driving a car or taking a train) is given by

$$u_{i0t} = \xi_{0t} + \epsilon_{i0t}. \tag{2}$$

A simple way to identify mean utility of the outside good is setting it as one of the inside goods. However, it is not desirable strategy because airline products are quite different services from those by other ground transportation modes. Alternatively, I normalize both ξ_{0t} and ϵ_{i0t} to be zero for all consumers. In this case, the coefficient of *Constant* will measure marginal utility from choosing any airline products.

Note that in the standard BLP model, consumer tastes vary with demographics and unobserved individual characteristics, following multivariate normal (or other continuous) distributions. Differently, the random coefficients here vary with finite passenger types, following discrete r-type distribution. Thus, I derive a market share

[14] This restricted information is available only in transaction-level data from Computer Reservation System. An analysis which uses the specific information can be found in Puller et al. (2012).

function by computing the weighted sum of the market share for each type, rather than by integrating purchase probability over continuous distributions. The weight is the percentage of type r consumers in the population (γ_r).

Assuming each type r consumer purchases one airline ticket which gives the highest mean utility ($x_{jt}\beta_r + \xi_{jt}$), the market share of jth product is given by

$$s_{jt}(x_t, \xi_t, \theta_d) = \sum_{r=1}^{2} \gamma_r \cdot \frac{e^{(x_{jt}\beta_r+\xi_{jt})/\lambda}}{\sum_{k\in J_t} e^{(x_{kt}\beta_r+\xi_{kt})/\lambda}} \cdot \frac{\left(\sum_{k\in J_t} e^{(x_{kt}\beta_r+\xi_{kt})/\lambda}\right)^{\lambda}}{1+\left(\sum_{k\in J_t} e^{(x_{kt}\beta_r+\xi_{kt})/\lambda}\right)^{\lambda}}, \tag{3}$$

where $x_t = (x_{1t}, \ldots, x_{Jt})$, $\xi_t = (\xi_{1t}, \ldots, \xi_{Jt})$, and J_t is the set of all airline products in market t. θ_d is the set of all demand parameters (α_r, ψ_r, φ, λ, γ_r). Each market provides two groups of products: all the airline services and outside option, thus the first term indicates within-group share of airline product j, and the second term denotes to group share of all the airline products.

II.2.2 Supply

In this section, I describe a two-stage oligopoly game where each carrier chooses optimal product characteristics first and then decides optimal prices to maximize the expected profit under Bertrand-Nash competition. Airline network structures such as markets, routes, airports served, and location of hub airports are assumed to be exogenous.[15]

At the first stage, firm f decides the set of product characteristics, $\bar{x}_j$=($\bar{x}_j^O$, $\bar{x}_j^F$,

[15] This assumption is justified by the fact that most airlines sign 'long-term use-and-lease agreements' with airports to occupy the airport facilities. The detailed information on the contractual practices between airports and airlines can be found in Ciliberto and Williams (2010) and Lee (2013). Also, considering that an airline product is a carrier-route combination, the assumption is analogous to a typical setting where the number of products offered is exogenously given.

$\bar{x}_j^M$, $\bar{x}_j^D$) to maximize the profit function[16]

$$\Pi_f^I = \sum_{j \in J_f} (p_j(\bar{x}) - mc_j(\bar{x}_j^F)) \cdot M \cdot s_j(p(\bar{x}), \bar{x}, \xi; \theta_d) - F(\bar{x}_f, \zeta_f; \tau) \tag{4}$$

where $\bar{x} = (\bar{x}_1, \ldots, \bar{x}_J)$, $\bar{x}_f = (\bar{x}_{1f}, \ldots, \bar{x}_{Jf})$, and $\zeta_f = (\zeta_{1f}, \ldots, \zeta_{Jf})$. J is the set of all products in a market, and J_f is the set of all products offered by firm f in a market. Throughout the supply model, a market subscript t is omitted for simplicity.[17] mc_j is the marginal cost of product j, and M is a market size which is the geometric mean of the MSA population of two end-point cities. $s_j(\cdot)$ is the demand-driven market share function of product j coming from equation (3), and $F(\cdot)$ is the fixed cost function.

In equation (4), a carrier's decision on the characteristics ($\bar{x}$) affects prices, marginal, and fixed cost. It also affects market share directly and indirectly.[18] To be specific, in each market, prices of all products are influenced by the characteristics of all products through $p_j(\bar{x})$ and $p(\bar{x})$. These interactions (arising from a two-stage oligopoly game) make the necessary equilibrium conditions difficult to be computed. The way of solving it is described in section 2.3.

Marginal cost of serving an additional passenger is given by the following linear function

$$mc_j = h_j \delta + \omega_j \tag{5}$$

where h_j denotes the set of cost characteristics. h_j includes $Frequency$ ($\bar{x}_j^F$) to

[16]The superscript O, F, M, and D denote the first letter of the endogenous product characteristics, respectively.

[17]Following Berry and Jia (2010), markets are assumed to be independent. Thus, all equations in this section are applied to each market without loss of generality.

[18]Even though price, marginal cost, and market share function also depend on other control variables, equation (4) is expressed with a focus on the endogenous characteristics.

capture marginal cost effect of the aircraft utilization. Among the four endogenous characteristics, only $Frequency$ is modeled to affect marginal cost because it is a quantity-related variable. h_j also controls $HubMC$, 1 if a flight departs from, connects at, or arrives at its hub airport. A carrier's hub operation can cause two countervailing effects on marginal cost. In hub-and-spoke system, a majority of passengers come from different origins and connect at a carrier's hub airport to reach their final destinations. This allows the carrier to generate high load factor on major routes, which contributes to decreasing the per-passenger cost. On the other hand, a carrier's hub operation causes massive air- and ground-side congestion at an airport. This can increase marginal cost. The coefficient reflects the net effect of the two factors. I control two distance measures, $Distance_{short}$ and $Distance_{long}$, considering that fuel efficiency can differ depending on aircraft size, and different sizes of fleets are allocated on short-haul and long-haul routes.[19] Similarly, I control $Layovers_{short}$ and $Layovers_{long}$. Connecting flights involve an additional landing/takeoff during which airplanes burn a large fraction of fuel, and the amount of fuel consumed is known to vary with aircraft size.[20] Finally, I set carrier dummies to control carrier-specific cost effect.

δ indicates a vector of cost parameters, and ω_j represents unobservable (to the econometrician) marginal cost shocks. It includes fluctuations in oil prices, quality of on-board meals, charges levied for landing, and other unobserved factors.

Following Fan (2013), I adopt a quadratic function to approximate the fixed cost function. Specifically, the slope of the fixed cost with respect to an endogenous

[19] I create an indicator variable I_{long}=1 if a market distance is longer than 3,500 miles and I_{short}=1 if a market distance is shorter than 3,500 miles. Then the distance measures are computed as $Distance_{long} = Distance * I_{long}$ and $Distance_{short} = Distance * I_{short}$.

[20] Similar to the distance measures, I compute the two $Layovers$ as $Layovers_{long} = Layover * I_{long}$ and $Layover_{short} = Layover * I_{short}$.

characteristic ($\bar{x}_j^k$, $k = O, F, M, D$) is given by

$$\frac{\partial F(\bar{x}_f, \zeta_f; \tau)}{\partial \bar{x}_j^k} = \tau_0^k + \tau_1^k \bar{x}_j^k + \zeta_j^k, \tag{6}$$

where τ is a vector of parameters, and ζ_j^k represents unobservable fixed-cost shock. Adjustments of the operational characteristics accompany consolidation of facilities (aircraft, gate, and ticket counter) and workforce (pilots, flight crew, gate/ticket takers, baggage handlers, and ticket booking agent). Using more or less of these resources influences the fixed cost. Other cost shocks such as advertising costs are captured by ζ_j^k.

Given a vector $\bar{x}_j$ chosen at the first stage, firm f decides price p_j at the second stage to maximize the following profit function,

$$\Pi_f^{II} = \sum_{j \in J_f} \Pi_j^{II} = \sum_{j \in J_f} (p_j - mc_j) \cdot M \cdot s_j(p, \bar{x}, \xi; \theta_d). \tag{7}$$

While the first stage profit function is specified as the difference between the variable profit and the fixed cost, carriers now maximize the variable profit under the Bertrand-Nash competition.

In airline industry, prices are easily changeable, but the product characteristics are not. For example, when a carrier increases flight frequency, it needs to adjust aircraft size and to hire more employees who manage flight schedule. Further, it may reallocate gates based on contract with airport authority. However, price decisions can be made relatively quickly and flexibly at the final stage. Hence, this sequential choice model better reflects airlines' decision-making process.

II.2.3 Necessary Equilibrium Conditions

I solve carriers' optimization problems by deriving necessary equilibrium conditions for the product characteristics and prices. From the conditions, I will recover the structural errors in marginal cost function (ω_j) and fixed cost function (ζ_j^O, ζ_j^F, ζ_j^M, ζ_j^D) in section 4.

Starting with the second-stage game based on backward induction, I take the derivative of the second-stage profit function Π_f^{II} with respect to prices (p_j, $j = 1, \ldots, J_f$) to generates the first-order condition $\partial \Pi_f^{II} / \partial p_j$,

$$s_j(p, \bar{x}, \xi; \theta_d) + \sum_{h \in J_f} (p_h - mc_h) \cdot \frac{\partial s_h(p, \bar{x}, \xi; \theta_d)}{\partial p_j} = 0. \tag{8}$$

Stacking all J_f products together yields

$$s_f(p, \bar{x}, \xi; \theta_d) + \Omega_{s_f, p_f} \cdot (p_f - mc_f) = 0, \tag{9}$$

where $s_f = [s_1, \ldots, s_{J_f}]'$, $p_f = [p_1, \ldots, p_{J_f}]'$, $mc_f = [mc_1, \ldots, mc_{J_f}]'$, and Ω_{s_f, p_f} is a $J_f \times J_f$ matrix given by

$$\Omega_{s_f, p_f} = \begin{bmatrix} \frac{\partial s_1}{\partial p_1} & \cdots & \frac{\partial s_{J_f}}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial p_{J_f}} & \cdots & \frac{\partial s_{J_f}}{\partial p_{J_f}} \end{bmatrix}. \tag{10}$$

Rearranging terms in equation (9) derives a carrier's optimal price function,

$$p_f = h_f \delta + \omega_f - \Omega_{s_f, p_f}^{-1} \cdot s_f(p, \bar{x}, \xi; \theta_d). \tag{11}$$

The right hand side be composed of two parts. The first two terms indicate the marginal cost and the remaining term (including negative sign) constitutes markup. Through the two components, the optimal price is affected by product characteristics. This dependency provides a link between the first stage and the second stage game.

Moving on to the first-stage game, I differentiate the profit function Π_f^I with respect to the product characteristics ($\bar{x}_j^k,\ j=1,\ldots,J_f,\ k=O,F,M,D$) to yield the first-order condition $\partial\Pi_f^I/\partial\bar{x}_j^k$,

$$\sum_{h\in J_f}\frac{\partial\Pi_h^{II}}{\partial\bar{x}_j^k}+\sum_{h\in J_f}\sum_{h'\in J}\frac{\partial\Pi_h^{II}}{\partial p_{h'}}\frac{\partial p_{h'}}{\partial\bar{x}_j^k}-\tau_0^k-\tau_1^k\bar{x}_j^k-\zeta_j^k=0. \tag{12}$$

While the adjustment of $\bar{x}_j^k$ has a direct effect on variable profit of product h (Π_h^{II}), it also has an indirect impact on Π_h^{II} by affecting prices of all products in a market.[21] Main computational difficulty arises from $\frac{\partial p_{h'}}{\partial\bar{x}_j^k}$ in the second term. This requires the derivative of all equilibrium prices with respect to all products' characteristics.[22] As a great way of computing it, Fan (2013) applies the implicit function theorem by taking the total derivative of the second-stage optimality condition (9) with respect to prices and product characteristics.[23] Since this approach relies on the observed product characteristics, one needs to rule out corner solutions where the equation (9) does not hold. I empirically solve it in a more explicit way. I plug the optimal price function (11) into the first-stage profit function (4) and differentiate the profit function with respect to each product characteristic. While both methods need an

[21]For $Frequency$ ($\bar{x}_j^F$), the exact expression for the first-order condition is equation (13) below, because the frequency affects marginal cost function. However, the optimal price function includes marginal cost in it, thus equation (12) and (13) are essentially same for $Frequency$.

$$\sum_{h\in J_f}\frac{\partial\Pi_h^{II}}{\partial\bar{x}_j^F}+\sum_{h\in J_f}\sum_{h'\in J}\frac{\partial\Pi_h^{II}}{\partial p_{h'}}\frac{\partial p_{h'}}{\partial\bar{x}_j^F}-\sum_{h\in J_f}\frac{\partial\Pi_h^{II}}{\partial mc_h}\frac{\partial mc_h}{\partial\bar{x}_j^F}-\tau_0^F-\tau_1^F\bar{x}_j^F-\zeta_j^F=0 \tag{13}$$

[22]Technically, the derivative requires us to compute $\frac{\partial(\Omega^{-1}_{s_f,p_f})}{\partial\bar{x}_f^k}$ and $\frac{\partial(\Omega^{-1}_{s_J,p_J})}{\partial\bar{x}_J^k}$.

[23]This approach was initially introduced by Villas-Boas (2007).

assumption that the optimal price function is smooth and differentiable with respect to the characteristics, they produce the same computational result for a two-stage oligopoly game.[24] However, since my approach directly computes the derivatives, it can be applied to more complicated optimization problems where multiple choice variables are correlated and decided sequentially (e.g. a three-stage oligopoly game).

II.3 Data

II.3.1 Sources

I collected the data from a variety of sources (see table 1). The primary data set is the Airline Origin and Destination Survey (DB1B) produced by the U.S. Department of Transportation (DOT).[25] Based on the DB1B, I defined the market and product, and created the variables varying by product ($Fare$ and $Layovers$), carrier (brand dummies), airport ($Slot-control$), carrier/airport ($HubDM$, $HubMC$), and market ($Distance$ and $Tour$).

The endogenous product characteristics come from three different sources, also produced by the DOT. I calculated $Ontime15$ based on the Airline On-Time Performance Data. The data contain monthly information on scheduled and actual departure/arrival times for a flight, covering all U.S. carriers that account for at least one percent of domestic scheduled passenger revenues.[26] $Frequency$ was constructed by using T-100 Domestic Segment Data. Among several departure-related terms, I used 'departures performed' which counts takeoffs by each carrier at an

[24] The four endogenous product characteristics in this research are reasonably continuous.

[25] The DB1B database is a 10% sample of airline tickets from reporting carriers, produced on a quarterly basis. There are three subcomponents to the DB1B: market, coupon, and ticket dataset. This study combines the last two dataset.

[26] With this data, one can create other discrete variables (e.g. Ontime30, Ontime60) or continuous variables (e.g. *Average minutes late*). Besides departure and arrival times, the data also provide information on the causes of delay and cancelations.

airport. Finally, I used Air Travel Consumer Report to create *Mishandled baggage* and *Denied boarding*. While the report is filed on a monthly basis, the statistics on *Mishandled baggage* and *Denied boarding* are updated by monthly and quarterly, respectively. Hence, I computed *Mishandled baggage* as the average value of the mishandled baggage rate of each month during a quarter.

Further, I used airline employment data and weather data to construct instrumental variables for the endogenous characteristics. The employment data come from Air Carrier Financial Reports (Schedule P-10). It contains annual employee statistics by labor category such as pilots/copilots, maintenance employees, and passenger handling employees. The weather data was collected from Weather Underground. This is a commercial weather service which gathers its most information from the National Weather Service (NWS). Typically, the weather reporting location for a particular city is its airport, which is appropriate for this research. The instruments will be explained in more detail in Section 4.

II.3.2 Sample Selection and Description

The Delta and Northwest Airlines merger was announced the second quarter of 2008. I define pre-merger period as the four quarters pre-dating the announcement. Hence, the sample period for estimating pre-merger demand and supply is from the second quarter of 2007 to the first quarter of 2008.

The criteria for sample selection is as follows. In ticket level, I focus on round-trip itineraries within U.S. continent with at most four coupons. Also, I drop tickets whose prices are lower than $50 or higher than $1,800. The lower bound is to eliminate tickets purchased using frequent flyer miles, and the higher bound is to restrict the sample to coach-class travel. In product level, I drop observations with fewer than five passengers because they are likely to be non-regular services.[27] I exclude products associated with open-jaw.[28] An open-jaw trip does not fit for applying the typical definitions of origin and destination city. Further, they are known to be subject to different pricing scheme relative to the ordinary round-trip tickets. In market level, I focus on medium to large metropolitan areas whose populations are more than 850,000. This is for reducing heterogeneity of demand and supply. As Berry and Jia (2010) states, the demand pattern and the operation cost among small-sized markets tend to be different from those among medium to large-sized markets.

The final sample contains 87,906 unique products in 9,117 markets.[29] Table 2 provides summary statistics for the estimation sample. Focusing on the endogenous characteristics, the mean value of $Ontime15$ indicates 75% of flights arrived on-time during the sample period. As extreme cases, 24 products have 100% on-time performance record. All of them are direct flights, and more than half of them are produced by the Southwest Airlines. As the worst cases, 160 products have 0% on-time performance. When using a rougher measure $Ontime30$, the on-time performance increases to 86%. Also, a continuous measure *Average minutes late* shows that flights arrived 12.6 minutes late on average. The statistics for $Frequency$ indicate that flights departed 4.3 times a day on average. It varies significantly across markets and products. To be specific, frequency is higher in tourism markets (4.52) than in others (4.23), and higher in short-haul markets (4.41) than in long-haul markets (4.20). Further, flights originating from a carrier's hub airports show high frequency (4.91) than others (4.27). Lastly, the number of mishandled baggages are

[27]Since the DB1B is a 10% random sample, those airline products are likely to carry less than fifty passengers during a quarter.

[28]An open-jaw trip is essentially a round trip in which the outward point of departure and the inward point of arrival are not the same.

[29]Travels on same itinerary but in different quarters are considered as different products in different markets.

6.4 per 1,000 passengers, and the number of denied boardings are 1.2 per 10,000 passengers. They also exhibit large variations across carriers and across quarters for each carrier.

II.4 Estimation

To estimate the model parameters, I recover the structural errors in the demand and supply specification as a function of model parameters and data. The errors include unobserved quality (ξ_t), marginal cost shock (ω_t), and fixed cost shocks (ζ_t^O, ζ_t^F, ζ_t^M, ζ_t^D). ξ_t is derived by inverting the market share function: $\xi_t = s^{-1}(x_t, \dot{s}_t, \theta_d)$. Given demand parameters θ_d=[α_r, ψ_r, φ, λ, γ_r] and data x_t, I solve for ξ_{jt} that equates the predicted market share to observed market share by using a contraction mapping (Berry et al., 1995; Berry and Jia, 2010),

$$\xi_{jt}^H = \xi_{jt}^{H-1} + \lambda[\ln \dot{s_{jt}} - \ln s_{jt}(x_t, \xi_t, \theta_d)], \tag{14}$$

where H denotes the H^{th} iteration, $\dot{s_{jt}}$ is the observed market share, and $s_{jt}(x_t, \xi_t, \theta_d)$ is the predicted market share defined by equation (3). This convergence process is carried out market by market because market share of product j depends on the characteristics of all products in market t.[30]

The marginal cost shock is recovered by necessary optimality conditions at the second stage. From the optimal price function (11), I derive ω_{jt} as a function of marginal cost characteristics h_{jt} and parameters δ,

$$\omega_{jt} = p_{jt} - h_{jt}\delta + \Omega_{s_{ft},p_{ft}}^{-1} \cdot s_{jt}(p_t, \bar{x}_t, \xi_t; \theta_d). \tag{15}$$

[30] I iterate the contraction mapping until the maximum difference between each iteration is smaller than 10^{-12}: $\|\xi^M - \xi^{M-1}\|_\infty = \max\{|\xi_1^M - \xi_1^{M-1}|, \cdots, |\xi_{J_t}^M - \xi_{J_t}^{M-1}|\} < 10^{-12}$.

Finally, the fixed cost shock for each endogenous characteristic is obtained by the optimality condition at the first stage. The first-order condition (12) yields ζ_{jt}^k $(k = O, F, M, D)$ as,

$$\zeta_{jt}^k = \left(\sum_{h \in J_{ft}} \frac{\partial \Pi_h^{II}}{\partial \bar{x}_{jt}^k} + \sum_{h \in J_{ft}} \sum_{h' \in J_t} \frac{\partial \Pi_h^{II}}{\partial p_{h'}} \frac{\partial p_{h'}}{\partial \bar{x}_{jt}^k} \right) - \tau_0^k - \tau_1^k \bar{x}_{jt}^k. \tag{16}$$

The marginal and fixed cost shocks are computed carrier by carrier within a market, considering that each firm maximizes profit from its own products. Notice that demand parameters θ_d enters the specifications of all structural errors. While θ_d enters the unobservable quality ξ_{jt} on the demand side, it becomes a factor of marginal cost shock ω_{jt} through the market share function, and of ζ_{jt}^k $(k = O, F, M, D)$ through the profit function. Moreover, marginal cost parameters δ included in ω_{jt} enters ζ_{kjt} through the profit function. This interrelation motivates us to jointly estimate the demand and supply parameters for enhancing efficiency.

I estimate the parameters by using the two-stage nonlinear Generalized Method of Moments. For product j in market t, let W_{jt}=$[W_{jt}^d \; W_{jt}^c \; W_{jt}^k]$ be a set of instruments for endogenous variables in demand, marginal cost, and fixed cost specification, respectively. As an identification assumption, I set the moment conditions by taking expectations of each structural error interacted with the exogenous instruments

$$\begin{aligned} &\forall j, t: \\ &E[W_{jt}^{d\prime} \xi_{jt}(\theta_d)] = 0, \\ &E[W_{jt}^{c\prime} \omega_{jt}(\theta_d, \delta)] = 0, \\ &E[W_{jt}^{k\prime} \zeta_{jt}^k(\theta_d, \delta, \tau^k)] = 0, \quad k = O, F, M, D. \end{aligned} \tag{17}$$

Let $g(\Theta)$ be the stacked vector of sample analogues to the moments (17), where

$\Theta = [\theta_d \quad \delta \quad \tau^k]$. I minimize the first-stage objective function $Q = g(\Theta)'Vg(\Theta)$ with a weighting matrix $V = (W'W)^{-1}$, assuming all error terms are homoscedastic. After obtaining parameter estimates $\widehat{\Theta}^1$, I compute the structural errors $\hat{\eta} = [\hat{\xi} \quad \hat{\omega} \quad \hat{\zeta}^k]$ to obtain the optimal weighting matrix $V = (W'\hat{\eta}\hat{\eta}'W)^{-1}$ for second stage. The objective function is minimized once again to produce the final parameter estimates $\widehat{\Theta}^2$.

II.4.1 Instruments

Carriers observe the product quality ξ_{jt} and the cost shocks (ω_{jt}, ζ_{jt}^k, $k = O, F, M, D$) before they decide optimal product characteristics and prices. Therefore, the carriers' decisions are correlated with the structural errors. As an example of price, airline tickets restricted to Saturday night stay-over, advance purchase, or non-refundability requirement tend to be cheaper than unrestricted tickets (Puller et al., 2012). Further, when carrier face significant marginal cost shocks (e.g. fuel cost, landing fee) and fixed cost shocks (e.g. insurance, FAA registration fee, advertising cost), they may reorganize flight operations and production facilities which can affect the product characteristics. In this sense, the price and the characteristics are endogenous.

The exogenous instruments for prices include the information on market and airport-carrier level. The number of routes within a market can represents the degree of the market competition, which is correlated with overall price level. Next, the number of cities directly connected from an origin airport by a carrier measures the carrier's network size from each airport. This airport-carrier specific variable is related to the attractiveness of frequent flier program and thus can capture a substantial portion of price premium. Finally, exogenous variables in the demand and supply specification are included.

The identification strategy for the product characteristics is to find exogenous factors influencing airline operations. I apply weather conditions at an airport, a carrier's hub status at an airport, and a carrier's employment statistics (see table 3). First, weather conditions such as wind, rain, and snowfall are beyond carriers' controls, but affect several product characteristics either directly or indirectly. *Ontime15* is affected most. Adverse weather conditions are the direct cause of most flight delays because it requires extra preparations for takeoff and landing. *Mishandled baggage* also falls under the direct effect since a delayed baggage is counted as a mishandled one.[31] The bad weather indirectly influences *Frequency* through flight cancelations. Since I measured *Frequency* based on departures performed (not on departures scheduled), the cancelation due to bad weather is correlated with *Frequency*. However, it is not easy to find a close relationship between the weather conditions and *Denied boarding*. Notably, when the U.S. DOT measure *Denied boarding*, it does not consider passengers affected by canceled, delayed, or diverted flights.

Second, a carrier's hub status at an airport, which can be treated as exogenous, significantly affects the product characteristics.[32] As Rupp et al. (2006) states, flights originating from hub airports tend to have lower on-time performance, because some of aircraft services such as cleaning, refueling, or catering occur only at hub airports, requiring a longer preparation time for the next same-day departure. Differently, flights connecting to hub airports tend to have better on-time performance in order to reduce inconvenience to connecting passengers. About *Frequency*, flights to and out of hub airports tend to exhibit high frequency to accommodate the dense traffic

[31] Wyld et al. (2005) provides a good example. During Christmas holiday season in 2004 when severe weather created disruptions, US Airways misplaced thousands of baggages across the Midwest, accumulating them at airports along the East Coast.

[32] The exogeneity assumption on a carrier's hub status at an airport is supported by DOT (1999). In most medium and large airports in the US, major airlines have entered into long term use-and-lease agreements, including residual, compensatory, and hybrid agreements to attain the status of hub (or signatory) carrier. The average length of the agreement was 28 years for a residual agreement, 17 years for a compensatory agreement, and 20 years for a hybrid agreement.

flows (Brueckner and Zhang, 2001). Since my sample is supporting the pattern, I include all hub-related variables in instruments. Baggages are mostly mishandled when transferred through hub airports during congested peak periods (Jayaraman and O'Connell, 2011). Hence, I consider only connection at a hub as an instrument for *Mishandled baggage*. Since *Denied boarding* is positively correlated with high load factor mostly observed from flights out of hubs, the origination from a hub is included.

The final group of instruments contains a carrier's employment statistics. Using Air Carrier Financial Report, I calculated the percentage of workers in each labor category over total number of employees in an airline company and identified how their works were related to each product characteristic. Suppose that significant malfunctions of aircraft systems are detected just before departure time, then many skilled maintenance workers would be necessary for the flight to be on-time. Similarly, carriers need a large number of pilots, copilots, and aircraft controllers to keep high *Frequency*. *Mishandled baggage* and *Denied boarding* can be affected by the number of cargo handling employees and the number of staff in statistical posts, respectively.

I conduct F-test by running reduced-form regressions. The test statistics (in bottom panel of table 3) indicate that the instruments are valid at 99% significance level.

II.4.2 Estimation Results

II.4.2.1 Demand parameters

The first column in table 4 reports the estimated demand parameters. First, price parameters are identified by sensitiveness of product shares in response to changes in prices. The coefficients of $Fare_1$ and $Fare_2$ are -0.098 and -0.999, respectively. While both groups receive disutility from price increase, type 2 passengers exhibit about ten times as much price sensitivity as type 1 passengers. Based on industry knowledge, we can regard type 1 as the business travelers and type 2 as the tourists.[33]

Positive coefficients of $Ontime15_1$ and $Ontime15_2$ suggest that better on-time performance increases passengers utility who do not want flight delay during their travels. It should be noted that consumers do not know whether they would experience flight delays or not at the time of ticket purchase. However, as Suzuki (2000) and Mazzeo (2003) state, passengers can form expectations of flight delays based on the carrier's past on-time performances on a specific route. In that sense, the parameters can be interpreted as marginal utility from the expected on-time arrival.[34] To calculate willingness-to-pay (WTP) for on-time performance, I divide the coefficients of $Ontime15_1$ and $Ontime15_2$ by those of $Fare_1$ and $Fare_2$, respectively. The result implies that business travelers show nearly eight times higher WTP than the tourists do: $\frac{\psi_{11}}{\alpha_1} / \frac{\psi_{12}}{\alpha_2} = 7.9$.

Next, an increase in *Frequency* has a positive effect on consumers' utility. The parameter estimate is 0.084. Consumers value a flight schedule with multiple departures because they are more able to depart at their preferred time. Increases in *Mishandled baggage* and *Denied boarding* will decrease the quality of airline products hurting passengers satisfaction. Reasonably, both characteristics have negative coefficients: -0.054 for *Mishandled baggage* and -0.253 for *Denied boarding*.[35]

[33]In Berry and Jia (2010), estimates of price coefficients are -0.07 and -0.78 for the business passengers and the tourists, respectively (using 1999 data). Berry et al. (2006) reported 0.068 and 0.696 for the business passengers and the tourists, respectively (using 1985 data). My estimates are close to them in terms of coefficient of each type and difference between the two coefficients.

[34]More specifically, one can set up a dynamic model where a consumer's decision at time t depends on past experiences of flight delays at time $t-1, \ldots, t-N$. One good reference is Suzuki (2000) who developed an aggregate-level Markovian type model.

[35]Similar to on-time performance, I posit that consumers form their expectations on whether the baggages will be damaged, lost, or delayed, and wether they will be denied boarding from flights

All other demand parameters have the expected signs. The coefficients of $Layovers_1$ and $Layovers_2$ are -1.255 and -1.085, respectively, indicating that connecting flights generate disutility to both groups. Going through an additional stopover at the connecting airport makes their travels not as smooth as flying on direct flights. In terms of WTP, the business group exhibits about twelve times higher WTP than the tourists do: $\frac{\psi_{21}}{\alpha_1}/\frac{\psi_{22}}{\alpha_2} = 11.8$. $Distance$ has a significantly positive coefficient, 0.105. In short-haul markets, airline products are competing with other transportation modes such as cars, buses, or trains. As a traveling distance increases, however, the substitutability to the outside goods becomes worse so that demand for air travel can grow.[36] $HubDM$ also has a positive coefficient, 0.056. It indicates that carriers attract more passengers at their hub airports. Borenstein (1989) called this phenomenon *airport dominance* by major carriers. The positive parameter is consistent with the finding.[37] The coefficient of $Slot - control$ is -0.071, indicating that passengers get disutility from traveling through slot-controlled airports. An obvious source is flight delays frequently observed at these airports. However, since this study controls the delays by $Ontime15$, I interpret the disutility to mean fatigue and discomfort passengers endure at the congested airports. It can include a longer waiting time at ticket check-in counter and security check gates. The positive coefficient of $Tour$ supports the well-known fact that tourist places attract more passengers.

The nested logit parameter λ measures the degree of product differentiation be-

based on past experiences.

[36] Many studies controlled distance squared to capture the curvature of demand. For example, Berry and Jia (2010) found negative sign of distance squared, implying that further increase in distance makes the travel less pleasant.

[37] Borenstein (1989) pointed out the airport dominance as the main cause of hub premium. A body of related studies suggest that the airport dominance is possible because of more convenient gate access and higher expected value from frequent flier program at hub airport. Recently, Lee (2013) suggests that the airport dominance is based on the gate contract between airport and major carriers. The estimates of a structural model reveal that a major carrier's gate dominance at its hub airport has a positive effect on consumers' utility.

tween all airline products. If λ is equal to 1, air transportation services are perfectly differentiated. The estimate 0.618 implies that there exists a mild substitution possibility among airline services. Finally, γ_1 measures the percentage of type 1 passengers in the population. The parameter 0.052 indicates that the business group accounts for only 5.2% of the potential travelers. However, the business passengers are much more likely to actually buy ticket compared to the price-sensitive tourists. Based on the consideration, I calculate the percentage of each type of consumers in the sample and find that the business group makes up 40.5% of the actual travelers.[38]

II.4.2.2 Marginal and fixed cost parameters

The second column in table 4 presents the cost parameters. Marginal cost parameters are estimated by regressing the difference between price and estimated markup on the marginal cost characteristics. Starting with $Frequency$, the parameter -0.021 indicates that when a carrier adds one more departure per day for a specific route, the cost of serving an additional passenger tends to decrease by \$2.1. Greater $Frequency$ contributes to increasing aircraft utilization (block hours per day) and to reducing turnaround times at airports. This makes per-flight and per-passenger cost decrease. The parameter of $HubMC$ (-0.184) indicates that the existence of hub airport on an itinerary tends to decrease marginal cost by \$18.4. Among two countervailing effects (described in section 2.2), the negative sign supports that cost reduction from high load factor is greater.

As expected, $Layovers_{short}$ and $Layovers_{long}$ have positive coefficients, 0.175 and 0.300, respectively. The additional fuel that a connecting flight spends during extra

[38] The estimates are close to those in Berry et al. (2006). Based on various specifications, they reported that the business travelers make up 2.5%-7.7% in the population, and 26.8%-39.9% in the sample. I calculate the percentage of the business group in the sample as: $\sum_{t=1}^{T} M_t \cdot \widehat{\gamma}_1 \cdot \frac{D_{1t}^{\lambda}}{1+D_{1t}^{\lambda}} / \sum_{t=1}^{T} \sum_{r=1}^{2} M_t \cdot \widehat{\gamma}_r \cdot \frac{D_{rt}^{\lambda}}{1+D_{rt}^{\lambda}}$, where $D_{rt} = \sum_{k \in J_t} e^{(x_{kt}\widehat{\beta}_r + \widehat{\xi}_{kt})/\widehat{\lambda}}$.

landing/takeoff increases marginal cost substantially. $Distance_{short}$ and $Distance_{long}$ also have positive coefficients, 0.226 and 0.130, respectively. As a market distance increases, the cost of carrying one more passenger rises. Interestingly, given the tendency of larger airplanes to serve long-haul markets, the $Layovers$ and $Distance$ coefficients imply that larger aircrafts tend to consume relatively more fuel during landing and takeoff phases, but tend to exhibit high fuel efficiency in the air.

The coefficients of carrier dummy variables show that American Airlines (omitted as a base carrier) appears to have the highest marginal cost, followed by US Airways, Delta, and Northwest in order of high cost. In order to check the validity of the carrier-specific cost effect, I looked into each carrier's operating cost per available seat mile (CASM) during the sample periods, using Air Carrier Financial Statistics (Schedule P-12). Table 5 and figure 2 indicate that the order of US Airways-Delta-Northwest still stands in CASM data. However, American Airlines reports the lowest CASM, which seems curious. This implies that there can exist other factors which are not captured by the model.[39] The low cost carriers Southwest and AirTran have reasonably low level of marginal costs than the legacy carriers.

The fixed cost parameters are estimated by regressing the derivative of the variable profit function on the fixed cost characteristics. Notice that the dependent variable is equivalent to the slope of fixed cost by equation (6) and (12), and thus the constant terms measure the marginal effect of the characteristics on the fixed cost. The coefficient of $Ontime15_{constant}$ indicates that as on-time performance improves from 0% to 100%, the fixed cost increases by \$0.24 million. Although the on-time performance is largely affected by exogenous factors such as weather, carri-

[39]One interesting point in figure 2 is that all carriers experienced substantial increases in CASM from the fourth quarter of 2007. This is mainly due to high fuel prices during the U.S. economic recession (beginning December 2007). Specifically, Schedule P-12 data reveal that legacy and LCC carriers, respectively, spent 23.0% and 27.3% of their operating costs for fuel in 2006, however, the proportions increased up to 30.2% and 34.7% by 2008.

ers can still take steps to improve it. They can make an investment to adopt newer aircraft with fewer maintenance problems, more efficient fuel/food delivery system, advanced crew scheduling, and better boarding procedures. All these steps increase the fixed cost significantly.

$Frequency_{constant}$ also has positive coefficient 6.605. Although raising $Frequency$ reduces marginal cost, it increases the fixed cost. Considering that increased frequency on a certain route requires more economic resources such as fleets, pilots and crew-member, ground-side services, the result makes sense.

Coefficients of $Mishandled\ baggage_{constant}$ and $Denied\ boarding_{constant}$ are -8.126 and -31.634, respectively. They suggest that as each of them decreases, the fixed cost increases. Since decreases in the characteristics make airline products better, the negative signs make intuitive sense. In order for baggages to be in the right place at the right time, efficient equipment and well-trained agents (e.g. check-in agents, ramp agents, and baggage handlers) are necessary at each baggage-handling point. Similarly, reducing the number of involuntarily bumping passengers (without hurting the load factor) needs to apply sophisticated forecasting system and to increase the aircraft capacity to some extent. All these improvements lead to higher fixed cost.

II.5 Merger Simulations

The primary purpose of this paper is to simulate how a merged carrier adjusts the product characteristics and prices, and how the post-merger equilibrium affects welfare. In this section, I simulate the Delta and Northwest Airlines merger based on pre-merger data, the structural model, and the parameter estimates. Section 5.1 describes simulation methodology, and section 5.2 provides the detailed simulation results. In section 5.3, I report changes in consumer and producer welfare. Finally, section 5.4 evaluates the simulation result by comparing it with actual post-merger data.

II.5.1 Simulation Methodology

I perform the simulation based on the last two quarters in the pre-merger sample,[40] and focus on the markets where the Delta and Northwest Airlines competed with each other.[41] Table 6 describes several statistics for the simulation sample. The merging airlines competed in 1,129 overlapped markets, including nine duopoly markets prior to the merger. They had very similar passenger share per market, but their products were significantly different in terms of the price and the characteristics.

Figure 3 illustrates three separate games: price model G^P, full model G^{FL}, and hypothetical model G^H. Pre is actual pre-merger data where P^{Pre} is a price, and X^{Pre} is a vector of the endogenous characteristics. In the price model, carriers can change only prices post-merger, holding the characteristics fixed at pre-merger level. This game corresponds to the standard merger simulation where change in price $P^P - P^{Pre}$ measures the cross-price effect CPE^P from the merger. On the other hand, the full model allows carriers to adjust both prices and the characteristics. In this case, $P^{FL} - P^{Pre}$ represents not only the cross-price effect CPE^{FL} but also demand and cost-driven effects $\Delta P\ from\ \Delta X$ (explained in section 1). I decompose the price change in the full model into two separate effects by simulating the hypothetical model. This game assumes pre-merger situation as if the Delta and Northwest

[40] At an early stage of this study, I simulated based on the last quarter in the pre-merger sample as most merger studies did. The results from that sample are largely consistent with what will be reported in section 5.2. However, since the last quarter has only three monopoly markets after ownership consolidation, I expand the simulation sample to provide more robust results not only for oligopoly markets but for monopoly markets.

[41] The focus on overlapped markets does not necessarily mean that merger effect in other markets is negligible. A series of papers studied the spill-over effect over non-overlapped markets. However, standard merger simulation has focused on the overlapped markets where merger effect arises from a loss of competition. To compare it with my simulation, I also concentrate those markets.

Airlines are separate carriers, but the characteristics are hypothetically equated to the post-merger characteristics in full model X^{FL}. Since this game does not consider the ownership consolidation, the price change comes from the adjustment of characteristics, that is, $P^H - P^{Pre}$ measures $\Delta P \; from \; \Delta X$. Consequently, $P^{FL} - P^H$ identifies CPE^{FL}.[42] Notice that magnitudes of two cross-price effects will be different because the product repositioning in the full model can cause higher differentiation or higher substitutability between the merged firm's products. In the case of higher differentiation, we expect $CPE^P > CPE^{FL}$, otherwise $CPE^{FL} > CPE^P$.

The full model derives post-merger characteristics and prices sequentially. Based on the post-merger ownership of the products, the simulation searches X_f^{FL}=$(\bar{x}_f^{k*}, k = O, F, M, D)$ for firm f by solving

$$X_f^{FL} = \arg\min \sum_k \frac{\partial \Pi_f^{I\,\prime}}{\partial \bar{x}_f^k} \frac{\partial \Pi_f^I}{\partial \bar{x}_f^k}, \quad k = O, F, M, D \tag{18}$$

where $\frac{\partial \Pi_f^I}{\partial \bar{x}_f^k}$ is the necessary optimality condition (12) at the first-stage game. After deriving X^{FL} for all carriers in all markets, it continues to derive P_f^{FL} by solving the optimal price function

$$P_f^{FL} = \widehat{mc}_f^* - \Omega_{s_f,p_f}^{post}(P^{FL}, X^{FL}, \hat{\xi}; \hat{\theta}_d)^{-1} \cdot s_f(P^{FL}, X^{FL}, \hat{\xi}; \hat{\theta}_d) \tag{19}$$

where $\widehat{mc}_f^*$ is marginal cost estimates calculated by using post-merger characteristics X_f^{FL}, and Ω_{s_f,p_f}^{post} is an analogous matrix to (10) based on post-merger ownership structure. I iterate this sequential process once more in spirit of best-response iteration.[43] The price model and the hypothetical model skip the derivation of a new

[42] This simulation design is an application of price-location game in Gandhi et al. (2008).

[43] I used a very tight tolerance to compute the equilibrium. The tolerance levels of product characteristics and prices are 1e-12 and 1e-15, respectively.

vector of product characteristics and search only new optimal prices.

After simulating the post-merger equilibrium, I compute quality index Q for each product by taking an inner product of the set of endogenous characteristics and their respective parameters,

$$Q_{jt} = \sum_{r=1}^{2} \sum_{k} \gamma_r \cdot \bar{x}_{jt}^{k} \beta_r^k, \quad k = O, F, M, D \tag{20}$$

where γ_r is the percentage of type r passengers in the population.[44]

Further, I quantify the magnitude of product differentiation with two quality-distance measures: *within-firm distance* and *within-market distance* (see figure 4). I define a within-firm distance of product j as the closest quality-distance to other goods produced by the same firm. For the merged firm's products, if the distance increases post-merger, it implies that the product becomes more differentiated so that the cross-price effect can be weaker. On the other hand, a within-market distance of product j is measured by the closest quality-distance to other goods produced by competitors in the same market. A longer within-market distance post-merger implies that the merged carrier can raise price easily based on less substitutability to its competitors' products.

II.5.2 Simulation Results

II.5.2.1 Changes in product characteristics

The histograms in figure 5 through 7 describe how the merged firm changes the product characteristics.[45] They show us two important findings: *overall quality*

[44] A primary reason of introducing the scalar-valued quality index is to provide more intuitive interpretations for changes in product characteristics. It does not affect simulation results.

[45] Each number mounted on each bar in figure 5 through 7 is an average value of product quality or characteristics over the corresponding products.

degradation and *higher product differentiation* post-merger. The first implication is shown by figure 5 (a). While the average quality index decreases for all groups of markets after the merger, the quality degradation is severe in markets where the merging carriers had market power before the merger.[46] Specifically, markets where both carriers had market power (indicated by DL & NW) show that the quality decreases by 1.5% from 1.241 to 1.222. Sub-figures from 5 (b) to (e) suggest that flight frequency changes the most, decreasing by 4.7% from 2.832 to 2.698. It amounts to 12 less flights for each product during a quarter. The mishandled baggage rate and denied boarding rate increase, respectively, by 1.1% from 6.048 to 6.113 and 2.1% from 1.072 to 1.095, also supporting the quality degradation. When either carrier had market power (DL only, NW only), the quality decreases as well. However, when neither carrier had market power (Neither), the quality rarely changes. In short, the combined firm lowers the product quality especially when it has a strong market power. However, the incentive of quality degradation becomes weaker when strong competitors exist because the potential risk of losing passengers increases.

To look at the second implication, I divide the merged firm's products into large-, medium-, and small-share goods (henceforth large, medium, and small goods, respectively).[47] Since a product is a unique combination of carrier and route, we can regard a large good as a major route (or a primary good), and a small good as a minor route (or a secondary good) in a market. A medium good refers to a route serving medium-sized enplanements. Figure 6 (a) illustrates the changes in average quality of three product groups in oligopoly markets. For the large goods including 692 products in 680 markets, the merged firm improves the quality by 0.8% from

[46] I define an airline has market power if it carries more than 25% of total market enplanements.

[47] If a product serves more than 50% of the carrier's enplanements in a market, it is defined as a large good. If less than 50% but at least 20%, it belongs to medium goods. The remaining goods with less than 20% constitute small goods.

1.319 to 1.330. Specifically, frequency increases by 1.6%, corresponding to adding 6 more flights per product during a quarter. Mishandled baggage rate and denied boarding rate decrease by 0.6% and 0.9%, respectively. The medium goods show very similar patterns. However, the small goods including 865 products in 3,598 markets deteriorate substantially. The quality index decreases by 1.0% from 1.285 to 1.272 and the underlying characteristics become worse. The frequency reduces by 2.9%, indicating 10 less flights per product during a quarter, and mishandled baggage rate and denied boarding rate increase by 0.5% and 1.0%, respectively.[48] To sum up, the merged firm increases the product differentiation post-merger by upgrading large and medium goods and downgrading small goods.

The higher product differentiation post-merger can be understood by the firm's profit-maximizing behavior. As I will show in subsection 5.2.2, the average profit from large goods is much bigger than that from small goods. This motivates the merged firm to move passengers from small goods to large or medium goods by adjusting the product quality. To verify this argument, I compute the number of passengers of each type who purchase the large, medium, and small goods pre- and post-merger.[49] It reveals that while total number of tickets sold in oligopoly markets decreases post-merger, the proportion of large goods increases from 70.6% to 71.6% and that of small goods decreases from 14.0% to 13.0%.[50] Specifically, table 14 shows that the business group purchases more large goods and less small goods, and the tourists' consumptions decrease the most for small goods after the merger.

[48] I tested different definitions of large, medium, and small goods. The quality index changed slightly depending on the definitions, but directions of quality changes were highly robust. The test results are available upon request.

[49] For example, I computed a percentage of the business passengers who actually bought large goods in the sample as: $\sum_{t=1}^{T} M_t \cdot \widehat{\gamma}_1 \cdot \frac{L_{1t}}{D_{1t}} \frac{D_{1t}^{\lambda}}{1+D_{1t}^{\lambda}} / \sum_{t=1}^{T} \sum_{r=1}^{2} M_t \cdot \widehat{\gamma}_r \cdot \frac{L_{rt}}{D_{rt}} \frac{D_{rt}^{\lambda}}{1+D_{rt}^{\lambda}}$, where $D_{rt} = \sum_{k \in J_t} e^{(x_{kt}\widehat{\beta}_r + \widehat{\xi}_{kt})/\widehat{\lambda}}$, $L_{rt} = \sum_{l \in L_t} e^{(x_{lt}\widehat{\beta}_r + \widehat{\xi}_{lt})/\widehat{\lambda}}$, and L_t is the set of large goods produced by Delta or Northwest Airlines in overlapped market t.

[50] We can check this based on table 14.

Intuitively, the large goods are associated with major routes where a carrier's hub airports exist and they generate considerable profits. Therefore, the merged firm takes better care of those routes to attract more passengers to them.

Figure 7 (a) provides the quality adjustment in monopoly markets. The simulation sample contains only 28 products in 9 monopoly markets, but the pattern of higher product differentiation post-merger still stands. A notable thing in monopoly markets is that the quality changes are greater in absolute value, relative to oligopoly markets. The quality of large goods increases by 6.4% from 1.342 to 1.428, and that of small goods decreases by 7.4% from 1.328 to 1.230. We can understand the greater quality changes by monopolist with table 14 again. After the merger, the business group takes higher proportion of large goods in monopoly markets (66.7%) than in oligopoly markets (53.9%). Also, the tourists buy bigger proportion of small goods in monopoly markets (61.6%) compared to oligopoly markets (55.1%). Without competition, monopolist can adjust product quality more flexibly toward extracting more profits from each group. Even though the provided qualities can be higher or lower than most preferred level by each type, consumers are more forced to choose a particular product as the monopolist leads.

II.5.2.2 Changes in prices

How and to what extent does the product repositioning affect post-merger prices? I present the results in table 7 and 8. Each table reports the quality index, the endogenous characteristics (whose values are identical to those in figure 6 and 7), and the quality-distance measures pre- and post-merger. Importantly, the bottom panel describes the simulated price changes from three separate games.[51]

Table 7A is about the large goods in oligopoly markets. Notably, the within-

[51] Each number in the table 7 and 8 indicates the average value over the corresponding products.

firm distance increases by 0.021 post-merger. This implies that the large goods become more differentiated from medium and small goods due to the quality improvement. Meanwhile, the within-market distance decreases very little, indicating that they become slightly more substitutable to competitors' products. Based on the repositioning of large goods, we can expect the merged firm to have a difficulty in internalizing cross-price effect.

I examine this hypothesis by comparing the cross-price effects CPE^P and CPE^{FL} in the bottom panel. The second column indicates the cross price effect in the price model: CPE^P =\$4.9. The third and fourth column present price changes under the full model and the hypothetical model, respectively, and finally the cross-price effect in the full model is calculated in the last column: CPE^{FL} =\$2.2. Consistent with the hypothesis, the merged carrier internalizes a lower cross-price effect given the quality adjustment: $CPE^P > CPE^{FL}$. Even though the quality improvement causes price increase: $\Delta P\ from\ \Delta X$ =\$1.5, it does not surpass the reduction of cross-price effect. Therefore, when the product characteristics are endogenized, the simulation predicts a lower price increase than the typical merger analysis due to the higher product differentiation: $P^P > P^{FL}$.

If so, why does the merged firm raise the product differentiation? This issue leads us to see profit changes. In table 7A again, the full model predicts lower marginal cost and more passengers relative to the price model. The cost reduction is possible due to the increased frequency, and the attraction of more consumers is based on the enhanced quality. All these changes allow the merged firm to increase profit per product by \$540 in the full model, which is much bigger than \$190 in the price model. The additional profits correspond to \$0.37 million and \$0.13 million, respectively, when multiplied by the number of large goods. To sum up, although the higher product differentiation reduces the ability of raising price, it can generate more profit.[52]

The medium goods show very similar patterns to the case of large goods (see table 7B). One difference is that the within-market distance slightly increases post-merger. It can positively affect the cross-price effect in the full model. However, it still predicts smaller price increase than the price model by showing $CPE^{P}(\$9.5) > CPE^{FL}(\$6.9)$ and $P^{P} > P^{FL}$.

Interestingly, small goods show very different aspects compared to large and medium goods. Even though the small goods become more differentiated from other product groups due to their quality degradation (the within-firm distance increases by 0.012 post-merger), the full model predicts a greater cross-price effect than the price model: $CPE^{FL}(\$34.2) > CPE^{P}(\$24.1)$. It seems implausible, but is still consistent with profit-maximizing decision in two aspects. First, unlike other product groups, the within-market distance considerably increases, implying that the small goods become less substitutable to competitors' products. This encourages the merged firm to increase price. Second, small goods generate very small profit per product pre-merger. The profits are \$59.1k, \$6.9k, and \$2.0k for large, medium, and small goods, respectively. Thus, the significant price increase (together with the quality degradation) of small goods can contribute to transferring consumers to other profitable goods.

Table 8 reports the simulation results for monopoly markets. While they exhibit similar patterns, one difference is that prices of all product groups increase to a greater extent in the monopoly markets than in the oligopoly markets. One possible explanation is that the monopolist does not consider the within-market substitutability.

[52]Section 5.3 will address the profit analysis more thoroughly.

II.5.3 Welfare Analysis

This section assesses how the post-merger equilibrium affects the welfare. The demand parameters indicate that two types of consumers have heterogeneous tastes for the characteristics and price. On the supply side, the simulation results reveal that the merged firm repositions the large, medium, and small goods differently. This encourage us to examine the consumer surplus of each type and the producer surplus from each product group.

II.5.3.1 Consumer welfare

I measure changes in consumer welfare by the compensating variation. Following Small and Rosen (1981), the compensating variation for a type r passenger in market t is given by

$$CV_{rt} = \frac{V_{rt}^{pre} - V_{rt}^{post}}{\alpha_r}, \tag{21}$$

where $\alpha_r < 0$ is the marginal disutility from price increase. Pre-merger term is defined as $V_{rt}^{pre} = \ln\left[1 + (\sum_{j \in J_t} e^{(x_{jt}^{pre}\beta_r + \xi_{jt})/\lambda})^{\lambda}\right]$, and V_{rt}^{post} is analogously defined to V_{rt}^{pre} replacing x_{jt}^{pre} by x_{jt}^{post}. Then, the change in the average per-passenger surplus in market t is measured by $CS_t = \sum_{r=1}^{2} \gamma_r \cdot CV_{rt}$, and the change in total consumer surplus is the sum of CS_t in all markets: $CS = \sum_t M_t \cdot CS_t$ where M_t is the market size.

Table 9 reports the welfare effect based on the price model G^P and the full model G^{FL}. In the first panel covering all markets, G^P predicts a decrease in consumer welfare for both types. Since this game predicts substantial price increase, holding the product characteristics fixed at pre-merger level, the welfare loss is a natural result.

However, G^{FL} predicts substantially different outcomes in two aspects. First, the overall consumer welfare increases. To be specific, the tourists still experience the welfare losses (-\$0.36 million), but the business passengers benefit significantly from the merger (\$2.22 million). For the price-insensitive business group, utility gains from large and medium goods (associated with the quality improvement and the lower price increase) are greater than their losses from small goods (associated with the quality degradation and the greater price increase). However, for the price-sensitive tourists, the welfare losses from the price increase surpass the potential gains from quality improvement of large and medium goods. In overall, the amount of benefits to the business group largely surpasses the losses to the tourists.[53] The result reveals that if the set of repositioned products exhibits more differentiation post-merger, it mitigates the welfare loss from the price increase and even leads to increases in consumer welfare. Recent studies on endogenous product choice have found that merger can have a positive effect on consumer welfare if the merged firm changes its product offerings which consumers value more (see, e.g. Mazzeo et al., 2013). My finding is consistent with the literature and provides new evidence from the airline industry.

Second, the tourist group experiences smaller loss in G^{FL} than in G^{P}. As table 14 shows, the number of tourists who purchase large or medium goods is not much different pre- and post-merger, but for small goods, it largely decreases. That is, a substantial portion of the tourists moves to large, medium, or outside goods, facing

[53]As section 4.2 showed, the tourists account for 59.5% of actual travelers and for 94.8% of potential travelers. Considering the significant proportions, it seems unreasonable that the tourists' welfare losses are much smaller than the business travelers' gains. However, the tourists are shown to exhibit about ten times as much price sensitivity as the business group ($\alpha_2/\alpha_1 = 10.2$). When computing the compensating variation for each type, a change in the indirect utility is divided by the respective price coefficient for converting it into dollar value. This makes a scale of the tourists' losses drop to a tenth so that it becomes largely surpassed by business travelers' gains.

the dramatic increase in price of small goods.[54] Since G^{FL} predicts lower prices for large and medium goods than G^P, the welfare losses by the tourists become smaller in G^{FL}.

In the second panel table 9, we can observe the same patterns of welfare changes in both monopoly and oligopoly markets. The bottom panel presents another aspect. I divide markets into Quality-increase (QI) and Quality-decrease (QD) markets. If a weighted average quality of the merged firm's products in a market increases post-merger, I define it as QI market, otherwise it belongs to QD market.[55] While the welfare changes in the QI markets follow the overall trend well, the consumer surplus in QD markets become worse off. This is because the overall quality degradation prevents the business group from getting significant welfare gains. I compare the features of two groups of markets (see table 12) and observe that QI markets consist of more competitive routes where the merging carriers had relatively small market presence pre-merger. This confirms that the lack of market competition results in worse product quality, and thus negatively affect the consumer welfare.

II.5.3.2 Profits and social welfare

Endogenizing product characteristics crucially affects firms' profits as well. In the top panel of table 10, the price model G^P predicts that merged carrier increases profits by \$0.17 million, but the merger lowers the competitors' profits by \$0.30 million, causing the overall producer surplus to decrease. On the other hand, the full model G^{FL} forecasts further increases in the merged firm's profit by \$0.68 million and smaller decreases in the competitors' profits by \$0.12 million, leading to increase in the producer surplus. A closer look at the computed outcome reveals that the

[54] In table 7 and 8, G^{FL} predicts that small goods become more expensive than large and medium goods on average post-merger.

[55] I use the number of passengers of each product as the weight.

higher gain to the merged firms is due to higher markup, and the lower losses to the competitors are based on increased number of consumers who switch from the merged firm due to the overall quality degradation and the price increase.[56] Once two carriers are combined, the pre-merger characteristics may no longer be at the profit-maximizing level. G^P ignores this, but G^{FL} finds new equilibrium characteristics and prices allowing higher profits for the merged carrier. The pattern of profit changes is observable in monopoly, oligopoly, and QI markets.

In QD markets, however, not only competitors but also the merged firm loses profit in G^{FL}, even though the amount of loss by the merged firm is very small. The main reason is a large decrease in the passenger enplanements. The merged firm carries less 0.9% of passengers in QI markets, but it loses 2.6% of passengers in QD markets, which is large enough to completely offset the gains from higher markups. Finally, the bottom panel shows that the merged firm increases profit from all groups of products, but mostly from large and medium goods.

Table 11 describes change in the social welfare. Expectedly, two simulations produce completely different outcomes. While G^P leads the social welfare to decrease by \$1.70 million, G^{FL} predicts it to increase by \$2.41 million based on the increase not only in consumer surplus but also in producer surplus. The quality improvement of large and medium goods contributes to increasing utility gains especially of business travelers, on the other hand, the merged firm extracts more profits from the consumers who switch to more profitable goods. In overall, when a merger simulation endogenizes product characteristics, it produces quite different results from traditional simulation in terms of the post-merger equilibrium and the welfare effects.

[56]The average markups of the merged firm are \$150.1 and \$157.4 in G^P and G^{FL}, respectively, and the average passenger enplanements by competitors are 172,304 and 172,733 in G^P and G^{FL}, respectively.

II.5.4 Comparison between Simulation Result and Actual Post-merger Outcome

In this section, I evaluate the predictive performance of my simulation by comparing the simulated result with actual post-merger data. Notice that both the price model G^P and the full model G^{FL} rely on the same set of assumptions regarding demand, cost, and firms' conduct. One difference is that only G^{FL} allows the changes in product characteristics post-merger. In this sense, the comparison can be a test of the endogeneity assumption.

To make such a comparison feasible, I exclude several markets from the comparison sample. Specifically, I drop a market if the merged carrier does not serve it any longer, or if the number of carriers, LCCs, and routes within a market substantially change after the merger.[57] This is for controlling the exogenous changes such as entry and exit occurrence in routes or markets that the model does not take account of. The final comparison sample consists of 244 markets. The bottom panel of table 13 shows that the characteristics of the selected markets do not change much over the integration period.

Importantly, I restrict this analysis to comparing flight frequency. I consider that the set of product characteristics is the first to be derived in the sequential choice model and the frequency changes the most among the endogenous characteristics. Hence, if the simulated frequency is substantially different from the actual post-merger frequency, further comparison analyses on prices and welfare effects would not be a very meaningful tasks.[58] I compare the frequencies by market level rather

[57] Among 1,129 markets in the simulation sample, I exclude 154 markets the merged carrier exited as of first quarter of 2010. Further, I drop 731 markets where a change in the number of carriers is greater than three, or a change in the number of LCCs is greater than two, or a change in the number of routes is greater than five.

[58] Other product characteristics are not appropriate for the comparison analysis. The data on mishandled baggage rate and denied boarding rate are available only at carrier level (see table 1), whereas the simulation outcomes are carrier-route specific. Also, on-time performance rarely changes according to the simulation.

than by product level because the set of merged firm's products in a market has changed post-merger.[59]

The top panel of table 13 presents the result. The first column reports average market frequency (henceforth, AMF) pre-merger which G^P relies on.[60] The second and the third column report the simulated AMF from G^{FL} and actual AMF post-merger, respectively. The table shows two clear trends. First, the simulated and actual AMF decrease from pre-merger AMF by 0.33 and 0.46, respectively. The reductions correspond to 7,247 (=$0.33 \times 90 \times 244$) and 10,102 (=$0.46 \times 90 \times 244$) less flights during a quarter in the selected markets. This pattern is observable in both monopoly and oligopoly markets. Second, the simulated and actual AMF move in the same direction. They increase in QI markets and decrease in QD markets, while actual AMF changes more. The results implies that even though G^{FL} under- or overestimates actual AMF, it better predicts post-merger outcomes than G^P.

To be more specific, I illustrate market frequency (henceforth, MF) of each market in figure 8. Figure 8 (a) shows that the probability density function of actual MF (solid line) shifts to the right from that of pre-merger MF (dotted line) in QI markets. Figure 8 (b) shows that actual MF generally lies above pre-merger MF. Both figures indicate the increase of actual MF in QI markets. A notable thing is that the simulated MF is located closer to actual one than pre-merger MF is. The density function of the simulated MF shifts to the right, and its bar plot in each market fits actual MF line better. Figure 8 (c) and (d) describe the result in QD markets. They

[59]For example, the merging carriers served the Chicago to New Orleans market with two connecting flights: (in order of origin-outward connecting-destination-inward connecting airport) **ORD**-ATL-MSY-ATL and ORD-MEM-MSY-**MEM** pre-merger, but **MDW**-ATL-MSY-ATL and ORD-MEM-MSY-**ATL** post-merger. Even though the number of routes are same, airports in the itineraries are slightly different. This prevents the comparison by product level.

[60]Market frequency (MF) is defined as sum of frequency of each product provided by merging/merged carriers in a market: $MF_t = \sum_{j=1}^{J_{ft}} Frequency_{jt}$, where j is a product and t is a market. Then, average market frequency (AMF) is mean value of market frequency across markets: $AMF = \frac{1}{T}\sum_{t=1}^{T} MF_t$.

show quite the opposite situation where the density function of the simulated MF shifts to the left following actual MF and its bar plot also fits in well with actual MF line mostly lying below pre-merger MF.

Figure 9 describes an overall pattern by getting QI and QD markets together. In figure 9 (a), the density function of actual MF significantly deviates from that of pre-merger MF, and the simulated MF is located between them in general. Finally, the bar plots in figure 9 (b) to (d) confirm again that the simulated MF better follows actual MF line than pre-merger MF does. In short, the comparison analysis suggests that endogenizing product characteristics is essential to better predict the actual post-merger outcome.

II.6 Conclusion

When a merger simulation ignores changes in product characteristics post-merger, it can lead to a significant bias in predicted prices and welfare effects. This paper overcomes the limitations by endogenizing both price and product characteristics in a two-stage oligopoly game. Using data from the U.S. Department of Transportation, I estimate the model parameters and then simulate the effect of the Delta and Northwest Airlines merger on product characteristics, fares, and welfare. To evaluate the predictive performance of the simulation, I compare the simulated outcome with actual post-merger data.

The main findings are as follows. First, the merged firm tends to increase product differentiation post-merger. The firm increases the quality of large and medium goods, but decrease that of small goods. The magnitude of the changes are stronger in monopoly markets. Since the large and medium goods are more profitable, the merged firm takes better care of their qualities to attract more passengers to them.

Second, the higher product differentiation affects the merged firm's incentive to raise prices. For large and medium goods, the full model predicts smaller cross-price effects than the price model. But for small goods, the cross-price effect is greater in the full model. The decreased quality and the increased price of small goods contributes to moving the consumers to large or medium goods.

Third, endogenizing product characteristics leads to quite different welfare effects. While the price model predicts decrease in consumer welfare for both types of passengers, the full model predicts that the business passengers benefit from the merger ($2.22 million) and the tourists experience smaller losses (-$0.36 million). This leads to an overall increase in consumer welfare. The finding highlights that a merger can increase consumer welfare if the merged firm brings the repositioned products that consumers can value more. About producer surplus, both models predicts higher profit for the merged firm and less profits for the competitors, but the additional profit gain for the merged firm is much bigger in the full model ($0.68 million) than in the price model ($0.17 million).

Finally, endogenizing product characteristics contributes to better predicting actual post-merger outcome. In QI markets, the simulated and actual post-merger frequency increase from pre-merger frequency. In QD markets, on the other hand, they decrease from pre-merger one. For both cases, the probability density function of the simulated is located between those of pre-merger and actual post-merger frequency.

CHAPTER III

AIRPORT-AIRLINE VERTICAL CONTRACT AND MARKET POWER IN THE U.S. AIRLINE INDUSTRY

III.1 Introduction

Vertical contracts between airline and airports are widely used and can benefit both parties. From an airport's point of view, long-term contracts can increase aeronautical revenues[61] by encouraging airlines to concentrate their traffics at the airport as part of a hub-and-spoke network (Brueckner, 2002). Hubbing, in turn, attracts more passengers so that it can generate higher concession revenues.[62] From a carrier's perspective, when it performs large-scale operations in terms of the number flights and the number of occupying gates at an airport, it is likely to increase own market share by providing frequent flight schedules on various routes.

Among various forms of vertical contracts,[63] this paper focuses on the case of "signatory carriers", which refers to a setting where airlines have fully executed Use-and-Lease Agreements with an airport.[64] Under the agreements, the airport grants three special rights to signatory airlines. First, the carriers are able to solely

[61]Aeronautical revenues include aviation service charges such as landing fees, terminal, and gate rentals paid by airlines. On the other hand, non-aeronautical (or concession) revenues encompass parking fees, car rentals, banking, catering, and other service revenues mostly received from passengers.

[62]In this sense, many studies indicate that there exists a positive demand externality between aeronautical services and concession revenues (Fu and Zhang, 2010; Oum and Fu, 2008).

[63]Main types of contracts are summarized well in Fu et al. (2011), who classify vertical alliances into 'signatory airlines', 'airline ownership of airport facilities', 'long-term use contracts', 'issuance of airport revenue bonds', and 'concession revenue sharing'.

[64]In this paper, I need to distinguish hub carrier from signatory carrier. Most Hub carriers are signatory carriers, but not vice versa. For example, as of Fiscal year 2004, Dallas/Fort Worth airport had 25 active signatory airlines. Among them, only two carriers, American and Delta airline were hub carriers (DFW, 2004).

occupy certain airport facilities such as departing/arriving gates, ticket counters, and baggage claim areas for extended periods (e.g. twenty years). Second, the airline can sublease any under-utilized facilities to other carriers possibly at premium prices. Finally, most large and medium sized airports allow Majority-In-Interest (MII) power wherein signatory carriers can delay or prevent airport capital-development projects. Several governmental reports (e.g. Department of Transportation, 1999; General Accounting Office, 1990) point out that these contractual practices can be anti-competitive because they can effectively limit competitors' access to gates and other key facilities. Recently, Ciliberto and Williams (2010) found that the limited access to airport facilities is a critical source of the well known hub premium.

Motivated by the previous studies, I aim to extend Ciliberto and Williams (2010) by providing more structural descriptions. Ciliberto and Williams (2010) uses the three business practices as measures of the barriers to entry and estimates a linear specification of the reduced-form pricing equation. With this approach, the paper could clarify to what extent the operating practices explain the hub premium. However the practices, especially a carrier's gate control can affect not only consumer utility but also its marginal cost. If a carrier's gate-dominance allows significant market power by shifting demand upward, it is likely to increases air fares. On the other hand, if gate dominance reduces its marginal cost through several possible channels (explained in section 2), then ticket prices can decrease. In this respect, the estimates from the reduced-form regression represent the net effect of the gate control on both sides. The primary goal of this paper is to identify the effects of the contractual arrangements on demand and supply separately. Initially, I estimate a pricing equation (similar to Ciliberto and Williams (2010)), and then deepen the analysis with structural estimation. Moreover, by utilizing advantage of the structural approach, I examine how hypothetical regulations affect carriers' fares, costs, and profits.

I work with three main data sources. First, Competition Plans collected from thirty one hub airports provide details on gate lease agreements, sublease agreements, and majority-in-interest (MII) clauses. I also use data sets DB1B containing fare and ticket information, published by the U.S. Department of Transportation (DOT). Finally, to create additional route characteristics, I utilize the T-100 Segment database, also maintained by the DOT .

From the reduced form estimation, I confirm that the three contractual practices are crucial determinants of the hub premium. Specifically, the coefficients of hub variables decrease by almost fifty percent after I control the contractual agreements.[65] Importantly, with following structural estimation, I find that gate-dominance enables signatory carriers to have substantial market power (shifting demand upwards), as well as to take cost advantages (shifting supply downwards). On demand side, a carrier's gate-occupancy has a positive effect on passenger utility, and business travelers have thirteen times larger Willingness to Pay (WTP) for gate than tourist travelers. The result supports that better services from more gates satisfy consumers who want convenience, and that the extensive airline network based on the control of a large fraction of gates can hold more appeal for business passengers. On supply side, a five percent increase in the gates leased at the origin airport leads to \$2.5 reduction in the airline's marginal cost. Furthermore, the existence of sublease agreement at an airport is likely to increase non-signatory carriers' marginal cost, whereas MII clauses increase signatory carriers' marginal cost. In overall, these cost effects associated with the clauses are more likely to occur at congested airports. From the counterfactual simulation, I find that the conversion of exclusive gates to commonly

[65] Hub variables include two dummies, $HubOrg$ and $HubDst$. $HubOrg$ ($HubDst$) equals 1 for a hub carrier at an origin (destination) airport.

available gates at airports can reduce the differentials in costs and profits between signatory and non-signatory airlines.

The paper is organized as follows. Section 2 provides a detailed discussion of business practices associated with the case of signatory airline. Section 3 describes the dataset. Section 4 presents the structural model of demand and supply. In section 5, I explain estimation procedures and instrumental variables. Section 6 report the results of the estimations and counterfactual analysis. Section 7 concludes the paper with a brief summary.

III.2 Contractual Practices between Signatory Airlines and Airports

In this section, I describe three key contractual practices and specify hypotheses on how the long-term gate contracts influence the demand and supply of aviation services.

III.2.1 Gate Use-and-Lease Agreements

Airports lease gates to carriers mainly through two gate lease agreements. Under 'exclusive' agreement, airlines have 'full rights' to gates. Full rights mean that the carrier does not have to share its gates with other carriers even if the gates are under-utilized.[66] In some cases, they can develop 'preferential' agreement,[67] which is similar to exclusive rights except there exists a 'use it or share it' requirement.[68] Through these agreements, signatory airlines can ensure gate dominance, and make

[66]In general gate utilization is based on number of daily operations. For example, a minimum of three flights/weekday is required for signatory airlines.

[67]According to ACI-NA survey (1998), 56 percent of gates at thirty hub airports were leased on exclusive basis, and the remaining gates were leased on preferential (33%), or on common basis (11%).

[68]According to the requirement, if minimum utilization criterion is not met, the signatory airline is subject to sharing its under-utilized gates with other carriers. But in most cases, signatory airlines do satisfy it.

it difficult for new entrants to obtain gates and serve the airport.

I expect gate dominance can be positively correlated with passenger utility in two ways. First, a dominant carrier may occupy more convenient gates, and it can produce better services in terms of on-time performance. As Mazzeo (2003) indicated, actual taxi-in times[69] for flights by major carriers was significantly lower than others.[70] Second, gate availability also permits an airline to expand the size of the airline network in terms of the number of routes and destinations served. Especially for consumers who regularly fly to multiple destinations, the extensive network becomes more attractive since it will increase the expected values of frequent flier programs (Lederman, 2008).

Next, from supply-side perspectives, I hypothesize that a carrier's gate-dominance can keep its marginal costs down. This is possible through three conceivable channels. Most directly, signatory airlines pay a lower price for use of the airport's facilities, compared to non-signatory carriers. As of January 2012, Chicago O'hare airport charged \$82/sqft of terminal rent and \$5.7/1,000lbs of landing fee for signatory airlines, but for non-signatory carriers, these charges were \$110.7/sqft and \$7.2/1000lbs, respectively. These fee differentials can be found at most U.S. airports (see table 16). In addition, long-term gate contracts can reduce transaction cost. The transactions include allocation of terminals, gates, ticket counters, loading bridges, and airline administrative spaces. Suppose that these facilities are assigned on a daily basis without long-term contract, and then airline and airport should manage plenty of operational transactions day after day, which cause increased cost with high frequency of transactions.

Finally, a carrier's gate dominance is closely related to economies of traffic den-

[69]This term refers to the time elapsed between wheels-on and gate arrival at the destination airport.

[70]A lower taxi-in-times can affect a carrier's cost, too.

sity.[71] Based on Competition Plans and T-100 dataset, I found a significantly positive correlation between gate dominance (average number of gates controlled by a carrier at both endpoint cities) and route dominance (the number of flights on the route). This in turn can lead to a greater traffic density which eventually contributes to reduced marginal cost of carrying an extra passenger.

III.2.2 Sublease Agreement

Signatory carriers can sublease their gates to new entrant carriers. As Ciliberto and Williams (2010) states, when a new entrant carrier want to begin flight service at an airport where there exist no gates available, its main alternative is to sublease gates from major carriers. Table 17 shows tenant/sub-tenant relationships at Dallas/Fort Worth airport in 2001. Note that such subleasing involves direct negotiation between signatory airlines and new-entrants without any arbitration or intervention by the airport authority. Even if the requesting airline successfully identifies unused gates, they may be required to use the ground-handling services of the primary tenant airline, while they desire to self-handle or use another party (DOT, 1999). Furthermore, many airport authorities exercise no control over sublease fees, possibly resulting in higher costs to the sublessee. According to Competition Plans collected, sublease agreements were being practiced at seventeen airports between 2002 and 2005, but only six had fixed limits on sublease fees.[72] Under the circumstances, I expect the existence of sublease agreement at an airport will increase sub-tenant carriers' marginal costs. However, I do not expect passenger utility to be affected by subleasing at an airport, mainly because whether a boarding gate for a passenger is subleased or not is rarely important in travel decisions. Thus, I consider sublease agreement only in

[71] Economies of density exist if marginal cost decrease as flights or seats are added on a route.

[72] the airports include Austin, Washington Reagan, Minneapolis, Oakland, San Antonio, and San Francisco airport.

marginal cost equation.

III.2.3 Majority-In-Interest Clauses

The MII provisions authorize signatory carriers not only to review a specific airport expansion project but also to approve or disapprove it. While the project may include construction of additional terminals, gates, and other essential facilities which can accommodate new entrants, the signatory carriers can deny it since the costs of the new project can be included in the rates and charges to themselves.[73] If the plan does not receive MII approval, the airport may have to delay or abandon it. For this reason, MII clauses have been criticized as anti-competitive (DOT, 1999). Competition Plans indicate that 22 out of 31 airports allow MII clauses (see table 18) and 11 airports experienced actual invocation.

I expect the MII provisions to have mixed effects on carriers' marginal cost. The existence of the clauses at an airport can raise signatory carriers cost because they are responsible for covering sufficient airport operating expenses based on a residual fee methodology. At the same time, it can decrease the carriers cost by reducing the number of airport projects financed by themselves. For a similar reason to the case of sublease agreement, whether an airport allows MII power or not does not seem to be relevant to traveler's utility, thus I specify the clause only in cost side.

[73]While use-and-lease agreement generally specifies terms and conditions for using airfield and terminal facilities, it also defines financial responsibility. Under a *residual agreement*, signatory airlines are financially responsible for airport operating expenses not covered by non-aeronautical revenue and aeronautical revenue paid by non-signatory airlines. Under a *compensatory agreement*, airlines are charged only for the facilities and services that they actually use. Finally, a *hybrid agreement* combines elements of the two agreements. 84% of the residual and 74% of hybrid use-and-lease agreements involve MII clauses (ACINA, 1998). The issue related with this typology has been further investigated by Hartmann (2006).

III.3 Data and Variable Construction

In this section, I describe data sources and explain how I constructed variables representing the contractual agreements and other control variables.

III.3.1 Competition Plan Data

In the interest of promoting competitive environment at the U.S. airports, the Wendell H. Ford Aviation Investment and Reform Act for the 21st Century (also known as AIR-21) was enacted on April 5, 2000. AIR-21 has targeted at medium to large hub airports dominated by one or two airlines with more than fifty percent of the airport's total enplanements.[74] While the number of airports covered varies each year, the act has required the airports to submit 'Airport Competition Plan' to the DOT.[75] In total, I collected thirty one plans by contacting with officials of each airport (see table 18). Each plan provides specific information on the total number of gates available, the number of gates leased on exclusive (or preferential) agreement, sublease arrangement, and MII clauses at the airport.

III.3.1.1 Competition plan variables

Based on the Competition Plans, several variables are constructed as follows. First, I create the variable $GateShareOrigin_{km}$, which represents the percentage of gates exclusively or preferentially leased to airline k at origin airport of route m. Similarly I define $GateShareDest_{km}$ for destination airport. I decided not to distinguish between exclusive and preferential gates because in practice two agreements are little

[74] If an airport carries less than 1.0%, but at least 0.25% of total national enplanements, it is categorized as medium-hub airport. Airports with at least 1.0% of total national enplanements are large-hub airports.

[75] During fiscal year 2004-2005 and 2010-2011, 41 and 36 airports submitted Competition Plans, respectively.

different in terms of retaining a primary right to use the gates.[76] Table 15 indicates that on average one airline controls 14 percent of gates at origin airport, and 12 percent at destination airport. As extreme cases, Continental airlines occupy 78.6% of gates at Houston Intercontinental (IAH), Northwest airlines control 79.0% at Memphis (MEM).[77] Figure 10 indicates the number of gates available and gates leased on exclusive (or preferential) agreements at thirty one medium and large hub airports.

Second, for sublease arrangement, I define $SubleaseOrigin_m$ as indicator variable, which is equal to 1 if sublease agreements were being practiced for the year shown in Competition Plan at origin airport of route m. In a similar way, $SubleaseDest_m$ is defined for destination airport. Table 18 shows that sublease agreements between signatory and small carriers exist at 17 out of 31 airports, including most large hub airports (e.g. Atlanta, Dallas/Fort Worth, Houston, Chicago O'Hare, Philadelphia airports).[78]

Finally, the variable $MiiOrigin_m$ equals 1 if an origin airport on route m allows MII provision in its use and lease agreements. Similarly, $MiiDest_m$ is constructed for destination airport. Table 18 indicates that 22 out of 31 airports were subject to MII power.[79]

Even though Competition Plans help to identify these variables, the data have one

[76]For the same reason, Ciliberto and Williams (2010) uses the variables '*OwnGatesOrigin*' and '*OwnGatesDest*', which measure the percentage of gates leased on an exclusive or preferential basis.

[77]In total, there are 103 gates at IAH and 81 gates at MEM as of 2004.

[78]Competition Plans also offer some information on whether the airport puts sublease fee ceilings, and on what the actual cap is. However, I decided not to use the information because not a few airports answered with a vaguely worded statement. For example, one airport answered as follows; If the requesting airline feels that the sublease fee proposed by the signatory airline is *too high*, the requesting airline may complain to airport manager. If airport manager agrees that the rate is *unreasonable*, it can deny the signatory airline's right to sublease the space unless a *more agreeable* cost structure is developed.

[79]To better understand the effect of MII clauses, I tried to find out whether MII power had been actually invoked to delay or prevent any capital construction projects at an airport. But I feel unsuccessful in identifying this point, because descriptions of the invocation of MII clause are also vague.

potential limitation. The airline data (DB1B and T-100 Segment Data) come from the second quarter in 2004, but Competition Plans (collected and used) are varying in terms of the filing year. In table 18, while 28 out of 31 plans were submitted during 2002, 2003, and 2004, remaining ones were produced during 2001, 2006, and 2007 by Ontario, Albuquerque, and Tucson airport, respectively.

To address this issue, first, I thoroughly compared multiple plans collected from the same airport but written in different years (e.g. the 2000, 2001, and 2003 plans of the San Francisco airport). This comparison reveals that most airports have experienced little change during filing years in terms of total number of gates and the number of gates controlled by each carrier. Table 19 details this aspect at San Francisco airport. During three fiscal years, the first six carriers (Alaska, American, Continental, Delta, Northwest, and United airline) did not change their gate occupancy, while the remaining carriers showed little variation. Also, neither sublease agreements nor MII clauses changed. Second, it is noteworthy that airport-airline contracts have been signed on a long-term basis. GAO (1990) reported that 27 percent of gates at 66 medium to large airports were leased for a 3-10 year period, 25 percent of gates for an 11-20 year period, and 35 percent of gates for a more than 20 year period.

III.3.2 Airline Data

The main source of airline data is the Airline Origin and Destination Survey (DB1B), published by the U.S. DOT. This database is a ten percent random sample of all domestic tickets that originate in the U.S. each quarter. It provides specific information on the route of travel, fare, and other data. Using this information, I defined market, product, and several control variables (see table 15) which represent carrier, airport, and route characteristics. I obtained additional route characteristics from

T-100 Domestic Segment Database, which contains domestic and nonstop segment data each month, reported by all U.S. carriers. With this database, I created flight frequency and the number of seats available for each carrier-route.

The airline data are from the second quarter of 2004. The primary reason for choosing the period is that domestic output (e.g. total passenger enplanements and revenue passenger-miles) had recovered from a post-9/11 downturn by 2004. Furthermore, the year 2004 is well-matched with filing years of Competition Plans collected.

The sample is restricted to all domestic routes between the thirty one hub airports. I keep only round-trip itineraries within U.S. continent with at most four segments. Also, I drop tickets cheaper than \$40 or more expensive than \$1,800. The lower bound is to eliminate tickets purchased using frequent flyer miles, and the higher bound is to restrict the sample to coach-class travel. The final sample contains 167,348 round-trip tickets.

III.3.2.1 Market and product

Following Berry and Jia (2010), market and product are defined as follows. A market is a directional round trip between origin and destination airport. For instance, Chicago-Detroit is a different market from Detroit-Chicago. This definition allows us to differentiate the characteristics of the origin city from those of destination city. The market size is the geometric mean of the MSA population of two end-point cities.

A product is a unique combination of market, carrier, direct (or connecting), and binned fare during a quarter. Given observed market and carrier, fares of many tickets are close to each other. For example, the sample has \$616 and \$617 tickets from Atlanta to Chicago by Delta airline. Facing these tickets, consumers may not recognize them as two different products. Based on the consideration, I combined tickets with similar fares into a single product by applying progressive fare bins.[80] Set of bins is as follows: $20 increments for all tickets between $40 and $700 (e.g. tickets between $500 and $520 with the same market and carrier are aggregated to have same price $510), $50 for tickets between $700 and $1000, and $100 for tickets between $1,000 and $1,800. In order to check whether the estimation results are sensitive to the bin size, I also estimated with smaller and larger bin size as a robustness check. However, I do not consider direct and connecting itinerary as the same product no matter how their fares are close to each other. In summary, the final sample is composed of 58,612 products in 888 different markets.

It should be noted that a true choice set of a consumer may only consists of tickets that are available for the desired travel date on or around the time of the purchase date. Unfortunately, DB1B database do not contain any information on date of purchase and date of travel. With the limited data, I have no choice but to rely on the assumption that all tickets observed in a given quarter are in any passenger's choice set during the quarter. Some other airline studies have used a panel of DB1B data using the mean price (or certain percentiles of the price distribution) for any given market. However, since I only have the Competition Plans at one point in time for each airport, this option is not desirable for this study. Ideally, one can overcome the possible misspecification of the choice set by using individual transaction level data which are only available from a large Computer Reservation System (CRS).

III.3.2.2 Control variables

To get more accurate effects of the Competition Plan variables, I control several factors affecting consumer utility and/or carrier marginal cost. On the demand side,

[80]When an individual round-trip ticket is considered as a product, memory requirement and estimation time are likely to seriously increase. This is because the product shares need to be inverted at each iteration in the frame of random coefficient logit model (described in section 4)

I control a $Constant$, $Distance$ (a round trip distance between origin and destination airport), and $Layovers$ (the number of total connections per round trip, 0 for direct flights, and 2 for connecting flights).[81] To account for possible inconvenience at congested airports, I include $Slot - control$ (the number of slot-controlled airports on itinerary). Two slot-controlled airports in the sample are Chicago O'Hare (ORD), Reagan National (DCA). As a measure of appeal to tourists, I define $Tour$ (a dummy variable, 1 if the itinerary has an endpoint in Florida or Nevada). Considering that a hub-and-spoke network affects both aircraft size and flight frequency (Brueckner, 2002), I include $Nseat$ (number of seats available in an aircraft) and $Frequency$ (average daily departures in a quarter by an airline) to control some part of hub-effects. Notably, both $Nseat$ and $Frequency$ can be endogenous in this research. In most airline studies, they are assumed to be pre-determined factors because carriers cannot adjust them at least in the short run. Unlike them, this paper considers the 'long-term' contractual agreements, and it is likely that gate availability affects aircraft size and flight frequency especially when facing the shift in the demand in the long run. To handle this potential endogeneity issue, I applied a set of instruments for the variables (discussed in section 5).

On the cost side, I expect that a carrier's marginal cost depends on several factors other than Competition Plan variables. I control two distance measures $Distance_{short}$ and $Distance_{long}$, considering that fuel efficiency can differ depending on aircraft size, and different sizes of fleets are allocated on short-haul and long-haul routes.[82] Similarly, I control $Layovers_{short}$ and $Layovers_{long}$ based on two considerations.

[81] Technically, 'direct' means that passengers do not change planes between origin and destination, while 'non-stop' means that the flight does not stop between origin and destination. In this paper, I use both terms to refer to flights that do not stop between origin and destination.

[82] I create an indicator variable I_{long}=1 if a market distance is longer than 3,000 miles and I_{short}=1 if a market distance is shorter than 3,000 miles. Then the distance measures are computed as $Distance_{long} = Distance * I_{long}$ and $Distance_{short} = Distance * I_{short}$.

Connecting flights involve an additional landing/takeoff during which airplanes burn a large fraction of fuel, and the fraction of fuel consumed at takeoff is known to vary with aircraft size.[83] On the other hand, the connections may allow carriers to generate high load factor in hub-and-spoke network system, resulting in decreased marginal cost. Thus, the coefficient of layovers will be determined by the magnitudes of two countervailing effects. Finally, I create carrier dummies on both demand and supply side in order to measure brand specific effects. Major airlines include Continental (CO), Delta (DL), Northwest (NW), United (UA), US Airway (US), and the base carrier, American (AA). Two low cost carriers are Southwest (WN) and JetBlue ($B6$). The remaining carriers are defined as Other Carriers (OT).

III.4 The Model

I consider a model with a discrete choice demand and an oligopolistic airline supply. Airlines provide a set of differentiated products in each market, and each consumer either purchases one product or takes the outside option of not flying. In each market, prices are determined by the Bertrand-Nash competition. Importantly, the Competition Plan variables are assumed to affect consumer utility and/or carriers marginal cost.

III.4.1 Demand

The demand model is a random coefficient discrete choice setting in spirit of Berry et al. (1995). In particular, I follow Berry and Jia (2010) in which there are only two types of consumers (r =1 or 2) in the air travel market.[84] Considering industry

[83] Similar to the distance measures, I compute the two $Layovers$ as $Layovers_{long} = Layover{*}I_{long}$ and $Layover_{short} = Layover * I_{short}$.

[84] Since this model allows random coefficient to have only two values, Berry and Jia (2010) called it a 'discrete type' version of the random coefficient logit model.

characteristics, we can think two types of passengers as tourist and business travelers. Especially I allow only three variables to have random coefficients: $Price$, $GateShare$ (the average of $GateShareOrigin$ and $GateShareDest$),[85] and $Layovers$ in order to see whether tourist and business travelers exhibit different level of preference toward price, the carrier's gate dominance, and direct flight. For product j in market m, the utility of consumer i, who is of type r, is given by

$$\begin{aligned} u_{ijm} &= X_{jm}\rho + \delta_r GateShare_{jm} + \eta_r Layovers_{jm} + \alpha_r p_{jm} + \xi_{jm} + \nu_{im}(\lambda) + \lambda\epsilon_{ijm} \\ &= x_{jm}\beta_r + \alpha_r p_{jm} + \xi_{jm} + \nu_{im}(\lambda) + \lambda\epsilon_{ijm} \qquad (22) \end{aligned}$$

where X_{jm} is a vector of observed characteristics of product j, including $Distance$, $Frequency$, $Slot-control$, $Tour$, $Nseat$, and carrier dummies

$GateShare_{jm}$ is the average percentage of gates leased to an airline producing product j in market m,

$Layovers_{jm}$ is the number of total connections round trip of product j,

p_{jm} is the price of product j,

ρ is the vector of tastes for product characteristics,

δ_r, η_r, α_r are, respectively, marginal utility associated with $GateShare_{jm}$, $Layovers_{jm}$, p_{jm} for type r consumers,

ξ_{jm} is the unobserved (to econometrician) product characteristic (e.g. product quality),

ν_{im} is a nested logit disturbance that is constant across all inside products in

[85]This specification has two intentions. First, it reduces the number of coefficients to be estimated. Second, it can measure aggregate level of consumer conveniences at origin and destination airport. For example, suppose that a passenger is taking a round trip from Houston to New York by Continental airline which controls a majority of gates at both airports. Departing from Houston, she likes better services from gate-dominance by Continental airline. Similarly, this advantage can also be applied for returning travel from New York.

market m, but differentiates air travel from the outside option (not flying),

λ is the nested logit parameter,

ϵ_{ijm} is an *i.i.d.* (across products and consumers) logit error,

$\nu_{im}(\lambda) + \lambda\epsilon_{ijm}$ follows the Type I extreme value distribution.

The utility from the outside good (e.g. driving a car or taking a train) is given by

$$u_{i0m} = \xi_{0m} + \epsilon_{i0m}. \tag{23}$$

A simple way to identify mean utility of the outside good is setting it as one of the inside goods. However, it is not desirable strategy because airline products are quite different services from other ground transportation services. Alternatively, I normalize both ξ_{0m} and ϵ_{i0m} to be zero for all consumers. In this case, the coefficient of Constant will measure marginal utility from choosing any airline products.

While all type r consumers are assumed to purchase one unit of good that gives the highest mean utility $(x_{jm}\beta_r + \alpha_r p_{jm} + \xi_{jm})$, the market share of product j is given by

$$s_{jm}(x_m, p_m, \xi_m, \theta_d) = \sum_{r=1}^{2} \gamma_r \frac{e^{(x_{jm}\beta_r + \alpha_r p_{jm} + \xi_{jm})/\lambda}}{D_{rm}} \cdot \frac{D_{rm}^{\lambda}}{1 + D_{rm}^{\lambda}}, \tag{24}$$

where

$$D_{rm} = \sum_{k \in J_m} e^{(x_{km}\beta_r + \alpha_r p_{km} + \xi_{km})/\lambda}, \tag{25}$$

$x_m = (x_{1m}, \ldots, x_{Jm})$, and J_m is the set of all inside products in market m. Notice that there are only two groups of products in each market (all airline products and the outside option of not flying), thus the first term of equation (24) denotes within-group share of airline product j, and the second one refers to group share of all the airline products. The set of demand parameters θ_d includes the taste for the observed product characteristics β_r, the marginal disutility of price α_r, the nested logit parameter λ, and the percentage of type r consumers in the population γ_r.

I set moment conditions which are the expectations of the unobservable ξ_{jm} interacted with exogenous instruments z_1. To do so, we need to derive unobservable ξ_m as a function of x_m, p_m, θ_d, and observed market share $\dot{s_m}$ as follows,

$$\xi_m = s^{-1}(x_m, p_m, \dot{s_m}, \theta_d). \tag{26}$$

Technically, this inversion of the market share equation is conducted through the contraction mapping method by

$$\xi_{jm}^{M} = \xi_{jm}^{M-1} + \lambda[\ln \dot{s_{jm}} - \ln s_{jm}(x_m, p_m, \xi_m, \theta_d)], \tag{27}$$

where M denotes the M^{th} iteration, and $s_{jm}(x_m, p_m, \xi_m, \theta_d)$ is defined by equation (24).

Finally, I take price p_{jm} as an endogenous variable in the demand equation, since it can be correlated with unobservable product quality ξ_{jm}. For example, tickets restricted to Saturday night stay-over, advance purchase, and non-refundable requirement are likely to have cheaper prices than unrestricted tickets. Since I have no reliable information on these restrictions, an exogenous set of instruments is required to predict endogenous prices (see section 5).

III.4.2 Supply

Airline companies are assumed to set optimal multi-product prices according to the Bertrand-Nash equilibrium, given prices and characteristics of competing products, and the characteristics of their own products.[86] Under these assumptions, firm f chooses p_{jm} to maximize profit:

$$\Pi_f = \sum_{j \in J_{fm}} (p_{jm} - mc_{jm}) M_m s_{jm}(x_m, p_m, \xi_m; \theta_d) \tag{28}$$

where mc_{jm} is the marginal cost of product j in market m,

M_m is market size,

$s_{jm}(\cdot)$ is the share of product j,

J_{fm} is the set of all products produced by firm f in market m.

Marginal cost of product j in market m is given by

$$mc_{jm} = h_{jm}\psi + \omega_{jm} \tag{29}$$

where h_{jm} is a vector of observed characteristics of product j,

ψ is a vector of cost parameters to be estimated,

ω_{jm} is an unobserved cost shock.

Note that h_{jm} contains Competition Plan variables such as $GateShareOrigin_{jm}$, $GateShareDest_{jm}$, $SubleaseOrigin_m$, $SubleaseDest_m$, $MiiOrigin_m$, and $MiiDest_m$ as well as other observed cost shifters.

[86]Ideally, one can set up two-stage game where carriers decide product characteristics (including $Nseat$ and $Frequency$) in the first stage, and decide prices in the second stage. This specification involves a serious computational burden and is beyond the scope of this paper. Instead, I applied instrumental variables for the first-stage choice variables. The two-stage oligopoly game has been extensively addressed in Fan (2013) and Lee (2013).

Then, any equilibrium price, p_{jm} must satisfy the first-order condition,

$$s_{jm}(x_m, p_m, \xi_m; \theta_d) + \sum_{k \in J_{fm}} (p_{km} - mc_{km}) \frac{\partial s_{km}}{\partial p_{jm}} = 0, \quad for\ \forall j \in J_{fm}. \tag{30}$$

Define $s_{fm} = [s_{1m}, \ldots, s_{J_{fm}}]'$, $p_{fm} = [p_{1m}, \ldots, p_{J_{fm}}]'$, and $mc_{fm} = [mc_{1m}, \ldots, mc_{J_{fm}}]'$, then in vector notation the first order condition can be written as

$$s_{fm}(x_m, p_m, \xi_m; \theta_d) + \Delta(x_m, p_m, \xi_m; \theta_d)(p_{fm} - mc_{fm}) = 0, \tag{31}$$

where $\Delta(\cdot)$ is a $J_{fm} \times J_{fm}$ matrix, given by

$$\Delta(x_m, p_m, \xi_m; \theta_d) = \begin{bmatrix} \frac{\partial s_{1m}}{\partial p_{1m}} & \cdots & \frac{\partial s_{J_{fm}}}{\partial p_{1m}} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_{1m}}{\partial p_{J_{fm}}} & \cdots & \frac{\partial s_{J_{fm}}}{\partial p_{J_{fm}}} \end{bmatrix}. \tag{32}$$

In order to set moment conditions, I first derive markup equation. By using equation (31), markup b_{fm}, which is the difference between price and marginal cost, is defined as

$$b_{fm}(x_m, p_m, \xi_m; \theta_d) = -\Delta(x_m, p_m, \xi_m; \theta_d)^{-1} \cdot s_{fm}(x_m, p_m, \xi_m; \theta_d). \tag{33}$$

Then, with equation (29), the cost-side unobservable (ω_{jm}) can be obtained,

$$\omega_{jm} = p_{jm} - b_{jm}(x_m, p_m, \xi_m; \theta_d) - h_{jm}\psi. \tag{34}$$

Notice that cost-side unobservable ω_{jm} is expressed as a function of price p_{jm}, demand and cost characteristics $(x_m, p_m, \xi_m, h_{jm})$, and demand and cost parameters (θ_d, ψ).

III.5 Empirical Model

III.5.1 Method of Estimation

To get consistent estimates, it would be enough to estimate the demand and cost parameters separately. However, I consider that a set of demand parameters θ_d enters not only ξ_{jm} but also ω_{jm} through the market share function. This interrelation creates an incentive to jointly estimate them for an enhancement of efficiency. I estimate the system of equations by using a two-stage nonlinear GMM method. Let $Z = [z_1 \quad z_2]$ be a set of instruments for the endogenous variables in demand and marginal cost, respectively. As an identification assumption, I set the moment conditions by taking expectations of each structural error interacted with the exogenous instruments

$$\begin{aligned} &\forall j, m : \\ &E[z'_{1jm}\xi_{jm}(\theta_d)] = 0, \\ &E[z'_{2jm}\omega_{jm}(\theta_d, \psi)] = 0. \end{aligned} \tag{35}$$

Let $g(\Theta)$ be the stacked vector of sample analogues to the moments (14), where $\Theta = [\theta_d \quad \psi]$. I minimize the first-stage objective function $Q = g(\Theta)'Vg(\Theta)$ with a weighting matrix $V = (Z'Z)^{-1}$, assuming all error terms are homoscedastic. After obtaining parameter estimates $\widehat{\Theta}^1$, I estimate the structural errors $\hat{\tau} = [\hat{\xi} \quad \hat{\omega}]$ to compute optimal weighting matrix $V = (Z'\hat{\tau}\hat{\tau}'Z)^{-1}$ for second stage. The objective function is minimized once again to produce the final parameter estimates $\widehat{\Theta}^2$.

III.5.2 Instruments and Identification

Before airlines choose fares, they know the unobserved (to econometricians) product quality ξ and the unobserved cost shock ω. Hence, the choice variables are likely to be correlated with the structural errors. For the endogenous prices, I applied four groups of instrumental variables.

First of all, I use the number of routes within a market as market characteristics. This factor can represent the degree of competition in a market which can affect overall price level.

The second group of instruments includes the number of cities directly connected from origin and destination airport, respectively. These airport characteristics measure the aggregate network size of all carriers serving an airport which can be related to price level at the airport. I also include dummies for arriving at and transferring at hub airport in the sense that cost can be affected by hub operation.

Further, following Berry and Jia (2010), the 25th and the 75th quantile of fitted fares are included. These measures can better capture the price dispersion[87] which has been commonly observed in airline industry. To obtain the fitted fares, I regressed ticket fares on carrier dummy, market level characteristics (distance, tourist places, market size), and a carrier's share at origin and destination city.

The last group of instruments contains the exogenous variables that directly enter the market share equation and the marginal cost equation.

To handle the potential endogeneity of $Nseat$ and $Frequency$, I apply several carrier, route, and market characteristics. They include a carrier's percentage of flights originated from hub airports, percentage of flights terminated at hub airports, the number of cities that a carrier flies nonstop from origin and destination airport,

[87] This issue was exhaustively analyzed in Borenstein and Rose (1994, 2007)

and the number of routes within a market.

The random coefficient model in demand side will produce two sets of parameter estimates for $Price$, $GateShare$, and $Layovers$. Then how do we identify two types of passengers in air travel market? In brief, the data cannot identify two types of consumers. The identification comes from the substitution pattern among similar products. Let's consider price-product share plot in figure 11. Given market and distance, on average, high priced tickets will be purchased by consumers who do not care much about price (business travelers), and thus a price increase in high priced products may have small effect on demand. On the other hand, low-priced products are likely to be purchased by price sensitive consumers (tourist travelers) so that a price change can have large effect on the demand. Based on this substitution pattern, the model fits this sort of data by estimating two coefficients.

III.6 Result

I report results from the reduced form pricing equation first, and then present parameter estimates from the structural model. The marginal cost and profit estimates will be discussed next. Finally, I propose a counterfactual analysis examining how the conversion of exclusive gates to commonly available gates at airports will affect carriers' marginal cost, fare, and profits.

III.6.1 Reduced Form Pricing Equation

One of the key questions of this paper is whether three contractual clauses are crucial determinants of the hub premium. To examine the hypothesis, I regress round-trip ticket fares on hub variables, Competition Plan variables, and other control variables.

In the first column in table 20, we can see unconditional hub premium (without controlling Competition Plan variables). The variables $HubOrigin$ and $HubDest$ are indicator variables (1 if origin and destination airport, respectively, is a carrier's hub). The coefficient of $HubOrigin$ ($HubDest$) is 0.885 (0.566), implying that hub carriers charge \$88.5 (\$56.6) as extra premiums for flights departing from (arriving at) their hub airports. Consistent with previous studies (Borenstein, 1989), the result points out that there exists significant hub premium with greater effect at origin airports.

Next, to address main issue, I include Competition Plan variables in the next two columns. In the second column, the coefficient of $GateShareOrigin$ has significantly positive value of 1.929, implying that a 5 percent increase in the gate occupancy at origin airport would lead to \$9.6 increase in the airline's overall prices: $0.05 \times 1.929 \times 100$. The similar argument is available for $GateShareDest$. The existence of sublease agreement increases the overall prices by \$19.3 (\$34.7) at origin (destination) airports. The allowance of MII power also increases ticket fares by \$12.7 at destination airports.

Finally, I include both hub and Competition Plan variables in the third column. We can see that conditional on Competition Plan variables, hub premium becomes quite smaller compared to the unconditional hub premium. The coefficient of $HubOrigin$ is now 0.450, down from 0.885 (49.2 percent decrease), and that of $HubDest$ is 0.291, down from 0.566 (48.6 percent decrease). The result suggests that nearly 50% of hub effect comes from signatory carriers' gate dominance and associated contractual practices.[88] Considering possible endogeneity of $Nseat$ and $Frequency$, similar specifications are estimated by IV regressions. In overall, the results (in column 4 through 6) do not show much difference compared to OLS estimates in terms of their magnitudes and signs.

[88] In a different way, I regressed ticket fares on hub variables to get predicted value, and then regressed the predicted value on Competition Plan variables. Adj.R-sq. was about 50% again.

However, these parameter estimates should be interpreted with caution. Since all estimates are derived from reduced form specifications, they represent 'net effect' of the variables on demand and supply side. For example, if a major carrier's gate-dominance allows significant market power by shifting demand upward, *GateShareOrigin* (*GateShareDest*) is likely to increases fares. On the other hand, if gate dominance can reduce its marginal cost through operational advantages over other carriers, ticket prices can decrease. Thus, the coefficients of *GateShareOrigin* and *GateShareDest* represent the overall magnitude of two opposite effects on demand and supply side. The decomposition of these separate effects, which is the main goal of this study, is done by structural analysis in the following section.

III.6.2 Structural Analysis

III.6.2.1 Demand parameters

The first column in table 21 presents demand parameter estimates from structural estimation. Most parameters are precisely estimated. First, the price parameters are identified by the variation of product shares in response to the changes in prices. The coefficients of type 1 and type 2 passengers are -0.639 and -0.077, respectively. While different types of passengers are expected to exhibit differing price sensitivity, and type 1 travelers exhibit 8.3 times as much price sensitivity as type 2 group. Based on industry knowledge, type 1 passengers (with high disutility of price) represent the tourist group.[89]

Consistent with the hypothesis that a consumer's utility increases with a carrier's gate share, the coefficients for both tourists ($GateShare1$) and business passengers

[89] In Berry and Jia (2010), estimates of price parameters were -0.78 and -0.07 for tourist and business passengers, respectively (using 1999 data). Berry et al. (2006) reported 0.696 and 0.068 for tourist and business travelers, respectively (using 1985 data). Thus, my estimates are quite close to them.

($GateShare2$) are significantly positive, and business travelers exhibit stronger preferences (0.917) than tourists (0.580). Comparing Willingness to Pay (WTP) for gate by dividing coefficients of $GateShare1$ and $GateShare2$ by price coefficient of each type, business travelers have thirteen times higher WTP ($\frac{\delta_2}{\alpha_2}/\frac{\delta_1}{\alpha_1} = 13.1$). The result supports that better services from more gates satisfy consumers who want convenience. Furthermore, the extensive airline network associated with control of a large fraction of gates can hold more appeal for business passengers.

The coefficients of $Layovers1$ and $Layovers2$ are -0.436 and -0.572, respectively, indicating that connecting flights generate disutility to both groups. While taking connecting flights, passengers go through an additional stopover, movement to the next departure gate, and boarding. This connection process makes their travels not as smooth as flying on direct flights. In terms of WTP, the business group exhibits about eleven times higher WTP than tourist group does: $\frac{\eta_2}{\alpha_2}/\frac{\eta_1}{\alpha_1} = 10.9$.

All other demand parameters have the expected signs. $\ln Distance$ has a significantly positive coefficient, 0.212. In short-haul markets, air transportation services are competing with other transportation modes such as cars, buses, or trains. However, as a traveling distance increases, the substitutability to the outside goods becomes worse so that demand for air travel can grow.

$Frequency$ is expected to capture two things. First, high flight frequency represents the carrier's presence at the airport, which can be correlated with the carrier's gate dominance. Thus control of frequency can deal with the omitted variable bias problem associated with $GateShare$. Second, high frequency can benefit consumers by reducing schedule delay and by allowing frequent departures at more convenient times (Brueckner, 2002), thus consumers' utilities are likely to increase in flight frequency. The parameter estimates is 0.054.

The coefficient of $Slot - control$ is -0.074. Slot-controlled airports are more congested due to high traffic, and passengers regard travels through crowded airports as unpleasant factor. As shown in many previous studies, the tendency that tourist places attract more consumers is supported by the coefficient of $Tour$, 0.266. By using the number of seats as a proxy, I controlled aircraft size in order to catch overall capacity effect. The estimated coefficient was 0.382. As Wei and Hansen (2005) suggested, this positive effect comes from greater perceived safety, higher amenity levels, and slightly higher cruise speeds of larger planes.

Carrier dummies, which represent the effects of unobservable firm specific characteristics (for example, brand loyalty), produce reasonable signs and magnitudes. The coefficients imply that consumers exhibit strong preferences for low-cost carriers (LCCs). The coefficients of JetBlue and Southwest are 0.529 and 0.062, respectively. Flights out of fringe airports, online booking, and provision of just-necessary level of onboard services can keep LCCs' prices down. Considering that price-sensitive tourist passengers take about 87% of consumers in population ($\gamma = 0.873$), strong preferences for LCCs make sense. Finally, the degree of product differentiation between within-group products (λ) is 0.728. If λ is equal to 0, the within-group products become perfectly substitutable, thus the estimate 0.728 implies that there exists a mild substitution chance among airline products.

III.6.2.2 Cost parameters

Marginal cost parameters are estimated by regressing the difference between product price and the estimated markup on several cost characteristics. The results are reported in the second column in table 21. Starting with carriers' gate occupancy, I find the coefficient of $GateShareOrigin$ to be negative (-0.504) at the 10% significance level. The magnitude of the parameter can be interpreted as follows. A five percent increase in the gates leased at origin airport would lead to \$2.5 reduction in an airline's marginal cost: $0.05 \times (-0.504) \times 100$. As section 2 described, the cost reduction can be realized from a lower price charged to the signatory airlines for the use of the airport's facilities, the reduction of transaction costs, or the utilization of economies of traffic density. However, the cost reduction is not found at destination airports.

Next, coefficients of both $SubleaseOrigin$ and $SubleaseDest$ are significantly positive, 0.094 and 0.123, respectively. The coefficient of $SubleaseOrigin$ implies that the presence of a sublease agreement at the origin airport raises carriers' marginal cost by \$9.4: $1 \times 0.094 \times 100$. Notably, the data do not tell whether an individual carrier is sub-tenant airline or not: $SubleaseOrigin$ and $SubleaseDest$ are not carrier specific variables but airport characteristics. However, considering that new entrant carriers lease gates directly from signatory carriers without airport authorities' intervention on sublease fee-setting, the cost increase can be mostly borne by sub-tenant carriers (This argument will be tested in section 6.3). With regard to MII clauses, the coefficients are not significant.

Other cost parameters are precisely estimated with the expected signs. The coefficients of distance are 0.213 and 0.122 respectively for short and long-haul routes, implying that as market distance is longer, the cost of carrying one more passenger rises and that marginal cost is lower on long-haul routes due to higher fuel efficiency. The coefficient for Layovers represents two countervailing effects (as described in section 3.2). The positive estimates of $Layovers-short$ and $Layovers-long$ suggest that fuel consumptions for an extra take-off and landing surpass the cost advantage from higher load factors. Understandably, the two LCCs, JetBlue and Southwest, have lower marginal costs than the legacy carriers.

Ciliberto and Williams (2010) considered that the effect of carrier's gate dominance on hub premium can be stronger at congested airports where gates are scarce resource. This is possible because the expected shadow cost of obtaining a gate at congested airports can be high for a new entrant than other airports. In order to maintain close relation between their reduced-form approach and my structural analysis, I also create the airport congestion variable and interact it with all Competition Plan variables.[90] The results are reported in the table 22.

Starting with gate-occupancy, I find significantly negative effects. Coefficients of the two variables, $GateShareOrigin * CongestedOrigin$ and $GateShareDest * CongestedDest$, are -0.266 and -0.254, respectively. Surprisingly, the effects of the primary variables $GateShareOrigin$ and $GateShareDest$ become insignificant. This result suggests that controlling a large fraction of gates reduces carriers' costs only at congested airport. The estimate of -0.266 at origin airport indicates that 5% increase in gate control leads to \$1.33 reduction in the carrier's marginal cost at origin airports where congestion levels are one standard deviation higher than the mean airport: $0.05 \times (-0.266) \times 1 \times 100$.[91]

MII clauses, which had no effect in table 21, become highly significant and positive when airports are congested. The coefficients of interaction terms are 0.14 and 0.21 for $MiiOrigin * CongestedOrigin$ and $MiiDest * CongestedDest$, respectively. The estimate of 0.14 at the origin airport implies that the provision of MII power is likely to increase carriers' marginal cost by \$14 at origin airport with one standard deviation higher congestion: $1 \times (0.14) \times 1 \times 100$. As described in section 2.3, the coefficients of MII clauses are expected to represent the effects of two factors: cost increases from paying for airport operating expenses and cost decreases from blocking additional airport projects paid for by MII carriers. The positive signs imply that

[90] $CongestedOrigin$ is calculated by the ratio of average daily departures performed (by all carriers) out of an origin airport in a given quarter over the total number of gates at the airport. Also $CongestedDest$ is created for destination airport. Average daily departures and total number of gates are calculated by using T-100 dataset and Competition Plans, respectively.

[91] For the convenient interpretation, congestion measure was standard normalized: $N(0, 1)$.

the former effect is larger.

The results support that Competition Plan variables significantly affect carriers' marginal cost especially at congested airports. Signatory carriers can exploit cost advantages from increased gate occupancy, but must take financial responsibility associated with MII clauses in exchange for creating a barrier to entry. Non-signatory airlines have to cope with cost disadvantages from sublease agreements. Other variables in table 22 have very similar estimates to those in table 21 at high significance level.

III.6.2.3 Other specifications

The reduced form estimation (section 6.1) shows that a large portion of the hub premium comes from the carrier's gate dominance and associated contractual practices. Then, will this be valid again in a structural framework? That is, will consumers' valuation for hub carrier largely depend on carriers' gate control? I examine this issue by estimating modified specifications reported in table 23. In the first column, I drop $GateShare1$ and $GateShare2$, and include $HubDM1$ and $HubDM2$.[92] As expected, both types of passengers exhibit strong preferences for hub carriers at origin and/or destination airport. The coefficients are 0.172 for tourists and 0.137 for business travelers. In the second column, I control $GateShare$ with other variables unchanged. Interestingly, the coefficient of $HubDM1$ decreases by 65 percent (0.061 from 0.172), the coefficient of $HubDM2$ becomes statistically insignificant, while the coefficient of $GateShare$ is significantly positive with a reasonable magnitude. The results confirm that carrier's gate dominance is a critical source of consumers' preference for hub carrier.

In order to check the robustness of the findings, five other specifications are

[92] $HubDM$ is defined as $HubOrigin + HubDest$.

estimated as in table 24. One might argue that the positive effect of *GateShare* on consumers' utility could be driven by the differentiation of some other services between major and small carriers. To address this concern, the first column restricts the sample to markets longer than 3,000 miles, which exceed the range of most small carriers. This restriction excludes about 58 percent of products and 37 percent of markets. The result shows that gate occupancy still increases passengers utility for both types, and that business travelers exhibit stronger preference again in terms of both marginal valuation and WTP for gate.

Similarly, the findings may represent a carrier's monopoly power, thus it may be valid only for monopoly markets. For example, when a carrier dominates an extremely high percentage of gates and passenger enplanements, consumers do not have little choice but to buy the monopoly carrier's products. To determine if this is the case, the second column includes only non-monopoly markets where multiple carriers serve. Once again, the result indicates that consumers' preferences for gate remain significant.

Next, I examine whether the bin size affects the results. Column 3 and 4 present estimates with finer and rougher set of bins, respectively.[93] In both cases, while the main findings still stand, tourist travelers show somewhat stronger preference for gate occupancy than the base specification in table 22.

Finally, some variation in the years of Competition Plans may weaken the finding. Considering it, the last column uses Competition Plans submitted only in 2004. The coefficient of $GateShare2$ was in great decline, but it did not hurt main results.

Regarding cost parameters, all specifications support the key findings in supply

[93] In column 3, the set of bins were $10 for tickets under $200, $15 for tickets between $200 and $400, $20 for tickets between $400 and $700, $50 for tickets between $700 and $1,000, $100 for tickets above $1,000. In column 4, the bins were $50 for tickets under $700, $70 for tickets between $700 and $1,000, $100 for tickets above $1,000.

side. High gate occupancy create cost advantages to signatory carriers at congested airport, and the presence of sublease agreement and MII clauses at congested airport force non-signatory and signatory airlines, respectively, to endure cost increase.

III.6.2.4 Price and gate elasticities

In the nested logit model, the coefficients do not provide a direct economic interpretation. To better understand their magnitudes, I calculated elasticities with respect to price and gate-occupancy in table 25. In the first column, price elasticities of type1 and type2 are -3.99 and -0.50, respectively. It tells that one percent increase in ticket prices tends to decrease demand of tourist and business travelers by four percent and half a percent, respectively. For tourists, the average elasticity is -3.49 with a range from -2.05 to -4.09 over different specifications. And the aggregate price elasticity -2.37 tells that the total demand decrease by about 2.4% in response to 1% increase in prices.[94]

The effect of gate occupancy on demand appears to be moderate. The estimated gate elasticity indicates that one percent increase in the number of gates controlled by each carrier raises demand by 0.13% for tourists and 0.14% for business travelers. These elasticities do not vary much across specifications.

III.6.3 Marginal Cost and Profit Estimates

By using parameter estimates $(\hat{\theta}_d,\ \hat{\psi})$, observed characteristics $(x,\ h)$, and the estimates of unobserved factors $(\hat{\xi},\ \hat{\omega})$, I calculated marginal costs, markups, and

[94] When calculating aggregate elasticities, I estimated the percentage of passengers who actually bought the tickets. It is defined by using γ and group share of all inside products: the percentage of type 1 passengers $= \gamma_1 \cdot \frac{D_{1m}^{\lambda}}{1+D_{1m}^{\lambda}} / \sum_{r=1}^{2} \gamma_r \cdot \frac{D_{rm}^{\lambda}}{1+D_{rm}^{\lambda}}$, where D_{rm}^{λ} is defined by equation (25). The bottom panel in table 25 reports that 54% of passengers are tourist travelers for the base case. The proportions are consistent with the results of Berry and Jia (2010) which reported that tourist travelers accounted for from 47% to 64% over several specifications.

profits. Throughout this analysis, I focus on flights originating from congested airports. Table 26 and 27, respectively, report the estimates at the airports where $CongestedOrigin > 0$ and $CongestedOrigin > 1$. Starting with marginal cost in the top panel of table 26, signatory carriers appear to take advantage of a lower marginal cost ($82) on average, compared to non-signatory carriers ($94).[95] In section 2.2 and 6.2, I explained that the cost increase from sublease agreement would be mostly borne by sub-tenant carriers. The second panel supports the argument. We can see that non-signatory carrier's costs increase to $96 at airports with sublease agreement relative to that in the first panel, whereas costs of signatory carrier do not. Note that a group of sub-tenant carriers is a subset of non-signatory carriers. Also I explained that the positive coefficient of MII clauses indicated increases in signatory carriers' costs from paying for airport operating expense. Indeed, the third panel shows that signatory carriers' costs rise to $85 at the airports with MII clauses, whereas non-signatory carriers' costs do not.

The last panel shows average marginal cost by carriers. Two LCCs (Jet Blue and Southwest) reasonably have lower costs ($58 and $50, respectively), and legacy carriers exhibit considerable variation. Continental (CO) and United airline (UA) exhibit high costs, and Northwest (NW) pays relatively low costs. As one possible explanation, CO and UA largely depend on connecting flights compared to NW. In the sample, connecting flights count for 53% of products by all carriers, but the proportion is 63% for CO and 65% for UA, but only 39% for NW. Considering that cost increases from connections surpass the scale economies, higher costs borne by CO and UA make sense. In overall, the average marginal cost for each product is $87, and the Lerner index, the ratio of markups to fares is around 0.81.

In column 4-6, I report quantity, profits, and revenues which are average measures

[95] An airline is assumed to be a signatory carrier if $GateShareOrigin_{km} > 0$.

per market, instead of per product. As the top panel shows, signatory carriers earn higher profits than non-signatory airlines. The profit ratio between two groups is around 2.56 where the ratio is defined as $\text{Profit}_{sig}/\text{Profit}_{non-sig}$. The profitability of signatory airline comes from higher fares, lower costs, and larger passenger enplanements. At airports where sublease agreements exist, the profit ratio goes up to 2.70. A closer look reveals that the additional profit differential mainly comes from bigger gap in marginal cost and quantity across carrier group. However, at airports with MII clauses, the profit ratio (2.53) is almost the same to the top panel. In this case, increase in price differentials and decrease in marginal cost and quantity cancel each other out. The table 27 presents the same analysis by focusing on more congested airports where $CongestedOrigin > 1$ and shows very similar pattern to table 26.

III.6.4 Counterfactual Analysis

AIR-21 has recommended the targeted airports to reduce the portion of exclusive or preferential gates for promoting broader access to gates. Even though the act does not carry legal binding force, the covered airports have actually reduced the portion to stay eligible for collecting passenger facility charges (PFCs).[96] Motivated by the intent of AIR-21, I performs a hypothetical analysis to examine how the limits on gate agreements can affect fares, costs, and profits of signatory and other carriers. Suppose that federal government put a ceiling of 75% on the proportion of exclusive gates at an airport, then airports where more than 75% of gates are leased exclusively (e.g. Dallas/Fort Worth, Newark, etc.) should take some gates from signatory carriers and make them common gates. The lower a ceiling is, the more carriers would have to give up their gates. I simulate three counter-factual

[96]Under AIR-21, airports can charge up to $4.50 for each passenger via ticket she purchases, and the collected fees become an important source of funding for airport capital investment.

scenarios with a ceiling of 75%, 50%, and 25%, respectively. The number of airports and signatory carriers affected by each scenario is summarized by table 28.

According to each scenario, $GateShare$, $GateShareOrigin$, and $GateShareDest$ are changed, and then I simulated a new vector of equilibrium prices (p^*_{fm}) which satisfy the first order condition below,

$$p^*_{fm} = \widehat{mc}^{post}_{fm} - \Delta(x^{post}_m, p^*_m, \hat{\xi}_m; \hat{\theta}_d)^{-1} \cdot s_{fm}(x^{post}_m, p^*_m, \hat{\xi}_m; \hat{\theta}_d) \tag{36}$$

where $\widehat{mc}^{post}_{fm}$ is marginal costs estimates obtained by using post-regulation product characteristics ($GateShareOrigin^{post}_m$, $GateShareDest^{post}_m$), the unobserved cost shock ($\hat{\omega}_{fm}$), and cost estimates ($\hat{\psi}$).[97]

The results are presented in table 29 and 30. The effects of counterfactual regulation at airports where $CongestedOrigin > 0$ are identified by comparing the top panel in table 26 with the first three panels in table 29. Under the first scenario of 75% ceiling, new optimal prices and costs of signatory carriers appear to slightly change. Reducing exclusive gates increase signatory carrier's marginal costs by $2 and fares by $1. Since only 9.5 gates from 2.7 carriers become common gates, the regulation has tenuous effects on supply side. However, demand side is influenced to a greater extent. Since higher fares and lower gate occupancy drop passengers' mean utility, the passenger enplanements decrease by 7%. In overall, signatory carriers' profits and revenues will decrease by 6%. Fare and marginal cost of non-signatory car-

[97]To make the analysis feasible, equation (36) makes several nontrivial assumptions. First, it assumes demand and cost estimates remain the same before and after the regulation. One concern is that passengers' marginal utilities of gates are changeable. The number of gates controlled by a carrier is closely related to the airline network size, thus the overall reduction in exclusive gates can depreciate potential benefits from frequent flier programs in aviation market. If true, my estimates would overestimate the impact on demand. However, when signatory carriers make up gates (as many as they lose) from common gates available, the assumption will be justified. Second, I assume that unobserved product quality ($\hat{\xi}$) and cost shock ($\hat{\omega}$) stay the same. These factors (e.g. ticket restrictions, oil price, the level of advertising, etc) are not likely to significantly interact with the level of gate occupancy.

riers remain almost the same because they do not control any gates to be converted. Notable thing is that their quantities and profits slightly decrease. To understand it, I cautiously compared predicted market shares before and after the regulation and found that within-group shares ($\frac{e^{(x_{jm}\beta_r+\alpha_r p_{jm}+\xi_{jm})/\lambda}}{D_{rm}}$) of non-signatory carriers actually increased. However, group share of all inside products ($\frac{D_{rm}^{\lambda}}{1+D_{rm}^{\lambda}}$) appears to significantly decrease. It suggests that gate reduction not only decreases demand for signatory carriers, but reduces total air travel demand.

While the second and third scenarios produce similar patterns, the magnitudes of the effect get stronger. Putting 50% ceiling drives up signatory carrier's costs by $7 and fares by $19. In demand side, decrease in passengers' mean utility reduces quantities by 15% and profits by 14%.[98] Under 25% ceiling, there becomes no difference in marginal cost between two groups of carriers, implying that cost advantage by signatory carrier completely disappears. The effects of regulation at airports where $CongestedOrigin > 1$ become much greater for each scenario. Comparison between table 27 and 30 shows that cost advantage by signatory carriers almost vanishes even under 75% ceiling.

Even though the counterfactual analysis reasonably predicts how costs and profits change, it leaves much room for improvement. The analysis does not consider the possibility that new carriers enter the airports when more common gates are available. If this entry-exit decision is incorporated with appropriate model and data, competitive effect of the regulation can be better predicted.

[98]The data indicate that each airport has about 7 signatory carriers on average, so cap of 50% would affect half of all signatory airlines.

III.7 Conclusion

Since the airline industry was deregulated, questions have continued to be brought up as to whether airline rivalry is as vigorous as expected. This concern has been supported by several government reports and academic studies identifying the existence and robustness of the hub premium. However, there have been limited studies identifying the feasible sources of the premium. In this study, I show that the major carriers' market power is largely based on their contractual relationships with airports. Unlike Ciliberto and Williams (2010) who addresses this issue with reduced-from approach, I work with a structural model to quantify the effects of the gate contracts on consumer utility and carriers' marginal cost separately. Using the data from the U.S. Department of Transportation, I estimate the demand and supply parameters and then simulate the effects of counterfactual regulation on prices, marginal costs, and profits.

Main findings suggest that in demand side, a signatory carrier's gate dominance has positive effect on passengers utility. Especially, business travelers have thirteen times higher WTP for gate than tourist travelers, mainly because the extensive airline network based on the gate occupancy can hold more appeal for business travelers. In supply side, the control of large fraction of gates contributes to the reduction of signatory carriers' marginal costs. A five percent increase in the gates leased at the origin airport leads to $2.5 reduction in the airline's marginal cost.

Furthermore, the existence of sublease agreement at an airport tends to raise non-signatory carriers' marginal cost, whereas MII provision at an airport is likely to increase signatory carriers' marginal cost. For sublease agreement and MII clauses, the parameter estimates may not provide such direct interpretations since two variables are measured at the airport level, but the subsequent marginal cost estimates reasonably support the explanation. Importantly, these cost effects become more significant and stronger at congested airports. Finally, the counterfactual analysis implies that the limits on gate agreements not only reduce the cost differentials between signatory and non-signatory airlines but decrease signatory carriers' passenger enplanements due to their higher fares and lower gate occupancy.

CHAPTER IV

CONCLUSION

This dissertation examines how horizontal merger between airline companies and vertical contract between airlines and airports affect market competition. Using an empirical structural model, I identify the effects of the collaborative strategies on both demand and supply, and derive welfare implications.

In Chapter II, I show that when a merger simulation ignores changes in product characteristics post-merger, the predicted prices and welfare effects can be substantially biased. I overcome the limitations by endogenizing both price and product characteristics in a two-stage oligopoly game.

Based on the estimation of airline demand and supply system, and simulation for the Delta and Northwest Airlines merger, I find that the merged carrier tends to increase product differentiation post-merger by raising the quality of the primary (large and medium) goods, but by reducing that of the secondary (small) goods. Since the primary goods are more profitable, the merged firm takes better care of their qualities to attract more passengers to them.

Second, the higher differentiation affects the merged carrier's ability of raising prices. For primary goods, the full model predicts smaller cross-price effects than the price model. But for secondary goods, the cross-price effect is greater in the full model.

Third, endogenizing product characteristics leads to significantly different welfare implications. The price model predicts decrease in consumer welfare for both types of passengers, but the full model predicts that the business passengers get welfare gains from the merger and the tourists also experience smaller losses. This causes an overall increase in consumer welfare.

Finally, when merger simulation considers endogeneity of product characteristics, it can better predict actual post-merger outcome. In Quality-Increased markets, the simulated and actual post-merger frequency increase from pre-merger frequency. In Quality-Decreased markets, on the other hand, they decrease from pre-merger one. For both groups of markets, the probability density function of the simulated frequency is located between those of pre-merger and actual post-merger frequency.

In Chapter III, I identify the effects of vertical contracts regarding gates on demand and supply. Initially, I estimate a pricing equation which is similar to Ciliberto and Williams (2010), and then deepen the analysis with structural estimation. Moreover, I facilitate the advantage of the structural approach to examine how hypothetical regulations affect carriers' fares, costs, and profits.

Main findings suggest that a signatory carrier's gate dominance has positive effect on passengers utility on the demand side. Especially, business travelers have thirteen times higher WTP for gate than tourist travelers. On the supply side, the control of large fraction of gates contributes to reducing signatory carriers' marginal costs. Furthermore, the existence of sublease agreement at an airport tends to raise non-signatory carriers' marginal cost, whereas MII provision at an airport is likely to increase signatory carriers' marginal cost.

This paper concludes with three notes for future research. Regarding Chapter II, the comparison analysis suggests that simulated result still under- or overestimates the actual post-merger outcome. The insufficient performance possibly comes from ignoring a change in unobserved product quality post-merger. If the link between unobserved and observed characteristics can be modeled through either structural or reduced form method, it can further improve the predictive performance of merger simulation.

About Chapter III, I do not model carriers' gate-occupying decisions, assuming that gate allocation is exogenously given. In a long-term perspective, however, carriers can decide how many gates should be controlled to maximize profits and to optimize their network structure. Financial obligations associated with the gate agreements and legislative restriction such as AIR-21 will significantly affect the decisions. I leave this subsequent question for future research.

Finally, for both studies, I modeled the consumer heterogeneity with two types of passengers and estimated the percentage of each type in the population (γ_r). An interesting point is that the distribution of the consumers can vary from market to market. For example, the Houston to Las Vegas market may have a higher proportion of the tourists to the business passengers than the Las Vegas to Houston market. Responding to these distributions, a carrier can choose different product offerings for each market. The relationship between the distribution of consumer types and firm' decisions on product offerings can be an interesting topic for future research.

REFERENCES

ACINA, "Airports gate Availability/PFC Survey," 1998. The Airports Council International-North America.

Berry, Steven, "Estimating discrete-choice models of product differentiation," *RAND Journal of Economics*, 1994, *25* (2), 242–262.

_ **and Ariel Pakes**, "Some applications and limitations of recent advances in empirical industrial organization: Merger analysis," *American Economic Review*, 1993, *83* (2), 247–252.

_ **and Joel Waldfogel**, "Do mergers increase product variety?: Evidence from radio broadcasting," *Quarterly Journal of Economics*, 2001, *116* (3), 1009–1025.

_ **and Panle Jia**, "Tracing the woes: An empirical analysis of the airline industry," *American Economic Journal: Microeconomics*, 2010, *2*, 1–43.

_ **, James Levinsohn, and Ariel Pakes**, "Automobile prices in market equilibrium," *Econometrica*, 1995, *60* (4), 889–917.

_ **, Michael Carnall, and Pablo T. Spiller**, "Airline hubbing, costs and demand ," *In D. Lee, ed., Advances in Airline Economics*, 2006, *1* (1).

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

_ , "Airline mergers, airport dominance, and market power ," *American Economic Review*, 1990, *80* (2), 400–404.

_ **and Nancy L. Rose**, "Competition and price dispersion in the U.S. airline industry ," *Journal of Political Economy*, 1994, *102* (4), 653–683.

_ **and** _ , "How airline markets work... or do they?: Regulatory reform in the airline industry," 2007. National Bureau of Economic Research Working Paper 13452.

Brueckner, Jan K., "Airport congestion When carriers have market power ," *American Economic Review*, 2002, *92* (5), 1357–1375.

_ **and Yimin Zhang**, "A model of scheduling in airline networks: How a hub-and-spoke system affects flight frequency, fare and welfare," *Journal of Transport Economics and Policy*, 2001, *2* (35), 195–222.

Byrne, David P., "The impact of consolidation on cable TV prices and product quality," 2012. SSRN Working Paper No.1802347.

Cho, Sungick, "Three essays on firms' quality choice," 2012. Ph.D. dissertation, Texas A&M University.

Chu, Chenghuan Sean, "The effect of satellite entry on cable television prices and product quality," *RAND Journal of Economics*, 2010, *41* (4), 730–764.

Ciliberto, Federico and Jonathan W. Williams, "Limited access to airport facilities and market power in the airline industry ," *Journal of Law and Economics*, 2010, *53* (3), 467–495.

Crawford, Gregory S., "Endogenous product choice: A progress report," *International Journal of Industrial Organization*, 2012, *30* (3), 315–320.

_ **and Matthew Shum**, "The welfare effects of endogenous quality choice: The case of cable television," 2006. mimeo, University of Arizona.

DFW, "FY 2004 Competition Plan update," 2004. Dallas/Fort Worth International Airport.

DOT, "Airport business practices and their impact on airline competition: FAA/OST task force study," 1999. U.S. Department of Transportation.

Draganska, Michaela, Michael Mazzeo, and Katja Seim, "Beyond plain vanilla: Modeling joint product assortment and pricing decisions," *Quantitative Marketing and Economics*, 2009, *7*, 105–146.

Fan, Ying, "Ownership consolidation and product characteristics: A study of the U.S. daily newspaper market," *American Economic Review*, 2013, *103* (5), 1598–1628.

Fu, Xiaowen and Anming Zhang, "Effects of airport concession revenue sharing on airline competition and social welfare ," *Journal of Transport Economics and Policy*, 2010, *44* (2), 119–138.

_ , Winai Homsombat, and Tae H. Oum, "Airport-airline vertical relationships, their effects and regulatory policy implications ," *Journal of Air Transport Management*, 2011, *17*, 347–353.

Gandhi, Amit, Luke Froeb, Steven Tschantz, and Gregory J. Werden, "Post-merger product repositioning," *Journal of Industrial Economics*, 2008, *56* (1), 49–67.

GAO, "Airline competition: Industry operating and marketing practices limit market entry," 1990. U.S. General Accounting Office.

Gerardi, Kristopher S. and Adam H. Shapiro, "Does competition reduce price dispersion? New evidence from the airline industry," *Journal of Political Economy*, 2009, *117* (1), 1–37.

Gotz, Georg and Klaus Gugler, "Market concentration and product variety under spatial competition: Evidence from retail gasoline," *Journal of Industry, Competition and Trade*, 2006, *6* (3-4), 225–234.

Hartmann, M.E., "Access to airport facilities: its impact on market competition ," *Advances in Airline Economics*, 2006, (1), 369–384.

Jayaraman, Sugandhi and John F. O'Connell, "An investigative study into the annual US$2.5 bn mishandled baggage problem," *Journal of Airport Management*, 2011, *5* (4), 325–334.

Kim, E.Han and Vijay Singal, "Mergers and market power: evidence from the airline industry," *American Economic Review*, 1993, *83* (3), 549–569.

Kwoka, John and Evgenia Shumilkina, "The price effect of eliminating potential competition: Evidence from an airline merger," *Journal of Industrial Economics*, 2010, *58* (4), 767–793.

Lederman, Mara, " Are frequent-flyer programs a cause of the hub premium?," *Journal of Economics and Management Strategy*, 2008, *17* (1), 35–66.

Lee, Jinkook, "Airport-airline vertical contract and market power in the U.S. airline industry," 2013. Working Paper.

Luo, Dan, "The price effects of the Delta-Northwest Airline merger," *Review of Industrial Organization*, 2011, pp. 1–22.

Mazzeo, Michael, "Product choice and oligopoly market structure," *Rand Journal of Economics*, 2002, *33* (2), 221–242.

_ , "Competition and service quality in the U.S. airline industry," *Review of Industrial Organization*, 2003, *22*, 275–296.

— , **Katja Seim, and Mauricio Varela**, "The welfare consequences of mergers with product repositioning," 2013. Working Paper.

McFadden, Daniel, "Econometric models of probabilistic choice, in Charles F. Manski and Daniel McFadden, eds., Structural analysis of discrete data with econometric applications," 1981. Massachusetts: MIT Press.

Morrison, Steven A., "Airline mergers: A longer view," *Journal of Transport Economics and Policy*, 1996, *30* (3), 237–250.

Oum, Tae H. and Xiaowen Fu, "Impacts of airports on airline competition: Focus on airport performance and airport-airline vertical relations," 2008. OECD Joint Transport Research Centre, Discussion Paper, 17.

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

Puller, Steven L., Anirban Sengupta, and Steven N. Wiggins, "Does scarcity drive intra-route price dispersion in airlines?," 2012. Working paper: Texas A&M University.

Richard, Oliver, "Flight frequency and mergers in airline markets," *International Journal of Industrial Organization*, 2003, *21* (6), 907–922.

Rupp, Nicholas, Doug Owens, and L. Wayne Plumly, "Does competition influence airline on-time performance?," 2006. In D.Lee, ed., Advances in airline economics, vol.1: Competition policy and antitrust.

Small, K.A. and H.S. Rosen, "Applied welfare Economics with discrete choice models," *Econometrica*, 1981, *49*, 105–130.

Suzuki, Yoshinori, "The relationship between on-time performance and airline market share: a new approach," *Transportation Research Part E*, 2000, *36*, 139–154.

Sweeting, Andrew, "The effects of mergers on product positioning: Evidence from the music radio industry," *RAND Journal of Economics*, 2010, *41* (2), 372–397.

Villas-Boas, Sofia Berto, "Vertical relationships between manufacturers and retailers: Inference with limited data," *Review of Economic Studies*, 2007, *74*, 625–652.

Wei, Wenbin and Mark Hansen, " Impact of aircraft size and seat availability on airlines demand and market share in duopoly markets," *Transportation Research Part E: Logistics and Transportation Review*, 2005, *41* (4), 315–327.

Werden, Gregory, Andrew Joskow, and Richard Johnson, "The effects of mergers on price and output: Two case studies from the airline industry," *Managerial and Decision Economics*, 1991, *12* (5), 341–352.

Werden, Gregory J. and Kuke M. Froeb, "The effects of mergers in differentiated products industries: Logit demand and merger policy," *Journal of Law, Economics, and Organization*, 1994, *10* (2), 407–426.

Wyld, David C., Michael A. Jones, and Jeffrey W. Totten, "Where is my suitcase? RFID and airline customer service," *Marketing Intelligence and Planning*, 2005, *23* (4), 382–394.

APPENDIX

TABLES AND FIGURES

Table 1. Data Sources

Database	Variables	Level of obs.	Sample periods
O&D Survey (DB1B)	Market, Product, Fare, Controls	ticket	‘07.2Q.∼‘08.1Q.
On-Time Performance	Ontime15	carrier-route	‘07.Apr.∼‘08.Mar.
T-100 Domestic Segment	Frequency	carrier-route	‘07.Apr.∼‘08.Mar.
Air Travel Consumer Report	Mishandled baggage, Denied boarding	carrier	‘07.Apr.∼‘08.Mar.
Air Carrier Financial Report	Employee statistics	carrier	‘07
Weather Underground	Wind, Rain, Snow	airport	‘07.Apr.∼‘08.Mar.
MSA Population	Market size	MSA city	‘07 estimates

Notes: Controls include Layovers, Distance, HubDM, hubMC, Slot-control, Tour, Carrier dummies.

Table 2. Variable Definitions and Summary Statistics for the Estimation Sample

Variable	Description	Mean	Std.dev.	Min	Max
Endogenous variables					
Fare	Average ticket fare ($100)	3.74	1.13	0.55	13.17
Ontime15	Percentage of flights that arrive less than 15 minutes late	0.75	0.08	0	1
Frequency	No. of average daily departures per quarter	4.32	2.42	0.01	26.18
Mishandled baggage	No. of mishandled baggages per 1,000 passengers	6.44	1.73	2.61	13.52
Denied boarding	No. of involuntary denied boardings per 10,000 passengers	1.19	0.72	0.01	4.48
Control variables					
Layovers	No. of connections per round trip	1.67	0.75	0	2
Distance	Market distance round trip (1,000 miles)	3.18	1.43	0.22	6.94
HubDM	No. of hub airports given carrier and itinerary	0.72	0.60	0	3
HubMC	1 if a flight departs from, connects at, or arrives at hub	0.64	0.48	0	1
Slot-control	No. of slot-controlled airports on itinerary	0.28	0.59	0	3
Tour	1 if destination airport is in either CA, FL, or NV	0.32	0.47	0	1
Carrier dummies					
AA	1 if a carrier is American Airlines	0.13	0.34	0	1
CO	1 if a carrier is Continental Airlines	0.07	0.25	0	1
DL	1 if a carrier is Delta Airlines	0.14	0.35	0	1
NW	1 if a carrier is Northwest Airlines	0.10	0.30	0	1
UA	1 if a carrier is United Airlines	0.10	0.30	0	1
US	1 if a carrier is US Airways	0.11	0.32	0	1
FL	1 if a carrier is AirTran Airways	0.05	0.22	0	1
WN	1 if a carrier is Southwest Airlines	0.17	0.38	0	1
OT	1 if a carrier is other carrier	0.13	0.33	0	1

Notes: The sample contains 87,906 unique products in 9,117 markets. Sample period is from ‘07. 2Q. through ‘08. 1Q.

Table 3. Instrumental Variables for Endogenous Product Characteristics

Instruments	Ontime15	Frequency	Mishandled Baggage	Denied Boarding
Weather (wind, rain, snow)	Yes	Yes	Yes	–
Carrier's Hub Status				
Hub Origin	Yes	Yes	–	Yes
Hub Connection	Yes	Yes	Yes	–
Hub Destination	–	Yes	–	–
Labor Category (%)				
General Managers	Yes	Yes	Yes	Yes
Pilots & Copilots	–	Yes	–	–
Passenger Svc. & Admin.	–	–	Yes	Yes
Maintenance	Yes	–	–	–
Aircraft Traffic Handling	–	Yes	–	–
Aircraft Control	Yes	Yes	–	–
Passenger Handling	–	–	–	Yes
Cargo Handling	–	–	Yes	–
Statistical	–	–	–	Yes
Traffic Soliciters	–	Yes	–	Yes
Validity of instruments				
F-statistics	724.5	806.6	1,600.5	2,903.6
R-squared	0.083	0.114	0.154	0.284

Notes: The weather data come from Weather Underground which gathers its most information from the National Weather Service (NWS). I used information on wind, rain, and snow condition at origin and destination airport. The employment data come from Air Carrier Financial Reports (Schedule P-10).

Table 4. Estimation Results on Model Parameters

Mean Utility		Marginal Cost ($100)	
Endogenous Characteristics		Frequency	-0.021** (0.002)
$\text{Fare}_{\mathbf{1}}$	-0.098** (0.004)	HubMC	-0.184** (0.017)
$\text{Fare}_{\mathbf{2}}$	-0.999** (0.019)	Layovers_{short}	0.175** (0.010)
$\text{Ontime15}_{\mathbf{1}}$	1.641** (0.164)	Layovers_{long}	0.300** (0.019)
$\text{Ontime15}_{\mathbf{2}}$	2.114** (0.155)	Distance_{short}	0.226** (0.005)
Frequency	0.084** (0.003)	Distance_{long}	0.130** (0.004)
Mishandled baggage	-0.054** (0.005)	US	-0.036** (0.008)
Denied boardings	-0.253** (0.018)	DL	-0.168** (0.011)
		NW	-0.289** (0.012)
Controls		UA	-0.010 (0.008)
$\text{Layovers}_{\mathbf{1}}$	-1.255** (0.013)	CO	-0.015 (0.010)
$\text{Layovers}_{\mathbf{2}}$	-1.085** (0.009)	FL	-0.559** (0.019)
Distance	0.105** (0.005)	WN	-0.223** (0.018)
HubDM	0.056** (0.010)	OT	-0.190** (0.016)
Slot-control	-0.071** (0.006)	Constant	1.721** (0.029)
Tour	0.238** (0.006)		
US	0.143** (0.014)	**Slope of Fixed Cost ($100)**	
DL	0.007 (0.027)	$\text{Ontime15}_{constant}$	2416.8** (0.742)
NW	-0.511** (0.019)	Ontime15	-2970.2** (0.518)
UA	0.124** (0.017)	$\text{Frequency}_{constant}$	6.605** (0.064)
CO	-0.119** (0.024)	Frequency	0.224** (0.005)
FL	-0.875** (0.020)	$\text{Mishandled baggage}_{constant}$	-8.126** (0.059)
WN	-0.329** (0.021)	Mishandled baggage	0.491** (0.005)
OT	-0.023 (0.017)	$\text{Denied boarding}_{constant}$	-31.634** (0.148)
Constant	-7.184** (0.130)	Denied boarding	7.005** (0.020)
λ	0.618** (0.003)		
γ_1	0.052** (0.004)	Number of observations: 87,906	

Note: Standard errors are in parentheses. ** indicates 99% level of significance. Subscript 1 and 2 attached to *Fare*, *Ontime*15, and *Layovers* indicate consumer types.

Table 5. Operating Cost per Available Seat Mile (CASM, in cents)

	2Q 2007	3Q 2007	4Q 2007	1Q 2008	Average
(By carrier)					
US*	16.3	15.8	16.4	17	16.4
DL*	14.3	14	15.2	16.5	15.0
NW*	13	13.6	14.7	16	14.3
UA	13	13.3	14.6	14.9	14.0
CO	13.5	13.5	14	14.9	14.0
AA*	12.8	13.1	13.7	14.4	13.5
FL*	9.4	9.5	9.9	10.9	9.9
WN*	9	9.1	9.4	9.7	9.3
(By carrier type)					
Legacy carriers	13.4	13.6	14.5	15.3	14.2
LCC carriers	9.6	9.6	9.5	10	9.7

Notes: Data sources of CASM are Air Carrier Financial Statistics (Schedule P-12) and T-100 Domestic Segment from U.S. DOT. The asterisk indicates that the brand-specific effects of the carriers are statistically significant.

Table 6. Description of Simulation Sample

Integration steps		
Announcement	2Q. 2008	
Completion	4Q. 2009	
Resulting entity	Delta Airlines	
Simulation sample (pre-merger)		
Sample period	4Q. 2007 ∼ 1Q. 2008	
Number of markets overlapped	1,129	
- Duopoly / Oligopoly markets	9 / 1,120	
Statistics by carrier	**Delta Airlines**	**Northwest Airlines**
Passenger share (per market) (%)	0.17	0.17
Number of products (per market)	2.62	2.13
Fare ($100)	3.81	3.35
On-time performance (%)	0.80	0.70
Flight frequency (per day)	4.51	3.35
Mishandled boarding rate (per 1,000 passengers)	7.51	4.67
Denied boarding rate (per 1,0000 passengers)	1.45	0.70

Notes: Simulation sample consists of the last two quarters of the estimation sample. The simulation is conducted for 1,129 overlapped market pre-merger.

Table 7. Changes in Price and Characteristics of Merged Firm's Products in Oligopoly Markets

A. Large share goods

	Pre-merger	Post-merger	Change
Quality index	1.319	1.330	0.011
Ontime15	0.756	0.756	0.000
Frequency	4.369	4.438	0.069
Mishandled Baggage rate	6.287	6.249	-0.038
Denied Boarding rate	1.141	1.131	-0.010
Quality Distance			
Within-firm distance	0.179	0.200	0.021
Within-market distance	0.111	0.107	-0.004

	Pre	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Fare($)	368.6	4.9	3.7	1.5	2.2
Marginal cost ($)	209.2	0.0	-0.1	-0.1	0.0
Passengers	327.4	-2.6	0.3	4.1	-3.8
Profits ($100)	591.2	1.9	6.4	5.4	1.0

Notes: Large share goods include 692 products in 680 markets. Each number indicates average values over the large goods.

B. Medium share goods

	Pre-merger	Post-merger	Change
Quality index	1.306	1.315	0.008
Ontime15	0.759	0.759	0.000
Frequency	4.097	4.166	0.068
Mishandled Baggage rate	6.241	6.222	-0.019
Denied Boarding rate	1.134	1.128	-0.006
Quality Distance			
Within-firm distance	0.096	0.106	0.011
Within-market distance	0.080	0.081	0.001

	Pre	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Fare($)	352.8	9.5	7.2	0.3	6.9
Marginal cost ($)	229.3	0.0	-0.1	-0.1	0.0
Passengers	47.7	-2.0	-0.8	1.2	-2.1
Profits ($100)	69.4	0.3	1.7	1.3	0.4

Notes: Medium share goods include 1,041 products in 676 markets. Each number indicates average values over the medium goods.

C. Small share goods

	Pre-merger	Post-merger	Change
Quality index	1.285	1.272	-0.013
Ontime15	0.754	0.754	0.000
Frequency	3.889	3.776	-0.113
Mishandled Baggage rate	6.230	6.263	0.033
Denied Boarding rate	1.108	1.119	0.011
Quality Distance			
Within-firm distance	0.064	0.075	0.012
Within-market distance	0.058	0.064	0.006

	Pre	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Fare($)	361.1	24.1	36.0	1.9	34.2
Marginal cost ($)	233.9	0.0	0.2	0.2	0.0
Passengers	12.4	-1.0	-1.0	0.2	-1.2
Profits ($100)	19.5	0.0	0.1	0.2	-0.1

Notes: Small share goods include 3,598 products in 865 markets. Each number indicates average values over the small goods.

Table 8. Changes in Price and Characteristics of Merged Firm's Products in Monopoly Markets

A. Large share goods

	Pre-merger	Post-merger	Change
Quality index	1.342	1.428	0.086
Ontime15	0.753	0.751	-0.001
Frequency	2.241	2.950	0.709
Mishandled Baggage rate	4.667	4.449	-0.217
Denied Boarding rate	0.663	0.590	-0.073
Quality Distance			
Within-firm distance	0.097	0.295	0.199
Within-market distance	–	–	–

	Pre	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Fare($)	428.0	60.9	26.6	1.6	25.0
Marginal cost ($)	115.1	0.0	-1.5	-1.5	0.0
Passengers	53.3	-3.6	3.8	5.5	-1.7
Profits ($100)	201.7	1.5	14.0	12.2	1.8

Notes: Large share goods include 6 products in 6 markets. Each number indicates average values over the large goods.

B. Medium share goods

	Pre-merger	Post-merger	Change
Quality index	1.350	1.362	0.012
Ontime15	0.796	0.796	0.000
Frequency	3.371	3.553	0.182
Mishandled Baggage rate	6.091	6.115	0.024
Denied Boarding rate	1.061	1.069	0.008
Quality Distance			
Within-firm distance	0.059	0.209	0.150
Within-market distance	–	–	–

	Pre	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Fare($)	370.3	65.0	48.0	2.3	45.7
Marginal cost ($)	175.1	0.0	-0.4	-0.4	0.0
Passengers	16.3	-2.5	0.8	2.9	-2.1
Profits ($100)	28.5	1.0	4.9	4.3	0.5

Notes: Medium share goods include 8 products in 5 markets. Each number indicates average values over the medium goods.

C. Small share goods

	Pre-merger	Post-merger	Change
Quality index	1.328	1.230	-0.098
Ontime15	0.777	0.779	0.002
Frequency	3.271	2.445	-0.826
Mishandled Baggage rate	6.074	6.335	0.261
Denied Boarding rate	0.962	1.032	0.070
Quality Distance			
Within-firm distance	0.102	0.218	0.116
Within-market distance	–	–	–

	Pre	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Fare($)	336.8	113.4	147.0	1.8	145.2
Marginal cost ($)	191.3	0.0	1.7	1.7	0.0
Passengers	7.8	-1.8	-2.6	-1.1	-1.4
Profits ($100)	11.0	0.4	-0.4	-1.0	0.5

Notes: Small share goods include 14 products in 6 markets. Each number indicates average values over the small goods.

Table 9. Change in Consumer Surplus (CS)

after the Delta and Northwest Airlines Merger

Markets	Price model (G^P) Change in CS ($100K)	Price model (G^P) Change in CS (%)	Full model (G^{FL}) Change in CS ($100K)	Full model (G^{FL}) Change in CS (%)	Quality change of DL/NW	Number of products (markets)
All markets						
Total	-15.59	-0.18	18.53	0.21		18,430
Business	-9.87	-0.12	22.16	0.28	-0.006	(1,129)
Tourists	-5.72	-0.72	-3.63	-0.45		
By market competitiveness						
Monopoly	-0.14	-4.18	0.06	1.73		28
Business	-0.08	-2.63	0.07	2.30	-0.027	(9)
Tourists	-0.06	-22.81	-0.01	-5.13		
Oligopoly	-15.45	-0.18	18.47	0.21		18,402
Business	-9.79	-0.12	22.09	0.28	-0.006	(1,120)
Tourists	-5.66	-0.71	-3.62	-0.45		
By quality change						
QI markets	-12.75	-0.19	19.86	0.30		12,782
Business	-8.22	-0.14	22.05	0.36	0.012	(712)
Tourists	-4.53	-0.69	-2.19	-0.33		
QD markets	-2.84	-0.14	-1.34	-0.07		5,648
Business	-1.65	-0.09	0.11	0.01	-0.042	(417)
Tourists	-1.18	-0.83	-1.44	-1.01		

Notes: QI and QD markets indicate quality-increase and quality-decrease markets, respectively. If a passenger-weighted average quality of merged firm's products increases after the merger, it belongs to QI markets, otherwise it belongs to QD markets. Number of products counts not only merged firm's products but also competitors' products.

Table 10. Change in Producer Surplus (PS) after the Delta and Northwest Airlines Merger

Markets	Pre-merger profit ($100K)	Price model (G^P)		Full model (G^{FL})		Number of products	Number of markets
		Change in PS ($100K)	% Change in PS (%)	Change in PS ($100K)	% Change in PS (%)		
All markets							
Total	2632.3	-1.38	-0.05	5.58	0.21	18,430	
DL/NW	553.3	1.66	0.30	6.82	1.23	5,359	1,129
Competitors	2079.0	-3.03	-0.15	-1.24	-0.06	13,071	
By market competitiveness							
Monopoly	1.6	0.02	1.40	0.12	7.35	28	9
Oligopoly	2630.7	-1.40	-0.05	5.46	0.21	18,402	
DL/NW	551.7	1.63	0.30	6.70	1.21	5,331	1,120
Competitors	2079.0	-3.03	-0.15	-1.24	-0.06	13,071	
By quality change							
QI market	2026.5	-0.92	-0.05	5.72	0.28	12,782	
DL/NW	384.3	1.18	0.31	6.83	1.78	3,549	712
Competitors	1642.2	-2.10	-0.13	-1.12	-0.07	9,233	
QD market	605.8	-0.46	-0.08	-0.14	-0.02	5,648	
DL/NW	169.0	0.47	0.28	-0.01	-0.01	1,810	417
Competitors	436.8	-0.93	-0.21	-0.12	-0.03	3,838	
By product quantity (for DL/NW only)							
Large goods	410.3	1.32	0.32	4.51	1.10	698	686
Medium goods	72.5	0.30	0.41	1.80	2.48	1,049	681
Small goods	70.5	0.03	0.05	0.51	0.72	3,612	871

Notes: QI and QD markets indicate quality-increase and quality-decrease markets, respectively. If a passenger-weighted average quality of merged firm's products increases after the merger, it belongs to QI markets, otherwise it belongs to QD markets. Markets for large, medium, and small goods are not mutually exclusive.

Table 11. Change in Total Surplus (TS) after the Delta and Northwest Airlines Merger (unit: $100K)

	Price model (G^P)			Full model (G^{FL})		
Markets	Change in CS	Change in PS	Change in TS	Change in CS	Change in PS	Change in TS
All markets	-15.59	-1.38	-16.96	18.53	5.58	24.11
Monopoly	-0.14	0.02	-0.12	0.06	0.12	0.17
Oligopoly	-15.45	-1.40	-16.85	18.47	5.46	23.93
QI markets	-12.75	-0.92	-13.67	19.86	5.72	25.58
QD markets	-2.84	-0.46	-3.29	-1.34	-0.14	-1.47

Notes: QI and QD markets indicate quality-increase and quality-decrease markets, respectively. If a passenger-weighted average quality of merged firm's products increases after the merger, it belongs to QI markets, otherwise it belongs to QD markets.

Table 12. Market Competitiveness of QI and QD markets Pre-merger

	QI markets	QD markets
Number of rival firms (within a market)	4.56	3.93
Number of LCCs (within a market)	1.73	1.45
Number of rival routes (within a market)	12.06	8.60
Delta/Northwest only		
Passenger share	0.29	0.37
Percentage of flights originating from hub	0.08	0.09

Notes: Each number indicates average values.

Table 13. Comparison of Average Market Frequency (AMF):

Pre-merger vs. Post-merger (Simulated) vs. Post-merger (Actual)

	Pre-merger	Post-merger (Simulated)	Post-merger (Actual)	Number of markets
Average market frequency				
All markets	14.10	13.77	13.64	244
Monopoly	8.17	6.15	4.43	3
Oligopoly	14.17	13.86	13.75	241
QI markets	15.27	16.02	17.79	117
QD markets	13.02	11.69	9.82	127
Measures of market similarity				
Number of carriers	6.00	5.00	5.03	244
Number of LCCs	1.35	1.35	1.38	244
Number of routes	10.81	10.81	9.59	244

Notes: Market frequency (MF) is defined as sum of frequency of each product provided by merging/merged carriers in a market: $MF_t = \sum_{j=1}^{J_{ft}} Frequency_{jt}$, where j is a product and t is a market. Then, average market frequency (AMF) is mean value of market frequency across markets: $AMF = \frac{1}{T}\sum_{t=1}^{T} MF_t$.

Table 14. Number of Consumers who Purchase Merged Firm's Products

Pre-merger	Oligopoly markets (1,000)		Pre-merger	Monopoly markets	
	Business (%)	Tourists (%)		Business (%)	Tourists (%)
Large goods	121.4 (53.6)	105.3 (46.4)	Large goods	216.3 (67.6)	103.8 (32.4)
Medium goods	22.2 (44.8)	27.4 (55.2)	Medium goods	48.1 (37.0)	81.8 (63.0)
Small goods	18.8 (42.0)	26.0 (58.0)	Small goods	37.9 (34.7)	71.1 (65.3)
Post-merger	Oligopoly markets (1,000)		Post-merger	Monopoly markets	
	Business (%)	Tourists (%)		Business (%)	Tourists (%)
Large goods	122.3 (53.9)	104.5 (46.1)	Large goods	228.7 (66.7)	114.1 (33.3)
Medium goods	22.5 (46.1)	26.3 (53.9)	Medium goods	52.5 (38.4)	84.2 (61.6)
Small goods	18.5 (44.9)	22.7 (55.1)	Small goods	28.1 (38.4)	45.1 (61.6)

Notes: This table is based on the simulation sample and results in the overlapped markets. I computed a percentage of the business passengers who actually bought large goods in the sample as: $\sum_{t=1}^{T} M_t \cdot \widehat{\gamma}_1 \cdot \frac{L_{1t}}{D_{1t}} \frac{D_{1t}^{\lambda}}{1+D_{1t}^{\lambda}} / \sum_{t=1}^{T} \sum_{r=1}^{2} M_t \cdot \widehat{\gamma}_r \cdot \frac{L_{rt}}{D_{rt}} \frac{D_{rt}^{\lambda}}{1+D_{rt}^{\lambda}}$, where $D_{rt} = \sum_{k \in J_t} e^{(x_{kt}\widehat{\beta}_r + \widehat{\xi}_{kt})/\widehat{\lambda}}$, $L_{rt} = \sum_{l \in L_t} e^{(x_{lt}\widehat{\beta}_r + \widehat{\xi}_{lt})/\widehat{\lambda}}$, and L_t is the set of large goods produced by Delta or Northwest Airlines in overlapped market t.

Table 15. Variable Definitions and Summary Statistics

Variable	Description	Mean	Std.Dev.	Min	Max
Competition Plan Variables					
GateShareOrigin	Percentage of gates leased on an exclusive or preferential agreement to an airline at origin airport	0.14	0.22	0	0.79
GateShareDest	Percentage of gates leased on an exclusive or preferential agreement to an airline at destination airport	0.12	0.20	0	0.79
SubleaseOrigin	1 if sublease agreement exists at origin airport	0.67	0.47	0	1
SubleaseDest	1 if sublease agreement exists at destination airport	0.66	0.47	0	1
MiiOrigin	1 if origin airport allows MII clauses	0.73	0.44	0	1
MiiDest	1 if destination airport allows MII clauses	0.73	0.45	0	1
Controls					
Fare	Ticket fare($100)	4.47	2.79	0.50	17.50
Layovers	Number of connections(0/2)	1.25	0.97	0	2
Frequency	Number of average daily departures	5.33	3.06	0.01	25.56
HubOrigin	1 if a flight departs from hub airport	0.22	0.41	0	1
HubDest	1 if a flight arrives at hub airport	0.17	0.37	0	1
Distance	Market distance(Round trip)(1,000miles)	2.87	1.45	0.13	10.17
Tour	1 if origin or destination airport is in either FL or NV	0.09	0.29	0	1
LCC	1 if a carrier is a LCC	0.10	0.30	0	1
LCCNum	Number of LCCs within a market	0.74	0.66	0	3
PopOrigin	Population of origin city(million)	3.74	2.39	0.35	9.81
PopDest	Population of destination city(million)	3.66	2.40	0.35	9.81
Slot-control	Number of slot-controlled airports on itinerary	0.32	0.60	0	4
Nseat	Numner of seats in aircraft(100)	1.25	0.35	0.3	2.57
CongestedOrigin	Ratio of average daily departures over the total number of boarding gates at origin airport(standardized)	0	1	-1.71	2.52
CongestedDest	Ratio of average daily departures over the total number of boarding gates at destination airport(standardized)	0	1	-1.71	2.50
Carrier Dummies					
AA	1 if a carrier is American Airline	0.15	0.36	0	1
CO	1 if a carrier is Continental Airline	0.08	0.27	0	1
DL	1 if a carrier is Delta Airline	0.13	0.34	0	1
NW	1 if a carrier is Northwest Airline	0.11	0.31	0	1
UA	1 if a carrier is United Airline	0.12	0.32	0	1
US	1 if a carrier is US Airway	0.04	0.18	0	1
B6	1 if a carrier is JetBlue	0.001	0.03	0	1
WN	1 if a carrier is Southwest Airline	0.06	0.23	0	1
OT	1 if a carrier is other carrier	0.31	0.46	0	1

Notes: The data include thirty one Airport Competition Plans, DB1B Origin and Destination Survey (2004.2Q), and T-100 Segment database (April 2004-June 2004). The final sample has 58,612 products in 888 markets.

Table 16. Terminal Rental Rates and Landing Fees

	Terminal Rental Rate ($)		Landing Fee ($)		Effective
Airport	Signatory	Non-sig.	Signatory	Non-sig.	Date
Anchorage	61.5	76.9	1.6	2.0	7.1.2012
Atlanta	85.0	117.5	0.8	1.5	9.1.2011
Dallas/Fort Worth	103.8	130.7	3.0	3.8	10.1.2011
Detroit	60.0	69.0	3.7	4.7	10.1.2012
Chicago O'hare	82.0	110.7	5.7	7.2	1.1.2012

Notes: The information on rates and fees are collected vis official website of each airport. Figures represent price per sqft per year for terminal rental rate, and price per 1,000 lbs for landing fees.

Table 17. Tenant and Sub-tenant Relationships at Dallas-Fort Worth Airport

Terminal	Primary tenant	Sub-tenant
A/C	American	American Eagle, TACA, Sabena
B	Continental	America West, Frontier
B	Trans World	Vanguard
B	US Airways	Midwest Express
E	Delta	Atlantic Southeast, AeroMexico, Canadian Airlines

Notes: This table is based on 2001 Competition Plan of Dallas/Fort Worth.

Table 18. Summary of Gate Agreement, Sublease Agreement, and MII Clauses at Thirty One Airports

Airport	Total gate	Exclusive gate (%)	Common gate (%)	Sublease agreement	MII clauses	Hub carrier	C.P. collected used	C.P. collected not used
Albuquerque	22	0.68	0.32	0	1		2006	
Anchorage	29	0.83	0.17	1	1	AS	2004	2003
Atlanta	176	0.81	0.19	1	1	DL	2004	2002
Austin	24	0.58	0.42	1	0		2002	
Nashville	51	0.9	0.1	0	1		2002	
Burbank	14	0.79	0.21	0	1		2002	2001
Dallas Love	26	0.73	0.27	0	0		2004	2002
Washington Reagan	44	0.95	0.05	1	1		2002	
Dallas/Fort Worth	137	0.93	0.07	1	1	AA,DL	2004	2001,2002
Detroit	86	1	0	1	1	NW	2004	2000,2001
Newark	96	0.99	0.01	1	0	CO	2004	2000
Houston Hobby	24	0.92	0.08	0	0		2004	2002
Washington Dulles	96	0.88	0.13	0	1	UA,US	2004	
Houston	103	0.97	0.03	1	0	CO	2004	2002
Chicago Midway	34	0.94	0.06	0	1	NW	2004	
Memphis	81	0.93	0.07	1	1	NW	2004	
Milwaukee	42	1	0	1	1	F9,FL	2002	2007
Minneapolis	77	0.9	0.1	1	1	NW	2004	2000
Oakland	24	0.88	0.13	1	0		2004	
Ontario	26	0.77	0.23	0	1		2001	
Chicago O'hare	157	0.99	0.01	1	1	AA,UA	2004	
Palm Beach	29	0.83	0.17	0	1		2002	
Philadelphia	120	0.91	0.09	1	1	US	2004	2000
Phoenix	95	0.94	0.06	0	0	HP	2002	
Providence	21	0.95	0.05	1	1		2004	2002
Reno	23	0.74	0.26	0	1		2004	
San Antonio	23	0.83	0.17	1	0		2004	
San Francisco	85	0.67	0.33	1	1	UA	2003	2000,2001
San Jose	31	0.81	0.19	0	1		2004	2008
Salt Lake City	81	0.88	0.12	0	0	DL	2004	
Tucson	19	0.74	0.26	0	1		2007	

Notes: Exclusive gate is the percentage of gates leased on exclusive or preferential agreements to all airlines serving an airport. Common gate represents the percentage of gates available for common use under an airport's own control.

Table 19. Contractual Practices at San Francisco International Airport

Exclusive and Preferential Gates	2000	2001	2003
Alaska	3	3	3
American	8	8	8
Continental	5	5	5
Delta	8	8	8
Northwest	3	3	3
United	23	23	23
US Airways	5	5	3
TWA	7	7	0
Southwest	2	0	0
ATA	0	0	2
America West	0	0	2
Total Exclusive Gates	64 (0.86)	62 (0.73)	57 (0.67)
Common Gates	10 (0.14)	23 (0.27)	24 (0.28)
Vacant	0	0	4(0.05)
Total Gates	74	85	85
Sublease agreement	existed	existed	existed
MII clauses	allowed	allowed	allowed

Notes: This table is based on 2000, 2001, and 2003 Competition Plan of San Francisco Airport. Figures in parenthesis indicate percentage.

Table 20. Estimation Results on Model Parameters

in Reduced-form Pricing Equation

	OLS			IV		
Dependent: Fare ($100)	1	2	3	1	2	3
HubOrigin	0.885***		0.450***	0.785***		0.457***
	(0.033)		(0.045)	(0.037)		(0.046)
HubDest	0.566***		0.291***	0.447***		0.298***
	(0.037)		(0.049)	(0.042)		(0.051)
GateShareOrigin		1.929***	1.390***		1.855***	1.405***
		(0.064)	(0.086)		(0.072)	(0.089)
GateShareDest		1.242***	0.969***		1.154***	0.987***
		(0.071)	(0.093)		(0.081)	(0.097)
SubleaseOrigin		0.193***	0.203***		0.175***	0.209***
		(0.026)	(0.026)		(0.027)	(0.027)
SubleaseDest		0.347***	0.364***		0.332***	0.369***
		(0.026)	(0.026)		(0.027)	(0.027)
MiiOrigin		0.035	0.038		0.039	0.037
		(0.026)	(0.026)		(0.026)	(0.026)
MiiDest		0.127***	0.126***		0.132***	0.124***
		(0.026)	(0.026)		(0.026)	(0.026)
Layovers	-0.418***	-0.413***	-0.348***	-0.528***	-0.453***	-0.335***
	(0.017)	(0.016)	(0.017)	(0.024)	(0.024)	(0.027)
lnDistance	1.136***	1.167***	1.140***	1.251***	1.207***	1.128***
	(0.025)	(0.025)	(0.025)	(0.031)	(0.031)	(0.032)
Frequency	0.070***	0.053***	0.048***	0.140***	0.079***	0.040**
	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.013)
Slot-control	0.009	0.015	-0.000	-0.029	-0.000	0.004
	(0.029)	(0.030)	(0.030)	(0.030)	(0.031)	(0.031)
Tour	-0.406***	-0.328***	-0.304***	-0.371***	-0.324***	-0.304***
	(0.040)	(0.042)	(0.042)	(0.041)	(0.042)	(0.042)
Nseat	-0.445***	-0.364***	-0.426***	-0.594***	-0.425***	-0.409***
	(0.047)	(0.046)	(0.047)	(0.052)	(0.054)	(0.054)
LCC	-0.253***	-0.298***	-0.293***	-0.210***	-0.279***	-0.298***
	(0.058)	(0.058)	(0.058)	(0.059)	(0.059)	(0.059)
LCCNum	-0.278***	-0.264***	-0.246***	-0.269***	-0.262***	-0.246***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
PopOrigin	-0.049***	-0.021***	-0.031***	-0.053***	-0.023***	-0.031***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
PopDest	-0.048***	-0.043***	-0.047***	-0.054***	-0.046***	-0.046***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Constant	4.716***	3.907***	3.960***	4.534***	3.878***	3.970***
	(0.071)	(0.079)	(0.079)	(0.077)	(0.080)	(0.081)
Carrier dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	58,612	58,612	58,612	58,612	58,612	58,612
Adjusted R-sq	0.094	0.102	0.104	0.090	0.101	0.104

Notes:Standard errors are in parentheses. *, **, *** indicate 95%, 99%, 99.9% level of significance. The coefficients of carrier dummies are not reported here. They are available upon request.

Table 21. Estimation Results on Model Parameters in Structural Model

Demand Variables		Cost Variables	
(Random Vars.)		(Competition Plan)	
Fare1	-0.639***(0.033)	GateShareOrigin	-0.504*(0.296)
GateShare1	0.580**(0.291)	GateShareDest	-0.262(0.289)
Layovers1	-0.436***(0.027)	SubleaseOrigin	0.094***(0.016)
Fare2	-0.077***(0.002)	SubleaseDest	0.123***(0.016)
GateShare2	0.917***(0.183)	MiiOrigin	0.002(0.014)
Layovers2	-0.572***(0.024)	MiiDest	0.003(0.014)
(Controls)		(Controls)	
lnDistance	0.212***(0.029)	Distance-short	0.213***(0.015)
Frequency	0.054***(0.004)	Distance-long	0.122***(0.008)
Slot-control	-0.074***(0.016)	Layovers-short	0.226***(0.049)
Tour	0.266***(0.057)	Layovers-long	0.292***(0.051)
Nseat	0.382***(0.032)		
(Carrier Dummies)		(Carrier Dummies)	
CO	-0.065**(0.032)	CO	0.086***(0.021)
DL	-0.210***(0.029)	DL	-0.141***(0.016)
NW	-0.065*(0.033)	NW	-0.052**(0.023)
UA	-0.063**(0.025)	UA	-0.006(0.017)
US	-0.300***(0.044)	US	-0.029(0.034)
B6	0.529***(0.107)	B6	-0.186***(0.058)
WN	0.062(0.047)	WN	-0.139***(0.027)
OT	0.091***(0.028)	OT	0.025(0.015)
(Other Coef.)		(Other Coef.)	
Constant	-11.096***(0.157)	Constant	0.232(0.176)
λ	0.728***(0.013)		
γ	0.873***(0.020)		
Function Value: 38.467			
First-order Optimality: 0.098			
Observations: 58,612			

Notes: Standard errors are in parentheses. *, **, *** indicate 90%, 95%, 99% level of significance.

Table 22. (Base Case) Structural Model with Airport Congestion Measure

Demand Variables		Cost Variables	
(Random Vars.)		(Competition Plan)	
Fare1	-0.638***(0.036)	GateShareOrigin*CongestOrg	-0.266***(0.083)
GateShare1	0.715**(0.354)	GateShareDest*CongestDst	-0.254***(0.087)
Layovers1	-0.430***(0.035)	GateShareOrigin	-0.301(0.357)
Fare2	-0.080***(0.003)	GateShareDest	-0.038(0.347)
GateShare2	0.776***(0.205)	SubleaseOrigin*CongestOrg	0.064*(0.038)
Layovers2	-0.553***(0.026)	SubleaseDest*CongestDst	-0.005(0.038)
(Controls)		SubleaseOrigin	0.116***(0.021)
lnDistance	0.197***(0.029)	SubleaseDest	0.102***(0.021)
Frequency	0.053***(0.004)	MiiOrigin*CongestOrg	0.140***(0.048)
Slot-control	-0.067***(0.016)	MiiDest*CongestDst	0.210***(0.051)
Tour	0.257***(0.059)	MiiOrigin	-0.005(0.018)
Nseat	0.385***(0.032)	MiiDest	0.013(0.018)
Carrier Dummies	Yes	CongestedOrigin	-0.154***(0.047)
(Other Coef.)		CongestedDest	-0.148***(0.047)
Constant	-11.095***(0.169)	(Controls)	
λ	0.712***(0.014)	Distance-short	0.216***(0.017)
γ	0.850***(0.026)	Distance-long	0.133***(0.009)
Function Value: 38.218		Layovers-short	0.216***(0.068)
First-order Optimality: 0.065		Layovers-long	0.277***(0.069)
Observations: 58,612		Carrier Dummies	Yes
		(Other Coef.)	
		Constant	0.111(0.217)

Notes: Standard errors are in parentheses. *, **, *** indicate 90%, 95%, 99% level of significance.

Table 23. Hub Specifications

	Hub Only	Hub and Gate-control
Demand Variables		
Fare1	-0.618***(0.034)	-0.636***(0.036)
HubDM1	0.172***(0.023)	0.061*(0.033)
Layovers1	-0.420***(0.028)	-0.408***(0.028)
Fare2	-0.077***(0.003)	-0.078***(0.003)
HubDM2	0.137***(0.020)	0.023(0.030)
Layovers2	-0.548***(0.023)	-0.562***(0.024)
GateShare	No	0.669***(0.131)
(Controls)	Yes	Yes
Cost Variables		
(Competition Plan)	Yes	Yes
(Controls)	Yes	Yes
Function Value	38.702	38.288
First-order Optimality	0.018	0.027
Observations	58,612	58,612

Notes: Standard errors are in parentheses. *, **, *** indicate 90%, 95%, 99% level of significance. Estimates for cost variables are very similar to those in table 21 in terms of figures and significance levels. Results are available upon request.

Table 24. Robustness Check

Demand Variables	Markets Longer than 3k Miles	Non-monopoly Markets	Small bin fare	Large bin fare	2004 Comp. Plans
Fare1	-0.386***(0.059)	-0.626***(0.035)	-0.689***(0.040)	-0.561***(0.029)	-0.532***(0.033)
GateShare1	0.706**(0.354)	0.953***(0.340)	0.815**(0.376)	1.003***(0.298)	0.942***(0.254)
Layovers1	-0.794***(0.072)	-0.436***(0.034)	-0.389***(0.042)	-0.561***(0.034)	-0.671***(0.040)
Fare2	-0.062***(0.007)	-0.079***(0.003)	-0.083***(0.003)	-0.070***(0.002)	-0.071***(0.003)
GateShare2	0.951***(0.149)	0.643***(0.206)	0.707***(0.187)	0.682***(0.168)	0.197*(0.118)
Layovers2	-0.408***(0.033)	-0.539***(0.025)	-0.511***(0.025)	-0.622***(0.023)	-0.552***(0.022)
λ	0.893***(0.019)	0.707***(0.014)	0.716***(0.014)	0.725***(0.013)	0.804***(0.014)
γ	0.719***(0.069)	0.843***(0.027)	0.829***(0.029)	0.822***(0.028)	0.735***(0.034)
(Controls)	Yes	Yes	Yes	Yes	Yes

Table 24. Continued

Cost Variables	Markets Longer than 3k Miles	Non-monopoly Markets	Small bin fare	Large bin fare	2004 Comp. Plans
GateShareOrigin*CongestedOrigin	-0.191**(0.087)	-0.300***(0.083)	-0.272***(0.086)	-0.195**(0.093)	-0.208***(0.053)
GateShareDest*CongestedDest	-0.330***(0.102)	-0.250***(0.088)	-0.298***(0.086)	-0.247*(0.095)	-0.202***(0.054)
GateShareOrigin	-0.346(0.521)	-0.042(0.349)	-0.262(0.346)	-0.095(0.328)	0.259(0.274)
GateShareDest	-0.247(0.520)	0.214(0.337)	0.045(0.339)	0.172(0.316)	0.554**(0.264)
SubleaseOrigin*CongestedOrigin	0.015(0.029)	0.064*(0.037)	0.073*(0.037)	0.026(0.036)	0.128***(0.031)
SubleaseDest*CongestedDest	-0.006(0.031)	-0.017(0.038)	0.036(0.036)	0.008(0.038)	0.106***(0.024)
SubleaseOrigin	0.062***(0.019)	0.111***(0.021)	0.102***(0.019)	0.094***(0.021)	0.106***(0.018)
SubleaseDest	0.051***(0.019)	0.099***(0.021)	0.090***(0.019)	0.098***(0.020)	0.113***(0.019)
MiiOrigin*CongestedOrigin	0.078*(0.032)	0.120**(0.048)	0.140***(0.045)	0.186***(0.051)	0.074***(0.025)
MiiDest*CongestedDest	0.152**(0.034)	0.207*(0.051)	0.224***(0.049)	0.204***(0.050)	0.078***(0.028)
MiiOrigin	-0.015(0.017)	0.000(0.018)	-0.010(0.017)	-0.004(0.018)	0.044***(0.016)
MiiDest	-0.013(0.018)	0.020(0.018)	-0.007(0.018)	0.003(0.017)	0.006(0.015)
CongestedOrigin	-0.082**(0.034)	-0.132***(0.047)	-0.159***(0.044)	-0.180***(0.049)	-0.150***(0.030)
CongestedDest	-0.102***(0.035)	-0.138***(0.047)	-0.182***(0.045)	-0.155***(0.046)	-0.115***(0.029)
(Controls)	Yes	Yes	Yes	Yes	Yes
Observations	24,502	58,397	65,136	38,478	25,760

Notes: Standard errors are in parentheses. *, **, *** indicate 90%, 95%, 99% level of significance. Estimates for control variables are not reported here. Results are available upon request.

Table 25. Elasticity Estimates on Price and Gate

Price Elasticity	Base Case	Long Market	Non Monopoly	Small Bin	Large Bin	2004 C.Plans
Type One	-3.99	-2.05	-3.95	-4.09	-3.75	-3.11
Type Two	-0.50	-0.33	-0.50	-0.49	-0.47	-0.42
Both Types	-2.37	-0.96	-2.36	-2.23	-2.25	-1.65
Gate Elasticity						
Type One	0.13	0.09	0.17	0.15	0.17	0.17
Type Two	0.14	0.12	0.12	0.13	0.11	0.04
Both Types	0.14	0.11	0.15	0.14	0.14	0.10
% of Population (γ)						
Type One	0.85	0.72	0.84	0.83	0.82	0.74
Type Two	0.15	0.28	0.16	0.17	0.18	0.26
% of Passengers						
Type One	0.54	0.36	0.54	0.48	0.54	0.46
Type Two	0.46	0.64	0.46	0.52	0.46	0.54

Notes: Price elasticity measures the percentage change in demand as prices of all products increase by 1%. Similarly, gate elasticity indicates the percentage change in demand when the number of gates controlled by each carrier increase by 1%. The percentage of population (γ) refers to percentage of type 1 and 2 passengers in the population. The percentage of passengers denotes the percentage of type 1 and 2 passengers who actually bought airline tickets.

Table 26. Predicted Marginal Cost and Profits for Base Case at Congested Airports

(At airports where congestion measure>0)

All airports	Fare ($100)	MC ($100)	Markup (%)	Quantity (100)	Profit ($100k)	Revenue ($100k)
Signatory	4.65	0.82	0.85	7.77	2.23	2.40
Non-Sig.	4.16	0.94	0.79	3.47	0.87	1.03
Airports with Sublease						
Signatory	4.75	0.81	0.85	9.09	2.78	3.08
Non-Sig.	4.33	0.96	0.79	3.90	1.03	1.23
Airports with MII Clauses						
Signatory	4.74	0.85	0.84	8.01	2.43	2.69
Non-Sig.	4.14	0.90	0.80	3.83	0.96	1.12
Carrier						
American	5.08	0.90	0.84	2.25	0.72	0.83
Continental	4.46	1.16	0.73	0.54	0.15	0.18
Delta	4.51	0.73	0.90	1.82	0.52	0.58
Northwest	4.95	0.68	0.87	2.41	0.83	0.91
United	4.62	0.97	0.79	1.57	0.43	0.49
US Airways	3.81	0.88	0.76	0.43	0.10	0.12
Jet Blue	3.95	0.58	0.86	4.64	1.12	1.38
Southwest	3.29	0.50	0.91	5.37	1.18	1.03
Others	3.98	0.96	0.77	1.99	0.46	0.57

Notes: Fare, marginal costs, and markups are average values for products specified above. Quantity, profits, and revenues are average values per market.

Table 27. Predicted Marginal Cost and Profits for Base Case
at Highly Congested Airports
(At airports where congestion measure>1)

All airports	Fare ($100)	MC ($100)	Markup (%)	Quantity (100)	Profit ($100k)	Revenue ($100k)
Signatory	4.79	0.85	0.83	7.07	2.22	2.41
Non-sig.	4.25	0.89	0.80	5.37	1.37	1.58
Airports with Sublease						
Signatory	4.79	0.85	0.83	7.07	2.22	2.41
Non-sig.	4.40	0.94	0.79	4.93	1.31	1.55
Airports with MII Clauses						
Signatory	4.85	0.87	0.82	6.76	2.27	2.55
Non-sig.	4.18	0.85	0.82	5.82	1.47	1.68
Carrier						
American	4.86	0.95	0.82	1.88	0.53	0.62
Continental	4.55	1.13	0.74	0.52	0.15	0.19
Delta	3.97	0.92	0.80	0.56	0.14	0.17
Northwest	5.17	0.61	0.90	3.56	1.26	1.37
United	4.79	0.91	0.81	2.45	0.68	0.78
US Airways	3.93	0.78	0.80	0.51	0.13	0.15
Jet Blue	3.95	0.58	0.86	4.64	1.12	1.38
Southwest	3.35	0.59	0.87	4.63	1.03	0.93
Others	3.95	1.00	0.76	1.64	0.38	0.46

Notes: Fare, marginal costs, and markups are average values for products specified above. Quantity, profits, and revenues are average values per market.

Table 28. Number of Airports and Carriers Affected by Counterfactual Scenarios

Scenarios	No. of airports affected	No. of carriers affected per airport	No. of Exclusive gates reduced per airport	std.dev of Exclusive gates across carriers
75% ceiling	25	2.7	9.5	0.13
50% ceiling	31	3.9	20.6	0.08
25% ceiling	31	4.8	32.3	0.04

Table 29. Counterfactual Analysis with Reduction in Exclusive Gates at Congested Airports

(At airports where congestion measure>0)

75% ceiling	New Fare ($100)	MC ($100)	Markup (%)	Quantity (100)	Profit ($100k)	Revenue ($100k)
Signatory	4.66	0.84	0.84	7.22	2.09	2.27
Non-sig.	4.17	0.94	0.79	3.35	0.84	1.00
50% ceiling						
Signatory	4.84	0.89	0.83	6.63	1.91	2.12
Non-sig.	4.17	0.94	0.79	3.31	0.84	0.99
25% ceiling						
Signatory	4.76	0.94	0.82	6.11	1.76	1.98
Non-sig.	4.16	0.94	0.79	3.29	0.83	0.98
Carrier (based on 50% reduction)						
American	5.11	0.96	0.83	1.94	0.62	0.73
Continental	4.47	1.16	0.73	0.48	0.13	0.16
Delta	4.53	0.78	0.88	1.56	0.46	0.52
Northwest	5.67	0.82	0.84	1.83	0.66	0.75
United	4.62	0.97	0.79	1.49	0.41	0.47
US Airways	3.86	0.91	0.76	0.38	0.09	0.11
Jet Blue	3.92	0.58	0.87	4.65	1.17	1.43
Southwest	3.38	0.55	0.90	4.75	1.05	0.94
Others	3.99	0.97	0.77	1.97	0.47	0.57

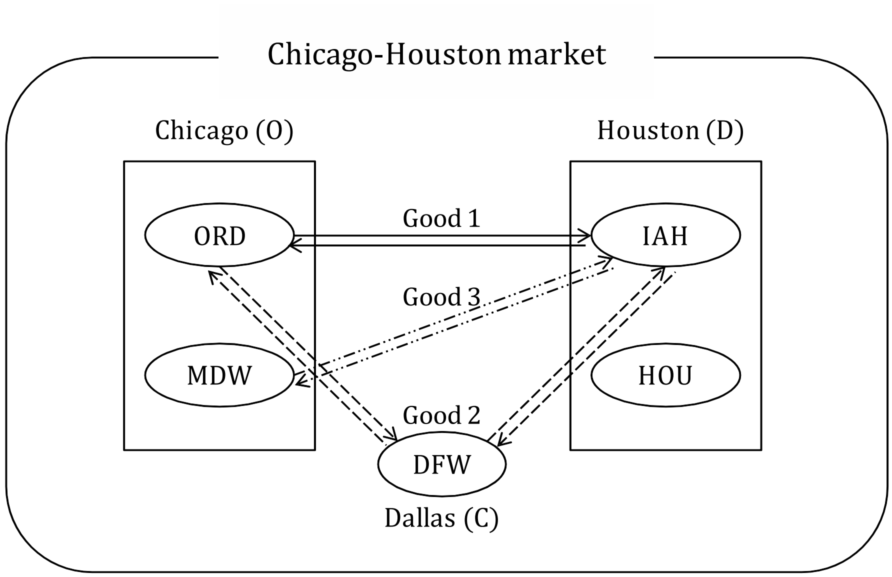
Notes: Fare, marginal costs, and markups are average values for products specified above. Quantity, profits, and revenues are average values per market.

Table 30. Counterfactual Analysis with Reduction in Exclusive Gates at Highly Congested Airports
(At airports where congestion measure>1)

75% ceiling	New Fare ($100)	MC ($100)	Markup (%)	Quantity (100)	Profit ($100k)	Revenue ($100k)
Signatory	4.81	0.88	0.82	6.48	2.07	2.26
Non-sig.	4.26	0.89	0.81	5.17	1.32	1.52
50% ceiling						
Signatory	5.23	0.94	0.81	5.91	1.87	2.08
Non-sig.	4.26	0.89	0.81	5.08	1.30	1.50
25% ceiling						
Signatory	5.02	1.00	0.80	5.37	1.69	1.93
Non-sig.	4.26	0.89	0.80	5.04	1.29	1.49
Carrier (based on 50% reduction)						
American	4.87	0.97	0.81	1.76	0.49	0.59
Continental	4.56	1.13	0.74	0.46	0.13	0.16
Delta	3.98	0.94	0.80	0.51	0.13	0.16
Northwest	6.06	0.78	0.87	2.66	0.99	1.12
United	4.79	0.90	0.82	2.30	0.64	0.73
US Airways	3.99	0.83	0.79	0.44	0.11	0.13
Jet Blue	3.92	0.58	0.87	4.65	1.17	1.43
Southwest	3.36	0.59	0.88	4.31	0.96	0.86
Others	3.95	1.00	0.76	1.66	0.39	0.48

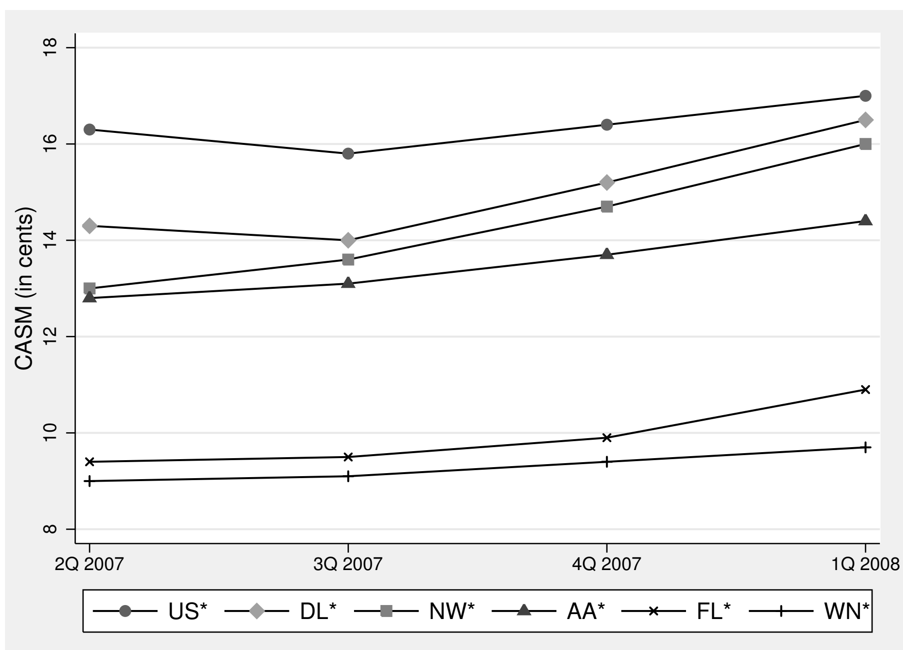
Notes: Fare, marginal costs, and markups are average values for products specified above. Quantity, profits, and revenues are average values per market.

Figure 1. An Illustration of Market and Product



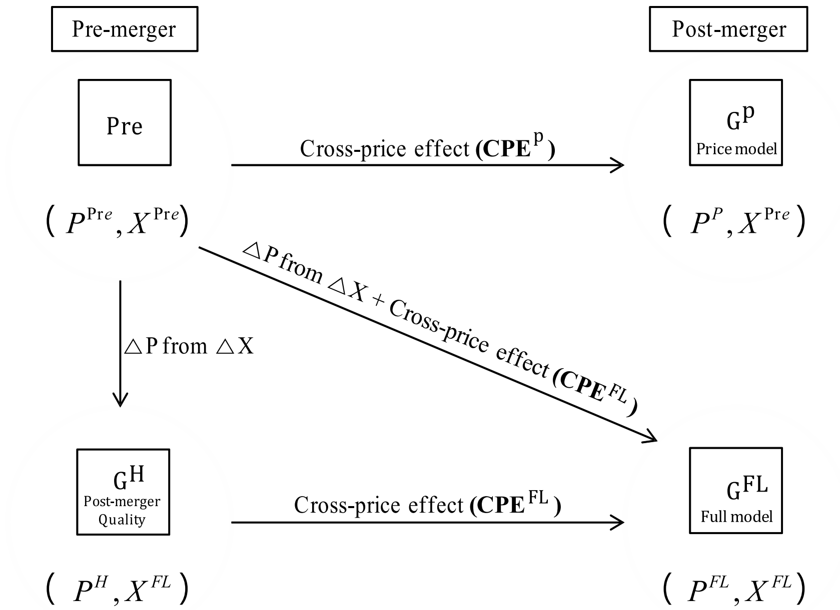
Notes: O, D, C indicate origin, destination, and connecting city, respectively. Given carrier, roundtrip ORD-IAH, ORD-DFW-IAH, and MDW-IAH are considered as different products.

Figure 2. Operating Cost per Available Seat Mile (CASM)



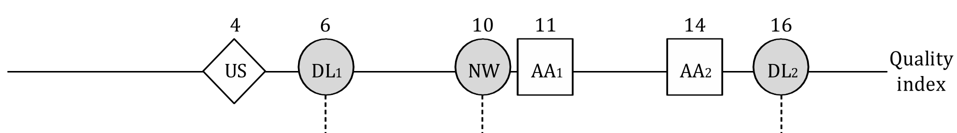
Notes: Data sources of CASM are Air Carrier Financial Statistics (Schedule P- 12) and T-100 Domestic Segment from U.S. DOT.

Figure 3. Simulation Design for Decomposing Sources of Price Change



Notes: *Pre* is the actual pre-merger data. G^P and G^{FL} indicate games based on the price model and the full model. P is a price and X is a vector of the endogenous product characteristics. G^H is a hypothetical game.

Figure 4. Measures for the Extent of Product Differentiation: Within-firm distance and Within-market distance

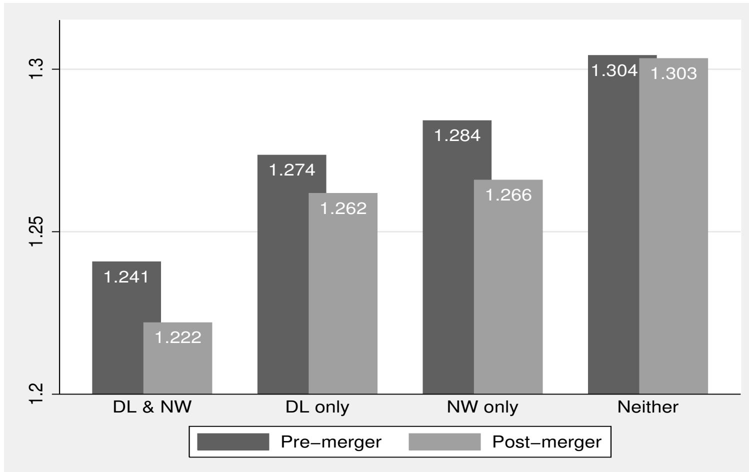


within-firm distance	4	4	6
within-market distance	2	1	2

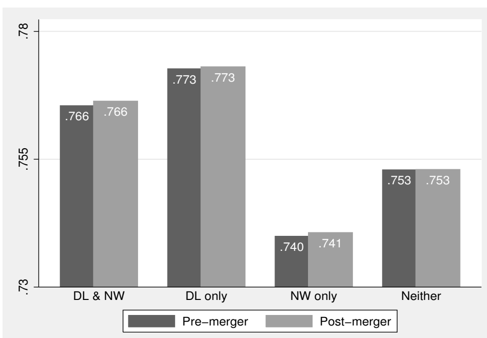
Notes: Within-firm distance of a product is the closest quality-distance from itself to other goods produced by the same firm. Within-market distance of a product the closest quality-distance from itself to other goods produced by competitors.

Figure 5. Quality Changes of Merged Firm's Products in All Markets

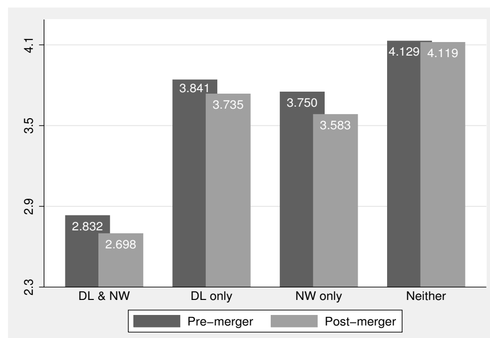
By market power



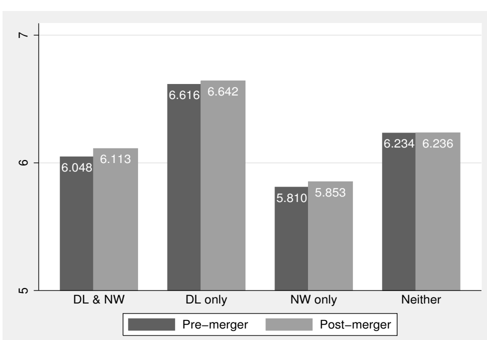
(a) Quality index



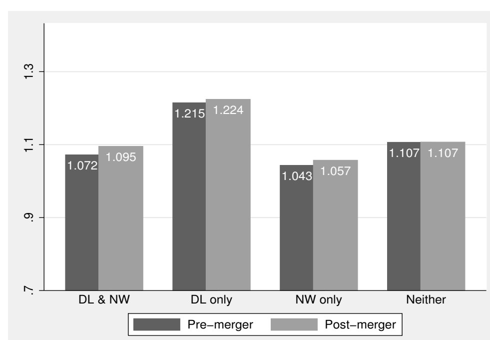
(b) Ontime15



(c) Frequency



(d) Mishandled baggage rate

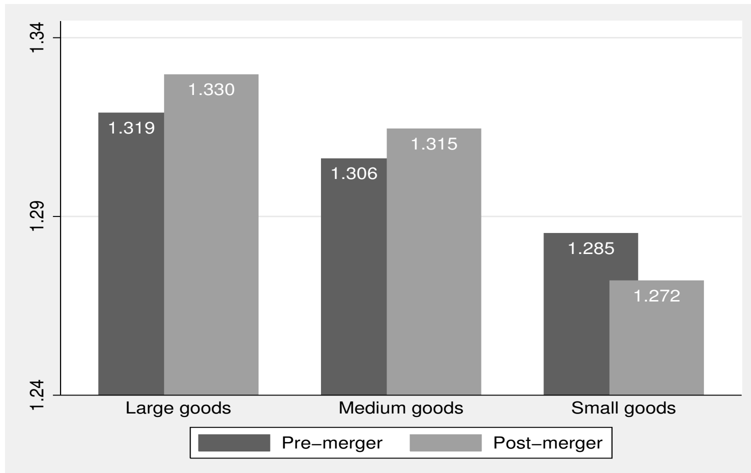


(e) Denied boarding rate

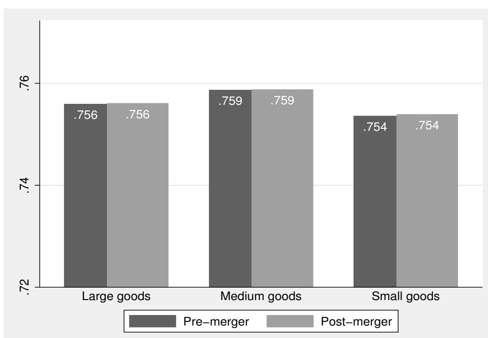
	DL & NW	DL only	NW Only	Neither
Number of markets	29	219	215	666
Number of products	122	1,011	816	3,410

Figure 6. Quality Changes of Merged Firm's Products in Oligopoly Markets

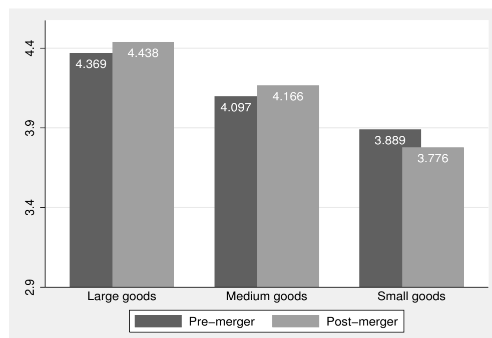
By product group



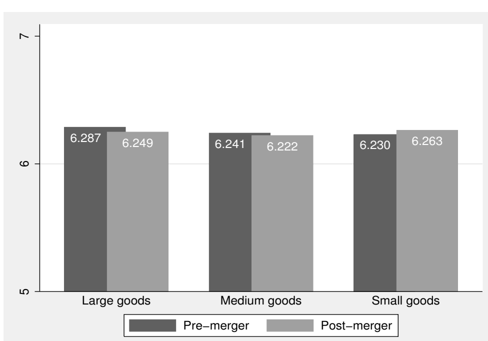
(a) Quality index



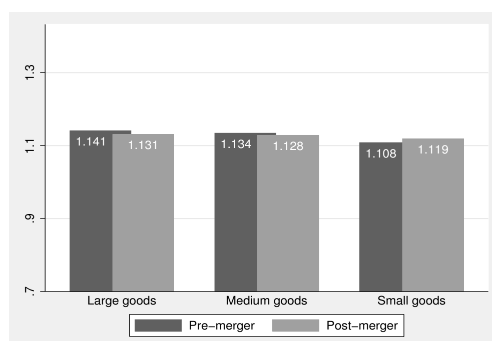
(b) Ontime15



(c) Frequency



(d) Mishandled baggage rate

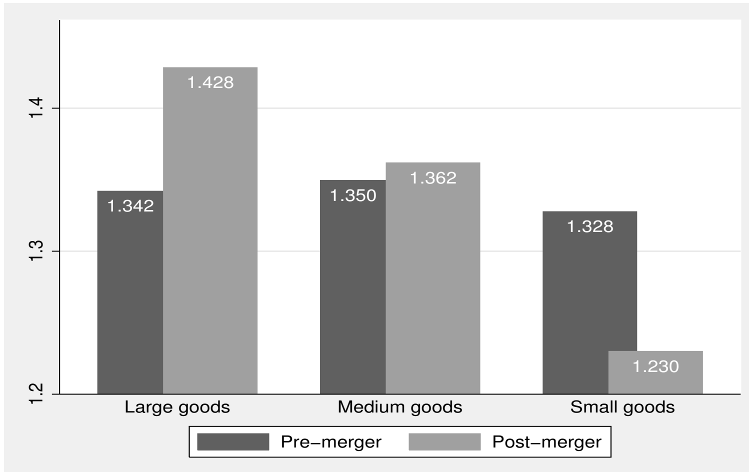


(e) Denied boarding rate

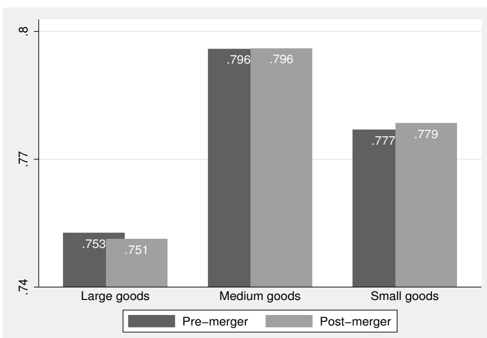
	Large goods	Medium goods	Small goods
Number of markets	680	676	865
Number of products	692	1,041	3,598

Figure 7. Quality Changes of Merged Firm's Products in Monopoly Markets

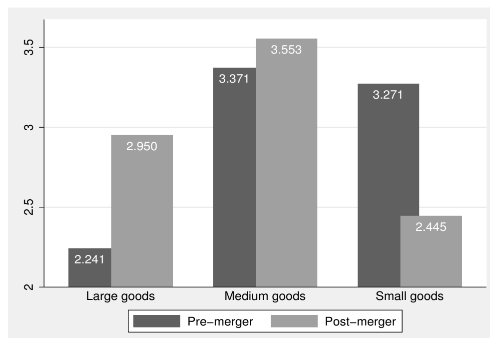
By product group



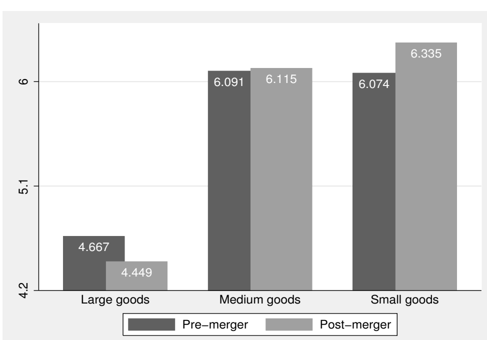
(a) Changes in Quality



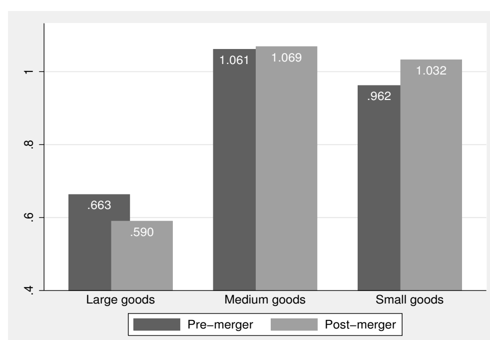
(b) Ontime15



(c) Frequency



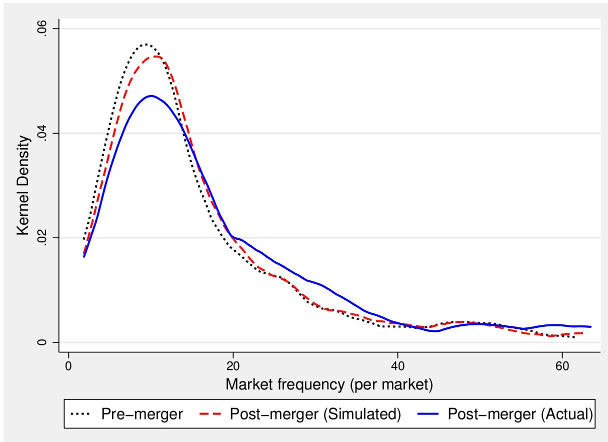
(d) Mishandled baggage rate



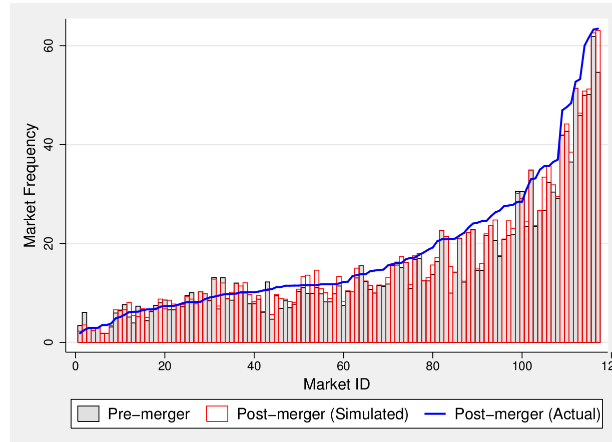
(e) Denied boarding rate

	Large goods	Medium goods	Small goods
Number of markets	6	5	6
Number of products	6	8	14

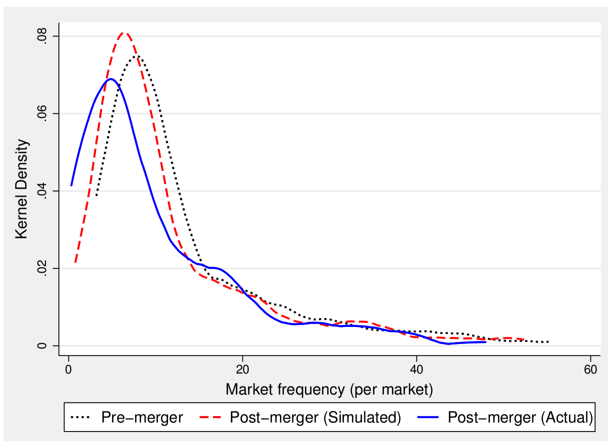
Figure 8. Distribution of Market Frequency in QI and QD Markets:
Pre-merger vs. Post-merger (Simulated) vs. Post-merger (Actual)



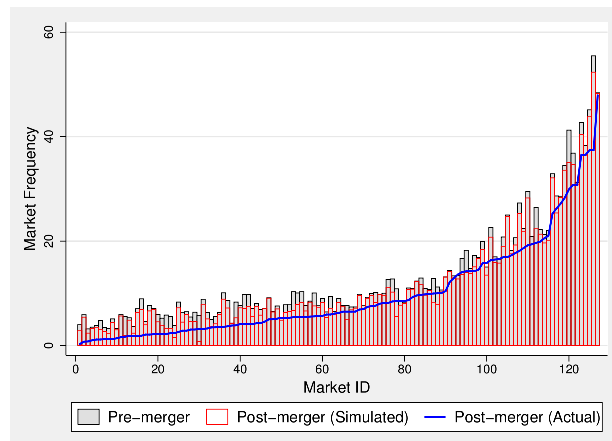
(a) Density of market frequency in QI markets



(b) Market frequency of QI markets

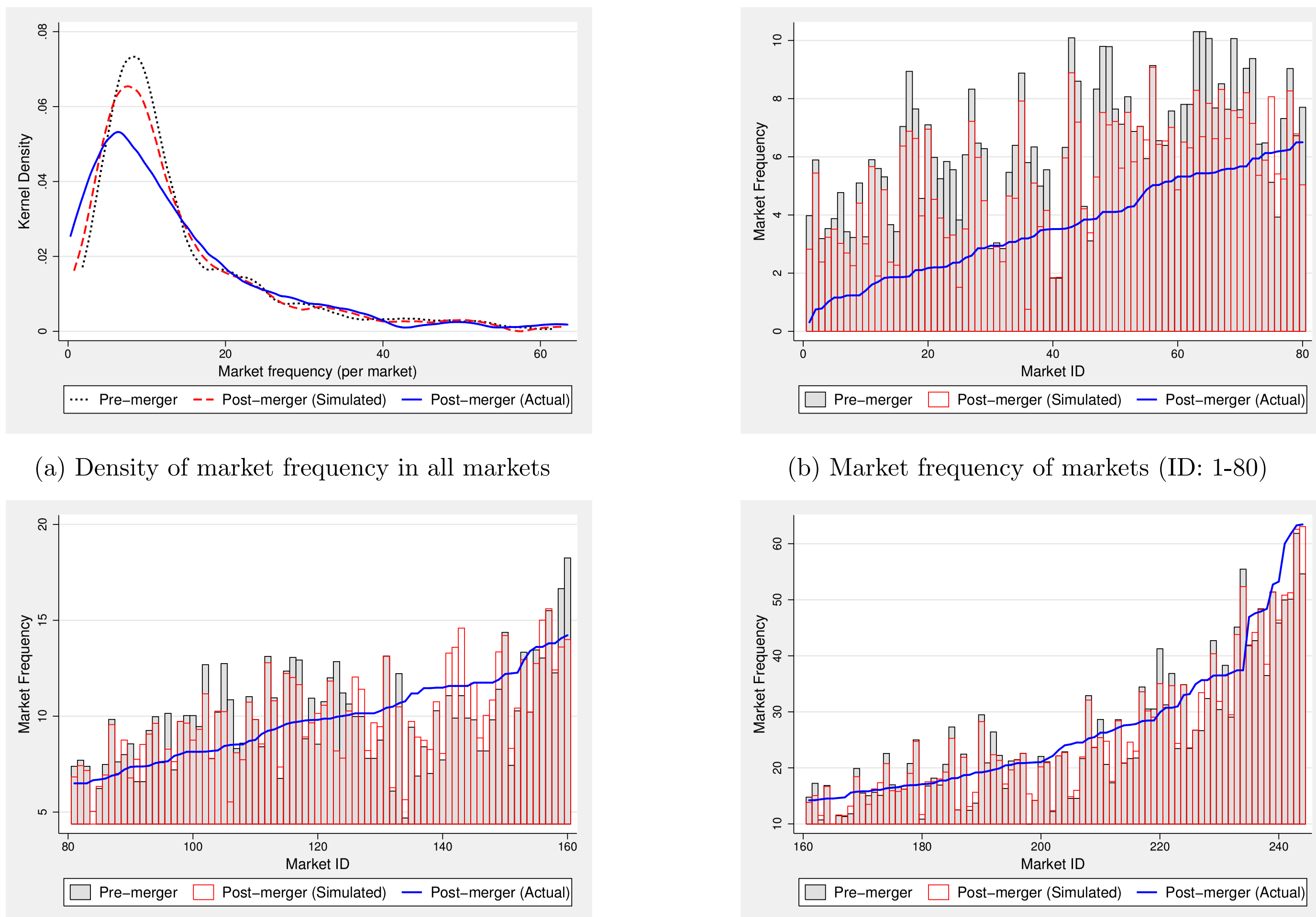


(c) Density of market frequency in QD markets



(d) Market frequency of QD markets

Figure 9. Distribution of Market Frequency in All Markets:
Pre-merger vs. Post-merger (Simulated) vs. Post-merger (Actual)



(a) Density of market frequency in all markets

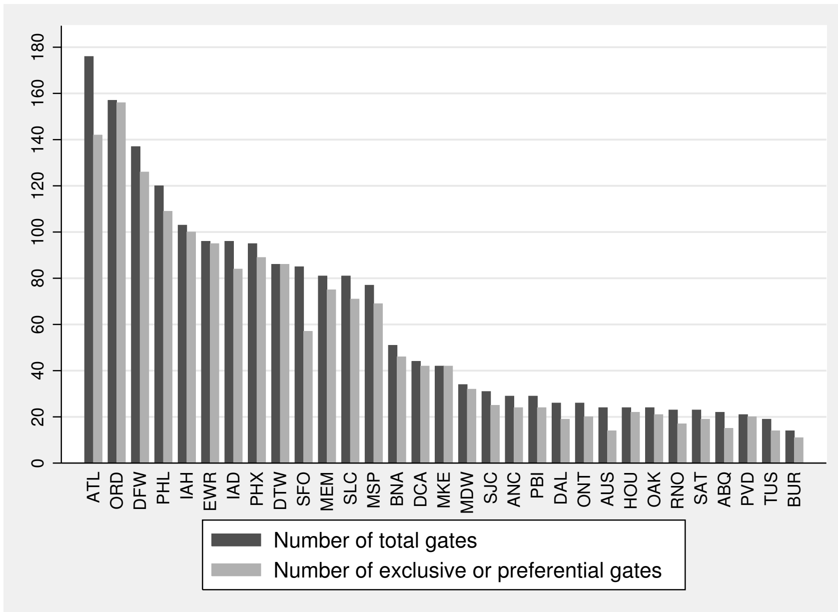
(b) Market frequency of markets (ID: 1-80)

(c) Market frequency of markets (ID: 81-160)

(d) Market frequency of markets (ID: 161-244)

Figure 10: Total Gates and Exclusive or Preferential Gates

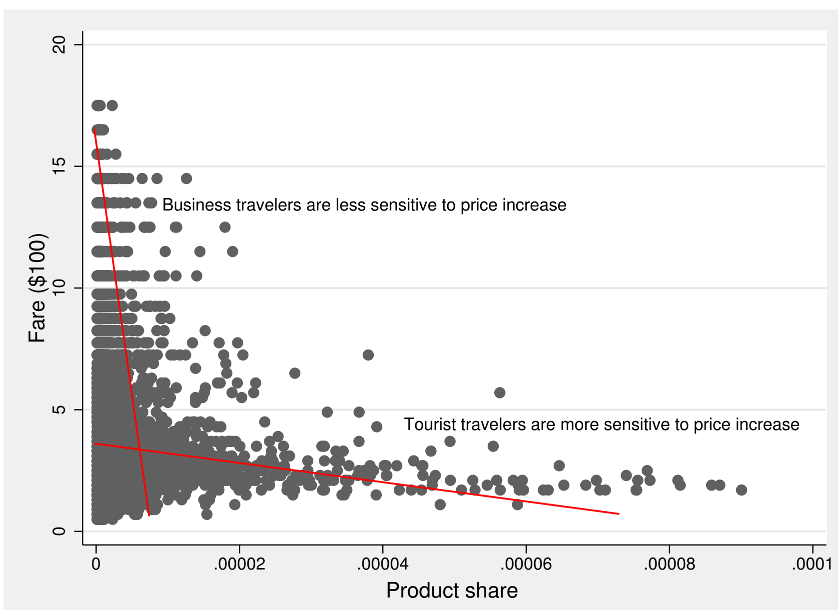
(Thirty one airports subjected to Airport Competition Plan)



Notes: Sources are Airport Competition Plans.

Figure 11: Fare and Product Share

(1,500 miles < Market Distance < 2,000 miles)



Notes: Source is DB1B Origin and Destination Survey (2004.2Q)