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

A number of empirical papers on airline codesharing have generally found that a reduction in airfares is associated with airline codesharing [Brueckner and Whalen (2000); Brueckner (2003); Bamberger, Carlton, and Neumann (2004); Ito and Lee (2007)]. However, much work is needed to better understand reasons why airline codesharing might be associated with lower airfares. One reason for the price reducing effect of codesharing that has been suggested in the literature is that 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(2001); Brueckner (2003); Ito and Lee (2007)]. Even though there is 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. 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.[1] As such, this paper focuses on traditional codesharing, and in what follows, codesharing should be interpreted in the traditional context.

Since codesharing combines the operating services of at least two separate carriers, where only

[1]See Ito and Lee (2007) for a detailed discussion of "Virtual" codesharing versus "Traditional" codesharing and airlines' incentives for engaging in each type. See Gayle(2007b) for an empirical investigation of the primary motive for "Virtual" codesharing.

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.[2] 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.

Why is it natural to expect a codeshare agreement to eliminate double marginalization? In the absence of an agreement between two carriers of an interline trip, each carrier chooses its fare to maximize its own profit on the segment of the trip it operates. In so doing, each carrier does not take into account the marginal profit of the unaffiliated complementary carrier on the interline trip, which results in an un-internalized externality much like the well-known vertical externality that sometimes arise between manufacturers and retailers.[3] By forming a codeshare agreement, the complementary carriers have an opportunity to negotiate a pricing contract[4] among themselves that potentially internalizes the externality and maximizes their joint profit.[5] Therefore, it is the opportunity to negotiate a pricing contract that maximizes the codeshare partners' joint profit, as oppose to noncooperative individual profit maximization in the absence of a codeshare agreement, which makes it natural to expect that such agreements will eliminate double marginalization.

Chen and Gayle (2007) present a formal theoretical analysis of codeshare contracting between airlines in which they identify circumstances in which the equilibrium contract between partner airlines may not eliminate the double markup. They argue that if no codeshare partner offers their

[2] It is important to note that I am defining the "upstream" carrier of a codeshare product as the pure operating carrier which might not be the carrier that the passenger boards first on the interline trip. Likewise, I refer to the ticketing carrier of a codeshare product as the "downstream" carrier even though the passenger could have boarded the ticketing carrier's plane first on the interline trip. In other words, throughout this paper "upstream" versus "downstream" is unrelated to the order in which a passenger uses partner airlines on a given interline trip.

[3] See pp. 174 in Tirole (1988) for a detail discussion of the basic vertical externality between manufacturers and retailers. For a discussion of similar externalities in the context of codeshare agreements see Brueckner (2003).

[4] Details on what constitute a pricing contract are given in the section where I outline the supply side of the model. Basically I define such a contract to include a per passenger price that the ticketing carrier must pay the upstream/pure operating carrier for operating services on a complementary trip segment needed for the interline trip, and a potential fixed transfer between partners which determines how the joint surplus is distributed.

[5] It must be noted that contract details on how partner airlines compensate each other on codeshare trips are not usually available to the public. The extent of what is known publicly is that the ticketing carrier typically sets the price for the entire round-trip and then compensates partner operating carriers for services provided on complementary trip segments.

own competing single-carrier[6] product in the concerned market, then the equilibrium codeshare contract indeed leads to true marginal cost pricing for the intermediate good (the upstream/pure operating carrier's trip segment); otherwise codesharing does not eliminate double marginalization. The intuition is that when the partners negotiate a price contract to maximize their joint profit, if the upstream/pure operating carrier also offers its own competing single-carrier product in the same market, this carrier has added incentive to raise final product prices indirectly by raising the price of its trip segment for the codeshare product. Such strategic behavior by the upstream/pure operating carrier effectively serves to soften downstream competition for its own single-carrier product.

My main empirical result mirrors the above theoretical prediction by Chen and Gayle. I find 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-carrier 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 empirical 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 empirical result may also be linked to one strand of the theoretical literature on vertical integration which predicts that under some circumstances 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 [Ordover, Saloner, and Salop (1992); Riordan and Salop (1995); Choi and Yi (2000); Chen (2001)].[7] However, an explicit modelling of these incentives of a vertically integrated firm is beyond the scope of the empirical model used in this paper.

While this paper may be the first to use a structural econometric model to investigate whether codesharing indeed leads to more efficient vertical pricing by eliminating double marginalization, it is not the first to present evidence suggesting that double marginalization might not be fully eliminated from codeshare products. In particular, Ito and Lee (2007) found that even though

[6] A 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.

[7] Vertical pricing issues of this nature also arise in the railroad industry. For example, Burton and Wesley (2006) provide evidence consistent with railroad firms use of vertical exclusion pricing. Grimm, Winston, and Evans (1992) estimate the welfare loss to shippers if a vertically integrated railroad firm forecloses competition from non-integrated railroad firms.

"traditional" codeshare products are roughly 11.6% less expensive than non-allied interline products, the said codeshare products are 6.4% more expensive than single-carrier[8] products in the same market.[9] The idea is that single-carrier products by definition do not have double marginalization and therefore if competing codeshare products do not have double marginalization their prices should not systematically differ from single-carrier products. In other words, since Ito and Lee found "traditional" codeshare products to be priced higher than competing single-carrier products, *ceteris paribus*, a reasonable interpretation of this finding is that double marginalization is not eliminated from "traditional" codeshare products. My findings go a step further to suggest why double marginalization might not be eliminated from some "traditional" codeshare products.

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 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, I outline a model of demand and supply of air travel. I start with the demand side which is modeled within a discrete choice framework. I 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

[8]What I refer to as single-carrier here, Ito and Lee refer to as "pure online". These are products that are operated and marketed by a single carrier.

[9]Ito and Lee go on to compare the prices of "virtual" codeshare products to the prices of single-carrier products. They found that "virtual" codeshare products are priced even lower than single-carrier products. The primary focus of their paper is to explain why "virtual" codeshare products are priced even lower than single-carrier products.

products explicitly included in the model are "online"[10] 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 I 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

$$\underset{j \in \{0,\ldots,J_t\}}{Max} \left\{ U_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + a_j + \xi_{jt} + \varepsilon_{ijt} \right\}, \tag{1}$$

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), β_i is a vector of individual-specific consumer taste parameters (assumed random) for different product characteristics, p_{jt} is the price, α_i represents individual-specific marginal utility of price, a_j are firm fixed effects (airline dummies) capturing characteristics of the products that are the same across markets, ξ_{jt} is the level of unobserved product quality, and ε_{ijt} is a mean zero random component of utility.

Following much of the discrete choice demand literature [see Nevo(2000a)], ε_{ijt} is assumed to 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

$$d_{jt}(x_{jt},\ p_{jt};\ \alpha,\ \beta,\ \sigma) = \int \frac{e^{\delta_{jt}+\mu_{ijt}}}{1 + \sum\limits_{l=1}^{J} e^{\delta_{lt}+\mu_{ilt}}} dF(\nu), \tag{2}$$

where δ_{jt} is the mean utility obtained from product j, μ_{ijt} is an individual-specific deviation from the mean utility level which depends on individuals' taste for each product characteristic, σ is a

[10] Virtual 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.

vector of taste parameters that enters the share function nonlinearly through μ_{ijt}, and $F(\cdot)$ is the standard normal distribution function. As is well known in the empirical industrial organization literature, there is no closed-form solution for equation (2) and thus it must be approximated numerically using random draws from $F(\nu)$. The numerical approximation yields the following predicted simulated product share function,

$$d_{jt} = \frac{1}{ns}\sum_{i=1}^{ns}\frac{e^{\delta_{jt}+\mu_{ijt}}}{1+\sum\limits_{l=1}^{J}e^{\delta_{lt}+\mu_{ilt}}}, \tag{3}$$

where ns is the number of random draws from $F(\cdot)$.[11]

Given a market size of measure M, which I assume to be 10% of the size of the population in the origin city,[12] *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 I describe how *observed* and *predicted* product market shares are used in estimation.

2.2 Supply

In this subsection, I 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

We may think of a codeshare agreement as a privately negotiated pricing contract between partners (s, T), where s is a per passenger price the ticketing carrier pays to an upstream operating carrier for their services needed to complete the trip, while T represents a potential fixed transfer between the partners which determines how the joint surplus is distributed. In what follows, only the level of s affects equilibrium final product prices. The equilibrium value of T depends on specific assumptions on the bargaining process. However, for the purposes of this paper I am not concerned how the surplus is distributed between partners through the fixed transfer T.[13] This modeling approach is a

[11] I use $ns = 1,000$.

[12] 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, my market size definition seems reasonable. However, I also experiment with different market size definitions to ensure that results are robust to changes in the market size definition.

[13] See Chen and Gayle (2007) for a similar theoretical modeling approach.

simplification of codeshare agreements since airlines may actually use more complicated mechanisms to compensate each other on codeshare flights. Specific compensation mechanisms actually used by partner airlines are not usually made known to the public and may even vary across partnerships. The extent of what is commonly known is that the ticketing carrier markets and sets the final price for the round-trip ticket and compensates the operating carrier for operating services provided on complementary trip segments. Therefore, the simplistic modeling approach of using (s, T) to represent a codeshare contract captures our basic understanding of what is commonly known without imposing too much structure on a contracting process we have little facts about.[14]

To obtain an empirical model that allows for double marginalization I assume that the price of codeshare products are determined within a sequential price setting game. In this game the upstream operating carrier (pure operating carrier) first sets the price for their segment of the trip, s, then the downstream ticketing carrier sets the final round-trip price p 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.

In what follows, I suppress the market index t only to avoid a clutter of subscripts. Therefore, when I 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 $\mathcal{F}_r$ 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

$$\begin{aligned} \Pi_r &= \sum_{j \in \mathcal{F}_r} (p_j - s_j^f - c_j^r) q_j \\ &= \sum_{j \in \mathcal{F}_r} (p_j - s_j^f - c_j^r) M \cdot d_j(\mathbf{p}), \end{aligned} \tag{4}$$

where $d_j(\mathbf{p})$ is market share of product j, $\mathbf{p}$ represents a vector of final prices, c_j^r is the constant marginal cost carrier r incurs in providing the services necessary to offer product j,[15] and as defined

[14] It is indeed possible that some partners may use some mileage-based prorate mechanism to determine compensation on codeshare flights, but to the best of my knowledge there is no evidence on how widespread this mechanism is used. Explicitly modeling such a compensation mechanism may be a fruitful topic for future research.

[15] Since the ticketing carrier also supply operating services for a portion of the trip, then c_j^r includes per unit operating expenses.

previously s_j^f 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:

$$d_j(\mathbf{p}) + \sum_{k \in \mathcal{F}_r} \left(p_k - s_k^f - c_k^r \right) \frac{\partial d_k(\mathbf{p})}{\partial p_j} = 0. \tag{5}$$

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

$$\Omega_r(k,j) = \begin{cases} 1 & \text{if there exist } r : \{k,j\} \subset \mathcal{F}_r \\ 0 & \textit{otherwise.} \end{cases}$$

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

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

$$\mathbf{d}(\mathbf{p}) + (\Omega_r * \triangle_r) \left(\mathbf{p} - \mathbf{s}^f - \mathbf{c}^r \right) = \mathbf{0}$$

or

$$\mathbf{p} - \mathbf{s}^f - \mathbf{c}^r = -\left(\Omega_r * \triangle_r \right)^{-1} \mathbf{d}(\mathbf{p}), \tag{6}$$

where $\mathbf{d}(\cdot)$, $\mathbf{p}$, $\mathbf{s}^f$, and $\mathbf{c}^r$ are $J \times 1$ vectors of product market shares, final prices, upstream operating carrier prices, and ticketing carriers' marginal cost respectively, while $\Omega_r * \triangle_r$ is an element by element multiplication of two matrices. Note that equation (6) 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 (6), I now turn to the problem of the upstream operating carriers. Let $\mathcal{S}_f$ be a subset of the J products to which carrier f supply pure operating services. Again, I allow carriers to offer pure operating services to multiple products. Given that final prices are a function of upstream prices via equation (6), then product market shares are also a function of upstream prices, that is, $d_j(\mathbf{p}(\mathbf{s}^f))$. Knowing that ticketing carriers behave according to equation (6), each upstream operating carrier solves the following problem:

$$\underset{s_j^f}{Max} \sum_{j \in \mathcal{S}_f} (s_j^f - c_j^f) M \cdot d_j(\mathbf{p}\left(\mathbf{s}^f\right)), \tag{7}$$

where c_j^f 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_j^f for any product j must satisfy the first-order condition:

$$d_j + \sum_{k \in \mathcal{S}_f} \left(s_k^f - c_k^f\right) \frac{\partial d_k}{\partial s_j^f} = 0. \tag{8}$$

Just as above, I 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, I can also conveniently represent the first-order conditions for the pure operating carriers in matrix notation. Let Ω_f be a $J \times J$ matrix which describes the pure operating carriers' ownership structure of the J products. Further, let $\Omega_f(j,k)$ represent an element in the Ω_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 pure operating carriers may differ.

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

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

or

$$\mathbf{s}^f - \mathbf{c}^f = -\left(\Omega_f * \triangle_f\right)^{-1} \mathbf{d}(\mathbf{p}), \tag{9}$$

where $\mathbf{d}(\cdot)$, $\mathbf{s}^f$, and $\mathbf{c}^f$ are $J \times 1$ vectors of market shares, pure operating carriers' prices, and pure operating carriers' marginal cost respectively, while $\Omega_f * \triangle_f$ is an element by element multiplication of two matrices. Note that equation (9) expresses the pure 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 $\triangle_p(k,j) = \frac{\partial p_j}{\partial s_k^f}$. 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 $\triangle_p$.[16] In the appendix, I 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, I sum equations (6) and (9), which yields:

$$\mathbf{p} - \mathbf{c}^r - \mathbf{c}^f = -\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p}) - \left(\Omega_f * \triangle_f\right)^{-1} \mathbf{d}(\mathbf{p}). \tag{10}$$

Note that equation (10) 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 (6)) is unchanged and apply to all products, while the new upstream equation for codeshare products is:

$$\mathbf{s}^f - \mathbf{c}^f = -\left(\Omega_f^{code} * \triangle_f^{code}\right)^{-1} \mathbf{d}(\mathbf{p})^{code}, \tag{11}$$

where Ω_f^{code} and $\triangle_f^{code}$ are square matrices containing the rows and columns of Ω_f and $\triangle_f$ which correspond to codeshare products, and $\mathbf{d}(\mathbf{p})^{code}$ 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 (11), plus the corresponding downstream markup, captured by equation (6), while online products only have a downstream markup.

[16] It turns out that obtaining matrix $\triangle_p$ is not a simple task (see Villas-Boas 2003).

The reason why rows and columns of Ω_f^{code} and $\triangle_f^{code}$ 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

I 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 $\left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Online}$ and $\left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Code}$, where $\left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Online}$ only contains rows for online products, and $\left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Code}$ only contains rows for codeshare products. Further, let vector $\mathbf{m}_d$ contain these two vectors stacked in a specific order as follows:

$$\mathbf{m}_d = \begin{pmatrix} \left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Online} \\ \\ \left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Code} \end{pmatrix}.$$

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,

$$\mathbf{m}_u = \begin{pmatrix} \mathbf{0}_{online} \\ \\ -\left(\Omega_f^{code} * \triangle_f^{code}\right)^{-1} \mathbf{d}(\mathbf{p})^{code} \end{pmatrix},$$

where $\mathbf{0}_{online}$ is a vector of zeros with the same dimension as $\left[-\left(\Omega_r * \triangle_r\right)^{-1} \mathbf{d}(\mathbf{p})\right]_{Online}$, and $-\left(\Omega_f^{code} * \triangle_f^{code}\right)^{-1} \mathbf{d}(\mathbf{p})^{code}$ contains margins for upstream operating carriers involved in suppling codeshare products. Note that the margin functions depend on prices and demand parameters, that is, $\mathbf{m}_d(\mathbf{p};\alpha, \beta, \sigma)$ and $\mathbf{m}_u(\mathbf{p};\alpha, \beta, \sigma)$. However, in much of what follows I simply use $\mathbf{m}_d$ and $\mathbf{m}_u$ only for notational convenience. For example, overall price-cost margins in a market containing both types of products is given by

$$\mathbf{p} - \mathbf{c}^T = \mathbf{m}_d + \mathbf{m}_u, \tag{12}$$

where $\mathbf{c}^T$ 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 I must leave such supply modelling for future research and focus on the two product types discussed above.

Equation (12) can also be expressed as:

$$\mathbf{p} = \mathbf{c}^T + \mathbf{m}_d + \mathbf{m}_u. \tag{13}$$

Since equation (13) is only intended to approximate the true supply behavior of airlines, I should appropriately include a random component to this equation. In addition, I want to parameterize it in a manner that allows me to empirically test whether codeshare contracts eliminate one of the margins. These considerations result in the following empirical formulation of equation (13):

$$\mathbf{p} = \exp(W;\gamma) + \lambda_1 \mathbf{m}_d + \lambda_2 \mathbf{m}_u + \boldsymbol{\psi}, \tag{14}$$

where $\mathbf{c}^T = \exp(W;\gamma)$, 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), γ is a vector of estimable parameters in the marginal cost function, λ_1 and λ_2 are estimable parameters that will tell us whether double marginalization is eliminated, and $\boldsymbol{\psi}$ is the random portion of the supply equation that captures unobserved determinants of price.[17]

The main parameters of interest are λ_1 and λ_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 (13) and (14) 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. I chose to estimate the demand

[17] For a discussion of identification issues in empirical supply models intended to capture vertical relationships such as equation (14), see Villas-Boas and Hellerstein (2006).

parameters separately from the supply parameters via a two-step procedure.[18] The demand parameters are estimated in the first step. These parameter estimates are then used to compute the downstream and upstream margin functions, $\mathbf{m}_d(\mathbf{p};\widehat{\alpha},\widehat{\beta},\widehat{\sigma})$ and $\mathbf{m}_u(\mathbf{p};\widehat{\alpha},\widehat{\beta},\widehat{\sigma})$. The supply parameters are estimated in the second step of the two-step procedure, where $\mathbf{m}_d(\mathbf{p};\widehat{\alpha},\widehat{\beta},\widehat{\sigma})$ and $\mathbf{m}_u(\mathbf{p};\widehat{\alpha},\widehat{\beta},\widehat{\sigma})$ are regressors in the supply equation.

Estimation of the random coefficients discrete choice demand model requires implementing an involved simulation-based nonlinear estimation algorithm, but details on the procedure are well documented in the empirical industrial organization literature so I do not repeat them here.[19] Estimating the supply equation is much more straightforward. The error term for the supply equation is $\psi_{jt} = p_{jt} - \exp(W_{jt};\gamma) - \lambda_1 m_{djt} - \lambda_2 m_{ujt}$. The GMM estimates of the supply parameters are obtained by solving the following problem,

$$\underset{\gamma,\,\lambda_1,\,\lambda_2}{Min}\ \psi' Z_s \Phi_s^{-1} Z_s' \psi, \tag{15}$$

where Z_s is the matrix of instruments that are assumed orthogonal to the error vector ψ, while Φ_s^{-1} 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 $\mathbf{m}_d(\cdot)$ and $\mathbf{m}_u(\cdot)$ 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, I take L random draws of the taste variation parameters, σ, assuming that $\sigma \sim N(\widehat{\sigma}, var(\widehat{\sigma}))$ where $\widehat{\sigma}$ is the point estimate of σ obtained from the previously estimated demand model. For each draw of $\sigma_{(l)}$, I recover the corresponding $\delta_{(l)}$, $\alpha_{(l)}$ and $\beta_{(l)}$, using $D_{jt} = d_{jt}(\delta_{jt};\sigma)$ and $\begin{pmatrix} \beta \\ \alpha \end{pmatrix} = (X_d' Z_d \Phi_d^{-1} Z_d' X_d)^{-1} X_d' Z_d \Phi_d^{-1} Z_d' \delta$.[20] The upstream and downstream margins, $\mathbf{m}_{d(l)}$ and $\mathbf{m}_{u(l)}$, are

[18] 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 misspesified, 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.

[19] Nevo(2000a) provides a detailed description of the random coefficients logit model of demand and the associated estimation procedure. For earlier discussions of this model see Berry (1994), Berry, Levinsohn, and Pakes (1995).

[20] Alternatively, each set of $\sigma_{(l)}$, $\delta_{(l)}$, $\alpha_{(l)}$ and $\beta_{(l)}$, could be obtained by making L random draws from the sample

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.[21]

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, ξ_{jt}, when setting prices, then prices will depend on ξ_{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, I make the identifying assumption that observed product characteristics in x_j are uncorrelated with the unobserved product quality, ξ_{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 ξ_{jt}. Hence, the identifying assumption seems reasonable.[22]

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.[23] 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.[24]

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

data and estimating the demand model on each of the drawn sample. However, since the demand model has to be estimated using a simulation-based algorithm, the increased computational burden makes this approach less practical relative to the procedure I use.

[21] I use $L = 50$ and $N = 100$, so confidence intervals are formed using 5,000 sets of supply parameter estimates.

[22] See Berry, Carnall, and Spiller (1997), Nevo(2000a), and Goldberg and Verboven (2001) for similar identifying assumptions.

[23] Interactions of these variables are also included as instruments.

[24] 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, their validity relies on the assumption that these strategic choices are made prior to the realization of unobserved shocks to demand or supply, $(\xi_{jt},\ \psi_{jt})$.[25] This is an admittedly strong assumption but it is typical in the literature as better alternatives are difficult to find.

Recall that the error term in the supply equation, ψ_{jt}, captures unobserved determinants of price. As such, the margin terms, m_{djt} and m_{ujt}, are likely to be correlated with ψ_{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.[26] 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 the realization of unobserved shocks to demand or supply.

4 Data

The data are 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

[25] I thank an anonymous referee for pointing this out.

[26] Since itinerary distance is included in the marginal cost function, it cannot instrument for the margin terms in the supply equation.

each itinerary in a directional market. The distance associated with each itinerary in a market may differ since each itinerary may use different connecting airports in transporting passengers from the origin to destination city. The data I use link each product to a directional market rather than a mere non-stop route or segment of a market. For this research, I focus on the U.S. domestic market in the first quarter of 2004.

To arrive at the final sample used for estimation, I imposed several restrictions on the original data set. First, following much of the empirical literature on the airline industry, I focus 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, I focus on codeshare and online products as defined previously. Thus, I 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 are 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 are 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 large enough to make estimation infeasible,[27] while ensuring that the sample has sufficient identifying information across product types in each market.[28] The resulting sample used in estimation covers 155 markets and has 4,559 observations. For this sample, Table A1 in the appendix lists the markets along with number of passengers and mean itinerary distance traveled in these markets.

Ito and Lee (2007) did not use the market selection criterion described above since "traditional" codeshare products were not their primary focus. In a significantly larger data set (14,470 markets) drawn from the third quarter of 2003, Ito and Lee document that "traditional" codeshare products are relatively rare in most U.S. domestic air travel markets. As such, my market selection criterion is the main reason why my final sample ended up with significantly less markets than in Ito and Lee

[27] The simulation-based estimation procedure required for estimating the demand model is difficult to perform on large data sets.

[28] 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.

and also why each market in my sample has a relatively high proportion of "traditional" codeshare products. However, as mentioned above, my market selection criterion is necessary for purposes of identification and estimation feasibility.

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 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^{th}, 50^{th}, and 75^{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
Summary Statistics

Statistics	Price	HUB	Codeshare	Convenient	Departures
Mean	263.33	0.32	0.25	1.23	63.71
Standard Deviation	181.59	0.47	0.43	0.30	88.60
n = 4,559					

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

5 Results

I 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 (α, and β), while the coefficients in the third data column measure the variation in taste for each product characteristic, (σ). 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 (2007a)]. 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.[29]

[29] To check the sensitivity of coefficient estimates to changes in the definition of market size, I re-estimated the demand model assuming two other market size definitions: (1) a market size equal to the size of the population in the origin city; (2) a market size that is twice the population in the origin city. The qualitative results remain robust to these very contrasting changes in the market size definition.

Table 2
Estimates for Demand Model

	Means (α, β)		Taste Variation (σ)	
	Coefficient Estimates	Robust Standard Errors	Coefficient Estimates	Robust Standard Errors
Constant	-5.09*	0.286	0.39	0.287
Price	-10.22*	0.180	0.51	0.372
Hub	0.22*	0.003	-	-
Departures	-0.28*	0.003	0.02	0.032
Convenient	-1.78*	0.230	1.08*	0.082
Codeshare	-2.13*	0.169	1.82*	0.102
GMM Obj.	3.88E-05			
Overidentification Test	$n = 4{,}559$ $n \times$ GMM Obj.= 0.177 $\chi^2(0.95,1)$=3.84			

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 I considered including "Departures" is that I 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.[30]

[30] 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" variable is capturing when this variable is excluded from the model, the "Hub" coefficient picks up this effect making it difficult to see the true effect of "Hub".

5.2 Supply

The supply model is first estimated on the full sample. Coefficient estimates and their corresponding bootstrap confidence intervals[31] are reported in table 3. All the marginal cost-shifting variables are statistically significant at conventional levels. First, I obtain the intuitively appealing result that marginal cost increases with itinerary distance. Second, the sign of the coefficient on the "codeshare" dummy uncovers a surprising 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 (2004)], the marginal cost of these products have not been compared to comparable online products.[32] Even after accounting for the potential cost savings effects of codesharing, it is not obvious why codeshare products would have lower marginal cost than online products. As such, this result needs further investigation in future research.

Table 3

Estimates for Supply Model (Full Sample[a])

	Coefficient Estimates	95% Confidence Intervals		99% Confidence Intervals	
Constant	-3.24	-5.23	-2.28	-6.24	-1.93
Hub	0.88	0.68	1.12	0.63	1.22
Distance	0.80	0.60	1.04	0.56	1.15
Codeshare	-34.77	-168.44	-6.39	-323.06	-4.63
λ_1	1.62	1.37	1.80	1.27	1.86
λ_2	0.94	0.73	1.21	0.65	1.31
GMM Obj.	1.28E-07				
Overidentification Test	n = 4,559 $n \times$ GMM Obj.= 0.0006 $\chi^2(0.95,5)$=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] The full sample contains 3,405 online products and 1,154 codeshare products.

[31] 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.

[32] See Chua, Kew, and Yong(2005) 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. In other words, entry by "low-cost" carriers into (or adjacent to) hub cities reduces the number of passengers choosing to fly on traditional hub and spoke carriers from hub cities. For a given capacity level (number of available seats) of traditional hub and spoke carriers, the reduction in their passenger volume may raise the carriers marginal and average cost of transporting a passenger.[33]

I am most interested in the estimates of λ_1 and λ_2. The confidence intervals suggest that both λ_1 and λ_2 are statistically different from zero. In other words, on average, codeshare contracts have not eliminated double marginalization. While λ_1 is statistically greater than one, λ_2 is not statistically different from one. Theoretically we expect $\lambda_1 = \lambda_2 = 1$ in the case where double marginalization is not eliminated, so why is λ_1 statistically greater than one?

The structural empirical model relies on the simplifying assumption that Bertrand-Nash equilibrium can approximate price setting behavior in the airline industry. In other words, the accuracy of the markup variables derived from the model depends on whether Bertrand-Nash equilibrium closely approximates price setting behavior in the airline industry. Such an assumption may not be appropriate for all airline markets especially those where firm conduct is likely to be collusive. However, for convenience I applied the simplifying Nash assumption across all markets considered in the analyses.[34] In other words, it is possible that the supply equation is misspecified for some markets, which could explain why λ_1, which is an average estimate across all markets, is statistically greater than one instead of being equal to one.[35] But even with the simplifying Nash assumption, more can be done to improve our understanding of why the results thus far have not been consistent with efficient vertical pricing for codeshare products.

[33] For a detailed analysis of incumbent responses to "low-cost" carrier entry see Ito and Lee (2004).

[34] Gayle (2007a) empirically evaluated the appropriateness of the Bertrand-Nash assumption for U.S. domestic air travel markets considered in that paper and found that the assumption resulted in a reasonably good approximation of price setting behavior in the markets he considered. Specifically, actual prices and predicted Bertrand-Nash prices had a correlation of 0.90.

[35] I thank an anonymous referee for suggesting this explanation.

In an attempt to understand what may be driving the results, I 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 offer online products in the said market ("integrated" case),[36] while upstream carriers of the codeshare products in the other sub-sample do not offer online products in the said market ("unintegrated" case). These sub-samples allow me 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 parameter estimates when the supply model is estimated on each sub-sample are reported in tables 4A and 4B.

Table 4A

Estimates for Supply Model

Sample includes only online and "unintegrated" codeshare products.[a]

	Coefficient Estimates	95% Confidence Intervals		99% Confidence Intervals	
Constant	-3.22	-5.19	-2.33	-6.025	-1.971
Hub	0.81	0.63	1.06	0.567	1.167
Distance	0.77	0.59	1.01	0.544	1.078
Codeshare	-32.18	-156.82	-0.90	-261.68	-0.237
λ_1	1.66	1.45	1.85	1.369	1.897
λ_2	0.67	0.29	0.92	-0.004	0.995
GMM Obj.	1.28E-07				
Overidentification Test	n = 4,047 $n \times$ 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.

[36] Almost half (44.4%) of the 1,154 codeshare products satisfied this criterion.

Table 4B
Estimates for Supply Model
Sample includes only online and "integrated" codeshare products.

	Coefficient Estimate	95% Confidence Interval		99% Confidence Interval	
Constant	-3.76	-6.09	-2.63	-7.60	-2.29
Hub	0.99	0.76	1.27	0.69	1.37
Distance	0.98	0.74	1.25	0.68	1.38
Codeshare	-31.74	-126.44	-6.42	-212.57	-5.29
λ_1	1.89	1.72	2.01	1.68	2.05
λ_2	0.96	0.75	1.20	0.70	1.26
GMM Obj.	1.72E-07				
Overidentification Test	$n = 3{,}917$ $n \times$ GMM Obj.= 0.0007 $\chi^2(0.95{,}5)$=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.

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 λ_2 is closer to zero when the upstream carrier is "unintegrated". In fact, based on the 99% confidence interval, I cannot reject the possibility that λ_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, λ_2 is unambiguously greater than zero. λ_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.[37]

While an explicit modelling of the strategic incentives of the upstream codeshare partner is beyond the scope of the empirical model used in this paper, it does appear that these incentives

[37] All qualitative supply results remain robust to changes in the market size definition. As mentioned previously, I experimented with two other market size definitions: (1) a market size equal to the size of the population in the origin city; (2) a market size that is twice the population in the origin city.

might be driving the results. 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 (integrated upstream carrier) is likely to differ from an upstream operating carrier that does not offer its own competing online product (unintegrated upstream carrier). Specifically, the integrated upstream operating carrier may optimally choose not to eliminate the upstream margin for their codeshare products. The reason is that by raising the price of the trip segment operated by the upstream carrier (the intermediate good price), this carrier is able to indirectly raise final product prices and soften downstream competition for its own online product.[38] As such, even when the codeshare partners negotiate a pricing contract that maximizes their joint profit, the equilibrium contract may not eliminate the upstream margin due to the upstream carrier's concern for the marginal profitability of its own competing online product.[39] By contrast, an unintegrated upstream carrier does not have this added concern and is more likely to negotiate a pricing contract with its codesharing partner that fully internalizes the vertical externality and maximizes their joint profit.

5.3 Alternative Test of the Hypothesis

As an alternative to the sub-sample analyses done above, the hypothesis that the upstream margin may be eliminated when the upstream carrier is unintegrated can be tested on the full sample by appropriately modifying the specification of the supply equation.[40] Consider the following specification of the supply equation,

$$\mathbf{p} = \exp(W;\gamma) + \lambda_1 \mathbf{m}_d + \lambda_2 \mathbf{m}_u + \lambda_3 \mathbf{m}_u \times UI + \boldsymbol{\psi}, \tag{16}$$

where the only difference between the previous specification and the specification in (16) is the interaction variable, $\mathbf{m}_u \times UI$. UI is a zero-one dummy variable that takes the value one only when the upstream carrier of the codeshare product is unintegrated or if the product is online. The hypothesis is that there is no upstream margin for online products or codeshare products where the upstream carrier does not offer its own substitute online product in the market. However, the upstream margin is not eliminated for codeshare products where the upstream carrier offers it own substitute online product in the same market. If the hypothesis is true, then we should expect

[38] One way to intuitively think about this is that the integrated carrier would rather tolerate an inefficiently priced (double marginalization not eliminated) codeshare product in lieu of the traffic diversion from its online product that would result from an efficiently priced (double marginalization eliminated) codeshare product. I thank an anonymous referee for suggesting this intuitive way of thinking about the results.

[39] This argument is presented formally in Chen and Gayle (2007).

[40] I thank an anonymous referee for suggesting that I explore this alternative approach.

$\lambda_3 = -\lambda_2$ which results in the following supply specification,

$$\mathbf{p} = \exp(W;\gamma) + \lambda_1 \mathbf{m}_d + \lambda_2 \mathbf{m}_u \times (I - UI) + \boldsymbol{\psi}, \tag{17}$$

where I is a column of ones.

Since equation (17) results from imposing a parametric restriction on equation (16), this provides a basis for using the value of the GMM objective function for each equation to construct a test of the parametric restriction. In particular, the test is based on $(n \times GMM_R - n \times GMM_{UR}) \xrightarrow{d} \chi^2[J]$, where n is the sample size, GMM_R is the value of the GMM objective function for the restricted model, GMM_{UR} is the value of the GMM objective function for the unrestricted model, and J is the number of parametric restrictions.[41] For the models above, $(n \times GMM_R - n \times GMM_{UR}) = 0.0001$ and $\chi^2(0.95, 1) = 3.84$. Therefore, I cannot reject the null hypothesis that the parametric restriction is true at conventional levels of significance. In other words, this alternative test is consistent with the findings of the sub-sample analyses done above.[42]

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 theoretical predictions in Chen and Gayle (2007) in particular, and may also have links to one strand of the theoretical literature on vertical integration which argues that, unlike an unintegrated upstream firm, under some circumstances 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.[43] This has

[41] This test is attributed to Newey and West (1987).

[42] The actual model estimates for equations (16) and (17) can be made available upon request. The bootstrap confidence intervals for λ_2 and λ_3 in equation (16) suggest that each of these parameters are not statistically different from zero at conventional levels of significance. However, in equation (17) the bootstrap confidence intervals for λ_2 suggest that λ_2 is statistically greater than zero at conventional levels of significance.

[43] See Ordover, Saloner, and Salop (1992); Riordan and Salop (1995); Choi and Yi (2000); Chen (2001).

the impact of increasing the competitive advantage of the downstream operations of the integrated firm.

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 A

Table A1
List of markets, their mean itinerary distance and number of passengers

Market			
Origin	**Destination**	**Mean Itinerary Distance (miles)**	**Number of Passengers**
Hartford, CT	Houston, TX	1763.78	248
Hartford, CT	Indianapolis, IN	911.81	351
Boston, MA	Columbus, OH	869.65	347
Boston, MA	Indianapolis, IN	919.00	726
Boston, MA	Salt Lake City, UT	2372.20	487
Boston, MA	Knoxville, TN	950.08	37
Burlington, VT	Denver, CO	1969.42	95
Burlington, VT	Orlando, FL	1326.90	278
Burlington, VT	Tampa, FL	1338.71	123
Buffalo, NY	Los Angeles, CA	2438.55	450
Buffalo, NY	Orlando, FL	1149.65	2204
Baltimore, MD	Los Angeles, CA	2500.95	3637
Charleston, SC	Boston, MA	884.57	190
Charlotte, NC	Las Vegas, NV	2299.46	1487
Charlotte, NC	Los Angeles, CA	2414.14	1173
Charlotte, NC	Chicago, IL	882.91	1567
Charlotte, NC	San Francisco, CA	2600.18	851
Columbus, OH	Boston, MA	737.27	319
Columbus, OH	Fort Lauderdale, FL	1246.72	416
Columbus, OH	Orlando, FL	1077.95	784
Columbus, OH	Ft. Myers, FL	1295.00	376
Columbus, OH	Tampa, FL	1111.36	1216
Denver, CO	Washington, DC	1981.62	3568
Denver, CO	Jacksonville, FL	1802.22	330
Denver, CO	Los Angeles, CA	1103.91	6295
Denver, CO	Manchester, NH	2046.30	332
Denver, CO	Norfolk, VA	1715.37	165
Denver, CO	Philadelphia, PA	1995.79	2283
Denver, CO	Pittsburgh, PA	1675.84	1064
Denver, CO	Raleigh/Durham, NC	1695.43	770
Denver, CO	Rochester, NY	1710.76	220
Dallas/Ft.Worth, TX	Atlanta, GA	1010.32	3530
Detroit, MI	Orlando, FL	1223.04	5174
Newark, NJ	Detroit, MI	689.59	1535
Newark, NJ	Tucson, AZ	2288.94	72
Fort Lauderdale, FL	Chicago, IL	1577.59	5026
Washington, DC	Denver, CO	2044.30	3536
Washington, DC	Los Angeles, CA	2674.39	3710
Washington, DC	Chicago, IL	874.17	2278
Houston, TX	Hartford, CT	1651.14	261
Houston, TX	Indianapolis, IN	1181.41	943
Houston, TX	Salt Lake City, UT	1449.47	1378

Table A1 continues

Market			
Origin	**Destination**	**Mean Itinerary Distance (miles)**	**Number of Passengers**
Indianapolis, IN	Hartford, CT	818.70	365
Indianapolis, IN	Washington, DC	696.90	935
Indianapolis, IN	Las Vegas, NV	2036.90	3565
Indianapolis, IN	San Francisco, CA	2305.45	923
Las Vegas, NV	Buffalo, NY	2263.33	1243
Las Vegas, NV	Charlotte, NC	2319.91	1541
Las Vegas, NV	Columbus, OH	2091.09	2820
Las Vegas, NV	Greensboro/High Point, NC	2194.00	151
Las Vegas, NV	Indianapolis, IN	1935.14	3691
Las Vegas, NV	Memphis, TN	2025.89	598
Las Vegas, NV	Philadelphia, PA	2410.89	4491
Las Vegas, NV	Pittsburgh, PA	2225.10	2189
Las Vegas, NV	Rochester, NY	2228.05	335
Los Angeles, CA	Boston, MA	2869.40	5446
Los Angeles, CA	Buffalo, NY	2466.28	417
Los Angeles, CA	Charlotte, NC	2495.03	1233
Los Angeles, CA	Dayton, OH	2164.87	178
Los Angeles, CA	Denver, CO	1249.03	6322
Los Angeles, CA	Washington, DC	2612.14	3677
Los Angeles, CA	Memphis, TN	2117.38	691
Los Angeles, CA	Chicago, IL	2479.55	7365
Los Angeles, CA	Norfolk, VA	2489.42	371
Los Angeles, CA	Philadelphia, PA	2643.86	4532
Los Angeles, CA	Pittsburgh, PA	2388.90	1400
Los Angeles, CA	Raleigh/Durham, NC	2432.68	769
Los Angeles, CA	Rochester, NY	2403.00	228
Orlando, FL	Burlington, VT	1313.64	339
Orlando, FL	Buffalo, NY	1148.27	2295
Orlando, FL	Columbus, OH	1091.35	822
Orlando, FL	Detroit, MI	1181.55	5241
Orlando, FL	Minneapolis/St. Paul, MN	1641.57	7729
Orlando, FL	Chicago, IL	1401.41	3835
Orlando, FL	Pittsburgh, PA	1087.64	2615
Orlando, FL	Portland, ME	1325.40	295
Orlando, FL	Rochester, NY	1145.29	1066
Orlando, FL	Salt Lake City, UT	2323.55	1453
Memphis, TN	Salt Lake City, UT	1626.15	79
Minneapolis/St. Paul, MN	Orlando, FL	1525.80	7720

Table A1 continues

Market			
Origin	**Destination**	**Mean Itinerary Distance (miles)**	**Number of Passengers**
Chicago, IL	Boston, MA	1066.91	3583
Chicago, IL	Charlotte, NC	922.80	1577
Chicago, IL	Denver, CO	1532.47	4317
Chicago, IL	Fort Lauderdale, FL	1565.61	4819
Chicago, IL	Washington, DC	843.07	2312
Chicago, IL	Los Angeles, CA	2353.70	7052
Chicago, IL	New York, NY	959.17	5518
Chicago, IL	Norfolk, VA	863.63	257
Chicago, IL	Pittsburgh, PA	708.60	1812
Norfolk, VA	Denver, CO	1675.64	107
Norfolk, VA	Los Angeles, CA	2502.47	229
Portland, OR	Austin, TX	2080.08	257
Portland, OR	Nashville, TN	2319.00	248
Philadelphia, PA	Columbus, OH	633.31	683
Philadelphia, PA	Indianapolis, IN	792.25	966
Philadelphia, PA	Las Vegas, NV	2449.49	4413
Philadelphia, PA	Los Angeles, CA	2661.07	4640
Philadelphia, PA	Orlando, FL	1152.33	7320
Philadelphia, PA	San Diego, CA	2585.39	1517
Philadelphia, PA	Seattle, WA	2665.29	1095
Philadelphia, PA	San Francisco, CA	2779.21	2999
Philadelphia, PA	Tucson, AZ	2254.50	203
Phoenix, AZ	Norfolk, VA	2176.47	293
Pittsburgh, PA	Denver, CO	1752.81	1067
Pittsburgh, PA	Las Vegas, NV	2180.89	2273
Pittsburgh, PA	Los Angeles, CA	2456.18	1471
Pittsburgh, PA	Orlando, FL	1084.52	2593
Pittsburgh, PA	Chicago, IL	641.83	1845
Pittsburgh, PA	San Diego, CA	2313.60	687
Pittsburgh, PA	Seattle, WA	2366.63	533
Pittsburgh, PA	San Francisco, CA	2455.70	1338
Portland, ME	Orlando, FL	1327.71	239
Portland, ME	Ft. Myers, FL	1543.09	346
Portland, ME	Tampa, FL	1370.00	274
Raleigh/Durham, NC	Los Angeles, CA	2435.62	773
Rochester, NY	Las Vegas, NV	2213.31	329
Rochester, NY	Los Angeles, CA	2571.44	253
Rochester, NY	Orlando, FL	1161.37	1100
Rochester, NY	San Francisco, CA	2614.60	130
Rochester, NY	Tampa, FL	1238.88	299

Table A1 continues

Market			
Origin	**Destination**	**Mean Itinerary Distance (miles)**	**Number of Passengers**
Ft. Myers, FL	Burlington, VT	1487.60	42
Ft. Myers, FL	Chicago, IL	1413.69	3472
San Diego, CA	Memphis, TN	2225.67	139
San Diego, CA	Philadelphia, PA	2449.38	1497
Louisville, KY	Boston, MA	950.10	72
Seattle, WA	Nashville, TN	2270.08	628
Seattle, WA	Philadelphia, PA	2794.15	1126
San Francisco, CA	Charlotte, NC	2610.51	869
San Francisco, CA	Dayton, OH	2264.56	147
San Francisco, CA	Washington, DC	2680.46	2286
San Francisco, CA	Memphis, TN	2273.52	272
San Francisco, CA	Philadelphia, PA	2791.42	3020
San Francisco, CA	Pittsburgh, PA	2591.18	1348
San Francisco, CA	Raleigh/Durham, NC	2682.89	567
San Francisco, CA	Rochester, NY	2647.63	152
Salt Lake City, UT	Atlanta, GA	2104.13	1113
Salt Lake City, UT	Nashville, TN	1739.70	339
Salt Lake City, UT	Baltimore, MD	2127.54	1570
Salt Lake City, UT	Columbus, OH	1834.88	271
Salt Lake City, UT	Dallas/Ft.Worth, TX	1447.82	1081
Salt Lake City, UT	Houston, TX	1497.15	1434
Salt Lake City, UT	Orlando, FL	2291.24	1433
Salt Lake City, UT	Memphis, TN	1766.11	126
Salt Lake City, UT	New Orleans, LA	1751.91	542
Salt Lake City, UT	Pittsburgh, PA	1933.82	175
Salt Lake City, UT	Raleigh/Durham, NC	2203.22	437
Tampa, FL	Burlington, VT	1374.85	140
Tampa, FL	Buffalo, NY	1167.77	942
Tampa, FL	Columbus, OH	1181.27	1278
Tampa, FL	Indianapolis, IN	1184.37	624
Tampa, FL	Chicago, IL	1440.59	2852
Tampa, FL	Portland, ME	1426.00	317
Tampa, FL	Rochester, NY	1189.14	332
Tucson, AZ	Newark, NJ	2313.53	73
Tucson, AZ	Philadelphia, PA	2225.00	196

Appendix B: Derivation of $\triangle_p$.

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

$$d_j(\mathbf{p}) + \sum_{k \in \mathcal{F}_r} \left(p_k - s_k^f - c_k^r\right) \frac{\partial d_k(\mathbf{p})}{\partial p_j} = 0 \tag{18}$$

If we totally differentiate equation (18) with respect to all final prices and an upstream price, s_n^f, then

$$\sum_{k=1}^{J} \left\{ \frac{\partial d_j}{\partial p_k} + \sum_{m=1}^{J} \left[\Omega_r(m,j) \frac{\partial^2 d_m}{\partial p_j \partial p_k} \left(p_m - s_m^f - c_m^r\right)\right] + \Omega_r(k,j) \frac{\partial d_k}{\partial p_j} \right\} \mathbf{d}p_k - \Omega_r(n,j) \frac{\partial d_n}{\partial p_j} \mathbf{d}s_n^f = 0 \tag{19}$$

where k, j, m, and n are all indexing products. Let G be a $J \times J$ matrix with elements $g(j,k)$, where $g(j,k) = \left\{ \frac{\partial d_j}{\partial p_k} + \sum_{m=1}^{J} \left[\Omega_r(m,j) \frac{\partial^2 d_m}{\partial p_j \partial p_k} \left(p_m - s_m^f - c_m^r\right)\right] + \Omega_r(k,j) \frac{\partial d_k}{\partial p_j} \right\}$. 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 $\left(p_m - s_m^f - c_m^r\right)$ can be expressed exclusively in terms of demand parameters [see equation (6)], matrix G does not require information on upstream prices or marginal costs.

Let H_n be a $J-$dimensional column vector with elements $h(j,n)$, where $h(j,n) = \Omega_r(n,j) \frac{\partial d_n}{\partial p_j}$. For a given upstream price s_n^f, equation (19) 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

$$G\ \mathbf{d}p - H_n\ \mathbf{d}s_n^f = \mathbf{0}$$

or

$$\frac{\mathbf{d}p}{\mathbf{d}s_n^f} = G^{-1} H_n \tag{20}$$

$\frac{\mathbf{d}p}{\mathbf{d}s_n^f}$ 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, $\triangle_p$, is obtained by stacking all J derivative vectors (one for each product n), $\frac{\mathbf{d}p}{\mathbf{d}s_n^f}$, together.

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