Domestic Airline Alliances and Consumer Welfare

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Abstract

This paper investigates the consumer welfare consequences of the recent code-share agreement between Continental Airlines and Northwest Airlines. We develop a discrete choice model based on individual flight characteristics. This structural model recognizes that consumers i) may have heterogenous preferences for flight attributes, and ii) may face different prices for the same flight. The empirical methodology also deals with the measurement error problem stemming from the absence of consumer level data on prices. The estimation results suggest that the consumer surplus per passenger fell after the implementation of the code-share agreement. Even once we account for endogenous changes in passenger volumes, we find that the code-share agreement did not significantly increase total consumer surplus. These findings contrast with those in prior analyses of regional and international code-share agreements.

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1. Introduction

Code-share agreements, whereby an airline can market seats on some of its partners' flights, have been a common practice in the airline industry for the past thirty years. Yet, recent alliances among major domestic carriers in the U.S. represent a significant development in code-share practices.[1] Airline executives have publicly emphasized that their "customers are the beneficiaries" because these new alliances "deliver more choices, more frequencies, and more destinations to the traveling public."[2] Consumer advocates, however, are concerned that these agreements may reduce competition and consumer welfare. Since alliances may be challenged by policy makers if they harm consumers, it is important to evaluate the precise impact of this new form of code-share agreements on consumers. In the present paper, we apply a discrete choice model to an original set of data, and we analyze the consumer welfare consequences of the first significant domestic code-share agreement among major U.S. carriers, the 1999 alliance between Continental Airlines ("CO") and Northwest Airlines ("NW").

Code-share agreements have been traditionally implemented to enable an airline to sell tickets in new markets without having to operate any additional aircraft. For instance, major airlines have long-standing regional code-share agreements at their hub airports with commuter carriers that serve smaller markets. Likewise, U.S. airlines faced with restrictions on entry in foreign markets (cabotage laws) have formed international alliances with foreign carriers that allow them to market flights within their partners' domestic network. These alliances have been shown to benefit consumers, as they not only allow the partner airlines to market new destinations, but they also typically lead to lower prices and higher passenger volumes.[3] These findings, however, may not extend to recent agreements between U.S. carriers, such as CO and NW, as they present distinctive features. In contrast with regional agreements, the CO-NW alliance spans the entire U.S. and involves major airlines competing across similar networks. In contrast with international alliances, CO and NW face no restrictions on entry in the U.S., and they

[1] See e.g. Continental Airlines and Northwest Airlines in 1999, US Airways and United Airlines in 2003, and Continental Airlines, Delta Airlines, and Northwest Airlines in 2003.

[2] From John Dasburg, Northwest Airlines president and CEO: "Our customers are the beneficiaries because this alliance gives them choice - choice in destinations, in schedules, in service options and in rewards." From Gordon Bethume, chairman and CEO of Continental Airlines : "Our alliance demonstrates how consumers can win when two companies work together to provide our customers a dramatically larger range of services than either of us could offer on our own. We will deliver more choice, more frequencies, and more destinations to the traveling public." Source: Detroit Metro News, 12/1998.

[3] See e.g. Brueckner and Whalen (2000), Brueckner (2001, 2003), as well as Park and Zhang (2000) for insightful discussions of international alliances. See Bamberger, Carlton and Neumann (2000) for valuable insights on the regional code-share agreements between CO and America West, as well as NW and Alaska Airlines, which were implemented in 1994-1995.

must compete in prices as they do not have antitrust immunity.

Although it generated much controversy at policy levels, the CO-NW code-share agreement was implemented in 1999 without being challenged by the U.S. Department of Transportation, or the U.S. Department of Justice.[4] Arguably, this agreement, as well as the other domestic code-share agreements that followed, remain subject to additional investigation under the antitrust laws, should evidence of significant consumer harm be brought forward. Few studies, however, have examined how the CO-NW agreement affected consumers.[5] Armantier and Richard (2005a) provide evidence suggesting that the CO-NW alliance had mixed effects on consumers. In particular, they find that prices increased significantly in markets in which CO-NW code-shared flights and had nonstop flights, whereas prices were lower in markets in which the partners code-shared flights but did not operate any nonstop flight.[6] Armantier and Richard (2005a), however, are unable to draw unambiguous conclusions because their reduced form analysis i) cannot formally aggregate gains and losses across markets, and ii) focuses exclusively on prices and passenger volumes, which prevents them from taking into consideration additional benefits stemming from (e.g.) the introduction of new flights or the improvements in the attributes of existing flights.

To measure adequately the multidimensional implications of the CO-NW code-share agreement on consumer welfare, we propose in the present paper a mixed logit discrete choice approach for the decision problem of the airline consumer. There are few comparable discrete choice applications in the airline literature, with the notable exceptions of Berry, Carnall and Spiller (1997), and Peters (2001). These papers analyze a passenger's decision to purchase a ticket on any one of the flights proposed by an airline on a specific itinerary (e.g. a seat on any one of NW's nonstop flights between JFK and LAX). Consumers are therefore assumed to value the aggregate characteristics of an airline's flights within an itinerary (e.g. the number of flights in the itinerary), rather than the characteristics of the specific flight on which the passenger actually travels (e.g. the actual price paid, the time of departure, the duration of travel). As we shall see, the

[4]In parallel to the announcement of the code-share agreement, NW acquired a controlling voting interest in CO. Although the terms of the code-share agreement were not challenged, the U.S. Department of Justice sued in October 1998 to challenge NW's equity acquisition, effectively blocking NW from exercising any control while the suit was pending. The matter was settled in November 2000, as NW divested most of its voting interest in CO.

[5]See e.g., Ito and Lee (2004) for an analysis of code-sharing and airfares, as well as the General Accounting Office's reports T-RCED-98-215 entitled "Proposed Domestic Airline Alliances Raise Serious Issues", and RCED-99-37 entitled "Effects on Consumers From Domestic Airlines Alliances Vary". See also Whalen (1999), and Armantier and Richard (2003) for welfare analyses of hypothetical domestic alliances.

[6]As further explained in Section 3, a market is defined here as a pair of airports in a specific quarter. In addition, when CO (respectively NW) can sell seats on a flight operated by NW (respectively CO), then this flight is said to be code-shared by CO-NW.

CO-NW agreement may affect the number as well as the characteristics of individual flights in a market. Therefore, we need a model of consumer decisions at the flight level if we are to measure properly the various effects of the agreement on consumer welfare. We develop a model of consumer utility in which a consumer decides to purchase a seat on a specific flight based on that flight's attributes. In doing so, we recognize that consumers may have heterogenous and possibly correlated preferences for flight attributes. Finally, unlike most discrete choice models developed for market level data, our model accounts for the fact that the price of a flight may differ across consumers (depending, e.g., on the date of purchase).

We apply the model to a primary sample consisting of flight schedule and ticket price data for the period 1998 to 2001 that precisely identifies code-share flights. In this application, we encounter a measurement error problem as the prices of the different flights in a market are not observed perfectly at the consumer level. To address this problem empirically, we acquired an auxiliary sample of airline tickets that provides detailed price, flight, and passenger information (e.g. dates of purchase and travel, flight schedule, Saturday night stay-over). This auxiliary sample is used to estimate the distribution of the measurement error, which is then integrated out of the discrete choice model.

The results suggest that the implementation of the code-share agreement resulted in a 3.11% drop in per consumer surplus, all of which may be traced to losses incurred by CO-NW passengers (-7.15%). Once we factor in the endogenous variations in passenger volumes generated by changes in the set of products supplied, we find that the code-share agreement did not increase significantly total consumer welfare. This does not imply, however, that the agreement had a neutral effect on all consumers. In particular, the total consumer surplus of CO-NW passengers appears to have decreased by 4.8% on markets affected by the agreement. Interestingly, these results cannot be explained solely by variations in prices, which in fact benefited slightly consumers. Instead, our analysis reveals that the losses in consumer surplus may be attributed to changes in a number of flight attributes, such as the duration of travel, or whether the flight is nonstop and takes off during peak-hours.

The paper is structured as follows. We outline in Section 2 the basics of the CO-NW code-share agreement. The discrete choice model is introduced in Section 3, and we discuss in Section 4 its estimation in the presence of measurement errors in prices. In Section 5, we describe the primary sample and the variables included in the discrete choice model. The auxiliary model is estimated in Section 6. We discuss the estimation results for the discrete choice model in Section 7, and their economic implications in Section 8. In Section 9, we present the consumer welfare results. We test in Section 10 the robustness of the results to alternative specifications. Finally, we conclude in Section 11.

2. The CO-NW Code-Share Agreement

In January 1998, CO and NW announced their intention to form a code-share agreement that included the U.S. market. Under the terms of the agreement, each airline is able to market seats on some of its partner's flights. The code-share flights are then listed twice in schedules and computer reservation systems, once by each airline with its own flight number and designator code. Moreover, the partners agree to coordinate flight schedules and operations to provide seamless service on code-share flights (e.g. one-stop check-in, automatic baggage transfers). The carrier operating the code-share flight determines seat availability for the marketing partner, but each airline commits to set prices competitively. All sales revenues go to the operating carrier. The marketing partner gets only a booking fee to cover handling costs (as travel agents do).[7] Finally, the airlines agree to implement linkages in their frequent-flyer programs.[8]

The principal argument advanced in favor of the code-share agreement was the opportunity for CO and NW to expand both flight offerings and markets served without any addition of aircraft.[9] Executives at CO-NW emphasized that their alliance would benefit consumers by not only opening new markets to their consumers, but also by expanding the number of flights and improving the attributes of existing flights, in markets in which they already operated. For instance, by pairing two of their existing nonstop flights the partners could generate code-share connecting flights with shorter travel and transit times than connecting flights they already offered. Finally, they claimed that their alliance would promote competition over the U.S. by creating "a fourth network to compete with the existing 'Big Three' airlines in the U.S. ... Over 150 cities, 2,000 city-pairs, and three million passengers will gain a new airline competitor and new online

[7] See Netessine and Shumsky (2005) for a discussion of revenue sharing rules, and Armantier, Giaume, and Richard (2005) for an analysis of the airlines' incentives and decisions to code share in specific markets.

[8] These reciprocal linkages allow a customer to use her frequent-flyer miles accumulated with one airline to book awards with the other airline, but combining mileage across programs to redeem awards was not allowed in the CO-NW agreement. Hence, a consumer may find it preferable to keep accumulating points in a single program and, thus, book seats on code-share flights through her preferred airline.

[9] Consider for instance three airports A, B and C, and assume that in a specific quarter CO (respectively, NW) only operates flights in the market A-B (respectively, B-C). Now by combining their existing flights, the alliance can offer a code-share flight, and enter the market A-C without having to operate a new aircraft. Note, however, that travelling between A and C was previously possible by purchasing two different tickets, one from CO and one from NW. These so called *interline* tickets are rare in practice (see Morrison and Winston 1995), as they often entail unfavorable features such as the need for double booking, multiple check-ins, longer distances between connecting gates, higher probability of lost luggage, uncertainty regarding the carriers responsibilities, but mostly, higher prices. In contrast, and as previously noted, the code-share alliance offers virtual *online* flights (i.e. online flights are flights that are sold and operated by a single marketing carrier), with seamless service and competitive prices.

connections through the alliance."[10]

The CO-NW proposal generated much controversy at policy levels, prompting numerous hearings on its competitive implications.[11] Concerns were primarily expressed about the possibility for the agreement to lower the incentives of CO and NW i) to enter markets in which only one of the partners already operated, ii) to maintain competing flights in markets in which they jointly operated, and iii) to compete in prices. In October 1998, the U.S. Congress granted the Department of Transportation (DOT) the authority to delay the implementation of domestic alliances pending a review of their effects. In November 1998, the DOT decided to allow the implementation of the alliance without a formal investigation, after CO and NW consented not to code-share flights in markets between their respective hub airports.[12] The DOT, as well as the U.S. Department of Justice, presumably retained the right, however, to challenge the agreement after data become available, to ensure that the alliance does not harm the public and is not anti-competitive.

The CO-NW code-share agreement became effective in January 1999. By 2000, CO and NW code-shared flights in 23% of the markets in which at least one of the two airlines was present. As described in our companion paper (Armantier and Richard 2005a), the fraction of markets in which both CO and NW were present increased by 8% between 1998 and 2001. CO and NW, as a group, supplied only 0.3% of their markets solely with code-share flights (i.e. in these markets CO and NW have no online flight of their own). In that regard, this alliance differs notably from traditional regional and international agreements, in which the partners essentially code-share flights in markets where none of them would otherwise operate.

When CO-NW code-shared flights in a market in 2000, an average of 9% of their passengers travelled with a code-share ticket. Almost all of these passengers (96%) travelled on itineraries with connecting flights. Hence, the overwhelming majority of code-share passengers who travelled on a CO-NW nonstop flight had for origin or destination an airport other than the endpoints of the nonstop flight. In that context, we introduce the following nomenclature: i) CO-NW code-share *in* a market (i.e. a pair of airports in a quarter) if they code-share flights that have for origin and destination the two airport-pairs in the market; and ii) CO-NW code-share *through* a market if code-share passengers who have an origin or a destination outside this market airport-pair fly on

[10]Source: p.6, Statement by Hershel I. Kamen, from Continental Airlines, to the U.S. Senate, 06/04/98.

[11]See p. 140-142 in Special Report 255, "Entry and Competition in the U.S. Airline Industry", from the Transportation Research Board; and Statement from Joel Klein, Department of Justice (DOJ), to the Senate Committee on Commerce, Science, and Transportation, 03/12/99.

[12]The General Accounting Office identifies Newark, Houston and Cleveland as hub airports for CO, and Minneapolis-St Paul, Memphis, and Detroit as hubs for NW.

one of the partners' nonstop flights in the market as part of their travel itinerary. To illustrate the difference between the two types of code-share markets, consider the following example. Assume that CO operates a nonstop flight between airport A and B, while NW operates a nonstop flight between airport B and C. If CO-NW decide to pair these two flights to form a connecting code-share flight between A and C during a given quarter, then the alliance code-shares *in* the market A-C, and *through* the markets A-B and B-C. Following the implementation of their alliance, CO-NW code-shared *through* 81% of the markets in which they had nonstop flights.

Armantier and Richard (2005a) provide evidence that, following the implementation of the code-share agreement, CO-NW's average prices were lower in 89.5% of the markets *in* which they code-shared (the mean price change was -3.2%), and their total passenger volume was higher in 68.3% of these markets (the mean change was +12.3%). In contrast, CO-NW's average prices were lower in only 6% of the market *through* which they code-shared (the mean change was +13.6%), and their total passenger volume was higher in 61.6% of these markets (the mean change was 6.7%).[13] As previously mentioned, these mixed results did not allow Armantier and Richard (2005a) to draw any consumer welfare conclusions for the CO-NW alliance. Indeed, their reduced-form analysis of changes in prices and passenger volumes does not provide the means to compare the relative gains and losses to consumers across markets, and it does not account for additional potential benefits, such as the introduction of new products, or the improvement of existing products.[14] In the present paper, we propose a discrete choice model of consumer decisions that quantifies the multi-dimensional welfare implications of the CO-NW code-share agreement.

3. A Discrete Choice Model

We start by formalizing some of the concepts on which we build our model. Following Berry et al. (1997), we define a market as a round-trip travel from an origin airport to

[13] As it regards markets through which CO-NW code-share, the conjecture in Armantier and Richard (2005a) is that the code-share agreement has allowed the partner airlines to expand their flight offerings without addition of aircraft and, thereby, increase the pool of passengers to whom they may sell seats on their aircraft. Their results then suggest that CO and NW have used this expansion to extract a higher price, on average.

[14] In particular, note that a before/after comparison of flights attributes, such as the duration of a flight or the time spent in transit at an intermediate airport, based on scheduling data publicly available could be misleading. Indeed, such comparison would identify variations across the products supplied by the airlines, but not necessarily across the products actually selected by the consumers. This drawback however does not apply to our discrete choice analysis, since we precisely model the consumers' decisions based on the products' characteristics.

a destination airport during a specific quarter.[15] Markets are defined directionally. For instance, a round-trip in a given quarter from Pittsburgh to Miami, and a round-trip from Miami to Pittsburgh in the same quarter are two different markets. A product in a market is a ticket for a seat on a sequence of flights that link the origin to the destination, and the destination to the origin. The product is nonstop if it consists of a single nonstop flight each way. If the product requires at least one transfer at an intermediate airport, then the product is said to be connecting. A product belongs to an airline-itinerary, where the airline is the carrier selling the ticket, and the itinerary is the sequence of airports that are part of the round-trip (origin, destination, and intermediate transfer airports, if any). When the airline marketing the product differs from the airline actually operating one of the flights in the product, then the product is a code-share. In contrast, the flights in an interline product are not only operated, but also marketed by two different airlines.

Each market also includes an outside good representing the decision of a consumer not to purchase any of the airline products in the market. The outside good is assumed to encompass all means of transportation between the origin and destination airports other than airlines. Finally, we assume that there are N potential consumers in a market. Following Berry (1990), and Berry et al. (1997), N is assumed to be proportional to POP_t, the geometric mean of the population in quarter t at the metropolitan areas for the airports in the market (source: U.S. Census data for 1998-2000). In addition, we specify the proportionality factor to allow for exogenous variations in the market size over time. In other words, we define $N = (\phi_0 + \phi_1 t)\, POP_t$, where (ϕ_0, ϕ_1) are parameters to be estimated.

The indirect utility derived by consumer $i = 1, ..., N$ from product $j = 1, ..., J$ is given by:

$$U_{i,j} = X'_{i,j}\delta_i + Z'_j\lambda + \xi_j + \varepsilon_{i,j} \qquad , \tag{3.1}$$

where $X_{i,j} = (P_{i,j}, Y_j)$; $P_{i,j}$ is the price of product j for consumer i; (Y_j, Z_j) are vectors of product characteristics observable to the econometrician; ξ_j represents the product characteristics that are unobservable to the econometrician (e.g. effect of advertisement, local reputation); δ_i is a vector of random and possibly non-independent coefficients specific to consumer i; λ is a vector of deterministic parameters; and $\varepsilon_{i,j}$ is an independently and identically distributed (hereafter i.i.d.) error term with a type I extreme value distribution, representing the unobserved idiosyncratic preferences of consumer i for product j. For identification purposes, and following convention, we normalize the mean indirect utility of the outside good to 0. Note that, unlike most discrete choice models developed for market level data, we allow for $X_{i,j}$ to depend on the consumer's

[15] To facilitate the presentation, we omit in the remainder of this section the subscript referring to the market under consideration. We therefore concentrate on the decision of a consumer in a given market.

characteristics.

Each consumer in the market purchases the good that maximizes her indirect utility. This optimization problem leads to the well-known logistic probability that consumer i purchases product j:

$$Prob_{i,j} = \frac{\exp\left(X_{i,j}'\delta_i + Z_j'\lambda + \xi_j\right)}{1 + \sum_{j'=1}^{J} \exp\left(X_{i,j'}'\delta_i + Z_{j'}'\lambda + \xi_{j'}\right)} \quad . \tag{3.2}$$

The market share of product j may then be written as the average purchase probability across all consumers in the market:

$$s_j = \int\int \frac{\exp\left(\delta_{i,1}P_{i,j} + Y_j'\delta_{i,-1} + Z_j'\lambda + \xi_j\right)}{1 + \sum_{j'=1}^{J} \exp\left(\delta_{i,1}P_{i,j'} + Y_{j'}'\delta_{i,-1} + Z_{j'}'\lambda + \xi_{j'}\right)} f\left(\delta_i\right) g\left(P_i\right) \partial\delta_i \partial P_i \quad , \tag{3.3}$$

where $(P_{i,j}, Y_j)$ was substituted for $X_{i,j}$, $\delta_i = (\delta_{i,1}, \delta_{i,-1})$, $f(\delta_i)$ and $g(P_i)$ are the joint distributions of respectively, the random parameters δ_i, and the vector of prices $P_i = (P_{i,1}, ..., P_{i,J})$.

4. Empirical Methodology

4.1. Measurement Error

Empirical applications of discrete choice models often run into a measurement error problem. In particular, the variations in the price of a product across consumers, based on (e.g.) location or time of purchase, are rarely observed perfectly. For instance, the data available from the DOT (Databanks 1A, 1B), which we use to construct our primary sample, i) represent only a 10% random sample of all tickets sold, and ii) only match the price of a ticket to an airline-itinerary, rather than to the actual flight with which the passenger traveled. In other words, we do not observe in our primary sample $P_{i,j}$, the price of each product to each consumer. Instead, the only price information we can infer is an estimate of the average price $\overline{P}_k$ for all products j within the airline-itinerary k. In many applications, such an average price, or the manufacturer recommended price, may be considered a good proxy for the unobserved price variable. In the airline industry, however, the measurement error $e_{i,j} = P_{i,j} - \overline{P}_k$ cannot be ignored, as ticket prices within the same airline-itinerary vary markedly across consumers and products.

To illustrate the possible adverse consequences of measurement errors in discrete choice models, let us substitute $\overline{P}_k + e_{i,j}$ for the unobserved price variable $P_{i,j}$ in the indirect utility function (3.1) :

$$U_{i,j} = \delta_{i,1}\overline{P}_k + Y_j'\delta_{i,-1} + Z_j'\lambda + \xi_j + \widetilde{\varepsilon}_{i,j} \quad \text{where} \quad \widetilde{\varepsilon}_{i,j} = \delta_{i,1}e_{i,j} + \varepsilon_{i,j} \ . \tag{4.1}$$

A possible approach to deal with the measurement error may consist in assuming that the compounded error term $\widetilde{\varepsilon}_{i,j}$ is i.i.d. with a type I extreme value distribution. When appropriate, this assumption enables one to write the traditional logit choice probabilities as a function of the average price $\overline{P}_k$. To be valid, however, this approach requires the following two conditions to be satisfied: first, $e_{i,j}$ must be uncorrelated with the product characteristics; and second, $\delta_{i,1}$ cannot be random and consumer-specific. Otherwise, $\widetilde{\varepsilon}_{i,j}$ is no longer i.i.d, which is a necessary condition to derive the traditional logit choice probabilities. In our application, both conditions are unlikely to be satisfied. Indeed, $\delta_{i,1}$, the marginal utility for the price, is likely to vary randomly depending (e.g.) on whether passengers travel for leisure or business. Likewise, we will see that, within the same airline-itinerary, the price of a ticket on a flight with attractive characteristics (e.g. a peak-hour departure) is more likely to exceed its corresponding average airline-itinerary price $\overline{P}_k$. Measurement errors in discrete choice analyses are therefore potentially more serious than in traditional econometric models. Indeed, they may prevent the analyst from writing the model to be estimated, and consequently the problem cannot be addressed directly with standard techniques such as the instrumental variables method.

In Section 6, we address the measurement error problem in our application by estimating the distribution of the measurement error $e_{i,j}$ as a function of the flight attributes and the passenger characteristics. As just explained, we cannot carry out this estimation with our primary sample since we do not observe passenger characteristics, nor the fare for each ticket. Therefore, we have acquired an auxiliary sample of ticketing data that provides detailed price, flight, and consumer information. Once estimated with the auxiliary sample, we use the distribution of the measurement error to integrate the price $P_{i,j} = \overline{P}_k + e_{i,j}$ out of the market share equations (3.3).

4.2. Evaluation of Market Shares

Two issues come into play when evaluating the market shares in (3.3). First, in the primary sample we observe market shares at the airline-itinerary level, not at the product level. Therefore, we must rewrite accordingly the theoretical market shares at the airline-itinerary level:

$$S_k = \sum_{j \in k} s_j = \int \int \frac{\sum\limits_{j \in k} \exp\left(\delta_{1,i} P_{i,j} + Y_j' \delta_{-1,i} + Z_j' \lambda + \xi_j\right)}{1 + \sum\limits_{j'=1}^{J} \exp\left(\delta_{1,i} P_{i,j'} + Y_{j'}' \delta_{-1,i} + Z_{j'}' \lambda + \xi_{j'}\right)} f(\delta_i)\, g(P_i)\, \partial \delta_i \partial P_i \,, \tag{4.2}$$

where $j \in k$ denotes a product j that belongs to airline-itinerary k.

This formulation of the market shares requires an additional assumption in order to apply the estimation method presented in the next subsection. Indeed, we have to assume that all products j within an airline-itinerary k have the same unobserved characteristics ξ_k. This assumption may be considered reasonable, since characteristics traditionally unobserved in the airline industry (e.g. effect of advertisement, quality of service, or local reputation) usually apply at the airline-itinerary level, rather than at the flight level. Note also that this definition of the unobserved characteristic is equivalent to that in Berry (1990), Berry et al. (1997), and Peters (2001). This does not imply, however, that the discrete choice models in these papers are equivalent to the one presented here. Indeed, consumers in our model select the flight they prefer based on that flight's characteristics, rather than their favorite airline-itinerary based on average attributes.

The second issue that comes into play when evaluating the market shares is the fact that there are two sets of integrals in (4.2). The inner integral is associated with the random parameters δ_i, and the outer integral is associated with the vector of individual prices P_i. Although these integrals do not have a closed form solution, they may be approximated numerically with arbitrary precision. For instance, one could replace the expectations by empirical means of simulated points. Such an approach, however, would be prohibitively time-consuming in our application given the relatively high dimension of the integrals involved. To partially circumvent this problem, we take the following steps. First, we approximate numerically the inner integral with the Efficient Importance Sampling method (see Richard and Zhang 1998, or Liesenfeld and Richard 2001).[16] Second, we approximate the outer integral by generating extensible lattice points modified by the baker's transformation (see Hikernell et al. 2000).[17]

[16] See Liesenfeld and Richard (2003a,b), and Richard and Van Horn (2004) for applications of the Efficient Importance Sampling method.

[17] This quasi Monte Carlo sampling method has been found by Sandor and Andras (2004) to outperform other numerical techniques for integrals of moderately high dimensions.

4.3. Econometric Estimator

We now turn to the inference method used to estimate $\theta \in \Theta$, the vector of unknown structural parameters in the discrete choice model. We apply a version of the Generalized Method of Moments (GMM) specifically designed to estimate discrete choice models with product level data. This estimation method has now become standard, and we only present it in its basic form. We refer the reader to Berry (1994), Berry, Levinsohn and Pakes (1995), and Nevo (2000) for additional theoretical and computational details.

Consider the i.i.d. sequence of observations $(\xi_k(\theta), \Psi_k)$ $(k = 1, ..., K)$, where Ψ_k is an appropriate vector of instrumental variables verifying $\dim(\Psi_k) \geq \dim(\theta)$, $\xi(\theta) = (\xi_1(\theta), ..., \xi_K(\theta))$ is the vector of unobservable flight characteristics solution of the system of non-linear equations $S_k(\xi, \theta) = \overline{S}_k$ $(k = 1, ..., K)$, $\overline{S}_k$ is the empirical market share of the airline-itinerary k observed in our primary sample, and $S_k(\xi, \theta)$ is the corresponding theoretic market share in equation (4.2) obtained for a specific value of θ.[18] We can then generate the moment conditions:

$$E_\theta \left[\Psi_k \xi_k(\theta)\right] = 0 \ .$$

The GMM estimator is based upon the empirical counterpart of the previous orthogonality conditions:

$$\widehat{\theta}_{GMM} = Arg \min_{\theta \in \Theta} B' \Omega^{-1} B \quad \text{ where } \quad B = \sum_{k=1}^{K} \Psi_k \xi_k(\theta) \ ,$$

and Ω is a symmetric positive definite weighting matrix that may be chosen optimally in order to minimize the variance of the estimator. In practice, the optimal matrix Ω is approximated by the covariance of an initial estimate of θ, in which Ω is set equal to the identity matrix.

The vector of instruments Ψ_k includes all the exogenous variables presented in the next section, except for the price and airport-share variables as they may be correlated with the unobserved product characteristics. Following Berry et al. (1997), as well as Nevo (2000), the vector of instruments also includes the average characteristics of the other products supplied i) by the same firm in the same market, and ii) by other firms in the same market. Finally, the instruments for the airport-share variable are the population and the total number of itineraries offered by the airline at the endpoint airports.[19]

[18] Our sample consists of panel data observed for different airport-pairs over several quarters. Recall that, for ease of presentation, we have omitted in this section the airport-pair and quarter subscripts.

[19] Note that the identification of the model does not require estimates of firms' costs. In addition, the paper's objective is to analyze the consumer welfare implications of the CO-NW code-share agreement,

The estimation of the discrete choice model is conducted in parallel on several workstations using Fortran and the mathematical library IMSL. To reduce further computational time, we have adopted most of the recommendations in Berry (1994), Berry et al. (1995), and Nevo (2000) to optimize the computer code. In particular, following Berry (1994), the unknown vector of parameters θ has been partitioned in two, depending on whether or not its components enter the model linearly. The computational burden, however, remains quite significant (the estimation procedure takes nearly a month to converge) because of the relatively large sample size and high dimensional integrals involved in the market shares.

5. The Sample and the Data

As mentioned earlier, our analysis relies on two different samples: a primary sample used to estimate the structural parameters of the discrete choice model, and an auxiliary sample used to estimate the distribution of the measurement error in the price variable. In this section, we concentrate on describing the primary sample, as well as the variables entering the discrete choice model. The auxiliary sample will then be discussed in the subsequent section.

The primary sample consists of data on flight schedules and prices obtained respectively from the Official Airline Guide (OAG) and the DOT. The OAG data list the time and itinerary for all flights supplied by commercial U.S. airlines. The DOT data is the Origin-Destination Survey Databank 1B. This Databank is a 10% random sample of tickets sold by U.S. airlines for travel in a quarter. From the observed round-trip tickets, we can derive the market share and the average price per airline-itinerary.[20] A key feature of Databank 1B, relative to the routinely used Databank 1A, is that it reports each of the operating and marketing carriers, which enables to identify separately online, code-share, and interline tickets.

To conduct our analysis we consider a random sample of 160 airport-pairs served by CO and/or NW between 1998 and 2001. The data are for the 1^{st} quarters of 1998 through 2001, and the 3^{rd} quarters of 1998 through 2000 (7 quarters in total). In other words, the data cover the January 1999 implementation of the CO-NW code-share agreement. The primary sample includes a total of 18 airlines supplying 207,516 products across 1,041 markets.[21] CO-NW code-share *in* 99 of the 160 airport-pairs, *through* another 30, and

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and information on airlines' costs is not required for this purpose. Finally, there is no consensus in the literature on how to model competition in the airline industry as markets and products are not independent. Therefore, we did not find it necessary to model the supply side of the airline industry.

[20] We use Borenstein and Rose (1994)'s guidelines to screen unusually high and low ticket prices.

[21] A description of the criteria used to construct our sample may be found on the first author's website at http://www.sceco.umontreal.ca/liste_personnel/armantier/index.htm.

they never code-share in the remaining 31 airport-pairs. As indicated in Table 1, where descriptive statistics for the primary sample are summarized, a sample market averages 199 products, 38 products per airline, 13 airline-itineraries, and 6,069 passengers.[22]

Let us now turn to the definition of the variables composing the vectors of product characteristics Y_j and Z_j in the consumer's indirect utility (3.1). In doing so, we assume that i) a code-share flight marketed by the two partners constitutes two distinct products; and ii) the airline-specific characteristics of a code-share product pertain to the marketing airline.[23] The first assumption is supported by the fact that, under the terms of their agreement, code-share flights are marketed separately by the two partners. In particular, CO and NW have pledged to compete in prices on code-share products.[24] The second assumption is supported by the fact that i) consumers may be unaware at the time of purchase that the product they are booking is a code-share;[25] and ii) consumers often do not know the exact obligations and level of commitment of the operating airline. In other words, one may reasonably assume that, when purchasing a ticket, a consumer considers the attributes of the airline with which she is contracting. Finally, note that we considered different partitions of the variables across the Y_j and Z_j vectors to estimate the model. We present below the partition that provided the best fit on a 25% random sample of our data.

5.1. Variables with a Random Parameter

The variables in Y_j include the following attributes of product j:

- $PEAK_j$ is a variable indicating whether the departure times for the outbound and inbound flights in a nonstop product are scheduled during peak travel hours (i.e. 5am to 9am, or 4pm to 8pm).[26] We include this variable as we acknowledge that some pas-

[22] To avoid redundancy, we refer the reader to our companion paper (Armantier and Richard 2005a) for a more extensive descriptive analysis of the CO-NW code-share agreement.

[23] Although they appear to affect slightly the estimation of some of the parameters in the discrete choice model, these assumptions are not critical to our main results regarding the effect of the CO-NW code-share agreement on consumer welfare.

[24] See Armantier and Richard (2005a) for evidence that the alliance airlines indeed appear to compete in prices on code-share products. Note also that in our primary sample data CO-NW code-share products are on average 11.6% cheaper than CO-NW online products.

[25] In fact, during our sample period, airlines and travel agents were not required to inform consumers that the flight they were booking was code-shared and might not be operated entirely by the marketing airline.

[26] $PEAK_j = 1$ if the departure times for both the outbound and inbound itineraries are scheduled during peak hours; $PEAK_j = 0.5$ if only one of the itineraries is scheduled during peak hours; and $PEAK_j = 0$ otherwise. Empirical tests suggest that the variable $PEAK_j$ is not relevant for connecting products. Finally, note that we also estimated the model after decomposing $PEAK_j$ in two dummy variables, one for the outbound flight, and one for the inbound flight. The estimation results and the economic implications did not vary significantly.

sengers, such as business travellers, may have higher valuations for peak-hours products (see Morrison and Winston 1995).

- $NONSTOP_j$ is a dummy variable equal to 1 if product j is nonstop. This fixed effect measures a consumer's valuation for not having to deal with the hassles of a stop at an intermediate airport, such as a higher probability of lost luggage, delays, or missed connections.

- $AIRPORT\_SHR_j$ is the share of passenger enplanements at the endpoint airports in the market for the airline marketing product j. Following Borenstein (1989, 1991), we recognize that a consumer's valuation of an airline's product may be affected by the airline's presence at the airports in the market. For instance, dominance at an airport confers an airline greater visibility in flight offerings, counter space, and gate access.

- HUB_j is a dummy variable equal to 1 if the origin airport in the market is a hub for the airline marketing product j. This variable is taken to capture the advantages the hub-airline may offer to passengers. Such advantages include a greater array of airport services (e.g. lounges, greater counter and gate access), more options in case of flight delays or cancellations, and a greater array of options and destinations for frequent-flyer rewards (see Borenstein 1989, 1991, Evans and Kessides 1993, Morrison and Winston 1995).

- INT_HUB_j is a variable denoting whether the intermediate transfer airports in a connecting product are hub airports for the airline marketing product j.[27] When intermediate transfers occur at a hub airport, a passenger may benefit from more convenient counter and lounge access, and from a greater availability of alternate flights in case of missed or cancelled connections.

In the indirect utility function in (3.1), we associate to the vector $X_{i,j} = (P_{i,j}, Y_j)$ a consumer-specific random parameter δ_i. Indeed, it is reasonable to suspect that valuations for the six attributes in $X_{i,j}$ may differ across airline consumers. The parameter vector δ_i is assumed to be exogenously determined by the simultaneous system of equations:

$$\delta_{i,l} = \overline{\delta}_l + \alpha_{1,l} INCOME + \alpha_{2,l} GMP + \omega_{i,l}, \quad \forall l \in \{1,..,6\} \tag{5.1}$$

where the error terms $\omega_{i,l}$ are jointly normally distributed with mean zero and variance σ_l^2; $INCOME$ and GMP are respectively the annual average per capita personal income and per capita gross metropolitan product across both metropolitan areas in the market.[28] Moreover, we allow for the random coefficients on $P_{i,j}$, $PEAK_j$,

[27] $INT\_HUB_j = 1$ if the intermediate airports in the outbound and inbound itineraries are hubs for the airline; $INT\_HUB_j = 0.5$ if only one of the intermediate airports is a hub; and $INT\_HUB_j = 0$ otherwise. Once again, decomposing INT_HUB_j in two dummy variables does not affect significantly the results.

[28] The sources for the $INCOME$ and GMP variables are respectively the U.S. Census data and the U.S. Conference of Mayors (http://www.usmayors.org). Note also that the variables $INCOME$ and

and $NONSTOP_j$, indexed by $l = 1, 2, 3$, to be correlated to each other; that is, we specify that $Cov(\delta_{i,l}, \delta_{i,l'}) = \sigma_{l,l'} \mathbb{I}_{\left[(l,l') \in \{1,2,3\}^2\right]}$, where $\mathbb{I}_{[.]}$ is the indicator function, and $(\sigma_{1,2}, \sigma_{1,3}, \sigma_{2,3})$ are unknown covariance parameters to be estimated. Indeed, some passengers (e.g. business travellers) may simultaneously place a lower emphasis on price, and a greater emphasis on nonstop travel and peak-hours departures.

5.2. Variables with a Deterministic Parameter

The variables in Z_j include the following attributes of product j:

- $AIRLINE_j$ is a $M \times 1$ vector of dummy variables, where M is the number of different airlines in the primary sample. If airline m markets product j, then the m^{th} component of $AIRLINE_j$ is equal to 1, and all other components are equal to 0. This variable accounts for a consumer's valuation of an airline's overall reputation, service, and frequent-flyer programs.

- $TRAVEL\_TIME_j$ is the scheduled travel time (in minutes) across the outbound and inbound itineraries (i.e. it includes all flight times and airport transit times, if any). Our hypothesis is that, all else equal, passengers prefer shorter flights.

- $TRANSIT\_TIME_j$ is the scheduled airport transit time (in minutes) at intermediate airports (if any). We include this variable since time spent at an intermediate airport may be perceived as an additional inconvenience by passengers.

- $CS\_CONW\_PROD_j$ and $CS\_CONW\_MKT_j$ are two dummy variables identifying the implementation of the CO-NW code-share agreement at the product and market levels. $CS\_CONW\_PROD_j$ equals 1 when product j is code-shared by CO-NW during the corresponding quarter, and $CS\_CONW\_MKT_j$ equals 1 for all CO-NW products in markets *in* which CO-NW code-share during that quarter. These variables should capture any fixed effect associated with code-sharing, such as differences in reputation and/or travel experience. Note that we have decided to distinguish two code-share variables, since it is unclear whether consumers in our sample were aware of the implementation of the agreement at either the product or market level.

- CS_REG_j is a dummy variable accounting for regional code-share agreements. It is equal to 1 when product j is code-shared by either CO and America West, or NW and Alaska Airlines. This variable may reveal whether the new form of code-share agreements initiated by CO-NW may be distinguished from regional agreements.

- $INTERLINE_j$ is a dummy variable equal to 1 when the product is an interline. Note that unlike the code-share variables, the interline variable is only defined at the product level. Indeed, passengers necessarily know that they are purchasing an interline

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GMP are defined in deviation from their mean, so that $\overline{\delta}_l$ may be interpreted as the unconditional mean of $\delta_{i,l}$.

ticket, as it requires two different bookings. This variable should enable us to test whether, beyond observed differences (e.g. higher average prices for interline tickets), code-share and interline products are perceived in a similar manner by the public.

- $STRIKE\_NW_j$ is a dummy variable equal to 1 in the third quarter of 1998 for all NW flights in markets where NW competed. This variable should capture the impact of the NW strike during that period.

- QTR_j is a 6×1 vector of dummy variables denoting the quarter in which travel takes place. These dummy variables account for any time-based variations in the valuation of airline travel, and they should be interpreted in contrast with the quarter of reference (i.e. the first quarter of 2001).

- $MILES_j$ and $MILES_j^2$, where $MILES_j$ represents the "great circle" distance (i.e. the distance of the most direct route) between the two airports in the market. Note that $MILES_j$ is defined at the market level, and therefore it takes the same value for all products (i.e. nonstop and connecting) in market j. Following Berry et al. (1997), we include these variables to measure the attractiveness of air travel compared to the outside good.

6. Estimation of the Auxiliary Model

6.1. The Auxiliary Model and Sample

This section is devoted to the estimation of the auxiliary model used to address the measurement error in the price variable. Recall that the problem stems from the fact that in the primary sample we only observe $\overline{P}_k$, the average price across consumers and products in airline-itinerary k, but not $P_{i,j}$, the price of product j to consumer i. The object here is to estimate with an auxiliary sample the distribution of the measurement error $e_{i,j} = P_{i,j} - \overline{P}_k$ conditional on individual and product characteristics. As further explained below, this estimated conditional distribution is then used to integrate the price $P_{i,j} = \overline{P}_k + e_{i,j}$ out of the market shares (3.3).

The specification adopted for the measurement error is of the form:

$$e_{i,j} = P_{i,j} - \overline{P}_k = A_j'\gamma + B_i'\widetilde{\gamma} + \eta_i + \eta_{i,j} \quad , \tag{6.1}$$

where product j belongs to the airline-itinerary k; A_j and B_i are vectors of observed product and consumer characteristics; η_i is an unobserved consumer-specific random effect with mean zero and variance ν^2; and $\eta_{i,j}$ is a normally distributed error term with mean zero. In addition, to account for possible heteroskedasticity in the data, we assume that $Var(\eta_{i,j}) = \sigma^2 \left(\overline{P}_k\right)^{\zeta}$, where σ and ζ are parameters to be estimated.

To estimate the model we acquired an auxiliary sample of ticketing data from the

SABRE Group.[29] These data include 64,197 tickets with an outbound flight for travel date in October 2002 across 78 airport-pairs.[30] Each ticket lists the ticket price, the purchase date, the travel dates, the flight times, and the class of travel (see Table 2 for summary statistics). The vector of product characteristics A_j therefore consists of $PEAK_j$, $TRAVEL\_TIME_j$, and $TRANSIT\_TIME_j$. These variables are defined here in identical fashion to their analog in the discrete choice model. The vector of observable individual characteristics B_i is composed of three sets of dummy variables representing i) the class of travel (i.e. the variables $FIRST$, $BUSINESS$, $COACH$, $DISCOUNT\_SAT$ and $DISCOUNT$ are equal to 1 when the passenger acquired respectively a first, business, coach, or discounted ticket with or without a Saturday night stay-over); ii) the number of days of advance purchase (i.e. the variable $BOUGHT\_a\_TO\_b\_DAYS$ equals 1 when the passenger bought his ticket between a and b days prior to its departure); and finally, iii) the number of days between the departure and return dates (i.e. the variable $TRIP\_a\_TO\_b\_DAYS$ equals 1 when the duration of the trip is between a and b days).[31] Finally, the measurement error $e_{i,j}$ is constructed by subtracting the price of each ticket $P_{i,j}$ in the auxiliary sample, from its airline-itinerary average $\overline{P}_k$.

The random effect η_i is assumed to capture any residual unobserved consumer specific effect, such as the consumer's age, or his need/taste for airline travel. Note, however, that the auxiliary sample does not possess a panel structure. Indeed, we only observe a single purchase decision for each consumer. To estimate the distribution of the random effect η_i, we therefore define different groups of consumers corresponding to the different possible combinations of the dummy variables in B_i (e.g., the group of business class passengers travelling for less than two days and purchasing their tickets less than two days in advance). The random parameter η_i then takes the same value for all passengers within a group, which enables the estimation of the distribution of η_i. The variation between passengers within the same group is then captured by the main error term $\eta_{i,j}$.

Before moving to the estimation results, let us briefly explain the specification adopted for the auxiliary model. The objective here is not to estimate an inverse demand function for airlines products.[32] Instead, the sole purpose of the auxiliary model is to estimate the conditional distribution of the measurement error $e_{i,j}$ in order to integrate

[29] The SABRE group offers the world's largest computer reservation system through more than 50,000 travel agents, as well as the internet (Travelocity).

[30] Note that since the auxiliary sample is not a time series, and does not overlap with the implementation of the CO-NW code-share agreement, we cannot use it directly to estimate the discrete choice model.

[31] Note that the "discretization" of the trip duration, and advance purchase variables are in fact consistent with most airlines pricing practices. Indeed, although the price of a given ticket can change on a daily basis, the major price variations typically occur on a weekly basis.

[32] In particular, the auxiliary model does not attempt to reflect the complex "yield management" practices used by airlines to price their products.

it out of the market shares (3.3). The specification of the auxiliary model is therefore essentially dictated by the variables available in the primary sample. In particular, the variables in A_j have been selected to be common to the discrete choice and the auxiliary models. Indeed, although we use the product characteristics observed in the auxiliary sample to estimate the auxiliary model, we must use the observations of A_j in the primary sample when substituting $\overline{P}_k + e_{i,j}$ for the unobserved price variable $P_{i,j}$ in the market shares (3.3). In contrast, consumer specific characteristics have been included in the auxiliary model, although they are not observed in the primary sample. Note, however, that as long as they enter the utility function in an additively separable way, individual specific variables may be ignored in the market shares (3.3), since they cancel out in the discrete choice model.[33] In other words, to integrate the price variable out of the market shares, we only need to replace $P_{i,j}$ by $\overline{P}_k + A_j'\widehat{\gamma} + \eta_{i,j}$, where $\overline{P}_k$ and A_j are observed in the primary sample, while the distributions of $\eta_{i,j}$ and $\widehat{\gamma}$ have been estimated in the auxiliary model.[34] Finally, fixed and random consumer effects have been included in the auxiliary model as they both capture a significant amount of the measurement error. As a result, the estimated distribution of the residual error term $\eta_{i,j}$ becomes tighter, and the numerical integration of $P_{i,j}$ out of the market shares (3.3) is significantly more accurate, than when individual characteristics are not included in the estimation of the auxiliary model.

To conclude, note that the method we devised to address the measurement problem on the price variable in our discrete choice model is only valid if the model estimated with the auxiliary sample, is consistent with the measurement error on the price variable in the primary sample. In other words, after controlling for the product attributes A_j and the consumer characteristics B_i, the distribution of prices around their airline-itinerary price $\overline{P}_k$ needs to be invariant whether we consider a market in the auxiliary or in the primary sample.[35] Unfortunately, this invariance hypothesis cannot be tested directly since prices in the primary sample cannot be matched to a specific product. A series of less formal tests, conducted at the airline-itinerary level, suggests no significant differences in the price distribution between the auxiliary and primary samples.[36] In

[33] Indeed, when deriving the probability to choose a product j, a consumer must compare the utility for product j, with the utility for any other product j'. In practice, this comparison involves subtracting the utilities for product j and j'. As a result, individual specific characteristics in a consumer utility function will not appear in either the choice probabilities or the market shares (see Nevo 2000).

[34] The numerical integration of the market shares with respect to the price variable accounts for the estimation error in the auxiliary model. In other words, to generate a simulated point for the quasi Monte Carlo integration method, we draw each time a pair $(\widehat{\gamma}, \eta_{i,j})$ from their respective estimated distributions.

[35] Note that, because of the specification of the auxiliary model, both the mean and the standard deviation of the measurement error are allowed to differ across airline-itineraires both within and across the primary and auxiliary samples.

[36] To conduct these informal tests we combine the primary and auxiliary samples to estimate various

addition, the invariance hypothesis is further supported by the fact that, by construction, the variable $\overline{P}_k$ controls for any time and airline-itinerary fixed effect. In other words, the assumption that the auxiliary model is consistent with the measurement error in the primary sample may be considered reasonable.

6.2. Results from the Auxiliary Model

Table 3 reports the estimation outcomes for the auxiliary model. Observe first that for obvious identification reasons, we have excluded the variables $TRIP\_30\_TO\_365\_DAYS$ and $BOUGHT\_30\_TO\_365\_DAYS$ when estimating the model. The consumer of reference in the estimation is therefore a passenger travelling for more than 30 days, and purchasing his ticket at least 30 days in advance.

Let us first concentrate on the vector of parameters γ associated with the product characteristics A_j. The estimated components of γ are all significantly different from zero at a 5% significance level. In particular, the estimation results indicate that, all else equal, prices for flights departing during peak-hours are higher than their airline-itinerary average. Moreover, we find that, within an airline-itinerary, prices decrease with the time spent in transit at an intermediate airport, while they increase with the total travel time.[37] The latter result may reflect the added cost incurred by an airline when flying longer distances.

Looking at the deterministic individual characteristics in B_i, we find, as expected, that prices rise significantly with the class of the ticket (e.g. from coach to first class). Prices are also significantly higher than average when the ticket is bought closer to the travel date and, to a lesser extent, when the trip lasts only a few days. It appears, however, as indicated by the insignificant parameters in Table 3, that prices remain essentially constant when the ticket is acquired at least 14 days in advance, or when the trip last for more than 3 days. In fact, Table 3 indicates that the remaining parameters are left essentially unchanged, when we re-estimate the model without these insignificant parameters.[38]

models such as: $P_{i,j} = \gamma_1 + \gamma_2 D_{i,j} + \overline{A}_k' \gamma_3 + \eta_{i,j}$, where $\overline{A}_k$ represents the average product characteristics within the airline-itinerary k, $D_{i,j}$ is a dummy variable equal to 1 when $P_{i,j}$ is observed in the primary sample, and the distribution of $\eta_{i,j}$ is specified as in the auxiliary regression. The regression results yield $\widehat{\gamma}_2 = -0.101$ with a standard deviation of 2.763, thereby supporting the hypothesis that the distribution of prices within an airline-itinerary does not differ significantly in the primary and auxiliary samples. Similar tests have been conducted after introducing a dummy variable in the slope coefficient γ_3, and in the specification of the heterogenous error term $\eta_{i,j}$. Again, these tests do not provide significant evidence indicating a difference between the two samples.

[37] This result does not imply that we predict cheaper prices on nonstop flights than on connecting flights. Indeed, our model only enables the comparison of prices for flights within the same itinerary.

[38] We use this re-estimated model consisting only of significant parameters when substituting $\overline{P}_k + e_{i,j}$ for the unobserved price variable $P_{i,j}$ in the market share (3.3).

The standard error (\$50.7) of the consumer specific random effect η_i represents slightly more than 15% of the average price in our sample. In other words, after controlling for observed individual characteristics, we are still able to capture a significant amount of the price variation across types of consumers. Finally, we find evidence of heterogeneity in the data since the parameter ζ is significantly different from zero.

In summary, the results for the auxiliary model confirm that the measurement error $e_{i,j} = P_{i,j} - \overline{P}_k$ is correlated with the product characteristics, and varies markedly across consumers. These findings support our two-step approach to deal with measurement error.[39]

7. The Discrete Choice Estimation Results

Estimation results for the discrete choice model are provided in Tables 4 to 6.[40] Let us first concentrate on the estimation of the random parameters $\delta_{i,l}$ in Table 4. The estimated mean values $\overline{\delta}_l$ of these random coefficients are all significantly different from zero, and they have the expected signs. For instance, we find that consumers dislike higher prices, and prefer nonstop flights, scheduled during peak-hours, from a hub-airline with a large airport share. Interestingly, we find that connecting passengers prefer to transit through the hub airports of the airline from which they bought their ticket (i.e. the parameter of INT_HUB is positive and significant). To the best of our knowledge, such a result has not been previously identified econometrically in the economic literature on airlines.

The next two columns in Table 4 report the effects on the random coefficients $\delta_{i,l}$ of the $INCOME$ and GMP variables, representing respectively the per capita income and per capita gross metropolitan product. We find that consumers in markets with high $INCOME$ and/or GMP are less sensitive to prices, but they have a greater valuation for nonstop flights. A higher GMP also appears to increase the marginal utility for the $PEAK$, HUB, and INT_HUB characteristics. This result is consistent with the fact that these flight attributes are usually of greater importance to passengers travelling for business. In addition, we find that valuation of the $AIRPORT\_SHR$ variable increases for passengers in markets with a higher GMP. This result suggests that passengers travelling for business value the greater scope of services and airport facilities that dominant airlines may offer. In contrast, we find that passengers in high-income areas have a lower valuation of an airline's airport share, suggesting that they may be less sensitive to (e.g.) frequent-flyer programs and other marketing devices.

[39] For a more detailed analysis of the determinants of airlines prices with the SABRE data, see Armantier and Richard (2005b).

[40] The standard deviations in these tables are asymptotically robust, and they have been corrected for simulation errors (see Berry et al. 1995).

The last column in Table 4 provides the standard deviations σ_l for the random coefficients $\delta_{i,l}$. These standard deviations are all significantly different from zero, thereby confirming that consumers have heterogenous valuations for the product attributes in Y_j. Note that the standard deviations on the $PEAK$, INT_HUB, and $NONSTOP$ variables are high relative to their estimated mean coefficient $\overline{\delta}_l$. As explained in Berry et al. (1995), this indicates that consumers with high marginal utility for these attributes will tend to substitute towards products with similar attributes.

In Table 5, we report the estimated correlations between the random parameters associated with the $PRICE$, $PEAK$, and $NONSTOP$ variables. We find that the valuation of $PRICE$ is highly and negatively correlated to the valuation of $PEAK$ and, to a lesser extent, to that of $NONSTOP$. The estimated correlations therefore confirm that passengers less sensitive to prices, such as passengers travelling for business, have a higher marginal utility for nonstop flights scheduled during peak-hours. As we shall see in Section 10, failure to account for these correlations may have a significant impact on some of the economic implications of the model.

Let us now turn to Table 6, where the estimation results for the deterministic parameters λ are presented. We find that the parameters associated with the variables $TRAVEL\_TIME$ and $TRANSIT\_TIME$ are significantly smaller than zero. In other words, consumers seem to prefer shorter flights, and experience an additional disutility when spending time in transit at an intermediate airport. These effects are interesting since, to the best of our knowledge, they have not been previously identified econometrically. In addition, they appear to support Morrison and Winston's (1995) conjecture that the increase in transit time (as a fraction of total travel time) that followed deregulation, adversely impacted consumers.

We also report in Table 6 that the parameter of the product level code-share dummy variable is significantly lower than zero (see CS_CONW_PROD). In other words, we find evidence of a disutility for flights code-shared by CO-NW. This estimated disutility is in fact non-negligible since, when taking into account the estimated parameters of the airline dummy variables for CO and NW in Table 6, we find that the passengers' valuation of a CO and NW product drops respectively from 0.101 to 0.059, and from 0.083 to 0.041, when the partners code-share the product. The agreement, however, does not appear to have affected the reputation of the non-code-share CO-NW products in markets *in* which the partners code-share. Indeed, the parameter of the market level code-share dummy variable is not significantly different from zero (see CS_CONW_MKT in Table 6). The disutility for CO-NW code-share products may be explained by a combination of factors. First, some passengers may dislike the fact that their flights are not entirely operated by the airline from which they purchase their ticket. Second, some passengers may dislike the fact that they do not know how the two partners share responsibilities in case of refunds, delays, cancellations, or lost luggage. Third, code-share products are often more congested, which may negatively impact passengers loyal to either CO or NW. Note, however, that these results are not sufficient to conclude unambiguously about the consequences of the code-share agreement on consumers. They only suggest that the reputation of CO and NW drops when they code-share a product. As we shall see, consumer surplus may still increase due to the creation of new products, or the improvement of existing products.

The estimation outcomes show no discernible effects for regional code-share and interline products, as the parameters of the variables CS_REG_PROD and $INTERLINE$ are not significantly different from zero in Table 6. Therefore, unlike CO-NW code-share products, regional code-share and interline products do not seem to be perceived by the public as being significantly different from other products. This implies in particular that, after controlling for the higher prices of interline tickets, the additional features of interline products listed footnote 9 (e.g. double checking and booking) do not appear to affect consumers' utility. Moreover, observe that the strike launched by NW employees in the third quarter of 1998, does not appear to have penalized the demand for NW products, as the parameter associated to the variable $STRIKE\_NW_j$ is found to be insignificant. This last set of results, however, should be interpreted with caution since we only possess a small number of observations for the regional code-share, interline, and strike variables.

The estimated values for the airline dummy parameters in Table 6 appear sensible, and broadly consistent with airline rankings at the time, such as the 2001 Airline Quality Ratings.[41] For instance, the dummy parameters are relatively higher for Southwest and Delta Airlines, and lower for TWA (whose assets were acquired out of bankruptcy by American Airlines in 2001). The parameters on the small regional carriers are mostly insignificant, maybe due to the fact that we have relatively few observations on these airlines.

When compared to the quarter of reference (the first quarter of 2001), the parameters on the quarter dummy variables suggest i) a seasonal effect with higher airline travel in the summer than in the winter, and ii) a modest positive time trend, indicating a slight erosion in the market share of the outside good over the three years spanned by our data. Moreover, we find evidence that the market size expanded exogenously, since the parameter ϕ_1 is significantly greater than zero in Table 6. Finally, the sign and magnitude of the parameters of the mileage variables ($MILES$, $MILES^2$) are consistent with findings in Berry et al. (1997). They reflect the dual relationship between air travel and distance; that is, we find that flying is more attractive than other means of transportation over intermediate distances, but the demand for travel falls when distances become too large.

[41] Source: The Airline Quality Ratings 2001 at www.unomaha.edu/~unoai/aqr/.

8. Economic Implications

We now turn to the economic implications of the estimated parameters. Note that although not directly related to the main object of the paper (i.e. the consumer welfare consequences of the CO-NW code-share agreement), the results presented in this section present a major economic interest in their own right. Indeed, to the best of our knowledge, some of the premium estimated here are unique in the economic literature on airlines.

We first conduct some simulations to examine the consequences of increasing prices across all products by 10%. We find that such an increase in price would lower the probability that a consumer purchases an airline product by 8.96%. Airline passengers would also be less likely to travel with a nonstop flight (−3.12%), and to use a hub-airline (−5.33%). As a result, although prices increase by 10% in the simulation, the average price actually paid by passengers only increases by 6.58%. These simulation results seem sensible as they suggest that passengers substitute high-priced nonstop and hub-airline flights for either cheaper flights or the outside good. We also conduct some simulations to evaluate the level of the "hub-premium". We find that a hub-airline can charge a fare up to 9.32% higher than non-hub-airlines for a flight taking-off from its hub, but with otherwise identical characteristics. The magnitude of the hub-premium, although slightly smaller, is consistent with Berry et al. (1997).[42] Likewise, we find that, all else equal, consumers are willing to pay an extra 6.41% on average to fly with one of American, Delta or United Airlines (the "Big 3" airlines in the U.S. market). This result may be explained in part by the marketing efforts realized by these airlines to generate consumer loyalty (e.g. these airlines have the most popular frequent-flyer programs). Moreover, our simulations indicate that passengers are willing to disburse 18.48% more for a nonstop flight, and an additional 4.75% if that nonstop flight takes off during peak-hours.[43] Hence, the opportunity to take a nonstop flight appears to be a key attribute for which passengers are willing to pay. Finally, to reduce by 10% the duration of their flight (roughly 30 minutes each way on average), or by 10% the time spent in transit at an intermediate airport (roughly 7 minutes per stop at an intermediate airport on average), consumers are willing to pay a fare that is higher by 5.26% and 1.95%, respectively. These effects, although modest, are significant statistically, and they should not be ignored when analyzing certain aspects of the airline industry, such as (e.g.) the consequences of deregulation (see Morrison and Winston 1995).

Table 7 displays the average own and cross-price elasticities of market shares implied by the results. To facilitate the discussion, we report the average elasticities across mar-

[42] For additional insights, see Borenstein (1989, 1991), Dresner and Windle (1992), Gordon and Jenkins (2003), as well as Lee and Luengo-Prado (2005).

[43] The 18.48% average for nonstop flights incorporates changes in both flight and transit times.

kets for five groups of airlines: i) CO and NW (the "Alliance" airlines); ii) American, Delta and United Airlines (the "Big Three"); iii) US Airways, TWA (the "Other Majors"); iv) Southwest and America West ("WN-HP");[44] and v) the "Regional" group that encompasses the remaining smaller carriers. Note first that the magnitudes of the elasticities are generally consistent with previous findings in the airline industry.[45] As one may expect, the "Big Three" have the lowest own-price elasticity (in absolute terms), while the market shares of the "WN-HP" and "Regional" groups are the most sensitive to price. Note also that the own-price elasticity of the "Alliance" airlines lays between the "Big Three" and the "Other Majors" groups. The cross-elasticities in Table 7 show that a price increase by any other group of airlines mostly benefits the "WN-HP" and "Regional" airlines groups, while it leaves the market shares of the "Big Three" essentially unaffected.

We focus in Table 8 on the price elasticities of CO and NW. We see that, overall, the own-price elasticity of NW is slightly higher than its partner (in absolute value), and the market shares of CO are less sensitive to an increase in the price of NW. We also compare the evolution of the CO and NW elasticities before and after the 1999 implementation of their alliance. Table 8 shows that CO and NW's own-price elasticities decrease slightly (in absolute values), and become more homogenous after the implementation of their code-share agreement. In other words, it appears that the alliance enabled CO and (especially) NW to become less sensitive to price in our sample of markets. The relatively low initial cross-price elasticities between CO and NW suggest that the airlines were good candidates to code-share flights in our sample markets, as they did not appear to be fierce price competitors on these markets. Note also that the cross elasticities increase after the implementation of the code-share agreement, suggesting that the alliance made the products supplied by CO and NW slightly better substitutes. This result was expected since CO and NW market some of the same products following the code-share agreement.

In summary, the estimation results and their economic implications appear sensible, and they attest to the ability of our discrete choice model to capture consumer behavior in the airline industry.

[44] By grouping Southwest and America West together, we are not implying that these two carriers are similar. It simply happens that their respective own and cross-price elasticities are comparable in our sample markets.

[45] See Oum, Gillen and Noble (1986), as well as Whalen (1999) for aggregate demand elasticities estimated from log-linear demand functions, and Peters (2001) for a discrete choice estimation of elasticities.

9. Consumer Welfare Analysis

We are now in a position to examine the consumer welfare implications of the CO-NW code-share agreement. Namely, we compare the expected consumer surplus calculated before and after the implementation of the code-share agreement in each of the 160 airport-pairs in our sample.[46] The pre-implementation (respectively, post-implementation) consumer surplus in a given airport-pair is the average expected consumer surplus across all quarters preceding (respectively, following) the implementation of the code-share agreement in that airport-pair.[47]

The simulation results are reported in Table 9. First, observe that we estimate the average consumer surplus of an airline passenger around \$30. We are not aware of equivalent measures in the literature. We also find that a passenger typically gets a slightly higher surplus when she flies with CO-NW rather than a different airline. This result may follow from the composition of our data which samples disproportionately from CO-NW markets, and it is not expected to generalize to the entire U.S.

We report in Table 9 that the consumer surplus per CO-NW passenger decreases by 4.14% after the partners code-share *in* a market. The decline is even more pronounced (-17.12%) in markets *through* which CO-NW code-share. In contrast, CO-NW passengers enjoy a 1.1% increase in their individual consumer surplus in markets where the alliance never code-shares. Likewise, passengers flying passengers flying on airlines other than CO and NW experience a growth in their individual consumer welfare, independently of the market in which they travel. In other words, it appears that per passenger consumer surplus only declines for CO-NW passengers in markets affected by the code-share agreement.

Note that the implementation of the code-share agreement in a market generated strategic reactions from the alliance competitors. In particular, we find in our companion paper (Armantier and Richard 2005a) that prices, as well as other product characteristics, were substantially modified by CO-NW competitors in a number of markets affected by the agreement (see Ito and Lee 2004 for similar evidence). To evaluate fully

[46] There exists well known formulae to calculate a representative consumer expected surplus under the logit framework (see e.g. McFadden 1981, Small and Rosen 1981, or Train 2003). We must however rely on simulations, as we are interested in the expected surplus conditional on whether or not the consumer purchased a product from the alliance. The basic premise of these simulations is that, by definition, the consumer surplus of an agent i in a given market is $\frac{1}{\delta_{1,i}} \underset{j=0,\ldots,J}{Max}\, U_{i,j}$, where $\delta_{1,i}$ is the marginal utility of income, and $U_{i,j}$ is agent i utility as defined in (3.1).

[47] In the period following the implementation of the agreement in a market, we only take into consideration the quarters during which CO-NW code-share. In other words, if the partners stop code-sharing in a market, then we ignore the quarters following that decision. Finally, in markets in which the partners never code-share, we compare the consumer surplus before and after January 1999, date at which the agreement became effective.

the consequences of the code-share agreement on consumers, one must therefore also measure the net effect of the agreement on the surplus of a representative consumer, irrespective of the airline she selected. Table 9 indicates that the average per passenger consumer surplus in markets affected by the code-share agreement declines by 3.11%, all of which may be traced to losses incurred by CO-NW passengers (−7.15%). This result contrasts once again with markets not affected by the agreement (last row of Table 9) where consumers see their individual surplus increase slightly and homogeneously irrespective of the airline they choose. In other words, it appears that the code-sharing agreement may be considered one of the principal factor behind the per passenger losses in markets affected by the CO-NW agreement.

The sharp consumer welfare decline (−17.12%) observed in markets *through* which CO-NW code-share may be essentially attributed to the 11.9% price increase for CO-NW nonstop products in these markets.[48] The rationale behind the drop in the surplus of a CO-NW consumer when the alliance code-shares *in* a market is more subtle to identify, as it cannot be linked to a single cause. The decomposition of this 4.14% drop into different sources (see Table 10), indicates that a consumer seems to benefit from the expansion in the number of products supplied by CO-NW when they code-share *in* a market. This result is consistent with our data, as the number of products supplied by the alliance airlines nearly doubles when they code-share *in* a market. Note also that a CO-NW consumer only appears to benefit marginally from lower prices. This result is again consistent with our data, as we only observe a 2.5% decrease in the average price of CO-NW products in markets *in* which they code-share. We note, however, that the decline in prices is not uniform across itineraries. In particular, the average price of CO-NW nonstop flights rises by 9.7% in markets *in* which the alliance code-shares. As indicated in Table 10, the gains generated by lower prices and the introduction of new products are offset by a combination of nearly homogenous losses produced by the variations in different product characteristics. A careful examination of the simulation outcomes indicates that this result may be essentially explained by changes in travelling patterns. In particular, some passengers appear to substitute nonstop CO-NW products, which as just mentioned became more expensive after the agreement took effect, in favor of cheaper code-share alternatives with slightly less favorable characteristics. As a result, flight attributes, such as nonstop, peak-hours or travel time, do not contribute as much to the surplus of a consumer after the implementation of the agreement. Note that these results illustrate the importance of taking into consideration all flight attributes, not only prices, when analyzing consumers' decisions.[49] Indeed, an analysis focusing

[48] For a detailed analysis of price variations in code-shared markets see Armantier and Richard (2005a), as well as Ito and Lee (2004).

[49] See Richard (2003) for similar evidence on airline mergers.

solely on prices, as is standard in policy reviews of alliances and mergers, might have erroneously concluded that the code-share agreement positively impacted the consumer surplus per passenger in markets *in* which the alliance code-share.

The welfare estimates presented until now do not take into consideration the variations in passenger volume within an airport-pair that followed the implementation of the code-share agreement. Indeed, our primary sample indicates that the number of CO-NW passengers increased by 13.4% (respectively, decreased by 5.2%) after the partners code-shared *in* (respectively, *through*) a market.[50] Once it accounts for variations in passenger volumes, our model predicts a 6.65% increase, from \$8.23 to \$8.78 millions dollars, in the total welfare of CO-NW consumers across airport-pairs *in* which the partners code-share (see Table 11). In other words, although the individual welfare of a CO-NW consumer declines, CO-NW, by expanding their consumer base, are able to increase the total welfare of their passengers in markets *in* which they code-share. In sharp contrast, both the surplus per CO-NW consumer and the number of CO-NW passengers decrease in airport-pairs *through* which CO-NW code-share. As a result, the total welfare of CO-NW consumers falls by 21.00% across airport-pairs *through* which these airlines code-share (from \$3.42 to \$2.70 millions). Interestingly, the total welfare of passengers travelling on airlines other than CO-NW increases by 15.07% in airport-pairs *in* which CO-NW code-share, and by 12.37% in airport-pairs *through* which CO-NW code-share. Hence, as previously conjectured, the implementation of the CO-NW code-share agreement appears to generate benefits to passengers on other airlines, possibly as a result of an increase in competition (see Armantier and Richard 2005a, as well as Ito and Lee 2004).

Once we aggregate changes across markets *in* and *through* which CO-NW code-share, we find that, although the total welfare of CO-NW passengers declines by 1.47%, the total welfare of passengers across all airlines rose by 6.69% in airport-pairs affected by the code-share agreement. These gains are non-negligible when compared to the 2.89% growth in total consumer welfare in airport-pairs not affected by the agreement. These comparisons, however, are misleading since part of the passenger increase may be attributed to exogenous factors such as the expansion of the market size, or the contraction of the outside good market share (see Section 7). Once we control for these exogenous factors, we find that the magnitude of the gains in total consumer surplus (respectively, 2.69% and 2.28%) is very similar whether the markets are affected or not by the code-share agreement (see the last three columns of Table 11). In other words, our

[50] The increase in the number of passengers in markets *in* which the alliance code-share is not necessarily inconsistent with the reduction in consumer surplus observed in Table 9. Indeed, the number and the attributes of the products supplied before and after the implementation of the code-share agreement differ. In addition, recall that the number of consumers also rises purely exogenously in our model from the combined expansion of the market size, and the market share of airline products (see Section 7).

results suggest that, while harming the per consumer surplus of the alliance passengers, the CO-NW code-share agreement does not improve significantly the total welfare of consumers.

To conclude, it is interesting to note that changes in total welfare are proportional to the extent of code-sharing in a market. Indeed, there is a 0.417 correlation (respectively, -0.735) between the percentage of CO-NW passengers that code-share, and the variation in per passenger consumer surplus when CO-NW code-share *in* (respectively, *through*) the market. Hence, the magnitude of the changes (positive or negative) in consumer surplus in a market increases with the proportion of code-share passengers in the market.

10. Robustness and Alternative Specifications

We test in this section the robustness of the results just presented by comparing our benchmark model to some alternative specifications.[51] We start by considering the consequences of ignoring the measurement error problem in the price variable. In other words, we estimate the model under the assumption that the price of a product for any consumer is systematically equal to the average price in Databank 1B for the corresponding airline-itinerary (i.e. $P_{i,j} = \overline{P}_k$ for any consumer i and any product j belonging to the airline-itinerary k). For parsimony, we only report in Table 12 the estimation outcomes for the most relevant variables, as well as the most important economic implications. According with intuition, passengers appear to be significantly less price sensitive when we set prices equal to their airline-itinerary averages. As a result, the airlines' own-price elasticities are smaller in absolute terms, while the hub and nonstop premiums are considerably inflated. Observe also that the remaining estimated parameters differ significantly from those obtained in Section 7 with our benchmark model, and they do not necessarily have the expected signs (see $TRAVEL\_TIME$). Moreover, although the consumer surplus appears to vary in the same direction after the implementation of the code-share agreement, the magnitude of the effect differs significantly from the benchmark model. To test which specification fits the data better, we follow the approach developed by Singleton (1985) for non-nested hypotheses. In other words, we create a structural model nesting as special cases both the benchmark and this alternative model. The P-values in the last two rows of Table 12 clearly indicate that one may reject the alternative model in favor of the benchmark.[52] This result therefore suggests that ignoring the measurement error on prices leads to significant biases both in the

[51] Due to the time required to estimate some of these models, we are limited in the number of comparisons we can conduct.

[52] The P-value of $1.254E-5$ indicates that we can reject the alternative in favor of the benchmark at any usual significance level. In addition, the P-value of 0.321 indicates that we cannot reject the benchmark model in favor the alternative at any usual significance level.

estimates and in their economic implications.

We now estimate a simplified model in which consumers' valuations of the $PRICE$, $PEAK$ and $NONSTOP$ attributes are constrained to be uncorrelated. Table 12 indicates that when we impose this restriction, consumers appear to be more sensitive to prices, while putting little or no weight on the other flight characteristics. As a consequence, the various price elasticities and premiums appear considerably lower. More importantly, ignoring the correlation between these flight attributes would have led us to conclude erroneously that the surplus per CO-NW consumer increases when the alliance airlines code-share *in* a market. To test whether the three correlation coefficients may be considered jointly significant, we adopt the extension to the general method of moment framework of the Wald test (see e.g., Newey and West 1987). The P-value in Table 12 indicates that one may reject the alternative model in favor of the benchmark.

We also estimate a pure logit model in which preferences for flight attributes are constrained to be deterministic and common to all consumers. The results in Table 12 suggest a significant variation in the parameters' estimates, although no obvious trend may be detected. Likewise, the economic interpretations, and the consumer welfare predictions, differ notably from the benchmark model, even if they are of the same signs. The P-value in Table 12 confirms that this alternative model does not fit the data as well as the benchmark model.

Up until now, we have implicitly assumed that the different options covered by the outside good (e.g. travel by automobile or train) are comparable to those of the inside goods (i.e. airline travel). Following Berry et al. (1997), and Peters (2001), we now add to our benchmark model a nest for the outside good. This nested logit specification recognizes that airline products may be better substitutes to one another by creating correlations among their utilities.[53] Table 12 indicates that the additional parameter ρ is not significantly different from 1, thereby rejecting the presence of a nest for the outside good. This result contrasts with Berry et al. (1997) and Peters (2001). We conjecture that this may be explained by the fact that we considered a richer model in which decision are made at the flight level, and that we accounted for measurement errors and possible correlations in the valuations of certain attributes. Note also that neither the estimated parameters, nor their economic implications change significantly under the nested logit specification.

Finally, we adopt a specification similar to Berry et al. (1997), in which consumers may be divided in two groups, implicitly representing business and tourist passengers. As a result, the individual specific random parameters are now assumed to follow a discrete two point distribution, with each mode representing a different group of con-

[53] Note that the utilities for products with similar characteristics were already correlated in the benchmark model, since we used a random coefficients specification.

sumers. According with Berry et al. (1997), the results in Table 12 indicates a class of price insensitive passengers, with high marginal valuations for peak-hours departure and nonstop flights, which in all evidence reflects the preferences of business passengers. The remaining estimated parameters and the economic implications, although of similar signs and magnitudes, differ somewhat from those obtained under the benchmark model. In fact, the P-values in Table 12 indicate that one may reject this alternative model in favor of the benchmark. In other words, simply distinguishing two classes of passengers does not appear to be sufficient to model adequately the behavior of consumers in the airline industry.

To summarize, the benchmark model appears to be robust to alternative specifications. In addition, a test of the overidentifying restrictions fails to reject the hypothesis that the benchmark model is correctly specified (P-value $2.035E-2$). The tests conducted in this section therefore reinforce the credibility of the results presented in this paper, and in particular of the results pertaining to the consumer welfare consequences of the CO-NW code-share agreement.

11. Conclusion

The objective of the paper was to quantify the consumer welfare consequences of the 1999 domestic code-share agreement between Continental Airlines and Northwest Airlines. To address this problem adequately, we developed a discrete choice model based on individual flight attributes, since a code-share agreement affects the number as well as the characteristics of the flights offered. Our model accounts for the facts that airline consumers may have heterogenous valuations of a flight's attributes, and that the price for the same flight varies across consumers, depending (e.g.) on the date of purchase. This approach introduces a measurement error problem, as prices for each possible flight and consumer are not observed in publicly available databases. To address this problem, we estimated with an auxiliary sample of ticketing data the distribution of the measurement error. This estimated distribution was then used to integrate the unobserved price variable out of the market shares in order to estimate consistently the discrete choice model with the method of simulated moments.

We find that a consumer's valuation of an airline product is significantly affected by a number of flight attributes, including the price, the flight duration, or the time spent in transit at an intermediate airport. Our results also suggest substantial heterogeneity in the valuation of flight attributes across consumers. In addition, we identify strong negative correlations between the valuation of the price of a flight, and the valuations for both the nonstop and the peak-hours departure characteristics. These findings are consistent with the presence of different types of consumers, such as passengers traveling for business or tourism (see Berry et al. 1997).

More importantly, our results suggest that the 1999 CO-NW alliance resulted in a 3.11% erosion in the consumer surplus per passenger in markets affected by the code-share agreement. This drop, which may be attributed entirely to losses incurred by CO-NW passengers (-7.15%), contrasts with the gains experienced by a passenger travelling in markets not affected by the agreement (1.57%). Once we account for endogenous variations in the number of passengers, we find that the code-share agreement did not increase significantly the total welfare of consumers. This is not to say, however, that the agreement had a neutral effect on consumers. Indeed, our results suggest that the total surplus of CO-NW passengers decreased by (23.18%) in markets *through* which the alliance airlines code-shared.

Policy reviews of the recent domestic code-share agreements, such as the 1999 CO-NW, the 2003 Delta-CO-NW, and the 2003 United-US Airways agreements, have traditionally focused on the overlap in markets served by the alliance partners, and on the potential for collusion in prices in markets *in* which the alliance airlines code-share.[54] Our findings, however, suggest that greater emphasis be placed on changes in product attributes other than price when analyzing these agreements, and more generally when analyzing alliances and mergers. Indeed, in spite of lower average prices, consumers in our study were harmed by variations in product characteristics such as the duration of travel, or the time of departure.[55] Moreover, our results indicate that it is in markets *through* which, rather than *in* which, the alliance airlines code-share that the most significant consumer losses are incurred. This therefore suggests that greater attention be paid to changes in markets other than those *in* which the alliance airlines code-share. In that regard, our structural methodology appears particularly relevant as data on the recent domestic code-share agreements become available, since it takes into consideration how changes in various flight attributes affect consumer welfare across different markets.

Finally, the methodology developed in this paper, and in particular the method devised to address measurement error problems on the price variable, should be of more general interest to analyze different aspects of the airline industry. In the past decade alone, major events such as mergers, bankruptcies, the emergence of low cost airlines, or the September 11 terrorist attack have significantly affected the mix of products offered across airline markets. Since our discrete choice approach provides a better accounting of the multi-dimensional implications of changes in flight attributes, it may help better quantify the consequences of such events on the welfare of airline consumers.

[54] See, e.g., the Statement by Joel I. Klein, Assistant Attorney General at the Antitrust Division of the U.S. Department of Justice, before the Committee on Commerce, Science, and Transportation of the United States Senate concerning Competition in the Airline Industry, in Charleston S.C. on March 12, 1999.

[55] In fact, an analysis focusing solely on prices may have led us to conclude erroneously that the code-share agreement positively impacted the consumer surplus per passenger.

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Table 1
Descriptive Statistics for the Primary Sample

	Mean	Std.	Minimum	Maximum
Per Market (1,041 observations)				
Number of Passengers [1]	6,068.66	5,145.85	100	35,550
Number of Products	199.34	142.69	6	1,260
Price ($, in 100s)	3.84	1.23	1.34	8.88
Number of Airline-Itineraries	13.44	9.20	1	61
Number of Airlines	5.23	1.80	1	11
Number of Passengers per Airline [1]	1,160.02	2,111.70	80	27,840
Number of Products per Airline	38.10	45.20	1	882
Number of Itineraries per Airline	2.57	2.28	1	24
POP (in 1,000,000s)	2.43	1.12	0.59	6.57
GMP [2] ($, in 100,000s)	0.00	0.80	-1.57	3.11
INCOME [2] ($, in 10,000s)	0.00	0.08	-0.18	0.31
MILES (in 1,000s)	1.38	0.65	0.33	2.71
Per Airline-Itinerary (13,987 observations)				
Number of Passengers [1]	451.67	1,325.11	10	25,790
Number of Products	14.78	13.89	1	169
PRICE ($, in 100s)	3.95	2.04	0.52	27.75
Per Product (207,516 observations)				
NONSTOP	0.09	0.29	0	1
PEAK [3]	0.38	0.34	0	1
TRAVEL_TIME (minutes, in 100s)	6.34	1.97	1.35	11.87
TRANSIT_TIME (minutes, in 100s)	1.11	0.51	0	3
HUB	0.17	0.37	0	1
INT_HUB	0.74	0.43	0	1
AIRPORT_SHR	0.17	0.13	0.01	0.65

[1] Predicted quarterly average from DB1B (i.e. value observed in Databank 1B multiplied by 10).
[2] On a per capita basis. Calculated as deviation from sample mean across markets.
[3] Reported as a fraction of NONSTOP.

Table 2

Descriptive Statistics for the Auxiliary Sample (64,197 Tickets)

Variable	Mean	Variable	Mean
PRICE ($, in 100s)	3.323 (2.757)	TRIP_0_TO_2_DAYS	0.415 (0.493)
PEAK	0.422 (0.387)	TRIP_3_TO_6_DAYS	0.460 (0.498)
TRAVEL_TIME (minutes, in 100s)	3.964 (2.223)	TRIP_7_TO_29_DAYS	0.121 (0.326)
TRANSIT_TIME (minutes, in 100s)	0.234 (0.503)	TRIP_30_TO_365_DAYS	0.004 (0.065)
FIRST	0.008 (0.088)	BOUGHT_0_TO_2_DAYS	0.096 (0.294)
BUSINESS	0.002 (0.046)	BOUGHT_3_TO_6_DAYS	0.169 (0.375)
COACH	0.074 (0.262)	BOUGHT_7_TO_13_DAYS	0.177 (0.382)
DISCOUNT	0.462 (0.499)	BOUGHT_14_TO_20_DAYS	0.161 (0.367)
DISCOUNT_SAT	0.454 (0.498)	BOUGHT_21_TO_29_DAYS	0.147 (0.354)
		BOUGHT_30_TO_365_DAYS	0.251 (0.433)

Numbers in parenthesis refer to standard deviations.

Table 3

Estimation Results for the Auxiliary Model

Variable	Estimate (Std.)		Variable	Estimate (Std.)	
TRAVEL_TIME	0.206* (0.008)	0.208* (0.008)	BOUGHT_0_TO_2_DAYS	174.219* (5.126)	177.554* (5.382)
TRANSIT_TIME	-0.156* (0.017)	-0.149* (0.015)	BOUGHT_3_TO_6_DAYS	136.912* (3.762)	135.388* (4.003)
PEAK	2.120* (0.871)	2.187* (0.852)	BOUGHT_7_TO_13_DAYS	93.187* (6.359)	96.470* (6.112)
FIRST	437.834* (17.692)	432.298* (16.766)	BOUGHT_14_TO_20_DAYS	8.116 (4.749)	—
BUSINESS	636.543* (18.723)	637.780* (19.124)	BOUGHT_21_TO_29_DAYS **	1.960 (3.652)	—
COACH	151.058* (9.778)	148.722* (10.427)			
DISCOUNT	-97.411* (7.618)	-96.851* (7.695)			
DISCOUNT_SAT	-196.780* (12.603)	-199.732* (10.102)	Variance Parameter	Estimate (Std.)	
TRIP_0_TO_2_DAYS	32.382* (6.011)	30.941* (6.221)	ν	50.732* (7.828)	52.208* (8.261)
TRIP_3_TO_6_DAYS	7.344 (12.842)	—	σ	0.256* (0.039)	0.264* (0.036)
TRIP_7_TO_29_DAYS **	-0.237 (7.115)	—	ζ	1.968* (0.032)	1.952* (0.035)

* indicates parameters significant at a 5% significance level.

** For identification purposes, the variables TRIP_30_TO_365_DAYS and BOUGHT_30_TO_365_DAYS are not included in the model.

Table 4

Estimation Results for the Discrete Choice Model

Estimates for the Random Parameters $\delta_{i,l}$

Variable	$\bar{\delta}_l$	INCOME	GMP	σ_l
PRICE	-0.878* (0.078)	0.108* (0.042)	0.232* (0.055)	0.181* (0.046)
PEAK	0.247* (0.046)	0.046 (0.037)	0.080* (0.029)	0.091* (0.018)
NONSTOP	1.240* (0.111)	0.224* (0.068)	0.192* (0.089)	0.420* (0.105)
AIRPORT_SHR	0.206* (0.054)	-0.029* (0.013)	0.055* (0.019)	0.045* (0.016)
HUB	0.654* (0.135)	-0.072 (0.045)	0.068* (0.027)	0.058* (0.019)
INT_HUB	0.082* (0.028)	-0.004 (0.028)	0.038* (0.014)	0.031* (0.006)

* indicates parameters significant at a 5% significance level.

Table 5

Estimation Results for the Discrete Choice Model
Estimated Correlations Between the Random Parameters

	PEAK	NONSTOP
PRICE	-0.615* (0.120)	-0.292* (0.078)
PEAK	__	0.276* (0.094)

* indicates parameters significant at a 5% significance level.

Table 6

Estimation Results for the Discrete-Choice Model
Estimates for the Deterministic Parameter λ

Variable	Estimate	Variable	Estimate	Variable	Estimate
TRAVEL_TIME	-0.142* (0.049)	US Airways (US)	-0.024 (0.020)	Reno Air (QQ)	-0.005 (0.042)
TRANSIT_TIME	-0.363* (0.122)	TWA (TW)	-0.086* (0.034)	QTR_1 1st quarter 1998	-0.013* (0.005)
CS_CONW_PRO	-0.042* (0.013)	Southwest Airlines (WN)	0.249* (0.096)	QTR_2 3rd quarter 1998	0.009* (0.004)
CS_CONW_MKT	-0.026 (0.019)	America West (HP)	0.088 (0.059)	QTR_3 1st quarter 1999	-0.008 (0.007)
CS_REG	0.108 (0.079)	Midway Airlines (JI)	-0.041 (0.043)	QTR_4 3rd quarter 1999	0.015* (0.006)
INTERLINE	-0.087 (0.093)	Frontier Airlines (F9)	0.020 (0.023)	QTR_5 1st quarter 2000	0.002 (0.011)
STRIKE_NW	-0.077 (0.048)	AirTran Airways (FL)	0.082* (0.039)	QTR_6 ** 3rd quarter 2000	0.017* (0.005)
Continental Airlines (CO)	0.101* (0.019)	American Trans Air (TZ)	-0.048* (0.021)	MILES	0.704* (0.148)
Northwest Airlines (NW)	0.083* (0.022)	Vanguard Airlines (NJ)	0.030 (0.063)	$MILES^2$	-0.117* (0.031)
American Airlines (AA)	0.196* (0.029)	Spirit Airlines (NK)	0.029 (0.036)	ϕ_0	6.852* (1.655)
Delta Airlines (DL)	0.230* (0.035)	Midwest Express (YX)	-0.072* (0.026)	ϕ_1	0.214* (0.083)
United Airlines (UA)	0.075* (0.031)	Sun Country Air (SY)	-0.039 (0.064)		

* indicates parameters significant at a 5% significance level.
** For identification purposes, the 1st quarter of 2001 is used as the reference quarter.

Table 7

Average Own and Cross Price Elasticity across Airline Groups

	CO-NW "Alliance"	AA-DL-UA "Big Three"	TWA-US "Other Majors"	WN-HP	Regional
CO-NW "Alliance"	-1.887	0.321	0.085	0.030	0.017
AA-DL-UA "Big Three"	0.061	-1.428	0.046	0.009	0.006
TWA-US "Other Majors"	0.096	0.174	-2.088	0.041	0.014
WN-HP	0.166	0.249	0.141	-2.321	0.020
Regional	0.332	0.394	0.298	0.277	-2.610

Notes: Row *i* column *j* indicates the percentage change in the market share of i when the price of j increases by one percent.
Regional group includes: F9, JI, FL, NJ, NK, YX, TZ, QQ, SY. See Table 6 for airline names.

Table 8

Average Own and Cross Price Elasticity for CO and NW

	Overall		Before Implementation		After Implementation	
	CO	NW	CO	NW	CO	NW
CO	-1.852	0.053	-1.868	0.038	-1.846	0.059
NW	0.065	-1.926	0.061	-2.110	0.066	-1.854

Note: Row *i* column *j* indicates the percentage change in the market share of i when the price of j increases by one percent.

Table 9

Average Consumer Surplus per Passenger (in $)
Before and After the Implementation of the CO-NW Code-Share Agreement

	Before Implementation			After Implementation		
Airport-Pairs:	CO-NW Passengers	Passengers on other Airlines	All Airlines	CO-NW Passengers	Passengers on other Airlines	All Airlines
In which CO-NW Code-Share	33.106	29.952	31.241	31.736 (-4.14%)	30.170 (0.73%)	30.800 (-1.41%)
Through which CO-NW Code-Share	28.982	27.852	28.752	24.021 (-17.12%)	28.615 (2.74%)	25.062 (-12.83%)
Airport-Pairs affected by the Agreement [1]	31.779	29.790	30.754	29.506 (-7.15%)	30.055 (0.89%)	29.798 (-3.11%)
Where CO-NW Never Code-Share	31.754	31.226	31.482	32.108 (1.11%)	31.855 (2.01%)	31.977 (1.57%)

[1] These cells represent the weighted average of the two previous rows.

Table 10

Decomposition by Effects of the Variation in Consumer Surplus of a CO-NW Passenger After the Implementation of the CO-NW Code-Share Agreement

Effect of:	New Products	Price	Peak Hours	Nonstop	Travel Time	Transit Time	Code Share
Variation in Consumer Surplus	4.28%	0.25%	-0.48%	-2.11%	-2.68%	-1.41%	-1.99%

Table 11

Total Consumer Welfare per Airport-Pair (in million $) Before and After the Implementation of the CO-NW Code-Share Agreement

	Before Implementation			After Implementation			After Implementation Controlling for Exogenous Increases in Passengers		
Per airport-pair:	CO-NW Passengers	Passengers on other Airlines	All Airlines	CO-NW Passengers	Passengers on other Airlines	All Airlines	CO-NW Passengers	Passengers on other Airlines	All Airlines
In which CO-NW code-share	8.235	10.779	19.014	8.783 (6.65%)	12.404 (15.07%)	21.187 (11.43%)	8.468 (2.84%)	11.896 (10.36%)	20.363 (7.10%)
Through which CO-NW Code-Share	3.422	0.840	4.262	2.703 (-21.00%)	0.944 (12.37%)	3.647 (-14.43%)	2.629 (-23.18%)	0.908 (8.14%)	3.538 (-16.98%)
Airport-Pairs affected by the Agreement [1]	11.657	11.619	23.276	11.486 (-1.47%)	13.348 (14.88%)	24.834 (6.69%)	11.097 (-4.80%)	12.805 (10.20%)	23.901 (2.69%)
Where CO-NW Never Code-Share	2.756	2.875	5.631	2.796 (1.43%)	2.998 (4.29%)	5.794 (2.89%)	2.790 (1.22%)	2.969 (3.29%)	5.760 (2.28%)

[1] These cells represent the sum of the two previous rows.

Table 12

Estimation Outcomes and Economic Implications of Alternative Models

	Benchmark Model	Alternative models					
		No Measurement Error in Prices	No Correlation in valuations of attributes	Pure Logit	Nested Logit	Benchmark model with only two types of consumers	
						Tourist	Business
PRICE [1]	-0.878* (0.078)	-0.420* (0.031)	-1.251* (0.136)	-1.142* (0.132)	-0.922* (0.084)	-1.488* (0.124)	-0.199* (0.048)
PEAK [1]	0.247* (0.046)	0.109 (0.065)	0.136* (0.058)	0.110 (0.068)	0.231* (0.038)	0.091 (0.054)	0.350* (0.088)
NONSTOP [1]	1.240* (0.111)	1.879* (0.089)	0.742* (0.141)	0.933* (0.077)	1.058* (0.100)	0.683* (0.176)	1.649* (0.102)
TRAVEL_TIME	-0.142* (0.049)	0.032 (0.021)	-0.099 (0.065)	-0.023 (0.027)	-0.129* (0.059)	-0.116* (0.039)	
CS_CONW_PROD	-0.042* (0.013)	-0.156* (0.024)	-0.030 (0.028)	-0.094* (0.023)	-0.037* (0.015)	-0.056* (0.024)	
"Big Three" Own Price Elasticity	-1.428	-0.651	-2.125	-1.730	-1.492	-1.386	
"CO-NW" Own Price Elasticity	-1.887	-0.782	-2.732	-2.219	-1.933	-1.627	
Hub Premium	9.32%	17.56%	3.07%	5.68%	8.86%	9.49%	
Non-Stop Flight Premium	18.48%	26.03%	5.26%	10.84%	16.97%	15.88%	
ρ (Nested Logit Parameter)	—	—	—	—	0.856 (0.092)	—	
Variation of CO-NW per passenger surplus on markets: *In* which they code-share	-4.14%	-8.18%	0.22%	-3.98%	-3.96%	-4.42%	
Variation of CO-NW per passenger surplus on markets: *Through* which they code-share	-17.12%	-6.53%	-11.46%	-15.21%	-15.21%	-18.97%	
P-value for Specification Test [2]	—	1.254E-5 (0.321)	4.362E-3	5.683E-4	3.874E-3	4.151E-3 (0.063)	

* indicates parameters significant at a 5% significance level.

[1] When the model includes random coefficients, the parameter reported corresponds to $\bar{\delta}_l$, the mean value of the random coefficient.

[2] When two numbers are reported, the first corresponds to the *P*-value for the test of the alternative.versus the benchmark, while the second (in parenthesis) corresponds to the *P*-value for the test of the benchmark versus the alternative.