Is the Decision to Code-share a Route Different for Virtual versus Traditional Code-Share Arrangements?

Yan Du[1] B. Starr McMullen[2]

Abstract

This paper analyzes factors that determine whether individual routes remain in or leave a code-share agreement in different scenarios: pooled, purely traditionally code-shared routes, purely virtual code-shared routes and routes both traditionally and purely code-share. The code-share alliance between Continental and America West Airlines is used as the case study for this analysis. Empirical results show that factors affecting alliance firms' code sharing decision significantly differ for virtual versus traditional code share agreements.

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[1] Assistant Professor, Division of Business and Management, Beijing Normal University-HongKong Baptist University United International College, Zhuhai, P.R.China, 519085. Phone: 86-756-3620176. Email: angeladu@uic.edu.hk.

[2] Professor of Economics, Oregon State University, 232 Ballard Extension Hall, Corvallis, OR, 97331. Phone: 1-541-737-1480. Email: s.mcmullen@oregonstate.edu.

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.[1] 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 1. The purpose of this paper is to examine why some routes were kept and others deleted.

According to the most recent study by Ito and Lee (2007), there are basically two different practices of code-sharing: traditional or virtual code-sharing. A traditional code-sharing itinerary involves the combination of the networks of two different operating carriers to create a connecting flight, which is the same as complementary code-sharing defined in Park (1997) and Du, McMullen and Kerkvliet (2008). For example, the operating carriers of a traditionally code-shared itinerary are Continental and America West (CO: HP) or America West and Continental Airlines (HP: CO) while the marketing carriers are just Continental (CO: CO) or America West (HP: HP). By contrast, a virtual code-sharing itinerary only involves a single operating carrier but the ticket is sold by a marketing carrier different from the operating one. Different from parallel code-sharing, operating and marketing carriers do not necessarily compete on the same flight routes when they are virtually code-shared. For example, a fully virtual code-

Table 1 Changes in the Number of Code-shared (CS) Routes

Quarter[2]	CS Routes	New CS Entries[3]	New CS Entries %[4]	New CS Exits	New CS Exits %[5]
1998Q1	731	N/A	N/A	N/A	N/A
1998Q2	765	351	45.9%	317	43.4%
1998Q3	635	246	38.7%	376	49.2%
1998Q4	620	282	45.5%	297	46.8%
1999Q1	823	446	54.2%	243	39.2%
1999Q2	627	251	40.0%	447	54.3%
1999Q3	803	396	49.3%	220	35.1%
1999Q4	889	350	39.4%	264	32.9%
2000Q1	760	217	28.6%	346	38.9%
2000Q2	770	272	35.3%	262	34.5%
2000Q3	515	137	26.6%	392	50.9%
2000Q4	503	193	38.4%	205	39.8%
2001Q1	425	140	32.9%	218	43.3%
2001Q2	331	139	42.0%	233	54.8%
2001Q3	305	140	45.9%	166	50.2%
2001Q4	358	182	50.8%	129	42.3%
2002Q1	277	93	33.6%	174	48.6%
2002Q2	208	71	34.1%	140	50.5%
2002Q3	28	17	60.7%	197	94.7%
2002Q4	14	13	92.9%	27	96.4%

share itinerary may consist of a connection between two Continental flights (CO: CO) or two America West flights (HP: HP) while the entire ticket is marketed or sold by America West (HP: HP) or Continental Airlines (CO: CO), respectively. Virtual code-sharing could happen on the direct flight itinerary as well: if the operating carrier is CO or HP but the marketing carrier is HP or CO, respectively. Furthermore, if only one segment of the ticket is sold by America West while the other segment is still sold by Continental (CO:HP or HP:CO), then the itinerary is called semi-virtually code-shared. In particular, Ito and Lee (2007) point out that the overwhelming majority of the U.S. domestic code-sharing is virtual code-sharing.

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 (2001, 2003), Hassin and Shy (2004), Bamberger, Carlton and Neumann (2004), Armantier and Richard (2005a, 2005b), Chua, Kew and Yong (2005), Gayle (2006) and Ito and Lee (2007)), 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 6 routes remained in the agreement for almost the entire 1998 - 2002 period. There were 1219 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 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.

Table 2 Time of Code-sharing for Different Code-shared Routes

Number of CS Routes	CS Time (in Qrts)
6	19
45	18
23	17
26	16
30	15
41	14
39	13
44	12
36	11
42	10
47	9
47	8
79	7
89	6
93	5
138	4
235	3
477	2
1219	1
Total: 2756	**Total[6]: 20**

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.[7] 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.[8] 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 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.[9] 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 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.

VARIABLE DEFINATIONS 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-shared, no matter they were traditionally or virtually code-shared, 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

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

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.[10]

1. **Average Yield from Previous Period ---** $YLD_{i,t-1}$ 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);
2. **The Number of One Stop Booking Frequencies from Previous Period ---** $FRE_{i,t-1}$ is defined as the number of all incumbents' one stop booking frequencies on route *i* at time *t-1*. The larger the number of one stop booking frequencies, 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 ---** $RHHI_{i,t-1}$ 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.[11]

City and Geographical Characteristics

1. **Population** --- POP_{it} are the multiplication of 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** --- $INCO_{it}$ are the multiplication of 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 ---**VAC_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 ($ORIHUB_i$ and $DESTHUB_i$) or the connecting airports ($CONHUB_i$) 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 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

Table 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
America West	PHX, LAS, PHL, CLT	PIT	DCA, LGA, BOS
ATA Airlines	MDW		HNL,OAK
Horizon Air	SEA, PDX, LAX		DEN
Frontier Airlines	DEN		
Southwest Airlines			LAS, MDW, PHX, BWI, OAK, HOU, DAL,LAX, MCO, SAN
JetBlue Airways			JFK, BOS, FLL, OAK, IAD

Yao, 2002).

Code-sharing Characteristics

1. **Code-sharing Dummies** --- TCS_i and VCS_i are used to distinguish whether the route is traditionally or virtually code-shared (fully or semi-virtual), respectively. On a specific route, if the operating carriers are CO:HP or HP:CO but the marketing carriers are CO:CO or HP: HP, then the route is traditionally code-shared. If the operating carriers are CO:CO or HP:HP but the marketing carriers are HP:HP or CO:CO, respectively, then the route is fully virtually code-shared; if the operating carriers are CO:CO or HP:HP but the marketing carriers are HP:CO or HP:CO, then the route is semi-virtually code-shared.

Time Characteristics

1. **Quarterly Dummies ---** WIN_t, SPR_t and SUM_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.

DATA SOURCE

The whole data sample has 55120 quarterly observations on a total of 2756 routes code-shared by Continental and America West Airlines at some time during 1998Q1 to 2002Q4 period. Among the 2756 code-shared routes, 1113 routes are purely traditionally code-shared, 793 routes are purely virtually code-shared and 850 routes are both traditionally and virtually code-shared. Every observation is route and time specific. Table 4 shows the descriptive statistics.

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. YLD_{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 booking frequencies FRE_{it} and the calculation of route concentration $RHHI_{it}$ are from DB1B Market. Hub dummies are identified from each air carrier's website.[12] The data for population POP_ORIGIN_{it} and POP_DEST_{it} and per capita income $INCOME\_ORIGIN_{it}$ and $INCOME\_DEST_{it}$ at

Table 4 Descriptive Statistics

Variables (Descriptions and Units)	Mean	Std
$DECISION_{it}$ (Equals 1 if the alliance firms code-shared on route *i*, otherwise 0)	0.1884	0.391
$ONESTOPYIELD_{it-1}$ (Average air fare from *t-1* in dollars per passenger mile in the one-stop market of route *i*)	0.0676	0.027
FRE_{it-1} (All incumbents' one-stop booking frequencies from *t-1* on route *i*)	421	337
$RHHI_{it-1}$ (HHI from *t-1* in the one-stop market of route *i*)	2739	1507
$INCOME\_ORIGIN_{it}$ (Per capita income in dollars at the MSA of the origin airport on route *i*)	18126	3262
$INCOME\_DEST_{it}$ (Per capita income in dollars at the MSA of the destination airport on route *i*)	18082	3288
POP_ORIGIN_{it} (Population at the MSA of the origin airport on route *i*)	4061988	4654822
POP_DEST_{it} (Population at the MSA of the destination airport on route *i*)	4075897	4667366
$SLOT_i$ (Equals 1 if either the endpoint or the connecting airport is slot-controlled)	0.0722	0.2589
$GATE_i$ (Equals 1 if either the endpoint or the connecting airport has gate constraints)	0.2496	0.4328
$VACATION_i$ (Equals 1 if either the endpoint or connecting airport on route *i* is in FL, HI or NV; otherwise 0)	0.3792	0.4852
$E\_ORI\_HUB_i$ (Equals 1 if the origin airport on route *i* is the alliance firms' dominated hub or focus city)	0.3266	0.469
$E\_CONN\_HUB_i$ (Equals 1 if the connecting airport on route *i* is the alliance firms' dominated hub or focus city)	0.8545	0.353
$E\_DEST\_HUB_i$ (Equals 1 if the destination airport on route *i* is the alliance firms' dominated hub or focus city)	0.3193	0.4662
$WINTER_t$ (Equals 1 if the quarter is in Jan-Mar; otherwise 0)	0.25	0.433
$SPRING_t$ (Equals 1 if the quarter is in Apr-Jun; otherwise 0)	0.25	0.433
$SUMMER_t$ (Equals 1 if the quarter is in Jul-Sep; otherwise 0)	0.25	0.433
TCS_i (Equals 1 if the route was once traditionally code-shared; otherwise 0)	0.7123	0.453
VCS_i (Equals 1 if the route was once virtually code-shared; otherwise 0)	0.5962	0.4907
$TIME_t$ (Equals 5 if in year 1998, 6 in 1999, 7 in 2000, 8 in 2001, 9 in 2002)	7	1.414

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

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).

ECONOMETRIC MODELS AND EMPIRICAL RESULTS

Following Molenberghs and Verbeke (2005) for the study of discrete longitudinal data, we apply Subject-specific Models for the analysis of the discrete longitudinal data set, in which the dependent variable is non-Gaussian repeated binary measures.[13]

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.[14] 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. We apply GLIMM regression into four different scenarios: a regression on the totally pooled 2756 code-shared routes and separate regressions on the 1113 purely traditionally code-shared (TVS) routes, 793 purely virtually code-shared (VCS) routes and 850 both traditionally and virtually code-shared (TVCS) routes, respectively. We then compare the regression results to find out the different impacts of those explanatory variables on the code-sharing decision from four different scenarios.

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

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

Rewrite the equation above as

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

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.[15] 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

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

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 5.

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,

Table 5 Comparison of GLIMM Regression Results in Different Scenarios (on Pooled, TCS, VCS or TVCS Routes)

Pooled Routes	*INT.*	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-1.04	3.07E-04	14.38	-1.70E-04	7.54E-04	2.09E-03	0.46	0.25	-0.05	-0.55	-1.28	-0.27	0.44	0.86	1.53	0.90
Std Error	0.17	9.30E-05	0.88	1.90E-05	3.43E-04	9.83E-04	0.04	0.04	0.04	0.01	0.12	0.07	0.06	0.06	0.09	0.06
t Value	-6.01	3.3	16.36	-9.17	2.2	2.12	12.61	6.67	-1.43	-52.1	-11.2	-4.07	7.67	13.71	16.84	14.39
Pr>|t|	.0001	.0001	.0001	.0001	.0282	0.0339	.0001	.0001	.1531	.0001	.0001	.0001	.0001	.0001	.0001	.0001
Odds Ratio	0.35	1.03[a]	4.21[b]	0.84[c]	1.000754	1.00209	1.58	1.28	0.95	0.58	0.28	0.76	1.55	2.35	4.60	2.47

TCS Routes	*INT.*	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-1.56	1.74E-04	6.82	-4.12E-05	-3.1E-04	8.00E-04	0.14	0.13	-0.08	-0.24	-0.60	-0.06	0.11	0.40	0.41	0.30
Std Error	0.20	1.14E-04	0.87	1.77E-05	3.34E-04	1.22E-03	0.07	0.07	0.07	0.02	0.14	0.06	0.06	0.06	0.09	0.07
t Value	-7.83	1.53	7.8	-2.33	-0.92	0.65	2.08	1.96	-1.13	-13.6	-4.25	-0.93	1.88	6.56	4.74	4.52
Pr>|t|	.0001	.1251	.0001	.0198	.3599	.5136	.0375	.0503	.258	.0001	.0001	.351	.0604	.0001	.0001	.0001
Odds Ratio	0.21	1.02[a]	1.98[b]	0.96[c]	0.999694	1.0008	1.15	1.14	0.92	0.78	0.55	0.94	1.11	1.49	1.50	1.34

VCS Routes	*INT.*	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	2.51	-5.32E-05	1.11	-1.21E-04	-3.9E-03	-3.3E-03	0.60	0.17	-0.01	-0.57	0.06	-0.05	0.06	-0.07	0.37	0.06
Std Error	0.31	1.54E-04	1.60	3.84E-05	5.92E-04	1.56E-03	0.08	0.08	0.08	0.02	0.13	0.11	0.09	0.11	0.14	0.10
t Value	8.11	-0.35	0.69	-3.16	-6.52	-2.1	7.86	2.14	-0.07	-24.8	0.43	-0.46	0.73	-0.63	2.75	0.59
Pr>|t|	.0001	.7299	.4906	.0016	.0001	.0355	.0001	.0326	.9433	.0001	.6673	.644	.4655	.5309	.006	.5556
Odds Ratio	12.25	1.00[a]	1.12[b]	0.9999[c]	0.996148	0.99673	1.83	1.19	0.99	0.57	1.06	0.95	1.06	0.94	1.45	1.06

TVCS Routes	*INT.*	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-0.84	7.35E-04	26.39	-5.44E-05	4.1E-03	1.99E-03	0.64	0.38	-0.07	-0.78	-2.04	-0.59	0.16	1.01	1.63	1.05
Std Error	0.36	1.64E-04	1.81	4.79E-05	6.79E-04	1.74E-03	0.06	0.06	0.06	0.02	0.26	0.13	0.11	0.12	0.21	0.12
t Value	-2.32	4.49	14.58	-1.14	6.04	1.14	11.47	6.83	-1.26	-45.8	-7.9	-4.54	1.42	8.53	7.86	8.9
Pr>|t|	.0205	.0001	.0001	.2506	.0001	.2544	.0001	.0001	.2063	.0001	.0001	.0001	.157	.0001	.0001	.0001
Odds Ratio	0.43	1.08[a]	14.01[b]	0.95[c]	1.004112	1.00199	1.90	1.47	0.93	0.46	0.13	0.56	1.17	2.74	5.12	2.86

a.

d.

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.

CONCLUSIONS

Our empirical results show that a successful code-sharing depends on many factors. Airport dominance is an important factor that affects alliance firm code-sharing decisions. 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 against 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.

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.

In addition, we find that both airport congestion measured by slot-control and gate constraints are important barriers that limit firm's use of code-sharing. 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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Table 6 Standardized Coefficients from GLIMM Regression in Different Scenarios (Pooled, TCS, VCS and TVCS Routes)

Pooled Routes	$INT.$	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	$TIME$	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-1.95	24.35	92.13	-60.62	14.84	14.77	46.43	24.95	-5.50	-182.88	-78.07	-27.50	50.04	94.22	126.25	98.89
Std Error	0.03	7.38	5.63	6.61	6.76	6.97	3.68	3.74	3.85	3.51	6.99	6.75	6.52	6.87	7.50	6.87
t Value	-70.93	3.3	16.36	-9.17	2.2	2.12	12.61	6.67	-1.43	-52.1	-11.2	-4.07	7.67	13.71	16.84	14.39
Pr>|t|	0.0001	0.0001	0.0001	0.0001	0.0282	0.0339	0.0001	0.0001	0.1531	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

TCS Routes	$INT.$	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	$TIME$	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-2.42	7.97	29.19	-11.40	-4.04	2.89	9.01	8.47	-5.09	-51.58	-20.57	-3.77	7.59	26.40	21.59	18.79
Std Error	0.03	5.20	3.74	4.89	4.41	4.42	4.33	4.33	4.50	3.79	4.84	4.04	4.04	4.02	4.56	4.16
t Value	-88.36	1.53	7.8	-2.33	-0.92	0.65	2.08	1.96	-1.13	-13.6	-4.25	-0.93	1.88	6.56	4.74	4.52
Pr>|t|	0.0001	0.1251	0.0001	0.0198	0.3599	0.5136	0.0375	0.0503	0.258	0.0001	0.0001	0.351	0.0604	0.0001	0.0001	0.0001

VCS Routes	$INT.$	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	$TIME$	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-2.56	-2.33	3.91	-18.10	-40.32	-13.89	32.97	9.48	-0.32	-101.11	2.34	-2.55	3.68	-3.88	18.92	3.39
Std Error	0.04	6.74	5.68	5.72	6.19	6.61	4.19	4.44	4.57	4.08	5.45	5.53	5.04	6.20	6.88	5.76
t Value	60.18	-0.35	0.69	-3.16	-6.52	-2.1	7.86	2.14	-0.07	-24.8	0.43	-0.46	0.73	-0.63	2.75	0.59
Pr>|t|	0.0001	0.7299	0.4906	0.0016	0.0001	0.0355	0.0001	0.0326	0.9433	0.0001	0.6673	0.644	0.4655	0.5309	0.006	0.5556

TVCS Routes	$INT.$	$FRE_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	$TIME$	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-0.62	32.37	79.11	-7.15	41.43	8.54	36.33	21.66	-4.06	-144.21	-57.02	-34.26	10.18	64.72	60.76	67.53
Std Error	0.05	7.21	5.43	6.30	6.86	7.49	3.17	3.17	3.21	3.15	7.22	7.55	7.19	7.58	7.73	7.59
t Value	-11.88	4.49	14.58	-1.14	6.04	1.14	11.47	6.83	-1.26	-45.8	-7.9	-4.54	1.42	8.53	7.86	8.9
Pr>|t|	0.0205	0.0001	0.0001	0.2506	0.0001	0.2544	0.0001	0.0001	0.2063	0.0001	0.0001	0.0001	0.157	0.0001	0.0001	0.0001

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[1] 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.

[2] 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.

[3] A route is defined as a new code-shared entry if carriers did not code-share in the previous period but code-share at the current period; A route is defined as new code-shared exit if carriers code-shared in the previous period but do not code-share at the current period.

[4] New code-shared entry percentage is calculated as new code-shared entries at the current period divided by code-shared routes at the current period.

[5] New code-shared exit percentage is calculated as new code-shared exits from the previous period divided by code-shared routes in the previous period.

[6] 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.

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

[8] 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.

[9] 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.

[10] 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.

[11] All these three covariates $YIELD_{i,t-1}$, $FRE_{i,t-1}$ and $RHHI_{i,t-1}$ 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.

[12] 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.

[13] 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.

[14] 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.

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