On the Efficiency of Codeshare Contracts Between Airlines: Is Double Marginalization Eliminated?

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Abstract
The literature on the economics of airline codesharing has suggested that codeshare agreements serve to eliminate double marginalization that exists when unaffiliated airlines independently determine the price for different segments of an interline trip. Using a structural econometric model, this paper investigates whether codeshare contracts do eliminate double marginalization. The results suggest that codeshare contracts may eliminate upstream margin, leaving marginal cost and downstream margin as the determinants of price. However, the elimination of the upstream margin depends crucially on whether the upstream operating carrier also offers competing downstream products in the concerned market. Specifically, the vertical codeshare contract is found not to eliminate the upstream margin when the upstream operating carrier also offers competing downstream products.

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1 Introduction

It is widely accepted that airline codesharing eliminates the double marginalization that exists when unaffiliated airlines independently determine the price for different segments of an interline trip [Brueckner and Whalen (2000), Brueckner (2003), Ito and Lee (2005)]. In fact, it is common to cite this efficiency gain as the primary reason why airlines form codeshare alliances. Surprisingly, there is no empirical test in the literature on whether codesharing actually eliminates double marginalization. The empirical literature on codesharing mainly investigates whether codesharing reduces market fares [Bamberger, Carlton, and Neumann (2001)]. Even though there is overwhelming evidence that codesharing reduces market fares, potentially such fare reduction could simply result from cost savings. It is thus interesting to empirically understand whether codesharing indeed leads to more efficient vertical pricing by eliminating double marginalization, as is often been claimed in the literature. Using a structural econometric model that disentangles the effect of cost from markup behavior on price, this paper provides the first attempt at testing whether codesharing eliminates double marginalization.

Codesharing constitutes a contractual agreement among airlines that allows a carrier, called the "ticketing carrier", to effectively market and sell seats on its partner’s plane for segments of a route operated by its partner ("operating carrier"). "Traditional" codeshare itineraries combine connecting operating services of partner carriers on a given route. For example, in traveling from Denver, Colorado, to Philadelphia, Pennsylvania a passenger may have bought the codeshare round-trip ticket from United Airlines, but the itinerary involves flying on United Airlines from Denver to Boston, then connecting to a US Airways flight from Boston to Philadelphia. There are cases in which codeshare itineraries only involve a single operating carrier for the entire trip even though the ticket for the trip was marketed and sold by a partner carrier. Such codeshare itineraries are referred to as "Virtual", but unlike traditional codesharing, it is argued that airlines’ incentive to offer virtual codeshare tickets is not related to their desire to eliminate double marginalization. As such, this paper focuses on traditional codesharing, and in what follows, codesharing should be interpreted in the traditional context.

1 Other notable contributions to this literature include Brueckner (2003), Brueckner (2001), Brueckner and Whalen (2000).

2 See Ito and Lee (2005) for a detailed discussion of "Virtual" codesharing versus "Traditional" codesharing and airlines' incentives for engaging in each type. See Gayle (2005b) for an empirical investigation of the primary motive for "Virtual" codesharing.
Since codesharing combines the operating services of at least two separate carriers, where only one of the carriers is responsible for marketing and setting the final price for the entire round-trip ticket and compensating the other carrier for their pure operating services on a segment of the trip, it is reasonable to view codesharing as a standard vertical relationship between upstream and downstream firms. The pure "operating carrier" is equivalent to an upstream supplier that provides an essential input (operate a trip segment) to the downstream "ticketing carrier" who then combines it with other inputs (complementary trip segments) in order to provide the final product to consumers. As such, the econometric model that is used to evaluate how well codeshare contracts eliminate one of the margins (upstream or downstream) is based on a sequential price setting game that allows for double marginalization.

The results suggest that whenever one of the margins is eliminated, it is the upstream margin. However, the elimination of the upstream margin depends crucially on whether the upstream operating carrier also offers competing single-carrier⁴ products in the concerned market. Specifically, the vertical codeshare contract seems not to eliminate the upstream margin when the upstream operating carrier also offers competing single-carrier products. This finding is important since the upstream operating carrier simultaneously offers competing single-carrier products in the said market for close to half (44.4%) of the codeshare products. The finding is consistent with the theoretical literature on vertical integration which predicts that a vertically integrated firm, unlike an unintegrated firm, has an incentive to raise the input price to rival downstream firms since this has the effect of increasing the competitive advantage of the downstream operations of the integrated firm [Ordoñez, Saloner, and Salop (1992), Riordan and Salop (1995), Choi and Yi (2000), Chen (2001)]. Another important finding is that codeshare products, on average, have lower marginal cost than single-carrier products. In other words, efficiency gains from codesharing may not only come from the elimination of double marginalization, but also with respect to reduced marginal cost. This finding highlights the importance of using an empirical model that disentangles the effects of marginal cost from markup behavior on prices.

The rest of the paper is organized as follows. Section 2 outlines the structural econometric model of air travel demand and supply. Estimation issues are discussed in section 3. Section

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⁴A single-carrier product is popularly referred to as an "online" product in the literature. In other words, an "online" product is defined as a product where the passenger remains on a single airline’s network throughout the entire trip even if the passenger changes planes. Further discussion and examples of these products are given in section 2 of the paper.
4 describes the data used in estimation. Results are discussed in section 5, and section 6 offers concluding remarks.

2 The Model

In this section, we outline a model of demand and supply of air travel. We start with the demand side which is modeled within a discrete choice framework. We then outline the supply side of the model which is where the vertical contracting is captured.

2.1 Demand

A market is defined as a directional round-trip air travel between an origin and a destination city. The assumption that markets are directional implies that a round-trip air travel from Denver to Philadelphia is a distinct market than round-trip air travel from Philadelphia to Denver. Further, this directional assumption allows for the possibility that origin city characteristics may influence market demand.

A flight itinerary is defined as a specific sequence of airport stops in traveling from the origin to destination city. Products are defined as a unique combination of airline(s) and flight itinerary. The products explicitly included in the model are "online" and codeshare products. An online product means that a passenger remains on a single carrier’s network for all segments of a round-trip. For example, three separate online products are, (1) a non-stop round trip from Denver to Philadelphia on US Airways, (2) a round-trip from Denver to Philadelphia with one stop in Charlotte on US Airways, and (3) a non-stop round-trip from Denver to Philadelphia on Northwest Airlines. Note that all three products are in the same market. In contrast, for codeshare products, passengers change airlines at least once on the round-trip but a single airline is responsible for marketing and selling the ticket for the entire round-trip.

Potential passenger $i$ in market $t$ faces a choice between $J_t + 1$ alternatives. There are $J_t + 1$ alternatives because we allow passengers the option ($j = 0$) not to choose one of the $J_t$ differentiated air travel products considered in the empirical model. A passenger chooses the product that gives them the highest utility, that is

$$\max_{j \in \{0, \ldots, J_t\}} \{U_{ijt} = x_{jt} \beta_i - \alpha_i p_{jt} + a_j + \xi_{jt} + \varepsilon_{ijt}\},$$

$\text{4Virtual codeshare products are treated as if they are just another differentiated online product offered by the ticketing carrier even though technically the ticketing carrier differs from the operating carrier.}$

3
where $U_{ijt}$ is the value of product $j$ to passenger $i$, $x_{jt}$ is a vector of observed product characteristics (a measure of itinerary convenience, whether or not the origin is a hub for the carrier, the carrier’s number of daily departures from the origin airport, whether or not the product is codeshare or online), $\beta_i$ is a vector of individual-specific consumer taste parameters (assumed random) for different product characteristics, $p_{jt}$ is the price, $\alpha_i$ represents individual-specific marginal utility of price, $a_j$ are product fixed effects (airline dummies) capturing characteristics of the products that are the same across markets, $\xi_{jt}$ is the level of unobserved product quality, and $\varepsilon_{ijt}$ is a mean zero random component of utility.

The random taste parameters, $\beta_i$ and $\alpha_i$, vary across consumers according to

$$
\begin{pmatrix}
\alpha_i \\
\beta_i
\end{pmatrix} = \begin{pmatrix}
\alpha \\
\beta
\end{pmatrix} + \Sigma v_i,
$$

where $v_i$ is a column vector that captures consumer $i$’s unobserved taste for each product characteristic, $\Sigma$ is a diagonal matrix where elements on the main diagonal are parameters that measure variation in taste across consumers for each product characteristic. Following the literature on random coefficients discrete choice models [see Nevo(2000a)], we assume that $v_i$ has a standard multivariate normal distribution, $N(0, I)$. Thus, the diagonal elements in $\Sigma$ represent the standard deviations of the random taste parameters, $\begin{pmatrix}
\alpha_i \\
\beta_i
\end{pmatrix}$.\footnote{Since the mean of $v_i$ is a zero vector based on the assumption that $v_i \sim N(0, I)$, then the mean of $\begin{pmatrix}
\alpha_i \\
\beta_i
\end{pmatrix}$ is $\begin{pmatrix}
\alpha \\
\beta
\end{pmatrix}$ and its variance is equal to the square of the elements on the main diagonal of $\Sigma$.}

The indirect utility from consuming product $j$ can now be re-written as

$$
U_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt},
$$

where $\delta_{jt}$ is the mean utility obtained from consuming product $j$ and is given by $\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + a_j + \xi_{jt}; \mu_{ijt} + \varepsilon_{ijt}$ is a mean zero, heteroskedastic deviation from the mean utility that captures the effects of the random coefficients, where $\mu_{ijt}(x_{jt}, p_{jt}, \nu_i; \sigma) = [-p_{jt}, x_{jt}] \times \Sigma \nu_i$. $\sigma$ is a vector containing the parameters along the main diagonal of $\Sigma$.

Let $\varepsilon_{ijt}$ be governed by an independent and identically distributed extreme value density. The probability that product $j$ is chosen, or equivalently the predicted (by the model) market share of product $j$ is

$$
d_{jt}(x_{jt}, p_{jt}; \alpha, \beta, \sigma) = \int \frac{e^{\delta_{jt} + \mu_{ijt}}}{1 + \sum_{l=1}^{J} e^{\delta_{lt} + \mu_{ilt}}} dF(\nu),
$$

\footnote{As usual, the mean utility level of the outside option, $\delta_{0t}$, is normalized to be a constant and equal to zero.}
where \( F(\cdot) \) is the standard normal distribution function.\(^7\) As is well known in the empirical industrial organization literature, there is no closed-form solution for equation (4) and thus it must be approximated numerically using random draws from \( F(\nu) \). The numerical approximation yields the following predicted simulated product share function,

\[
d_{jt} = \frac{1}{ns} \sum_{i=1}^{ns} \frac{e^{\delta_{jt} + \mu_{jlt}}}{1 + \sum_{l=1}^{J} e^{\delta_{lt} + \mu_{ilt}}},
\]

where \( ns \) is the number of random draws from \( F(\cdot) \).\(^8\)

Note that \( d_{jt}(x_{jt}, p_{jt}; \alpha, \beta, \sigma) \) is predicted by the demand model and therefore not observed. Given a market size of measure \( M \), which we assume to be 10% of the size of the population in the origin city,\(^9\) observed market share of product \( j \) in market \( t \) is \( D_{jt} = \frac{q_j}{M} \), where \( q_j \) is the actual number of travel tickets sold for a particular itinerary-airline(s) combination called product \( j \). The observed market share for each product is computed analogously. In section 3 we describe how observed and predicted product market shares are used in estimation.

### 2.2 Supply

In this subsection, we derive a supply equation that approximates airlines’ optimizing behavior for each type of product supplied (codeshare, and online). In the spirit of Villas-Boas (2003), behavioral equations are derived which express price-cost margins as a function of demand parameters.

#### 2.2.1 Codeshare Products

The price of codeshare products are assumed to be determined within a sequential price setting game. In this game, the upstream operating carrier first sets the price for their segment of the trip, then the downstream ticketing carrier sets the final round-trip price given the agreed upon price for the services supplied by an upstream operating carrier. To solve for the subgame perfect Nash equilibrium in sequential games, it is standard to start by looking at the final subgame in the sequential game. The final subgame in this vertical model is a Bertrand-Nash game between downstream ticketing carriers.

\(^7\) As in equation (4), \( a_j \) in the mean utility function is suppressed in what follows only for notational convenience. As such, from this point on we can interpret \( \beta \) as also including the coefficients on the airline dummies intended to capture \( a_j \).

\(^8\) I use \( ns = 1,000 \).

\(^9\) As discuss in the data section, the data set used in this research is drawn from the U.S. Bureau of Transportation Statistics database which is itself a 10% sample of airline tickets from reporting carriers. Given that the database is a 10% sample, our market size definition seems reasonable.
In what follows, we suppress the market index \( t \) only to avoid a clutter of subscripts. Therefore, when we specify an airline’s profit function, it represents the airline’s profit only in market \( t \).

Let \( r = 1, ..., R \) index ticketing carriers that compete in a downstream market and let \( f = 1, ..., F \) index the corresponding upstream operating carriers. Further, let \( F_r \) be a subset of the \( J \) codeshare products that are offered for sale by ticketing carrier \( r \). Thus carriers are allowed to offer multiple products for sale. The profit of carrier \( r \) is given by

\[
\Pi_r = \sum_{j \in F_r} (p_j - s_f^j - c_r^j)q_j
\]

where \( d_j(p) \) is market share of product \( j \), \( p \) represents a vector of final prices, \( c_r^j \) is the constant marginal cost carrier \( r \) incurs in providing the services necessary to offer product \( j \),\(^{10} \) \( s_f^j \) is the price the ticketing carrier pays to upstream operating carrier \( f \) for their services needed to complete the trip.

A pure strategy Nash equilibrium in final prices requires that \( p_j \) of any product \( j \) offered by carrier \( r \) must satisfy the first-order condition

\[
d_j(p) + \sum_{k \in F_r} \left( p_k - s_f^k - c_r^k \right) \frac{\partial d_k(p)}{\partial p_j} = 0
\]

The first-order conditions are a set of \( J \) equations, one for each product. Following Nevo (2000b) and Villas-Boas (2003), a few additional definitions allow for a more convenient representation of the first-order conditions using matrix notation.

First, let \( \Omega_r \) be a \( J \times J \) matrix which describes the ticketing carriers’ ownership structure of the \( J \) products. Let \( \Omega_r (j,k) \) denote an element in \( \Omega_r \), where

\[
\Omega_r (j,k) = \begin{cases} 
1 & \text{if there exist } r : \{j,k\} \subset F_r \\
0 & \text{otherwise}
\end{cases}
\]

In other words, \( \Omega_r (j,k) = 1 \) if products \( j \) and \( k \) are offered by the same ticketing carrier, otherwise \( \Omega_r (j,k) = 0 \).

Second, let \( \Delta_r \) be a \( J \times J \) matrix of first order derivatives of product market shares with respect to final prices, where element \( \Delta_r (j,k) = \frac{\partial d_j}{\partial p_k} \). In vector notation, the system of \( J \) first-order conditions for the downstream ticketing carriers can now be represented conveniently by

\[
d(p) + (\Omega_r \ast \Delta_r) \left( p - s_f - c^r \right) = 0
\]

\(^{10}\)Since the ticketing carrier also supply operating services for a portion of the trip, then \( c_r^j \) includes per unit operating expenses.
\[
p - s^f - c^r = - (\Omega_r \ast \Delta_r)^{-1} d(p)
\]  
(8)

where \(d(\cdot), p, s^f,\) and \(c^r\) are \(J \times 1\) vectors of product market shares, final prices, upstream operating carrier prices, and ticketing carriers’ marginal cost respectively, while \(\Omega_r \ast \Delta_r\) is an element by element multiplication of two matrices. Note that equation (8) expresses the ticketing carriers’ price-cost margins as a function of demand side parameters.

Having characterized the price-cost markup behavior of ticketing carriers, as captured by equation (8), we now turn to the problem of the upstream operating carriers. Let \(S_f\) be a subset of the \(J\) products to which carrier \(f\) supply operating services. Again, we allow carriers to offer operating services to multiple products. Given that final prices are a function of upstream prices via equation (8), then product market shares are also a function of upstream prices, that is, \(d_j(p(s^f))\). Knowing that ticketing carriers behave according to equation (8), each upstream operating carrier solves the following problem

\[
\max_{s^f_j \in S_f} (s^f_j - c^f_j)M \cdot d_j(p(s^f))
\]  
(9)

where \(c^f_j\) is the marginal cost that carrier \(f\) incurs when providing operating services to product \(j\). A pure strategy Nash equilibrium in upstream prices requires that \(s^f_j\) for any product \(j\) must satisfy the first-order condition

\[
d_j + \sum_{k \in S_f} \left( s^f_k - c^f_k \right) \frac{\partial d_k}{\partial s^f_j} = 0
\]  
(10)

Just as above, we have a set of \(J\) first-order conditions, one for each product.

Using procedures analogous to the ones used when representing the first-order conditions for the ticketing carriers in matrix notation, we can also conveniently represent the first-order conditions for the operating carriers in matrix notation. Let \(\Omega_f\) be a \(J \times J\) matrix which describes the operating carriers’ ownership structure of the \(J\) products. Further, let \(\Omega_f (j, k)\) represent an element in the \(\Omega_f\) matrix. \(\Omega_f (j, k) = 1\) if products \(j\) and \(k\) receive operating services from the same operating carrier, otherwise \(\Omega_f (j, k) = 0\). Note that \(\Omega_f \neq \Omega_r\), since the subsets of the \(J\) products owned by ticketing and operating carriers may differ.

Let \(\Delta_f\) be a \(J \times J\) matrix of derivatives of product market shares with respect to upstream operating carrier prices, where element \(\Delta_f (j, k) = \frac{\partial d_j}{\partial s^f_k}\). In vector notation, the system of \(J\)
first-order conditions for the upstream operating carriers can now be represented conveniently by

\[ \mathbf{d}(\mathbf{p}) + (\Omega_f \ast \triangle_f) \left( \mathbf{s}^f - \mathbf{c}^f \right) = 0 \]

or

\[ \mathbf{s}^f - \mathbf{c}^f = - (\Omega_f \ast \triangle_f)^{-1} \mathbf{d}(\mathbf{p}) \]  \hspace{1cm} (11)

where \( \mathbf{d}(\cdot) \), \( \mathbf{s}^f \), and \( \mathbf{c}^f \) are \( J \times 1 \) vectors of market shares, operating carriers’ prices, and operating carriers’ marginal cost respectively, while \( \Omega_f \ast \triangle_f \) is an element by element multiplication of two matrices. Note that equation (11) expresses the operating carriers’ price-cost margins as a function of demand side parameters.

Let \( \triangle_p \) be a matrix of derivatives of all final prices with respect to upstream operating prices. In other words, \( \triangle_p \) tells an upstream operating carrier how all downstream final prices change given a change in the price for her operating services. Thus an element in \( \triangle_p \) is given by \( \triangle_p(j,k) = \frac{\partial p_j}{\partial s_k} \). Since \( \triangle_f = \triangle_p \triangle_r \) and we already know how to compute \( \triangle_r \), to obtain \( \triangle_f \) the only additional computation needed is \( \triangle_p \).\footnote{It turns out that obtaining matrix \( \triangle_p \) is not a simple task (see Villas-Boas 2003).} In the appendix, we discuss how \( \triangle_p \) is computed. There, it will become clear that computation of \( \triangle_p \) does not require information on upstream operating prices, but computation of the hessian for \( d_j \) is required. As such, the curvature of \( d_j \) plays an important role in equilibrium price behavior.

Finally, to derive an expression for the overall price-cost margin for codeshare products, we sum equations (8) and (11), which yields

\[ \mathbf{p} - \mathbf{c}^r - \mathbf{c}^f = - (\Omega_r \ast \triangle_r)^{-1} \mathbf{d}(\mathbf{p}) - (\Omega_f \ast \triangle_f)^{-1} \mathbf{d}(\mathbf{p}) \]  \hspace{1cm} (12)

Note that equation (12) has the useful property that estimation of overall price-cost margins do not require information on the prices that upstream operating carriers charge their downstream ticketing partner carrier. The property is useful since data on the prices that airlines agree to trade services among themselves at are difficult to obtain.

### 2.2.2 Online Products

In presenting the vertical pricing model above, it is implicitly assumed that all \( J \) products in the market are supplied using a codeshare structure. However, in a more realistic setting a subset of the \( J \) products are likely to be online products. This can be captured in the model above...
by assuming that online products represent cases where the downstream and upstream carriers are vertically integrated. Such vertical integration serves to eliminate the upstream markup and therefore \( s_k^f = c_k^f \) for any online product \( k \). As such, in modifying the supply model to capture cases where some products are online, the downstream markup equation (equation (8)) is unchanged and apply to all products, while the new upstream equation for codeshare products is

\[
\mathbf{s}^f - \mathbf{c}^f = - \left( \Omega_f^{\text{code}} \ast \Delta_f^{\text{code}} \right)^{-1} \mathbf{d}(\mathbf{p})^{\text{code}}
\]

(13)

where \( \Omega_f^{\text{code}} \) and \( \Delta_f^{\text{code}} \) are square matrices containing the rows and columns of \( \Omega_f \) and \( \Delta_f \) which correspond to codeshare products, and \( \mathbf{d}(\mathbf{p})^{\text{code}} \) is a vector containing market shares of codeshare products in \( \mathbf{d}(\mathbf{p}) \). Thus the overall price-cost margin for each codeshare product is given by the upstream markup, captured in equation (13), plus the corresponding downstream markup, captured by equation (8), while online products only have a downstream markup.

The reason why rows and columns of \( \Omega_f^{\text{code}} \) and \( \Delta_f^{\text{code}} \) are only for codeshare products is due to the fact that suppliers of online products do not optimize over upstream prices. Upstream prices for online products are simply determined by the marginal cost for upstream services, that is, \( s_k^f = c_k^f \) for any online product \( k \). In other words, a carrier’s choice of upstream price for its codeshare product does not affect its choice of upstream price for its online product.

### 2.2.3 A Unified Supply Equation

We now generalize the notation to handle both product types in a market containing \( J \) products. Let the rows for the downstream margins be decomposed according to \( \left[ - (\Omega_r \ast \Delta_r)^{-1} \mathbf{d}(\mathbf{p}) \right]_{\text{Online}} \), and \( \left[ - (\Omega_r \ast \Delta_r)^{-1} \mathbf{d}(\mathbf{p}) \right]_{\text{Code}} \), where \( \left[ - (\Omega_r \ast \Delta_r)^{-1} \mathbf{d}(\mathbf{p}) \right]_{\text{Online}} \) only contains rows for online products, and \( \left[ - (\Omega_r \ast \Delta_r)^{-1} \mathbf{d}(\mathbf{p}) \right]_{\text{Code}} \) only contains rows for codeshare products. Further, let vector \( \mathbf{m}_d \) contain these two vectors stacked in a specific order as follows

\[
\mathbf{m}_d = \begin{pmatrix}
- (\Omega_r \ast \Delta_r)^{-1} \mathbf{d}(\mathbf{p})_{\text{Online}} \\
- (\Omega_r \ast \Delta_r)^{-1} \mathbf{d}(\mathbf{p})_{\text{Code}}
\end{pmatrix}
\]

Note that \( \mathbf{m}_d \) is a \( J \times 1 \) vector containing downstream margins.

Let \( \mathbf{m}_u \) be a \( J \times 1 \) vector containing upstream margins,

\[
\mathbf{m}_u = \begin{pmatrix}
\mathbf{0}_{\text{Online}} \\
- (\Omega_f^{\text{code}} \ast \Delta_f^{\text{code}})^{-1} \mathbf{d}(\mathbf{p})^{\text{code}}
\end{pmatrix}
\]
where \( 0_{\text{online}} \) is a vector of zeros with the same dimension as \([- (\Omega_r \ast \Delta_r)^{-1} \, d(p)]_{\text{online}} \), and

\[- \left( \Omega_{f,\text{code}} \ast \Delta_{f,\text{code}} \right)^{-1} \, d(p)_{\text{code}} \]

contains margins for upstream operating carriers involved in supplying codeshare products. Note that the margin functions depend on prices and demand parameters, that is, \( m_d(p; \alpha, \beta, \sigma) \) and \( m_u(p; \alpha, \beta, \sigma) \). However, in much of what follows we simply use \( m_d \) and \( m_u \) only for notational convenience. For example, overall price-cost margins in a market containing both types of products is given by

\[
p - c^T = m_d + m_u
\]

(14)

where \( c^T \) is a \( J \times 1 \) vector containing aggregate marginal costs for supplying each product.

Though less popular than the two types of products considered in the supply model, there exist more complicated products where a subset of the round-trip segments are codeshared and other segments are operated and marketed by distinct unaffiliated carriers. Even less popular in domestic air travel markets are products that have each of their trip segments operated and marketed by unaffiliated carriers. Unfortunately, the supply model in its current form cannot handle such complexity, and we must leave such supply modelling for future research and focus on the two product types discussed above.

Equation (14) can also be expressed as

\[
p = c^T + m_d + m_u
\]

(15)

Since equation (15) is only intended to approximate the true supply behavior of airlines, we should appropriately include a random component to this equation. In addition, we want to parameterize it in a manner that allows us to empirically test whether codeshare contracts eliminate one of the margins. These considerations result in the following empirical formulation of equation (15)

\[
p = \exp(W; \gamma) + \lambda_1 m_d + \lambda_2 m_u + \psi
\]

(16)

where \( c^T = \exp(W; \gamma) \), \( W \) is a vector of variables that shift marginal cost (itinerary distance, whether or not the origin is a hub for the carrier offering the product, whether or not the product is codeshare or online, airline dummies), \( \gamma \) is a vector of estimable parameters in the marginal cost function, \( \lambda_1 \) and \( \lambda_2 \) are estimable parameters that will tell us whether double marginalization is eliminated, and \( \psi \) is the random portion of the supply equation that captures unobserved
The main parameters of interest are $\lambda_1$ and $\lambda_2$. Codeshare contracts fail to eliminate double marginalization if $\lambda_1 > 0$ and $\lambda_2 > 0$. Conversely, these contracts successfully eliminate upstream margin if $\lambda_1 > 0$ and $\lambda_2 = 0$, while downstream margin is eliminated if $\lambda_1 = 0$ and $\lambda_2 > 0$. A comparison of equations (15) and (16) suggests that the empirical model fits the theoretical model perfectly if $\lambda_1 = 1$ whenever $\lambda_1 > 0$, and $\lambda_2 = 1$ whenever $\lambda_2 > 0$.

3 Estimation

The demand and supply parameters are estimated using Generalized Methods of Moments (GMM). All the parameters can either be estimated jointly or separately. We chose to estimate the demand parameters separately from the supply parameters via a two-step procedure. The demand parameters are estimated in the first step. These parameter estimates are then used to compute the downstream and upstream margin functions, $m_d(p; \hat{\alpha}, \hat{\beta}, \hat{\sigma})$ and $m_u(p; \hat{\alpha}, \hat{\beta}, \hat{\sigma})$. The supply parameters are estimated in the second step of the two-step procedure, where $m_d(p; \hat{\alpha}, \hat{\beta}, \hat{\sigma})$ and $m_u(p; \hat{\alpha}, \hat{\beta}, \hat{\sigma})$ are regressors in the supply equation.

Since details on the procedure to estimate the random coefficients discrete choice demand model laid out above are well documented in the empirical industrial organization literature [see Berry (1994), Berry, Levinsohn, and Pakes (1995), and Nevo (2000a)] we only briefly summarize here. The GMM estimates of the demand parameters are obtained by solving the following problem,

$$
\text{Min}_\alpha,\beta,\sigma \xi' Z_d \Phi_d^{-1} Z_d' \xi, 
$$

where $Z_d$ is the matrix of instruments that are assumed orthogonal to the error vector $\xi$, while $\Phi_d^{-1}$ is the standard weight matrix. Since the structural demand error is given by $\xi_{jt} = \delta_{jt} - (x_{jt}\beta - \alpha p_{jt})$, then we can see that $\alpha$ and $\beta$ enter the objective function linearly. By taking the first order condition of the objective function with respect to $\alpha$ and $\beta$ we can show that,

$$
\begin{pmatrix}
\beta \\
\alpha
\end{pmatrix} = (X_d' Z_d \Phi_d^{-1} Z_d' X_d)^{-1} X_d' Z_d \Phi_d^{-1} Z_d' \delta
$$

where $X_d$ is the design matrix containing $x_{jt}$ and $p_{jt}$. We can

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12 For a discussion of identification issues in empirical supply models intended to capture vertical relationships such as equation (16), see Villas-Boas and Hellerstein (2006).

13 The two-step estimation approach offers several advantages. First, the computational burden is significantly reduced compared to joint estimation [see Goldberg and Verboven (2001)]. Second, to the extent that the supply side may be misspecified, this would not affect the demand side results [see Goldberg and Verboven (2001)]. However, a possible disadvantage of the two-step procedure is that it is less efficient compared to joint estimation.

14 Recall that we suppressed $a_j$ for notational convenience and therefore interpret $\beta$ more broadly to include the coefficients on the airline dummies intended to capture $a_j$. 

11
then substitute the expression for \( \begin{pmatrix} \beta \\ \alpha \end{pmatrix} \) in the objective function and effectively concentrate the objective function in the unknown variable \( \delta_{jt} \).

For a given value of \( \sigma \), \( \delta_{jt} \) is the mean level of utility that makes the observed product shares, \( D_{jt} \), equal to the predicted product shares, \( d_{jt} \). That is, \( \delta_{jt} \) must be such that \( D_{jt} = d_{jt}(\delta_{jt}; \sigma) \).\(^{15}\) So in principle, for any assumed value for the parameter, \( \sigma \), we can compute the value of the objective function by first solving \( D_{jt} = d_{jt}(\delta_{jt}; \sigma) \) for \( \delta_{jt} \), then plugging \( \delta_{jt} \) into the objective function, \( \xi' Z_d \Phi^{-1}_d Z_d' \xi \). The optimization problem is thus structured so that minimization of \( \xi' Z_d \Phi^{-1}_d Z_d' \xi \) is performed just over \( \sigma \). When this optimization process is complete, we can then use \( \hat{\sigma} \) along with \( D_{jt} = d_{jt}(\delta_{jt}; \hat{\sigma}) \) and \( \begin{pmatrix} \beta \\ \alpha \end{pmatrix} = (X_d' Z_d \Phi^{-1}_d Z_d' X_d)^{-1} X_d' Z_d \Phi^{-1}_d Z_d' \delta \) to recover estimates of \( \alpha \) and \( \beta \).

Estimating the supply equation is much more straightforward. The error term for the supply equation is

\[
\psi_{jt} = p_{jt} - \exp(W_{jt}; \gamma) - \lambda_1 m_{djt} - \lambda_2 m_{wjt}.
\]

The GMM estimates of the supply parameters are obtained by solving the following problem,

\[
\min_{\gamma, \lambda_1, \lambda_2} \psi' Z_s \Phi^{-1}_s Z_s' \psi,
\]

where \( Z_s \) is the matrix of instruments that are assumed orthogonal to the error vector \( \psi \), while \( \Phi^{-1}_s \) is the standard weight matrix.

The asymptotic covariance matrix for the supply parameters ought to be corrected to account for the fact that the margins depend on the previously estimated demand parameters which effectively introduce additional variance in the supply parameter estimates. However, this correction is extremely complicated to implement because \( m_d(\cdot) \) and \( m_u(\cdot) \) are highly nonlinear functions of the demand parameters [see Villas-Boas (2003) and associated supplements]. As such, statistical inferences for the supply parameters are based on bootstrap confidence intervals rather than asymptotic standard errors.

A two-step process is used to compute the bootstrap confidence intervals. In the first step, we take \( L \) random draws of the taste variation parameters, \( \sigma \), assuming that \( \sigma \sim N(\hat{\sigma}, \text{var}(\hat{\sigma})) \) where \( \hat{\sigma} \) is the point estimate of \( \sigma \) obtained from the previously estimated demand model. For each draw of \( \sigma(l) \), we recover the corresponding \( \delta(l) \), \( \alpha(l) \) and \( \beta(l) \), using \( D_{jt} = d_{jt}(\delta_{jt}; \sigma) \) and \( \begin{pmatrix} \beta \\ \alpha \end{pmatrix} = (X_d' Z_d \Phi^{-1}_d Z_d' X_d)^{-1} X_d' Z_d \Phi^{-1}_d Z_d' \delta \).\(^{16}\)

\(^{15}\)See Berry, Levinsohn, and Pakes (1995) and Nevo (2000a) for details on numerical methods used to solve \( D_{jt} = d_{jt}(\delta_{jt}; \sigma) \) for \( \delta_{jt} \) in the case of the random coefficients logit model. I used their contraction mapping method in this paper.

\(^{16}\)Alternatively, each set of \( \sigma(l), \delta(l), \alpha(l) \) and \( \beta(l) \), could be obtained by making \( L \) random draws from the sample.
\( \mathbf{m}_{u(l)} \), are then computed for each set of \( \sigma(l), \delta(l), \alpha(l) \) and \( \beta(l) \). In other words, \( L \) sets of upstream and downstream margins are computed. In the second step of the two-step procedure, the supply parameters are estimated \( N \times L \) times by taking \( N \) random draws from the sample for each set, \( l \), of the margins. The \( N \times L \) sets of parameter estimates are then used to form confidence intervals of each supply parameter.\(^{17}\)

The first step of the two-step bootstrap procedure is necessary to capture the additional variance in the supply parameter estimates that is due to the previously estimated demand parameters. The second step follows the conventional sampling with replacement bootstrap technique.

### 3.1 Instruments

Since it is reasonable to assume that airlines take into account unobserved (to the researcher) product quality, \( \xi_{jt} \), when setting prices, then prices will depend on \( \xi_{jt} \). As such, the estimated coefficient on price will be inconsistent if appropriate instruments are not found for prices. Following much of the literature on discrete choice models of demand, we make the identifying assumption that observed product characteristics in \( x_j \) are uncorrelated with the unobserved product quality, \( \xi_{jt} \). Since airline dummies are included in the mean utility function, it is only the portion of product quality not specific to airlines that is captured in \( \xi_{jt} \). Hence, the identifying assumption seems reasonable.\(^{18}\)

The demand instruments include, (1) itinerary distance; (2) the squared deviation of a product’s itinerary distance from the average itinerary distance of competing products offered by other airlines; (3) the number of competitor products in the market; (4) the number of other products offered by an airline in a market.\(^{19}\) All these instruments are motivated by supply theory which predicts that equilibrium price will be affected by changes in marginal cost and changes in markup. For example, the marginal cost of servicing an itinerary is assumed to be a function of itinerary distance, while instruments (2) to (4) are assumed to influence the size of an airline’s markup on each of its products.\(^{20}\)

Instrument (2) is a measure of how closely substitutable an airline’s product is relative to its

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\(^{17}\)We use \( L = 50 \) and \( N = 100 \), so confidence intervals are formed using 5,000 sets of supply parameter estimates.

\(^{18}\)See Berry, Carnall, and Spiller (1997), Nevo(2000a), and Goldberg and Verboven (2001) for similar identifying assumptions.

\(^{19}\)Interactions of these variables are also included as instruments.

\(^{20}\)See Lederman (2003) for similar instruments in this context.
competitors’ products. The smaller the deviation a product’s itinerary distance is from other products in the same market, the closer substitute it is for competing products and the smaller the markup an airline is able to charge on the product. Instrument (3) is a measure of the level of competition an airline’s product faces. The greater the number of competing products, the lower the markup an airline is able to charge on the product, ceteris paribus. Instrument (4) exploits the fact that a multi-product firm is able to charge a higher markup on each of its competing products relative to the case where these competing products are each produced by distinct competitors.

Even though it is reasonable and correct to argue that instruments (2) to (4) are strategic choices of an airline and therefore they are not strictly exogenous, we justify them as valid instruments on the grounds that these strategic choices are made prior to price competition. Since the empirical model is intended to capture short-run price competition, instruments (2) to (4) are effectively predetermined variables and therefore valid instruments.

Recall that the error term in the supply equation, $\psi_{jt}$, captures unobserved determinants of price. As such, the margin terms, $m_{djt}$ and $m_{ujt}$, are likely to be correlated with $\psi_{jt}$ in the supply equation. Based on the discussion of the validity of instruments used in the demand equation, instruments (2) to (4) above are also valid for the supply equation. In addition, non-price product characteristics in the demand equation that do not enter the supply equation (e.g. number of an airline’s daily departures from an origin city) are included as instruments for the supply equation. Again, identification rests on the assumption that non-price product characteristics are predetermined, that is, an airline chooses the number of daily departures, its routing between an origin and destination city (itinerary convenience) etc. prior to price competition.

4 Data

The data set is drawn from the Origin and Destination Survey (DB1B), which is a 10% sample of airline tickets from reporting carriers. This database is maintained and published by the U.S. Bureau of Transportation Statistics. Some of the items included in DB1B are, number of passengers that chose a given flight itinerary, fares of these itineraries, the specific sequence of airport stops each itinerary uses in getting passengers from the origin to destination city, and distance flown on each itinerary in a directional market. The distance associated with each itinerary in a market may

\[\text{Since itinerary distance is included in the marginal cost function, it cannot instrument for the margin terms in the supply equation.}\]
differ since each itinerary may use different connecting airports in transporting passengers from the origin to destination city. The data we use link each product to a directional market rather than a mere non-stop route or segment of a market. For this research, we focus on the U.S. domestic market in the first quarter of 2004.

To arrive at the final sample used for estimation, we imposed several restrictions on the original data set. First, following much of the empirical literature on the airline industry, we focussed on round-trip rather than one way itineraries. Second, itineraries with price less than $100 are excluded due to the high probability that these may be coding errors when constructing the database. Third, we focus on codeshare and online products as defined previously. Thus, we do not consider complicated products where a subset of the trip segments are codeshared while other segments are operated by unaffiliated carriers.

After applying the above restrictions, the data is then collapsed by averaging the price and aggregating the number of passengers purchasing products as defined by itinerary-airline(s) combination. In other words, before the data is collapsed, there are several observations of a given itinerary-airline(s) combination that are distinguished by prices paid and number of passengers paying each of those prices. Last, markets remained in the final data set only if more than 5% of the products are codeshared. In light of the estimation techniques and objectives of the paper, this filter is necessary to obtain a sample size that is not larger enough to make estimation infeasible, while ensuring that the sample has sufficient identifying information across product types in each market. The resulting sample used in estimation covers 155 markets and has 4,559 observations.

The observed product characteristics are, "Price", "Hub", "Departures", "Convenient", "Codeshare", while airline dummies are used to control for a portion of unobserved product fixed effects. "Price" is the mean fare of a given itinerary-airline(s) combination, "Hub" is a dummy that takes the value 1 if the origin airport is a hub for the carrier offering the product and 0 otherwise, "Departures" is the average number of scheduled daily departures from the origin airport throughout the previous year for the carrier offering the product, "Convenient" is the ratio of itinerary distance to the non-stop distance between the origin and destination airports, and "Codeshare" is a dummy taking the value 1 if the product is codeshared, and 0 otherwise. "Convenient" takes a value of 1

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22 The simulation-based estimation procedure required for estimating the demand model is difficult to perform on large data sets.
23 For example, since online product is the most popular product type, with little or no codeshare products in a number of markets it is not possible to estimate whether consumers perceive a difference between online and codeshare products.
when the itinerary uses a single non-stop flight between the origin and destination city. Thus, an itinerary is presumed to be less convenient the further its "Convenient" measure is from 1.

Some defining characteristics of the data are as follows. 25.3% of the products are codeshared, while the remaining products are online. For 44.4% of the codeshare products, the upstream operating carrier also offers their own competing online products in the same market. The 25\textsuperscript{th}, 50\textsuperscript{th}, and 75\textsuperscript{th} percentile of the "Convenient" variable is almost identical for codeshare and online products, (1.03, 1.13, 1.34) and (1.01, 1.10, 1.33) respectively. Additional summary statistics are reported in table 1.

Table 1

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Price</th>
<th>HUB</th>
<th>Codeshare</th>
<th>Convenient</th>
<th>Departures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>263.33</td>
<td>0.32</td>
<td>0.25</td>
<td>1.23</td>
<td>63.71</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>181.59</td>
<td>0.47</td>
<td>0.43</td>
<td>0.30</td>
<td>88.60</td>
</tr>
<tr>
<td>n = 4,559</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Level of observation is itinerary-airline(s) combination.

5 Results

We first discuss the demand estimates and then the supply estimates. The main conclusions are drawn from the supply estimates.

5.1 Demand

The coefficient estimates for the demand model are displayed in table 2. The first data column reports the mean marginal (dis)utility for each product characteristic (\(\alpha\), and \(\beta\)), while the coefficients in the third data column measures the variation in taste for each product characteristic, (\(\sigma\)). The estimates suggest that, on average, passengers are less likely to choose a flight itinerary the higher its price. Second, they are more likely to choose hub rather than non-hub products. It has been suggested that owing to frequent flyer programs, hub airlines might have more brand loyal customers at their hub airports which explains the positive coefficient on "Hub" [Berry, Carnall, and Spiller (1997)]. Third, as expected, they prefer itineraries that are more convenient and use a less circuitous route in traveling from the origin to destination city [Gayle (2005a)]. Fourth, the negative coefficient on the codeshare dummy suggests that passengers perceive codeshare products
as an inferior substitute to online products. Since a codeshare product requires that a passenger change airlines on a given trip, one explanation for the fourth result is that partner airlines have not been able to make passengers transition across airlines seamless, thus resulting in codeshare products being inferior substitutes for online products. Last, the taste variation parameters suggest that passenger’s are most heterogenous with respect to their taste for convenience and codeshare itineraries.

### Table 2
Estimates for Demand Model

<table>
<thead>
<tr>
<th></th>
<th>Means ((\alpha, \beta))</th>
<th>Taste Variation (Diagonal elements in (\Sigma))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Standard Error</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.09*</td>
<td>0.286</td>
</tr>
<tr>
<td>Price</td>
<td>-10.22*</td>
<td>0.180</td>
</tr>
<tr>
<td>Hub</td>
<td>0.22*</td>
<td>0.003</td>
</tr>
<tr>
<td>Departures</td>
<td>-0.28*</td>
<td>0.003</td>
</tr>
<tr>
<td>Convenient</td>
<td>-1.78*</td>
<td>0.230</td>
</tr>
<tr>
<td>Codeshare</td>
<td>-2.13*</td>
<td>0.169</td>
</tr>
<tr>
<td>GMM Obj.</td>
<td>3.88E-05</td>
<td></td>
</tr>
<tr>
<td>Overidentification Test</td>
<td>(n = 4,559)</td>
<td>(n \times \text{GMM Obj.} = 0.177)</td>
</tr>
</tbody>
</table>

Notes: * indicates statistical significance at the 5% level. Airline dummies are included when estimating the model even though these coefficient estimates are not reported.

The negative coefficient on the "Departures" variable was unexpected since it suggests that passengers are less likely to choose a product offered by an airline with a large number of daily departures out of the origin airport in the previous year, ceteris paribus. The reason we considered including "Departures" is that we thought it would be less noisy and do a better job than the "Hub" dummy in capturing the larger demand that hub-airlines may have at their hub airports. However, the "Hub" dummy seems to have captured the expected effect sufficiently well which makes the significant explanatory power of the "Departures" variable even more perplexing. Further, the significant explanatory power of the "Departures" variable makes it difficult to justify throwing it out since it might be capturing an effect that we are yet to fully understand.\(^{24}\)

\(^{24}\)I also estimated the demand model without the "Departures" variable and the only difference in the qualitative results is that the coefficient on "Hub" became negative. This suggests that whatever effect the "Departures"
5.2 Supply

The supply model is first estimated on the full sample. Coefficient estimates and their corresponding bootstrap confidence intervals\(^{25}\) are reported in Table 3. All the marginal cost-shifting variables are statistically significant at conventional levels. First, we have the intuitively appealing result that marginal cost increases with itinerary distance. Second, the sign of the coefficient on the "codeshare" dummy uncovers a new result about codesharing. The negative coefficient suggests that, on average, codeshare products have a lower marginal cost relative to online products, *ceteris paribus*. While the existing literature has recognized that codesharing likely yields cost savings since alliance partners often jointly use each others facilities (lounges, gates, check-in counters etc.), and may also practice joint purchase of fuel [see Bamberger, Carlton, and Neumann (2001)], the marginal cost of these products have not been compared to comparable online products.\(^{26}\) In other words, irrespective of whether or not codeshare contracts eliminate double marginalization, the explicit marginal cost comparison done here allows us to see that airlines have an incentive to form codeshare alliances and offer codeshare products even in markets where they currently offer their own online service. This result highlights the importance of using an econometric model that has the ability to separate the effects of marginal cost from markup behavior on equilibrium price.

<table>
<thead>
<tr>
<th>Table 3 Estimates for Supply Model (Full Sample(^a))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coefficient Estimates</strong></td>
</tr>
<tr>
<td><strong>95% Confidence Intervals</strong></td>
</tr>
<tr>
<td><strong>99% Confidence Intervals</strong></td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Hub</td>
</tr>
<tr>
<td>Distance</td>
</tr>
<tr>
<td>Codeshare</td>
</tr>
<tr>
<td>(\hat{\lambda}_1)</td>
</tr>
<tr>
<td>1.62</td>
</tr>
<tr>
<td>(\hat{\lambda}_2)</td>
</tr>
<tr>
<td>0.94</td>
</tr>
<tr>
<td>GMM Obj.</td>
</tr>
<tr>
<td>Overidentification Test (n = 4,559) (n \times) GMM Obj. = 0.0006 (\chi^2(0.95,5) = 11.07)</td>
</tr>
</tbody>
</table>

Notes: The bootstrap confidence intervals are based on 5,000 point estimates for each parameter. See section 3 for details on the bootstrap procedure. Airline dummies are included when estimating the model even though these coefficient estimates are not reported.

\(^a\) The full sample contains 3,405 online products and 1,154 codeshare products.

\(^{25}\) As discussed in section 3, the bootstrap methodology is preferable since the correct asymptotic covariance matrix for the supply equation is difficult to compute given that the margin variables are highly non-linear functions of the demand parameters.

\(^{26}\) See Chua, Kew, and Yong (2003) for an analysis of potential cost savings from codeshare alliances.
An unexpected result is the positive coefficient on the "Hub" dummy in the marginal cost function, suggesting that marginal cost is higher for airlines offering products out of their hub airport. This is unexpected since airlines normally channel a significant number of passengers through their hubs, which should serve to exploit potential economies of density [see Berry, Carnal, and Spiller (1997)]. However, with the recent success of "low-cost" carriers in challenging traditional hub and spoke carriers at their hub cities, this result might be suggesting that the hub and spoke carriers might be less able to exploit economies of density.

We are most interested in the estimates of $\lambda_1$ and $\lambda_2$. The confidence intervals suggest that both $\lambda_1$ and $\lambda_2$ are statistically different from zero. In other words, on average, codeshare contracts have not eliminated double marginalization. While $\lambda_1$ is slightly greater than 1, $\lambda_2$ is not statistically different from 1. Since theoretically we expect $\lambda_1 = \lambda_2 = 1$ in the case where double marginalization is not eliminated, the estimates come remarkably close to our theoretical expectation.

In an attempt to understand what may be driving the results, we organize the data into two sub-samples. Both sub-samples include the online products, but upstream operating carriers of the codeshare products in one sub-sample also offered online products in the said market ("integrated" case),27 while upstream carriers of the codeshare products in the other sub-sample did not offer online products in the said market ("unintegrated" case). These sub-samples allow us to explore whether elimination of double marginalization depends on whether or not the upstream operating carrier is also a downstream competitor in the market. The idea is that the strategic incentives of an upstream operating carrier of a codeshare product who also offers its own online product in the said market is likely to differ from an upstream operating carrier that does not offer its own competing online product. This is analogous to comparing the strategic incentives of a vertically integrated firm to an unintegrated upstream firm.

The theoretical literature on vertical integration argues that, unlike an unintegrated upstream firm, a vertically integrated firm has the incentive to raise the input cost of downstream rivals by charging a higher price for inputs sold to downstream rivals. This has the impact of increasing

27 Almost half (44.4%) of the 1,154 codeshare products satisfied this criterion.
the competitive advantage of the downstream operations of the integrated firm [see Riordan and Salop (1995), Ordover, Saloner, and Salop (1992), Chen (2001), Choi and Yi (2000)]. Therefore, upstream operating carriers of codeshare products who also offer online products in the said market may optimally choose not to eliminate the upstream margin for their codeshare products. In this case, the price of these codeshare products are likely to be determined by marginal cost, downstream margin, and upstream margin. The parameter estimates when the supply model is estimated on each sub-sample are reported in tables 4A and 4B.

<table>
<thead>
<tr>
<th>Table 4A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates for Supply Model</td>
</tr>
<tr>
<td>Sample includes only online and “unintegrated” codeshare products. a</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Coefficient Estimates</th>
<th>95% Confidence Intervals</th>
<th>99% Confidence Intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-3.22</td>
<td>-5.19,-2.33</td>
<td>-6.025,-1.971</td>
</tr>
<tr>
<td>Hub</td>
<td>0.81</td>
<td>0.63,1.06</td>
<td>0.567,1.167</td>
</tr>
<tr>
<td>Distance</td>
<td>0.77</td>
<td>0.59,1.01</td>
<td>0.544,1.078</td>
</tr>
<tr>
<td>Codeshare</td>
<td>-32.18</td>
<td>-156.82,-0.90</td>
<td>-261.68,-0.237</td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>1.66</td>
<td>1.45,1.85</td>
<td>1.369,1.897</td>
</tr>
<tr>
<td>( \lambda_2 )</td>
<td>0.67</td>
<td>0.29,0.92</td>
<td>-0.004,0.995</td>
</tr>
<tr>
<td>GMM Obj.</td>
<td>1.28E-07</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overidentification Test

\( n = 4,047 \)
\( n \times \text{GMM Obj.} = 0.0005 \)
\( \chi^2(0.95,5) = 11.07 \)

Notes: The bootstrap confidence intervals are based on 5,000 point estimates for each parameter. See section 3 for details on the bootstrap procedure. Airline dummies are included when estimating the model even though these coefficient estimates are not reported.

a Of the 1,154 codeshare products, 642 are unintegrated.
First, the qualitative results for the cost-shifting variables obtained in the full sample (see table 3) are robust across sub-samples. Second, table 4A reveals that the point estimate of $\lambda_2$ is closer to zero when the upstream carrier is "unintegrated". In fact, based on the 99% confidence interval, we cannot reject the possibility that $\lambda_2$ may be zero in the sub-sample where upstream carriers are "unintegrated". However, in table 4B where upstream carriers are "integrated" into the downstream market, $\lambda_2$ is unambiguously greater than zero. $\lambda_1$ is statistically greater than zero across both sub-samples. The sub-sample analyses suggest that double marginalization pricing behavior is robust for codeshare products where the upstream operating carrier also offers online products in the said market. However, this pricing behavior is weak when the upstream carrier of the codeshare product is unintegrated. Thus codeshare contracts may eliminate the upstream margin in the case where the upstream carrier does not offer online products in the said market. This result was masked in the full sample estimates.

6 Conclusion

Using a structural econometric model, this paper investigated whether codeshare contracts eliminate double marginalization that exists when unaffiliated airlines independently determine the price.
for different segments of an interline trip. The results suggest that codeshare contracts may eliminate upstream margin leaving marginal cost and downstream margin as the determinants of price. However, the elimination of the upstream margin depends crucially on whether the upstream operating carrier also offers competing online products in the said market. Specifically, the vertical codeshare contract seems not to eliminate the upstream margin when the upstream operating carrier also offers competing online products. This result is consistent with the theoretical literature on vertical integration which argues that, unlike an unintegrated upstream firm, a vertically integrated firm has the incentive to raise the input cost of downstream rivals by charging a higher price for inputs sold to downstream rivals. This has the impact of increasing the competitive advantage of the downstream operations of the integrated firm.

The results also suggest that, on average, codeshare products have a lower marginal cost relative to online products, *ceteris paribus*. Since double marginalization is not eliminated when the upstream operating carrier also offers competing online products in the said market, it is likely that the potential cost savings from codesharing might be the most important stimulus for airlines to codeshare in these markets.

As this paper only constitutes a first attempt at an explicit empirical analysis of the vertical aspects of airline codesharing, there are several ways in which future research may build upon the model and the issues explored in this paper. For example, the supply side of the model in its current form is unable to handle air travel products that have a subset of their trip segments codeshared while the other segments operated by unaffiliated carriers. Second, the model in its current form does not capture products that have each trip segment operated and marketed by unaffiliated carriers. Modifying the supply model to capture these types of products may prove to be extremely useful if the model is used to study international air travel markets where these products are more popular. Thus another possible extension to this research is to use the model to study international air travel markets where codeshare partners are distinct national carriers and less likely to offer competing online services in the said market.
Appendix 1: Derivation of $\Delta_p$.

Identical to derivation process outlined in Villas-Boas (2003), we start with a first-order condition for a downstream firm. Recall that the downstream first-order condition for a codeshare product is given by

$$
d_j(p) + \sum_{k \in F_r} \left( p_k - s^f_k - c^r_k \right) \frac{\partial d_k(p)}{\partial p_j} = 0
$$

(19)

If we totally differentiate equation (19) with respect to all final prices and an upstream price, $s^f_n$, then

$$
\sum_{k=1}^J \left\{ \frac{\partial d_j}{\partial p_k} + \sum_{m=1}^J \left[ \Omega_r(m, j) \frac{\partial^2 d_m}{\partial p_j \partial p_k} \left( p_m - s^f_m - c^r_m \right) \right] + \Omega_r(k, j) \frac{\partial d_k}{\partial p_j} \right\} dp_k - \Omega_r(n, j) \frac{\partial d_n}{\partial p_j} ds^f_n = 0
$$

(20)

where $k$, $j$, $m$, and $n$ are all indexing products. Let $G$ be a $J \times J$ matrix with elements $g(j, k)$, where

$$
g(j, k) = \left\{ \frac{\partial d_j}{\partial p_k} + \sum_{m=1}^J \left[ \Omega_r(m, j) \frac{\partial^2 d_m}{\partial p_j \partial p_k} \left( p_m - s^f_m - c^r_m \right) \right] + \Omega_r(k, j) \frac{\partial d_k}{\partial p_j} \right\}.
$$

Note that matrix $G$ requires computing second order derivatives of the demand function, $\frac{\partial^2 d_m}{\partial p_j \partial p_k}$. Since $\left( p_m - s^f_m - c^r_m \right)$ can be expressed exclusively in terms of demand parameters [see equation (8)], matrix $G$ does not require information on upstream prices or marginal costs.

Let $H_n$ be a $J$-dimensional column vector with elements $h(n, j)$, where $h(n, j) = \Omega_r(n, j) \frac{\partial d_n}{\partial p_j}$. For a given upstream price $s^f_n$, equation (20) is computed for each of the $J$ products. Given the above definitions for $G$ and $H_n$, these $J$ equations can be compactly represented by

$$
G \, dp - H_n \, ds^f_n = 0
$$

or

$$
\frac{dp}{ds^f_n} = G^{-1} H_n
$$

(21)

$\frac{dp}{ds^f_n}$ is a $J \times 1$ derivative vector where the $j^{th}$ element tells us how the final price of product $j$ changes as a result of a change in the upstream price of product $n$. The $J \times J$ matrix, $\Delta_p$, is obtained by stacking all $J$ derivative vectors (one for each product $n$), $\frac{dp}{ds^f_n}$, together.
References


