

Endogenous Product Characteristics in Merger Simulation: A Study of the U.S. Airline Industry

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Motivation: Changes in Product Characteristics

The prime concern of the Department of Justice (DOJ) is the effect of the merger on consumer welfare.

The merged firm can exercise the market power by adjusting

- **prices of products**
- **product characteristics**

In airline industry, the combined carrier may adjust

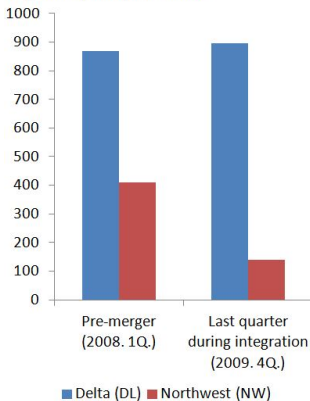
- Ticket prices (Kim and Singal, 1993, and many studies)
- Flight frequency (Peters, 2006), On-time performance (Mazzeo, 2003)

The **changes** in both **prices** and **characteristics** will affect the **consumer welfare**.

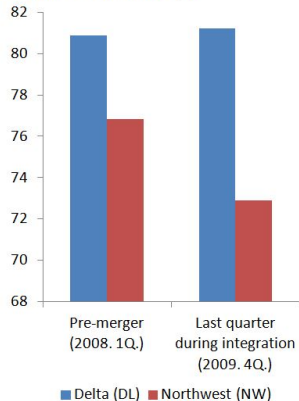
Motivation: Changes in Product Characteristics

The Delta-Northwest Airlines Merger

Flight Frequency (per quarter)



On-time Performance (%)



- Market: Denver-Washington, D.C.
- Source: DB1B, T-100, and On-time performance data from U.S. DOT.

Motivation: Changes in Product Characteristics

Traditional merger analyses have **focused only on** changes in **prices**.

- the set of **characteristics** are assumed to be **identical** pre- and post-merger.

Limitations traditional approach has.

- the predicted prices can be biased.
 - Δ characteristics $\rightarrow \Delta$ (demand & firm's cost) $\rightarrow \Delta$ price
 - Δ characteristics $\rightarrow \Delta$ degree of cross-price effect $\rightarrow \Delta$ price
- the predicted welfare effect can be biased.

This study endogenizes both prices and characteristics to overcome the limitations.

- **Price model (G^P) vs. Full model (G^{FL})**

Research Questions

Price model (G^P) vs. Full model (G^{FL})

1 The effects of the merger on product characteristics: G^{FL}

- Overall quality level: \uparrow or \downarrow
- The extent of product differentiation: $\Leftarrow \Rightarrow$ or $\Rightarrow \Leftarrow$

2 The effects of product repositioning on prices: G^P vs. G^{FL}

- Δ characteristics $\rightarrow \Delta$ (demand & firm's cost) $\rightarrow \Delta$ price
- Δ characteristics $\rightarrow \Delta$ degree of **cross-price effect** $\rightarrow \Delta$ price
: Cross-price effect in G^P vs. Cross-price effect in G^{FL}

3 The effects of the merger on welfare: G^P vs. G^{FL}

- Change in consumer welfare
- Change in profits of the merged firm and its competitors

Literature and Contributions

1 Extends **merger literature**.

- Reduced-from model: Borenstein (1990), Kim and Singal (1993), Kwoka and Shumilkina (2010)
- **Structural model**: Richard (2003), Peters (2006)

2 Extends **the on-going literature on endogenous product choice**.

- One-stage game: Crawford and Shum (2006), Gandhi et.al. (2008), Draganska et.al. (2009), Chu (2010), Crawford and Shcherbakov (2011)
- **Two-stage game**: Fan (August 2013 AER)

3 Adds evidence regarding **the effect of a merger on product positioning**.

- **Higher product differentiation**: Gandhi et al. (2008), Sweeting (2010)
- Lower product differentiation: Gots and Gugler (2006)

Research Outline

- 1 Identify four endogenous product characteristics.**
 - **Flight frequency:** Number of average daily departures
 - **On-time15:** Percentage of flights that arrive less than 15 minutes late
 - **Mishandled baggage rate:** Number of mishandled baggage (per 1,000)
 - **Denied boarding rate:** Number of involuntary denied boardings (per 10,000)
- 2 Set up a structural model of demand and supply.**
- 3 Estimate the model parameters.**
- 4 Predict post-merger prices and product characteristics.**
 - Simulate the Delta-Northwest Airlines merger using G^P , G^{FL} , G^H .
- 5 Analyze changes in product characteristics, prices, and welfare.**

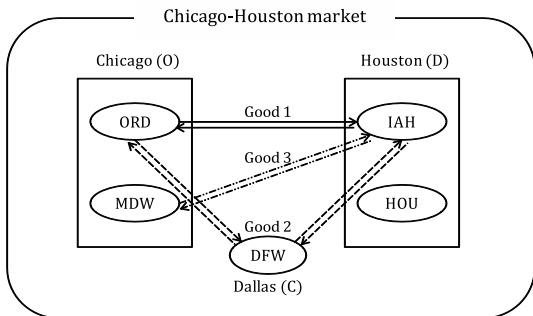
The Model: An Example

Market: Directional round trip between **origin** and **destination city**.

- The Chicago-Houston is a different market from the Houston-Chicago.

Product: Airport pair served by a particular carrier.

- Given a route and a carrier, tickets are aggregated to form a representative product.



Demand Model

Random coefficient logit model with **finite consumer types**

- Berry, Levinsohn, and Pakes (1995), **Berry and Jia (2010)**

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

- j (product), t (market), i (consumer), r (consumer type, $r = 1, 2$).
- p_{jt} : a passenger-weighted average ticket prices of product j .
- y_{jt} : a two-dimensional vector of *Layovers* (0 or 2) and **O***ntime15*(\bar{x}_j^O),
- z_{jt} : **F***requency*(\bar{x}_j^F), **M***ishandled baggage*(\bar{x}_j^M), **D***enied boarding*(\bar{x}_j^D), and controls (*HubDM*, *Distance*, *Slot-control*, *Tour*, *Carrier dummies*).
- ξ_{jt} : the unobserved (to econometrician) product quality,
- $\nu_{it}(\lambda) + \lambda\epsilon_{ijt}$ follows the Type I extreme value distribution.

▶ Market Share Function

Data Sources

Database	Variables	Level of Obs.	Sample Period
O&D Survey (DB1B)	Market / Product Price, Controls*	ticket	'07.2Q.~'08.1Q.
On-Time Performance	On-time15	carrier-route	'07.Apr.~'08.Mar.
T-100 Domestic Segment	Frequency	carrier-route	'07.Apr.~'08.Mar.
Air Travel Consumer Report	Mis. baggage Denied boardings	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

Controls*: Layovers, Distance, Hub, Slot-control, Tour, Carrier dummies.

Number of observations (products): 87,906. Number of markets: 9,117.

Estimation: Instruments

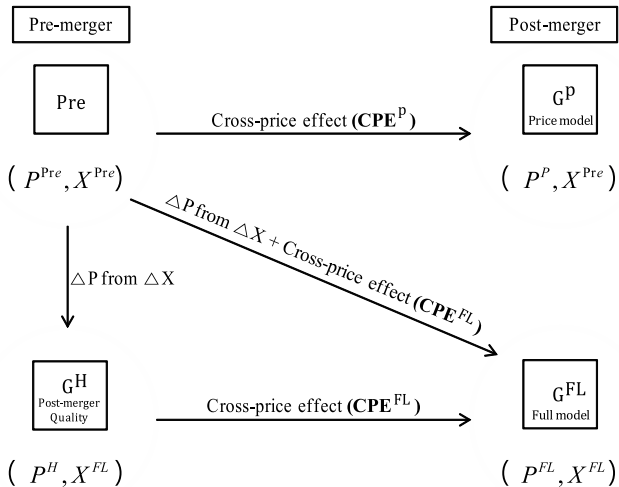
Instruments for the endogenous product characteristics

Instruments	Ontime15	Frequency	Mis. 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

Data source: Weather Underground Organization, Air Carrier Financial Report.

Simulation Design

Simulation design for decomposing sources of price change



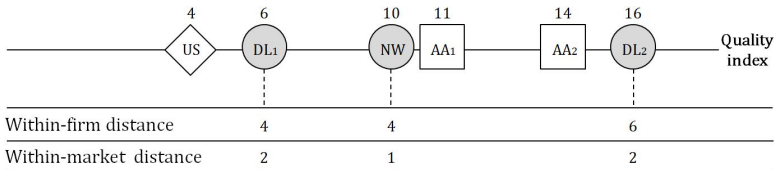
Quality Index and Quality Distance

Quality index: $Q_j = \sum_{r=1}^2 \sum_k \gamma_r \cdot \bar{x}_j^k \beta_r^k$, $k = O, F, M, D$

- \bar{x}_j^k : each endogenous characteristic.
- γ_r, β_r^k : model parameters.

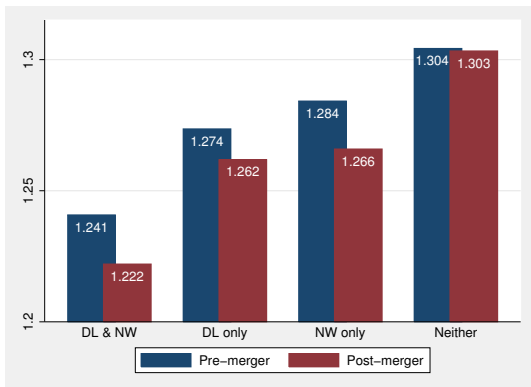
Quality distance

- **Within-firm distance:** the closest distance to other goods produced by same firm.
- **Within-market distance:** the closest distance to other goods produced by other firms.



Changes in Product Quality (1): Overall Quality Degradation

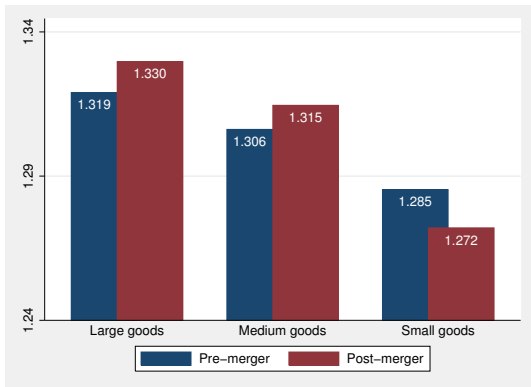
- 1 The merged firm tends to reduce product quality.



- **DL only:** DL had more than 25% of total market enplanements pre-merger.
- **DL & NW:** Both carriers had more than 25% of total market enplanements.
- Quality degradation became severe when merging carriers had strong market presence.

Changes in Product Quality (2): Higher Product Differentiation

- 2 The merged firm tends to differentiate products.



- **Large good:** serves more than 50% of the carrier's enplanements in a market.
- **Medium good:** serves less than 50% but at least 20%.
- **Small good:** serves less than 20%.

Changes in Prices (1): Large 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	6.287	6.249	-0.038
Denied Boarding	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

	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Price(\$)	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 goods include 692 products in 680 markets. Each number indicates average values over the large goods.

Changes in Prices (2): Medium 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	6.241	6.222	-0.019
Denied Boarding	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

	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Price(\$)	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 goods include 1,041 products in 676 markets. Each number indicates average values over the medium goods.

Changes in Prices (3): Small Goods

	Pre-merger	Post-merger	Change
Quality index	1.285	1.272	-0.013
Overtime	0.754	0.754	0.000
Frequency	3.889	3.776	-0.113
Mishandled Baggage	6.230	6.263	0.033
Denied Boarding	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

	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
Price(\$)	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 goods include 3,598 products in 865 markets. Each number indicates average values over the small goods.

Change in Consumer Surplus (CS)

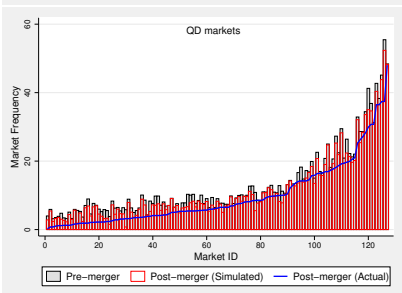
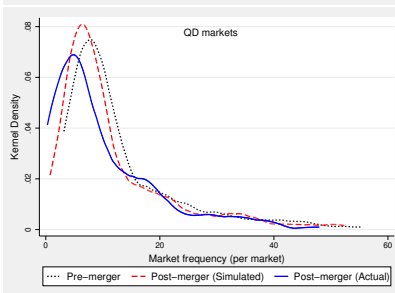
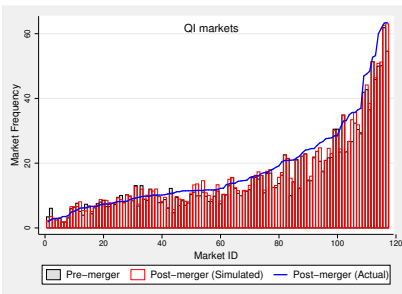
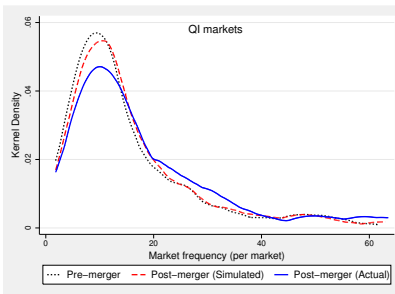
Markets	Price model (G^P)	Full model (G^{FL})	Quality change of DL/NW	Number of products (markets)
	Change in CS (\$100K)	Change in CS (\$100K)		
All markets				
Total	-15.59	18.53		18,430
Business	-9.87	22.16	-0.006	(1,129)
Tourists	-5.72	-3.63		
By quality change				
QI markets	-12.75	19.86		12,782
Business	-8.22	22.05	0.012	(712)
Tourists	-4.53	-2.19		
QD markets	-2.84	-1.34		5,648
Business	-1.65	0.11	-0.042	(417)
Tourists	-1.18	-1.44		

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.

Change in Producer Surplus (PS)

Markets	Pre-merger profit (\$100K)	Price model (G^P)	Full model (G^{FL})	No. of products	No. of markets
		Change in PS (\$100K)	Change in PS (\$100K)		
All markets					
Total	2632.3	-1.38	5.58	18,430	
DL/NW	553.3	1.66	6.82	5,359	1,129
Competitors	2079.0	-3.03	-1.24	13,071	
By quality change					
QI market	2026.5	-0.92	5.72	12,782	
DL/NW	384.3	1.18	6.83	3,549	712
Competitors	1642.2	-2.10	-1.12	9,233	
QD market	605.8	-0.46	-0.14	5,648	
DL/NW	169.0	0.47	-0.01	1,810	417
Competitors	436.8	-0.93	-0.12	3,838	
By product quantity (for DL/NW only)					
Large goods	410.3	1.32	4.51	698	686
Medium goods	72.5	0.30	1.80	1,049	681
Small goods	70.5	0.03	0.51	3,612	871

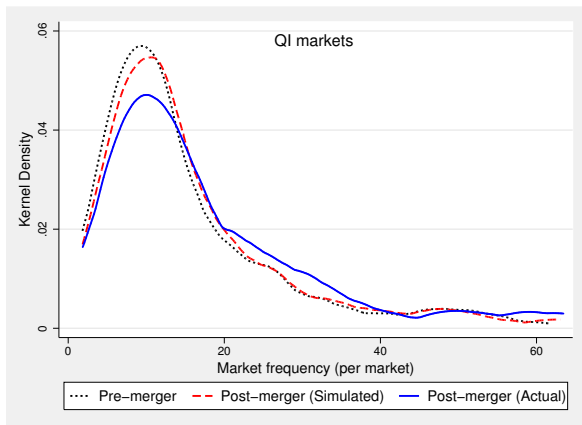
Comparison between the Simulated and Actual Post-merger Frequency



Comparison between the Simulated and Actual Post-merger Frequency

Quality-Increased (QI) markets

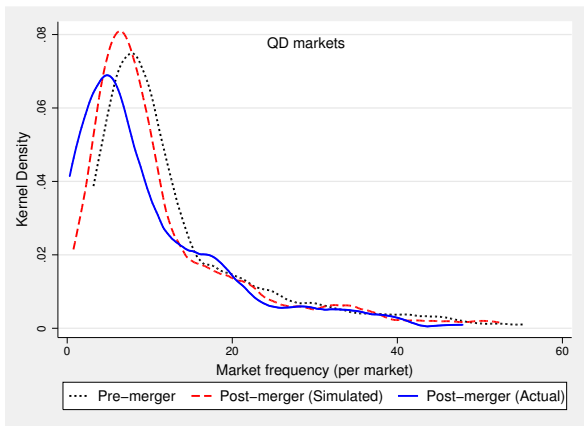
- A passenger-weighted average quality of the merged firm's products increases post-merger.



Comparison between the Simulated and Actual Post-merger Frequency

Quality-Decreased (QD) markets

- A passenger-weighted average quality of the merged firm's products decreases post-merger.



Conclusion

The traditional merger simulations ignore changes in product characteristics, leading to a bias in predicted prices and welfare effects.

This paper overcomes the limitations by endogenizing both price and product characteristics.

Main findings

- Merged firm tends to increase product differentiation post-merger.
- Higher product differentiation reduces the firm's incentive to raise prices.
- Changes in characteristics and prices increase not only the merged firm's profit but also consumer welfare.
- Endogenizing product characteristics is essential to better predict the actual outcome.

Demand Model: Market Share Function

- Each type r consumer purchases one airline ticket which gives the highest mean utility $(x_{jt}\beta_r + \xi_{jt})$ or takes the outside option.
- **Market share of j th product** is predicted by

$$s_{jt}(x_t, \xi_t, \theta_d) = \sum_{r=1}^2 \gamma_r \cdot \frac{e^{(x_{jt}\beta_r + \xi_{jt})/\lambda}}{\sum_{k \in J_t} e^{(x_{kt}\beta_r + \xi_{kt})/\lambda}} \cdot \frac{(\sum_{k \in J_t} e^{(x_{kt}\beta_r + \xi_{kt})/\lambda})^\lambda}{1 + (\sum_{k \in J_t} e^{(x_{kt}\beta_r + \xi_{kt})/\lambda})^\lambda}, \quad (4)$$

- $x_t = (x_{1t}, \dots, x_{J_t})$, $\xi_t = (\xi_{1t}, \dots, \xi_{J_t})$.
- J_t is the set of all airline products in market t .
- θ_d is the set of all demand parameters.
- γ_r : **the percentage of type r consumers** in the population.

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Supply Model: Cost Specification

Marginal cost is assumed to be,

$$mc_{jt} = h_{jt}\delta + \omega_{jt} \quad (5)$$

- h_{jt} : cost characteristics (including **Frequency**).
- δ : cost parameters
- ω_{jt} : unobserved cost shock.

Following Fan (2013), the **slope of the fixed cost** with respect to the k^{th} endogenous characteristic, \bar{x}_{kjt} is,

$$\frac{\partial F(\cdot)}{\partial \bar{x}_{kjt}} = \tau_{k0} + \tau_{k1}\bar{x}_{kjt} + \zeta_{kjt} \quad (6)$$

- ζ_{kjt} : unobserved cost shock ($k = O, F, M, D$)

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Supply Model: Necessary Optimality Conditions

- 1 In the **first stage**, the necessary optimality condition for the k^{th} characteristic is driven by $\partial \Pi_f^I / \partial \bar{x}_{kjt}$

$$\frac{\partial \Pi_f^I}{\partial \bar{x}_{kjt}} = \frac{\partial \Pi_f^{II}}{\partial \bar{x}_{kjt}} - \frac{\partial F(\cdot)}{\partial \bar{x}_{kjt}} + \sum_{h' \in J_t} \frac{\partial \Pi_f^{II}}{\partial p_{h't}} \frac{\partial p_{h't}}{\partial \bar{x}_{kjt}} = 0 \quad (7)$$

for $k = O, F, M, D$, and $\forall j \in J_{ft}$.

- 1 In the **second stage**, the necessary optimality condition for the price is driven by $\partial \Pi_f^{II} / \partial p_{jt}$

$$s_{jt}(p_t, \bar{x}_t, \xi_t; \theta) + \sum_{h \in J_{ft}} (p_{ht} - mc_{ht}) \cdot \frac{\partial s_{ht}(p_t, \bar{x}_t, \xi_t; \theta)}{\partial p_{jt}} = 0 \quad (8)$$

for $\forall j \in J_{ft}$.

Summary Statistics in Estimation Sample

Variable	Description	Mean	Std.Dev.	Min	Max
Endogenous variables					
Ontime15	Percentage of flights that arrive less than 15 minutes late	0.75	0.08	0	1
Frequency	Number of average daily departures	4.32	2.42	0.01	26.18
Mishandled baggage	Number of mishandled baggage (per 1,000 passengers)	6.44	1.73	2.61	13.52
Denied boarding	Number of involuntary denied boardings (per 10,000 passengers)	1.19	0.72	0.01	4.48
Price	Ticket price (\$100)	3.74	1.13	0.55	13.17
Controls					
Layovers	Number of connections (per round trip)	1.67	0.75	0	2
Distance	Round trip distance (1,000 miles)	3.18	1.43	0.22	6.94
Hub	Number of hub airports on itinerary given carrier	0.72	0.60	0	3
HubMC	1 if there is a hub airport on itinerary given carrier	0.64	0.48	0	1
Slot-control	Number of slot-controlled airports on itinerary	0.28	0.59	0	3
Tour	1 if a destination airport is in either California, Florida, or Nevada	0.32	0.47	0	1
Carrier dummies	CO, DL, NW, UA, US, FL, WN, OT				

Number of observations (products): 87,906. Number of markets: 9,117.

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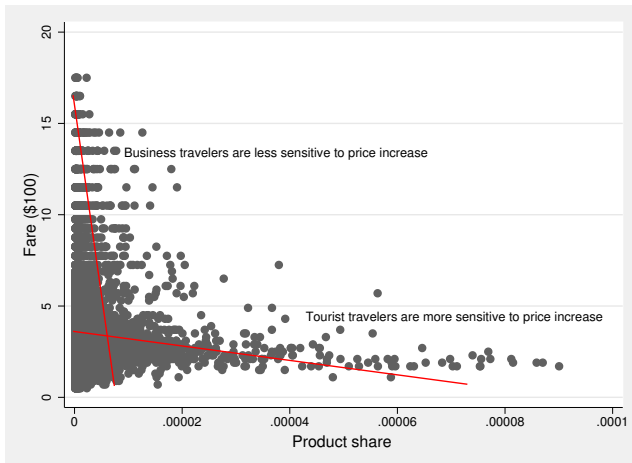
Estimation: A Two-stage Nonlinear GMM

- 1 Solve for all structural error terms: $\xi(\theta_d)$, $\omega(\theta_d, \delta)$, $\zeta_k(\theta_d, \delta, \tau_k)$.
- 2 Set the moment conditions: $g(\Theta)$
 - $E(w'_d \cdot \xi(\theta_d)) = 0$ for demand error.
 - $E(w'_c \cdot \omega(\theta_d, \delta)) = 0$ for marginal cost error.
 - $E(w'_k \cdot \zeta_k(\theta_d, \delta, \tau_k)) = 0$, $k = 1, 2, 3, 4$ for fixed cost error.
- 3 Derive the GMM objective function. $Q = g(\Theta)' V g(\Theta)$
 - 1st stage estimation: $\hat{\eta} = \begin{bmatrix} \hat{\xi} \\ \hat{\omega} \\ \hat{\zeta}_k \end{bmatrix}$, given $V = (W'W)^{-1}$.
 - 2nd stage estimation: $\hat{\Theta} = [\hat{\theta}_d \quad \hat{\delta} \quad \hat{\tau}_k]$, given $V = (W' \hat{\eta} \hat{\eta}' W)^{-1}$.

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Price and Share Plots

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



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

Elasticity and Semi-elasticity of Characteristics

The table displays the percentage change in market demand when the relevant product characteristics is changed as specified.

Changes in Characteristics	Change in Demand (%)			Products
	Type 1	Type 2	Both	
Price elasticity	-0.6	-5.8	-3.7	All
Ontime15 (10% increase)	13.1	17.2	15.6	//
Layovers (direct → connecting)	-94.2	-92.1	-93.0	Direct flights
Frequency (adding one daily departure)			8.7	All
Mishandled baggages (10% increase)			-3.4	//
Denied boardings (10% increase)			-3.1	//

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A Study of the U.S. Airline Industry

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Abstract

Standard merger simulations focus solely on price changes while constraining the set of product characteristics to be identical pre- and post-merger. Recent papers have begun to address this issue (see, e.g. Fan, August 2013 AER). To overcome the limitations of traditional simulations, 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 (i) the merged firm tends to increase product differentiation post-merger; (ii) the higher product differentiation reduces the firm's incentive to raise prices; (iii) 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.

JEL classification: C51, D43, L11, L93

Keywords: Endogenous product characteristics, Product differentiation, Merger simulation, Consumer heterogeneity, Airline industry.

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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 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

¹Throughout 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, Levinsohn and Pakes (1995).

²Merger 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.

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

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 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, Levinsohn and Pakes, 1995) and particularly adopts random coefficient logit model with finite consumer types (Berry, Carnall and Spiller, 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,

⁴Since 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>.

on-time performance, mishandled baggage rate, and denied boarding rate - at the first stage, 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 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 anal-

⁵For 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.

⁶A 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.

yses. 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, Joskow and Johnson (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 (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, Mazzeo and Seim (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

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

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 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, Seim and Varela, 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.

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.

2.1 Demand

The demand model follows discrete choice framework with heterogeneous consumer preferences (Berry, Levinsohn and Pakes, 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 type r from choosing product j in market t is assumed to be

$$\begin{aligned} u_{ijt} &= p_{jt}\alpha_r + y_{jt}\Psi_r + z_{jt}\Phi + \xi_{jt} + v_{it}(\lambda) + \lambda\varepsilon_{ijt} \\ &= x_{jt}\beta_r + \xi_{jt} + v_{it}(\lambda) + \lambda\varepsilon_{ijt}, \end{aligned} \quad (1)$$

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

⁸A 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.

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

¹⁰The 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.

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 involuntary 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 - *Ontime15*, *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

¹¹In 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.

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

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

(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 night stay-over, advance purchase, non-refundability, minimum or maximum stay restriction, and in-flight meal service quality.¹⁴ v_{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 $v_{it} = 0$), 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 $v_{it}(\lambda) + \lambda\varepsilon_{ijt}$ 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

$$u_{i0t} = \xi_{0t} + \varepsilon_{i0t}. \quad (2)$$

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 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).

¹⁴This 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, Sengupta and Wiggins (2012).

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 j th product is given by

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

where $x_t = (x_{1t}, \dots, x_{J_t})$, $\xi_t = (\xi_{1t}, \dots, \xi_{J_t})$, and J_t is the set of all airline products in market t . θ_d is the set of all demand parameters $(\alpha_r, \psi_r, \varphi, \lambda, \gamma_r)$. 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.

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, $\bar{x}_j = (\bar{x}_j^O, \bar{x}_j^F, \bar{x}_j^M, \bar{x}_j^D)$ to maximize the profit function¹⁶

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

where $\bar{x} = (\bar{x}_1, \dots, \bar{x}_J)$, $\bar{x}_f = (\bar{x}_{1f}, \dots, \bar{x}_{J_f})$, and $\zeta_f = (\zeta_{1f}, \dots, \zeta_{J_f})$. 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.

¹⁵This 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.

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

¹⁷Following 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.

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

$$mc_j = h_j\delta + \omega_j \quad (5)$$

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

¹⁸Even 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.

¹⁹I 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 $Distance_{short} = Distance * I_{short}$.

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

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

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

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,

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

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.

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 ($\zeta_j^O, \zeta_j^F, \zeta_j^M, \zeta_j^D$) 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 ($p_j, j = 1, \dots, J_f$) to generate the first-order condition $\partial \Pi_f^II / \partial p_j$,

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

Stacking all J_f products together yields

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

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

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

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

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

The right hand side can 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 ($\bar{x}_j^k, j = 1, \dots, J_f, k = O, F, M, D$) to yield the first-order condition $\partial \Pi_f^I / \partial \bar{x}_j^k$,

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

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^I by affecting prices of all products in a market.²¹ Main computational difficulty arises from $\frac{\partial p_{h'}}{\partial \bar{x}_j^F}$ 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 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).

3 Data

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*).

²¹For *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*.

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

²²Technically, the derivative requires us to compute $\frac{\partial(\Omega_{f,p_f}^{-1})}{\partial \bar{x}_j^F}$ and $\frac{\partial(\Omega_{j,p_j}^{-1})}{\partial \bar{x}_j^F}$.

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

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

²⁵The 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.

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 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.

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

²⁶With 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 cancellations.

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

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 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.

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 ($\zeta_t^O, \zeta_t^F, \zeta_t^M, \zeta_t^D$). ξ_t is derived by inverting the market share function: $\xi_t = s^{-1}(x_t, s_t, \theta_d)$. Given demand parameters $\theta_d = [\alpha_r, \psi_r, \varphi, \lambda, \gamma_r]$ and data x_t , I solve for ξ_{jt} that equates the predicted market share to observed market share by using a contraction mapping

²⁸An 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.

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

(Berry, Levinsohn and Pakes, 1995; Berry and Jia, 2010),

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

where H denotes the H^{th} iteration, 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 ,

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

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,

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

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_{jt}^k 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

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

instruments

$$\begin{aligned}
& \forall j, t : \\
& E[W_{jt}^{d'} \xi_{jt}(\theta_d)] = 0, \\
& E[W_{jt}^{c'} \omega_{jt}(\theta_d, \delta)] = 0, \\
& E[W_{jt}^{k'} \zeta_{jt}^k(\theta_d, \delta, \tau^k)] = 0, \quad k = O, F, M, D.
\end{aligned} \tag{17}$$

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 $\widehat{\eta} = [\widehat{\xi} \quad \widehat{\omega} \quad \widehat{\zeta}^k]$ to obtain the optimal weighting matrix $V = (W'\widehat{\eta}\widehat{\eta}'W)^{-1}$ for second stage. The objective function is minimized once again to produce the final parameter estimates $\widehat{\Theta}^2$.

4.1 Instruments

Carriers observe the product quality ξ_{jt} and the cost shocks ($\omega_{jt}, \zeta_{jt}^k, k = O, F, M, D$) 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, Sengupta and Wiggins, 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, Owens and Plumly (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 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

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

³²The 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.

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.

4.2 Estimation Results

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

³³In 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, Carnall and Spiller (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.

³⁴More 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 $t - 1, \dots, t - N$. One good reference is Suzuki (2000) who developed an aggregate-level Markovian type model.

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

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 between 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,

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

³⁶Many 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.

³⁷Borenstein (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.

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

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 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

³⁸The estimates are close to those in Berry, Carnall and Spiller (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: $\sum_{t=1}^T M_t \cdot \hat{\gamma}_1 \cdot \frac{D_{it}^\lambda}{1+D_{it}^\lambda} / \sum_{t=1}^T \sum_{r=1}^2 M_t \cdot \hat{\gamma}_r \cdot \frac{D_{it}^\lambda}{1+D_{it}^\lambda}$, where $D_{it} = \sum_{k \in J_t} e^{(x_{it} \hat{\beta}_r + \xi_{it}) / \hat{\lambda}}$.

³⁹One interesting point in figure 2 is that all carriers experienced substantial increases in CASM from the fourth quarter of

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, carriers 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.

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

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.

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.

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 . P^{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 ΔP from ΔX (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 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 ΔP from ΔX . Consequently, $P^{FL} - P^H$ identifies CPE^{FL} .⁴² Notice that magnitudes of two cross-price effects will be

⁴⁰At 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.

⁴¹The 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.

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

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

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

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

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

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 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,

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

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

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

⁴⁴A 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.

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.

5.2 Simulation Results

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 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

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

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

⁴⁷If 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.

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 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. 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

⁴⁸I 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.

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

⁵⁰We can check this based on table 14.

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.

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-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: ΔP 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: $P^P > P^{FL}$.

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

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.

⁵²Section 5.3 will address the profit analysis more thoroughly.

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.

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

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

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, Seim and Varela, 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 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.

⁵³As 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.

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

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

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 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.

⁵⁶The 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.

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 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.

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.

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: $MF_t = \sum_{j=1}^{J_t} Frequency_{jt}$, where j is a product and t is a market. Then, average market frequency (AMF) is mean value of market frequency across markets: $AMF = \frac{1}{T} \sum_{t=1}^T MF_t$.

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 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.

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.

This paper concludes with two notes for future research. First, 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. Second, this paper addresses the consumer heterogeneity with two types of passengers and estimates 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.

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Table 1. Data Sources

Database	Variables	Level of observation	Sample periods
O&D Survey (DB1B)	Market/Product, Fare, Controls	ticket	'07. 2Q. ~ '08. 1Q.
On-Time Performance	Ontime15	carrier-route	'07. April ~ '08. March
T-100 Domestic Segment	Frequency	carrier-route	'07. April ~ '08. March
Air Travel Consumer Report	Mishandled baggage, Denied boarding	carrier	'07. April ~ '08. March
Air Carrier Financial Report	Employee statistics	carrier	'07
Weather Underground	Wind, Rain, Snow	airport	'07. April ~ '08. March
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 airport	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)
Fare ₁	-0.098** (0.004)	HubMC	-0.184** (0.017)
Fare ₂	-0.999** (0.019)	Layovers _{short}	0.175** (0.010)
Ontime15 ₁	1.641** (0.164)	Layovers _{long}	0.300** (0.019)
Ontime15 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)
		UA	-0.010 (0.008)
Controls		CO	-0.015 (0.010)
Layovers ₁	-1.255** (0.013)	FL	-0.559** (0.019)
Layovers ₂	-1.085** (0.009)	WN	-0.223** (0.018)
Distance	0.105** (0.005)	OT	-0.190** (0.016)
HubDM	0.056** (0.010)	Constant	1.721** (0.029)
Slot-control	-0.071** (0.006)		
Tour	0.238** (0.006)		
US	0.143** (0.014)	Slope of Fixed Cost (\$100)	
DL	0.007 (0.027)	Ontime15 _{constant}	2416.8** (0.742)
NW	-0.511** (0.019)	Ontime15	-2970.2** (0.518)
UA	0.124** (0.017)	Frequency _{constant}	6.605** (0.064)
CO	-0.119** (0.024)	Frequency	0.224** (0.005)
FL	-0.875** (0.020)	Mishandled baggage _{constant}	-8.126** (0.059)
WN	-0.329** (0.021)	Mishandled baggage	0.491** (0.005)
OT	-0.023 (0.017)	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*, *Ontime15*, 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 1,000 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		
Overtime15	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		
	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
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		
Overtime15	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		
	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
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		
Overtime15	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		
	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
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		
Overtime15	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	-	-	-		
	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
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		
Overtime15	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	-	-	-		
	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
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		
Overtime15	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	-	-	-		
	<i>Pre</i>	$G^P - Pre$	$G^{FL} - Pre$	$G^H - Pre$	$G^{FL} - G^H$
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)		Full model (G^{FL})		Quality change of DL/NW	Number of products (markets)
	Change in CS (\$100K)	% Change in CS (%)	Change in CS (\$100K)	% Change in CS (%)		
<i>All markets</i>						
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		
<i>By market competitiveness</i>						
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		
<i>By quality change</i>						
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)

Markets	Price model (G^P)			Full model (G^{FL})		
	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

	Quality-increase markets	Quality-decrease 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
<i>Delta/Northwest only</i>		
Passenger share	0.29	0.37
Percentage of flights originating from hub	0.08	0.09

Notes: Each number indicates average values. 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 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
<i>Average market frequency</i>				
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
<i>Measures of market similarity</i>				
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

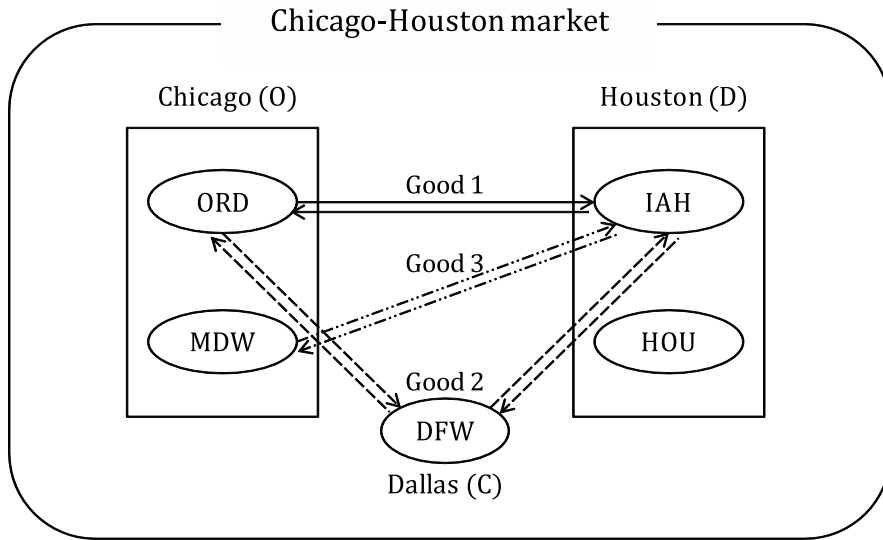
Notes: Market frequency (MF) is defined as sum of frequency of each product provided by merging/merged carriers in a market: $MF_t = \sum_{j=1}^{J_t} Frequency_{jt}$, where j is a product and t is a market. Then, average market frequency (AMF) is mean value of market frequency across markets: $AMF =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

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)

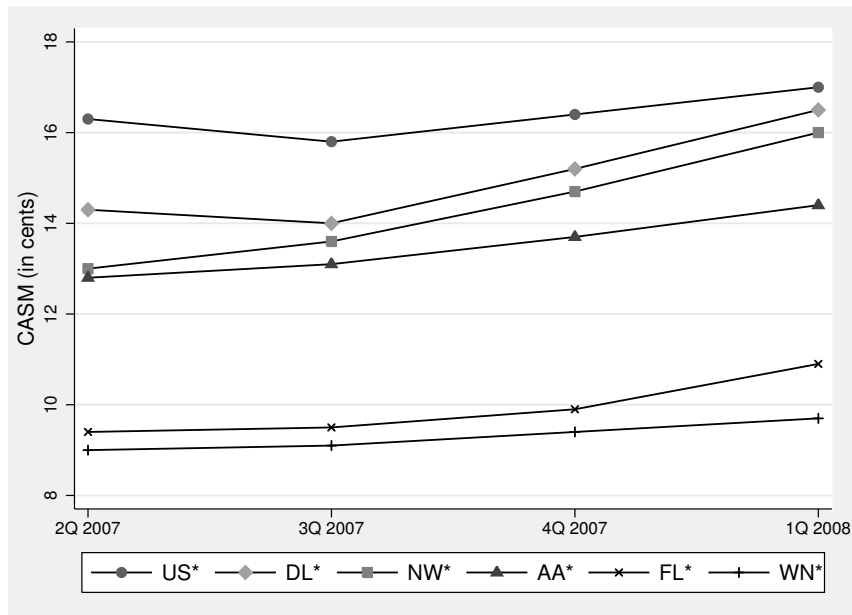
Notes: This table is based on the simulation sample and results in the overlapped markets. I computed a percentage of the business passengers who actually bought large goods in the sample as: $\frac{\sum_{t=1}^T M_t \cdot \hat{\gamma}_1 \cdot \frac{L_{1t}}{D_{1t}} \frac{D_{1t}^k}{1+D_{1t}^k}}{\sum_{t=1}^T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

Figure 1. An Illustration of Market and Product



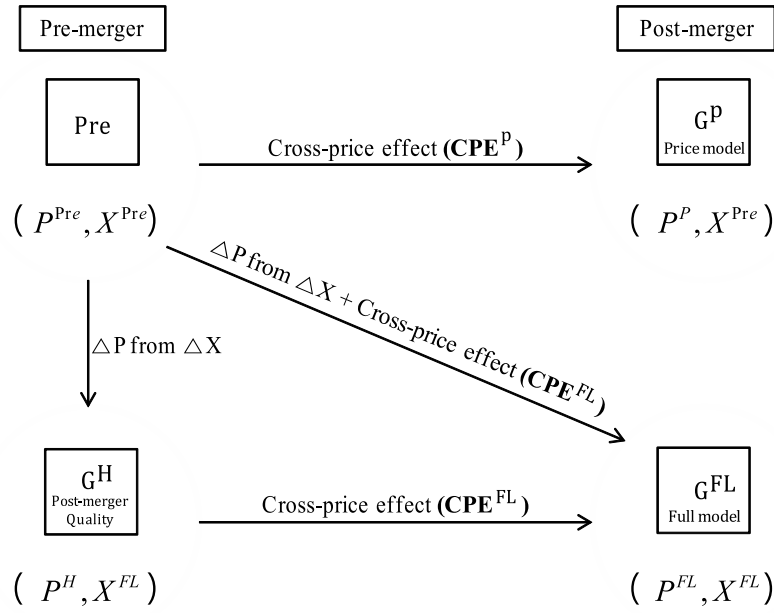
Notes: O, D, C indicate origin, destination, and connecting city, respectively. Given carrier, roundtrip ORD-IAH, ORD-DFW-IAH, and MDW-IAH are considered as different products.

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.

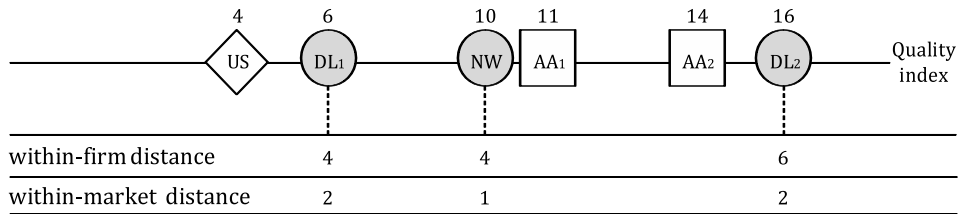
Figure 3. Simulation Design for Decomposing Sources of Price Change



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:

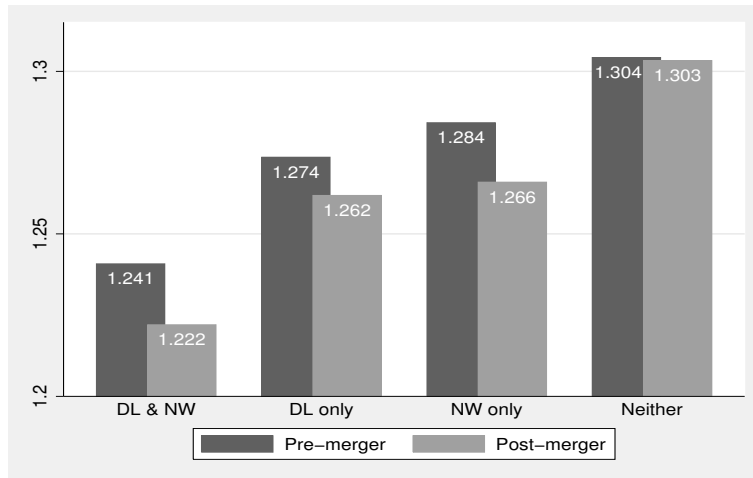
Within-firm distance and Within-market distance



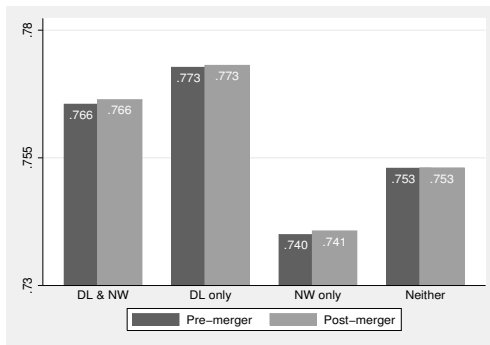
Notes: Within-firm distance of a product is the closest quality-distance from itself to other goods produced by the same firm. Within-market distance of a product the closest quality-distance from itself to other goods produced by competitors.

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

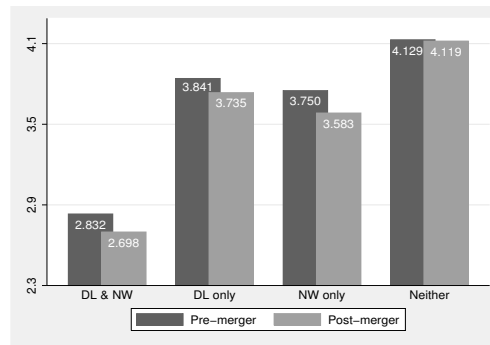
By market power



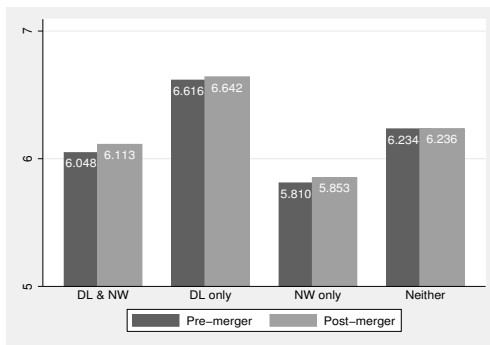
(a) Quality index



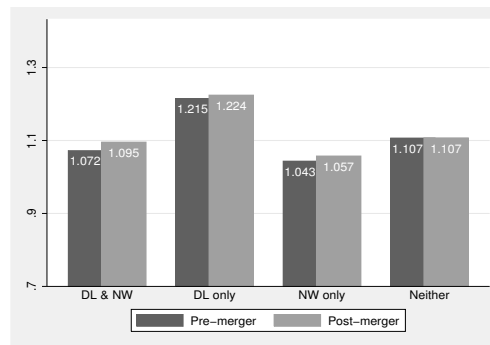
(b) Ontime15



(c) Frequency



(d) Mishandled baggage rate

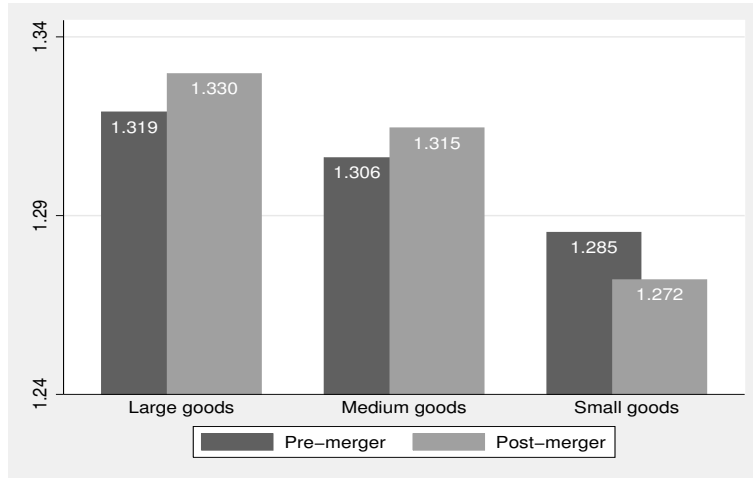


(e) Denied boarding rate

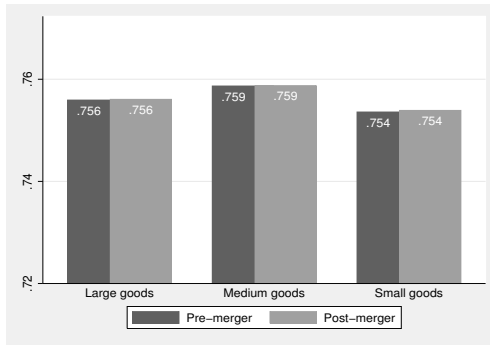
	DL & NW	DL only	NW Only	Neither
Number of markets	29	219	215	666
Number of products	122	1,011	816	3,410

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

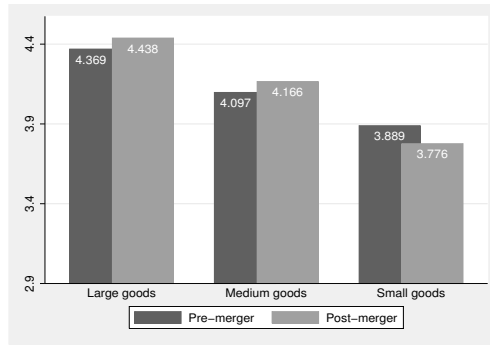
By product group



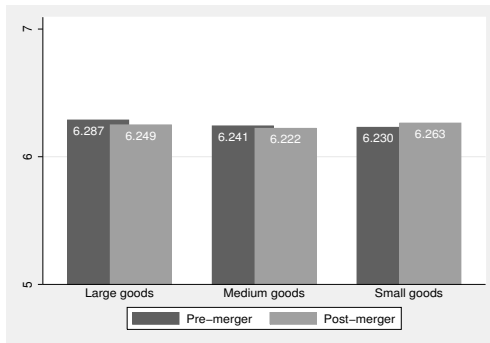
(a) Quality index



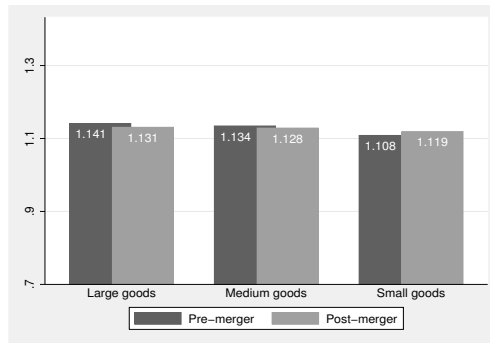
(b) Ontime15



(c) Frequency



(d) Mishandled baggage rate

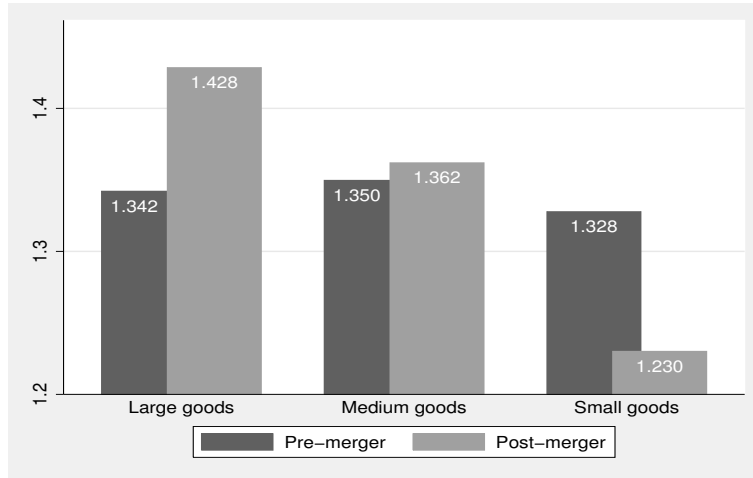


(e) Denied boarding rate

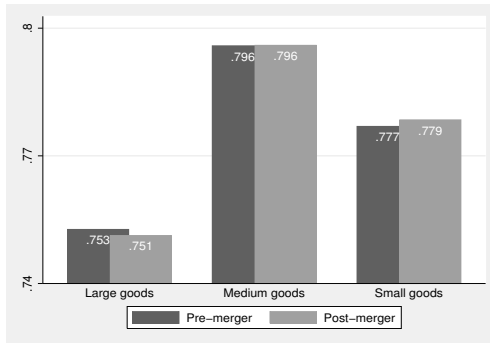
	Large goods	Medium goods	Small goods
Number of markets	680	676	865
Number of products	692	1,041	3,598

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

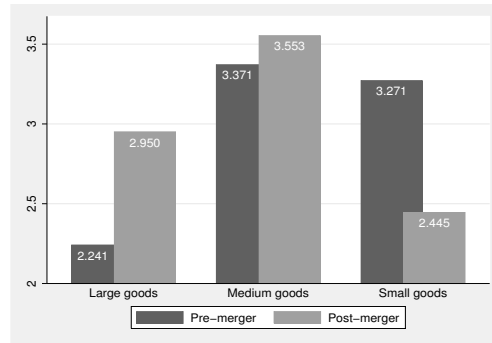
By product group



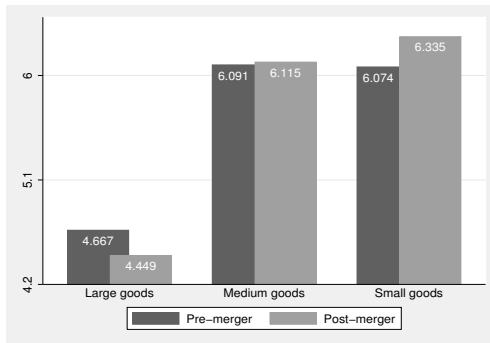
(a) Changes in Quality



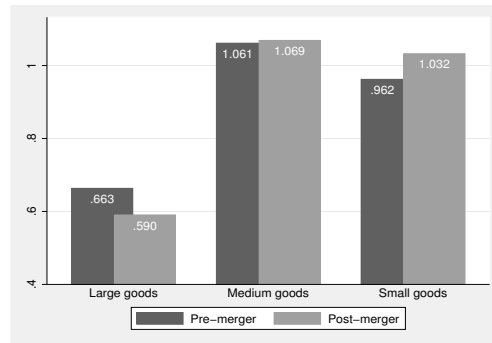
(b) Ontime15



(c) Frequency



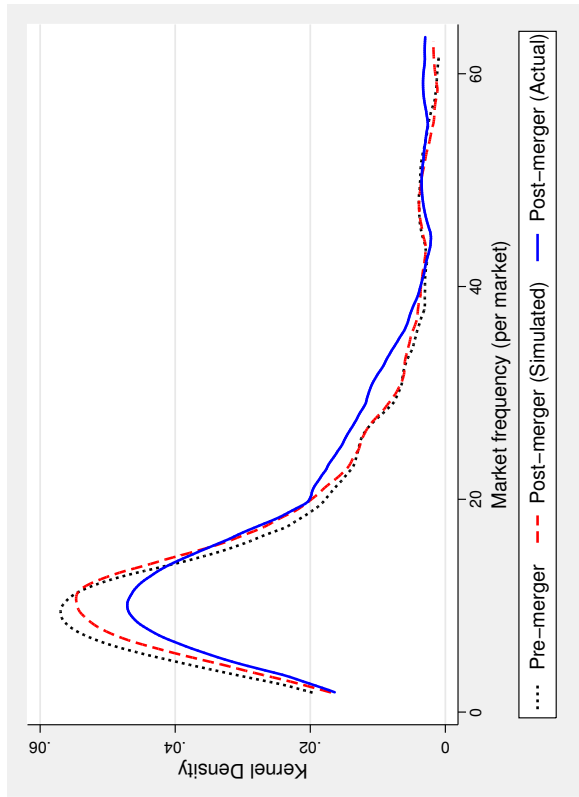
(d) Mishandled baggage rate



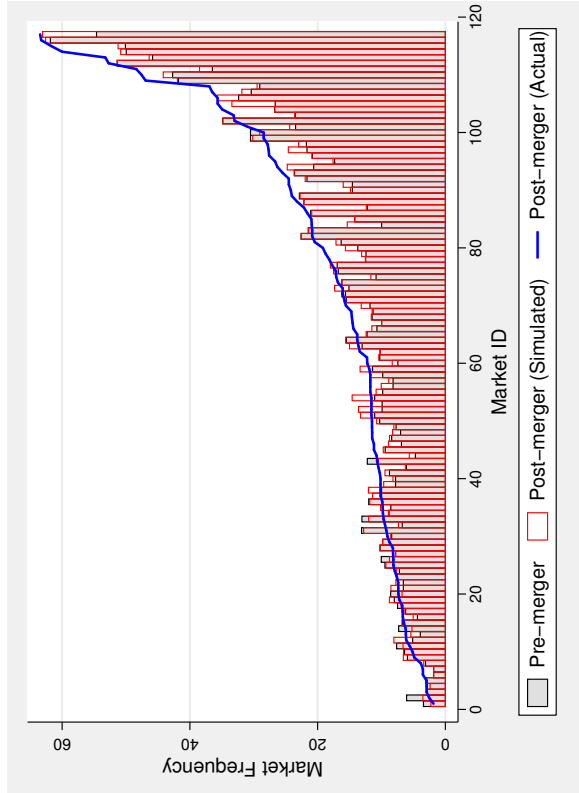
(e) Denied boarding rate

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

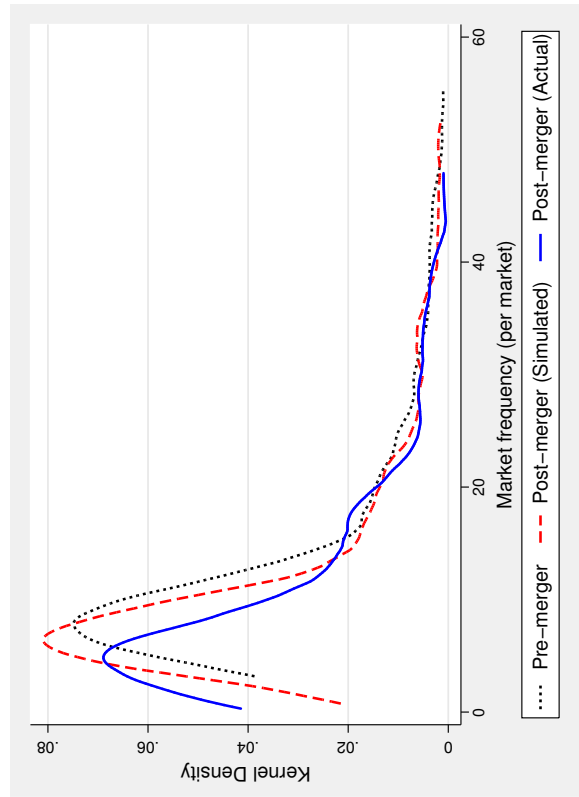
Figure 8. Distribution of Market Frequency in QI and QD Markets:
Pre-merger vs. Post-merger (Simulated) vs. Post-merger (Actual)



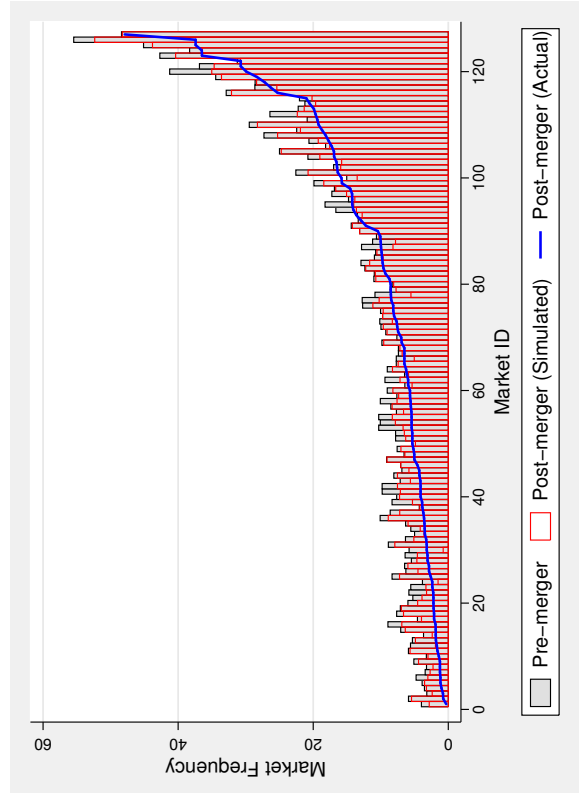
(a) Kernel density of market frequency in QI markets



(b) Market frequency of QI markets

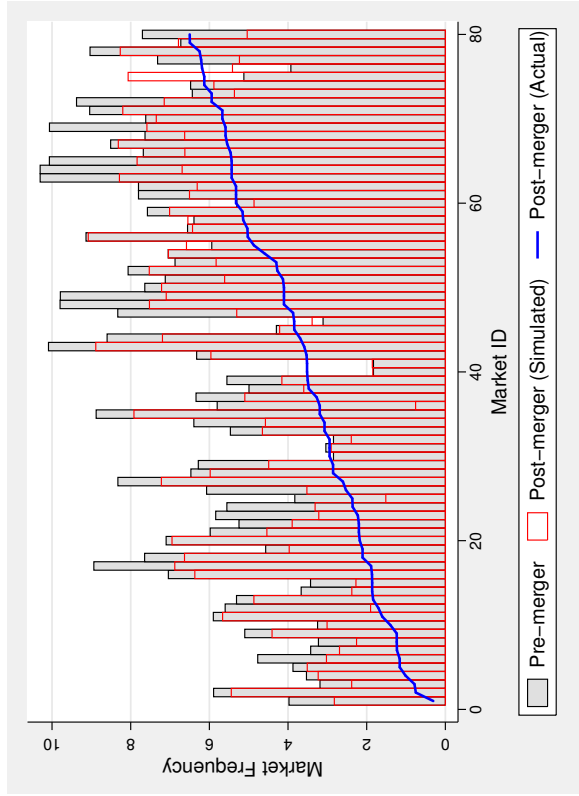
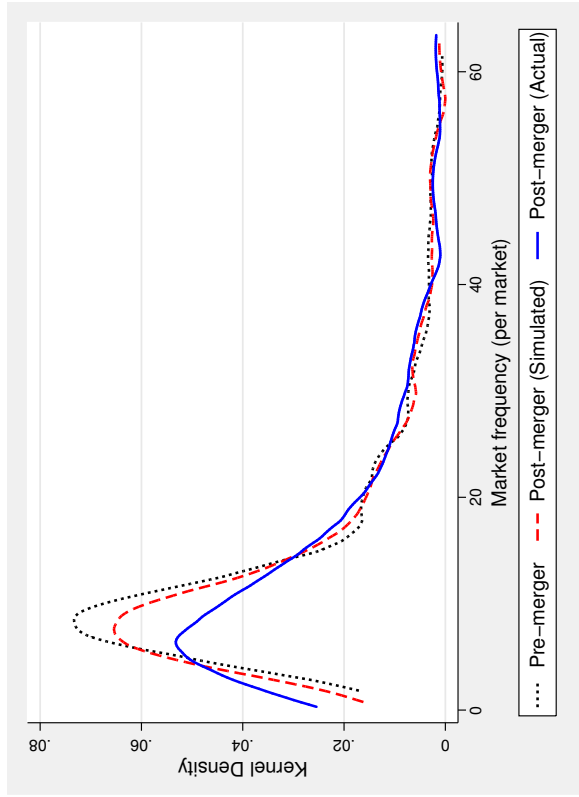


(c) Kernel density of market frequency in QD markets



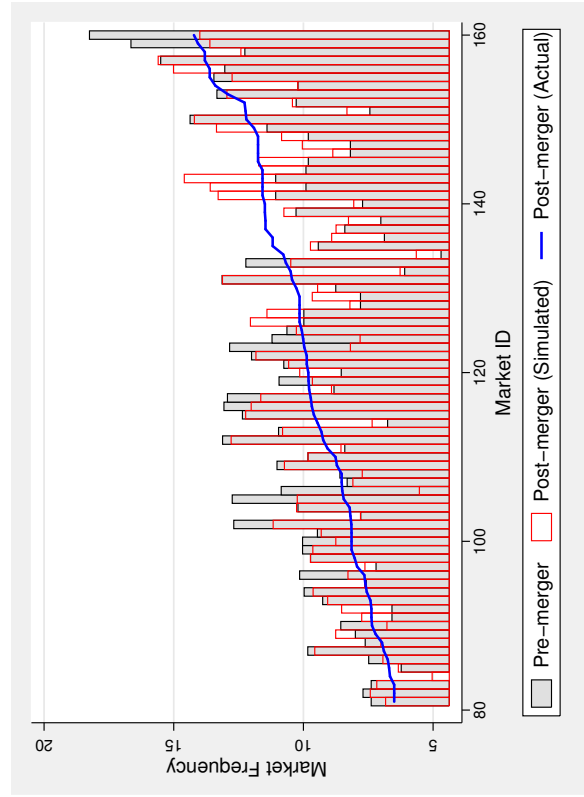
(d) Market frequency of QD markets

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

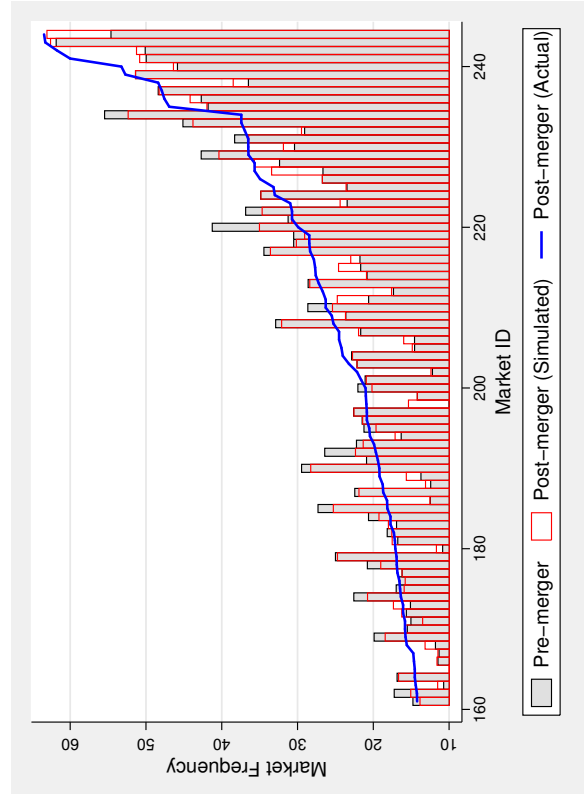


(a) Kernel density of market frequency in all markets

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



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



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