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This dissertation consists of two essays that address code-sharing alliances in the U.S. domestic airline industry.

The first essay examines the economic impact of code-sharing using data from the complementary code-sharing agreement between Southwest and ATA Airlines. This code-share agreement is found to decrease air fares and increase passenger volumes for incumbent firms, while increasing both consumer and producer surplus on code-shared routes to and from the Denver airport. In addition, these markets are found to exhibit characteristics of Bertrand competition, as opposed to previous findings of the less competitive Cournot result in international markets and in other domestic U.S. markets.

The second essay employs three alternative econometric models (Generalized Linear Mixed Models (GLIMM), Generalized Estimating Equations (GEE) and Transition Models (TM)) analyze factors that determine whether individual routes remain in or leave a code-share agreement. The code-share alliance between Continental and America West Airlines is used as the case study for this analysis. Empirical results show that routes with higher flight frequencies and higher yields lead to a higher probability of remaining in the code-share agreement. Alliance firms tend to code-share routes where the origin, connecting or destination airport is one of their hub cities or the route is a vacation route. Airport congestion and high route concentration are found to be important barriers that limit use of code-sharing.

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Yan Du, Author

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Code-sharing in the U.S. Airline Industry

Chapter 1

Introduction

This dissertation addresses issues of code-sharing alliances in the U.S. airline industry. Under code-sharing, alliance firms merge their computer reservation systems and each carrier can issue tickets on flights operated by other contracting carriers by display of their own flight numbers. Since the first code-sharing was implemented in the U.S. in the middle of the 1990's, there has been a heated discussion about the advantages and disadvantages of code-sharing alliances. Alliance firms argue that code-sharing may bring benefits to customers because code-sharing helps generate more flight options and connecting routes for passengers. However, some airline researchers worry that code-sharing may decrease competition between contracting carriers themselves and the competition between code-shared firms and market incumbents.

In Chapter 2, we examine the economic impact of code-sharing on airfares, passenger volumes and social welfare using data from the complementary code-sharing agreement between Southwest and ATA Airlines. Previous studies investigating the impact of code-sharing either on passenger volumes or air fares have ignored the simultaneity between market demand and supply. Therefore, results may not be consistent. Accordingly, we employ Bresnahan's (1989) conjectural variation (CV) approach to build a supply relation and demand function. This approach allows us to test for market power in the market studied.

Empirical results from regressions using Nonlinear Three Stage Least Squares (NL3SLS) show that the ATA/Southwest code-share agreement decreased air fares and increased passenger volumes for incumbent firms. Further, both consumer and producer surpluses increased on code-shared routes. Finally, these markets were found to exhibit characteristics of Bertrand competition, as opposed to previous findings of the less competitive Cournot result in international markets and in other domestic U.S. markets. Our finding of Bertrand competition suggests that previously expressed concerns regarding possible anti-competitive effects from code-sharing are unwarranted in these markets.

In Chapter 3, we examine the determinants of successful code-sharing alliances. Since the implementation of the first code-sharing agreement, code-sharing has become increasingly popular in the U.S. airline industry. However, alliance firms keep changing their code-shared route arrangements, adding new routes and dropping the old ones. In Chapter 3 we present a theoretical model in which two equilibrium conditions are derived: one showing when code-shared firms will initially enter a code-share alliance and the other indicating conditions when partner firms will choose to remain in or exit a particular code-shared route after the initial entry. The empirical part of this paper uses discrete longitudinal analysis to examine the code-sharing agreement between Continental and America West. We employ three alternative econometric models (Generalized Linear Mixed Models (GLIMM), Generalized Estimating Equations (GEE) and Transition Models (TM)) for the analysis. Empirical results show that routes with higher flight frequencies and higher yields lead to a higher probability of remaining in a code-share agreement. Alliance firms tend to code-share routes where the origin, connecting or destination airport is one of their hub cities or the route is a vacation route. Airport congestion and high route concentration are found to be important barriers that limit use of code-sharing. Population and income in the origin and destination metropolitan statistical areas are also important factors affecting firms' code-sharing decisions.

Chapter 4 summarizes the study conclusion and provides a discussion of policy implications.

Chapter 2

The Economic Impact of the ATA/Southwest Airlines Code-share Alliance - a Case Study from Denver International Airport

I. Introduction

In October 2004, ATA Holdings and its subsidiaries filed for Chapter 11 bankruptcy protection.[1] Subsequently, Southwest Airlines injected capital into ATA Airlines that resulted in Southwest having a 27.5% ownership stake in ATA upon their exit from Chapter 11 bankruptcy proceedings. As part of the deal, Southwest entered into a code-sharing arrangement with ATA. This was Southwest's first domestic code-sharing arrangement. ATA chose 11 cities that had not been served by Southwest as the code-sharing cities with Chicago Midway Airport as the connecting airport for both airlines. Southwest cities that were part of the code- share agreement are listed in Table 2.1.

Southwest Airlines is based in Dallas, Texas. It is the third largest airline in the world, measured in terms of the number of passengers carried, and the largest with destinations exclusively in the United States. Despite the restrictions on its home base, Dallas Love Field, since 1978, Southwest has built a successful business by flying multiple short quick trips into the secondary airports of major cities using primarily Boeing 737 aircraft.[2] ATA Airlines is an American low cost

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[1] "Chapter 11 is a chapter of the United States Bankruptcy Code which governs the process of reorganization under the bankruptcy laws of the United States. The Bankruptcy Code itself is Title 11 of the United States Code; therefore reorganization under bankruptcy is covered by Chapter 11 of Title 11 of the United States Code. In contrast Chapter 7 governs the process of a liquidation bankruptcy."

[2] When airline deregulation came in 1978, Southwest began planning to offer interstate service from Dallas Love Field (DAL), but a number of interest groups affiliated with DAL Airport, including American Airlines and the city of Fort Worth, pushed the Wright Amendment through Congress to restrict such flights. Southwest was barred from operating, or even ticketing passengers on flights from

and charter airline based in Indianapolis, Indiana. ATA operates scheduled passenger flights from a hub at Midway Airport in Chicago, Illinois, and charter flights across the globe.

As a low-cost air carrier, Southwest is well known as a "discount airline" compared to its domestic rivals and it is the only U.S. airline which has been profitable every year since 1973. Past studies of Southwest deal with various aspects of Southwest’s entry or potential entry on pre-existing market behavior such as Bennet and Craun (1993), Morrison (2001), Boguslaski, Ito and Lee (2004) and Fu, Dresner and Oum (2006). Most find that entry or potential entry by Southwest into a market significantly lowers market fares, which is the well known “Southwest Effect”.

The purpose of this paper is to examine the impact of the 2005 code-sharing agreement between Southwest and ATA on air fares and passenger volumes in the Denver markets. What is unique about this code share agreement is that it is the first time that Southwest has entered a market in this way. While it is clearly a complementary code-sharing agreement, there is the question of whether this

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Love Field beyond the states immediately surrounding Texas. In 1997, the Shelby Amendment added the states of Alabama, Mississippi, and Kansas to the list of permissible destination states. Since late 2004, Southwest has been actively seeking the full repeal of the Wright Amendment restrictions. In late 2005, Missouri was added to the list of permissible destination states via a transportation appropriations bill. New service from Dallas Love Field to St. Louis and Kansas City quickly started in December of 2005. In 2006, Southwest and American Airlines both required approval from the Federal Aviation Administration to begin one-stop flights from Love Field to destinations outside the Wright limits. In October 2006, Southwest announced that it would begin one-stop or connecting service between Love Field and 25 destinations outside the Wright zone.

Table 2.1 Southwest/ATA Code-shared (CS) Cities

Southwest CS City	ATA City	Southwest Non-CS City
Albuquerque	Boston	Albany
Baltimore Washington	Denver	Amarillo
Birmingham	Ft Myers Naples	Austin
Cleveland	Honolulu	Boise
Columbus	Minneapolis St Paul	Buffalo
Detroit Metro	Newark	Burbank
Ft Lauderdale Hollywood	New York LaGuardia	Corpus
Hartford Springfield	San Francisco	Dallas
Houston	Sarasota Bradenton	Dulles
Indianapolis	St Fetersburg	El Paso
Jackson	Washington National DC	Harlingen
Jacksonville		Lubbock
Kansas City		Midland/Odessa
Las Vegas		Norfolk
Little Rock		Orange County
Long Island Macarthur		Pittsburgh
Los Angeles		Reno
Louisville		Salt Lake City
Manchester		San Antonio
Nashville		San Jose
New Orleans		Spokane
Oakland		
Oklahoma City		
Omaha		
Ontario		
Orlando		
Philadelphia		
Phoenix		
Providence		
Raleigh Durham		
Sacramento		
San Diego		
Seattle		
St Louis		
Tampa Bay		
Tucson		
Tulsa		
West Palm Beach		

agreement will have the same impact on fares and competition that Southwest's direct entry has had in other markets. From a policymaker's point of view, code-sharing alliances should be implemented if they have a net positive impact on social welfare. The purpose of this paper is to provide policymakers additional information on which to assess the effects of this code share agreement.

The next section provides a review of the literature on code-share agreements, followed by presentation of the theoretical model. Section III explains the empirical model and Section IV details the data sources. The empirical results are then presented and discussed, followed by future research plans.

II. Background on Code-sharing Alliances

Code-sharing alliances began on international airline routes in 1986 and by the end of the 1990s had become one of the most popular alliance forms in the airline industry. Generally speaking, code-sharing arrangements have two basic forms: complementary and parallel alliances. Complementary alliances occur when contracting air carriers link existing flight networks, resulting in a new complementary network to provide services for connecting passengers (Park, 1997). On the other hand, parallel (or overlapping) alliances refer to collaboration between contracting air carriers competing on the same flight routes.

In the case of the ATA/Southwest code-share agreement, we are mostly dealing with complementary alliances. In this case, there is no concern that the agreement is eliminating an existing competitor as could be the situation with a parallel agreement.

Code-shared flights have several advantages for both alliance firms and passengers. First, the connecting flight is listed as a single-carrier flight under either the ticketing or operating airline’s designation code and thus appears before listings of interline connections on Computer Reservation System (CRS) screens.[3] This listing priority can give alliance airlines an advantage over their competitors. Second, code-shared flights can provide as much convenience as a single-carrier flight. Customers only need to buy a single ticket for the entire route and their baggage will be transferred at the connecting airport by airline employees. Third, code-sharing combines alliance airlines’ current route networks and consequently results in a substantial increase in the number of flight options that partner airlines can offer without adding additional aircraft departures.

Thus, alliance firms can benefit by generating additional passengers who might otherwise have chosen direct flights or flown through other hubs served by competitors in the absence of code-sharing. These expanded service options may attract new passengers and result in alliance firms coordinating and offering more frequent flights, thus attracting even more passengers. In the presence of economies of density, domestic traffic gains from code-sharing alliances may help lower the

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[3] Airline designation codes are two-letter codes assigned by the IATA (International Air Transport Association), which form the first two letters of a flight code. They are listed for use in reservations, timetables, tickets, tariffs, air waybills and in airline interline telecommunications, as well as in the airline industry applications.

marginal operating cost of carrying an additional passenger.[4] In addition, joint use of airport facilities and development of new routes that may restructure the current network may also reduce costs. Therefore, partner airlines may be able to lower air fares to passengers as a result of the code sharing alliance.

However, it has also been argued that code-sharing may harm market competition and decrease consumer welfare. According to the U.S. General Accounting Office (1998), the listing priority given code-shared flights on the CRS screen may decrease market competition with competitors operating on the same routes. Second, although code-sharing is not regarded as a merger, it may reduce the incentive for alliance partners to compete with each other on hundreds of nonstop, one-stop or multiple-stop long-haul markets. Currently these routes are the most competitive markets because they offer the greatest number of airlines from which consumers can choose. If the alliance airlines successfully gain market share, market incumbents could be driven out and entry could become more difficult. Limited competition and increased market concentration on these routes could result in an increased possibility of collusion, leading to airfare increases and decreases in service quality. Thus, it is possible that code-sharing agreements could have a negative impact on customers and incumbent carriers.

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[4] Economies of density mean that within a network of given size, increases in the size of aircraft will lead to a decrease in unit cost. Please see Caves, Christensen, Tretheway (1984) and Oum and Tretheway (1982) for details.

Most studies of code-sharing alliances have involved international code-sharing practices. Oum, Park and Zhang (1996), Park (1997), Park and Zhang (2000), Park, Zhang and Zhang (2001), Park, Park and Zhang (2003), Brueckner and Whalen (2000), Shy (2001), Brueckner (2001, 2003), Hassin and Shy (2004) examine the impact of international code-sharing alliances on firm output, air fares and economic welfare, either empirically or theoretically. Almost all of these found that complementary international code-sharing alliances are likely to increase passenger volumes, decrease air fares and improve consumer welfare.

To date, studies of domestic code-sharing and its competitive effects include Bamberger, Carlton and Neumann (2004), Armantier and Richard (2005a, 2005b), Chua, Kew and Yong (2005) and Gayle (2006). Bamberger, Carlton and Neumann (2004) find that complementary code-sharing between Continental and America West decreases average air fares and increases total traffic in a code-shared market while Gayle (2006) predicted that alliance firms’ air fares would fall after a *parallel* code-sharing agreement between Continental, Delta and Northwest was proposed in 2002. Armantier and Richard (2005a) find that air fares increased significantly in markets where partner firms (Continental (CO) and Northwest Airlines (NW)) offered code-shared flights and had nonstop direct flights as well, whereas air fares were lower in markets where firms code-shared flights but did not operate any nonstop flight. Armantier and Richard (2005b) further find that consumer surplus per passenger falls after code-sharing between CO and NW. Chua, Kew and Yong (2005) use firm-specific panel data to assess the impact of code-sharing on operating cost and find that large alliance partners have a negative effect while small alliance partners have a positive effect on firm operating costs.

This paper will make several contributions to the existing literature: It is the first to analyze U.S. complementary code-sharing by estimating both demand and supply sides simultaneously. It is also the first to analyze the effect of code-sharing between two U.S. low cost air carriers on the market incumbents. Previous researchers have examined code sharing alliances between U.S. legacy air carriers. But, low cost carriers are known to have different business model practices than legacy carriers.[5] The case studied here is unique in that this is Southwest's code sharing with ATA, the first domestic code sharing alliance that Southwest has entered. Although many previous studies of market power in the airline industry such as Brander and Zhang (1990, 1993), Oum, Zhang and Zhang (1993), Park and Zhang (2000), Fischer and Kamerschen (2003) assume product homogeneity, this is generally not the case in the airline industry. Important service quality differences may take the forms of flight frequency, on-time performance such as arrival and departure delay, air time, ground transportation availability, advertising, departure schedule, day of the week and safety and accident reputation. Oum, Park and Zhang (1996) and Borenstein and Netz (1999) find that either flight frequency

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[5] In contrast to legacy carriers who are usually engaged in complicated yield management, operating practices of low cost air carriers include: a) a single passenger class, b) a single type of air plane, reducing training, servicing and maintenance costs, c) a simple fare scheme, d) flying to cheaper, less congested secondary airports and flying early in the morning or late in the evening to avoid air traffic delays and take advantage of lower landing fees, e) short flights and fast turnaround times.

or departure time is significantly different across firms. Thus, we assume product differentiation in this study of how individual incumbents responded to the Southwest and ATA code-sharing strategy.

III. Theoretical Model

We follow previous researchers (Brander and Zhang (1990, 1993), Oum, Park and Zhang (1996), Captain and Sickles (1997) and Fischer and Kamerschen (2003)) and use a general conjectural variation reduced form approach. The basic model was originally suggested by Iwata (1974) and later extended and generalized by Bresnahan (1989). This methodology allows us to find the average degree of market power and estimate the price-cost margin while imposing less demanding data requirements than a structural conjectural variation model. Further, instead of regarding the conjectural variation as a firm's expectation, it can be interpreted as "a market parameter to capture the whole range of market performance and dynamic patterns can be approximated by repeated, one-shot static equilibrium game" in the airline industry (Fischer and Kamerschen, 2003).

In this paper, we regard a city-pair flight route as a market and assume that n incumbent airlines (firm i=1,…n) offer flight services. Further, we assume that the passenger volume demanded from each incumbent air carrier is a function of its own air fare, its competitors' air fares and other exogenous variables that affect its demand. Then incumbent firm 1's inverse market demand function can be written as:

$$P_1 = P_1(Q_1, Q_{-1}, \Gamma, \alpha) \tag{2.1}$$

where Q_1 is the passenger volumes for firm 1; P_1 is its price; Q_{-1} is the aggregate of rivals' output; Γ denotes the exogenous variables that affect market demand and α is the unknown parameter vector. Similarly, for other firms, their demand function can be written using column vector notations as follows:

$$P_j = P_j(Q_j, Q_{-j}, \Gamma_j, \alpha_j)\ j=2,..n \tag{2.2}$$

where P_j is firm *j*'s price ($j \neq 1$) in the market, Q_j is firm *j*'s output and Q_{-j} is firm *j* rival's aggregate output. Γ_j denotes the exogenous variables that affect firm *j*'s market demand and α_j is the unknown parameter vector. Then, firm 1's profit function can be written as:

$$\pi_1 = P_1(Q_1, Q_{-1}, \Gamma, \alpha)Q_1 - C_1(Q_1, W_1, Z_1, \beta_1) \tag{2.3}$$

where C_1 stands for firm 1's total cost which is a function of firm 1's output Q_1, input prices W_1 and other exogenous variables Z_1 (such as flight distance, traffic density etc.); β_1 is the unknown parameter vector.

If we assume firms are profit maximizers and compete on output, then the Cournot Nash equilibrium is represented by taking first order conditions:

$$\begin{aligned}\frac{\partial \pi_1}{\partial Q_1} &= P_1 + Q_1 P_1^{'}(Q_1, Q_{-1}, \Gamma, \alpha) - c_1 \\ &= P_1 + Q_1\left(\frac{\partial P_1}{\partial Q_1} + \frac{\partial Q_{-1}}{\partial Q_1}\right) - c_1 \\ &= P_1 + Q_1\frac{\partial P_1}{\partial Q_1}\left(\frac{\partial Q_1}{\partial Q_1} + \sum_{j=2}^{n}\frac{\partial Q_j}{\partial Q_1}\right) - c_1 \\ &= P_1 + Q_1\frac{\partial P_1}{\partial Q_1}(1+v_1) - c_1 \\ &= 0\end{aligned} \tag{2.4}$$

where $v_1 = \frac{\partial Q_{-1}}{\partial Q_1}$ and c_1 stands for the marginal cost of firm 1.

So $$P_1 + Q_1\frac{\partial P_1}{\partial Q_1}(1+v_1) - c_1 = 0 \tag{2.5}$$

In the symmetric oligopoly model, v_1 equals 0 for Cournot competition; v_1 equals -1 for Bertrand competition and v_1 equals 1 for the cartel solution. Because we do not know whether the firms are competing on output or price, or whether they are colluding, we have to adopt more general supply relations to describe the quantity or price setting conduct and other oligopoly behaviors generalized by Bresnahan (1989) as follows:

$$P_1 = c_1 - \frac{\partial P_1}{\partial Q_1}\lambda_1 Q_1 \tag{2.6}$$

where $\lambda_1 = 1 + v_1$ ($\lambda_1 \geq 0$) is defined as the market power parameter. As λ_1 moves farther from 0, the conduct of firm 1 moves farther from perfect competition. Accordingly, firm *j*'s supply relation can be written as:

$$P_j = c_j - \frac{\partial P_j}{\partial Q_j} \lambda_j Q_j \tag{2.7}$$

One way to measure the effect of code-sharing on the market incumbents' prices and passenger volumes is to estimate the *n* structural demand equations (2.1)-(2.2) and supply relations (2.6)-(2.7) simultaneously as a system of equations, with code-sharing as an explanatory variable.

IV. Empirical Model Specifications

IV.1. Demand Equation

The market demand functions are specified as follows:

$$\begin{aligned} Q_{ijt} &= \alpha_0 + \beta_1 CS_{it} + \beta_2 P_{ijt} + \beta_3 CS_{it} P_{ijt} + \beta_4 ORIPOP_{it} + \beta_5 ORIINCO_{it} + \beta_6 DESTPOP_{it} \\ &\quad + \beta_7 DESTINCO_{it} + \beta_8 FREQ_{ijt} + \beta_9 CS_{it} FREQ_{ijt} + \sum_{j=1}^{N-1} \gamma_j FIRM_j + \sum_{i=1}^{M-1} \psi_i ROUTE_i \\ &\quad + \sum_{t=1}^{2} \varphi_t YEAR_t + \varpi_{ijt} \end{aligned} \tag{2.8}$$

where Q_{ijt} is the incumbent firm *j*'s specific demand on route *i* at time *t*; CS_{it} is the code-sharing dummy variable which equals 1 if the route was in a code-sharing arrangement in 2005, and equals 0 if not.[6] We expect the coefficient of CS_{it} to be negative because code sharing offers passengers more flight options and thus may decrease market demand for incumbent airlines' services. However, incumbents may also make full use of their frequent flyer program or increase their departure frequency to attract more passengers and thus possibly increases their demand. Compared with code-sharing services, incumbents' nonstop flights are of higher service quality. In this case, code sharing may indirectly increase incumbents' demand so the coefficient sign may also be positive. P_{ijt} is firm *j*'s air fare on route *i* at time *t* and we expect this coefficient to be negative. $CS_{it}P_{ijt}$ captures the interaction between code-sharing and firm *j*'s air fare. We expect this coefficient sign to be negative because code sharing service can work as a substitute, thus making incumbent firm *j*'s passengers more responsive to firm *j*'s price changes. $ORIPOP_{it}$, $DESTPOP_{it}$ are exogenous variables defined as the population of the origin and destination metropolitan statistical areas and their coefficients are expected to be positively related to the market demand. Similarly, $ORIINCO_{it}$, $DESTINCO_{it}$ are defined as the per capital incomes of the

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[6] There are some concerns that alliance firms may choose to code share in thick markets, which brings about the endogeneity issue of code sharing in the demand equation. However, in the case of code-sharing between ATA and Southwest, the code sharing route arrangement was made and implemented at the beginning of 2005, so the passenger volumes and air fares from 2005 should not be considered as factors that affect alliance firms' decisions. Correlation test shows that there is no significant linear correlation between code sharing decisions and passenger volumes in 2003, 2004 and 2005 respectively. The descriptive statistics shows that both in 2003 and 2004, incumbents' passenger volumes on the routes that were chosen for code-sharing in 2005 were fewer than those on the routes that were not.

origin and destination cities, respectively with coefficients expected to be positive for normal goods and negative for interior goods.

Flight frequency is one of the most important elements that affect airline demand and service quality.[7] Passengers usually prefer airlines that offer more frequent flights and thus reduce schedule delay time. So we include $FREQ_{ijt}$ (the number of firm *j*'s performed departures on route *i* at time *t*) and expect its coefficient to be positively related to the demand. $CS_{it}FREQ_{ijt}$ captures the interaction between code-sharing and firm *j*'s departure frequency on route *i* at time *t* and we expect the coefficient sign to be positive if code-sharing between code sharing helps increase incumbent firm *j*'s departure frequency and negative if decrease incumbent' firm *j*'s departure frequency. $FIRM_j$, $ROUTE_i$ and $YEAR_t$ are dummy variables that account for unobserved firm, route and time specific fixed effects, respectively. ϖ_{ijt} is the normally distributed error term that might be contemporaneously correlated across equations.

IV.2. Supply Relation

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[7] There is a possibility that flight frequency is endogenous because as the air travel demand increases, airlines may offer more frequent flight departures. However, Wald test (Green, 2003) shows the null hypothesis that flight frequency is exogenous can not be rejected: Wald statistics=1.3859945, which is less than 5.02 critical value at 5% confidence interval. We use the predicted value of flight frequency as the instrument in the test and least square estimates for the predicted value are good with high adjusted *R square* =99.96%. Possible reasons for the exogeneity of flight frequency can be that as the air travel demand increases, airlines tend to adopt larger aircrafts with more seats to avoid more landing and take-off fees associated with the increasing number of departures given that the airport capacity is limited as well.

To estimate the supply relation equation (2.4), we need to consider the marginal cost function. However, precise definition and estimation of marginal cost is problematic for the airline industry. Researchers have addressed airline costs in a variety of ways. Brander and Zhang (1990, 1993), use average cost as a proxy for marginal costs, a method later adopted by Oum, Zhang and Zhang (1993) and Morrison and Winston (1995). However, most of these papers estimate the firm-specific total and marginal cost on a domestic system-wide level rather than on the specific route level.

For the purposes of this study, we need to specify marginal costs at the route level. It is generally accepted that the airline industry is characterized by constant returns to scale technology (CRS). This conclusion is supported by previous researchers (Caves (1962), Eads, Nerlove and Raduchel (1969), Douglas and Miller (1974), Keeler (1978), Caves, Christensen and Tretheway (CCT, 1984), Gillen, Oum and Tretheway (1990), Oum and Zhang (1991), Brueckner and Spiller (1994) and Creel and Farell (2001)). However, CRS assumption is not appropriate on the route level. On a specific route, the more passengers an airline's aircraft carries, the lower the marginal cost given that the number of flight departure does not change. We refer this as the economies of aircraft size, which is the reason for the existence of economies of traffic density (Morrison, 2006).

Thus, we specify the marginal cost function for an individual firm *j* on a specific route *i* at time *t* as:

$$
\begin{aligned}
MC_{ijt} = {} & \chi_2 W_{ijt}^F + \chi_3 W_{ijt}^L + \chi_4 W_{jt}^K + \chi_5 W_{jt}^M + \chi_6 CRAFTSIZE_{ijt} + \chi_7 DIST_i + \chi_8 Q_{ijt} \\
& + \sum_{j=1}^{N-1} \gamma_j^{'} FIRM_j + \sum_{i=1}^{M-1} \psi_i^{'} ROUTE_i + \sum_{t=1}^{2} \varphi_t^{'} YEAR_t
\end{aligned} \tag{2.9}
$$

where W_{ijt}^F is the average fuel price measured as dollars per gallon for firm *j* on route *i* at time *t*;[8] W_{ijt}^L is the average labor price measured by employees' average hourly wage rate---dollars per worker for firm *j* on route *i* at time *t*;[9] W_{jt}^K is the capital input price defined as firm specific capital cost per unit of airline capacity (available seat miles) at time *t*;[10] W_{jt}^M is the material input price measured by firm specific material cost per available seat mile which, except fuel, labor and capital

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[8] Since some air carriers, especially large air carriers use contractual or storage fuels to decrease their fuel cost, average fuel prices are actually different across airlines especially between large airlines and small ones. Moreover, according to *Petroleum Marketing Annual* published by *Energy Information Administration, Office of Oil and Gas, US Department of Energy*, fuel prices are also different across regions and states. Thus, after regional and firm adjustments, average fuel prices change with routes, firms and time. Please refer to Section V for detailed descriptions of adjustment calculation.

[9] According to *Bureau of Transportation Statistics, US Department of Transportation*, individual firm's financial report shows that labor cost is different across airlines as well. Following the same logic, we make some regional adjustment of firm level labor cost based on the *Occupational Employment Statistics (OES) Annual Survey* provided by *Bureau of Labor Statistics, US Department of Labor* at the website http:/stat.bls.gov/oes/home.htm. Please see Section V for details.

[10] Capital cost are the total cost of operating property and equipments which include flight equipment, ground property and equipment, and leased property under capital leases. We assume capital input prices do not change with flight routes. There is an alternative way to measure the capital input prices and will be adopted when the data are available in the future research. Please see Section V for details.

costs, includes all the other expenditures such as maintenance, passenger food, advertising, insurance, communication, traffic commissions and etc;[11] We expect the coefficient signs of these four input prices to be positively related to the marginal cost. $CRAFTSIZE_{ijt}$ is the average number of available seats per aircraft operated by firm *j* on route *i* at time *t* and we expect the sign of its coefficient to be negative because the larger the number of seats, the larger the aircraft body size, the lower the cost per passenger due to the economies of traffic density in the airline industry and the lower the air fare is.[12] $DIST_i$ is the distance of route *i* and we expect its coefficient sign is positive because air fares are usually higher for longer haul markets. Q_{ijt} is the number of passengers carried by incumbent firm *j* on route *i* at time *t*. We expect the coefficient on Q_{ijt} to be negative because of the economies of aircraft size (or economies of traffic density); however, if one more additional passenger leads to crossing flights, then the marginal cost could increase dramatically. Therefore, the overall effect is uncertain.

IV.3. Market Power Parameter Specification

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[11] We assume as well that airline firms buy those materials based on their whole system operation. Therefore, material input prices only change with firms and time but not with routes. Please see Section V for details.

[12] Because firms operate different types of aircrafts on different routes at different time, and different types of aircrafts have a different number of available seats, $CRAFTSIZE_{ijt}$ may also change with route, firm and time. Please see Section V for details.

We specify the market power parameter as follows:

$$\lambda_{it} = \rho_1 + \rho_2 RHHI_{it} + \rho_3 ORIHHI_{it} + \rho_4 DESTHHI_{it} \tag{2.10}$$

where $RHHI_i$ is the route Herfindahl-Hirschman index calculated by the number of passengers carried by individual firms on route *i*. We expect that the higher the route HHI, the higher the firms' average market power on route *i*. On the other hand, firms may face the threat of potential entry, which discourages them from charging higher prices above marginal cost, so the overall effect of route HHI on market power is uncertain. $ORIHHI_i$ and $DESTHHI_i$ are the Herfindahl-Hirschman indices for the origin and destination airports respectively. High airport HHI means some carriers have hub dominance, which provides them with exclusive advantages---high flight frequency from a hub may indicate better service quality, raise the value of airlines' frequent flyer programs and create brand loyalty. Further, long-term leasing of airport space to individual carriers gives them the power to decide when, to whom and at what price to sublease space to their rivals.

Substituting the MC_{ijt} expressed in (2.9) and λ_{it} expressed in (2.10) into supply relation, we have

$$\begin{aligned} P_{ijt} = {} & \chi_2 W_{ijt}^F + \chi_3 W_{ijt}^L + \chi_4 W_{jt}^K + \chi_5 W_{jt}^M + \chi_6 CRAFTSIZE_{ijt} + \chi_7 DIST_i + \chi_8 Q_{ijt} \\ & - \frac{\rho_1 + \rho_2 RHHI_{it} + \rho_3 ORIHHI_{it} + \rho_4 DESTHHI_{it}}{\beta_2 + \beta_3 CS_{it}} Q_{ijt} + \sum_{j=1}^{N-1} \gamma_j' FIRM_j \\ & + \sum_{i=1}^{M-1} \psi_i' ROUTE_i + \sum_{t=1}^{2} \varphi_t' YEAR_t + \delta_{ijt} \end{aligned} \tag{2.11}$$

where δ_{ijt} represents the error term that might be contemporaneously correlated across equations. Let $Q^*_{ijt} = -\frac{Q_{ijt}}{\beta_2 + \beta_3 CS_{it}}$ and we can rewrite (2.11) as follows:

$$\begin{aligned} P_{ijt} = {} & \chi_2 W^F_{ijt} + \chi_3 W^L_{ijt} + \chi_4 W^K_{jt} + \chi_5 W^M_{jt} + \chi_6 CRAFTSIZE_{ijt} + \chi_7 DIST_i + \chi_8 Q_{ijt} + \rho_1 Q^*_{ijt} \\ & + \rho_2 RHHI_i Q^*_{ijt} + \rho_3 ORIHHI_i Q^*_{ijt} + \rho_4 DESTHHI_i Q^*_{ijt} + \sum_{j=1}^{N-1} \gamma^{'}_j FIRM_j \\ & + \sum_{i=1}^{M-1} \psi^{'}_i ROUTE_i + \sum_{t=1}^{2} \varphi^{'}_t YEAR_t + \delta_{ijt} \end{aligned} \tag{2.12}$$

If we estimate the demand function (2.8) and supply relation (2.11) simultaneously, we will find the effect of code-sharing on firm's air fares and passenger volumes on specified routes. Specifically, both β_2 and β_3 are shared by two equations to be estimated.

V. Data Sources and Variable Definition

The data set used in this paper is panel data from 2003 to 2005. Since Southwest and ATA airlines entered into a code-sharing agreement in December 2004 and implemented it in February 2005, the sample data period was chosen to include observations from before and after the code-sharing agreement. Routes with incomplete operating carrier information from 2003 to 2005 are excluded from the study. In this study we have decided to concentrate our analysis on flights to and from the Denver airport for the reasons explained below.

Of the eleven ATA airports, there was very limited code-share service in either Sarasota Bradenton or St. Petersburg. Eventually, ATA discontinued service to Boston, Minneapolis-St.Paul, and Newark in October 2005. Although Southwest did not have service to San Francisco till late 2007, it did have service to Oakland, which is an alternative for travellers in the San Francisco Bay area. Thus, it is possible that there could be some parallel code-sharing impacts in the case of San Francisco airport. Southwest directly entered the Ft. Meyers/Naples airport in October 2005, so any further code-sharing through that airpot would be parallel rather than complemenatry code-sharing.

This left Honolulu---a very isolated airport in a vacation market, not typical of most domestic routes and La Guardia, Arlington, and Denver. In the case of La Guardia and Arlington there are other airports in the area that offered competition, once again introducing the possibility of parallel dimensions to code-sharing. Accordingly, we selected Denver for the case study to use in this analysis.

As of 2007 Denver was the fifth businest airport in the U.S. and the eleventh largest in the world. It had no nearby airport competition so this is an airport the impact of a complementary code sharing could best be examined. Further, Denver is the second largest hub airport for United Airlines (one of the “Big Three” legacy airlines in the U.S. domestic market) as well as being the major hub for Frontier Airlines, a regional carrier. During the 2003-2005 time period of this study, Southwest did not serve Denver or any nearby airports directly. Thus, the only way Southerst had access to flights to or from Denver was through its code-share arrangement with ATA. Interestingly, Southwest later directly entered Denver in January 2006, leading to speculation that the code-share arrangement may have been a way to “test the waters” without incurring the costs of directly entering the market at the outset.

Given data limitations on multiple stop flight services, we focus on the routes where passenger volumes from direct flights account for more than 90% of the total passenger volume.[13] Therefore, our data sample includes 486 observations across 68 routes to or from Denver International Airport, in which 19 routes were code-shared by ATA and Southwest in 2005.

V.1. Demand Function Variables

Firm specific average air fares, P_{ijt} and passenger volumes, Q_{ijt} are from *Bureau of Transportation Statistics (BTS) US Department of Transportation (DOT) Origin and Destination Survey DB1B Market*, a 10% ticket random sample data. The number of passenger volumes used in the regression is ten times that of passenger volumes in the DB1B Market data. Q_{ijt} is the number of passengers firm *j* carries on its non-stop market of route *i* at time *t* while P_{ijt} is the passenger-weighted average air fares of incumbent firm *j* on its non-stop market of route *i* at time *t*. Given the limit of data information, we cannot distinguish business-class or

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[13] We also examined the economic impact of code sharing between ATA and Southwest on the incumbent firms on those more comparable one-stop markets for the same route data sample, but most of the coefficient estimates are not statistically significant.

unrestricted coach class tickets from other tickets. Besides, we also include zero-fare itineraries in the data sample. Code sharing routes (CS_{it}) are identified from *Southwest Airlines News Releases "Southwest Airlines Announces Cities for Code-share Flights with ATA Airlines"* at http://www.southwest.com. $FREQ_{ijt}$ is defined as the total number of departures performed by firm *j* on route *i* at time *t* and the data are from *BTS DOT Air Carrier Traffic Statistics T-100 Domestic Segment*. To make the characteristics of non code- shared routes comparable to those of code shared routes, we identify non code-shared routes as those with one end from Denver, the city chosen by ATA for code sharing, and the other end is from Southwest's destination cities that were not included in the code share agreement. The data for the population of origin and destination cities are from *Population Division US Census Bureau Annual Population Estimates of the Metropolitan Statistical Areas*.[14] The data for the per capita personal income (in dollars) of origin and destination cities are based on Metropolitan Statistical Areas level (MSA) provided by *Bureau of Economic Analysis, US Department of Commerce*.

V.2. Supply Relation Variables

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[14] The reason that we prefer to use population estimate by Metropolitan Statistical Areas (MSA) where either origin or destination city is located instead of population estimate by either origin or destination city only is due to the fact that the number of passengers may not be limited to the number of population in the departure city itself. Take Portland, Oregon for example: Besides the population of the Portland city itself, people around Portland such as those living in Beaverton Oregon may also choose Portland International Airport as the departure airport.

Fuel price, W_{ijt}^{F} is regionally adjusted based on the average fuel price of firm *j* at time *t*, calculated by dividing the total domestic fuel cost of firm *j* by total domestic gallons used by firm *j* in year *t*. Data for total domestic fuel cost and gallons are from *BTS DOT Form 41 Air Carrier Financial Statistics Schedule P-12A.* Since some air carriers (especially large air carriers), may have contractual and storage fuel advantages over small ones, firm level average fuel prices are not completely the same as the concurrent market fuel prices and differences in average fuel prices may exist between large and small air carriers. To control for regional (state level) differences in average fuel prices, we normalize regional average fuel prices to provide route and firm specific average fuel price. To illustrate how we do this, suppose American Airlines' (AA) average fuel price in all domestic operations was $1.67 per gallon in 2005 and the average fuel price at the national level in 2005 was $1.74 per gallon. We take the national average fuel price as our base value and calculate the regional average fuel price on the flight route, for example, from Boston, MA (BOS) to Los Angles, CA (LAX) by taking the arithmetic means of fuel prices from both the state of the origin city---MA and that of the destination city---CA.[15] Suppose the regional average fuel prices on the route BOSLAX we get here is $1.70. Then, AA's final average fuel price on the route BOSLAX is obtained as $1.67 \times \frac{1.70}{1.74} = 1.632$ dollars per gallon in 2005. In this way, differences in average fuel prices at route level are captured in addition to differences across

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[15] One assumption we make here is that air carriers add fuel at both origin and destination cities.

firms. Data for the fuel prices at both national and regional level (based on states) are available in the *Petroleum Marketing Annual (2003, 2004 and 2005)* published by *Energy Information Administration, Office of Oil and Gas, US Department of Energy*.

We derive route level labor input prices W_{ijt}^{L} for firm j on route i at time t using a similar normalization technique. We calculate firm level hourly average wage per worker by dividing firm j's total expenditure on salaries and related fringe benefits by the product of total employees and working hours per year.[16] The data are from *BTS DOT Form 41 Air Carrier Financial Statistics Schedule P-6* and *Schedule P-10* respectively. In order to take into consideration the regional (Metropolitan Statistics Area level---MSA level) differences in the hourly average wage per worker, we choose the hourly average wage per worker in transportation occupations at the national level as our base value and take the arithmetic means of hourly average wages from the origin and destination MSA cities to obtain regional hourly average wage per worker. Then following the same logic as the calculation of route level and firm specific average fuel price, we will have route and firm level hourly average wage per worker for a specific year. The data for the hourly average wages at the national and MSA level are available in the *Occupational Employment Statistics (OES) Survey (Nov 2003, Nov 2004 and May 2005 Estimates)*

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[16] We assume 2,080 working hours for a full-time worker per year.

Transportation and Material Moving Occupation reported by *Bureau of Labor Statistics US Department of Labor.*

Airline capital assets mainly include flight equipment, ground property and equipment (GPE) such as maintenance and engineering equipment, ramp equipment and other miscellaneous ground equipment, land, construction work in progress, leased property under capital leases such as aircraft leases and etc. Compared to aircraft expenditures, GPE costs are relatively small. Although we would prefer to follow Oum and Yu (1998) and use aircraft lease rates as a proxy for capital cost, this information was not available to us.

Alternatively, we follow Chua, Kew and Yong (2005) and use total cost of operating property and equipment per unit of airline capacity (measured by available seat miles) that includes all the mentioned expenses above (GPE, land, construction work and leased property under capital leases) less allowance for depreciation as our firm level capital input prices. The data for the firm specific capital cost and total number of available seat miles are available in *BTS DOT Form 41 Air Carriers Financial Statistics Schedule B-1* and *BTS DOT Air Carrier Traffic Statistics T-100 Air Carrier Summary T-2*.

Material input prices W_{jt}^{M} are calculated as a firm level materials and services cost per available seat mile. Materials and services cost includes all the expenditures except fuel, labor and aircraft leasing cost, such as maintenance materials, passenger food, advertising and promotions, communication and insurance and etc. The data for the firm level total materials and services cost are available in *BTS DOT Form 41 Air Carrier Financial Statistics Schedule P-6*. We assume that airlines buy these materials and services based on their entire system operations so the material input prices do not change with flight routes but only change across airlines and time.

$CRAFTSIZE_{ijt}$ is measured as the average number of available seats per aircraft operated by firm j on route i at time t. The larger the aircraft body size is, the more available seats in the fleet. We use firm and route specific total number of available seats divided by the total number of departures performed to get the average number of available seats per aircraft. $DIST_i$ is the market distance between the origin and destination cities and data for all of these variables are available from the *BTS DOT Air Carrier Traffic Statistics T-100 Domestic Segment*. $RHHI_{it}$ is the route Herfindahl-Hirschman index on route i. It is calculated by the sum of the squares of the individual firms' market share where market share is calculated as the number of individual firm's passengers divided by the total number of passengers carried by all firms on route i. $ORIHHI_{it}$ and $DESTHHI_{it}$ are the origin and destination airport Herfindahl-Hirschman index respectively. Following the same logic, they are calculated using the market share of passengers originating (or arriving) at an airport for each carrier serving the airport. All the data for the number of passengers carried by individual airlines are available from *Bureau of Transportation Statistics (BTS) US Department of Transportation (DOT) Origin and Destination Survey DB1B Market*.

All dollar values in the demand equation are deflated by the Consumer Price Index (All Urban Consumers, All items, 1982-84=100) and those in the supply equation are deflated by the Producer Price Index (All commodities, 1982-84=100), obtained from the *Bureau of Labor Statistics US Department of Labor*. Descriptive statistics for all variables are listed in Table 2.2.

VI. Empirical Results

Empirical results are presented in Table 2.3 and Table 2.4 for both code-shared and non code-shared routes to or from Denver airport. We estimate both demand and supply functions simultaneously using Nonlinear Three State Least Squares (NL3SLS). Instrument variables are all the remaining exogenous variables in the equations.

VI.1. Demand Function

First, the estimate of air fares is negative as expected and statistically significant at p=0.01 level. Second, compared to non code-shared routes, code-sharing between Southwest and ATA significantly increases incumbents' demand by 162809 passengers per year. Thus, code-sharing between entrants does not decrease passenger demand for incumbents' flight services, a result consistent with

Table 2.2 Descriptive Statistics

Variables (Descriptions and Units)	**Mean**	**Std**
Q (Firm *j*'s passengers on non-stop market of route *i*)	42784.51	36414.44
P (Firm *j*'s air fare in dollars on non-stop market of route *i*)	170.9938	37.90606
CS (Equals 1 if the route was in code-sharing in 2005)	0.236626	0.425448
ORIPOP (Population in the origin MSAs)	2394473	1686644
ORIINCO (Per capita income in dollars in the origin MSAs)	36252.59	4904.613
DESTPOP (Population in the destination MSAs)	2401816	1667021
DESTINCO (Per capita income in dollars in the destination MSAs)	36450.89	4762.899
FREQ (Firm *j*'s departures on non-stop market of route *i*)	1213.426	888.2739
W^F (Firm *j*'s fuel prices in dollars per gallon)	1.219384	0.28094
W^L (Firm *j*'s labor prices in dollars per hour per worker)	33.82447	9.702598
W^K (Firm *j*'s capital prices in dollars per available seat mile)	0.144664	0.06385
W^M (Firm *j*'s material prices in dollars per available seat mile)	0.013791	0.00218
CRAFTSIZE (Firm *j*'s available seats per aircraft on non-stop market of route *i*)	120.7976	34.09199
DIST (Market distance of route *i* in miles)	894.4691	370.3058
RHHI (HHI index on route *i*)	3623.638	1005.612
ORIHHI (HHI index at the origin airport)	1898.409	431.807
DESTHHI (HHI index at the destination airport)	1927.913	483.321
AA (Equals 1 if the carrier is American Airlines)	0.024691	0.15534
AS (Equals 1 if the carrier is Alaska Airlines)	0.024691	0.15534
CO (Equals 1 if the carrier is Continental Airlines)	0.012346	0.11054
DL (Equals 1 if the carrier is Delta Air Lines)	0.030864	0.17313
F9 (Equals 1 if the carrier is Frontier Airlines)	0.296296	0.45709
HP (Equals 1 if the carrier is America West Airlines)	0.024691	0.15534
NW (Equals 1 if the carrier is Northwest Airlines)	0.012346	0.11054
UA (Equals 1 if the carrier is United Airlines)	0.388889	0.488
US (Equals 1 if the carrier is US Airways)	0.012346	0.110537
OO (Equals 1 if the carrier is Trans State Airlines)	0.123457	0.3293
QX (Equals 1 if the carrier is Horizon Air)	0.018519	0.134956
ZW (Equals 1 if the carrier is Air Wisconsin)	0.018519	0.134956
YEAR2003 (Equals 1 if in the year 2003)	0.333333	0.47189
YEAR2004 (Equals 1 if in the year 2004)	0.333333	0.47189

All dollars are measured in real terms (1982-84 dollars).

Table 2.3 NL3SLS Regression Results - Demand Function Parameter Estimates

Demand Function Parameter	**Estimate**	**Std Error**	**t Value**
CONSTANT	11140.58	111355	0.1
CS	162808.7	68622.9	2.37***
P	-311.845	105.2	-2.96****
*CS*P*	-1072.03	419.2	-2.56****
ORIGINPOP	0.015969	0.0064	2.49****
ORIINCOME	-1.14209	0.7813	-1.46*
DESTPOP	0.012173	0.0461	0.26
DESTINCOME	0.225103	0.7961	0.28
FREQ	16.39144	1.9618	8.36****
*CS*FREQ*	61.5065	16.1899	3.80****
AA	3421.544	9795.8	0.35
AS	28607.97	10170.5	2.81****
CO	42027.32	13075.2	3.21****
DL	-19309.8	10754.8	-1.80**
F9	21734.86	8260.2	2.63****
HP	9710.389	10032.1	0.97
NW	57787.01	12781.5	4.52****
OO	9844.093	8236.5	1.2
QX	5901.17	10696.2	0.55
UA	30814.72	7985.6	3.86****
US	19883.35	12750.9	1.56*
ZW	4568.732	10584	0.43
YEAR2003	-3692.12	3458.9	-1.07
YEAR2004	-296.271	2538.3	-0.12
Adjusted R square	77.17		

*p=0.20 level; **p=0.10 level; ***p=0.05 level; ****p=0.01 level.

findings by Oum, Park and Zhang (1996). Flight frequency is found to be a significant and positive determinant of airline demand. The interaction between code sharing and incumbents’ flight frequency is positive and significant as well, suggesting that code sharing results in incumbent firms increasing flight frequency, thus resulting in higher service quality.

Table 2.4 NL3SLS Regression Results – Supply Relation Parameter Estimates

Supply Relation Parameter	Estimate	Std Error	t Value
FUEL	137.5877	33.3069	4.13****
LABOR	0.401796	0.5092	0.79
CAPITAL	155.3111	142.2	1.09
MATERIAL	-3402.8	2205.7	-1.54
CRAFTSIZE	-0.42518	0.1422	-2.99****
DIST	0.030218	0.00971	3.11****
Q	0.000398	0.00021	1.90***
*Q**	-0.93416	0.3743	-2.50****
*RHHIQ**	-0.000091	0.000039	-2.34****
*ORIHHIQ**	0.00045	0.00017	2.67****
*DESTHHIQ**	0.00029	0.000132	2.20****
AA	-23.3451	26.4905	-0.88
AS	-45.0234	23.5703	-1.91***
CO	6.291873	27.5291	0.23
DL	-32.4742	29.6187	-1.1
F9	-41.4996	24.8404	-1.67**
HP	-8.19999	28.1013	-0.29
NW	5.25298	28.048	0.19
OO	-56.7337	26.1254	-2.17***
QX	-50.0688	20.5488	-2.44****
UA	-29.3355	27.9378	-1.05
US	-12.2162	24.2	-0.5
ZW	-42.0761	23.721	-1.77**
YEAR2003	70.05195	17.372	4.03****
YEAR2004	41.87595	11.0529	3.79****
Adjusted R square	64.30		

*p=0.20 level; **p=0.10 level; ***p=0.05 level; ****p=0.01 level.

The estimated interaction between code sharing and air fares is negative and statistically significant. If we evaluate the price elasticity of demand on both code-shared and non code-shared routes at the mean value of price and quantity demanded, we find that the price elasticity of demand on the non code shared routes is 1.25 while on the code shared routes, it is 5.50. This suggests that code sharing makes passengers more responsive to the incumbent firms' price changes.

The population and per capita income in the origin airport MSAs has a significant impact on demand, but population and per capita income in the destination airport MSAs has no significant impact. Estimates of most route and airline dummies are strongly significant, suggesting that unobserved route specific fixed effects are important as are unobserved airline fixed effects.

VI.2. Supply Relation

The coefficient of Q_{ijt} is positive χ_8 =0.000398 and statistically significant, which means that the increase in marginal cost associated with more landing and take-offs due to more frequent departures is greater than the cost of carrying one more additional passenger. Airport dominance, measured by HHI, is a significant and important source of market power. This result is consistent with previous studies by Bailey and Williams (1988), Borenstein (1989, 1990, 1991), Berry (1990, 1992), Evans and Kessides (1993), Brueckner and Spiller (1994) and Oum, Zhang and Zhang (1995). However, high route concentration level tends to decrease market power, which shows that the threat from potential entry is strong enough to discourage incumbent airlines to charge monopoly price.

According to our theoretical model, the market power parameter is $\lambda = 1 + \nu$ =0.14906 (We get this by substituting the mean values of all the explanatory variables back into the equation (2.10)). Therefore, ν = -0.85094, showing that in the domestic airline market, firms are closer to Bertrand price-setting than the Cournot quantity-setting competition. This suggests that the nature of competition in domestic markets tends to be more competitive than in international markets (Oum, Park and Zhang (1996) and Park and Zhang (2000)) and also more competitive than in domestic airline markets in the 1980s (Brander and Zhang (1990, 1993)). This result also supports the Bertrand assumption made by Gayle (2006) in his research on domestic code-sharing alliances.

The signs of three input prices, fuel, labor, capital in the supply relation are positively related to the price as expected, with the estimates of fuel prices strongly significant at 1% level of confidence. Estimates of labor, material and capital input prices are not significant.

Distance tends to increase air fares and aircraft body size is strongly significant with the expected negative sign, indicating lower marginal costs, a result consistent with previous studies such as Gillen, Oum and Tretheway (1990), Capital and Sickles (1997), Fischer and Kamerschen (2003) and Morrison (2006).

Coefficients for airline dummies including AS (Alaska Airlines), F9 (Frontier Airlines), OO (Trans State Airlines), QX (Horizon Air) and ZW (Air Wisconsin) are significant with the expected negative signs. We expect marginal cost and thus air fares for these air carriers to be lower because all of these firms are well-known low cost carriers. Coefficients for two year dummies are significant as well, which captures the cost changes from 2003 to 2005 due to the dramatic increase in the world oil prices.

VI.3. Incumbent Air Fares and Passenger Volumes

Code sharing tends to increase market demand for incumbents' nonstop service but also has an effect on the slope of supply relation curve through $\left(-\frac{\partial P}{\partial Q}\right)$. Specifically, since the slope of the supply curve is equal to 0.000575 in the presence of code sharing and increases to 0.000876 in the absence of code sharing, we expect an increase in equilibrium passenger volumes but are uncertain of the change in equilibrium air fares. In order to measure the exact changes before and after Southwest/ATA code sharing on both code-shared and non code-shared routes, we follow Oum, Park and Zhang (1996) and Park and Zhang (2000) and derive reduced-form equations for the incumbents' price and passenger volumes from equation (2.8) and (2.11):

$$Q = AP + B \text{ and } P = CQ + D$$

where $A = \beta_2 + \beta_3 CS_{it}$;

$$\begin{aligned} B = \alpha_0 &+ \beta_1 CS_{it} + \beta_4 ORIPOP_{it} + \beta_5 ORIINCO_{it} + \beta_6 DESTPOP_{it} + \beta_7 DESTINCO_{it} \\ &+ \beta_8 FREQ_{ijt} + \beta_9 CS_{it} FREQ_{ijt} + \sum_{j=1}^{N-1} \gamma_j FIRM_j + \sum_{i=1}^{M-1} \lambda_i ROUTE_i + \sum_{t=1}^{2} \varphi_t YEAR_t \\ &+ \varpi_{ijt} \ ; \end{aligned}$$

(If $CS = 0$, then $B^{'} = B$.)

$$C = \chi_8 - \frac{\lambda}{\beta_2 + \beta_3 CS_{it}} = \chi_8 - \frac{\lambda}{A};$$

and

$$D = \chi_2 W_{ijt}^F + \chi_3 W_{ijt}^L + \chi_4 W_{jt}^K + \chi_5 W_{jt}^M + \chi_6 CRAFTSIZE_{ijt} + \chi_9 DIST_i + \sum_{j=1}^{N-1} \gamma_j^{'} FIRM_j + \sum_{i=1}^{M-1} \lambda_i^{'} ROUTE_i + \sum_{t=1}^{2} \varphi_t^{'} YEAR_t + \delta_{ijt}$$

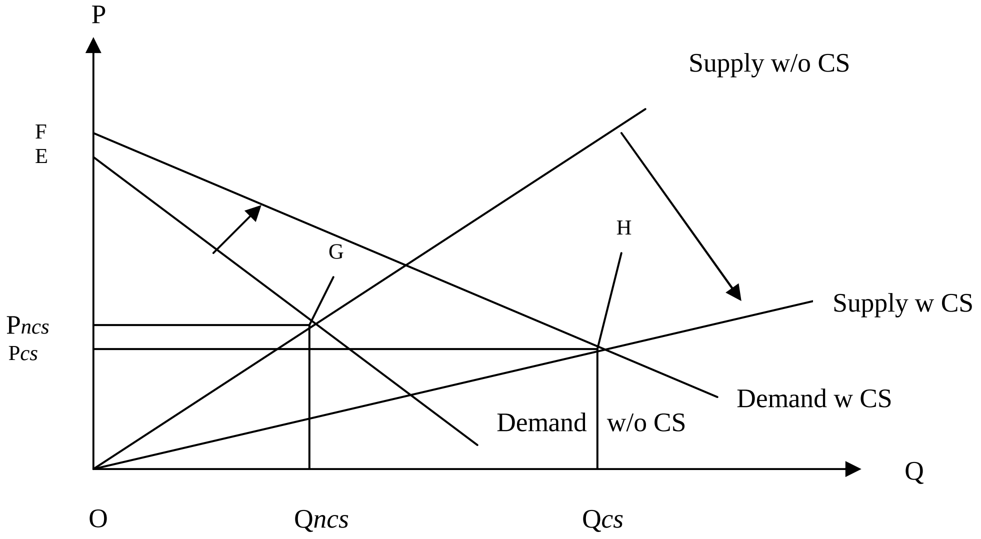
Therefore, on code-shared routes, where $CS = 1$, equilibrium air fares and passenger volumes are $P_{cs} = \frac{(\chi_8(\beta_2 + \beta_3) - \lambda)B + (\beta_2 + \beta_3)D}{(1 + \lambda - \chi_8(\beta_2 + \beta_3))(\beta_2 + \beta_3)}$ and $Q_{cs} = (\beta_2 + \beta_3)P_{cs} + B$. On non code-shared routes, where $CS = 0$, equilibrium passenger volumes and air fares are $P_{ncs} = \frac{(\beta_2 \chi_8 - \lambda)B^{'} + \beta_2 D^{'}}{(1 + \lambda - \chi_8 \beta_2)\beta_2}$ and $Q_{ncs} = \beta_2 P_{ncs} + B^{'}$. If we substitute the coefficient estimates back into the expressions above and calculate the air fare and passenger volume for each route and each year and then take the average of these numbers, we have $\Delta Q = Q_{cs} - Q_{ncs} = 117009 - 23071 = 93938$ and $\Delta P = P_{cs} - P_{ncs} = 119 - 179 = -60$, indicating increase in passenger volumes and decrease in air fares.

These results show that code sharing between Southwest and ATA decreases incumbents' equilibrium air fares by $60 and increases passenger volumes by 93938 persons. The decrease in the incumbents' air fares is consistent with previous studies documenting the well-known “Southwest Effect”, which occurs when Southwest directly enters a market. This result suggests that the “Southwest Effect” is also seen when the carrier enters through code sharing rather than direct entry. Lower air fares and higher passenger volumes due to code sharing are also consistent with all previous studies for both international and domestic code sharing (Oum, Park and Zhang (1996), Park (1997), Park and Zhang (2000), Park, Zhang and Zhang (2001), Park, Park and Zhang (2003), Brueckner and Whalen (2000), Brueckner (2001, 2003), Bamberger, Carlton and Neumann (2004) and Armantier and Richard (2005a)).

VI.4. Welfare Analysis of Code sharing

To measure social welfare under code sharing, we need to calculate the area *OFH* in Figure 1 while social welfare without code sharing is equal to the area *OEG*. We calculate social welfare by setting all exogenous variables at mean values. We find that total social welfare gain due to code sharing in this market is equal to 8.97 million dollars, which means that code sharing between Southwest and ATA helps increase social welfare. We find that both consumer and producer surplus

Figure 2.1 Effects of Code Sharing on Incumbents' P and Q



gains ($\Delta CG = 4.90$ million and $\Delta PG = 4.07$ million), a result supported by Park (1997), Park and Zhang (2000) but contrary to Armantier and Richard (2005b) who found that consumer welfare decreased after complementary code sharing between Continental and Northwest Airlines in the US markets. Possible reasons for this difference could be due to the nature of two code sharing alliances: Continental and Northwest Airlines are two major legacy air carriers but Southwest and ATA Airlines are two well-known low cost air carriers. Different business practice models between low cost and legacy carriers may bring about different effects of code-sharing alliances.

VII. Conclusions and Future Research

Our empirical results show that the code sharing agreement between Southwest and ATA in the Denver market increases both producer and consumer surplus, a finding consistent with studies of international code sharing (Park (1997), Park and Zhang (2000)) but contrary to Armantier and Richard (2005b) in domestic markets. We find that this complementary code sharing arrangement decreases incumbent carriers' air fares and increases their passenger volumes. Furthermore, we also find that the domestic airline market structure is more competitive with competition on price, as opposed to quantity competition in international markets (Oum, Park and Zhang (1996) and Park and Zhang (2000)) and in domestic markets in the 1980s (Brander and Zhang (1990, 1993)). This difference may be due to the fact that our study focuses on domestic code-shared routes where 90% of the passenger volume comes from direct flight services whereas international code-shared markets are mainly interline markets prior to code sharing. Also, international markets tend to have fewer carriers and often have regulatory restrictions that prevent the degree of competition observed in the domestic markets. Our results provide preliminary evidence that the “Southwest Effect” prevails even when Southwest entry occurs through code sharing rather than direct entry.

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Chapter 3

Determinants of Successful Code-sharing: A Case Study of Continental and America West Airlines Alliances --- A Discrete Longitudinal Analysis

I. Introduction

Six major domestic U.S. airlines (Delta and United Airlines, American and US Airways, Northwest and Continental Airlines) proposed various kinds of alliances in 1998. All of these alliances combined frequent flier programs and club facilities. Northwest Airlines planned to buy an equity share in Continental Airlines. Delta and United and Northwest and Continental entered into code-sharing agreements.

Code-sharing has emerged as one of the most important forms of alliance in the airline industry. Under code-sharing, contracting firms merge their computerized reservation systems so that each contracting carrier can issue tickets with their own flight numbers on flights operated by other contracting air carriers. Through code-sharing, partner firms effectively link their networks without operating additional aircraft and gain exposure in markets where they do not operate directly but participate via display of their flight numbers. As a result, airlines are able to make use of hub-and-spoke systems to generate greater passenger volumes. Due to economies of traffic density, the marginal operating cost of carrying an additional passenger drops with increased volume, explaining why code-sharing has become a popular form of airline alliance.

The first major code-sharing alliance in the US airline industry began in the middle of the 1990s between Continental and America West Airlines. America West Airlines, the second largest low cost air carrier in the US, now operating as US Airways, was one of the greatest business successes in the US airline industry in the 1980s. But rapid expansion growth without proper handling of large operating losses placed the company at the verge of bankruptcy by 1986. With the pressure from increasing fuel costs due to concerns about stability in the Gulf States in the lead-up to the Persian Gulf War, America West was forced to file for bankruptcy in 1991. In 1994, America West managed to secure reorganization, with a large portion of the airline owned by a partnership with Continental Airlines. This partnership resulted in a code-sharing arrangement with Continental and heralded the beginning of code-sharing alliances in the domestic airline industry.

The America West and Continental code-sharing arrangement lasted 8 years, from 1994 to 2002.[17] During the code-sharing period, individual routes were added and old routes dropped. Indeed, the route structure of the code-share agreement was very dynamic as indicated in Table 3.1. The purpose of this paper is to examine why some routes were kept and others deleted.

Previous studies have examined the effect of code-sharing on air fares, passenger volumes, operating costs and consumer welfare (Oum, Park and Zhang (1996), Park (1997), Park and Zhang (2000), Park, Zhang and Zhang (2001), Park, Park and Zhang (2003), Brueckner and Whalen (2000), Shy (2001), Brueckner

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[17] Continental Airlines, the fourth largest US airline with headquarters in Houston, Texas and operations throughout the US, Canada, Latin America, Europe and the Asia-Pacific region, has entered a number of subsequent alliances. As of 2007, it had more than 3,000 daily departures, serving 151 domestic and 120 international destinations and has 42,200 employees. In September 2004, Continental became a member of the SkyTeam Alliance, in which it participates with Delta Air Lines, Northwest Airlines and KLM Royal Dutch Airlines. It also initiated code-sharing with Amtrak rail services to some cities in the northeastern United States, which is the first code-sharing agreement between airline and rail services.

Table 3.1 Changes in the Number of Code-shared (CS) Routes

Quarter[18]	CS Routes at the Current Period	New CS Entries from the Previous Period	New CS Exits from the Previous Period
1998Q1	367	N/A	N/A
1998Q2	436	231	162
1998Q3	405	165	196
1998Q4	402	172	175
1999Q1	466	235	171
1999Q2	494	234	206
1999Q3	582	275	187
1999Q4	655	294	221
2000Q1	599	208	264
2000Q2	600	228	227
2000Q3	382	108	326
2000Q4	388	173	167
2001Q1	314	118	192
2001Q2	274	130	170
2001Q3	279	128	123
2001Q4	341	178	116
2002Q1	258	91	174
2002Q2	178	57	137
2002Q3	5	1	174
2002Q4	3	0	2

(2001, 2003), Hassin and Shy (2004), Bamberger, Carlton and Neumann (2004), Armantier and Richard (2005a, 2005b), Chua, Kew and Yong (2005) and Gayle (2006)), but no empirical research has been done to determine why code-sharing is proposed and implemented on some city pairs, but not on others. In the case of the Continental and America West code-sharing alliance, of all the routes that were code-shared, only 33 routes remained in the agreement for the entire 1998 - 2002

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[18] Information on code-shared routes between Continental and America West is available from Bureau of Transportation Statistics (US Department of Transportation) only from 1998 because of reporting requirements adopted by the Congress in 1998.

period. There were 936 routes that were in the agreement for one quarter and then were dropped (See Table 3.2). Different decisions in these code-shared route arrangements reflect different operating strategies in response to route market structure and entry-deterring actions taken by incumbent firms. Analysis of these entry and exit decisions can identify the determinants of code-sharing choices to ascertain whether or not these choices are affected by anticompetitive behavior of incumbent

Table 3.2 Time of Code-sharing for Different Code-shared Routes

Number of CS Routes	CS Time (in Quarters)
33	18
24	17
21	16
17	15
23	14
32	13
20	12
35	11
31	10
37	9
40	8
45	7
71	6
80	5
82	4
151	3
325	2
936	1
Total: 2003	**The Whole CS Period[19]: 18**

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[19] The whole period of code sharing time is only calculated from the first quarter of 1998 due to the data unavailability before 1998 from Bureau of Transportation Statistics U.S. Department of Transportation.

firms. For government agents and policy makers, identification of the determinants of code-sharing can provide information as how to regulate alliances and predict that which specific factors should be considered when reviewing a proposed code-share agreement. The results from this study should help policy makers determine the extent they should be concerned with antitrust issues when considering approval of a new agreement. For individual firms considering which routes to include in a code-share agreement, this study provides information on which are the relevant factors to consider.

II. Literature Review

The importance of entry conditions and their impact on economic performance in the process of competition has long been of concern in the industrial organization literature. Extra-normal or excess economic profits in an industry suggest that entry barriers may exist to keep other firms from entering and taking advantage of the market profitability. Bain’s (1956) pioneering work points out that economies of scale, absolute cost and product differentiation advantages of incumbent firms are three elements that affect the ability of incumbent firms to protect positive profits from entry.

However, the nature of Bain’s paradigm is entirely static with entry barriers taken as exogenous, problems which have been addressed in the game-theoretic literature. Sutton (1991) provides a two-stage game formulation and offers a detailed study of the role sunk costs play, either endogenously or exogenously, as entry barriers.[20] In the airline literature, the most noteworthy work regarding entry conditions has been the theory of contestable markets. Bailey and Panzar (1981) argued that long haul airline markets served by local service monopolists were basically contestable. Baumol (1982) formally defined a perfectly contestable market as a market with freedom of entry and exit without incurring loss of sunk cost. Perfect contestability guarantees absence of excess profits and cross subsidization even under monopoly or oligopoly situations. Bailey and Baumol (1984) further point out that even though airline markets could theoretically be represented as contestable, labor contracts, slot controls, airport dominance and long-term lease of airport facilities all may prevent contestability from occurring.[21] This conclusion is consistent with Morrison and Winston (1987), Hurdle *et al*. (1989), Strassmann (1990) and Winston and Collins (1992) who agree that perfect contestability did not characterize the airline industry after deregulation. In particular, Morrison and Winston (1987), Sinclair (1995), Dresner, Lin and Windle (1996), Morrison (2001), Dresner, Windle and Yao (2002) find that slot controls were a significant entry deterrent.

Bailey and William (1988), Borenstein (1989, 1990, 1991), Berry (1990, 1992), Evans and Kessides (1993) and Oum, Zhang and Zhang (1995) argue that

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[20] For a detailed review of empirical studies of entry and exit, please refer to Siegfried and Evans (1994).

[21] Since 1968, four airports in the U.S. have limits on the number of takeoffs and landings that may take place during any given hour. They are Chicago O’ Hare, New York Kennedy and La Guardia and Washington Reagan National Airports. But in 1986, the U.S. Department of Transportation permitted airlines to buy and sell their takeoff and landing slots.

airport dominance (hub concentration) is an important source of market power and monopoly rents, representing a dominant strategy in the oligopolistic deregulated airline industry. From the demand side, a dominant reputation can be acquired by a scale-driven carrier as a consequence of operating most flights at its hub airport, raising the value of the airline's frequent flyer program and creating brand loyalty. Large scale operations by an incumbent carrier can result in higher flight frequency------an important indicator of service quality, and may also inhibit potential competitors' abilities to obtain gates and other facilities necessary for entry or expansion of service. From the cost side, increased flight frequency may increase traffic density, which leads to lower marginal operating cost and generates cost advantages over potential entrants if the increase in costs associated with an increase in flight frequency is less than revenues produced by the additional passengers.[22] From both demand and cost sides, economies of density play an important role in creating entry barriers.

Travel agent commission override bonuses and biases due to computer reservation systems may benefit incumbent carriers; long-term leases of airport space to particular carriers give them the power to decide when, to whom and at what price to sublease space to competitors.

High route concentration may also be a significant deterrent to entry in the airline industry. Hurdle etc. (1989) and Strassmann (1990) find that entry barriers

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[22] Please see also Caves, Christensen and Tretheway (1984), Brueckner, Dyer and Spiller (1992), Brueckner and Spiller (1994) and Hendricks, Piccione and Tan (1995) for details of economies of aircraft size and economies of traffic density as an important reason of adopting hub-and-spoke systems.

exist in the highly concentrated airline markets due to incumbents' large scale flight operations at their hub airports.

With the formation of hub-and-spoke networks after deregulation, airport congestion has become an important entry barrier to potential entrants. Abramowitz and Brown (1993) and Dresner, Windle and Yao (2002) find that airport congestion measured either by the number of takeoffs and landings or by gate constraints and utilization are significant barriers to entry.

Finally, what is worth mentioning is that perfect contestability theory assumes that all players in the market have the same cost structure so the entrants can serve the market demands with the same technology by engaging in "hit-and-run" entry without incurring sunk cost. But this is not true in the airline industry. Low cost air carriers usually enjoy a cost advantage and can earn profits at prices that are not compensatory to incumbent carriers. Low cost carriers are able to do this because they use a different business model than legacy carrier, such as only operating a single type of airplane, servicing a single passenger class, managing a simple fare scheme, and flying to cheaper, less congested secondary airports to avoid air traffic delays and take advantage of lower landing fees. Whinston and Collins (1992) provide an example of the successful entry of a low cost air carrier People Express, which led to significant value reductions for incumbent firms. Bennett and Craun (1993), Windle and Dresner (1995), Dresner, Lin and Windle (1996), Richards (1996), Morrison (2001), Bamberger and Carlton (2006) all find that the entry of low cost air carrier Southwest Airlines leads to significant air fare decreases.

III Theoretical Model

III.1. Before Code-sharing

Following Sinclair (1993), we assume that a monopolist airline operates a hub-and-spoke system which consists of the hub city *H* and other N spoke cities, *i*=1, 2, …, N. So the air travel demand between any spoke city *i* and the hub city *H* (including travel demand from both H to *i* and *i* to H) is given by

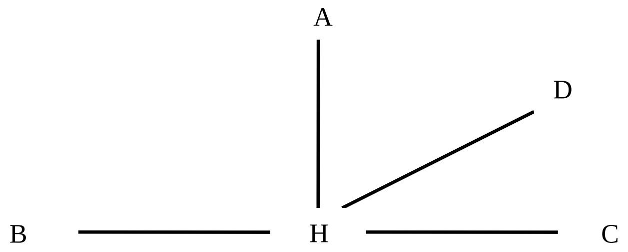
$$q_{Hi} = a_{Hi} - b_{Hi}P_{Hi}, \qquad i = 1,...N \tag{3.1}$$

and the air travel demand between any two spoke cities *i* and *j* ($j \neq i$) including the travel from *i* to *j* and from *j* to *i* through the hub city *H* is given by

$$q_{ij} = a_{ij} - b_{ij}P_{ij}, \qquad i = 1,...N;\ j = 1,...N;\ j \neq i \tag{3.2}$$

Let c_{Hi} be the marginal cost of servicing a passenger between *i* and H and c_{ij} be the marginal cost of servicing a passenger between *i* and *j* through *H* where c_{ij} is the sum of the marginal costs on the two segments c_{Hi} and c_{Hj} , i.e.; $c_{ij} = c_{iH} + c_{Hj}$. For example, before code-sharing, one code sharer --- firm 1 operates a monopoly hub-and-spoke flight system with H as its hub and A, B, C and D as its spoke cities. We also assume that the cost savings from offering indirect hub delivery such as flights A-H-B are greater than the loss of revenue from forgoing the more lucrative direct service A-B, so the firm will prefer to provide flight service A-H-B rather than A-B.[23]

Figure 3.1 Firm 1's Airline Hub-and-spoke System



Then firm 1's profits before code-sharing from operating this hub-and-spoke system are written as:

$$\pi_1^{NCS} = \underbrace{\frac{(a_{HA}-b_{HA}c_{HA})^2}{4b_{HA}} + \frac{(a_{HB}-b_{HB}c_{HB})^2}{4b_{HB}} + \frac{(a_{HC}-b_{HC}c_{HC})^2}{4b_{HC}} + \frac{(a_{HD}-b_{HD}c_{HD})^2}{4b_{HD}}}_{\text{Profits on routes into or out of the hub}}$$

$$\underbrace{\begin{aligned} &+\frac{(a_{AB}-b_{AB}(c_{AH}+c_{HB}))^2}{4b_{AB}} + \frac{(a_{AC}-b_{AC}(c_{AH}+c_{HC}))^2}{4b_{AC}} + \frac{(a_{AD}-b_{AD}(c_{AH}+c_{HD}))^2}{4b_{AD}} \\ &+\frac{(a_{BC}-b_{BC}(c_{BH}+c_{HC}))^2}{4b_{BC}} + \frac{(a_{BD}-b_{BD}(c_{BH}+c_{HD}))^2}{4b_{BD}} + \frac{(a_{CD}-b_{CD}(c_{CH}+c_{HD}))^2}{4b_{CD}} \end{aligned}}_{\text{Profits on spoke routes}} \qquad (3.3)$$

Similarly, the other code-sharer---firm 2 also operates a monopoly hub-and-spoke system with $H^{'}$ as its hub and $A^{'}$, $B^{'}$, $C^{'}$ and $D^{'}$ as its spoke cities. Besides, the market incumbent --- firm 3 operates its own monopoly hub-and-spoke system with $H^{''}$ as its hub and $A^{''}$, $B^{''}$, $C^{''}$ and $D^{''}$ as its spoke cities.

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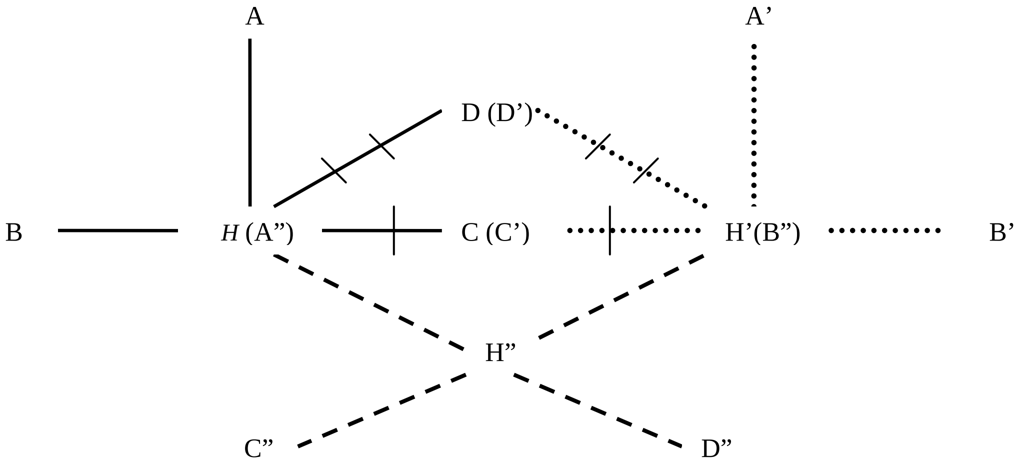
[23] Please see Sinclair (1993) for the equilibrium conditions of adopting a hub-and-spoke system rather than a direct flight service.

III.2. After Code-sharing

Under code-sharing, firm 1 (firm 2) chooses several spoke cities in its own hub-and-spoke system as the connecting airport cities and constitutes the complementary code-shared routes with firm 2 (firm 1). We limit our attention to one-stop (two segments) complementary code-shared flights only, so there are actually three airport cities involved --- the origin airport, the connecting airport and the destination airport. Every airport acts as either the hub or the spoke city in the code-sharing. If we assume alliance firms are symmetric, then there are totally eight ways of setting up code-sharing ------ Hub-Hub-Hub, Hub-Hub-Spoke, Hub-Spoke-Hub, Hub-Spoke-Spoke, Spoke-Hub-Hub, Spoke-Hub-Spoke, Spoke-Spoke-Hub and Spoke-Spoke-Spoke. If a city is the hub city for one firm but a spoke city for another firm, we regard this city as a hub city. For example, H-C-H' and H-D-H' are two "Hub-Spoke-Hub" kind of code-shared routes. To keep the model as succinct as possible without losing any generality, the theoretical model and profit function specified in the paper is based on Hub-Spoke-Hub code-sharing route arrangement. However, the profit function from other code-sharing route arrangements can be specified similarly without changing the essence of equilibrium conditions derived from the paper. Please refer to Figure A1 for details. In Figure 3.2, both city *C (C')* and *D (D')* are the spoke cities in firm 1 and 2's hub-and-spoke systems respectively. Before code-sharing, neither of the firms provides services on the trip with city *H* as the origin and city *H'* as the destination but the market incumbent---firm 3 provides one-stop flights *A"(H)-H"-B"(H')*

Figure 3.2 Code-sharing Alliances under Airlines' Hub-and-spoke Flight Systems



through its own hub *H"* and enjoys the monopoly profits. Under code-sharing, alliance firms choose their spoke cities such as *C (C')* and *D(D')* as the connecting airport cities and provide code-shared flights *H-C-H'* and (or) *H-D-H'* on the trip with city *H* as the origin and city *H'* as the destination. Therefore, through code-sharing, firm 1 and firm 2, acting as one firm, enter route *HH'* and compete with the one-stop flights offered by the market incumbent---firm 3. Due to economies of traffic density, the increased passenger volumes from code-shared flights will decrease the marginal operating cost on segments *HC(H'C')* and *HD(H'D')* in both firm 1 and firm 2's hub-and-spoke system, assuming all other things stay the same. Let $\underline{c}_{Hi}$ be the marginal cost on the segment *Hi* after code-sharing where $\underline{c}_{Hi}$ satisfies $\underline{c}_{Hi} < c_{Hi}$ --- the marginal cost on the segment *Hi* before code-sharing. The decrease in marginal costs on the segments *HC* and *HD* also helps decrease the marginal cost of flight itineraries that contain either of the two segments such as *A-H-C, B-H-C, A-H-D, B-H-D* and *C-H-D*. For example, the marginal cost of flights on route *A-H-D* after code-sharing, denoted by $\underline{c}_{AD}$ ($\underline{c}_{AD} = c_{AH} + \underline{c}_{HD}$), satisfies $\underline{c}_{AD} < c_{AD}$ ---the marginal cost on route *A-H-D* before code-sharing ($c_{AD} = c_{AH} + c_{HD}$) because $\underline{c}_{HD} < c_{HD}$. Accordingly, the marginal operating cost of firm 2 will decrease by the same way as well.

However, the marginal cost of the market incumbent (firm 3) on segment *HH”* and *H”H’* will increase because some passengers may choose code-shared flights offered by firm 1 (or firm 2) instead of one-stop flights offered by firm 3. Decreased passenger volumes of firm 3 on the segments *HH” (A”H”)* and *H”H’ (H”B”)* will increase the marginal cost on these segments and on the flight itineraries that contain either of these segments. Let $\bar{c}_{HH'}$ ($\bar{c}_{HH'} = \bar{c}_{HH''} + \bar{c}_{H''H'}$) be the incumbent’s marginal cost on the contested route *HH’* after code-sharing where $\bar{c}_{HH''} > c_{HH''}$ and $\bar{c}_{H''H'} > c_{H''H'}$ with $c_{HH''}$ and $c_{H''H'}$ as the incumbent’s marginal cost on the segment *HH”* and *H”H’* before code-sharing. So $\bar{c}_{HH'} > c_{HH'}$, where $c_{HH'} = c_{HH''} + c_{H''H'}$. In addition, the incumbent’s marginal cost on flight itineraries in its hub-and-spoke system that contain the contested segment also increases. For example, the marginal cost on route *H-H”-D”* after code-sharing, denoted by $\bar{c}_{HD''}(\bar{c}_{HD''} = \bar{c}_{HH''} + c_{H''D''})$, satisfies $\bar{c}_{HD''} > c_{HD''}$ $(c_{HD''} = c_{HH''} + c_{H''D''})$, where $c_{HD''}$ is the incumbent’s marginal cost on route *H-H”-D”* before code-sharing. Hence, code-sharing between firm 1 and firm 2 actually affects the marginal costs of all three firms in their respective hub-and-spoke systems.

We specify the demand and profit functions for firm 1 in its hub-and-spoke system after code-sharing with firm 2 as follows:

a. The demand and profit functions between the spoke city *i* and the hub city *H*---the segment *Hi* where *Hi* is not a code-shared segment are given by

$$q_{Hi} = a_{Hi} - b_{Hi} P_{Hi}, \qquad i = 1, \ldots L \tag{3.4}$$

and

$$\pi_{Hi} = (P_{Hi} - c_{Hi}) q_{Hi}\ , \qquad i = 1, \ldots L \tag{3.5}$$

where c_{Hi} is the marginal cost of firm 1 on the non code-shared segment *Hi*;

b. The demand and profit functions on the segment *Hm* where *Hm* is a code-shared segment are given by

$$q_{Hm} = a_{Hm} - b_{Hm} P_{Hm}, \qquad m = 1, \ldots G,\ G = N - L \tag{3.6}$$

and

$$\pi_{Hm} = (P_{Hm} - \underline{c}_{Hm}) q_{Hm}\ , \quad \underline{c}_{Hm} < c_{Hm}, \quad m = 1, \ldots G,\ G = N - L \tag{3.7}$$

where $\underline{c}_{Hm}$ is the after-code-sharing marginal cost of firm 1 on the segment *Hm* and c_{Hm} is the before-code-sharing marginal cost of firm 1 on the segment *Hm*;

c. The demand and profit functions between two spoke cities *i* and *j* through the hub *H* where *i-H-j* or *j-H-i* does not contain code-shared segments are given by

$$q_{ij} = a_{ij} - b_{ij}P_{ij}, \qquad i = 1,\ldots L;\ j = 1,\ldots L;\ j \neq i \tag{3.8}$$

and

$$\pi_{ij} = (P_{ij} - c_{iH} - c_{Hj})q_{ij}\ , \quad i = 1,\ldots L;\ j = 1,\ldots L;\ j \neq i \tag{3.9}$$

where c_{iH} and c_{Hj} are the marginal costs of firm 1 on the segment *iH* and *Hj* respectively;

d. The demand and profit functions between two spoke cities *i* and *m* through the hub where *i-H-m* or *m-H-i* contains one code-shared segment are given by

$$q_{im} = a_{im} - b_{im}P_{im}, \qquad i = 1,\ldots L;\ m = 1,\ldots G;\ G = N - L \tag{3.10}$$

and

$$\pi_{im} = (P_{im} - c_{iH} - \underline{c}_{Hm})q_{im}\ ,\ \underline{c}_{Hm} < c_{Hm}, \quad i = 1,\ldots L;\ m = 1,\ldots G;\ G = N - L \tag{3.11}$$

where c_{iH} is the marginal cost of firm 1 on the segment *Hi* which is not a code-shared segment while c_{Hm} and $\underline{c}_{Hm}$ are the before and after code-sharing marginal costs of firm 1 on the segment *Hi*;

e. The demand and profit functions between two spoke cities *n* and *m* through the hub where both segments on *n-H-m* or *m-H-n* are code-shared segments are given by

$$q_{nm} = a_{nm} - b_{nm}P_{nm}, \qquad m = 1,\ldots G;\ n = 1,\ldots G;\ m \neq n; G = N - L \tag{3.12}$$

and

$$\begin{aligned}\pi_{nm} = (P_{nm} - \underline{c}_{nH} - \underline{c}_{Hm})q_{nm}\ ,\ \underline{c}_{nH} < c_{nH},\ \underline{c}_{Hm} < c_{Hm}, \\ m = 1,\ldots G;\ n = 1,\ldots G;\ m \neq n; G = N - L\end{aligned} \tag{3.13}$$

where c_{nH} and c_{Hm} are the before-code-sharing marginal costs of firm 1 on the segment *nH* and *Hm* while $\underline{c}_{nH}$ and $\underline{c}_{Hm}$ are the after code-sharing marginal costs of firm 1 on these two segments;

f. The demand function on the code-shared routes with firm 2 with one segment in firm 1's hub-and-spoke system and the other one in firm 2's --- that is, the travel demand from city *H* as the origin to city *H'* as the destination, is given by (take the code-shared route *HH'* in Figure 3.2 as example)

$$q_{HH'} = a_{HH'} - b_{HH'} P_{HH'}, \tag{3.14}$$

We base our specification of the demand function in this category on the origin and destination cities of a flight itinerary while ignoring which city is chosen as the connecting city by the code-shared alliance firms. Note that alliance firms may choose several cities as the connecting cities to set up their code-shared route agreements. It is the code-shared routes like *HH'* including both *H-C-H'* and *H-D-H'* that are facing the strategic responses from the market incumbent, firm 3, because firm 3 enjoys the monopoly profits before firm 1 and firm 2's code-sharing. We denote the profits gained by alliance firms from code-sharing on the route *HH'* as $\pi_{HH'}$ and they share the profits according to some proportion determined before the alliance. We assume that firm 1 gains part of the profits denoted as $\theta\pi_{HH'}$ and firm 2 gains $(1-\theta)\pi_{HH'}$ where $0 < \theta < 1$.

Therefore, firm 1’s profits from its hub-and-spoke system illustrated in Figure 3.2 if code-shared with firm 2 is given by:

$$
\begin{aligned}
\pi_1^{CS} = {} & \underbrace{\frac{(a_{HA} - b_{HA}c_{HA})^2}{4b_{HA}} + \frac{(a_{HB} - b_{HB}c_{HB})^2}{4b_{HB}}}_{\substack{\text{Profits on routes into or out of hub} \\ \text{that are not code-shared segments}}} + \underbrace{\frac{(a_{HC} - b_{HC}\underline{c}_{HC})^2}{4b_{HC}} + \frac{(a_{HD} - b_{HD}\underline{c}_{HD})^2}{4b_{HD}}}_{\substack{\text{Profits on routes into or out of hub} \\ \text{that are code-shared segments}}} \\
& + \underbrace{\frac{(a_{AB} - b_{AB}(c_{AH} + c_{HB}))^2}{4b_{AB}}}_{\substack{\text{Profits on spoke routes through the hub} \\ \text{that do not contain code-shared segements}}} + \underbrace{\frac{(a_{CD} - b_{CD}(\underline{c}_{CH} + \underline{c}_{HD}))^2}{4b_{CD}}}_{\substack{\text{Profits on spoke routes of which} \\ \text{both segments are code-shared}}} + \underbrace{\frac{(a_{BD} - b_{BD}(c_{BH} + \underline{c}_{HD}))^2}{4b_{BD}}}_{\substack{\text{Profits on spoke routes of which} \\ \text{one of the segments are code-shared}}} \\
& + \underbrace{\frac{(a_{AC} - b_{AC}(c_{AH} + \underline{c}_{HC}))^2}{4b_{AC}} + \frac{(a_{AD} - b_{AD}(c_{AH} + \underline{c}_{HD}))^2}{4b_{AD}} + \frac{(a_{BC} - b_{BC}(c_{BH} + \underline{c}_{HC}))^2}{4b_{BC}}}_{\substack{\text{Profits on spoke routes of which} \\ \text{one of the segments are code-shared}}} \\
& + \underbrace{\theta\pi_{HH'}}_{\substack{\text{Profits gained from code} \\ \text{-sharing on the code-shared route HH'}}} \qquad (3.15)
\end{aligned}
$$

III.3. Profits on the Code-Shared Route HH’

We assume that after initial code-sharing route arrangement, whether or not staying in or exiting code-sharing on an individual code-shared route *HH’* depends on two factors: demand shocks and strategic interaction from the market incumbent on route *HH’*.[24] Based on the findings by Gayle (2006) and Du, McMullen and Kerkvliet (2008), we assume that the oligopolistic competition on the contested routes is Bertrand competition with differentiated products and that the cost structures of both the market incumbent and potential entrants (code-shared firms) are well-known to each other. Thus, firms choose prices simultaneously on the

---

[24] It has been long established that the travel demand in the airline industry is quite seasonal with high demand during booms and low demand during recessions. Therefore, besides the strategic interaction from the market incumbent, we assume the demand shock also plays a role when the alliance firms decide whether to stay code-shared or exit code-sharing on an individual route at a specific time period.

contested route *HH’* every time period. We also assume that there is a probability γ, that the economy is experiencing a boom period and travel demand on route *HH’* and the firm’s whole hub-and-spoke system is high and a probability of $(1-\gamma)$ that the economy is in a recession and travel demand is low. Therefore, the entrant (assume code-shared firms are acting as one firm) competes with the market incumbent on the contested route *HH’* via the demand functions in the case of high demand during booms given by

$$q_E^H = a^H - b^H P_E^H + d^H P_I^H \tag{3.16}$$

$$q_I^H = a^H - b^H P_I^H + d^H P_E^H \tag{3.17}$$

where q_E^H and q_I^H are the number of passengers carried by the entrant and incumbent respectively during booms; P_E^H and P_I^H are the air fares charged by the entrant and incumbent respectively during booms.[25]

Let c_E^H and c_I^H be the marginal costs of the entrant and incumbent respectively on route *HH’* during booms where $c_E^H = \frac{\underline{c}_{H-C-H'}^H + \underline{c}_{H-D-H'}^H}{2}$ and $c_I^H = \bar{c}_{HH''} + \bar{c}_{H''H'}$. In accordance to the notation of marginal costs defined on spoke cities earlier in the paper, $\underline{c}_{H-C-H'}^H = \underline{c}_{HC}^H + \underline{c}_{CH'}^H$ and $\underline{c}_{H-D-H'}^H = \underline{c}_{HD}^H + \underline{c}_{DH'}^H$. Let c_E^L and c_I^L be the marginal costs of the entrant and incumbent respectively on route *HH’* during recessions. Then due to the economies

---

[25] Through the paper, the superscripts H and L means high and low demand. The subscript H means the hub city and the subscripts E and I mean the entrant and incumbent respectively.

of traffic density, low demand during recessions will lead to higher marginal cost: $c_E^H < c_E^L$ and $c_I^H < c_I^L$. By the same token, the marginal cost of firm 1 during booms on the routes that contain code-shared segments after alliances will be lower than the marginal cost during recessions. For example, the after-code-sharing marginal cost of firm 1 on the code-shared segment *HC* during booms, denoted as $\underline{c}_{HC}^{H}$, satisfies $\underline{c}_{HC}^{H} < \underline{c}_{HC}^{L}$, where $\underline{c}_{HC}^{L}$ is the after-code-sharing marginal cost during recessions. Then the profit functions of the entrant and incumbent are given by

$$\pi_E^H = (P_E^H - c_E^H)q_E^H \tag{3.18}$$

$$\pi_I^H = (P_I^H - c_I^H)q_I^H \tag{3.19}$$

A simultaneous solution to equation (3.16) and (3.17) gives us the equilibrium prices of the entrant and incumbent respectively as follows:

$$P_E^H = \frac{a^H d^H + 2a^H b^H + 2(b^H)^2 c_E^H + b^H d^H c_I^H}{(d^H)^2 - 4(b^H)^2} \tag{3.20}$$

$$P_I^H = \frac{a^H d^H + 2a^H b^H + b^H(4b^H - d^H)c_E^H + 2b^H(d^H - b^H)c_I^H}{(d^H)^2 - 4(b^H)^2} \tag{3.21}$$

Substitute P_E^H in equation (3.20) into (3.18), we will get π_E^H ($\pi_{HH'}^H$).

The entrant's (firm 1) profits from its flight system during booms are given by

$$
\begin{aligned}
(\pi_E^{CS})^H = {} & \underbrace{\frac{(a_{HA}^H - b_{HA}^H c_{HA}^H)^2}{4b_{HA}^H} + \frac{(a_{HB}^H - b_{HB}^H c_{HB}^H)^2}{4b_{HB}^H}}_{\substack{\text{Profits on routes into or out of hub} \\ \text{that are not code-shared segments}}} + \underbrace{\frac{(a_{HC}^H - b_{HC}^H \underline{c}_{HC}^H)^2}{4b_{HC}^H} + \frac{(a_{HD}^H - b_{HD}^H \underline{c}_{HD}^H)^2}{4b_{HD}^H}}_{\substack{\text{Profits on routes into or out of hub} \\ \text{that are code-shared segments}}} \\
& + \underbrace{\frac{(a_{AB}^H - b_{AB}^H (c_{AH}^H + c_{BH}^H))^2}{4b_{AB}^H}}_{\substack{\text{Profits on spoke routes through the hub} \\ \text{that do not contain code-shared segements}}} + \underbrace{\frac{(a_{CD}^H - b_{CD}^H (\underline{c}_{CH}^H + \underline{c}_{HD}^H))^2}{4b_{CD}^H}}_{\substack{\text{Profits on spoke routes of which} \\ \text{both segments are code-shared}}} + \underbrace{\frac{(a_{BD}^H - b_{BD}^H (c_{BH} + \underline{c}_{HD}^H))^2}{4b_{BD}^H}}_{\substack{\text{Profits on spoke routes of which} \\ \text{one of the segments are code-shared}}} \\
& + \underbrace{\frac{(a_{AC}^H - b_{AC}^H (c_{AH} + \underline{c}_{HC}^H))^2}{4b_{AC}^H} + \frac{(a_{AD}^H - b_{AD}^H (c_{AH} + \underline{c}_{HD}^H))^2}{4b_{AD}^H} + \frac{(a_{BC}^H - b_{BC}^H (c_{BH} + \underline{c}_{HC}^H))^2}{4b_{BC}^H}}_{\substack{\text{Profits on spoke routes of which} \\ \text{one of the segments are code-shared}}} \\
& + \underbrace{\theta \pi_{HH'}^H}_{\substack{\text{Profits gained from code} \\ \text{-sharing on the code-shared route HH'}}} \qquad (3.22)
\end{aligned}
$$

Accordingly, we can write out firm 1's profits from its whole flight system after code-sharing during recessions as $(\pi_E^{CS})^L$. So the expected profits of firm 1 before and after code-sharing are given by $E\pi_E^{NCS} = \gamma(\pi_E^{NCS})^H + (1-\gamma)(\pi_E^{NCS})^L$ and $E\pi_E^{CS} = \gamma(\pi_E^{CS})^H + (1-\gamma)(\pi_E^{CS})^L$ respectively. If we assume that the entrant and incumbent are playing supergames on a finite time horizon from t=1,…T, then the equilibrium price and profits obtained in every time period are the equilibrium price and profits for the whole time horizon. Therefore, firm 1 (firm 2) will enter code-sharing alliances if

$$\frac{1-\delta^{T+1}}{1-\delta} E\pi_E^{CS} - F > \frac{1-\delta^{T+1}}{1-\delta} E\pi_E^{NCS} \qquad (3.23)$$

where δ is the one period inter-temporal discount factor common to both players and F stands for the sunk cost in the event of code-sharing, which reflects any non-recoverable start-up investment cost associated with entering code-sharing alliances such as the purchase of airport gates, advertisement, leasing payment or equity ownership investment. Define

$$X = \frac{1-\delta^{T+1}}{1-\delta} E\pi_E^{CS} - F - \frac{1-\delta^{T+1}}{1-\delta} E\pi_E^{NCS} \tag{3.24}$$

Hence, if $X > 0$, then firm 1 (firm 2) enters code-sharing; otherwise, they operate their own hub-and-spoke system without alliances.

After initial start-up investment costs in entering code-sharing, the entrant (firm 1) will choose to stay code-shared on the contested route *HH'* if

$$\frac{1-\delta^{T+1}}{1-\delta}(E\pi_E^{CS})_{w/t\ HH'\ code-shared} > \frac{1-\delta^{T+1}}{1-\delta}(E\pi_E^{CS})_{w/o\ HH'\ code-shared} - \delta^{t-1}C_{exit-HH'} \tag{3.25}$$

where $(E\pi_E^{CS})_{w/o\ HH'\ code-shared}$ is the expected profits from firm 1's hub-and-spoke system with once-code-shared route *HH'* dropped while other code-shared routes still exist in the system and $C_{exit-HH'}$ is the exit cost of dropping route *HH'* from code-sharing. Define

$$Y = \frac{1-\delta^{T+1}}{1-\delta}(E\pi_E^{CS})_{w/t\ HH'\ code-shared} - (\frac{1-\delta^{T+1}}{1-\delta}(E\pi_E^{CS})_{w/o\ HH'\ code-shared} - \delta^{t-1}C_{exit-HH'})$$

------ (3.26)

Hence, if $Y > 0$, then firm 1 (firm 2) will choose to stay code-shared on route *HH'*; otherwise, they will drop *HH'* from code-sharing while keeping other code-shared routes in their hub-and-spoke systems.

The following represents all possible equilibrium outcomes:

E1: No code-sharing if $X \le 0$;

E2: Enter code-sharing and stay if $X > 0$ and $Y \geq 0$;

E3: Enter code-sharing and exit if $X > 0$ and $Y < 0$.

Obviously, the equilibrium of this game can be easily extended to include other code-shared route arrangements mentioned in Figure A1 in Appendices.

IV. Variable Definitions and Empirical Hypotheses

Due to data limitations, our data sample does not include the routes on which Continental (CO) and America West (HP) Airlines never code-shared. During the 1998-2002 sample period, they code-shared on each route for at least one quarter. On some flight routes, they chose to code-share from the very beginning and stay code-shared for the entire alliance period while on other routes they chose to code-share at certain time but dropped code- sharing later, sometimes adding and dropping a route several times. Some routes were only code-shared for one quarter and then dropped forever.

To account for all of these circumstances, we assume firms make their code- sharing decisions at the beginning of each quarter for each route. Thus, our dependant variable is a qualitative response variable. At any specific time, if alliance firms were code-sharing, then the code-share decision is valued 1; and if alliance firms were not, then the code-share decision is valued 0. Alliance firm’s different responses on route *i* at time *t* are determined by characteristics of both incumbents and code–sharer’s flight operations, those of the markets (both routes and airports) and other related factors such as government regulation. We assume the density of the dependent variable $DECISION_{it}$ follows an exponential distribution with the probability of success denoted as π_{it}. The classical logistic regression model is then specified as

$$\log(\frac{\pi_{it}}{1-\pi_{it}}) = f(\beta_0, X) + \varepsilon_{it} \tag{3.27}$$

where X is a matrix of the explanatory variables defined as follows:

Route Characteristics

Because code-shared flights are fundamentally one stop flight service, market situations in the one stop market on the route level is more comparable for the analysis than those in the direct or multi-stop or whole flight markets. Accordingly, we focus on explanatory variables that represent route characteristics in one stop markets.[26]

1. **Average Yield from Previous Period ---** $ONESTOP\_YIELD_{i,t-1}$ is defined as the average price per passenger mile in the one stop market on route *i* in the previous quarter *t-1*. Average price is calculated as the weighted average of per passenger air fare of different air carriers. Staying or dropping decisions will depend on the average yield of last period. The higher the average yield from last period; the higher the probability of code-sharing because of the resulting higher profits from code-sharing (Strassmann, 1990; Dresner, Lin and Windle, 1996; Dresner, Windle and Yao, 2002);

---

[26] We also used the number of flights, yield and route HHIs calculated from the direct service, multi-stop or the whole market (including direct, one-stop and multi-stop services) on a route as the covariates, but the parameter estimates were strongly insignificant.

2. **The Number of One Stop Flights from Previous Period ---** $ONESTOPFLTS_{i,t-1}$ is defined as the number of all incumbents' one stop flights on route *i* at time *t-1***.** The larger the number of one stop flights, the more frequent the service and the higher the service quality, which makes the alliance firms' code-shared flights more comparable to the market incumbents' one stop flight services, thus leading to the higher probability of code-sharing (Whinston and Collins, 1992);

3. **Route Competition Level from Previous Period ---** $ONESTOPRHHI_{i,t-1}$ is defined as Herfindahl Hirschman Index (HHI) in the one stop market on route *i* at time *t-1*. HHI is calculated by using the number of passengers carried by individual air carriers on a specific route. According to Sutton (1991), "Higher concentration implies higher margins and higher profitability", so a market with less intense competition pre-entry may be more profitable and thus be more attractive to entry (Morrison and Winston, 1995; Dresner, Lin and Windle, 1996; Boguslaski, Ito and Lee, 2004; Oh, 2006). However, both Hurdle *et al.* (1989) and Strassmann (1990) find that entry is significantly deterred in the highly concentrated airline markets because of large scale flight operations at hub airports. So the overall effect of route competition level on the probability of code-sharing is uncertain.[27]

---

[27] All these three covariates $ONESTOP\_YIELD_{i,t-1}$, $ONESTOPFLTS_{i,t-1}$ and $ONESTOPRHHI_{i,t-1}$ are taken the average of their values in the past four quarters from *t-1* to *t-4* to smooth out the seasonal effect on these variables.

City and Geographical Characteristics

1. **Population** --- $ORINPOP_{it}$ and $DESTPOP_{it}$ are the populations at the endpoints of the Metropolitan Statistical Areas (MSAs) on route *i* at time *t*, which is a proxy for the potential market size. The larger the population, the higher the travel demand and the higher the probability of code sharing (Sinclair, 1995; Dresner, Lin and Windle, 1996; Boguslaski, Ito and Lee, 2004);
2. **Per Capita Income** --- $ORIINCOME_{it}$ and $DESTINCOME_{it}$ are per capita income at both endpoints of MSAs on route *i* at time *t*. According to Morrison (2006), "It's generally agreed that demand for air travel is very responsive to changes in income. In particular, the income elasticity of demand is probably around 1.5." So we expect the higher per capita income, the higher the air travel demand and the higher the probability of code sharing (Dresner, Lin and Windle, 1996; Boguslaski, Ito and Lee, 2004);
3. **Vacation Dummies ---**$VACATION_i$ is equal to 1 if one of the endpoint airports is in Florida, Hawaii, Nevada and Puerto Rico otherwise it is equal to 0. We expect the coefficient sign to be positively related to the probability of code- sharing since vacation routes will generate more passengers than non-vacation routes, all other factors being equal. (Dresner, Lin and Windle, 1996; Morrison, 2001; Boguslaski, Ito and Lee, 2004)

Airport Characteristics

1. **Hub Dummies for Code-shared Firms**. If either one of the endpoint airports ($E\_ORI\_HUB_i$ and $E\_DEST\_HUB_i$ **)** or the connecting airports ($E\_CONN\_HUB_i$ **)** are hubs for code-shared firms, then the value takes 1. This variable represents the advantages of alliance firms' hub-and-spoke network systems. We expect that the alliance firms' hubs at either endpoint or connecting airport will increase the probability of code-sharing on the routes. Table 3.3 provides a list of hubs for all major carriers in the US (Borenstein, 1989; Brueckner and Spiller, 1994);
2. **Slot Control Dummy ---** $SLOT_i$. Four airports in the U.S. have limits on the number of takeoffs and landings that may take place during any given hour. They are Chicago O'Hare, New York J.F. Kennedy and La Guardia and Washington Reagan National Airport. If any of the endpoint or connecting airports is a slot-controlled airport, then $SLOT_i$ equals 1 otherwise 0. We expect a negative relationship between the probability of code-sharing and the slot control dummy (Morrison and Winston, 1987; Strassmann, 1990; Sinclair, 1995; Dresner, Lin and Windle, 1996; Morrison, 2001; Dresner, Windle and Yao, 2002);
3. **Gate Constraints Dummy ---** $GATE_i$. There are six airports in which long-term, exclusive use gates are thought to be barriers to entry (GAO report, 1993). They are Charlotte, Cincinnati, Detroit International, Minneapolis, Newark and Pittsburgh. If the endpoint or connecting airport

Table 3.3 U.S. Major Air Carriers and Their Hubs and Focus Cities

Major Carriers	Hubs	Second Hubs	Focus Cities
American Airlines	DFW, ORD, MIA, STL, SJU	JFK, LGA	BOS, LAX, RDU
Alaska Airlines	SEA, ANC, PDX, LAX		SFO
Continental Airlines	IAH, EWR, CLE		
Delta Air Lines	ATL, SLC, CVG, JFK	LAX	MCO, LGA, BOS
Northwest Airlines	DTW, MSP, MEM		IND, HNL
United Airlines	ORD, DEN, IAD, SFO, LAX		
US Airways	CLT, PHL, PHX, LAS		DCA, LGA, PIT
Southwest Airlines			LAS, MDW, PHX, BWI, OAK, HOU, DAL,LAX, MCO, SAN
America West	PHX, LAS, PHL, CLT	PIT	DCA, LGA, BOS
ATA Airlines	MDW		HNL,OAK
JetBlue Airways			JFK, BOS, FLL, OAK, IAD
Horizon Air	SEA, PDX, LAX		DEN
Frontier Airlines	DEN		

is a gate-constrained airport, then $GATE_i$ equals 1 otherwise 0. We assume code-sharing will be deterred in the airports with gate constraints due to airport congestion (Dresner, Windle and Yao, 2002).

Time Characteristics

1. **Quarterly Dummies ---** $WINTER_t$, $SPRING_t$ and $SUMMER_t$ are used to control for seasonal fixed effects (Dresner, Li and Windle, 1996; Morrison, 2001);

2. **Time since the Initial Alliance ---** $TIME_t$ is used to measure how long (in years) the initial code-sharing alliance has been in place. For instance, if the

code-share alliance began in 1994, then $TIME_t$ =5 in year 1998, 6 in year 1999, 7 in year 2000, 8 in year 2001 and 9 in year 2002. On one hand, we expect a negative relationship between alliance duration and the probability of code-sharing because the longer the time, the more information firms will have about the profitability of alliances. As time passes, market situations may change dramatically, firms' financial situations and operating strategies may change, government policy may change, etc. On the other hand, the longer firms stay in an alliance, the better the reputation of the alliance and the lower the continuation cost so there could be a positive relationship between the time and the probability of code-sharing. Thus, the expected sign of the time coefficient is uncertain.

Lagged Dependent Variables

1. **Code-Sharing Decisions from Last Period** --- $DECISION_{i,t-1}$ Firms' decisions to stay or drop code-sharing at time *t* may depend on their decisions from last period. We expect that the decision of whether or not to code-share on route *i* at time *t-1* may positively affect the decision on route *i* at the current time *t*;

IV. Data Source

The whole data sample has 39260 quarterly observations on a total of 1963 routes code-shared by Continental and America West Airlines at some time during 1998Q1 to 2002Q4 period. Every observation is route and time specific. Table 3.4 shows the descriptive statistics.

Table 3.4 Descriptive Statistics

Variables (Descriptions and Units)	**Mean**	**Std**
$DECISION_{it}$ (Equals 1 if the alliance firms code-shared on route *i*, otherwise 0)	0.186246	0.38931
$ONESTOPYIELD_{it-1}$ (Average air fare from *t-1* in dollars per passenger mile in the one-stop market of route *i*)	0.06473	0.026428
$ONESTOPFLTS_{it-1}$ (All incumbents' one-stop flights from *t-1* on route *i*)	401.1002	331.6551
$ONESTOPRHHI_{it-1}$ (HHI from *t-1* in the one-stop market of route *i*)	2827.13	1611.28
$INCOME\_ORIGIN_{it}$ (Per capita income in dollars at the MSA of the origin airport on route *i*)	18050.73	3211.91
$INCOME\_DEST_{it}$ (Per capita income in dollars at the MSA of the destination airport on route *i*)	17979.46	3277.1
POP_ORIGIN_{it} (Population at the MSA of the origin airport on route *i*)	3907724	4456131
POP_DEST_{it} (Population at the MSA of the destination airport on route *i*)	3933258	4561028
$SLOT_i$ (Equals 1 if either the endpoint or the connecting airport is a slot-controlled airport on route *i*)	0.052471	0.222977
$GATE_i$ (Equals 1 if either the endpoint or the connecting airport is a gate-constrained airport on route *i*)	0.271014	0.444489
$VACATION_i$ (Equals 1 if either the endpoint or connecting airport on route *i* is in FL, HI or NV, otherwise 0)	0.403464	0.490599
$E\_ORI\_HUB_i$ (Equals 1 if the origin airport on route *i* is the alliance firms' dominated hub or focus city)	0.333673	0.471531
$E\_CONN\_HUB_i$ (Equals 1 if the connecting airport on route *i* is the alliance firms' dominated hub or focus city)	0.877229	0.328179
$E\_DEST\_HUB_i$ (Equals 1 if the destination airport on route *i* is the alliance firms' dominated hub or focus city)	0.317371	0.465459
$WINTER_t$ (Equals 1 if the quarter is in Jan-Mar, otherwise 0)	0.25	0.433018
$SPRING_t$ (Equals 1 if the quarter is in Apr-Jun, otherwise 0)	0.25	0.433018
$SUMMER_t$ (Equals 1 if the quarter is in Jul-Sep, otherwise 0)	0.25	0.433018
$TIME_t$ (Equals 5 if in year 1998, 6 in 1999, 7 in 2000, 8 in 2001, 9 in 2002)	7	1.414232

All the dollar values are deflated by Consumer Price Index (1982-84=100).

The data for the number of passengers and per passenger air fares for individual carriers on route *i* at time *t* are from *Bureau of Transportation Statistics*

(BTS) US Department of Transportation (DOT) Origin and Destination Survey DB1B Market, a 10% ticket random sample data set. $ONESTOPYIELD_{it}$ is calculated as the average price per passenger mile on route *i* in its one stop market at time *t* where average price is calculated as the weighted average of the per passenger air fare for all air carriers operating on that route. The data for the code-sharing decision $DECISION_{it}$ are identified from the same data set by tracking each route once code-shared by Continental and America West Airlines quarter by quarter. The data for the number of one stop flights $ONESTOPFLTS_{it}$ and the calculation of route concentration $ONESTOPRHHI_{it}$ are from DB1B Market. Hub dummies are identified from each air carrier's website.[28] The data for population POP_ORIGIN_{it} and POP_DEST_{it} and per capita income $INCOME\_ORIGIN_{it}$ and $INCOME\_DEST_{it}$ at origin and destination airport MSAs are from *Bureau of Economic Analysis US Department of Commerce*. The slot control and gate constraints dummies are obtained from reports by *US General Accounting Office* (1993).

V. Econometric Models and Empirical Results

Following Molenberghs and Verbeke (2005) for the study of discrete longitudinal data, we apply three different models including Marginal Models, Subject-specific Models and Transition Models for the analysis of the discrete

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[28] We also use the number of flights, yield and route HHI calculated from the direct service market or the whole market, which includes direct, one-stop and multi-stop services on a route as the covariates, but the parameter estimates are strongly insignificant.

longitudinal data set, in which the dependent variable is non-Gaussian repeated binary measures.[29] Each model has its own model assumptions and estimation methods, therefore resulting in different numerical values and interpretations of coefficient estimates.

V.1. Subject-specific Models

In subject-specific models, when responses are binary, the effect of covariates on the response probabilities is conditional upon the level of the subject-specific effect. A unit change in the covariate translates into an appropriate change in probability, keeping the level of the subject-specific effect fixed (Neuhaus, Kalbfleisch and Hauck, 1991). Even though subject-specific parameters can be dealt with either as fixed effects or as random effects, the fixed effects approach is in many cases flawed.[30] So we use the Generalized Linear Mixed Models (GLIMM) proposed by Breslow and Clayton (1993) in this paper, which is the most frequently used random effects model in the context of discrete repeated measurements.

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[29] In longitudinal settings, each individual has a vector of responses with a natural (time) ordering among the components. Non-Gaussian longitudinal cases include repeated binary or ordinal data, or longitudinally measured counts.

[30] Neyman and Scott (1948) show that in a fixed-effect model, if the number of subjects is getting larger while the number of time points remains constant, the number of parameters is increasing at the same rate as the sample size, which leads to inconsistency of the so-obtained maximum likelihood estimates. This is a well-known result in the context of logistic regression for binary data. Breslow and Day (1989) have an extensive discussion in this context.

Let Y_{it} be the *t*th outcome measured for subject *i*, *i*=1, …, *N*, *t*=1, …, t_i and Y_i is the t_i-dimensional vector of all measurements available for subject *i*. The GLIMM model is then formalized as follows:

$$Y_{it}|b_i \sim Bernoulli(\pi_{it})$$

The conditional means $E(Y_{it} \mid b_i)$ are given by

$$E(Y_{it} \mid b_i) = \frac{\exp(\beta_0 + b_i + \beta X)}{1 + \exp(\beta_0 + b_i + \beta X)} \tag{3.28}$$

Rewrite (3.28) as

$$\log\mathrm{it}(\pi_{it}) = \log(\frac{\pi_{it}}{1 - \pi_{it}}) = \beta_0^{RE} + b_i + \beta^{RE} X \tag{3.29}$$

where $\pi_{it} = P(Y_{it} = 1 \mid b_i, X)$, β_0^{RE} is the constant term, and β^{RE} is a *p*-dimensional vector of unknown fixed regression coefficients, common to all subjects.[31] We assume that *q*-dimensional random effects b_i are drawn independently from the *N (0, G)* and the responses Y_{it} of Y_i are independent with densities of the form

$$f_i(y_{it} \mid b_i, \beta, \phi) = \exp\{\phi^{-1}[y_{it}\theta_{it} - \varphi(\theta_{it})] + c(y_{it}, \phi)\} \tag{3.30}$$

with ϕ a scale parameter, i.e. $\eta(\mu_{it}) = x_{it}^{'}\beta + z_{it}^{'}b_i$ for a known link function $\eta(.)$, and for x_{it} and z_{it} two vectors containing known covariates. The density of the *N (0, G)* distribution for the random effects b_i is denoted as $f(b_i \mid G)$. Estimated through Penalized Quasi-likelihood (PQL) methods, GLIMM results are shown in Table 3.5 and Table 3.6.

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[31] Superscript RE stands for the coefficient estimates in the random effect models.

Table 3.5 GLIMM Regression Results for Random Effect Models[32]

Fixed Effect Parameter	Estimate	Std Error	t Value	Odds Ratio	Odds Ratio 95% C.I.	
INTERCEPT	-3.298	0.2809	-11.74****	0.04	0.02	0.06
ONESTOPFLTS$_{i,t-1}$	0.0004	0.0001	3.85****	1.04[a]	1.02	1.06
ONESTOPDYIELD$_{i,t-1}$	18.4469	1.0091	18.28****	6.33[b]	5.19	7.71
ONESTOPRHHI$_{i,t-1}$	-0.00015	2.03E-05	-7.19****	0.86[c]	0.83	0.90
INCOME_ORIGIN	3.72E-05	1.01E-05	3.69****	1.45[d]	1.19	1.77
INCOME_DEST	4.54E-05	9.93E-06	4.57****	1.57[d]	1.30	1.91
POP_ORIGIN	1.92E-08	7.80E-09	2.47****	1.02[e]	1.00	1.04
POP_DEST	2.14E-08	7.54E-09	2.85****	1.02[e]	1.01	1.04
WINTER	0.2621	0.0427	6.14****	1.30	1.20	1.41
SPRING	0.2246	0.0427	5.26****	1.25	1.15	1.36
SUMMER	-0.0978	0.0440	-2.22***	0.91	0.83	0.99
TIME	-0.4295	0.0121	-35.37****	0.65	0.64	0.67
SLOT	-1.6243	0.1523	-10.67****	0.20	0.15	0.25
GATE	-0.3866	0.0745	-5.19****	0.68	0.59	0.79
VACATION	0.3309	0.0643	5.15****	1.39	1.23	1.58
E_ORI_HUB	0.93845	0.0699	13.42****	2.56	2.23	2.93
E_CONN_HUB	1.2992	0.1043	12.46****	3.67	2.99	4.50
E_DEST_HUB	1.0011	0.0708	14.13****	2.72	2.37	3.13
-2 Residual log Pseudo-Likelihood		204655.7				
Generalized Chisquare/DF		0.89				

a. Odds ratio for a 100-unit increase in the number of flights;
b. Odds ratio for a 0.1- unit increase in the yield;
c. Odds ratio for a 1000- unit increase in the route HHI;
d. Odds ratio for a 10,000-unit increase in the income;
e. Odds ratio for a 1,000,000-unit increase in the number of population.
***p=0.05 level; ****p=0.01 level;

Table 3.6 Covariance Parameter Estimate

Parameter	Subject	Estimate	Standard Error
INTERCEPT	*ROUTE*	1.2576	0.05640

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[32] GLIMMIX regression results in Table 3.5 only list out the parameter estimates for fixed effect coefficients. Parameter estimates for random effects (measured by intercepts only in the paper) are available upon request.

GLIMM regression results show that on a specific route, the number of flights and the average yields on the one stop market in the previous quarter are significant factors affecting the probability of code-sharing. The probability of code-sharing is higher when the yield is higher and the number of flights is increasing on the one stop market from the previous period. For a given route, the odds of code-sharing increases 6.33 times for every increase of 0.1 dollar in the yield (5.19 times to 7.71 times at 95% confidence interval) and 1.04 times (1.02 times to 1.06 times at 95% confidence interval.) for every increase of 100 flights on the one stop market. In contrast to Sutton (1991), Morrison and Winston (1995), Dresner, Lin and Windle (1996), Boguslaski, Ito and Lee (2004) and Oh (2006), who found that higher concentration induces entry, we find that route concentration level has a negative impact on the probability of code-sharing: the higher the concentration in the one stop market, the lower the probability of code-sharing, consistent with Hurdle *et al* (1989) and Strassmann (1990). Large scale operations from the market incumbents on a specific highly concentrated route in their one stop market could deter the probability of code-sharing greatly. The odds of code-sharing increase only 0.86 times (0.83 times to 0.90 times at a 95% confidence interval) for every increase of 1000 in route competition as measured by the HHI.

Regression results also tell that as expected, on a specific route, the probability of code-sharing is lower if the origin and connecting airports on the route are slot-controlled or have gate constraints. This means that airport congestion measured by slot control and gate constraints are significant entry barriers for code-sharing on individual routes, consistent with previous findings by Morrison and Winston (1987), Strassmann (1990), Sinclair (1995) and etc. Specifically, the occurrence of code-sharing is only 0.20 as likely to occur on a route with slot-controlled airports as on a route without slot control, given other factors constant. This difference could be as little as 0.15 or as much as 0.25 with a 95% confidence interval. Compared with routes whose origin and connecting airports have no gate constraints, the odds of code-sharing are only 0.68 times the odds on the route whose airports are with gate constraints. The change in the odds could be as little as 0.59 or as much as 0.79 with a 95% confidence interval.

Whether individual route is a vacation route also turns out to be an important factor affecting the probability of code-sharing. The probability of code-sharing is found here to be higher on a vacation route than on a non-vacation route. For a given route, the odds of code-sharing, ($DECISION_{it} = 1$) if it is a vacation route, are 1.39 times the odds of code-sharing if it is not a vacation one, holding other things constant (1.23 times to 1.58 times at 95% confidence interval). Consistent with previous studies (Dresner, Lin and Windle, 1996; Morrison, 2001; Boguslaski, Ito and Lee, 2004), this result supports the hypothesis that vacation routes generate more passengers than non-vacation routes, therefore increasing the probability of code-sharing. Carriers may choose to code-share on vacation routes because of the route density.

On a specific route, whether or not its endpoint or connecting airports is an alliance firm hub strongly affects the probability of code-sharing. The probability of code- sharing is higher if the airports are alliance firm hubs than if not. In particular, the odds of code-sharing when the origin, connecting and destination airports are alliance firm hubs or focus cities on an individual route are 2.56, 3.67 and 2.72 times the odds of code- sharing when these airports are not their hubs or focus cities respectively. This is consistent with studies by Bailey and William (1989), Borenstein (1989, 1990 and 1991) and Brueckner and Spiller (1994) who argue that airport dominance is an important source of market power and monopoly rent in the airline industry. Alliance firms make use of their hubs to combine their existing operating systems and compete with the market incumbents.

Results also show that on a given route, per capita income and population at the endpoint MSAs are significant factors affecting the code-sharing decision. The higher the per capita income and population on a specific route, the higher probability of code- sharing because of the resulting higher travel demand. On a given route, the odds of code sharing increase 1.45 and 1.57 times respectively as the per capita income at the origin and destination MSAs increases by 10,000 dollars. The odds of code-sharing increase 1.02 and 1.02 times for every increase of 1,000,000 persons in the number of origin and destination MSA population.

As time passes, the probability of code-sharing tends to decrease as expected. The odds of code-sharing increase 0.65 times on a specific route (0.64 times to 0.67 times at 95% confidence interval.) as one more year passes by. Seasonal effects significantly affect the code-share decisions with the lower probability of code-sharing in the summer and higher probability in the winter and spring. On a specific route, the odds of code-sharing in the winter and spring are 1.30 times and 1.25 times the odds of code-sharing in other seasons, respectively. The odds of code-sharing in the summer are only 0.91 times the odds of code-sharing in other seasons for a given route. This may be because code- sharing helps generate traffic in off season whereas demand is seasonally high in summer.

V.2. Marginal Models (or Population-Averaged Models)

In contrast to the subject-specific models, in marginal models, a unit change in the covariates translates into a change in the response probability, marginal over the subject-specific effects. It is assumed that

$$Y_{it} \sim Bernoulli(\pi_{it})$$

The marginal average evolution $E(Y_{it})$ is obtained from averaging (3.28) over the random effects, i. e.[33]

$$E(Y_{it}) = E[E(Y_{it} \mid b_i)] = E[\frac{\exp(\beta_0 + b_i + \beta X)}{1 + \exp(\beta_0 + b_i + \beta X)}] \tag{3.30}$$

Rewrite (3.30) as

$$\log\text{it}(\pi_{it}) = \log(\frac{\pi_{it}}{1 - \pi_{it}}) = \beta_0^M + \beta^M X \tag{3.31}$$

where $\pi_{it} = P(Y_{it} = 1 \mid X)$, β_0^M is the constant term, and β^M is the vector of unknown regression coefficients.[34] Compared with the random effect models,

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[33] “In case the random intercept variability is large, parameters from fitting marginal and random effect models will be very different, while equal parameter values hold if the variance of the random effect equals zero” (Molenberghs and Verbeke, 2005).

where the vector β^{RE} models the evolution of each individual subject respectively, β^{M} tells on average, in marginal models, the success probability evolved in the population.

Generalized Estimating Equations (GEE) initially proposed by Liang and Zeger (1986) are the best and most frequently used marginal or population-averaged model for correlated discrete repeated data. “Correlated” means that the components Y_{it} of Y_i are assumed correlated but individual subjects Y_i and $Y_{j(i \neq j)}$ are independent, i.e., code- share decisions on route *i* and route *j* are independent but code-sharing decisions on route *i* at time *t* and *t-1* (or *t-k*) may be correlated. GEE method combines estimating equations for the regression parameters associated with the expected values of an individual’s vector of binary responses with moment-based estimation for the association between pairs of outcomes in terms of marginal correlations. The score equations for a multivariate marginal normal model $Y_i \sim N(X_i\beta, V_i)$ are given by[35]

$$S(\beta) = \sum_{i=1}^{N} X_i^{'} (A_i^{1/2} R_i A_i^{1/2})^{-1} (Y_i - X_i\beta) = 0 \qquad (3.32)$$

The covariance matrix of Y_i is modeled as

$$V_i(Y_i) = \phi A_i^{1/2} R_i(\alpha) A_i^{1/2} \qquad (3.33)$$

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[34] Superscript M stands for the coefficient estimates in the marginal models.

[35] X_i includes a constant term.

where A_i is an $n_i \times n_i$ diagonal matrix with $v(\mu_{it})$ as the *t*th diagonal element and R_i is an $n_i \times n_i$ marginal correlation matrix of Y_i that is unknown and needs to be estimated. When there is truly no correlation between the repeated measurements for the subject *i*, then GEE is reduced to the Generalized Linear Models (GLM) (McCullagh and Nelder, 1989).[36]

As for the assumption of the correlation structure, the nature of the equally spaced time periods in our data set for individual subjects means that a time dependence correlation structure such as AR(1) or M-dependent (Stationary) process is among the best alternatives. Pan (2001) derives a new measure called the Quasilikelihood under the Independence Model Information Criterion (QIC) to choose the best correlation structure from alternatives.[37] The smallest QIC statistic provides the most efficient correlation structure.[38] Our calculations shows that the independence structure has the smallest QIC, even smaller than the QIC

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[36] For a detailed description and application of GEE methodology, please refer to Hardin and Hilbe (2003) and Molenberghs and Verbeke (2005).

[37] Please refer to Appendix 2 for the specifications of different working correlation structures including Fixed, Independent, Autoregressive-AR(1), M-dependent, Exchangeable and Unstructured structures and corresponding estimators.

[38] Even though QIC provides a good measurement to choose the most efficient correlation structure, it “should not be blindly followed”. “When there is some motivating scientific evidence of a particular correlation structure, then that specification should be used” (Hardin and Hilbe, 2003). QIC statistics in Table 3.7 show that the difference among Independence, M-dependent(1) and AR(1) is very tiny.

measurements under M-dependent(1) and AR(1) correlation structures.[39] Please see Table 3.7.

Table 3.7 Results for QIC Statistics

CORRELATION	QIC
INDEP	34048.36
M-DEP(1)	34050.30
AR(1)	34053.57
M-DEP(2)	34057.30
M-DEP(3)	34068.80
M-DEP(4)	34083.80
EXCH	34392.31
UNSTR	34565.54

Through Iterative Generalized Least Squares (IGLS), which is an extension of quasi-likelihood methods, GEE estimation results with the independence correlation structure are shown in Table 3.8. We also list GEE estimation results with the M-dependent(1) and AR(1) correlation structures in the Table A2 and Table A3 in Appendices for reference.

Compared to the GLIMM regression results for the random-effect models, the marginal models give a different numerical value for each coefficient estimate and the parameter estimates also have a different interpretation.

Consistent with the results from the random effect model, every parameter estimate in the marginal model has the same coefficient sign. Higher yield from last period tends to increase the probability of code-sharing. On average, the odds of code-sharing increase 2.41 times (1.93 times to 3.01 times at 95% confidence

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[39] We also tried to calculate QIC statistics by assuming that the subject *i* is time dimension instead of route dimension, the results show that independence structure is still the one with the smallest QIC statistics.

Table 3.8 GEE Regression Results for Marginal Models with Independence Correlation Structure

Parameter	Estimate	Empirical Std Error	Z value	Odds Ratio	Odds Ratio 95% C. I.	
INTERCEPT	-2.15	0.295	-7.29****	0.12	0.07	0.21
ONESTOPFLTS $_{i,t-1}$	9.83E-05	0.0001	0.84	1.01[a]	0.99	1.03
ONESTOPYIELD $_{i,t-1}$	8.79	1.1375	7.72****	2.41[b]	1.93	3.01
ONESTOPRHHI $_{i,t-1}$	-0.00015	2.5E-05	-5.81****	0.87[c]	0.82	0.91
INCOME_ORIGIN	1.15E-05	1.03E-05	1.11	1.12[d]	0.92	1.37
INCOME_DEST	2.18E-05	1.05E-05	2.08***	1.24[d]	1.01	1.53
POP_ORIGIN	3.09E-08	8.14E-09	3.79****	1.03[e]	1.02	1.05
POP_DEST	3.21E-08	7.72E-09	4.15****	1.03[e]	1.02	1.05
WINTER	0.195	0.03	6.53****	1.22	1.15	1.29
SPRING	0.17	0.031	5.55****	1.19	1.12	1.26
SUMMER	-0.087	0.031	-2.82****	0.92	0.86	0.97
TIME	-0.339	0.012	-29.5****	0.71	0.70	0.73
SLOT	-1.555	0.137	-11.3****	0.21	0.16	0.28
GATE	-0.364	0.077	-4.71****	0.70	0.60	0.81
VACATION	0.180	0.066	2.73****	1.20	1.05	1.36
E_ORI_HUB	0.963	0.073	13.25****	2.62	2.27	3.022
E_CONN_HUB	1.343	0.126	10.63****	3.83	2.99	4.91
E_DEST_HUB	1.034	0.0749	13.81****	2.81	2.43	3.26
Log Likelihood		-16952.06				
Pearson Chi-Square/DF		1.001124				

a. Odds ratio for a 100-unit increase in the number of flights;
b. Odds ratio for a 0.1- unit increase in the yield;
c. Odds ratio for a 1000- unit increase in the route HHI;
d. Odds ratio for a 10,000-unit increase in the income;
e. Odds ratio for a 1,000,000-unit increase in the number of population;
***p=0.05 level; ****p=0.01 level.

interval) for every increase of 0.1 dollar in yield for the whole study population. In contrast, the odds would increase 6.33 times for the same unit increase on a specific route in the random effect model. Even though the number of one stop flights from last period is a significant factor affecting the probability of code- sharing on a specific route, it does not affect the probability of code-sharing significantly in terms of the whole study population. On average, the level of route competition is still an important variable affecting the firms' code sharing decisions. A high route HHI from the previous period decreases the probability of code-sharing. The odds of code-sharing increase 0.87 times (0.82 to 0.91 times at 95% confidence interval) for the whole route sample when the HHI increases by 1000, a result very similar to the odds change (0.86 times) on a specific route.

Vacation routes tend to increase the probability of code-sharing for the whole sample. The odds of code-sharing on the vacation routes are 1.20 times (1.05 times to 1.36 times at 95% confidence interval) the odds of code sharing on the non-vacation routes, a little smaller than the odds change (1.39 times) on a specific route. For the covariates --- slot-control and gate constraints, the marginal model also shows that they decrease the probability of code-sharing. On average, the odds of code-sharing from slot-controlled and gate-constrained routes are only 0.21 and 0.69 times the odds on routes without airport congestion, similar to the odds changes (0.20 and 0.68 times respectively) on a specific route.

Alliance firm hub dominance plays an important role in their code-sharing decisions. For the whole route sample, the odds of code-sharing when the origin, connecting and destination airports are alliance firms' hubs or focus cities are respectively 2.62, 3.83 and 2.81 times the odds of code-sharing in the case that alliance firms do not enjoy hub advantages in these airports, a result a little bigger than the odds changes (2.56, 3.67 and 2.72 times) on a specific route.

For the whole study sample, population at both endpoint MSAs also has a significant effect on the probability of code-sharing but only per capita income at the destination airport MSAs significantly affects the probability of code sharing. Results from the marginal model show that the effect of the parameter estimates for population on the log-odds are much bigger with 3.09E-08 and 3.21E-08 than those obtained for a specific route with 1.93E-08 and 2.15E-08 in the random effect model while the effect of those of the per capita income is much smaller with 1.15E-05 and 2.18E-05 than those for a specific route with 3.73E-05 and 4.54E-05 even though the difference in the odds changes is tiny between two models due to the very small numerical values of these coefficient estimates. Seasons also have a significant effect on the probability of code- sharing in the marginal model. The numerical values of the odds change for the whole study population is similar to those for a specific route. Time has the same negative effect on the probability of code-sharing for the whole study population as on a specific route and with a similar odds change as well.

V.3. Transition Models

In a transition model, a measurement Y_{it} in a longitudinal sequence is described as a function of previous outcomes (or a subset of previous outcomes), i.e., conditional on the history $h_{it} = (Y_{i1}, ..., Y_{i,t-1})$. We assume

$$Y_{it} \sim Bernoulli(\pi_{it})$$

Decomposing the outcome $Y_{it} = \mu_{it}^T + \varepsilon_{it}^T$ (“*T*” standing for transition), the mean and variance of a transition model can be written in terms of the history h_{it} :

$$\mu_{it}^T = E(Y_{it} \mid h_{it}) \tag{3.34}$$

$$\phi v^T(\mu_{it}^T) = \text{var}(Y_{it} \mid h_{it}) \tag{3.35}$$

The function of the mean is then written as follows:

$$\eta(\mu_{it}^T) = x_{it}^{'}\beta + \kappa(h_{it}, \beta, \alpha_1) \tag{3.36}$$

where κ is a linear function of the history. The estimation for Y_{it}, given the history h_{it}, leads to independent GLM regressions with the density of the form

$$f_i(y_{it} \mid h_{it}, \beta, \phi) = \exp\{\phi^{-1}[y_{it}\theta_{it} - \varphi(\theta_{it})] + c(y_{it}, \phi)\} \tag{3.37}$$

If assuming the stationary first-order autoregressive type (or called first-order Markov chain) (Cox, 1970 and Korn and Whittemore, 1979), a logistic regression model for binary responses fitted in the transition model context is specified as:

$$\log\text{it}(\pi_{it}) = \log\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = \beta_0^T + \beta_x^T X + \alpha_1 y_{i,t-1} = X\beta^T + \alpha_1 y_{i,t-1} \tag{3.38}$$

where $\mu_{it}^T = \pi_{it} = P(Y_{it} = 1 \mid X, Y_{i,t-1} = y_{i,t-1}, \beta, \alpha_1)$ and $\beta = (\beta_0^T, \beta_x^T)$. The transition matrix for the first-order Markov chain is then written as follows:

Table 3.9 Transition Matrix for the First Order Markov Chain

	Y_{it}	
$Y_{i,t-1}$	0	1
0	π_{00}	π_{01}
1	π_{10}	π_{11}

where π_{ab} = Pr ($Y_{it} = b \mid Y_{i,t-1} = a$), *a*, *b* = 0, 1. A very general model uses a separate logistic regression for Pr ($Y_{it} = 1 \mid Y_{i,t-1} = y_{i,t-1}$), $y_{i,t-1}$ = 0, 1, i.e.

$$\log\text{it}\ \Pr(Y_{it} = 1 \mid Y_{i,t-1} = 0) = X\beta^T \tag{3.39}$$

and

$$\operatorname{logit} \Pr(Y_{it} = 1 \mid Y_{i,t-1} = 1) = X\beta^{TT} \tag{3.40}$$

where β^{T} and β^{TT} may differ. In other words, this model assumes that the effects of covariates may differ depending on the previous responses. A more concise form for the same model can be specified as:

$$\operatorname{logit} \Pr(Y_{it} = 1 \mid Y_{i,t-1} = y_{i,t-1}) = X\beta^{T} + y_{i,t-1}X\alpha \tag{3.41}$$

so that $\beta^{TT} = \beta^{T} + \alpha$. When $\alpha = (\alpha_1, 0)$, equation (3.41) is reduced to (3.38), which means the covariates have the same effect on the response probability no matter $y_{i,t-1} = 0$ or $y_{i,t-1} = 1$.

If we ignore dependence on covariates for the moment, the observed first-order transitions are presented in Table 3.10. Note that there are 37297 transitions among 39260 observations, since we do not observe firms' code sharing decisions prior to 1998Q1. For the routes that firms did not code share the prior quarter, the frequency of code sharing was 9.9%; for the routes that firms code-shared the prior quarter, the frequency of code sharing was 54.5%, or 5.51 times as high.

Table 3.10 Number of Transitions from Code sharing Decisions $Y_{i,t-1}$ at time *t-1* to Decisions Y_{it} at time *t*

$Y_{i,t-1}$	Y_{it} 0	Y_{it} 1	**Total**
0	27017 (0.901)	2971 (0.099)	29988 (1.00)
1	3327 (0.455)	3982 (0.545)	7309 (1.00)
			37297

Estimated by pseudo-likelihood (PL) methods, transition model results are presented in Table 3.11 and 3.12. Empirical results show that as expected, the number of flights, yield and the route HHI on one stop markets are still important factors affecting a firm's decision but only the effect of the route HHI on the probability of code-sharing significantly depends on the firms' code-sharing decisions in the prior quarter. A larger number of flights on one-stop markets increase the probability of code-sharing with the odds increasing 1.02 times (1.00 to 1.03 times at a 95% confidence interval) for every increase of 100 more flights. Higher yield increases the probability of code-sharing with the odds increasing 1.71 times (1.47 to 1.98 times at a 95% confidence interval) for every increase of \$0.1 in the yield. A higher level of route competition from the previous quarter decreases the probability of code-sharing at time *t* more than if firms were in code-sharing at *t-1*. Specifically, for every increase of 1000 in the HHI, the odds increase 0.90 times (0.84 to 0.95 times at a 95% confidence interval) if the firms code- shared in the prior quarter but increase 0.94 times (0.91 to 0.97 times at a 95% confidence interval.) if firms did not.

Slot-controlled airports decrease the probability of code-sharing with a stronger effect if firms code-shared during the prior quarter. The odds of code-sharing on slot- controlled routes are 0.54 times (0.44 to 0.65 times at a 95% confidence interval) the odds on the routes without slot-controlled airports if firms did not code-share at *t-1* while this change in odds is 0.14 times (0.11 to 0.20 times at a 95% confidence interval) if firms stay code-shared during the previous

Table 3.11 Parameter Estimates for the First-order Transition Model

Parameter	Estimate	Standard Error	Chi-Square
INTERCEPT	-1.0578	0.1734	37.2****
$ONESTOPFLTS_{i,t-1}$	0.0002	8E-05	4.26***
$ONESTOPYIELD_{i,t-1}$	5.354	0.77	48.4****
$ONESTOPRHHI_{i,t-1}$	-6E-05	2E-05	15.5****
INCOME_ORIGIN	2E-07	7E-06	0.001
INCOME_DEST	9E-06	7E-06	2.04
POP_ORIGIN	7E-09	5E-09	1.8
POP_DEST	8E-09	5E-09	2.37
WINTER	0.2796	0.0579	23.4****
SPRING	0.142	0.0528	7.24****
SUMMER	-0.1602	0.0559	8.2****
TIME	-0.3892	0.0149	685****
SLOT	-0.6154	0.099	38.7****
GATE	-0.0745	0.0483	2.38
VACATION	0.1946	0.0421	21.3****
E_ORI_HUB	0.4795	0.0451	113****
E_CONN_HUB	0.7309	0.0684	114****
E_DEST_HUB	0.5495	0.0457	144****
$ONESTOPFLTS_{i,t-1} * Y_{i,t-1}$	-5E-05	0.0001	0.18
$ONESTOPYIELD_{i,t-1} * Y_{i,t-1}$	-0.5168	1.4204	0.13
$ONESTOPRHHI_{i,t-1} * Y_{i,t-1}$	-6E-05	3E-05	3.75***
$INCOME\_ORIGIN * Y_{i,t-1}$	1E-05	1E-05	1.60
$INCOME\_DEST * Y_{i,t-1}$	1E-05	1E-05	1.07
$POP\_ORIGIN * Y_{i,t-1}$	3E-08	8E-09	12.5****
$POP\_DEST * Y_{i,t-1}$	3E-08	8E-09	13.8****
$WINTER * Y_{i,t-1}$	-0.1798	0.0969	3.44**
$SPRING * Y_{i,t-1}$	-0.1706	0.09	3.59**
$SUMMER * Y_{i,t-1}$	-0.1638	0.0911	3.24**
$TIME * Y_{i,t-1}$	0.1438	0.0251	32.9****
$SLOT * Y_{i,t-1}$	-1.3251	0.183	52.4****
$GATE * Y_{i,t-1}$	-0.4117	0.08	26.5****
$VACATION * Y_{i,t-1}$	-0.1921	0.0689	7.78****
$E\_ORI\_HUB * Y_{i,t-1}$	0.6911	0.0754	84****
$E\_CONN\_HUB * Y_{i,t-1}$	0.5581	0.1114	25.1****
$E\_DEST\_HUB * Y_{i,t-1}$	0.6288	0.0756	69.2****
Log likelihood	-13697.6	*Pearson Chi-square/ df*	0.98

**p=0.10 level; ***p=0.05 level; ****p=0.01 level

(p-value for Chi- square distribution at 1% with degree of freedom equaling one is at 6.63, 5% at 3.84 and 10% at 2.71).

Table 3.12 Comparison of Odds Ratios between Different Responses for $Y_{i,t-1}$ in the First-order Transition Model

	$Y_{i,t-1}$= 0			$Y_{i,t-1}$= 1		
Parameter	**Odds Ratio**	**Odds Ratio 95% C.I.**		**Odds Ratio**	**Odds Ratio 95% C.I.**	
ONESTOPFLTS $_{i,t-1}$[40]	1.02[a]	1.00	1.03	1.02[a]	1.00	1.03
ONESTOPYIELD $_{i,t-1}$	1.71[b]	1.47	1.98	1.71[b]	1.47	1.98
ONESTOPRHHI $_{i,t-1}$	0.94[c]	0.91	0.97	0.90[c]	0.83	0.95
POP_ORIGIN [41]	1	0.997	1.02	1.03[e]	1.01	1.05
POP_DEST	1	0.998	1.02	1.03[e]	1.01	1.05
WINTER	1.32	1.18	1.48	1.105	0.95	1.29
SPRING	1.15	1.04	1.28	0.972	0.84	1.12
SUMMER	0.85	0.76	0.95	0.723	0.63	0.83
TIME	0.68	0.66	0.70	0.782	0.75	0.82
SLOT	0.54	0.44	0.65	0.144	0.11	0.19
GATE	1	0.84	1.02	0.663	0.54	0.7
VACATION	1.21	1.12	1.32	1.002	0.90	1.12
E_ORI_HUB	1.62	1.48	1.76	3.224	2.86	3.64
E_CONN_HUB	2.08	1.82	2.38	3.629	3.03	4.35
E_DEST_HUB	1.73	1.58	1.89	3.249	2.88	3.67

a. Odds ratio for a 100-unit increase in the number of flights;
b. Odds ratio for a 0.1- unit increase in the yield;
c. Odds ratio for a 1000- unit increase in the route HHI;
d. Odds ratio for a 10,000-unit increase in the income;
e. Odds ratio for a 1,000,000-unit increase in the number of population.

period. Gate constraints only decrease the probability of code sharing significantly when firms code-shared in the prior quarter, with the odds on the gate-constrained routes 0.66 times (0.54 to 0. 70 times at a 95% confidence interval) the odds on non-constrained routes. Vacation routes increase the response probability but with a

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[40] Because Table 3.11 shows that the parameter estimates for the interaction items *ONESTOPFLTS**$Y_{i,t-1}$ and *ONESTOPYIELD**$Y_{i,t-1}$ are not statistically significant, the odds ratios for the number of flights and yield are the same for the different responses from the prior quarter $Y_{i,t-1}$.

[41] If the coefficient estimate is not statistically significant from 0, then the odds ratio equals $e^0 = 1$.

smaller effect if firms code-shared in the previous period. The odds of code-sharing on the vacation routes are 1.00 times (0.90 to 1.12 times at 95% C.I.) the odds on the non-vacation routes if firms stay code-shared at time *t-1* and this change increases to 1.22 times if firms did not.

Seasons still play a significant role in affecting the response probability. If firms did not code-share in the prior quarter, the odds of code-sharing in the winter and spring are 1.32 and 1.15 times the odds of code-sharing in other seasons and the odds of code- sharing in the summer are only 0.85 times the odds of code-sharing in other seasons. These changes in odds are 1.11, 0.97, 0.72 times respectively if firms code-shared at *t-1*, which means that the seasonal effects of the winter and spring on the probability of code-sharing becomes smaller and the effect of the summer becomes larger if firms code-shared in the prior quarter. The probability of code-sharing decreases with time. But the odds of code-sharing increases 0.78 times if firms code-shared in the prior quarter and increases 0.68 times if firms do not.

Alliance firms take full advantage of their hubs in the code-shared route arrangement. The effect of airport dominance on the probability of code-sharing is stronger if firms code-shared in the prior quarter than if not. In particular, if firms did not code-share at *t-1*, the odds of code-sharing when the origin, connecting and destination airports are alliance firms’ hubs or focus cities are 1.62, 2.08, 1.73 times the odds of code-sharing when alliance firms do not enjoy hub dominance in these airports. These changes in odds increase to 3.22, 3.63, 3.25 times respectively if firms code-shared in the prior quarter.

Population affects the probability of code-sharing significantly only when firms code-shared in the prior quarter. The odds of code-sharing increase 1.03 and 1.30 times for every increase of 1,000,000 in population at the endpoint MSAs. Per capita incomes do not affect the response probability significantly no matter firms code-shared in the previous period or not.

VI. Conclusions

Our empirical results show that a successful code-sharing depends on many factors. The larger the number of flights and the higher the yield on one-stop markets, the higher the probability of code-sharing. Airport dominance is an important factor that affects alliance firm code-sharing decisions. Alliance firms tend to code-share flight routes whose origin, connecting or destination airports are their hub cities. In addition, we find that both airport congestion measured by slot-control and gate constraints and a high route concentration level on one-stop markets are important barriers that limit firm’s use of code-sharing. Firms prefer to code-share on vacation routes because of the larger number of potential passengers. Population and per capita incomes are also important determinants of successful code-sharing. The probability of code sharing tends to be higher in the markets with more population and higher income. The airline industry is characterized by seasonal demand, which significantly affects code-sharing decisions.

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Chapter 4

Conclusion

This research provides evidence that the overall effect of complementary code-share agreements can be beneficial. Air fare decreased and passenger volumes increased on non-stop markets served by the incumbent carriers on Denver routes following entry onto those routes by ATA and Southwest Airlines through a complementary code-share agreement. Further, both consumer and producer surpluses were found to increase on these routes after initiation of the code-share agreement. These results are similar to those of previous research that document the competitive impact of direct entry onto routes by Southwest Airlines --- it appears that entry via code-hearing may be a less costly way to promote competitive results in markets similar to Denver. Thus, policy makers interested in promoting airline market competition and industry efficiency should be careful not to dismiss code-sharing as a way to promote competition in markets where direct entry may not be a feasible option.

As far as routes that are likely to result in successful code-share arrangements contracting carriers try to take advantage of their hub dominance to build code-shared routes with their partners. Since there is previous research (Bailey and William (1988), Borenstein (1989, 1990, 1991), Berry (1990, 1992), Evans and Kessides (1993) and Oum, Zhang and Zhang (1995)) that suggests there may be monopoly rents enjoyed by carriers serving concentrated hubs, policy makers including the Department of Transportation and the Department of Justice should pay special attention to the code-shared routes proposed to or from alliance firms' hubs to insure again the possible exercise of market power on individual routes. High route level concentration was found to discourage carriers from staying in a code-share arrangement after initial entry, which could be a sign for policy makers to be alert for anti-competitive behavior on the part of market incumbents on highly concentrated routes. High average yields on a route were found to induce alliance firms to stay in a code-share arrangement.

Government policies to deal with airport congestion by instituting slot controls and gate restrictions have generally discouraged firms from entering into and staying in code-share agreements on those routes. Thus, regulators need to continue to monitor competitive conditions at those airports where gate and slot controls are in effect as this not only discourages direct entry but also code-share entry which is another way that competitive outcomes can be achieved.

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APPENDICES

Figure A1: Code-sharing between Alliance Firms' Hub-and-Spoke Systems

Figure A1.1 Spoke-Hub-Hub

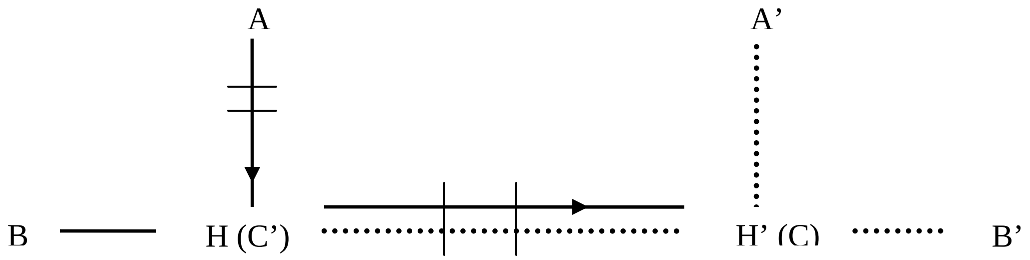

Figure A1.2 Hub -Hub- Spoke

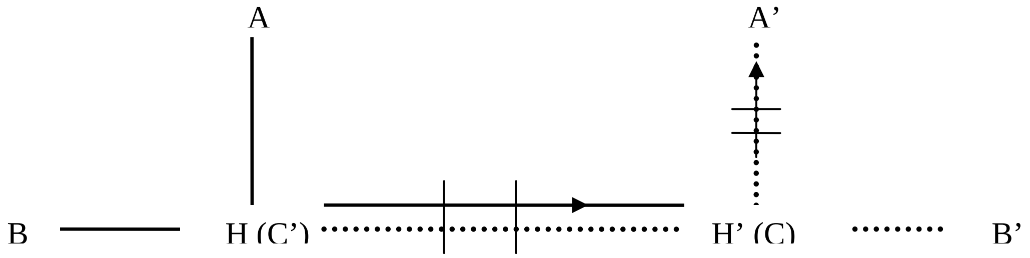

Figure A1.3 Hub-Hub-Hub

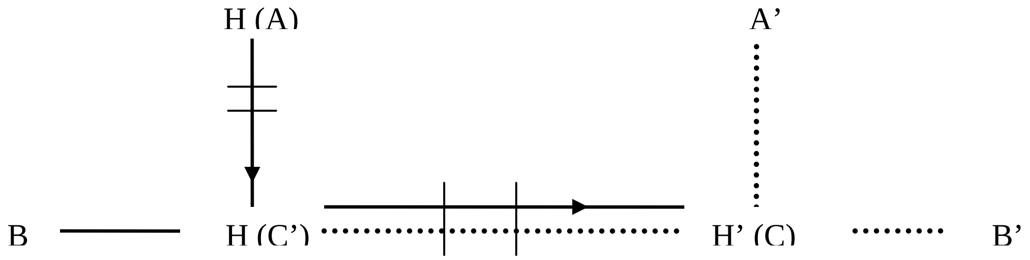

Figure A1: Code-sharing between Alliance Firms' Hub-and-Spoke Systems (Continued)

Figure A1.4 Spoke-Hub-Spoke

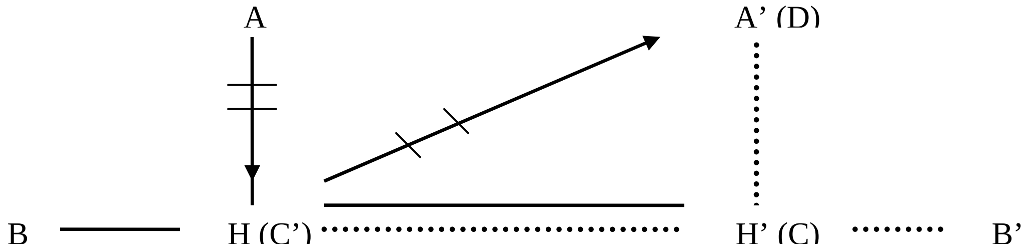

Figure A1.5 Hub-Spoke-Spoke

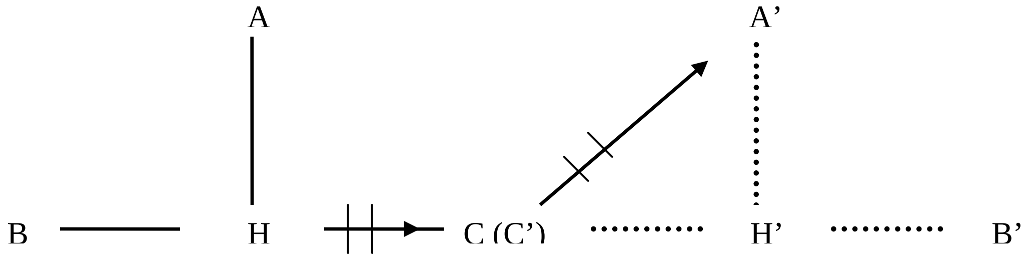

Figure A1.6 Spoke-Spoke-Spoke

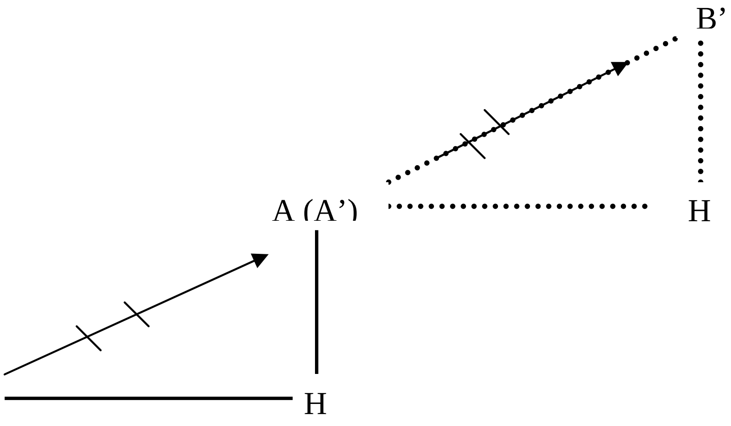

Figure A1: Code-sharing between Alliance Firms' Hub-and-Spoke Systems (Continued)

Figure A1.7 Spoke-Spoke-Hub

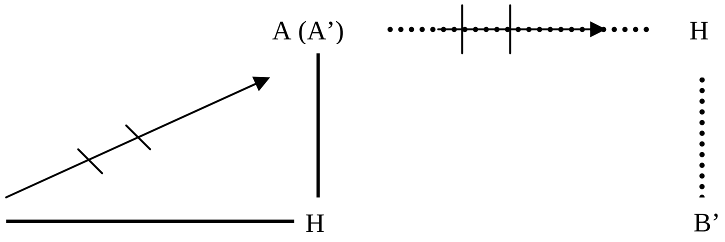

Table A1 GEE Working Correlation Structures and Their Estimators[42]

Working Correlation Structure	**Estimator**
Fixed $Corr(Y_{ij}, Y_{ik}) = r_{jk}$ where r_{jk} is the *jk*th element of a constant, user-specified correlation matrix R_0 .	**The working correlation is not estimated in this case.**
Independent $Corr(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ 0 & j \neq k \end{cases}$	**The working correlation is not estimated in this case.**
M-dependent (Stationary) $Corr(Y_{ij}, Y_{ij+t}) = \begin{cases} 1 & t = 0 \\ \alpha_t & t = 1, 2, ..., m \\ 0 & t > m \end{cases}$	$\widehat{\alpha_t} = \frac{1}{(N_t - p)\phi} \sum_{i=1}^{N} \sum_{j \le n_i - t} e_{ij} e_{i,j+t}$ $N_t = \sum_{i=1}^{N} (n_i - t)$
Exchangeable $Corr(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ \alpha & j \neq k \end{cases}$	$\widehat{\alpha} = \frac{1}{(N^* - p)\phi} \sum_{i=1}^{N} \sum_{j \neq k} e_{ij} e_{ik}$ $N^* = \sum_{i=1}^{N} n_i (n_i - 1)$
Unstructured $Corr(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ \alpha_{jk} & j \neq k \end{cases}$	$\widehat{\alpha}_{jk} = \frac{1}{(N - p)\phi} \sum_{i=1}^{N} e_{ij} e_{ik}$
Autoregressive AR(1) $Corr(Y_{ij}, Y_{ik}) = \alpha^t$ $for\ t = 0, 1, 2, ..., n_i - j$	$\widehat{\alpha} = \frac{1}{(N_1 - p)\phi} \sum_{i=1}^{N} \sum_{j \le n_i - 1} e_{ij} e_{i,j+1}$ $N_1 = \sum_{i=1}^{N} (n_i - 1)$

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[42] The information source is from *SAS/STAT GENMOD Procedure, SAS OnlineDoc: Version 8,* SAS Inc, 2006.

Table A2 GEE Results for Marginal Models with AR(1) Correlation Structure

Parameter	**Estimate**	**Empirical Std Error**	**Z Value**	**Odds Ratio**	**Odds Ratio 95% C.I.**	
INTERCEPT	-3.59	0.30	-12.04****	0.03	0.02	0.05
ONESTOPFLTS$_{i,t-1}$	0.00012	0.00012	1.01	1.01[a]	0.99	1.03
ONESTOPYIELD$_{i,t-1}$	9.60	1.11	8.68****	2.61[b]	2.10	3.24
ONESTOPRHHI$_{i,t-1}$	-0.00014	2.43E-05	-5.93****	0.87[c]	0.83	0.91
INCOME_ORIGIN	1.16E-05	1.02E-05	1.14	1.12[d]	0.92	1.37
INCOME_DEST	2.12E-05	1.05E-05	2.02****	1.24[d]	1.01	1.52
POP_ORIGIN	3.03E-08	8.11E-09	3.73****	1.03[e]	1.01	1.05
POP_DEST	3.14E-08	7.71E-09	4.07****	1.03[e]	1.02	1.05
WINTER	0.20	0.031	6.48****	1.22	1.15	1.30
SPRING	0.20	0.031	6.35****	1.22	1.15	1.30
SUMMER	-0.06	0.031	-1.97***	0.94	0.88	1.00
TIME	-0.35	0.011	-30.36****	0.71	0.69	0.72
SLOT	-1.56	0.139	-11.25****	0.21	0.16	0.27
GATE	-0.36	0.077	-4.73****	0.69	0.60	0.81
VACATION	0.20	0.066	2.97****	1.22	1.07	1.38
E_ORI_HUB	0.96	0.073	13.20****	2.60	2.26	3.00
E_CONN_HUB	1.34	0.126	10.59****	3.80	2.97	4.87
E_DEST_HUB	1.03	0.075	13.82****	2.81	2.42	3.25
Log Likelihood		-16952.2				
Pearson Chi-square /DF		1.00				

a. Odds ratio for a 100-unit increase in the number of flights;

b. Odds ratio for a 0.1- unit increase in the yield;

c. Odds ratio for a 1000- unit increase in the route HHI;

d. Odds ratio for a 10,000-unit increase in the income;

e. Odds ratio for a 1,000,000-unit increase in the number of population;

***p=0.05 level; ****p=0.01 level.

Table A3 GEE Results for Marginal Models with M-dep(1) Correlation Structure

Parameter	Estimate	Empirical Std Error	Z Value	Odds Ratio	Odds Ratio 95% C.I.	
INTERCEPT	-3.57	0.30	-11.9****	0.03	0.02	0.05
ONESTOPFLTS$_{i,t-1}$	0.000144	0.0001	0.98	1.01[a]	0.99	1.03
ONESTOPYIELD$_{i,t-1}$	9.24	1.12	8.25****	2.52[b]	2.02	3.14
ONESTOPRHHI$_{i,t-1}$	-0.0001	2.46E-05	-5.86****	0.87[c]	0.82	0.91
INCOME_ORIGIN	1.15E-05	1.03E-05	1.12	1.12[d]	0.92	1.37
INCOME_DEST	2.12E-05	1.05E-05	2.01****	1.24[d]	1.01	1.52
POP_ORIGIN	3.04E-08	8.12E-09	3.75****	1.03[e]	1.01	1.05
POP_DEST	3.16E-08	7.7E-09	4.10****	1.03[e]	1.02	1.05
WINTER	0.20	0.03	6.52****	1.22	1.15	1.30
SPRING	0.21	0.03	6.75****	1.23	1.16	1.31
SUMMER	-0.05	0.03	-1.59	0.95	0.90	1.01
TIME	-0.34	0.01	-29.8****	0.71	0.70	0.73
SLOT	-1.56	0.14	-11.3****	0.21	0.16	0.27
GATE	-0.36	0.08	-4.7****	0.70	0.60	0.81
VACATION	0.19	0.07	2.85****	1.21	1.06	1.37
E_ORI_HUB	0.96	0.07	13.25****	2.61	2.27	3.01
E_CONN_HUB	1.34	0.13	10.61****	3.82	2.98	4.89
E_DEST_HUB	1.03	0.07	13.84****	2.81	2.43	3.25
Log Likelihood		-16952.06				
Pearson Chi-square /DF		1.00				

a. Odds ratio for a 100-unit increase in the number of flights;

b. Odds ratio for a 0.1- unit increase in the yield;

c. Odds ratio for a 1000- unit increase in the route HHI;

d. Odds ratio for a 10,000-unit increase in the income;

e. Odds ratio for a 1,000,000-unit increase in the number of population;

***p=0.05 level; ****p=0.01 level.

Table A4 GEE Estimated AR(1) Working Correlation Matrix

	c1	**c2**	**c3**	**c4**	**c5**	**c6**	**c7**	**c8**	**c9**	**c10**
r1	1									
r2	0.34	1								
r3	0.12	0.34	1							
r4	0.04	0.12	0.34	1						
r5	0.01	0.04	0.12	0.34	1					
r6	0.005	0.01	0.04	0.12	0.34	1				
r7	0.002	0.005	0.01	0.04	0.12	0.34	1			
r8	0.001	0.002	0.005	0.01	0.04	0.12	0.34	1		
r9	0.00	0.001	0.002	0.005	0.01	0.04	0.12	0.34	1	
r10	0.00	0.00	0.001	0.002	0.005	0.01	0.04	0.12	0.34	1
r11	0	0.00	0.00	0.001	0.002	0.005	0.01	0.04	0.12	0.34
r12	0	0	0.00	0.00	0.001	0.002	0.005	0.01	0.04	0.12
r13	0	0	0	0.00	0.00	0.001	0.002	0.005	0.01	0.04
r14	0	0	0	0	0.00	0.00	0.001	0.002	0.005	0.01
r15	0	0	0	0	0	0.00	0.00	0.001	0.002	0.005
r16	0	0	0	0	0	0	0.00	0.00	0.001	0.002
r17	0	0	0	0	0	0	0	0.00	0.00	0.001
r18	0	0	0	0	0	0	0	0	0.00	0.00
r19	0	0	0	0	0	0	0	0	0	0.00
r20	0	0	0	0	0	0	0	0	0	0

	c11	**c12**	**c13**	**c14**	**c15**	**c16**	**c17**	**c18**	**c19**	**c20**
r11	1	1								
r12	0.34	0.34								
r13	0.12	0.12	1							
r14	0.04	0.04	0.34	1						
r15	0.01	0.01	0.12	0.34	1					
r16	0.005	0.005	0.04	0.12	0.34	1	1			
r17	0.002	0.002	0.01	0.04	0.12	0.34	0.34			
r18	0.001	0.001	0.005	0.01	0.04	0.12	0.12	1		
r19	0.00	0.00	0.002	0.005	0.01	0.04	0.04	0.34	1	
r20	0.00	0.00	0.001	0.002	0.005	0.01	0.01	0.12	0.34	1

Table A5 GEE Estimated M-dep(1) Working Correlation Matrix

	c1	**c2**	**c3**	**c4**	**c5**	**c6**	**c7**	**c8**	**c9**	**c10**
r1	1									
r2	0.34	1								
r3	0	0.34	1							
r4	0	0	0.34	1						
r5	0	0	0	0.34	1					
r6	0	0	0	0	0.34	1				
r7	0	0	0	0	0	0.34	1			
r8	0	0	0	0	0	0	0.34	1		
r9	0	0	0	0	0	0	0	0.34	1	
r10	0	0	0	0	0	0	0	0	0.34	1
r11	0	0	0	0	0	0	0	0	0	0.34
r12	0	0	0	0	0	0	0	0	0	0
…	**…**									
r20	0	0	0	0	0	0	0	0	0	0

	c11	**c12**	**c13**	**c14**	**c15**	**c16**	**c17**	**c18**	**c19**	**c20**
r11	1									
r12	0.34	1								
r13	0	0.34	1							
r14	0	0	0.34	1						
r15	0	0	0	0.34	1					
r16	0	0	0	0	0.34	1				
r17	0	0	0	0	0	0.34	1			
r18	0	0	0	0	0	0	0.34	1		
r19	0	0	0	0	0	0	0	0.34	1	
r20	0	0	0	0	0	0	0	0	0.34	1

Table A6 Parameter Estimates for First-order Transition Models[43]

Parameter	Estimate	Std Error	Chi-Square	Odds Ratio	Odds Ratio 95% C.I.	
INTERCEPT	-3.22	0.16	415.98****	0.04	0.03	0.05
DECISION$_{i,t-1}$	2.09	0.03	4279.4****	8.10	7.61	8.62
ONESTOPFLTS$_{i,t-1}$	8.65E-05	6.06E-05	2.04	1.01[a]	1.00	1.02
ONESTOPYIELD$_{i,t-1}$	5.03404	0.66	57.38****	1.65[b]	1.45	1.88
ONESTOPRHHI$_{i,t-1}$	-8.5E-05	1.35E-05	39.49****	0.92[c]	0.89	0.94
INCOME_ORIGIN	9.32E-06	5.41E-06	2.96**	1.10[d]	0.99	1.22
INCOME_DEST	1.65E-05	5.29E-06	9.74****	1.18[d]	1.06	1.31
POP_ORIGIN	2E-08	3.89E-09	26.48****	1.02[e]	1.01	1.03
POP_DEST	2.16E-08	3.79E-09	32.62****	1.02[e]	1.01	1.03
WINTER	0.23	0.05	26.51****	1.26	1.16	1.38
SPRING	0.0999	0.04	5.56***	1.11	1.02	1.20
SUMMER	-0.21	0.04	22.48****	0.81	0.75	0.89
TIME	-0.34	0.01	761.76****	0.71	0.69	0.73
SLOT	-1.08	0.09	160.78****	0.34	0.29	0.40
GATE	-0.25	0.04	42.34****	0.78	0.72	0.84
VACATION	0.10	0.03	9.73****	1.11	1.04	1.18
E_ORI_HUB	0.71	0.04	400.68****	2.03	1.90	2.18
E_CONN_HUB	0.94	0.06	285.57****	2.55	2.29	2.85
E_DEST_HUB	0.75	0.04	436.23****	2.11	1.97	2.26
Log Likelihood		-13825.9				
Pearson Chi-square/DF		1.00				

a. Odds ratio for a 100-unit increase in the number of flights;
b. Odds ratio for a 0.1- unit increase in the yield;
c. Odds ratio for a 1000- unit increase in the route HHI;
d. Odds ratio for a 10,000-unit increase in the income;
e. Odds ratio for a 1,000,000-unit increase in the number of population;
***p=0.05 level; ****p=0.01 level (p-value for Chi-square distribution at 1% with degree of freedom equaling one is at 6.63, 5% at 3.84 and 10% at 2.71).

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[43] This regression model assumes that the parameter estimates are the same no matter the firms' code sharing decisions $Y_{i,t-1}$= 0 or 1.