Is the Decision to Code-Share a Route Different for Virtual and Traditional Code-Share Arrangements

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This paper analyzes factors that determine whether alliance carriers choose to remain in or leave a code-share agreement on individual routes. Different types of code-sharing are considered: traditional code-shared routes, virtual code-shared routes and those routes with both traditional and virtual code-sharing. Empirical results show that factors affecting alliance firms' code-sharing decisions significantly differ for virtual versus traditional code-share agreements. Virtual code-sharing tends to take place in less dense markets and is not significantly affected by yields. This provides tentative support for the Ito and Lee (2005) argument that virtual code-sharing provides a mechanism by which carriers practice price discrimination (for instance, filling unoccupied seats in less dense markets). In contrast traditional code-sharing is found to be more likely to occur in dense markets and higher yields increase the probability of such arrangements. Thus, traditional code-sharing seems to be used to achieve the networking economics and cost savings derived from dense markets and thus appears to be more effective as an instrument to introduce competition into a market.

INTRODUCTION

Code-sharing, a phenomenon originally observed in international airline markets, emerged as a popular and important form of alliance in the U.S. domestic airline industry in the mid-1990s. Considerable research has focused on the impact of code-sharing on air fares, passenger volumes, and consumer welfare either in the international or U.S. domestic airline markets (Brueckner 2001, 2003; Brueckner and Whalen 2000; Hassin and Shy 2004; Oum, Park and Zhang 1996; Park 1997; Park and Zhang 2000; Park, Park, and Zhang 2003; Park, Zhang, and Zhang 2001; Bamberger, Carlton, and Neumann 2004; Armantier and Richard 2006, 2008; Du, McMullen, and Kerkvliet 2008; Heimer and Shy 2006; Gayle 2008).

However, Ito and Lee (2005, 2007) have suggested that it may be important to distinguish between traditional code-sharing and virtual code-sharing. Whereas traditional code-sharing typically refers to combining the networks of two distinct operating carriers, virtual code-sharing involves a single operating carrier and a marketing carrier that differs from the operating carrier.[1] Ito and Lee (2005) argue that the majority of the U.S. domestic code-sharing fit the definition of virtual code-sharing. They find that fares in virtual code-share markets tend to be lower than pure online or traditional code-share fares. This leads them to hypothesize that virtual code-sharing is used by carriers as a means of product differentiation rather than as a means to enter markets and exploit profitable opportunities as usually thought for traditional code-share arrangements. They argue that the customer of an individual carrier may place a greater value on that carrier's service; thus the price that consumers are willing to pay for a pure online Continental flight for instance, which is both operated and marketed by Continental may be higher than the price for the same flight if marketed by America West. The fact that some frequent flyer programs may not count the flight if it is marketed by a code-share partner makes the incentive for virtual code-sharing even stronger.

To provide more information on the motivation for entering into virtual rather than traditional code-share arrangements on individual routes, this paper extends a recent study by McMullen and Du (2012) in which the determinants of route level participation in the America West and Continental code-share agreement were examined. McMullen and Du (2012) find the decision to enter into code-sharing on a route was positively influenced by the yield, alliance firm hub dominance, booking frequencies, and vacation routes; code-sharing was less probable when the route was concentrated and when there was airport congestion. However, in that study there was no distinction made between traditional and virtual code-shared routes.

The purpose of this paper is to see whether the decision to enter into code-sharing on a route is significantly different for virtual and traditional code-shared routes. If virtual code-sharing is used more as a tool for product differentiation as hypothesized by Ito and Lee (2005, 2007), the decision to virtually code-share a route may depend on different factors than those for traditional code-share arrangements. In that case, it may be appropriate for government regulators to consider the nature of code-sharing (virtual or traditional) first when considering the possible competitive implications of such arrangements.

BACKGROUND

The America West and Continental code-share arrangement, which spanned the 1994-2002 period, was the first domestic code-share alliance between U.S. carriers and was one of the longest lasting domestic code-share agreements When this arrangement started, America West Airlines was the second largest low-cost air carrier in the U.S. (later operating as U.S. Airways) and was one of deregulation's greatest successes. However, rapid expansion without proper handling of large operating losses placed the company at the verge of bankruptcy, and rising fuel prices due to instability in the Persian Gulf finally led America West to file for bankruptcy in 1991. In 1994, America West was able to secure reorganization resulting in a large portion of the airline being owned by a partnership with Continental Airlines. This ultimately resulted in the code-shared arrangement with Continental and heralded the beginning of code-sharing alliances for the domestic U.S. airline industry. Previous to this agreement, code-sharing had been used extensively in international markets but not on solely domestic routes.

Although the America West-Continental code-share agreement went into effect in 1994, data are only available from 1998Q1 to 2002Q4.[2] Throughout the arrangement, firms continually reassessed their decision to code-share on individual routes and then changed their code-share arrangements accordingly (McMullen and Du 2012).

EMPIRICAL HYPOTHESES AND VARIABLE DEFINITIONS

In this paper, we focus only on code-shared routes that involve one-stop flight service. Compared with non-stop or multi-stop flights, a one-stop flight through a code-share arrangement is more comparable to a pure online flight (operated by a single carrier) that has one stop. Due to the limitations of our data set, we include only routes on which Continental and America West code-shared for at least one quarter during the1998-2002 sample period. On some routes, code-sharing began at the very start of the alliance agreement and lasted for the entire alliance period, while on other routes, code-sharing occurred for a time period after which the route was dropped. Sometimes a route was added and dropped several times during the alliance period, whereas others were code-shared for one quarter and then dropped forever.

To account for all these circumstances, we assume firms make their code- sharing decisions at the beginning of each quarter for each route. Thus, our dependent variable is a qualitative response variable that represents the code-share decision. The dependent code-share decision variable $DECISION_{it}$ is valued at 1if alliance firms engaged in code-sharing on that route during period t and valued at 0 if there was no code-sharing on the route during period t.

We assume the density of the dependent variable $DECISION_{it}$ follows an exponent distribution with the probability of code-sharing denoted as π_{it}. The classical logistic regression model is then specified as

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

Where X is a matrix of the explanatory variables that includes characteristics of both incumbents and alliance firms' flight operations as well as those of relevant routes and airport markets.

Finally, we include the same set of explanatory variables used by McMullen and Du (2012) to control for route specific characteristics on each route. This allows us to compare the results found when no distinction is made between the two types of code-share arrangements (traditional and virtual) to results for each type of code-sharing separately. Accordingly, the matrix of explanatory variables, X, includes the following:

Average Yield. $YLD_{i,t-1}$ is defined as the average price per passenger mile on route i in the previous quarter t-1. Average price is calculated as the weighted average of per passenger air fares from all carriers operating in the market. For traditional code-sharing we expect higher average yields from the previous period to increase the probability of code-sharing because high yields indicate high profitability from a code-sharing alliance.

Booking Frequencies. $FRE_{i,t-1}$ is defined as the number of bookings by incumbent carrier customers on route i in the previous time period, t-1**.** This is used as a proxy for flight frequency, which was not available for this data set. It is hypothesized that increases in flight frequency indicate higher potential market demand that results in a greater probability of entry into code-sharing. Note that both $FRE_{i,t-1}$ and $YLD_{i,t-1}$ are lagged one period to avoid any potential endogeneity.

Route Level Competition Level. $RHHI_{i,t-1}$ is defined as Herfindahl Hirschman Index (HHI) on route i at time t-1. HHI is calculated using the number of passengers carried by individual carriers on a specific route. If high concentration creates an effective barrier to entry, this may make code-sharing less likely on routes with a high HHI. However, if profits are high on high HHI routes and code-sharing is an easier way to enter than entering with new service, code-sharing may be more likely to occur. Thus, the overall effect of route competition level on the probability of code-sharing is uncertain.[3]

Population. POP_{it} is defined as the product of the populations at the endpoints of the Metropolitan Statistical Areas (MSAs) on route i at time t. This is a proxy for the potential market size, and we expect that a larger population will lead to higher travel demand and thus a higher probability of code-sharing.

Per Capita Income. $INCO_{it}$ is defined as the product of the per capita income for MSAs at endpoints of route i at time t. We expect higher per capita income to result in higher air travel demand and therefore a greater probability of code-sharing.

Vacation Dummy. VAC_i was set equal to 1 if one of the endpoint airports was in Florida, Hawaii, Nevada, or Puerto Rico, otherwise it is equal to 0. We expect the sign to be positive as vacation routes will generate more passengers than non-vacation routes, all other factors being equal.

Hub Dummies for Code-shared Firms. If either the endpoint airports ($ORIHUB_i$ and $DESTHUB_i$) or the connecting airport ($CONHUB_i$) are hubs for code-shared firms, then the dummy variable takes a value of 1. These variables are chosen to capture the benefits carriers may obtain from economies of traffic density on their hub-and-spoke network systems. We expect that the alliance firm hubs at either endpoint or at the connecting airport may increase the probability of code-sharing on the route. Table A1 in the Appendix provides a list of hubs for all major carriers in the United States during this study time period.

Slot Control Dummy. $SLOT_i$. During the time period for this study, the USDOT had limits set on the number of takeoffs and landings that could take place in any given hour period at four airports: Chicago, O'Hare; New York, J.F. Kennedy and La Guardia; and Washington, Reagan National

Airport. If either end point or connecting airport is a slot-controlled airport, then $SLOT_i$ equals 1 otherwise 0. A negative coefficient is expected, indicating that the presence of slot controls reduces the probability of code-sharing.

Gate Constraints Dummy. $GATE_i$. In addition to slot controls, there were six airports (Charlotte, Cincinnati, Detroit International, Minneapolis, Newark, and Pittsburgh) in which long-term, exclusive use gates are thought to create barriers to entry (USGAO 1993). If either 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 Yao 2002).

Quarterly Dummies. WIN_t , SPR_t , SUM_t were used to control for seasonal fixed effects on air travel demand.

Time. $TIME_t$ measures the longevity (in years) of the initial code-sharing alliance. For instance, if the code-share route arrangement 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. The expected sign of the time coefficient is ambiguous. On one hand, the longer firms stay in an alliance, the better the reputation of the alliance and the lower the continuation cost, suggesting a positive relationship between $TIME_t$ and the probability of code-sharing. However, as time passes, market situations may change dramatically, firms' financial situations and operating strategies may change, government policy may change, and experience in the market may either increase or decrease the attractiveness of code-sharing.

DATA

Our complete data sample has 55,120 quarterly observations on a total of 2,756 routes that were code-shared by Continental and America West Airlines at some time during 1998Q1 to 2002Q4 period. Among the 2,756 code-shared routes, 1,113 (or 40%) of routes were purely traditional code-shared routes (TCS), 793 (or 29%) of routes were purely virtual code-shared (VCS) and 850 (or 31%) of routes contained both traditional and virtual code-shared segments (TVCS). Every observation is route and time specific. Table 1 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 the U.S. Department of Transportation (USDOT), Bureau of Transportation Statistic's (BTS) 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* 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 collected by tracking each route that was ever code-shared by Continental and America West Airlines, quarter by quarter. The data for the number of booking frequencies $FLTS_{it}$ and the calculation of route concentration $RHHI_{it}$ are from DB1B Market. Hub dummies are identified from each air carrier's website.[4] 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 the U.S. Department of Commerce, Bureau of Economic Analysis (BEA). The slot control and gate constraints dummies are obtained from reports by the U.S. General Accounting Office (1993).

Table 1: Descriptive Statistics

Variables (Descriptions and Units)	Mean	Std Dev
$DECISION_{it}$ (Equals 1 if the alliance firms code-shared on route *i*, otherwise 0)	0.1884	0.391
YLD_{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 incumbent customers' 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
VAC_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
$ORIHUB_i$ (Equals 1 if the origin airport on route *i* is the alliance firms' dominated hub or focus city)	0.3266	0.469
$CONHUB_i$ (Equals 1 if the connecting airport on route *i* is the alliance firms' dominated hub or focus city)	0.8545	0.353
$DESTHUB_i$ (Equals 1 if the destination airport on route *i* is the alliance firms' dominated hub or focus city)	0.3193	0.4662
WIN_t (Equals 1 if the quarter is in Jan-Mar; otherwise 0)	0.25	0.433
SPR_t (Equals 1 if the quarter is in Apr-Jun; otherwise 0)	0.25	0.433
SUM_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).

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.[5]

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). Although subject-specific parameters can be dealt with either as fixed or random effects, the fixed effects approach is subject to criticism due to possible inconsistency of the so-obtained maximum likelihood estimates. Therefore, we follow McMullen and Du (2012) and use Generalized Linear Mixed Models (GLIMM) estimated using Penalized Quasi-likelihood (PQL) methods from Breslow and Clayton (1993), the most frequently used random effects model in the context of discrete repeated measurements.[6,7,8]

We apply the GLIMM methodology to four different regression scenarios: the first regression duplicates the McMullen and Du (2012) pooled sample of all 2,756 code-shared routes in which there is no distinction between the TCS, VCS, or TVCS types of code-sharing. The additional three regressions are run on three mutually exclusive subsets of this pooled data set, namely: the 1,113 pure traditional code-shared (TCS) routes, the 793 purely virtual code-shared (VCS) routes, and the 850 routes that involved both traditional and virtual code-sharing (TVCS). We then compare the regression results to see whether there are differences in the importance of specific variables affecting the decision to enter into a TCS differ versus a VCS arrangement.

Table 2 compares the fixed effect parameter estimates from the GLIMM regression in the four different regressions. More detailed regression results and a comparison of standardized coefficients from the GLIMM regression on the pooled routes, TCS, VCS and TVCS routes are provided in Appendix Table 4 and 5.[9]

GLIMM regression results for the TVCS sample are very similar to those reported for the pooled sample of code-share routes as in McMullen and Du (2012). The main difference is that the route level concentration as measured by the Herfindahl Hirschman Index (HHI) does not have a significant impact on the decision to engage in this TVCS kind of code-shared route.

The first notable difference between the TCS and VCS results is that higher yields have a positive and significant impact on the decision to engage in a TCS arrangement, but no significant effect at all upon the decision to engage in a VCS arrangement.[10]

Consistent with the McMullen and Du (2012) results for the pooled sample, route concentration level, as measured by HHI, significantly deters code-sharing entry on both TCS and VCS routes.[11] While airport congestion, measured by slot control (SLOT) and gate constraints (GATE), have significant and negative coefficients in the pooled sample and SLOT also significantly reduces TCS, for VCS routes neither congestion measure has a statistically significant coefficient.[12] A vacation route significantly affects the probability of code-sharing in the pooled sample and on the TCS routes but not on the VCS routes. This result supports the hypothesis that vacation routes generate more passengers than non-vacation routes, therefore increasing the probability of code-sharing. Carriers choose to traditionally code-share on vacation routes because of the potential route density.

The significant and negative coefficients for INCO and POP for VCS routes show that carriers engage in VCS arrangements in less dense, less congested, and lower income markets. These results provide further evidence that VCS routes are not being used to generate more passengers, but to allow segmentation of the passengers in the market that is necessary for price discrimination, supporting Ito and Lee's (2005, 2007) argument that VCS routes serve to price discriminate rather than as a mechanism for firms to compete with each other in the market.

On a specific route, as found in the pooled sample, hub dominance at the end point or connecting airports positively and strongly affects the probability of code-sharing on the TCS routes. On the VCS routes, only hub dominance at the connecting airport (CONHUB) has a significant impact on the probability of code-sharing. Hub dominance at the origin (ORIHUB) or destination (DESTHUB) does not affect alliance firms' virtual code-share decisions.[13] This difference between code-share decisions for TCS and VCS routes reflects alliance firms' marketing strategies: carriers may take advantage of hub dominance to exercise market power and extract monopoly rents through traditional code-share agreements. However, hub-dominated airports where economies of scale or traffic density can be achieved are not necessarily the top priority for virtual code-sharing.

Table 2: Comparison of GLIMM Regression Results in Different Scenarios on Pooled, TCS, VCS or TVCS Routes

	Pooled Routes	TCS Routes	VCS Routes	TVCS Routes
INT	**-1.04****** (-6.01)	**-1.56****** (-7.83)	**2.51****** (8.11)	**-.84***** (-2.32)
$FLTS_{i,t-1}$	**3.07E-04****** (3.3)	1.74E-04 (1.53)	-5.32E-05 (-.35)	**7.35E-04****** (4.49)
$YLD_{i,t-1}$	**14.38****** (16.36)	**6.82****** (7.8)	1.11 (.69)	**26.39****** (14.58)
$RHHI_{i,t-1}$	**-1.70E-04****** (-9.17)	**-4.12E-05****** (-2.33)	**-1.21E-04****** (-3.16)	-5.44E-05 (-1.14)
$INCO_{it}$	**7.54E-04***** (2.2)	-3.1E-04 (-.92)	**-3.9E-03****** (-6.52)	**4.1E-03****** (6.04)
POP_{it}	**2.09E-03***** (2.12)	8.00E-04 (.65)	**-3.3E-03***** (-2.1)	1.99E-03 (1.14)
$SLOT_i$	**-1.28****** (-11.2)	**-.60****** (-4.25)	0.06 (.43)	**-2.04****** (-7.9)
$GATE_i$	**-.27****** (-4.07)	-0.06 (-.93)	-0.05 (-.46)	**-.59****** (-4.54)
VAC_i	**.44****** (7.67)	**.11**** (1.88)	0.06 (.73)	0.16 (1.42)
$ORIHUB_i$	**.86****** (13.71)	**0.40****** (6.56)	-0.07 (-0.63)	**1.01****** (8.53)
$CONHUB_i$	**1.53****** (16.84)	**0.41****** (4.74)	**0.37****** (2.75)	**1.63****** (7.86)
$DESTHUB_i$	**0.90****** (14.49)	**0.30****** (4.52)	0.06 (.59)	**1.05****** (8.9)
TIME	**-0.55****** (-52.1)	**-0.24****** (-13.6)	**-0.57****** (-24.8)	**-0.78****** (-45.8)
WIN_t	**0.46****** (12.61)	**0.14***** (2.08)	**0.60****** (7.86)	**0.64****** (11.47)
SPR_t	**0.25****** (6.67)	**0.13***** (1.96)	**0.17***** (2.14)	**0.38****** (6.83)
SUM_t	-0.05 (-1.43)	-0.08 (-1.13)	-0.01 (-0.07)	-0.07 (-1.26)

**p=0.1 level; ***p=0.05 level; ****p=0.01 level.

As time passes, the probability of code-sharing tends to decrease significantly in every scenario though the impact level is different. The odds of code-sharing decrease by 43% on a VCS route and by 22% on a TCS route as one more year passes.[14] This implies that alliance firms tend to end the virtual code-sharing more easily than the traditional one as time passes, which only makes sense since a VCS arrangement involves no actual deployment of resources to operate flights and thus is easier to enter or exit.

Finally, alliance firms tend to code-share in the winter and spring on TCS, VCS, TVCS routes and the pooled sample. Summer, as well, does not significantly affect any type of code-sharing. This is because code-sharing helps generate traffic in off-seasons such as winter, spring, and fall, whereas the travel demand is usually seasonally high in the summer, leading to smaller incentives to code-share.

CONCLUSIONS

Our empirical results show that code-sharing decisions are influenced by different factors for virtual (VCS) versus traditional (TCS) code-shared routes. The decision to engage in a traditional code-share arrangement is significantly influenced by average yield from previous period, slot controls, whether the route is a vacation route, and hub dominance at both the connecting and endpoint (origin and destination) airports. These same factors do not appear to be important determinants of the decision to engage in virtual code-sharing. While income and population were not found to be significant determinants of the decision to engage in traditional code-sharing, higher incomes and populations significantly lower the probability of virtual code-sharing. Finally, greater route concentration as measured by the Herfindahl Index significantly lowers the probability of code-sharing for both traditional and virtual code-shared routes.

Overall, these findings imply that virtual code-sharing tends to take place in less dense markets, which may not support many carriers or flights, in contrast to traditional code-sharing, which is undertaken to achieve the networking economics and cost savings derived from dense markets. These results support Ito and Lee's (2005, 2007) argument that virtual code-sharing is used by alliance firms as a generic or qualitatively inferior product to further segment customers between those who are willing to purchase the branded premium product (pure on-line ticket) and those who are not. VCS fares are generally lower than TCS fares and also lower than fares on routes where no code-sharing occurs (the operating carrier is the same as the ticketing carrier for the entire route). Thus, code-sharing may provide the airline a way to practice price discrimination on a flight to fill up seats without losing revenue by having to lower fares for all customers.

From the perspective of government agencies or policy makers, the distinction between traditional and virtual code-sharing may have important implications for policy. Virtual code-sharing takes place in less dense markets and is not significantly affected by yields, therefore does not appear to be a mechanism by which carriers compete with each other for market share but rather allows a carrier that is already providing service on a route to fill up planes in less dense markets. Traditional code-sharing seems to be more effective as an instrument by which competition is introduced into a market as higher yields in a market definitely increase the probability of such arrangements. However, the results here show that although code-sharing may help increase competition in markets by inducing entry when prices are high, such entry, either by traditional or virtual code-share arrangements, is significantly impeded by high market concentration on the route. Therefore, monitoring competitive conditions on the VCS routes to insure against the possible exercise of market power in the alliance carriers' hubs (or focus cities) are not as important as for the TCS routes, though government agencies should be alert for anti-competitive behavior on the part of market incumbents on highly concentrated TCS or VCS routes.

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Endnotes

1. For example, a virtual code-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 also occur on a direct flight itinerary if the operating carrier was CO or HP but the marketing carrier was HP or CO, respectively. If the operating carrier is Continental on both segments of an itinerary (CO: CO) but one segment of the ticket is sold by America West

while the other segment is sold by Continental (CO: HP or HP: CO), then the itinerary is called semi-virtually code-shared. Even though under virtual code-sharing, the marketing carrier does not receive any operating revenue other than a nominal commission, it benefits from a more frequent flight schedule due to its larger virtual network provided by the operating carrier.

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. All these three covariates $YLD_{it\text{-}1}$, $FRE_{it\text{-}1}$, and $RHHI_{it\text{-}1}$, are the moving averages in the past four quarters from *t-1* to *t-4* to smooth out the seasonal effect on these variables.

4. 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.

5. 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.

6. 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.

7. 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 $Y_{it} \mid b_i$ – – *Bernoulli*(π_{it}) where random effects b_i are assumed to be drawn independently from the *N (0, G)* and the responses Y_{it} of Y_i are independent with densities of an exponential distribution. The conditional means $E(Y_{it} \mid b_i)$ are given by $E(Y_{it} \mid b_i) = \dfrac{\exp(\beta_0 + b_i + \beta X)}{1 + \exp(\beta_0 + b_i + \beta X)}$ which can be rewritten as $\operatorname{log it}(\pi_{it}) = \log(\dfrac{\pi_{it}}{1-\pi_{it}}) = \beta_0 + b_i + \beta X$ where $\pi_{it} = P(Y_{it} = 1 \mid b_i, X)$, β_0 is the constant term, and β is a *p*-dimensional vector of unknown fixed regression coefficients, common to all subjects.

8. The density of an exponential distribution for Y_{it} takes the form as follows $f_i(y_{it} \mid b_i, \beta, \phi) = \exp\{\phi^{-1}[y_{it}\theta_{it} - \varphi(\theta_{it})] + c(y_{it}, \phi)\}$ with ϕ a scale parameter, i.e. $\eta(\mu_{it}) = x_{it}^{'}\beta + z_{it}^{'}b_i$ for a known link function η(.), 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 $f(b_i \mid G)$.

9. Standardized coefficients are the estimates resulting from an analysis performed on variables that have been standardized so that they have variances of 1. It is usually used to answer the question of which of the independent variables has a greater impact on the dependent variable in a multivariate regression analysis, when the variables are measured in different units of measurement.

10. On the TCS routes, the odds of code-sharing increase 98% for every increase of 0.1 dollar in the yield. The calculation is as follows: 1.98-1=0.98, in which 1.98 is the odds of code-sharing for the variable average yield ($YLD_{it\text{-}1}$). Please refer to the odds for different variables provided in Appendix Table A2. The calculation of odds for other variables follows the same way.

11. Please refer to Table A2 in the Appendix. For every increase of 1,000 in the value of HHI, the odds of code-sharing decrease by 4% on TCS routes (0.96-1 = -0.04 = -4%, in which 0.96 is the odds ratio of code-sharing for the variable $RHHI_{it-1}$) but only 0.01% on VCS routes. (0.9999 -1 = -0.0001 = -0.01%, in which 0.9999 is the odds ratio of code-sharing for the variable $RHHI_{it-1}$.)

12. See Table A2 in the Appendix. The odds ratio of code-sharing on a slot-controlled TCS route is only 0.55 times the odds on a TCS route without slot-control.

13. See Table A2 in the Appendix. On the TCS routes, the impact of the hub airports is smaller than in the pooled sample: the odds ratios of code-sharing when the origin, connecting, and destination airports are hubs (or focus cities) are 1.49, 1.50, and 1.34 times (compared with 2.35, 4.6, and 2.47 in the pooled sample) the probability of code-sharing when none of the airports is a hub (or focus city), respectively. By contrast, the odds ratio of code-sharing is 1.45 times the probability if the connecting airport is not a hub on the VCS route.

14. Please refer to the odds for different variables provided in Table A2 in the Appendix. The calculation is as follows: 0.57-1 = -0.43 = -43% and 0.78-1 = -0.22 = -22%, in which 0.57 and 0.78 are the odds ratios of code-sharing for the variable TIME on the VCS and TCS routes, respectively.

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APPENDIX

Table A1: 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

***Lists of Airport Abbreviations and the Full Names**

Abbr.	Full Name
DFW	Dallas-Fort Worth International Airport
ORD	Chicago O'Hare International Airport
MIA	Miami International Airport
STL	Lambert-St. Louis International Airport
SJU	Luis Munoz Marin International Airport in Puerto Rico.
JFK	John F. Kennedy International Airport
LGA	LaGuardia Airport
BOS	Boston Logan International Airport
LAX	Los Angeles International Airport
RDU	Raleigh-Durham International Airport
SEA	Seattle-Tacoma International Airport
ANC	Ted Stevens Anchorage International Airport
PDX	Portland International Airport
SFO	San Francisco International Airport
IAH	Houston George Bush Intercontinental Airport
EWR	Newark Liberty International Airport
CLE	Cleveland Hopkins International Airport
ATL	Hartsfield-Jackson Atlanta International Airport
SLC	Salt Lake City International Airport
CVG	Cincinnati/Northern Kentucky International Airport
MCO	Orlando International Airport
DTW	Detroit Metropolitan Airport
MSP	Minneapolis-Saint Paul International Airport
MEM	Memphis International Airport
IND	Indianapolis International Airport
HNL	Honolulu International Airport
DEN	Denver International Airport
IAD	Washington Dulles International Airport
CLT	Charlotte Douglas International Airport
PHL	Philadelphia International Airport
PHX	Phoenix Sky Harbor International Airport
LAS	McCarran International Airport
DCA	Ronald Reagan Washington National Airport
PIT	Pittsburgh International Airport
MDW	Chicago Midway Airport
OAK	Oakland International Airport
BWI	Baltimore/Washington International Thurgood Marshall Airport
HOU	Houston George Bush Intercontinental Airport
DAL	Dallas Love Field Airport
MCO	Orlando International Airport
SAN	San Diego International Airport
FLL	Fort Lauderdale-Hollywood International Airport

Table A2: Comparison of GLIMM Regression Results in Different Scenarios (on Pooled, TCS, VCS or TVCS Routes)

Pooled Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
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
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
Odds Ratio	0.35	1.03[a]	4.21[b]	0.84[c]	1.08[d]	1.23[e]	1.58	1.28	0.95	0.58	0.28	0.76	1.55	2.35	4.60	2.47
-2 Residual log Pseudo-Likelihood			290149.5			Generalized Chi-Square/ DF				0.89						
TCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
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
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
Odds Ratio	0.21	1.02[a]	1.98[b]	0.96[c]	0.97[d]	1.08[e]	1.15	1.14	0.92	0.78	0.55	0.94	1.11	1.49	1.50	1.34
-2 Residual log Pseudo-Likelihood			119904.1			Generalized Chi-Square/ DF				0.93						
VCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
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**
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**
Odds Ratio	12.25	1.00[a]	1.12[b]	0.9999[c]	0.68[d]	0.72[e]	1.83	1.19	0.99	0.57	1.06	0.95	1.06	0.94	1.45	1.06
-2 Residual log Pseudo-Likelihood			86237.4			Generalized Chi-Square/ DF				0.76						
TVCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
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
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
Odds Ratio	0.43	1.08[a]	14.01[b]	0.95[c]	1.51[d]	1.22[e]	1.90	1.47	0.93	0.46	0.13	0.56	1.17	2.74	5.12	2.86
-2 Residual log Pseudo-Likelihood			83275.4			Generalized Chi-Square/ DF				0.87						

a. Odds ratio for a 100 unit increase in the booking frequencies;
b. Odds ratio for a 1/10 unit increase in the yield;
c. Odds ratio for a 1000 unit increase in the route HHI;
d. Odds ratio for a 1.0E+06 unit increase in the income;
e. Odds ratio for a 1.0E+10 unit increase in the population.

Table A3: Standardized Coefficients from GLIMM Regression in Different Scenarios (Pooled, TCS, VCS and TVCS Routes)

Pooled Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	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
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
TCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	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**
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**
VCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	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
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
TVCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	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**
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**

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