

Analysis of Airline Alliance Member's Code-sharing Cooperation

by

Ge Gao

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I.H. Asper School of Business

University of Manitoba

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Abstract

Strategic alliance is an important cooperation approach in which firms share resources to obtain strategic advantages while remaining separate entities. In the airline industry, there exist two kinds of common strategic alliance, namely airline alliance, and code-sharing. The airline alliance is the most popular form of multilateral strategic alliance while the code-sharing is commonly adopted for bilateral strategic alliance. This thesis focuses on airline alliance member's code-sharing partnership. To be more specific, we explore factors that influence airline alliance member's choice of code-sharing pattern (codeshare with an airline inside the airline alliance or with an airline outside the airline alliance) and the relationships among contingency factors (firm size, operating scope and duration of alliance membership), code-sharing, and airline performance. To achieve the aims, we first examine the factors that influence the number of airline alliance members' code-sharing inside and outside the airline alliance by employing multivariate multiple regression. The empirical results indicate that the duration of airline alliance membership and the number of destinations are significant factors. The results also identify that the three airline alliances are not statistically different in terms of the number of their members' code-sharing partnerships inside the alliance. Second, based on contingency theory, structural equation modeling is used to verify the hypothetical relationships among contingency factors, code-sharing and airline performance proposed in this study. The results show that firm size and the duration of airline alliance membership positively influence the number of code-sharing partners and airline performance. Code-sharing also has a positive influence on airline performance. Furthermore, the results reveal that partial mediation

effects of code-sharing occur from firm size to airline performance and duration of airline alliance membership to airline performance.

Keywords: Strategic alliance, Code-sharing, Multivariate multiple regression, Structural equation modeling, Contingency theory

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Chapter 1 Introduction

Strategic alliances have been a widely used form of cooperation among firms in many industries. In the airline industry, code-sharing is the most common form of bilateral cooperation between airlines (Min and Joo, 2016). In the past few decades, multilateral strategic alliances have emerged globally in the airline industry. An airline alliance is an organization formed by several airlines to cooperate on a substantial level in the global aviation industry. Today, the three global airline alliances: Star, SkyTeam and oneworld have dominance in the airline business, together occupying a share of about 70% in worldwide revenue passenger kilometers (Jiang et al., 2015).

Historically, Wings Alliance, established by Northwest Airlines, Continental Airlines, KLM and Alitalia in 1989, was the first global airline alliance. In 1997, Star Alliance was founded by Lufthansa, Air Canada, SAS, United, and Thai Airways. In 1998, American Airlines, Canadian Airlines, British Airways, Cathay Pacific and Qantas united together to build oneworld alliance. In 2000, SkyTeam Alliance was formed by five core members, including Delta, CSA, Air France, Aeromexico, and Korean Air. By 2004, when most of its members joined SkyTeam, Wings Alliance was extinct. However, Star, oneworld, and SkyTeam continued their expansion steps, actively trying to recruit new members.

Nowadays, almost all major airlines belong to one of the three airline alliances (see Appendix A for a list of the current members of the three airline alliances). The global airline alliance is a significant driving force in getting at least a limited form of multilateral cooperation. By joining an airline alliance, airlines can improve their operating efficiency

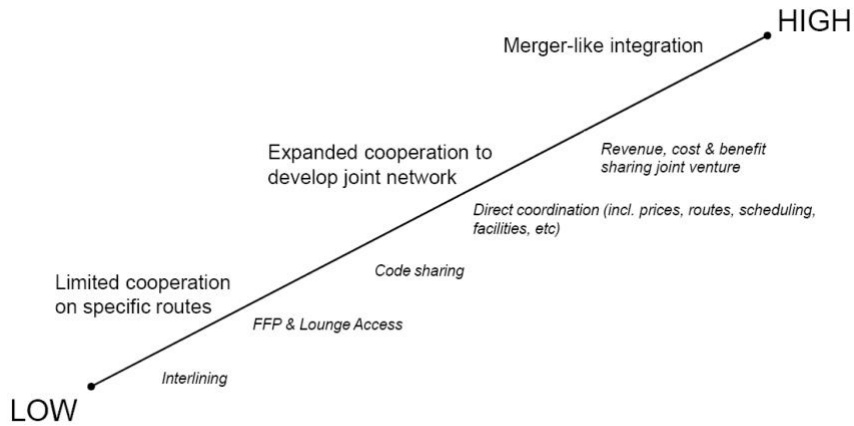
and reduce their expenses by cutting back on fixed costs. Alliance members also share airport facilities and ground handling arrangements and staff.

There are many different cooperation styles in airline alliances. As shown in Figure 1.1, the spectrum of cooperation by alliance partners is wide, ranging from basic arrangements such as interlining¹ and frequent-flyer programs² (FFP) to highly combined joint ventures (JVs). One common characteristic of collaboration among members of an airline alliance is the code-sharing agreement, which allows an airline to market flights operated by partner airlines using its own code as shown in its published timetable. These code-sharing agreements provide a way of avoiding the route authority restriction, allowing airlines to build partnerships with other airlines to provide service to destinations they cannot reach. An airline usually lacks the ability to provide a direct route relying on its own aircraft. The main reason is not carrier capacity but rather lack of route authority. Goh and Yong (2006) point out that airlines can enjoy both economies of density and economies of scale and scope by joining an airline alliance since the reach of their networks is extended by code-sharing.

¹ Interlining means that one carrier accepts passengers holding tickets sold by other carriers.

² A frequent-flyer program is a loyalty program offered by an airline which is essentially a rebate made after the purchase of a certain amount of air service. It is a popular approach to tie a customer to a particular airline or a group of airlines.

Figure 1.1 Spectrum of airline alliance cooperation



Source: European Commission and U.S. Department of Transportation (2010)

In this thesis, we focus on airline alliance members' code-sharing partnerships. Basically, for an airline who joined an airline alliance, it can codeshare with an airline in the same alliance or with an airline belongs to other alliances or with an airline did not join any airline alliance. In other words, airline alliance members have two code-sharing patterns: codeshare with an airline inside the airline alliance or codeshare with an airline outside the airline alliance. It is unknown that how airline alliance membership and code-sharing partnerships are linked with each other. We want to have a better understanding of what factors will influence the choice of code-sharing pattern for an airline alliance member. In chapter 3, the multivariate multiple regression model is used to analyze which factors may influence the three global airline alliance members' code-sharing partnerships inside and outside the alliance.

Although the literature tends to support that code-sharing agreement is beneficial for airline

performance, it remains unclear what factors influence an airline alliance member to codeshare with other airlines. Based on contingency theory, the contingency factors in this study include firm size, operating scope and duration of airline alliance membership. In chapter 4, we study the relationships among these contingency factors, code-sharing and airline performance by constructing a structural equation model. Two research questions we aim to answer in chapter 4 are: first, to understand the influence of contingency factors on the number of code-sharing partners and airline performance; second, does code-sharing mediate the relationships between contingency factors and airline performance.

The remaining thesis is organized as follows: Chapter 2 reviews the previous literature on strategic alliance, airline alliance, code-sharing, and contingency theory. In chapter 3, we introduce methodologies we used in chapter 4 and chapter 5. Chapter 4 employs the multivariate multiple regressions to explore factors influencing the three global airline alliance members' code-sharing partnerships inside and outside the alliance. In chapter 5, structural equation modeling approach is used to the relationships among contingency factors, code-sharing, and airline performance. Finally, summary, conclusions, contributions and limitations can be found in chapter 6.

Chapter 2 Literature Review

2.1 Strategic Alliance

A strategic alliance forms when two or more firms share resources and cooperate to pursue a set of agreed upon business objectives (Johnson et al., 2008). Strategic alliances are dedicated resource exchange agreements between firms (Stuart, 1998). Goetz and Shapiro (2012) define strategic alliances as “any voluntary partnership that represents neither a simple transactional relationship nor a significant structural merging of the entities”. Gulati (1995) points out that the purpose of forming alliances among organizations is to satisfy the need for crucial strategic interdependence. When firms intend to form strategic alliances, attributes should be usually considered are firm size, age, scope, and resources etc. Besides, the external environment also influences the formation of strategic alliance. Famous firms with prestige and plentiful resources can usually take an advantage in alliance negotiations. Prestige is typically measured by indicators such as firm size and financial performance (Stuart, 1998; Cialdini, 1989).

The benefits of entering a strategic alliance are widely discussed. Galaskiewicz (1985) asserted that firms join strategic alliances to access new resources which they do not have. Similarly, Das and Teng (2000) assert that the obvious advantage of strategic alliances is to gain precise resources that are needed, with minimum superfluity. Other benefits of alliances include entering new markets, sharing cost and risk, and coordinating capabilities and activities (Hagedoorn and Schakenrad, 1990; Harrigan, 1988; Mody, 1993). Williamson (1991) point out that strategic alliances are favoured by many organizations

because they can get more resources while remaining independent.

In the airline industry, code-sharing is one of the most popular and common ways of strategic alliances. Multilateral strategic alliances in the airline industry are global airline alliances. In this research, multilateral strategic alliances refer to three global airline alliances: Star, SkyTeam and oneworld.

2.2 Airline Alliance

Since airline alliance is an important form of multilateral cooperation among airlines, a number of studies have focused on this topic. Despite numerous studies in this topic, interest has not faded away. Most of the previous studies pay attention to the operational and strategic influences of airline alliances. Park and Zhang (1998) study the effects of airline alliances on aligned airlines' traffic. Their results show that most of the airlines have greater traffic increases on their alliance routes compared to non-alliance routes, implying that an airline failing to embrace the ongoing alliance formation could be harming its market share and profitability. Brueckner (2001) studies the effect of global airline alliances on traffic levels, fares, and welfare. He finds that alliances have many positive effects which can offset any negative impacts.

Iatrou and Alamdari (2005) analyze the impact of airline alliances on airline operations and they conclude that alliance members get substantial benefits from alliances no matter what form of cooperation they make with partners. Their results indicate that passenger volume and load factors increase and costs decline after joining an airline alliance. Therefore, airline alliances can improve airlines' revenue. Gagnepain and Marín (2010) create an

empirical model of global airline alliances to study whether one alliance member's network has a substitutional or complementary relationship with another alliance member's network. Their results show that many airline alliance members' networks are potential substitutes. They also examine the effects of alliances on airlines' prices and costs, and find, on average, airlines enjoy a cost reduction and passenger increase after joining the alliance. Gaggero and Bartolini (2012) investigate determinants of airline alliances and they find out that passenger volume has a positive impact on an airline's probability of joining an alliance. Chung and Feng (2016) point out that joining an airline alliance will increase an airline's brand awareness. For local dominant carriers, joining an alliance will not only strengthen their brand locally but also enable them to exploit foreign markets.

On the other hand, some researchers also suggest that there might be potential risk embedded in airline alliances. Gudmundsson and Rhoades (2001) use Rhoades-Lush typologies to classify airline alliances and show that alliances including marketing activities and joint purchasing had a lower risk of cessation than alliances involving equity. Moreover, they report that alliances spanning more than two typologies showed a lower risk of cessation than one and two typology alliances. Min and Joo (2016) find that an airline's comparative operating efficiency may not necessarily be improved by joining an airline alliance. In addition, smaller alliances such as oneworld and SkyTeam may perform better than larger alliances such as Star Alliance on airline efficiency because the assimilation process of larger alliances will be more time-consuming. Kottas and Madas (2018) implement a data envelopment analysis (DEA) to assess the effect of airline alliance membership on airline efficiency. The results suggest that alliance membership is not

related to superior airline efficiency.

2.3 Code-sharing agreement

The code-sharing arrangement grew very quickly in the US domestic airline market after the airline deregulation in 1978 and it spread to international airlines in the late 1980s (Dresner, 2010). Goetz and Shapiro (2012) find that airlines form code-sharing in response to the threat of entry. By using a within-segment, fixed-effects linear probability estimator, they estimate that when an airline's segment is eroded by a low-cost entrant, its possibility to codeshare with its partner is improved by 25 percent.

There has been plenty of research analyzing the effects of code-sharing on airline performance. Zou and Chen (2017) study the effect of code-sharing on airline profitability. Their results indicate that the profit margin of an airline had a positive relationship with its number of code-sharing partners. Moreover, an airline's profit margin from code-sharing increases if it has a higher percentage of code-sharing partnerships with aligned airlines. Yimga (2017; 2018) measures the effects of code-sharing on partners' on-time performance, concluding that code-sharing can improve alliance partners' on-time performance. Cho et al. (2007) find positive effects of code-sharing agreements on overall revenues, suggesting that airlines can improve performance by using code-sharing as a strategic tool.

Code-sharing also has an impact on airfares. Brueckner (2003) finds that airfares are reduced by 8 to 17 percent if carriers have code-sharing agreements on an international interline itinerary. Ito and Lee (2007) find that the average airfare of code-sharing flights

is lower than the average airfare of flights without code-sharing. Goetz and Shapiro (2012) report similar findings and they suggest that the reason is that code-sharing may indeed improve network efficiencies. Hassin and Shy (2004) study the effect of code-sharing on airfares, market shares, profits, and passengers' welfare. The results reveal that code sharing is a Pareto improvement³.

Seredyński et al. (2017) study the codeshare connectivity of airlines from the three global airline alliances. They find that more than 25 percent of the entire potential code-sharing connections between aligned airlines remain unutilized. They indicate that although airline alliances promote code-sharing cooperation between their members, an airline will not sign code-sharing agreements with all other alliance members or give up partnerships with non-aligned airlines and airlines from competing alliances.

2.4 Contingency theory

The contingency theory of organizations is one of the main theoretical lens used to study organizations. It provides many insights and has considerable empirical support. The essence of the contingency theory is that the effectiveness of an organization stems from fitting characteristics of the organization. The name of contingency theory comes from the conclusion that there is no best form or strategy to organize for an organization, but it is contingent on the internal and external situation which the organization encounters

³ A Pareto improvement occurs when an economic action increases welfare without making anyone be worse off.

(Lawrence and Lorsch, 1967). Contingencies mainly include organizational size (Child, 1975), the environmental change (Burns and Stalker, 1981), and organizational strategy (Chandler, 1990).

The theory asserts that the performance of an organization is determined by how well they adapt to the environments and that organizational structures and strategies are the contingent actions of how organizations take reaction to changes in their environment (Alexander, 2014). In terms of strategic alliances, alliances can be regarded as new types of organizational structure that firms use as strategies to respond to the environmental risks they encounter (Muthoka and Kilika, 2016).

The contingency theory mainly focuses on organization effectiveness because it has been concerned to explain the success or failure of an organization (Donaldson, 2001). However, organizational effectiveness has a broad spectrum, including efficiency, profitability, innovation rate and employee satisfaction. Organizational effectiveness means the ability to reach the goals set by itself (Parsons, 1956) or by the ability to operate well as a system (Yuchtman and Seashore, 1967) and it is a similar concept with performance (Donaldson, 2011). The core concept of contingency theory is fit. Contingency theory holds that if the organizational structure fits the contingency, higher performance results (Donaldson, 2001). In other words, fit will positively influence performance.

Contingency theory has been adopted to study operation management in many topics, such as manufacturing strategy (Schroeder et al., 2011), buyer-supplier relationship (Narayanan et al., 2015), performance measurement (Rejc, 2004) and capacity planning (Tenhiälä,

2011). Especially, in OM researches, contingency theory is mostly used for the study of quality management and performance improvement (Larson and Foropon, 2018). Zhao et al. (2004) identify that some contextual factors which include geographic scope of operation, organizational size, and environmental uncertainty will influence the organizations choice of quality systems. Sila (2007) employ contingency theory and institutional theory to explore the impact of contextual factors on the application of total quality management (TQM). The contingency factors they study are company size and scope of operations. These factors also can apply to the airline industry, where company size can represent by fleet size and scope of operations refers to geographic reach (i.e. the number of destinations). Jayaram et al. (2010) design a culture-quality system design-outcomes framework for TQM implementation to study the differences in total effects relationships among TQM constructs across four contingencies: firm size, industry type, degree of unionization and TQM duration. The measurement of manufacturing performance is another area can apply contingency theory. Taylor and Taylor (2014) investigate the influence of firm size on the implementation of performance measurement system. They found that size affects the efficiency of performance measurement system.

In summary, important contingency factors involve in OM include organization size, geographic scope of operations, duration, environmental uncertainty, and industry type.

The contingency theory also has been applied in the empirical strategic alliance study especially the alliance networks. There are several studies reveal that the effect of an organization' alliance portfolio on performance relies on some contextual factors, including, firm nationality (Koka and Prescott, 2002), market conditions (Gulati and

Higgins, 2003), growth stage (Hite and Hesterly, 2001) and organizational structure (Geletkanycz et al., 2001).

However, very few research in transportation adopted contingency theory (e.g. Mockler, 1997). In chapter 5, we will apply the contingency theory to the airline industry to study airline strategic alliance and airline performance. We believe this is the first time to apply contingency theory in research related to the code-sharing cooperation.

Chapter 3 Methodology

The methodologies adopted in this thesis are all quantitative. In chapter 4, we conduct a multivariate multiple regression analysis to explore factors that influence the three global airline alliance members' code-sharing partnerships inside and outside the airline alliance. In Chapter 5, we used structural equation modeling to study the relationships among contingency factors, code-sharing, and airline performance.

3.1 Multivariate multiple regression

Multivariate multiple regression (MMR) analysis is widely used to relate a set of independent variables and a group of dependent variables in many different areas due to its simplicity. MMR is multivariate because the model contains more than one dependent variables. MMR is multiple because the model contains more than one independent variables. The multiple regression model is linear in the parameters:

$$y_i = \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + \varepsilon_i ; i = 1, \dots, n.$$

In the above equation, y_i are the dependent variables, x_{ki} are the independent variables, β_k are coefficients, ε_i are error terms. The difference of multivariate multiple regression model with multiple regression model is that the former has more than more dependent variables.

In multivariate multiple regression analysis, there are typically many independent variables as initial inputs. Some of the independent variables may not contribute to the dependent variables. Therefore, variable selection is often performed. The backward stepwise

regression process is a popular way to identify the significant variables to be retained in the model (Montgomery et al., 2012). In practice, the backward stepwise regression selection begins with including all independent variables in the model, and then iteratively removes the unqualified independent variables which with the largest p-value in the sense those variables have no contribution to the dependent variables, one-at-a-time.

The multivariate multiple regression model usually suffers from some statistical problems such as multicollinearity and heteroscedastic errors. Therefore, we should test if these problems in the estimated model and fix them if these problems exist.

Multicollinearity is a phenomenon when one or more independent variables can be expressed or roughly expressed as the linear combinations of other independent variables. Multicollinearity arises from many different causes, such as small sample-to-variable ratio, and collinearity between different variables. As the result of multicollinearity, the regression coefficients become highly variable (even sign changes of the regression coefficients), the standard errors may be high, or over-fitting might be an issue. A number of methods can be used to reduce the negative effects of multicollinearity, such as principal component analysis (PCA) regression and ridge regression (Montgomery et al., 2012). Or multicollinearity can be eliminated by just removing redundant variables. Variance inflation factor (VIF) is one commonly used statistic to determine the severity of multicollinearity among the independent variables although there are many other quantities or methods can be used, such as condition number, or principal component analysis. Various recommendations for acceptable levels of VIF can be found in the literature. Perhaps most commonly, a value of 10 has been suggested as the maximum level of VIF

(Hair et al., 1998; Montgomery et al., 2012; Wooldridge, 2015). However, a recommended maximum VIF value of 5 (e.g., Akinwand et al., 2015) can be found in the literature. A VIF exceeds 5 indicates high correlation that could be problematic.

In a linear regression model, the errors have been assumed to be identically distributed, or in other words, the errors are homoscedastic. However, in practice, the errors are often heteroscedastic. Heteroscedasticity can render the statistics used to test hypotheses under the Gauss-Markov assumptions invalid. The OLS estimators, under the heteroscedastic errors, are not unbiased anymore (Wooldridge, 2015). Heteroskedasticity can cause faulty inferences and inefficient parameter estimates (White, 1980). Therefore, we should make sure the error terms of the model are homoscedastic. The White method is a test which has been extremely widely used for heteroscedasticity in OLS residuals. The null hypothesis of the White test is the variances for the errors are equal which means heteroscedasticity absent and the alternative hypothesis of the White test is the variances are not equal which means heteroscedasticity present.

In chapter 4, after constructing the multivariate multiple regression model, we will use VIF to test for the multicollinearity and White test to find out whether heteroscedasticity exists.

3.2 Structural Equation Modeling

3.2.1 The feature of structural equation modeling

Structural equation modeling (SEM) is a comprehensive statistical technique which integrates characteristics of confirmatory factor analysis (CFA), path analysis and structural regression models. The main feature of SEM is that it can combine both observed

and latent variables into the process of one analysis. A latent variable is not observable directly and it has to be measured by several explicit indicators which can be observed directly. In the research of chapter 5, airline performance is a latent variable which uses multiple indicator variables to represent.

The main advantage of SEM is that it can be used to study research questions involving the observed and latent observation of one or more independent variables or one or more dependent variables. The main goal of SEM is to establish and validate a proposed model. We use goodness of fit statistics to measure whether the model we build is appropriate or need further revision.

3.2.2 SEM procedure

Usually, there are two steps for the SEM procedure. The first step involves the confirmatory factor analysis (CFA) which is also known within SEM as the measurement model and the second step concerns the building of structural equation model (Anderson and Gerbing, 1988). Firstly, we conduct a confirmatory factor analysis (CFA) for the latent variable. Since there are several indicators to measure the latent variable, we need to assess convergent and discriminant validity. Secondly, we construct a structural equation model to investigate the relationships among variables.

3.2.3 Confirmatory factor analysis

Confirmatory factor analysis (CFA) is a multivariate statistical technique that is used to determine the degree of model fit and the choice of explanatory indicators for the measurement model (Gallagher and Brown, 2013). Actually, it is a special case of

structural equation modeling which focuses on the modeling relationships between observed indicators and the corresponding latent variable.

After building the measurement model, the next step is to examine the reliability and validity of the measurement model. If the reliability and validity are all satisfactory, the choice of explanatory indicators is acceptable.

3.2.4 Path analysis

Path Analysis is the application of SEM without latent variables. One of the advantages of path analysis is that it contains the relationships among all the variables that act as predictors in one model (Webley and Lea, 1997). Another advantage of path analysis is that it is a very intuitive and efficient way to assess mediation.

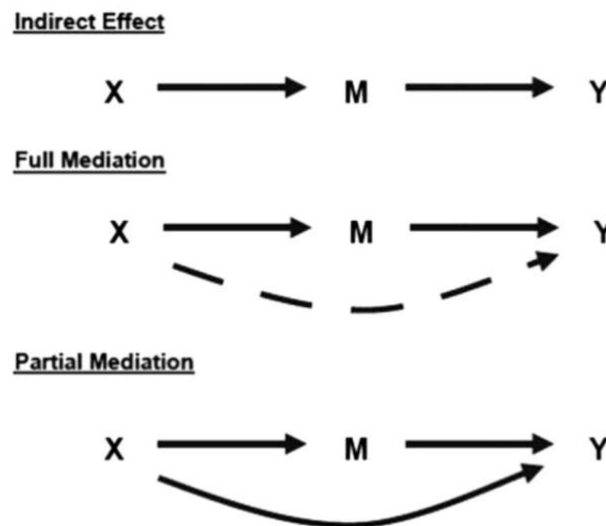
To construct a path diagram, we draw an arrow from one variable to any other variable based on the hypothesized relationships. An output path diagram illustrates the results of a statistical analysis, from which we can find the real relationships between two variables.

3.2.5 Mediation analysis

Another important analysis involved in SEM is mediation effect analysis. Mediation refers to “the transmission of the effect of an independent variable on a dependent variable through one or more other variables” (Mathieu and Taylor, 2006). Therefore, a mediator can explain the underlying mechanism of the relationship between an independent variable on a dependent variable. When a mediator exists between two variables, three conditions can happen as follows (see Figure 3.1):

1. Indirect effect: If the effect of X on M and the effect of M on Y are both statistically significant but the relationship between X and Y does not exist, then the indirect effect exists.
2. Full mediation: If the effect of X on M and the effect of M on Y are both statistically significant but the effect of X on Y is not statistically significant, then the full mediation exists.
3. Partial mediation: If the effect of X on M, the effect of X on Y and the effect of M on Y are all statistically significant, the partial mediation exists.

Figure 3.1 The comparison of indirect effect with full and partial mediation effects

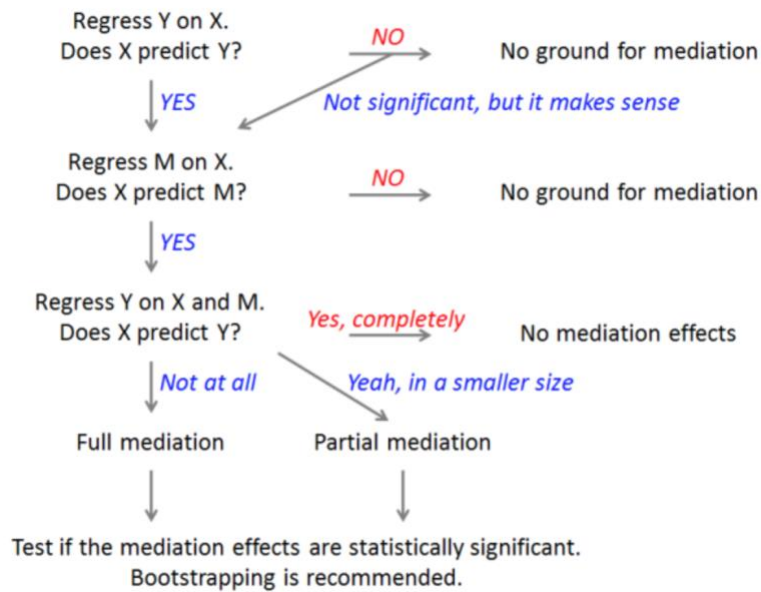


Source: Mathieu and Taylor (2006)

Bootstrapping is a popular method of examining the indirect effects (see, Mackinnon et al., 2002; Shrout and Bolger, 2002). It is a resampling method with replacing samples many times, e.g., 5000 times. A sampling distribution can be empirically produced by computing the indirect effect of each of the samples. Usually a bias-corrected bootstrapping test with

5000 bootstrap samples is performed to investigate the indirect effects, with 95% confidence intervals. If the indirect effect is significant, and zero is not in the confidence interval, then we can be confident that the indirect effect is different from zero (Cheung and Lau, 2008), which means the effect is either fully or partially mediated through a factor. The process of mediation analysis is summarized in Figure 3.2.

Figure 3.2 The flowchart for mediation analysis



Source: Bommae Kim (2016)

Chapter 4 Exploring Factors Influencing the Three Global Airline Alliance

Members' Code-sharing Partnerships Inside and Outside the Airline Alliance

4.1 Introduction

Code-sharing agreement is the most common cooperation way among airline alliance members, however, code-sharing agreements are not limited within airline alliance members. Code-sharing can happen between any two airlines, no matter whether these two airlines are in the same airline alliance or not. For an airline which is an airline alliance membership, it can codeshare with airlines in the same airline alliance or codeshare with airlines outside the airline alliance. The reciprocal code-sharing cooperation is beneficial to revenue growth and cost savings for many airlines, whether carriers are in the same alliance or not. Therefore, although airlines are encouraged to forge close partnerships with members of the alliance, they also have the motivation to acquire and sustain partnerships with non-alliance airlines or even with opponent alliance members (Zou and Chen, 2017). That said, it is well known that after joining a global alliance, an airline has to accept the alliance's regulations and make some compromises. For example, Gerlach et al. (2016) point out that alliances increase the intricacy of airline's planning, causing a negative impact on performance. When it comes to bilateral cooperation between airlines, it is commonly believed that the three airline alliances have different attitudes about their members pursuing partnerships with other airlines outside the alliance. Among the three global alliances, Star puts tough restrictions on allowing members to pursue partnerships with airlines outside the alliance. New members can sustain partnerships with airlines outside the alliance before joining the alliance; however, new partnerships outside the

alliance must be approved. oneworld is the loosest of the three alliances and is regarded as the most flexible alliance in terms of outside cooperation (Airline Leader, 2016). In general, SkyTeam and oneworld do not interfere in such partnerships while Star has adopted a more defensive posture.

Although alliance members can gain many benefits from the alliance, they have to accept the alliance's regulations and make some compromises. Gerlach et al. (2016) point out that alliances increase the intricacy of airline's planning, causing a negative impact on performance. When it comes to bilateral cooperation between airlines, the three airline alliances have different attitudes about their members pursuing partnerships with other airlines outside the alliance. Among the three global alliances, Star puts tough restrictions on allowing members to pursue partnerships with airlines outside the alliance. New members can sustain partnerships with airlines outside the alliance before joining the alliance; however, new partnerships outside the alliance must be approved. oneworld is the loosest of the three alliances and is regarded as the most flexible alliance in terms of outside cooperation (Airline Leader, 2016). In general, SkyTeam and oneworld do not interfere in such partnerships while Star has adopted a more defensive posture. However, whether the difference in management features of airline alliance is an important factor that can influence airline alliance members' partnerships inside and outside the alliance is still unknown.

It is thus natural to question how airline alliance membership and code-sharing partnerships are linked with each other. It is worthwhile to investigate whether an airline tends to codeshare more with the same alliance members and less with other airlines after it joins a

particular alliance. It is also relevant to study whether there is a substantial difference in terms of code-sharing partnerships among members of the three global alliances. To answer these questions, we conduct a multivariate multiple regression model to explore factors that influence the three global airline alliance members' code-sharing partnerships inside and outside the airline alliance.

4.2 Data

Secondary data, gathered and published by *Airline Leader* (Issue 36, 2016), is used in this study. This is cross-sectional data based on observations in late August 2016. LATAM is removed from the dataset because it is formed by two airlines: LATAM Chile and LATAM Brasil⁴. Unlike other airlines, this creates two values for one variable. The sample size is 61, including 28 airlines in the Star Alliance, 20 airlines belonging to SkyTeam and 13 airlines in the oneworld alliance.

The number of code-sharing partners an airline has inside and outside the alliance is an indicator of an airline's partnership activities. Therefore, the number of code-sharing partners an airline has, inside and outside an alliance, creates two dependent variables. The explanatory variables include the duration of airline alliance membership, domestic seats, destinations, fleet size and passenger volume. Since there are three airline alliances, two dummy variables are created. A third dummy variable is used to account for private versus

⁴ Chile's LAN Airlines and Brazil's TAM Airlines were two airlines before. In 2012, LATAM was founded as a result of merger between LAN and TAM.

government ownership of an airline. Finally, a fourth dummy indicates whether an airline is a listed company or not. We estimate that the number of airline alliance members' code-sharing partnerships inside and outside the alliance might be influenced by these explanatory variables. Next, we will build multivariate multiple regression models to test these variables.

Table 4.1 Variable Descriptions

Variable	Explanation
Duration	Duration of airline alliance membership in years
Destinations ⁵	The number of passenger destinations of an airline
Domestic seat	The percentage of domestic market share
Fleet size	Number of aircraft
Pax	Passenger volume (measured by passenger number per year)
Alliance1	Dummy variable (1= SkyTeam; 0= not SkyTeam)
Alliance2	Dummy variable (1= oneworld; 0= not oneworld)
Ownership	Dummy variable (1= privately owned; 0= government owned)
List	Dummy variable (1= listed; 0= not listed)
CSI	The number of code-sharing partners inside the alliance
CSO	The number of code-sharing partners outside the alliance

4.3 Model Specification and Data Analysis

⁵ It refers to destinations operated by airlines' own aircraft, excluding destinations from code-sharing agreement.

In this study, multivariate multiple regression is adopted to build a model between a set of variables in the airline industry and two dependent variables (codeshare inside the alliance and codeshare outside the alliance) to test whether the independent variables have similar or disparate effects on the dependent variables. The models are represented by the following equations:

$$CSI_i = \beta_0 + \beta_1 Duration_i + \beta_2 Destination_i + \beta_3 Domestic\ seat_i + \beta_4 Fleet\ size_i + \beta_5 Alliance1_i + \beta_6 Alliance2_i + \beta_7 Ownership_i + \beta_8 List_i + \varepsilon_i ; i=1,2,\dots,61 \quad (1)$$

$$CSO_i = \beta_0 + \beta_1 Duration_i + \beta_2 Destination_i + \beta_3 Domestic\ seat_i + \beta_4 Fleet\ size_i + \beta_5 Alliance1_i + \beta_6 Alliance2_i + \beta_7 Ownership_i + \beta_8 List_i + \varepsilon_i ; i=1,2,\dots,61 \quad (2)$$

Written more concisely, the model can be expressed, using matrix notation, as follows

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (3)$$

Where⁶,

$$\mathbf{Y}_{n \times 2} = \begin{bmatrix} y_{11} & y_{21} \\ y_{12} & y_{22} \\ \vdots & \vdots \\ y_{1n} & y_{2n} \end{bmatrix} \quad (4)$$

⁶ $y_{1n} = CSI_i; y_{2n} = CSO_i; x_{1n} = Duration_i; x_{2n} = Destination_i; x_{3n} = Domestic\ seat_i; x_{4n} = Fleet\ size_i; \dots; x_{8n} = List_i (n = 61)$

$$\boldsymbol{\beta}_{9 \times 2} = \begin{bmatrix} \beta_{10} & \beta_{20} \\ \beta_{11} & \beta_{21} \\ \vdots & \vdots \\ \beta_{18} & \beta_{28} \end{bmatrix} \quad (5)$$

$$\mathbf{X}_{n \times 9} = \begin{bmatrix} 1 & x_{11} & x_{21} & \cdots & x_{k1} \\ 1 & x_{12} & x_{22} & \cdots & x_{k2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1n} & x_{2n} & \cdots & x_{kn} \end{bmatrix} \quad (6)$$

$$\boldsymbol{\varepsilon}_{n \times 2} = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{21} \\ \varepsilon_{12} & \varepsilon_{22} \\ \vdots & \vdots \\ \varepsilon_{1n} & \varepsilon_{2n} \end{bmatrix} \quad (7)$$

In this model, it has been assumed that \mathbf{X} has no errors. The errors are only in \mathbf{Y} and i.i.d. (independent and identically distributed) normal. Base on the least square method or the principle of maximum likelihood estimation, the regression coefficients can be estimated by

$$\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad (8)$$

We conduct the backward stepwise regression selection to choose which independent variables should be retained in the model and which independent variables should be removed from the model. The removing criterion in this work is set to p-value ≥ 0.15 . After removing all the ineligible independent variables, the remaining independent variables in the model are *Duration*, *Destination*, *Fleet size*, *Alliance 1* and *Alliance 2*.

Another commonly encountered issue is the multicollinearity of the independent variables. VIF can be used to test if the multicollinearity exists or not. As we mentioned early, a VIF

exceeds 5 indicates high correlation that could be problematic.

Table 4.2 The outcome of VIF

Variable	VIF	1/VIF
<i>Destination</i>	5.54	0.1804
<i>Fleet size</i>	5.27	0.1896
<i>Alliance1</i>	1.21	0.8260
<i>Duration</i>	1.19	0.8388
<i>Alliance2</i>	1.17	0.8566
Mean VIF	2.88	

In this work, the VIF was used. The table above shows that all VIF values are less than 10. However, VIFs for *Destination* and *Fleet size* are over 5, which means the correlation between *Destination* and *Fleet size* is high, causing multicollinearity. Therefore, one of the correlated variables should be removed. To decide which variable should be eliminated, we drop *Destination* and *Fleet size* separately from the model. Finally, we decide to take *Fleet size* out of the model.

To identify whether the model suffer from heteroscedasticity, we perform the White test for heteroscedasticity. The null hypothesis of the White test is that the errors are homoscedastic. Results of the White test (P-value = 0.0284 < 0.05) show that the equation (2) suffers from heteroscedasticity.

Due to the existence of heteroscedastic errors, a robust method was used in this work. The use of robust standard errors has become a common practice for dealing with issues of heteroscedasticity (Wooldridge, 2015). OLS makes the assumptions that errors are both

independent and identically distributed (i.i.d.); robust standard errors loosen those assumptions. The use of robust standard errors will make the p-value be more accurate, but coefficient estimates remain unchanged. Therefore, we report the results after using heteroscedasticity-robust standard errors in the model. After using robust standard errors, the p-values change but level of significance remains the same, except for *Alliance1* in the equation (2). This p-value changed from 0.05 to 0.1 level of significance.

Results of the final regression model are presented in Table 4.3.

Table 4.3 The results of multivariate multiple regression model

Independent Variable	Dependent Variable	
	<i>CSI</i>	<i>CSO</i>
<i>Duration</i>	0.2920*** (0.0830)	0.2854* (0.1352)
<i>Destination</i>	0.026*** (0.0065)	0.0200** (0.0106)
<i>Alliance1</i>	-2.6282** (1.0307)	3.6674** (1.6586)
<i>Alliance2</i>	-6.1568*** (-1.1564)	4.3377** (1.8833)
Intercept	8.5136*** (1.1121)	3.7191 (1.8111)
R-square	0.5573	0.2636

The number in parentheses is called a standard errors.

*** Significant at 0.01 level; ** Significant at 0.05 level; * Significant at 0.1 level.

From Table 4.3, we can see all the independent variables are statistically significant at the 1% level, 5% level or 10% level of significance. The positive sign on *Duration* for both

dependent variables implies that duration of airline alliance membership is positively associated with number of code-sharing partners inside and outside the alliance. Since the coefficient values of *Duration* for CSI and CSO are very close, the effect of *Duration* has a similar impact on the number of code-sharing partners inside and outside the alliance. The positive sign on *Destination* for both dependent variables implies that airlines with more destinations have more code-sharing partners inside and outside the alliance.

The negative sign on dummy variables *Alliance1* and *Alliance2* for dependent variable CSI reveals that SkyTeam members and oneworld members have fewer aligned code-sharing partners compared with Star members. On average, Star members have 2.4 more code-sharing partners inside the alliance than SkyTeam members and 5.9 more code-sharing partners inside the alliance than oneworld members. For dependent variable CSO, the signs on dummy variables *Alliance1* and *Alliance2* are positive, which means SkyTeam members and oneworld members have more non-aligned code-sharing partners compared with Star members. On average, SkyTeam members have 4.17 more code-sharing partners outside the alliance than Star members and oneworld members have 4.66 more code-sharing partners outside the alliance than Star members.

Since the number of members in the three airline alliances is different, we also need to test whether the difference in the number of airline alliance members' code-sharing partnerships inside the alliance is caused not by the alliance per se but rather by the difference in number of members in the three airline alliances. To test this, we create a new variable *CSIpercentage*, the ratio of the number of code-sharing partners inside the alliance to the number of total members of the alliance. The assumption of conducting the

one-way ANOVA test is all populations involved are normally distributed. We conduct the Skewness-Kurtosis test for *CSIpercentage* and the results show that *CSIpercentage* is normally distributed (Park, 2004). Therefore, we can conduct one-way analysis of variance (ANOVA) for this variable. The one-way ANOVA compares the means of two or more independent groups to determine whether there are any statistically significant differences between the means of two or more independent groups. (H. M. Park, 2009). In this study, we want to test whether the means of *CSIpercentage* of three airline alliances are statistically significant different.

Table 4.4 Skewness-Kurtosis test for Normality

Variable	Obs	Pr (Skewness)	Pr (Kurtosis)	adj chi2 (2)	Prob>chi2
<i>CSIpercentage</i>	61	0.8096	0.2883	1.23	0.5409

Table 4.5 Summary of *CSIpercentage* mean

Alliance	Summary of <i>CSIpercentage</i> Mean
SkyTeam	0.565
Star	0.5102
oneworld	0.6509
Total	0.5582

Table 4.6 Analysis of variance

Source	SS	df	MS	F	Prob>F
Between groups	0.1771	2	0.0886	2.37	0.1024
Within groups	2.1661	58	0.0373		
Total	2.3432	60	0.039		

The results of ANOVA indicate that there is no statistically significant difference between the means of *CSIpercentage* of three airline alliances since the p-value is 0.1024. Therefore, the difference in the number of airline alliance members' code-sharing partnerships inside and outside the alliance among the three alliances is caused just by the difference in number of members in three airline alliances. In other words, airline alliance is not a significant factor to determine the number of airline alliance members' code-sharing partnerships inside the alliance.

4.4 Discussion

Code-sharing agreement has become a popular way of bilateral cooperation between two airlines and it is not restricted within an airline alliance. For an airline alliance member, it can codeshare with both aligned and non-aligned airlines. The number of code-sharing agreements with aligned and non-aligned airlines was both found to increase as the duration of airline alliance membership increases. The results imply that after joining an alliance, airlines will increase code-sharing partnerships with aligned airlines, but they do not stop seeking partnerships outside that alliance. This is consistent with observations from Zou and Chen (2017) and Seredyński et al. (2017). Zou and Chen (2017) argue that alliance members still have the motivation to develop bilateral relationships with airlines outside the alliance. Seredyński et al. (2017) show that while airlines seek partnerships with other airlines within alliances, they also look to partner with airlines from competing alliances. The phenomenon might be explained as follows: an airline joining an alliance enjoys benefits that promote business expansion. But the cooperation with only aligned airlines cannot satisfy its development goals. Thus, an airline also needs partners outside the

alliance. However, for most airlines, the majority of their non-member partners are non-aligned airlines. Only two airlines (Adria Airways and Croatia Airlines) have more non-member partners that are members of competing alliances, indicating that airlines try to avoid conflict with their alliance when seeking partnerships with outsiders.

Star members have more code-sharing partners inside and fewer code-sharing partners outside compared to SkyTeam and oneworld. However, it cannot be concluded that that airline alliances have a great influence on the number of code-sharing partners inside and outside the alliance. The results of one-way ANOVA show that the reason for this phenomenon is that airline alliances have different numbers of members. Star has 28 members, SkyTeam has 20 members and oneworld has 13 airlines. Therefore, Star members have more opportunity to codeshare with aligned airlines compared with SkyTeam and oneworld. This conclusion is not consistent with what we previously thought. The results indicate that although the three airline alliances have different attitudes about their members pursuing partnerships with other airlines outside the alliance (Airline Leader, 2016), airline alliance is not a significant influencing factor.

The number of destinations is another important factor which affects the number of code-sharing partners inside and outside an airline alliance. The more destinations an airline has, the more code-sharing partners it has. Code-sharing is a good way to broaden the network and bring about cost savings. An airline can extend its number of destinations by cooperating with other airlines. Therefore, the more destinations an airline has, the more airlines want to codeshare with it to increase their geographic reach.

4.5 Conclusion

In this chapter, we investigate factors that influence the number of airline alliance members' partnerships inside and outside the alliance. Using cross-sectional data gathered in 2016 for 61 airlines in the three global alliances (i.e., Star, SkyTeam and oneworld Alliance), multiple regression is used to test which factors are significant. Duration of airline alliance membership, number of passenger destinations and the fleet size were found to influence the number of airline partnerships inside and outside the alliance. Duration of airline alliance membership has a positive relationship with the number of code-sharing partners, both inside and outside the alliance. This implies that airline alliance members do not give up code-sharing cooperation with non-aligned airlines after they join the airline alliance. The number of code-sharing agreements with non-aligned airlines also increases after an airline joins an airline alliance.

We also find that a specific airline alliance (Star, SkyTeam or oneworld) does not have a significant influence on the number of code-sharing partners inside the alliance. The difference in the number of code-sharing partners inside the alliance is mainly caused by the difference in the number of alliance members.

This study finds out some important factors which have significant influences on the number of airline alliance members' code-sharing inside and outside the alliance. The outcome of this study provides useful information for non-aligned airlines when they consider joining an alliance. Despite its meaningful conclusions, this study has some shortcomings. First, the data we used in this study is a cross-sectional data due to the lack

of date source. In the future, we would like to collect the panel data to supplement this research endeavor, since measurements over time could improve the accuracy and credibility of the results. Second, other factors not included in the study such as market share may also have significant influence on the number of airline alliance members' code-sharing partnerships inside and outside the alliance. The R square (0.596 for equation (1) and 0.371 for equation (2) in the model is not very large, especially for the dependent variable CSO. Future research could include more variables such as market share in the model to improve its explanatory power.

Chapter 5 Exploring the Relationships among Contingency Factors, Code-sharing, and Airline Performance

5.1 Introduction

As a popular and common form of bilateral strategic alliance, code-sharing agreement has been adopted by many airlines. As was mentioned in the previous chapter, code-sharing partnerships can bring many benefits to airlines such as expanding operating network without increasing its own resources. Much research has concentrated on the effects of code-sharing agreement on airline performance (see Brueckner, 2003b; Goetz and Shapiro, 2012; Hassin and Shy, 2004; Ito and Lee, 2007; N. K. Park and Cho, 1997; Yimga, 2017; Zou and Chen, 2017). However, it remains unclear what factors influence the code-sharing agreement formation. It is also worthwhile to explore what other factors influence airline performance and whether code-sharing influence the airline performance as a mediator.

Since contingency theory has been applied to study the strategic alliance and firm performance, it is appropriate to study the antecedent–code-sharing–performance relationships based on contingency theory. In the airline industry context, the contingency factors we study in this study include firm size, operating scope, and duration of airline alliance membership. In this chapter, we study the relationships among contingency factors, code-sharing, and airline performance by using a structural equation modeling approach.

Two research questions we want to answer are:

1. To understand the influence of contingency factors on the number of code-sharing partners and airline performance.

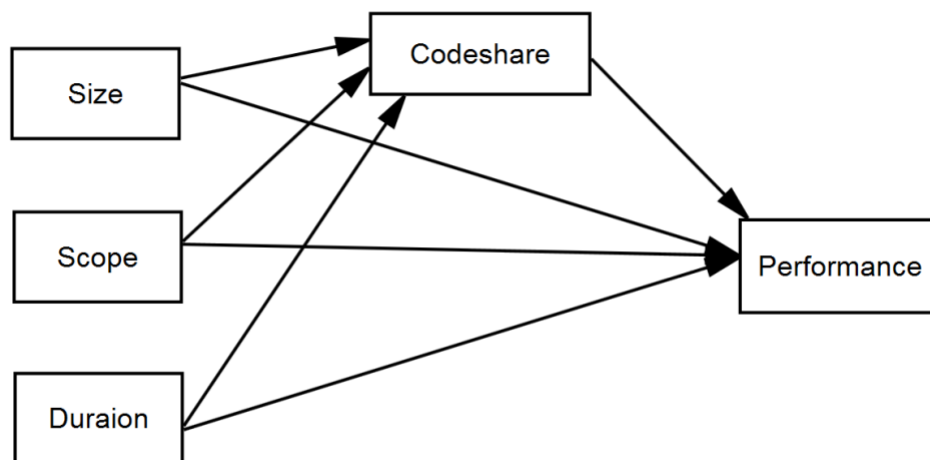
2. Does code-sharing mediate the relationships between contingency factors and airline performance?

Answers to these questions can help fill the research gap in the strategic alliance literature on the antecedent–code-sharing–performance relationships in the airline industry context.

5.2 Research Model and Hypothesis Development

Our research model contains five constructs namely size, scope, duration, code-sharing and performance. Size is measured by fleet size and scope is measured by destination. Duration refers to the duration of airline alliance membership. Code-sharing means the total number of code-sharing partners an airline alliance member has. Performance is a latent variable which is measured by multiple indicators. The proposed research model is shown in Figure 5.1.

Figure 5.1 Research model



5.2.1 Performance

The airline performance is one of the most important outcomes of an airline company assessment. How to measure the airline performance is discussed in many previous researches. Ismail and Jenatabadi (2014) summarize that four indicators which commonly used to measure airline performance are load factor, market share, RPKs and operating profit. Shibata (2001) adopts passenger volume, ASKs, aircraft departures, passenger load factor and RPKs, to evaluate airline performance. Morrish and Hamilton (2002) choose available seat kilometers (ASKs) and passenger load factor to estimate the benefits of alliances. Teo and Leong, (2007) focus on three performance indicators: passenger load factor, RPKs, ASKs.

In this research, in order to measure the airline performance more comprehensively, we define airline performance as a combination of traffic and financial indicators. Traffic indicators include passenger volume, load factor and RPKs. Financial indicators include operating revenue and profitability. Demydyuk (2012) point out that operating profit per passenger or per RPKs is the most appropriate variable to measure airline profitability. Therefore, in this study, profitability is measured by operating profit per RPKs (revenue passenger kilometers). The calculation formula can be seen below.

$$Profitability = \frac{Operating\ profit}{RPKs}$$

5.2.2 Contingency factors

In this study, the model contains three contingency factors: size, scope, and duration. Size is measured by fleet size and scope is measured by destination. Duration refers to the duration of airline alliance membership.

Narula and Hagedoornb (1999) find that firm size is significantly correlated with the interest in joining strategic alliances and large firms join more alliances than smaller firms do. From the resource-based view, Eisenhardt and Schoonhoven (1996) find that large firms with large and experienced management teams are more likely to form a strategic alliance than smaller firms.

Song et al. (2016) study the reason why airlines form strategic alliances. They prove that firm size, the number of destinations and number of hubs all positively influence the formation of strategic alliances. Therefore, we can propose that:

Hypothesis 1. The airline size is positively related to the airline's total number of code-sharing partners.

Hypothesis 2. The airline scope is positively related to the airline's total number of code-sharing partners.

Contingency theory holds that if the organizational structure fits the contingency, higher performance results (Donaldson, 2001). For two contingency factors: size and scope, since a firm with a large size and scope of operations imply that it has more resources, it should promote its performance. Therefore, we propose that:

Hypothesis 3. The airline size is positively related to airline performance.

Hypothesis 4. The airline scope is positively related to airline performance.

Jayaram et al. (2010) suggest that the duration of TQM implementation positively influence product and process quality performance. Similarly, in the airline industry, duration of

airline alliance membership might also positively influence airline performance. As we discussed before, joining an airline alliance will bring many benefits to an airline (see Brueckner, 2003; Cho et al., 2007; Goetz and Shapiro, 2012; Iatrou and Alamdari, 2005; Teo and Leong, 2007; Yimga, 2017; Zou and Chen, 2017). Therefore, it will contribute to the improvement of performance. Based on the discussion above, we propose that:

Hypothesis 5. The airline duration of airline alliance membership is positively related to the airline performance.

Nowadays, the majority of airlines have code-sharing partnerships with other airlines, and code-sharing is an important feature of the major airline alliances. Code-sharing is the most common bilateral cooperation form between airline alliance members. Therefore, after an airline joined an airline alliance, it should have more code-sharing partners. We propose that:

Hypothesis 6. The airline duration of airline alliance membership is positively related to the airline's total number of code-sharing partners.

According to Muthoka and Kilika (2016), strategic alliance can be regarded as a new type of organizational structure that firms use as a strategy to response the environmental pressures they encounter. As one of the most common types of strategic alliance in the airline industry, code-sharing brings a lot of benefits to the airlines (see Section 2.3). Donaldson (2001) point out that if the organizational structure fits the contingency, higher performance results. Based on the discussion above, we propose that:

Hypothesis 7. The airline's total number of code-sharing partners is positively related to

airline performance.

5.3 Empirical Analysis

The empirical analysis in this study includes CFA analysis, path analysis and mediation effect analysis. The software we used to conduct these analyses is AMOS 22.

5.3.1 Data

The data are collected from *Airline Leader* (Issue 36, 2016), *Air Transport World* (ATW) airline report 2016 and *FlightGlobal* world airline rankings 2017. This is cross-sectional data which values are observations in 2016. The sample size is 61, including 28 airlines in the Star Alliance, 20 airlines belonging to SkyTeam and 13 airlines in the oneworld alliance. Table 5.1 lists the definition of the five constructs, namely fleet size, destinations, duration, code-sharing and airline performance.

Table 5.1 Definition of research variables

Construct	Definition of the variable
Duration	<i>Duration</i> : Duration of airline alliance membership in years
Scope	<i>Destination</i> : Number of an airline's passenger destinations
Size	<i>Fleet Size</i> : Number of an airline's aircrafts
Code-sharing	<i>Code-sharing</i> : Number of an airline's code-sharing partnerships
Performance	<i>Passenger Volume</i> : The total number of passengers carried in one year
	<i>Operating Revenue</i> : The revenue generated from a company's primary operations

Load Factor: The percentage of an airline's passenger carrying capacity is used

RPKs: the number of kilometers traveled by paying passengers.

Profitability: Operating profit per passenger

5.3.2 CFA analysis

In our structural equation model, airline performance is a latent variable measured by several indicators. To facilitate the subsequent SEM evaluation, we conduct a confirmatory factor analysis to examine the reliability and validity of the performance measurement model using AMOS 22 software. The performance measurement model is shown below in Figure 5.2.

Figure 5.2 The performance measurement model

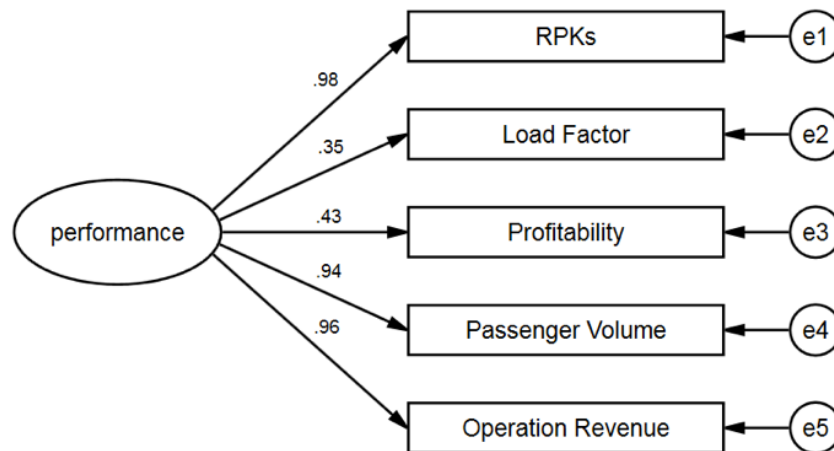


Table 5.2 Model fit index

Fit index	χ^2/df	GFI	AGFI	NFI	TLI	CFI	RMSEA
Acceptable value	<3	>0.9	>0.9	>0.9	>0.9	>0.9	<0.08
Model value	0.822	0.972	0.917	0.985	1.007	1.000	0.000

Table 5.3 Factor loading estimates

Indicator	Standardized factor loadings	S.E.	C.R.	P-value
RPKs	0.977	7252.007	10.424	0.000
Load Factor	0.350	0.631	2.764	0.006
Profitability	0.433	0.001	3.482	0.000
Passenger Volume	0.939	3.095	9.686	0.000
Operating Revenue	0.958	919.446	10.041	0.000

As presented in Figure 5.1, the measurement model illustrates the relationships between the latent variable performance and its measurements. Table 5.1 shows that all the indices of goodness of fit reach the acceptable value, indicating that the fit of the measurement model is satisfactory.

According to Hair et al. (2010), factor loading estimates should be larger than 0.40. Table 5.3 shows that only the factor loading of load factor is below 0.4. However, the p-value of load factor is significant at 1% level of significance and as we discussed in section 5.2.1, load factor, as efficiency index, is an important indicator to measure the airline

performance. Brown (2014) pointed out that usually loadings below 0.3 cannot be considered salient. The factor loading of load factor reaches $0.35 > 0.3$. Therefore, we keep load factor in the measurement model.

Based on the standardized factor loadings in Table 5.3, we can calculate the composite reliability of performance construct is 0.874 larger than 0.8 (Brown, 2014), which suggests that the construct reliability is acceptable. Average variance extracted (AVE) is the criterion for testing convergent validity. The value of AVE should be larger than 0.5 (Fornell and F., 1981). The AVE of performance construct is $0.613 > 0.5$, showing the convergent validity is suitable. In summary, the construct reliability and convergent validity of the performance measurement model are satisfactory.

5.3.3 Path analysis

Based on the proposed research model and the hypothesis, we use AMOS 22 to build the estimated model shown in Figure 5.3. From Figure 5.3, we observe that the correlation between size and scope is 0.9, which means these two constructs are highly correlated. As the result, the coefficients might not be estimated accurately (even sign changes of the coefficients). Therefore, we need to remove one of the constructs from the model. We choose to drop scope because after that the fit of model is better compared with dropping size. The final estimated model is shown in Figure 5.4. Table 5.4 illustrates the results of some common model fit indices. All indices are acceptable except RMSEA. However, the value of RMSEA (0.084) is very close to the acceptable value (< 0.08). Based on these results, it can be claimed that the fit of the model is satisfactory.

Figure 5.3 Estimated model

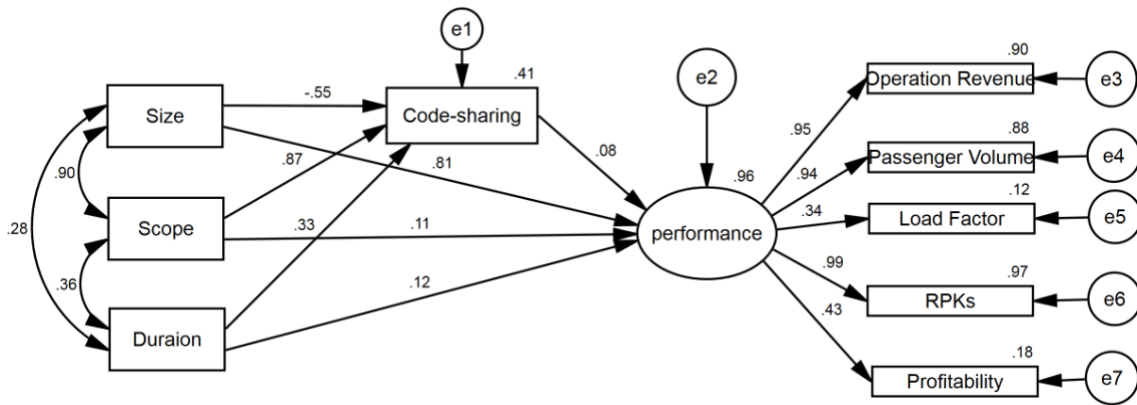


Figure 5.4 The Final estimated model

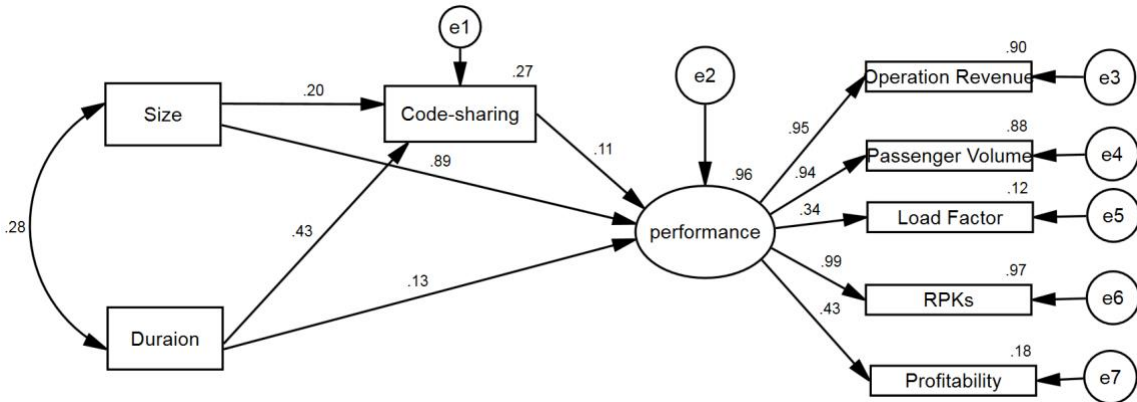


Table 5.4 Model fit index

Fit index	χ^2/df	GFI	AGFI	NFI	TLI	CFI	RMSEA
Acceptable value	<3.00	>0.9	>0.8	>0.9	>0.9	>0.9	<0.08

Figure 5.5 Output diagram of path analysis

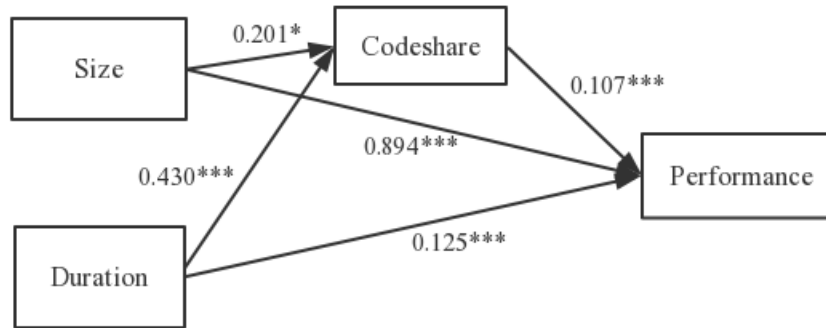


Table 5.5 Path evaluation results for the research model

Hypothesis	Path	Standardized coefficient	P-value	Result
H1	Size → Code-sharing	0.201	0.079*	Accept
H3	Size → Performance	0.894	***	Accept
H5	Duration → Performance	0.125	***	Accept
H6	Duration → Code-sharing	0.430	***	Accept
H7	Code-sharing → Performance	0.107	***	Accept

Note: *** Significant at 0.01 level; ** Significant at 0.05 level; * Significant at 0.1 level.

According to the results of the final estimated model we build in AMOS 22, we create the diagram of path analysis. The path evaluation results are displayed in Table 5.5. The results of the structural model provide support for all hypotheses except hypothesis 2 and 4 since scope was removed from the proposed model. The results indicate that size ($\beta = 0.201, p < 0.1$) and duration ($\beta = 0.430, p < 0.01$) has positive and statistically significant effects on the total number of code-sharing partners, providing support for H1 and H6. Size ($\beta = 0.894, p < 0.01$), duration ($\beta = 0.125, p < 0.01$) and code-sharing

($\beta = 0.107, p < 0.01$) all have positive and statistically significant effects on the performance, providing support for H3, H5, and H7.

5.3.4 Mediation effect analysis

Although there are many empirical research assessing the influence of code-sharing on airline performance, the mediating effects of code-sharing between some contingency factors and airline performance are unexplored.

As we mentioned in chapter 3, bootstrapping method is a common way to study the mediation effect. We conduct a bias-corrected bootstrapping test with 5000 bootstrap samples and 95% confidence intervals using AMOS 22. The standardized indirect effect of size on performance, as mediated through code-sharing, is statistically significant ($\beta = 0.021, p = 0.012, 95\% \text{ CI } [0.004, 0.085]$). A further examination of the standardized direct effect reveals that the direct effect of size on performance is statistically significant ($\beta = 0.894, p = 0.004, 95\% \text{ CI } [0.796, 0.942]$). This suggests that the effect of size on performance is only partially mediated through code-sharing.

The standardized indirect effect of duration on performance, as mediated through code-sharing, is statistically significant ($\beta = 0.046, p = 0.007, 95\% \text{ CI } [0.012, 0.128]$). As the direct effect of duration on performance is also statistically significant ($\beta = 0.125, p = 0.001, 95\% \text{ CI } [0.059, 0.222]$), we can conclude that the effect of duration on performance is also partially mediated through code-sharing. The results of the mediation analysis are summarized in Table 5.6.

Table 5.6 The results of the mediation analysis

Hypothesis	Direct effect	Indirect effect	Result
Size→Code-sharing→Performance	0.894***	0.021**	Partial Mediation
Duration→Code-sharing→Performance	0.124***	0.046***	Partial Mediation

Note: *** = $p < 0.01$ **= $p < 0.05$ *= $p < 0.1$

5.4 Discussion and Conclusions

In this study, we mainly analyze the relationships among contingency factors (size and duration), code-sharing and airline performance. The results indicate that airline size and the duration of airline alliance membership have positive effects on the airline's total number of code-sharing partners. Large airlines tend to have more code-sharing partners. The reason might be large airlines own plenty of resources, therefore they can utilize the resources more effectively by code-sharing. Since code-sharing is the most common cooperation way among airline alliance members, it is expected that duration of airline alliance membership positively influences the airline's total number of code-sharing partners. Therefore, the longer the duration of airline alliance membership, the more code-sharing partners.

The effects of strategic alliance on performance have been widely studied. In the airline industry, there has been plenty of researches analyzing the effects of code-sharing on airline performance (Brueckner, 2003; Goetz and Shapiro, 2012; Hassin and Shy, 2004; Ito and Lee, 2007; Zou and Chen, 2017). However, these researches usually measure the airline performance with a single indicator. In this study, we build a comprehensive

performance combined with both financial performance and operating performance. The results show that airline size, duration of airline alliance membership and the number of total code-sharing partners all have positive effects on airline performance. We further identify the influencing mechanism by conducting mediation analysis. The results imply that the effects of airline size and duration of airline alliance membership on airline performance are partially mediated through code-sharing.

The findings indicate that the effect of airline size on airline performance is partially mediated through code-sharing, which means for large airlines, the increase of code-sharing partners will offer benefits to the improvement of airline performance. Besides, the effect of duration of airline alliance membership on airline performance is partially mediated through code-sharing. This implies that for an airline alliance member, the longer it joined the alliance, the better performance it got, and the improvement of performance is partially caused by the increase of code-sharing partners. The key managerial implications of this study include that after an airline became an airline alliance member, it should seek more code-sharing partners to improve the airline performance. Also, for large airlines, having more code-sharing partners will be beneficial to the improvement of airline performance.

Though we got some meaningful findings, some limitations that should be considered when interpreting the results. First, the data was collected for only 61 airlines which are one of the three global airline alliance membership, and the time span considered was just for one year. The small sample size may weaken the accuracy of the estimated model. Therefore, in the future research, we can increase the time span to get time series data, then the

problem of small sample size is solved. For example, if we collect five years' data, then our sample size will expand to 305 from 61. Second, the measurement of firm size could have multiple indicators. For example, firm size can also be measured by total assets or employees. Besides, there are also many other indicators such as passenger satisfaction, market share, punctuality to assess the airline performance. However, due to the lack of data, we did not adopt these indicators. Third, since the samples are all airline alliance members, the conclusions cannot apply to airlines without joining an airline alliance. In the future, we would like to include airlines did not join any airline alliance, then we can study whether the effect of code-sharing on airline performance to alliance members is different from non-alliance airlines.

Chapter 6 Conclusion

6.1 Summary

In this thesis, we first explore how airline alliance membership and code-sharing partnerships are linked with each other. We investigate whether an airline tends to codeshare more with airlines in the same alliance and less with other airlines after it joins a particular alliance and we further study whether there is a substantial difference in terms of code-sharing partnerships among members in the three global airline alliances. We answer these questions above by conducting a multivariate multiple regression model. We find the factors that influence the three global airline alliance members' code-sharing partnerships inside and outside the alliance: the duration of airline alliance membership and the number of airline destination. These two factors both have a significant and positive influence on the number of airline alliance members' code-sharing partnerships inside and outside the alliance. That is to say, the longer an airline joined the alliance, the more code-share partners it has, and an alliance member has more destinations will have more code-sharing partners inside and outside the alliance. The results also indicate that airline alliance per se is not a significant factor which influences the number of code-sharing partners inside the alliance. The difference in the number of code-sharing partners inside the alliance among the three alliances is caused by the difference in the number of alliance members.

Second, based on contingency theory, in the airline industry, contingency factors contain duration of airline alliance membership and firm size. We construct a structural equational

model to study the relationships among these contingency factors, code-sharing and airline performance. The results reveal that airline size and duration of airline alliance membership have positive influences on the airline's total number of code-sharing partners. In addition, airline size, duration of airline alliance membership and the number of total code-sharing partners all have positive effects on airline performance. We further study the mediating effects of code-sharing between these contingency factors and airline performance. The results indicate that the effects of duration of airline alliance membership and size on performance are partially mediated through code-sharing. That is to say, for an airline alliance member, the longer it joined the alliance, the better performance it got, and the improvement of performance is partially caused by the increase of code-sharing partners. Similarly, for large airlines, having more code-sharing partners will be beneficial to the improvement of airline performance.

6.2 Contribution

This thesis provides a better understanding of how airline alliance membership and code-sharing partnerships are linked with each other and the relationships among contingency factors, code-sharing, and airline performance.

Firstly, we identify whether airline alliances can influence their members' choice of code-sharing partners substantially, i.e. whether an airline alliance member tends to codeshare more with airlines in the same alliance and less with other airlines after it joins a particular alliance. This study empirically shows that the choice of airline alliance member's code-sharing partners inside and outside the alliance could be predicted by assessing duration of

airline alliance membership, number of destinations.

Secondly, this thesis applies contingency theory for the first time in research related to the code-sharing cooperation. It empirically assesses the influence of contingency factors (firm size and duration of alliance membership) on the total number of code-sharing partners and airline performance. Our findings provide a new perspective for airlines to improve their performance.

6.3 Limitation and Future Research

There are several limitations in this thesis. First, the data we used in this thesis is cross-sectional data which values are observations at a point in time, causing the sample size is not very large (61 samples). A small sample size may weaken the accuracy of the estimated model. Due to the lack of data source, we did not find the previous years' dataset. In the future, we plan to collect five years' data then we can have the panel data containing 305 samples which is definitely a large sample size. Second, in chapter 5, the SEM only identified a one-directional relationship rather than two-directional relationships between two variables. Because cross-sectional data cannot prove causality but help to generate causal hypotheses (Rong and Wilkinson, 2011). Therefore, future studies should consider alternative approaches such as conducting a study with panel data to supplement this research endeavor. Third, the structural model can be improved by adding more indicators for the measurement of performance and size if relevant data is available to collect. Finally, since the samples are all airline alliance members, the conclusions cannot apply to airlines without joining any airline alliances. In the future, we would like to include airlines did not

join any airline alliances, then we can conduct comparison studies for issues such as whether the effect of code-sharing on airline performance to alliance members is different from non-alliance airlines.

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Appendix

Member airlines of Star Alliance, Sky Team and oneworld, status August 2016.

Star Alliance	SkyTeam	oneworld
Adria Airways (2004-11-01)	Aeroflot (2006-04-14)	Air Berlin (2012-03-20)
Aegean Airlines (2010-06-01)	Aerolíneas Argentinas (2012-08-29)	American Airlines (1999-02-01)
Air Canada (1997-05-01)	AeroMexico (2000-06-22)	British Airways (1999-02-01)
Air China (2007-12-01)	Air Europa (2007-09-04)	Cathay Pacific (1999-02-01)
Air India (2014-07-11)	Air France (2000-06-22)	Finnair (1999-09-01)
Air New Zealand (1999-03-01)	Alitalia (2001-07-27)	Iberia (1999-09-01)
All Nippon Airways (1999-10-01)	China Airlines (2011-09-28)	Japan Airlines (2007-04-01)
Asiana Airlines (2003-03-01)	China Eastern Airlines (2011-06-21)	LATAM Brasil (2014-04-01)
Austrian Airlines (2000-03-01)	China Southern Airlines (2007-11-15)	LATAM Chile (2000-06-01)
Avianca (2012-06-01)	Czech Airlines (2001-03-25)	Malaysia Airlines (2013-02-01)
Avianca Brazil (2015-07-22)	Delta Air Lines (2000-06-22)	Qantas (1999-02-01)
Brussels Airlines (2009-12-01)	Garuda Indonesia (2014-03-05)	Qatar Airways (2013-10-30)
Copa Airlines (2012-06-01)	Kenya Airways (2007-09-04)	Royal Jordanian (2007-04-01)
Croatia Airlines (2004-11-01)	KLM (2004-09-13)	S7 Airlines (2010-11-15)
EgyptAir (2008-06-01)	Korean Air (2000-06-22)	SriLankan Airlines (2014-05-01)
Ethiopian Airlines (2011-12-01)	Middle East Airlines (2012-06-28)	
EVA Air (2013-06-01)	Saudia (2012-05-29)	
LOT Polish Airlines (2003-10-01)	TAROM (2010-06-25)	
Lufthansa (1999-05-01)	Vietnam Airlines (2010-06-10)	
Scandinavian Airlines (1997-05-01)	XiamenAir (2012-11-21)	
Shenzhen Airlines (2012-11-01)		
Singapore Airlines (2000-04-01)		
South African Airways (2006-04-01)		
Swiss International Air Lines (2006-04-01)		
TAP Portugal (2005-03-01)		
Thai Airways (1997-05-01)		
Turkish Airlines (2008-04-01)		
United Airlines (1997-05-01)		