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The effects of major U.S. domestic airline code sharing and profit-sharing rule

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Abstract

This paper presents a structural model of code sharing among major U.S. domestic airlines and estimates a profit-sharing rule. The profit-sharing rule between partner firms in code sharing is estimated at 0.92, which suggests that the operating carrier acquires around 92% of profits from a round-trip, and the marketing carrier retains 8% as a commission fee. Meanwhile, the economies of code sharing reduces marginal cost, and firms are able to price at higher markups. This implies that demand increases and consumers have larger surplus if code sharing creates new products.

1 | INTRODUCTION

My primary goal is to measure the extent to which code sharing agreements between major U.S. domestic airlines affected consumer surplus, firms' costs, and social welfare. Code sharing is an agreement between two (or three, in one case) carriers, in which one carrier (the operating carrier) allows another carrier (its code-share partner, the marketing carrier) to market and sell seats on some of the operating carrier's flights under the marketing carrier's reservation code.[1] When a proposal of code sharing between two major airlines is initiated, a debate often ensues between the policy-makers (U.S. Department of Justice) and carriers. The U.S. Department of Justice hesitates to approve such proposals due to concerns that these agreements may reduce competition and hence induce a loss of consumer welfare, given the fact that potential code sharing partners already have high market shares. However, carriers have claimed that passengers benefit from code sharing because it provides more product choices and destinations. This paper lays out the first step and explicitly models these code sharing activities and quantifies its effects on consumers, carriers, and social welfare.

The model considers a discrete choice setting for consumer demand and an oligopolistic airline supply side. To incorporate code sharing into the model, I offer an approach that involves specifying the supply side as multi-product firms maximizing profits by choosing a set of prices when they share profits for code-shared products according to a certain rule, which is parameterized by λ. Moreover, my model also takes into account how the economies of code sharing affect firms' marginal costs, and quantifies consumers' direct (non-pecuniary) preference for code-shared flights.

The estimation results suggest that the operating carrier extracts around 92% of profits on average for a code-shared product, which means that the ticketing carrier retains 8% as a commission fee. The identification of this profit-sharing rule comes from the variation between code sharing tickets and non-code sharing tickets. In the same market, where I observe both code sharing and non-code sharing tickets, the data allow my model to estimate λ.

The results show that code-shared products are priced cheaper by the marketing firms compared to prices of products owned by the marketing firms. Also, code sharing has a strong effect on cost saving so that partner firms can price code-shared products at higher markups, although consumers have slightly higher elasticities for these products. The sources of cost reduction may

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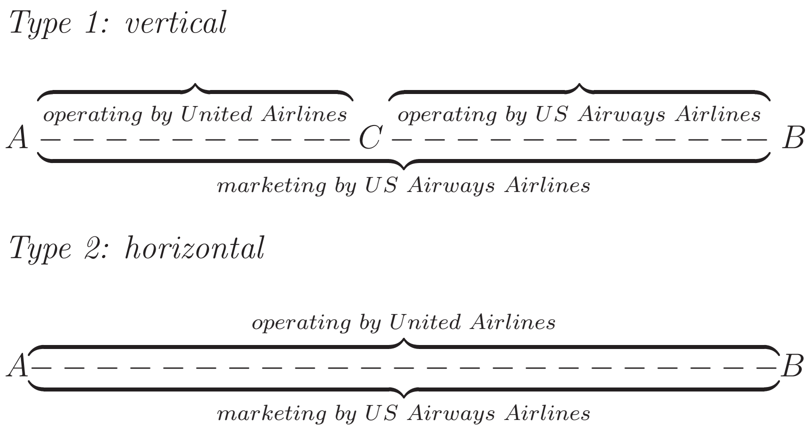

FIGURE 1 The two types of code sharing flights

come from the increase in passengers and the economies of code sharing, which allows airlines to specialize along different routes. Brand loyalty and an improvement in marketing co-operation after code sharing are factors that have a positive effect on filling the capacities of airplanes.

The welfare consequence of code sharing is investigated in two selected markets. I separate the counterfactual analysis into two cases. In the first case, code sharing does not create new products. The counterfactual analysis simulates a new set of prices without code sharing, keeping the number of products unchanged. In both markets, I find a small amount of reduction in consumer surplus due to the negative direct utility effect. The second case is when code sharing induces the entry of new products. In this case, consumer surplus and firms' profits are calculated taking into account the entry of the new (code-shared) products. The results show that code sharing generates large welfare gain from the new products; in particular, both consumer surplus and firms' profits increase significantly. In the market with a bigger market size, the total welfare gain is larger. If a particular code sharing agreement follows in between these two extreme scenarios, one can expect consumer may benefit. This result shows some evidence to justify the current approvals of code sharing agreement by the Department of Justice.

The remainder of the paper is organized as follows. Section 2 explains code sharing agreements in detail; Section 3 reviews the related literature; Section 4 outlines the model; Section 5 describes the data; Section 6 proposes the empirical strategy; Section 7 reports and discusses the estimation results and the counterfactual analysis; Section 8 presents the conclusions.

2 | CODE SHARING

In practice, there are two types of code sharing: vertical and horizontal. Figure 1 illustrates one example of these two types.[2] Vertical code sharing happens when each partner flies part of the flight route on which they code-share. Horizontal code sharing only refers to the situation when the operating carrier operates the entire route while its partner (the marketing carrier) sells the tickets. It is important to note that the same flight could be listed twice with different codes in the computer reservation system (CRS). For example, UA 54 is the same flight as US 6001, which is from Kona, Hawaii to San Francisco, operated by United Airlines but also code-shared with US Airways Airlines. In this case, there are two ticketing carriers for selling the same seats on a flight.

For vertical code sharing, the code-shared flight is a product that each partner operates partially. It may or may not exist before code sharing and could be sold by one carrier or both carriers. However, vertical code sharing does vertically integrate two carriers in the way that only one carrier markets the tickets as a whole product. For horizontal code sharing, it appears that one airline sells its partner's tickets; however, the marketing and operating roles differ across markets.

3 | LITERATURE REVIEW

Over the past two decades, increasing attention has been paid to code sharing agreements. The related literature begins with theoretical papers on international code sharing alliances. These models are Park (1997) and Brueckner (2001), both of which analyze changes in firms' profits, outputs, and airfares pre- and post-alliance. Park (1997) introduces a model of two types of code sharing alliances: complementary and parallel alliances. In the current paper, the complementary alliance is vertical code sharing and the parallel alliance is horizontal code sharing. Brueckner (2001) develops a new theoretical framework and shows that fares are reduced in the interline city-pair markets after code sharing, although the interhub-market passengers are harmed. A few other theoretical papers on the similar topic include Park, Zhang, and Zhang (2001), Hassin and Shy (2004), Bilotkach (2005), and Zhang and Zhang (2006).

The empirical literature on code sharing also starts with analyses in international markets. Most papers find competitive price effect and increase in passenger volume. Examples of these studies are Brueckner and Whalen (2000), Park and Zhang (2000), Brueckner (2003), and Whalen (2007). They apply reduced-form analysis, hence there is no formal results obtained in welfare analysis.

Although international code sharing alliances have primarily been studied, code sharing among U.S. domestic airlines has received attention recently. A number of papers use reduced-form empirical models. Competitive effects in price are found in a series of papers: Bamberger, Carlton, and Neumann (2004), Ito and Lee (2007), and Gayle (2008). Meanwhile, Goetz and Shapiro (2012) find the entry deterrence effect of code sharing. Shen (2015) tests Brueckner (2001) using domestic data and finds consistent results.

Structural models of code sharing between U.S. domestic carriers have been developed. Armantier and Richard (2008) use a discrete choice model of demand to measure the consumer welfare consequences of code sharing between Continental and Northwest. In their analysis, there is no supply side. My study explicitly models the effect of code sharing on firms' costs. Gayle (2007) models both consumer demand and firms' supply, and develops a method to quantify the competitive effects of a proposed alliance: Delta/Continental/Northwest. My analysis differs in two ways: (1) I analyze code sharing using data in all major U.S. domestic alliances; (2) I use data post-alliance. Another paper adopts a structural model is Gayle (2013). It uses a vertical relation approach to test the existence of double marginalization between code sharing partners.

There exists a few models, which focus only on the effects of code sharing on the cost side. For example, Chua, Kew, and Yong (2005) and Goh and Yong (2006) use trans-log cost function to assess the effects. Both papers find that code sharing alliances lower costs for major airline alliances.

This paper intends to lay out the first step in modeling code sharing agreements explicitly. I estimate profit-sharing rule between partners. I develop a structural model of both consumer demand and firms' optimal pricing equations in the presence of code sharing. This model allows me to analyze the effect of code sharing on firms' costs, markups and profits, and consumer welfare. I apply the model to data of overall U.S. domestic code sharing partners in quarter III of 2004.

4 | MODEL

I consider a model with a standard discrete choice setting for consumers' demand and an oligopolistic airline supply side. Airlines offer a set of differentiated products in each market, and each consumer either buys one product or takes the outside option of not purchasing. In each market, prices and product shares are determined in a Bertrand–Nash equilibrium, assuming that code sharing is one characteristic which affects demand and costs. Assumptions are explained below in detail.

4.1 | Demand

Following Brueckner, Lee, and Singer (2014), a market is defined as a *directional* origin/destination city pair, with grouping airports in many large metropolitan areas. This definition takes into account that the characteristics of the origin city may have different effects on the demand than those of the destination city. For example, demand may differ from Cincinnati–Los Angeles to Los Angeles–Cincinnati. The market size is the geometric mean of MSA population of the end-point cities.

A product is defined as a unique combination of origin/connecting/destination cities, ticketing/operating carriers. For example, a combination (Boston-Seattle, United-US Airways) is a product, where the origin city is Boston, the destination city is Seattle, the marketing carrier is United Airlines, and the operating carrier is US Airways Airlines. Products are indexed by j. A product is a code-shared product when there exists at least one segment of the trip in which the operating carrier is different from the ticketing carrier.

I attribute price dispersion mostly to unobserved factors, such as the time of purchase, weekend flights and the frequent flyer discounts. Products are also differentiated by unobserved quality (to researchers), such as luggage services, the quality of food on the trip, etc. Therefore, it is important to include an unobservable product characteristic, which is likely to be correlated with price. The product price is an average price when grouping the tickets.

The consumers know whether the itinerary is code-shared or not. In practice, if it is a code-shared flight, that is, the operating carrier is different from the ticketing carrier, the marketing airline would specify the operating carrier on the itinerary.

The demand model is a discrete choice model in spirit of Berry (1994) and Berry and Jia (2010). The utility of consumer i from product j in market m is given by

$$U_{ijm} = x_{jm}\beta + \gamma d_{jm} - \alpha p_{jm} + \xi_{jm} + v_{im}(\sigma) + (1-\sigma)\varepsilon_{ijm},$$

where

x_{jm} is a vector of product characteristics,
β is a vector of "tastes for characteristics,"
d_{jm} is a dummy of code sharing,
γ is the marginal utility (disutility if γ is negative) of code sharing,
α is the marginal disutility of a price increase,
p_{jm} is the product price,
ξ_{jm} is econometrician's unobservable product characteristic (e.g., product quality),
v_{im} is a nested logit disturbance that follows a distribution such that $v_{im}(\sigma) + (1-\sigma)\varepsilon_{ijm}$ is an extreme value random variable conditional on that ε_{ijm} is an i.i.d. extreme random variable. v_{im} is constant across all products in a market, and it differentiates the outside option (not flying),
σ is the nested logit parameter.

The utility from the outside good is given by

$$U_{i0m} = v_{i0m}(\sigma) + (1-\sigma)\varepsilon_{i0m}$$

The market share of product j in market m is given by

$$s_{jm}(x_m, d_m, p_m, \xi_m, \theta_d) = \frac{e^{(x_{jm}\beta + \gamma d_{jm} - \alpha p_{jm} + \xi_{jm})/(1-\sigma)}}{D_{gm}^{\sigma}\left(1 + D_{gm}^{(1-\sigma)}\right)},$$

where

$$D_{gm} = \sum_{j \in J_{gm}} e^{(x_{jm}\beta + \gamma d_{jm} - \alpha p_{jm} + \xi_{jm})/(1-\sigma)},$$

and J_{gm} is the set of all inside products in market m. Notice that there are only two groups in each market: all inside products and the outside option (not flying). The set of demand parameters is θ_d, which includes the taste for characteristics (β), the marginal utility of code sharing (γ), the marginal disutility of price (α), and the nested logit parameter (σ).

Following Berry (1994), the log transformation of relative product share gives the equation below

$$lns_{jm} - lns_{0m} = c_1 + x_{jm}\beta + \gamma d_{jm} - \alpha p_{jm} + \sigma lns_{(jm|gm)} + \xi_{jm},$$

where c_1 is a constant and $lns_{(jm|gm)}$ is the log transformation of the market share of product j within group g.

4.2 | Supply

Each firm maximizes profits over all products across all markets. One of the primary interests of this paper is to explain how code sharing affects firms' profit-maximizing decisions. Hence, it is important to explain how I model code sharing into firms' profit maximization problem. For each code-shared product, the marketing firm is different from the operating firm. I assume that the marketing firm decides the price.[3] In particular, for a code-shared product, the marketing firm decides the price, retains a proportion $(1-\lambda)$ of the total profit and gives the rest to the operating firm. In marginal cost, code-shared products may experience some cost savings.[4] Finally, the marketing firm receives a certain amount as commissions from other firms as itself is an operating firm in other code-shared products.

One might think of a vertical integration model, that is, the operating carrier sets the price for code-shared products. However, this type of model may not fit the institutional background of code sharing tickets. One of the major concerns about code sharing is that the partners may collude. In the current setting, this concern can be explained by the fact that the partners take into account each other's profits when maximizing one's own. This jointing pricing feature may not be existing in a vertical integration model. Therefore, a vertical integration model may not be suitable for the analysis of the existence of collusion.[5]

Let there be F firms; firm f sells a subset of products J_{fm} in market m. Firm f chooses p_{jm}, the price of product j in market m, to maximize total profit:

$$\pi_f = \sum_m \sum_{j \in J_{fm}} \pi_{jm},$$

$$\pi_f = \sum_m \sum_{j \in J_{fm}} (1 - \lambda d_{jm})(p_{jm} - mc_{jm} - cd_{jm}) M_m s_{jm}(x_m, d_m, p_m, \xi_m, \theta_d) + C_f - F_f,$$

where

d_{jm} is a dummy capturing if product j in market m is code-shared,

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

c measures the cost savings in the marginal cost due to code sharing,

M_m is the size of market m,

s_{jm} is the share of product j in market m,

F_f is the fixed cost of production for firm f,

C_f is the total compensation that firm f receives from other firms as an operating code sharing partner. C_f is given by

$$C_f = \sum_m C_{fm},$$

where C_{fm} is defined by

$$C_{fm} = \sum_{h \in H_{fm}} \lambda d_{km}(p_{km} - mc_{km} - cd_{km}) M_m s_{km}(x_m,\ d_m,\ p_m,\ \xi_m,\ \theta_d).$$

The index h denotes a product belonging to H_{fm}, the set of products in market m that firm f operates (for its code-shared partner) but *not* markets.

The following assumptions are made to derive the FOC:

1) Markets are independent; there are no cross price effects among markets.

2) Firms are Bertrand–Nash players; firms do not internalize cross price effects among them.

3) Firms set optimal multi-product prices; firms take into account the cross price effects among their own products.

4) Firm f only sets the prices for products which it markets, *not* the ones it operates for its code-shared partner. However, firm f does take into account the profits that it receives from the partner carrier when f sets the prices.

Under these assumptions, any equilibrium price p_{jm} must satisfy the first-order condition

$$(1 - \lambda d_{jm}) s_{jm}(x_m,\ d_m,\ p_m,\ \xi_m,\ \theta_d\ ) + \sum_{k \in J_{fm}} (1 - \lambda d_{km})(p_{km} - mc_{km} - cd_{km}) \frac{\partial s_{km}}{\partial p_{jm}}$$
$$+ \sum_{h \in H_{fm}} \lambda d_{hm}(p_{hm} - mc_{hm} - cd_{hm}) \frac{\partial s_{hm}}{\partial p_{jm}} = 0.$$

Define $\widetilde{s}_{jm} = (1 - \lambda d_{jm}) s_{jm}$ and $\widetilde{s}_{fm} = (\widetilde{s}_{1m}, \ldots, \widetilde{s}_{J_F m})$. In vector notation the first order conditions can be written as

$$\widetilde{s}(p, x, \xi, \theta) - \Delta(p, x, \xi, \theta)[p - mc - cd] = 0, \text{ where}$$

Δ_{rj} is a $J * J$ matrix (J is the total number of products in market m) given by

$$\Delta_{rj} = \begin{cases} \frac{\partial s_r}{\partial s_j} \text{ if } j \text{ and } r \text{ belong to firm } f, r \text{ is not a code-shared product} \\ (1-\lambda)\frac{\partial s_r}{\partial s_j} \text{ if } j \text{ belongs to firm } f \text{ which markets product } r \text{ for its partner} \\ \lambda\frac{\partial s_r}{\partial s_j} \text{ if } j \text{ belongs to firm } f \text{ which operates product } r \text{ for its partner} \\ 0 \text{ otherwise.} \end{cases}$$

4.3 | The equation system

In summary, demand and pricing equations are given by the following system:

$$lns_{jm} - lns_{0m} = c_1 + x_{jm}\beta + \gamma d_{jm} - \alpha p_{jm} + \sigma lns_{(jm|gm)} + \xi_{jm}, \tag{1}$$

$$\widetilde{s}(p, x, \xi, \theta) - \Delta(p, x, \xi, \theta)[p - mc - cd] = 0. \tag{2}$$

To conclude, this model has three features:

1) Code sharing may directly affect consumer's utility.

2) Code sharing may affect firm's marginal cost.

3) Thus, code sharing is relevant for firms' pricing decisions: the system is based on an equilibrium with a profit-sharing rule between code-shared partners, and it is parameterized by λ.

5 | DATA

The source of data for this study is the Airline Origin and Destination Survey (DB1B), which is published by the U.S. Department of Transportation (DOT). This is a 10% random sample of airline tickets from U.S. reporting carriers in a given quarter for every year. Each observation contains detailed information on fare, ticketing/operating carriers for each coupon, origin/connecting/destination airports, and the number of passengers travelling on the itinerary.

The sample period is the third quarter of 2004. Two separate code sharing agreements between major airlines were initiated in January and June of 2003. United Airlines and US Airways started their code sharing in January of 2003. In June of 2003, the three-way code sharing among Continental Airlines, Delta Air Lines, and Northwest Airlines was established.[6]

The sample observations in this study are selected by the following criteria: (1) tickets within continental U.S.; (2) round-trip tickets with at most four coupons; (3) ticket prices lie between \$25 and \$2,000; (4) the ticketing and operating carriers are both U.S. carriers for each segment; (5) a single ticketing carrier for the entire trip; (6) airports are located in medium to large metropolitan areas with at least 1 million people.

Table 1 reports the summary statistics of variables in both the demand equation and the pricing equation. Dependent variables are labeled with * and the explanatory variables are labeled with +. The mean of the dependent variable, $lns_{jm} - lns_{0m}$, is −9.95. Price is in 2004 dollars and divided by 100. The average price of products is 3.57 with the minimum 0.25 and the maximum 20. The average product share is 3.7E-04, which implies that on average there are around 3.7 of 10,000 passengers purchasing each product in every market.[7] 17% of products are code-shared products.

An average trip in the sample is 3,340 miles. Each product has 1.74 connections on average. Slot Control is the number of slot-controlled airports the itinerary passed through.[8] On average, each product experiences 0.42 slot-controlled airports. SlotMC is a dummy if Slot Control is bigger than one. HubMC is constructed as a dummy and equal to one when the entire trip went through at least one hub of ticketing carrier at either the original, a connecting or the destination airport. It measures possible convenience for consumers. 76% of products pass through at least one hub at some point. Distance is a sum of each coupon's distance in an itinerary.

LCC is a dummy to indicate the low cost ticketing carriers.[9] 13% of products are marketed by low cost carriers.

Table 2 shows the market-level summary statistics. A total of 2,726 markets are included in the sample. On average, there are around 31 products and 6 ticketing carriers in each market.

TABLE 1 Variable summary statistics

Variable	Demand	Cost	Mean	S.D.	Min	Max
Price (in 100s)	+	*	3.57	1.87	0.25	20
Product Share			3.7E-04	2.2E-03	2.5E-06	0.12
$lns_{jm} - lns_{0m}$	*		−9.95	1.57	−12.87	−1.94
$lns_{(jm\|gm)}$	+		−5.43	1.95	−10.78	0
Code Sharing	+	+	0.17	0.38	0	1
Distance (in 1,000s)	+	+	3.34	1.42	0.06	10.37
Distance Square	+		13.16	9.82	0.00	107.47
Connections		+	1.74	0.54	0	2
Slot Control	+		0.42	0.72	0	4
SlotMC		+	0.29	0.45	0	1
HubMC		+	0.76	0.43	0	1
Hub Transfer	+		0.52	0.50	0	1
LCC			0.13	0.34	0	1
Observation			84,412			

TABLE 2 Market-level summary statistics

	Mean	S.D.	Min	Max
No. Products	31	24	1	261
No. Ticketing Carriers	6	2.51	1	13
No. Passengers (in 1,000)	41	83	0.04	1,555
Total No. Markets	2,726			

TABLE 3 Carriers' shares of products

Carriers	Mean
American	0.125
Alaska	0.008
JetBlue	0.003
Continental	0.096
Delta	0.165
Frontier	0.009
AirTran	0.010
America West	0.034
Northwest	0.133
ATA Airlines	0.006
United	0.182
US Airways	0.123
Southwest	0.102
Others	0.004
Total	100

Table 3 reports carriers' shares of products. The six major carriers are American, Continental, Delta, Northwest, United, and US Airways. The three-way code sharing partner firms Continental, Delta, and Northwest account for 40% of the products. The other code sharing partners United and US Airways account for 30% of the products. Southwest is the biggest low cost carrier, accounting for 10% of the products.

6 | EMPIRICAL MODEL

6.1 | Specification and method of estimation

I estimate the system of equations jointly. Joint estimation increases the efficiency of estimates. Although separately estimating each equation will not destroy the consistency of the estimates, the precision will be higher for each estimate in the joint estimation.

In the equation system, the primary parameters of interest are α, σ and λ. The first two parameters enter into both equations, and hence it implies a cross-equation constraint. Although α and σ appear linearly in the demand equation, parameters α, σ and λ are entangled nonlinearly in the pricing equation. All other parameters enter linearly, including the coefficients of dummy variables of carriers. In order to ameliorate the heavy computational burden, I focus on searching for the nonlinear parameters, α, σ and λ, and concentrate out the linear ones: β, γ, δ, c and all dummy variables coefficients.[10]

I use a two-stage nonlinear GMM estimation method to estimate the equation system. Instrumental variables are specified in the next section. Moments are formed as follows:

$$E\begin{bmatrix} z_1 & \\ & z_2 \end{bmatrix}' \begin{bmatrix} \xi \\ e \end{bmatrix} = E\begin{bmatrix} z_1'\xi \\ z_2' e \end{bmatrix} = 0,$$

where $\begin{bmatrix} z_1 & \\ & z_2 \end{bmatrix}$ is $2N \times (l_1 + l_2)$ matrix of instruments, and $\begin{bmatrix} \xi \\ e \end{bmatrix}$ is the vector of unobservables. N is the number of observations, l_1 is the number of instruments in the demand equation, and l_2 is the number of instruments in the pricing equation.

In the first stage, the program searches the value of the parameters that minimize the objective function below[11]

$$\left(\begin{bmatrix} z_1 & \\ & z_2 \end{bmatrix}' \begin{bmatrix} \xi \\ e \end{bmatrix}\right)' \begin{bmatrix} z_1'z_1 & z_1'z_2 \\ z_2'z_1 & z_2'z_2 \end{bmatrix}^{-1} \begin{bmatrix} z_1 & \\ & z_2 \end{bmatrix}' \begin{bmatrix} \xi \\ e \end{bmatrix}.$$

With just-identification (the number of instruments in each equation is equal to the number of parameters to estimate), the objective function should be minimized at zero. In an over-identified case, the minimized objective function will typically be different from zero. Let

$$Z = \begin{bmatrix} z_1 & \\ & z_2 \end{bmatrix} \quad \text{and} \quad u = \begin{bmatrix} \xi \\ e \end{bmatrix}.$$

I compute the following robust covariance matrix in the first stage:

$$V = (G'AG)^{-1}G'AZ'uu'ZAG(G'AG)^{-1},$$

where

$A = (Z'Z)^{-1}$,

$G = [\frac{\partial(Z'u)}{\partial\theta}]$ is the derivative matrix with respect to *nonlinear* parameters α, σ and λ, and concentrated out parameters.

In the second stage, the objective function changes to

$$(Z'u)'(Z'\widehat{u}\widehat{u}'Z)^{-1}Z'u,$$

using the residuals $\widehat{u}$ from the first-stage estimation. And the covariance matrix also changes to

$$(G'Z'\widehat{u}\widehat{u}'ZG)^{-1}.$$

6.2 | Instrumental variables

The endogenous variables are price in the demand equation and firm's shares (both market share and market code sharing share) in the pricing equation. Different sets of instruments are applied to each equation. Table 4 lists all instruments and the equations for which they are used. On the demand side, I construct the following three instruments: (1) the number of cities that the ticketing carrier flies nonstop from the destination airport; (2) the percentage of nonstop routes that rivals operate in the same market; (3) dummy indicating whether the destination is a hub for the ticketing carrier. On the pricing side, five instruments are used:

TABLE 4 Instrumental variables

Instrumental Variables	Demand Equation	Price Equation
No. Nonstop Cities Carrier Flies From Dest.	×	
Percentage Rival Nonstop Routes	×	×
Dest. is a Hub	×	×
Market Average Distance		×
Market Pop/No. of Products in Market		×
Market Pop/No. of Carriers in Market		×

instruments (2) and (3) from the demand side, and (4) market product-level average distance; (5) market population divided by the total number of products in the market; (6) market population divided by the total number of carriers in the market.

The power of instruments are reported in Table 16 in Appendix D. It presents the results of OLS regressions of endogenous variables on their excluded exogenous variables. All coefficients are statistically significant at 95% confidence interval. The R^2 statistics are 0.20 and 0.29, respectively. If I include the exogenous variables as instruments, the R^2 statistics increase to 0.22 and 0.43, respectively. This indicates that the instruments are not weak. Furthermore, the correlation among the excluded instruments in the demand equation is over 0.30 with each other. In the pricing equation, the correlation among other instruments is over 0.12, where the correlation between 5) and 6) are over 0.70. This suggests that the analysis is not overidentified.

6.3 | Identification

I focus on explaining the identification of λ because it is a key parameter and the remaining parameters, β, γ, α, δ, and c, are standard and relatively easy to identify. The parameter σ is identified from the variation in the aggregate market share when the number of products and observed characteristics change. In order to identify λ, one needs to have at least one code-shared product and another non-code-shared product of a given carrier in the same market. The parameter λ is identified when one observes variations in product share from changes in prices for both code-shared product and non-code-shared product. For convenience recall the first-order condition described in the model:

$$(1-\lambda d_{jm})s_{jm}(x_m,\ d_m,\ p_m,\ \xi_m,\ \theta_d) + \sum_{k\in J_{fm}} (1-\lambda d_{km})(p_{km}-mc_{km}-cd_{km}) + \sum_{h\in H_{fm}} \lambda d_{hm}(p_{hm}-mc_{hm}-cd_{hm})\frac{\partial s_{hm}}{\partial p_{jm}} = 0.$$

When one observes both $d_{jm}=1$ or $d_{hm}=1$ and $d_{km}=0$ for some k in the same market, the parameter λ can be identified. For markets where $d_{km}=0$ for all products, λ drops from the equation. At the same time, in markets where $d_{km}=1$ for all k (all products are code-shared as a marketing carrier or operating carrier), λ could be any number.

7 | RESULTS

In this section, I report: (1) parameter estimates; (2) demand elasticities, marginal cost and markups; (3) social welfare changes from the counterfactual analysis.

7.1 | Parameter estimates

Table 5 reports the parameter estimates for the two-equation system. The three estimates of the primary parameters of interest, α, σ, and λ are presented at the top of Table 5. Below the left hand side shows the demand parameters' estimates and instruments used in the demand equation. The right hand side presents the cost parameters' estimates and instruments used in the pricing equation. At the bottom of Table 5, the number of observations is reported. First, I analyze the demand side parameters. Marginal cost parameters are commented in the next section.

TABLE 5 Parameter estimates

Parameters	Mean	S.E			
Alpha	0.56***	0.06			
Lambda	0.92***	0.02			
Sigma	0.29***	0.02			
Dependent Variable: *lnSjm-lnS0m*			**Dependent Variable: *Price***		
Demand Variables	**Mean**	**S.E.**	**Cost Variables**	**Mean**	**S.E.**
Code Sharing	−0.50***	0.03	Code Sharing	−1.17***	0.14
Slot Control	−0.16***	0.03	SlotMC	0.04***	0.01
Nonstop	2.53***	0.08	HubMC	−0.67***	0.03
Hub	0.54***	0.04	Connections	0.08***	0.01
Distance	0.02	0.02	Distance	0.14***	0.01
Distance Square	−0.01***	0.00	Constant	2.31***	0.14
Constant	−6.57***	0.12			
Carrier Dummy			**Carrier Dummy**		
Alaska (AS)	−0.11*	0.07	Alaska (AS)	−0.53***	0.07
JetBlue (B6)	0.03	0.08	JetBlue (B6)	−0.59***	0.08
Continental (CO)	−0.36***	0.03	Continental (CO)	−0.08***	0.03
Delta (DL)	−0.24***	0.03	Delta (DL)	−0.24***	0.03
Frontier (F9)	0.39***	0.05	Frontier (F9)	−1.03***	0.05
AirTran (FL)	0.49***	0.05	AirTran (FL)	−1.26***	0.04
America West (HP)	0.03	0.04	America West (HP)	−0.28***	0.03
Northwest (NW)	−0.40***	0.04	Northwest (NW)	−0.28***	0.03
ATA Airlines (TZ)	0.78***	0.06	ATA Airlines (TZ)	−1.12***	0.04
United (UA)	−0.07***	0.02	United (UA)	−0.10***	0.03
US Airway (US)	−0.55***	0.05	US Airway (US)	−0.49***	0.04
Southwest (WN)	0.08***	0.03	Southwest (WN)	−1.04***	0.03
Instruments for price			**Instruments for firms' shares**		
Percentage Rival Nonstop Routes			Market average distance		
Dummy for dest. is a hub			Market pop/no. of products in market		
No. nonstop cities carrier fly from dest.			Market pop/no. of carriers in market		
			Percentage rival nonstop routes		
			Dummy for dest. is a hub		
Observations:	84412				

Note: *** significant at 1% level. * significant at 10% level. The omitted baseline airline in carrier dummy is the American Airlines.

7.1.1 | Demand parameters

A consumer's utility from choosing a product depends on the price, whether or not the product is code-shared, how many slot-control airports it passed through, whether or not the product is a nonstop flight, whether or not the itinerary stopped at a hub airport, the round-trip distance, distance square and the carrier dummy.

Slot Control variable is one way to differentiate a more congestive airport from the rest less concentrated airports, and also to test whether consumers care much about the traffic in the airports.[12] The estimate of the coefficient of the Slot Control variable is −0.16. The result tells that passengers find traveling through crowded airports as an unpleasant factor and it becomes worse if airports with more traffic are on the route. The coefficient of the nonstop dummy is 2.53, which shows that consumers have a strong preference for direct flights. Moreover, coupled with the increase of internet sales of airline tickets, it is easier now for consumers to shop and compare around for purchasing a nonstop itinerary. Passing through a hub airport brings consumers not only the convenience from the hub-and-spoke network structure, but also the value of frequent flier programs. The constructed hub variable in the demand side is the dummy whether the itinerary stopped by at least one hub of the ticketing carrier, including the origin and destination airports. The estimate of the coefficient is 0.54. The positive sign suggests that consumers receive positive utility from traveling through any hub airport. Distance coefficients show that consumer dislike very short-haul and long-haul routes. Finally, low cost carriers are more preferred than major airlines, holding other variables constant. They usually focus on operating point to point routes. The consequences of a more direct operating pattern may generate comfortable trips: such as better schedule, easy to accommodate if a customer missed a flight, high quality of food and drinks, 4-star quality of luggage handling, etc.

The parameter α, the coefficient of price, is estimated at 0.56. It measures the consumers' price sensitivity. The result shows that consumers have an average price coefficient of 0.56. The parameter is identified by the variation of product shares in response of the changes in prices. The current estimate has sensible value. The demand elasticity of price is more intuitive to reflect consumers' demand behaviors. It is calculated in the next section based on the estimate of α.

The measurement of the within-group products' substitution ability, σ , is 0.29. Notice that the within-group products become perfect substitutes in the extreme case where σ is equal to one. Thus, the estimates 0.29 reflects a mild substitution possibility among products.

Code sharing has a significantly negative effect on consumers' utility. The coefficient of code sharing dummy is -0.50. Consumers' dislike for code sharing may imply some inconvenience of code-shared products. The disadvantage of a code-shared product is the switching between operating carriers. The cooperation between two carriers may not be as smooth as flying on a single airline, such as transferring at one carrier's hub airport to look for the other carrier's gate. In some case, if the first flight is cancelled or delayed, it may be more difficult in the case of a code-shared product to catch the next connecting flight rather than an online trip. Also, a code-shared product would have less convenient access to the boarding gates and the luggage services. However, once we take into account that code sharing creates new products, it is a successful market cooperative action for two carriers connecting their routes, and consumers welfare increased significantly from code sharing. More detailed analysis of consumer welfare generated by the current setting is displayed below.

7.1.2 | Cost parameters

Marginal cost is estimated jointly with demand. More specifically, marginal cost is a regression of the gap between product price and the estimated markup onto several cost related variables. Markup is predicted by demand parameters estimates and firms' product shares. Cost variables include the code sharing dummy, round-trip distance, the number of connections, hub dummy, slot control dummy, and a constant.

The profit-sharing rule between code-shared partners λ is estimated around 0.92. This result means that the operating carrier acquires around 92% of the total profits from the round-trip product. Because there have no estimation of this kind of parameter, it is hard to compare with other studies. Ito and Lee (2007) discussed that all domestic code sharing adopted what is known in the industry as the free-sale model. Under a free-sale model, the operating carrier maintains and controls the seat inventory but allows its code-shared partner(s) to market and sell seats on designated code-shared flights under their own marketing code. The operating carrier receives all of the ticket revenue, regardless of which carrier actually sells the seat. In return for selling a seat on a code-shared flight, the operating carrier usually pays the marketing carrier a nominal commission to cover costs (e.g., the cost to the marketing carrier of issuing its frequent-flyer miles). Both code-shared partners' role as operating/marketing carriers on different markets are well negotiated and balanced. Also, another plausible explanation makes the value of λ sensible: given that the estimates of α and σ are believable and the estimated marginal cost seems reasonable, the markup and hence the parameter λ should be about the right size.

Code sharing is estimated to lower the marginal cost. The coefficient is -1.17, which means a code-shared product on average is \$117 less expensive than a non-code-shared product. This result is consistent with some research studies in the previous literature. Chua et al. (2005) and Goh and Yong (2006) analyzed code sharing effects on firms' costs by estimating a translog cost function, both showing that code sharing reduces firms' costs. The economies of code sharing may generate from an efficient market co-operation after code sharing: an increase in demand. With code sharing, carriers may reduce excess supply on their previously non-code-shared routes, and increase the number of passengers for each flight to fill the capacity. There are two possible major reasons why code sharing may increase demand: first, code sharing implies a single marketing carrier, which may gain consumers; second, there is evidence showing that major airline code-shared partners' flight schedule shifts before and after code sharing, which shows a significant change of flight frequency after code sharing.

Marginal cost is increasing in round-trip distance. The estimate shows that on average the marginal cost increases \$14 per 1,000 miles for a round trip. The coefficient of the number of connections shows that marginal cost increases with more connections. Berry and Jia (2010) found a positive coefficient of connections in 2006 but a negative coefficient in 1999. They explained that there had been two offsetting factors: connecting flight might generate denser traffic, increase the load factor and decrease costs with more passengers; and a large fraction of the fuel consumed at landings and takeoffs increases costs. The different factor dominated in different years in their results. The current estimate indicates that adding one more connection will increase the marginal cost by $8, significantly.

That passing through a hub airport decreases the marginal cost may be due to the economies-of-scale. The estimate shows that going through a hub airport reduces marginal cost by $67. The slot-controlled airports may require more service fees, hence a possible higher marginal cost.

Coefficients of airline dummies are also reported including both major airlines and low cost carriers, among which AirTran, ATA Airlines, Southwest, and Frontier are the largest. The omitted airline is American Airlines. As expected, most low cost carriers have lower marginal costs.

7.2 | Elasticity, marginal cost, and markups

Before reporting the results of calculated elasticities, marginal costs, and markups, I analyze on the theoretical predictions of these variables. Recall that the following price equation and the utility for product j[13]

$$p_j = w_j\delta + markup_j,$$

$$\ln s_j - \ln s_0 = x_j\beta - \alpha p_j.$$

One can obtain

$$U_j = x_j(\beta - \alpha\delta) - \alpha * markup_j$$

if we assume w_j and x_j are same characteristics. As long as $\beta - \alpha\delta > 0$, for an optimizing multi-product firm in equilibrium, the most desirable product (with higher x_j) has the following features:

- a higher product price;
- a higher product share;
- a lower Lerner index;[14]
- a lower semi-elasticity;
- a higher elasticity.

In the following, I first calculate the elasticity of demand with respect to price; the demand and cost semi-elasticity with respect to code sharing; marginal cost and markups at the product level. Second, I compute multiple ratios/differences of variables corresponding to code-shared products and non-code-shared products of each firm in each market, and then take the average.

Table 6 shows the product-level price elasticities, code sharing semi-elasticities, marginal costs, and markups.[15] The average price elasticity is around −2.79.[16] Code sharing semi-elasticities of demand and of cost are negative, suggesting that code sharing lowers both consumers direct utility and firms' marginal costs. The average marginal cost for each product is $219, whereas the average markups is $138. The Lerner index is around 0.37.

One of the primary questions in the paper is how the code-shared products are different from non-code-shared products. The following ratio/difference analysis may help to uncover some facts. Table 7 reports the multiple ratios/differences between the variables corresponding to code-shared products and non-code-shared products. Let me explain how I compute the ratios/differences with an example. For instance, the average observed price ratio between code-shared product and non-code-shared product is 0.95. First, take the average observed price of code-shared products for each firm in each market; Second, take the average observed price of non-code-shared products for each firm in each market; Third, compute the ratios of the above

TABLE 6 Price elasticity, code sharing, semi-elasticity, marginal cost, and markups

Price Elasticity	−2.79
Code sharing Semi-Elasticity (Demand)	−0.56
Code sharing Semi-Elasticity (Cost)	−0.58
Marginal Cost	219
Markups	138
Lerner Index	0.37
Observations	84,412

TABLE 7 The ratios between code-share and non-code-shared products

Pcs/Pncs (Observed Price)	0.95
Scs/Sncs (Product Share)	0.46
Lcs_Lncs (Lerner Index)	0.25
Ecs_Encs (Price Elasticity)	−0.19
MCcs/MCncs (Marginal Cost)	0.53
Observations	3,989

two averages for each firm in each market; Last, calculate the average of the ratios across all firms. Instead of computing ratios, I use the differences for Lerner index and elasticity.

Results show that code-shared products have lower observed prices, lower product shares, higher Lerner index, higher (absolute value) elasticity, lower marginal cost. With a higher elasticity, we expect code-shared products to have lower prices. Note that the Lerner Index is higher for code sharing products, which shows that code sharing products have relatively higher markups.

7.3 | Counterfactual analysis

In order to calculate the changes of consumer surplus and the changes of firms' profits (hence, the total welfare changes) after code sharing, the first step of the counterfactual study is to compute the model-predicted new set of equilibrium prices when eliminating code sharing. The consumer surplus changes and firms' profits changes are then computed based on the new equilibrium prices (as well as the new product shares). Details are explained in the following sections.

Because the model does not predict the decision of code sharing by each firm, it is not clear how many products exist before code sharing. To better understand the possible benefits generated by code sharing, I separate the counterfactual analysis into two different/extreme cases: (1) the number of products in a market do not change without code sharing; (2) the code-shared products do not exist without code sharing. In the first case, code-shared partners may have only shifted their flights schedule to achieve better market co-operations. However, in the second case code sharing creates new products.

7.3.1 | The new equilibrium prices

I choose two markets for the counterfactual analysis: (1) PIT-SMF, from Pittsburgh, PA to Sacramento, CA; (2) BHM-SEA, from Birmingham, AL to Seattle, WA.

In market PIT-SMF, I observe 17 products (8 non-code-shared products, 9 code-shared products) and 7 different ticketing carriers (American, Continental, Delta, America West, Northwest, United and US Airways). Code-shared products are between Continental/Northwest and United/US Airways. All products have connections with the average distance 4,685 miles and an average price $492.

In market BHM-SEA, I observe 32 products (24 non-code-shared products, 8 code-shared products) and 7 difference ticketing carriers (American, Continental, Delta, Northwest, United, US Airways, and Southwest). All products have connections with the average distance 3,522 miles and an average price $462.

For market PIT-SMF, Table 8 shows the equilibrium prices with and without code sharing in the situation where there is no change in the number of product. Results suggest that code-shared products priced mostly 35%–60% lower, whereas most of the non-code-shared product price increased 10%–30%. These results imply that firms price higher for non-code-shared products and decrease prices for code-shared products after introducing code sharing. The pricing strategy is the second degree price discrimination, which is consistent with the fact that code sharing products have lower quality. Meanwhile, Table 9 reports the results from the situation where the code-shared products do not exist. It suggests that the non-code-shared product price increases are consistent with Case I. Prices for most of products have been increased. The significant large increase in the price of the non-code-shared product means that code sharing creates new products which provides higher variety of product quality.

For market BHM-SEA, Table 10 shows the equilibrium prices with and without code sharing in the situation where there is no change in the number of product. Results suggest that code-shared products priced mostly 6%–25% lower, whereas most of the non-code-shared product price increased 1%–35%. These results have similar pattern as that in market PIT-SMF. Table 11 reports the results from the case where the code-shared products do not exist. Prices for most of products have been increased, which shows the same as in the other market.

Overall, the counterfactual analysis in both PIT-SMF and BHM-SEA markets gives similar patterns and consistent results.

TABLE 8 Equilibrium prices with and without code sharing (Case I)

Case I: No change in the number of products				
Code Share	**Price w/Code Sharing**	**Price w/o Code Sharing**	**Δ Price**	**%Δ Price**
Firm 1-Product 1	\$317	\$267	\$50	18.7%
Firm 2-Product 1	\$755	\$1,263	−\$508	−40.2%
Firm 2-Product 2	\$670	\$1,198	−\$528	−44.1%
Firm 2-Product 3	\$412	\$1,114	−\$702	−63.0%
Firm 2-Product 4	\$904	\$1,387	−\$483	−34.8%
Firm 2-Product 5	\$422	\$1,116	−\$694	−62.2%
Firm 3-Product 1	\$453	\$1,102	−\$649	−58.9%
Firm 3-Product 2	\$613	\$1,157	−\$545	−47.1%
Non-Code share				
Firm 1-Product 2	\$424	\$378	\$46	12.1%
Firm 2-Product 6	\$482	\$377	\$105	27.9%
Firm 2-Product 7	\$410	\$369	\$41	11.1%
Firm 3-Product 3	\$651	\$1,232	−\$581	−47.2%
Firm 4-Product 1	\$443	\$382	\$61	16.0%
Firm 4-Product 2	\$413	\$382	\$31	8.1%
Firm 5-Product 1	\$240	\$383	−\$143	−37.3%
Firm 6-Product 1	\$330	\$382	−\$52	−13.5%
Firm 7-Product 1	\$430	\$378	\$52	13.9%

TABLE 9 Equilibrium prices with and without code sharing (Case II)

Case II: Code share products do not exist before code sharing				
Non-Code Share	**Price w/Code Sharing**	**Price w/o Code Sharing**	**ΔPrice**	**%ΔPrice**
Firm 1-Product 2	\$424	\$373	\$51	13.6%
Firm 2-Product 6	\$482	\$378	\$104	27.6%
Firm 2-Product 7	\$410	\$370	\$40	10.8%
Firm 3-Product 3	\$651	\$1,225	−\$574	−46.9%
Firm 4-Product 1	\$443	\$383	\$60	15.7%
Firm 4-Product 2	\$413	\$383	\$30	7.8%
Firm 5-Product 1	\$240	\$383	−\$43	−37.3%
Firm 6-Product 1	\$330	\$382	−\$52	−13.5%
Firm 7-Product 1	\$430	\$378	\$52	13.9%

7.3.2 | Consumer surplus, firms' profits, and change in total welfare

Following Petrin (2002) and Train (2003), the change in consumer surplus (in one market) is:

$$\Delta E(CS) = \frac{1}{\alpha}\left[\ln\left(\sum_{j=1}^{J^1} e^{\delta_j^1}\right) - \ln\left(\sum_{j=1}^{J^0} e^{\delta_j^0}\right)\right],$$

where the superscripts 0 and 1 refer to before and after code sharing; δ_j is the mean utility of product j.

For case I in which the number of products do not change, I decompose the changes in consumer surplus into two separating effects: (1) price effect: consumers' surplus may increase due to that the code-shared products have lower prices; (2) direct utility effect: consumers' surplus may decrease because the code-shared dummy gives a negative direct effect on utility, which implies a lower product quality. The expression is as follows:

$$E(CS)|_{(D=1,P=codeshare)} - E(CS)|_{(D=1,P=noncodeshare)}$$
$$+E(CS)|_{(D=1,P=noncodeshare)} - E(CS)|_{(D=0,P=noncodeshare)},$$

TABLE 10 Equilibrium prices with and without code sharing (Case I)

Case I: No change in the number of products				
Code Share	**Price w/Code Sharing**	**Price w/o Code Sharing**	**Δ Price**	**%Δ Price**
Firm 2-Product 2	$367	$246	$121	49.2%
Firm 3-Product 9	$227	$277	−$50	−18.1%
Firm 3-Product 10	$227	$301	−$74	−24.6%
Firm4-Product 7	$272	$299	−$27	−9.0%
Firm4-Product 8	$428	$331	$97	29.3%
Firm4-Product 9	$292	$318	−$26	−8.2%
Firm5-Product 5	$287	$306	−$19	−6.2%
Firm5-Product 6	$287	$310	−$23	−7.4%
Non-Code share	**w/ Code sharing**	**w/o Code sharing**	**Δ Price**	**%Δ Price**
Firm 1-Product 1	$338	$329	$9	2.9%
Firm 2-Product 1	$322	$338	−$16	−4.7%
Firm 3-Product 1	$375	$357	$18	5.1%
Firm 3-Product 2	$313	$358	−$45	−12.5%
Firm 3-Product 3	$342	$340	$2	0.7%
Firm 3-Product 4	$341	$330	$11	3.3%
Firm 3-Product 5	$375	$357	$18	5.0%
Firm 3-Product 6	$423	$357	$66	18.5%
Firm 3-Product 7	$405	$358	$66	18.5%
Firm 3-Product 8	$414	$356	$58	16.2%
Firm 4-Product 1	$381	$338	$43	12.7%
Firm 4-Product 2	$348	$349	$9	2.7%
Firm 4-Product 3	$388	$341	$47	13.8%
Firm 4-Product 4	$321	$315	$6	1.9%
Firm 4-Product 5	$329	$323	$7	1.8%
Firm 4-Product 6	$385	$373	$12	3.1%
Firm 5-Product 1	$257	$333	−$76	−22.8%
Firm 5-Product 2	$303	$339	−$36	−10.8%
Firm 5-Product 3	$433	$336	$97	28.9%
Firm 5-Product 4	$400	$360	$40	11.0%
Firm 6-Product 1	$268	$313	−$45	−14.4%
Firm 7-Product 1	$421	$313	$108	34.4%
Firm 7-Product 2	$370	$285	$85	29.7%
Firm 7-Product 3	$633	$1,028	−$395	−38.4%

where $D = 1$ means code sharing dummy is equal to one. The first two terms generate the price effect and the last two terms represent the direct utility effect.

For case II in which code sharing creates new products, the decomposition of the changes in consumer surplus are: (1) the gain of variety (more options to choose from different products); and (2) the gain or (loss) from the old product after code sharing. The expression is as follows:

$$E(CS)|_{(J=J^1)} - E(CS)|_{(J=J^1_{noncodeshare})}$$
$$+ E(CS)|_{(J=J^1_{noncodeshare})} - E(CS)|_{(J=J^0)},$$

where the first two terms generate the consumer surplus from the new products, the last two terms generate the consumer surplus (or loss) from the old product after code sharing.

TABLE 11 Equilibrium prices with and without code sharing (Case II)

Case II: Code-shared products do not exist before code sharing				
Non-Code Share	**w/ Code Sharing**	**w/o Code Sharing**	**ΔPrice**	**%ΔPrice**
Firm 1-Product 1	$338	$327	$11	3.5%
Firm 2-Product 1	$322	$335	−$13	−3.9%
Firm 3-Product 1	$375	$345	$30	8.8%
Firm 3-Product 2	$313	$345	−$31	−9.2%
Firm 3-Product 3	$342	$327	$15	4.7%
Firm 3-Product 4	$341	$318	$23	7.2%
Firm 3-Product 5	$375	$344	$31	9.0%
Firm 3-Product 6	$423	$344	$79	23.0%
Firm 3-Product 7	$405	$346	$58	17.0%
Firm 3-Product 8	$414	$344	$70	20.3%
Firm 4-Product 1	$381	$328	$53	16.2%
Firm 4-Product 2	$348	$328	$20	6.1%
Firm 4-Product 3	$388	$330	$58	17.6%
Firm 4-Product 4	$321	$304	$17	5.6%
Firm 4-Product 5	$329	$312	$17	5.3%
Firm 4-Product 6	$385	$362	$23	6.2%
Firm 5-Product 1	$257	$329	−$72	−21.9%
Firm 5-Product 2	$303	$332	−$29	−8.9%
Firm 5-Product 3	$433	$329	$104	31.6%
Firm 5-Product 4	$400	$353	$47	13.1%
Firm 6-Product 1	$268	$308	−$40	−13.0%
Firm 7-Product 1	$421	$312	$109	34.8%
Firm 7-Product 2	$370	$283	$87	30.6%
Firm 7-Product 3	$633	$1,150	−$517	−45.0%

TABLE 12 Consumer surplus change

	PIT-SMF Case I	**PIT-SMF Case II**	**BHM-SEA Case I**	**BHM-SEA Case II**
$\Delta E(CS)$	−$13	$43	−$28	$63
Price Effect	−$5		−$16	
Direct Utility Effect	−$8		−$12	
Surplus from New Products		$71		$109
Surplus (Loss) from Old Products		−$28		−$46

Table 12 reports the consumer surplus changes for a representative passenger in each market, respectively. When the number of products do not change after code sharing, the consumer surplus is decreased around $13 and $28 in both markets, respectively. The reduction in consumer surplus is contributed from the negative direct utility effect of code sharing and the price effect. This result means that each consumer loses $5 in PIT-SMF ($16 in BHM-SEA) from second degree price discrimination after code sharing, and $8 (and $12) for lower quality code-share products. For case II, in which the code-shared products do not exist before code sharing, the consumer surplus increase by $43 and $63, respectively. The large increase is due to the benefit from creating more choices of new products after code sharing. In this specific case, there are 8 new products introduced.

Firms' profit variation after code sharing comes from the changes in marginal cost and markups, taking into account that the multi-product maximization decisions. The total profit changes also depends on the market share change of each product. Table 13 reports firms' profits changes for both cases in the two markets. The results show that some firms make negative profits and the rest have positive profits in both cases. The negative profits come from more intense competition after code sharing. In case I, code sharing partner firms use the second degree of price discrimination to extract consumer's willingness to pay. More specifically, partner firms charge higher prices for higher quality products (noncode-shared products) and lower prices

TABLE 13 Firms' profits changes

	PIT-SMF	PIT-SMF Case I		PIT-SMF Case II	
	$\Pi_{codeshare}$	$\Pi_{noncodeshare}$	$\Delta\Pi$	$\Pi_{noncodeshare}$	$\Delta\Pi$
Firm 1	$14,473	$62,958	−$48,486	$65,621	−$51,148
Firm 2	$6,362	$54,061	−$47,699	$56,349	−$49,987
Firm 3	$9,579	$33,142	−$23,563	$34,462	−$24,883
Firm 4	$147,430	$35,216	$112,214	$36,603	$110,827
Firm 5	$58,830	$81,150	−$22,320	$39,725	$19,105
Firm 6	$247,356	$57,076	$190,280	$58,484	$18,872
Firm 7	$84,813	$462	$84,389	$165	$84,648
	BHM-SEA	**BHM-SEA Case I**		**BHM-SEA Case II**	
	$\Pi_{codeshare}$	$\Pi_{noncodeshare}$	$\Delta\Pi$	$\Pi_{noncodeshare}$	$\Delta\Pi$
Firm 1	$231,367	$47,745	$183,622	$49,457	$181,910
Firm 2	$88,562	$90,251	−$1,689	$45,804	$42,758
Firm 3	$695,329	$373,218	$322,111	$334,349	$360,980
Firm 4	$173,991	$321,584	−$147,592	$278,992	−$105,001
Firm 5	$208,102	$196,276	$11,827	$150,611	$57,491
Firm 6	$3,453	$53,578	−$50,124	$54,171	−$50,718
Firm 7	$350,456	$57,003	$293,450	$59,088	$291,368

TABLE 14 Total welfare changes

	PIT-SMF Case I	PIT-SMF Case II	BHM-SEA Case I	BHM-SEA Case II
Total Consumer Surplus (Gain or Loss)	−$29,120	$96,320	−$301,280	$650,160
Total Firm Profits Gain	$244,775	$277,433	$611,603	$778,788
Total Welfare Change	$215,655	$373,753	$310,323	$1,428,948

for code-shared products to capture higher price sensitive consumers. In case II, the introduction of new products helps partner firms gaining more profits compared to that before code sharing.

The total welfare change is calculated by the aggregated consumer surplus and firm profits for both cases. Table 14 presents the results. In PIT-SMF market, the total welfare increases are around $215K and $370k for each case, respectively. In case I, consumer bear a −$29k loss due to price discrimination after code sharing. However, consumer gain more than $96k once we consider that code sharing creates the entering of new products. In market BHM-SEA, the welfare gains are larger. In case II, there is over $1.4 million dollars gain after code sharing.

I compare the welfare analysis to previous literature. The welfare results in Armentier and Richard (2008) conclude that, in code-shared market, the average individual consumer surplus has decreased by 1.51% after code sharing. Accounting for endogenous variation in passenger volumes, the consumer surplus has increased by 3.44%. The surplus change comes from a mixed result, which is 5.9% surplus decrease in nonstop passengers and 2.45% increase in connecting consumer. My analysis finds that, in PIT_SMF market, the changes are −2.4% and 6.9% in two cases, respectively. Therefore, the welfare gain-loss bound in the current study covers the amount of welfare gain, which is found in Armentier and Richard (2008). In market BHM_SEA, the consumer welfare changes are −6.0% and 13.4% in two cases, respectively.

There are evidences in the existing literature supporting the scenario in which code sharing creates new products and increases demand. Two research studies on U.S. domestic code sharing have suggested that code sharing increases traffic in the related markets. Bamberger et al. (2004) documents that the total traffic increased by 6% after the creation of CO/HP (Continental/America West) alliance. They also find that NW/AS alliance increased traffic. Similarly, Gayle (2008) finds that code sharing agreement among Delta/Continental/Northwest accounts for a 10.7–12.3% increase in overall city-pair traffic for city pairs where they code share (alliance city pairs) and a 19.8–24.4% increase in the partners' city-pair traffic for alliance city pairs.

To summarize, code sharing has shown not only to directly reduce firms' marginal costs and consumers' utility, but also induces second degree price discrimination and probably to enlarge the number of products to an extent that we do not exactly know. Welfare consequences of code sharing are related to the following three main effects: (1) a negative direct utility effect causes a negative consumer surplus; and a large positive effect on saving firms' marginal costs induces the increase in profits; (2) the second degree price discrimination creates large increase in profits for code sharing partner firms; (3) the entry of new products could bring an overwhelming positive effect on both consumer surplus and firms' profits. The overall welfare implication after code sharing could be a large increase with a bigger value in the case where to the extent that code sharing allows the entry of new products.

8 | CONCLUSION

This paper analyzes the effects of code sharing agreements among U.S. domestic airlines. This paper presents a structural model of code sharing. It consists of consumer demand and oligopoly firm supply, where consumer's demand is directly affected by code sharing and firms explicitly take into account code sharing when maximizing profits. I explicitly model how firms share their profits for code-shared products. The paper uses a two-stage nonlinear GMM estimation method to estimate the equilibrium equation system.

Results show that the profit-sharing rule is 92%, which means that the marketing carrier keeps 8% of the profit of a code-shared product. Partner firms practice the second degree price discrimination with code-shared products. The results also suggest that code-shared product has lower marginal cost but with higher markup. The counterfactual analysis shows that when consumers do benefit, the source is the introduction of new products. The total social welfare significantly increases after code sharing agreements.

The findings from this paper have important policy implications. Depending on different conditions, the policy maker may find himself in different scenarios. I summarize the conclusions in the following four points. First, code sharing can increase firms' market power. Results show that markup for code-shared product is higher. This finding justifies the cautious behavior of the policy makers toward code sharing approvals. Second, code sharing reduces marginal cost by a large magnitude. This suggests that there exists efficiency gain from code sharing agreements. This finding implies that the approvals of current code sharing agreements may be correct. As a result, with efficiency gain on the cost side, firms are able to price code-shared products at lower prices. Third, the counterfactual analysis indicates that the large amount of consumer welfare increase comes from the introduction of new products due to code sharing agreements. This finding suggests that the policy makers should be more open to code sharing agreements, which are more likely to generate new products. Fourth, the counterfactual analysis shows that if there are no new products generating from code sharing agreements, consumers may have lower welfare due to the negative direct utility from purchasing code sharing tickets. This implies that the policy makers should be more cautious to code sharing proposals, in which there is less possibility to create new products.

Because this paper does not model firms' code sharing decisions, the market structure before code sharing is taken as given. I have no means to predict the number of products *ex ante*. I leave for subsequent research a more sophisticated game theoretic model where firms choose how and on which routes to code-share.

NOTES

[1] The International Air Transport Association (IATA) assigns two-character codes to all airlines; for example, American Airlines has the code AA.

[2] Notice that a horizontal type does not necessarily need to be a nonstop flight.

[3] This assumption follows the institutional explanation on code sharing by Ito and Lee (2007) and Gayle (2013). More specifically, they describe what is known in the industry as free-sale model. Under a free-sale model, the operating carrier maintains and controls the seat inventory but allows its code-share partner(s) to market and sell seats on designated code-share flights under their own marketing code.

[4] Goh and Yong (2006) estimated a truncated third-order trans-log cost function and showed that code sharing lowered cost.

[5] To further support the assumption that marketing carrier sets the price, a price comparison has been done between horizontal code-shared products and non-code-shared products with the same operating carrier. Results are reported in Table D1 in Appendix D. It shows that the prices are significantly different, which means the operating carrier may not set prices. The results show that horizontal code-shared products are around 7% less expensive than single-carrier products. This is consistent with Ito and Lee (2007), which finds it 5–6% less expensive. The reason is that for at least some travelers, horizontal code-shared itineraries are perceived as imperfect substitutes to otherwise identical, non-code-shared itineraries operated by the same carrier. As described in Ito and Lee (2007), code-shared product is a generic product, whereas the single-carrier non-code-shared product is a brand-name product.

[6] Due to the large sample data set, I use a cross-section sample of the third quarter of 2004, instead of a panel data. In the future, I plan to extend the estimation to cover more periods.

[7] Each product share is computed by the following steps: first, collapsing the total number of passengers traveling on the same product; second, dividing it by the market size; finally, times 40 because it is a 10% sample of a quarter in a single year.

[8] The four slot-controlled airports are LaGuardia (LGA) and Kennedy in New York (JFK), National in D.C. (DCA), and O'Hare in Chicago (ORD).

[9] LCC includes JetBlue (B6), Frontier (F9), AirTran (FL), Southwest (WN), and many other small low cost carriers. Note America West (HP) is considered as a major airline, not a low cost carrier.

[10] I use transformations for parameter α and λ in the estimation to make sure that they are bounded. Delta method is therefore used to calculate the standard deviation of α and λ.

[11] The number of observations N cancels in the formula.

[12] Recall only four airports are slot-controlled: LGA, JFK, DCA, and ORD.

[13] The market index m is omitted for simplicity.

[14] Notice that the model predicts same markups for different products for the same firm.

[15] Calculations are shown in the Appendix.

[16] Armantier and Richard (2008) obtain own price elasticity from −1.54 to −2.79 for difference alliances and regional airlines. Meanwhile, Berry and Jia (2010) find it ranging from −1.55 to −2.01 for different specifications in different years.

REFERENCES

Armentier, O., & Richard, O. (2008). Domestic airline alliances and consumer welfare. *Rand Journal of Economics*, *39*(3), 875–904.

Bamberger, G., Carlton, D., & Neumann, L. (2004). An empirical investigation of the competitive effects of domestic airline alliances. *Journal of Law and Economics*, *47*(1), 195–222.

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

Berry, S., & Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *AEJ Microeconomics*, *2*(3), 1–43.

Bilotkach, V. (2005). Price competition between international airline alliances. *Journal of Transport Economics and Policy*, *39*(2), 167–189.

Brueckner, J. (2001). The economics of international codesharing: An analysis of airline alliances. *International Journal of Industrial Organization*, *19*, 1475–1498.

Brueckner, J. (2003). International airfares in the age of alliances: The effects of codesharing and antitrust immunity. *The Review of Economics and Statistics*, *85*(1), 105–118.

Brueckner, J., Lee, D., & Singer, E. (2014). City-pairs versus airport-pairs: A market-definition methodology for airline industry. *Review of Industrial Organization*, *44*, 1–25.

Brueckner, J., & Whalen, W. T. (2000). The price effects of international airline alliances. *Journal of Law and Economics*, *43*(2), 503–545.

Chua, C. L., Kew, H., & Yong, J. (2005). Airline code-share alliances and costs: Imposing concavity on translog cost function estimation. *Review of Industrial Organization*, *26*, 461–487.

Gayle, P. (2007). Airline code-share alliances and their competitive effects. *Journal of Law and Economics*, *50*, 781–819.

Gayle, P. (2008). An empirical analysis of the competitive effects of the delta/continental/northwest code-share alliance. *Journal of Law and Economics*, *51*, 744–766.

Gayle, P. (2013). On the efficiency of codeshare contracts between airlines: Is double marginalization eliminated? *American Economic Journal: Microeconomics*, *5*(4), 244–273.

Goetz, C., & Shapiro, A. (2012). Strategic alliance as a response to the threat of entry: Evidence from airline codesharing. *International Journal of Industrial Organization*, *30*(6), 735–747.

Goh, M., & Yong, J. (2006). Impacts of code-share alliances on airline cost structure: A truncated third-order translog estimation. *International Journal of Industrial Organization*, *24*, 835–866.

Hassin, O., & Shy, O. (2004). Code-sharing agreements and interconnections in markets for international flights. *Review of International Economics*, *12*(3), 337–352.

Ito, H., & Lee, D. (2007). Domestic code sharing, alliances, and airfares in the U.S. airline industry. *Journal of Law and Economics*, *50*, 356–380.

Park, J. H. (1997). The effects of airline alliances on markets and economics welfare. *Transportation Research Part E: Logistics and Transportation Review*, *33*(3), 181–195.

Park, J. H., & Zhang, A. (2000). An empirical analysis of global airline alliances: Cases in North Atlantic markets. *Review of Industrial Organization*, *16*, 367–383.

Park, J. H., Zhang, A., & Zhang, Y. (2001). Analytical models of international alliances in the airline industry. *Transportation Research*, *35*, 865–886.

Shen, C. (2015). Code sharing and merger: Continental, delta and northwest. *Frontiers of Economics in China 10*(4), 643–663.

Whalen, W. T. (2007). A panel data analysis of code-sharing, antitrust immunity, and open skies treaties in international aviation markets. *Review of Industrial Organization*, *30*, 39–61.

Zhang, A., & Zhang, Y. (2006). Rivalry between strategic alliances. *International Journal of Industrial Organization*, *24*(2), 287–301.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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