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Burak Cem Konduk

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The Origins of Mutual Forbearance: Learning to Trust to Mutually Forbear

BY

Burak Cem Konduk

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

*GEORGIA STATE UNIVERSITY
ROBINSON COLLEGE OF BUSINESS
2013*

ACCEPTANCE

This dissertation was prepared under the direction of the Burak Cem Konduk Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctoral of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

The origins of Mutual Forbearance: Learning to Trust to Mutually Forbear

BY

Burak Cem Konduk

05/01/2013

Committee Chair: Pamela S. Barr

Major Academic Unit: Managerial Sciences

Multi-market contact can either escalate or deescalate rivalry. Recent empirical work has revealed an inverted U-shaped relationship between multi-market contact and rivalry. These findings have lead many to suggest that mutual forbearance (MF), a switch from competition to cooperation across markets, is a natural outcome of increasing multi-market contact between two firms. Despite the relatively widespread acceptance of this suggestion, we do not have a theoretically grounded explanation for how this switch from rivalry to mutual forbearance occurs. This dissertation takes up this task. Theories of learning and trust are used as the grounding for the development of a theoretical model of the process by which multi-market rivals switch from competition to cooperation across markets. The model is tested using data from the U.S. Scheduled Passenger Airline Industry. Results support the general theoretical foundations of the model and provide new insights into the genesis of mutual forbearance.

DEDICATION

To Tolga and Yeliz

ACKNOWLEDGEMENTS

I would like to thank to the following people for their continuous support.

Most of all, I would like to express my sincere gratitude to my dissertation committee chair Professor Pamela S. Barr for her guidance, assiduousness, patience, encouragement and support. Professor Pamela S. Barr taught me how to question thoughts and express ideas. Her patience and support helped me overcome many crisis situations and finish this dissertation.

I also owe a debt of gratitude to Professor William C. Bogner for introducing me to the literature on competitive dynamics and mutual forbearance. I would like to acknowledge Professor William C. Bogner for numerous discussions and lectures on related topics that helped me improve my knowledge in the area.

I am grateful to Professor Elisa Alvarez-Garrido for her encouragement and advice. I am also thankful to her for reading previous drafts of this dissertation and providing many valuable comments that improved the presentation and contents of this dissertation.

I would like to thank to Professor Bruce Seaman for helping me understand and enrich my ideas.

I am also thankful to the information systems staff for helping me use various supercomputers.

This thesis is dedicated to Tolga and Yeliz. I would like to thank them for being there for me. This dissertation could not have been finished without their support, dedication, and encouragement.

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CHAPTER 1

1.1 Investigating the Switch from Multi-Market Competition to Mutual Forbearance and the Process of Mutual Forbearance

In today's business environment, firms often find themselves competing in multiple markets and often against the same firms across those markets. One of the counter-intuitive consequences of competition between two firms across markets is that after prolonged periods of intense rivalry, competition often unexpectedly de-escalates, leading to an outcome termed mutual forbearance (MF). According to the literature, the main reason for the de-escalation of rivalry is the threat of punishment of aggression not only in the market where aggression has taken place but also in some or all of the jointly contested markets (Hughes and Oughton, 1993; Jayachandran et al., 1999).

Contemporary research has improved our understanding of MF. Particularly, studies of MF in the literature indicate that; MF exists (Baum and Korn, 1999), there is an inverted U relationship between market overlap and MF (Baum and Korn, 1999), deterrence is a causal factor in the development of MF (Gimeno, 1999; Gimeno and Woo, 1999), and MF is not a deliberate but an emergent outcome of multi-market competition (Korn and Rock, 2001).

Though our understanding of MF has increased significantly over the years, there are still three crucial gaps in our understanding. First, we do not know much about the role of cooperation in MF. Although deterrence and cooperation are proposed as the two theoretical drivers of MF by the original theoreticians of MF, subsequent research on MF has not investigated cooperation. This is problematic because MF, in essence, is a strategy of cooperation and the empirical and theoretical support for the deterrence mechanism is weaker

than that of the cooperation mechanism. The extant literature on deterrence does not go beyond listing the type of markets that are effective to establish deterrence and thus does not directly investigate the deterrence mechanism. In addition, the empirical evidence shows that firms do not exercise deterrence as a response to chiseling. Actually, they support the defection behavior of their rivals through cooperative conduct. Recognizing the limitations of the deterrence mechanisms as a causal force and the weak empirical support for its direct impact, there is a need to bring cooperation back into the core of MF and explain how multi-market rivals form MF through cooperative behavior across markets (Scott, 1991; Busse, 2000; Kang et al., 2010).

Second, we still do not know what motivates multi-market rivals to mutually forbear. Much of the current literature on MF still assumes that MF is a deliberate strategy and thus multi-market rivals that execute a MF strategy are motivated to forbear from the beginning. However contemporary empirical evidence suggests that MF is an emergent strategy and that firms establish contacts across markets without the premeditated intention to mutually forbear from competition. In light of such evidence, we need to modify MF theory and explain what motivates multi-market rivals to forbear from competition and re-deploy their contacts across markets to cooperate. More specifically, we need to explain how MF emerges out of the competitive interactions of rivals and the *causes* of the *switch* that transform competition into cooperation across markets.

Third, because the majority of the studies examine the sign and functional form of the relationship between multi-market contact and mutual forbearance, we do not know how firms coordinate their actions to move to the MF equilibrium (Busse, 2000) rather than to competing equilibriums, such as limited war, all out war, or maintenance of the status quo (Karnani and Wernerfelt, 1985). More specifically, we do not know how firms use contacts across markets to

learn how to cooperate (Scott, 1991) and signal their intent to mutually forbear (Busse, 2000). In addition, we do not know how signals of multi-market firms to establish cooperation fail and the impact of such failures on the genesis of MF. Thus, we need theories that explain the process by which multi-market rivals move to the MF equilibrium.

1.2 Research Questions and Guiding Theoretical Perspectives

To address each of these gaps in our understanding, I develop and test a theoretical model that uses theories of trust formation and learning to explain the emergence of MF between a pair of rivals. I argue that the process of multi-market competition sets the stage for the formation of inter-organizational trust between a dyad of rivals which in turn provides the motive to cooperate. In particular, I postulate that by impairing firm performance and creating norms of competition, multi-market competition activates different antecedents of inter-organizational trust. While multi-market competition itself activates the interdependence and deterrence antecedents of trust, norms of rivalry set in motion the predictability antecedent of trust. Finally, poor performance sparks the risk taking precursor of trust and brings about trust formation among rivals.

The formation of inter-organizational trust leads to attempts to cooperate. Being rivals, multi-market firms gradually escalate their commitment to cooperation and test each other's trustworthiness through two temporally linked stages of cooperation. The incremental nature of cooperation provides the opportunity to teach and learn cooperation across markets and reduces the cost of cooperation. In the first stage of cooperation, multi-market rivals cooperate at the tactical level. When initial attempts results in positive feedback and reciprocity, rivals escalate their commitment to cooperation. In the case of defection, they fall back to competition. Following the successful completion of the tactical stage of cooperation, multi-market rivals

escalate their commitment to cooperation and commence to cooperate at the deeper strategic level. If a pair of rivals mutually reciprocates each other's cooperative moves at the strategic stage of cooperation, they commence to mutually forbear and assign markets to one another. If a rival defects to maximize its rate of return at the expense of its cooperating partner, rivalry resumes.

This model specifically addresses each of these gaps in our understanding with three research questions:

- (i) What is the role of cooperation in the development of MF?
- (ii) Does trust enable a dyad of multi-market rivals move from rivalry to cooperation and, if so, how?
- (iii) Does learning theory explain the process by which a dyad of multi-market rivals moves to MF?

I use theories of trust and learning as guiding perspectives in the development of the model. Trust, as a construct, is relevant to MF theory because it is associated with both cooperation and deterrence and it confirms to the prospective orientation of MF theory. I argue that trust is particularly relevant in the context of multi-market competition because the processes associated with multi-market competition are consistent with the formation of inter-organizational trust. In addition, the core of MF strategy requires firms to make themselves vulnerable to retaliation across markets (Greve, 2000). Such willingness to be vulnerable is the definition of trust for scholars that conceptualize trust as a social orientation towards others (Mayer et al., 1995; Malhotra, 2004; Rousseau et al., 1998). Thus, the formation of trust is argued to be the trigger that motivates the move from rivalry to cooperation.

I take an organizational learning perspective to develop hypotheses about how cooperation evolves and how multi-market rivals coordinate their actions to move to mutual forbearance equilibrium rather than to competing equilibriums. Theories of organizational learning are relevant to MF theory because multi-market contact provides many opportunities to learn (Scott, 1991) and acts as information conduit that facilitates all types of learning (Wegberg and Witteloostuijn, 2001). “Facing the same other seller in different markets affords a learning opportunity that is not present when a different rival is faced in every market” (Feinberg and Sherman, 1988, p: 986). In addition, an organizational learning perspective complements and enriches the prospective orientation of MF with an historical perspective that also shapes firm conduct. Examining MF through the lens of organizational learning provides a more realistic and comprehensive approach to study MF because it acknowledges that both past and future influence cooperative and competitive actions of firms.

1.3 The Contributions of the Dissertation

This dissertation makes several contributions to the field of strategic management in general and to the literature on multi-market competition in particular. The three main contributions of the study are summarized below and discussed in greater detail in chapter 6.

First, the theoretical model developed in the dissertation provides a process-based explanation of the origins of MF and seeks to redirect the extant literature on MF to a new line of inquiry. In particular, the theoretical model and hypotheses are initial steps away from variance models toward process models and an understanding of the origins and genesis of MF. Now that we know that multi-market firms do eventually refrain from competing with one another, this dissertation explains the process by which multi-market competition is transformed into MF (Van de Ven, 2007). Unlike existing studies that constrain the outcome of multi-market

competition to be MF, this dissertation allows for the defection-based breakdown of cooperation at different points in time between a dyad of multi-market rivals. As such, the theoretical model reflects the natural progress and development of multi-market competition and explains the processes by which multi-market firms either move to MF equilibrium (Busse, 2000) or escalate their level of rivalry.

The second major contribution of this dissertation is that it investigates whether competition across markets paves the ground for the unintentional formation of MF by forming inter-organizational trust that in turn provides the ex-post motive to cooperate among rivals. In doing so, I am able to explain the *emergent* formation of MF and the *cause* of the *switch* that transforms competition into cooperation across markets. The empirical results of this dissertation demonstrate that organizational trust indeed emerges as a byproduct of multi-market competition and leads to the motivation to attempt cooperation, reflecting the emergent nature of the motive to cooperate and MF strategy. Four findings of this dissertation are particularly important in this regard: (i) the impact of the interaction of multi-market contact and norms on tactical cooperation is not significant (ii) the impact of the interaction of multi-market contact and performance failure on tactical cooperation is not significant (iii) the impact of the interaction of norms and performance failure on tactical cooperation is not significant (iiii) the impact of the three-way interaction of multi-market contact, norms and performance failure on tactical cooperation is significant and positive. This set of findings provide empirical support for the argument that inter-organizational trust emerges unwittingly out of the competitive interactions of rivals and motivates rivals to re-deploy their contact across markets to initiate and sustain cooperation.

The third major contribution of this dissertation is the clarification and refinement of the deterrence mechanism and its joint investigation with the cooperation mechanism, reflecting the intellectual origins of MF theory and providing a more comprehensive theoretical account of MF than the available accounts in the literature. The empirical findings show that deterrence as a mechanism does not retain the same level of importance and effect through different stages of cooperation. In particular, deterrence plays a crucial role for the formation of inter-organizational trust by activating two antecedents of trust, deterrence and interdependence, making it one of the factors that are required to motivate cooperation and MF. However when multi-market rivals start actual cooperation and commence to execute their MF strategy, deterrence as a causal mechanism becomes irrelevant. The findings of this dissertation demonstrate that both cooperation and defection, either at the tactical or strategic level, lead to further cooperation. Rival firms actually cooperate or do not exercise deterrence and punish the defection of their rivals during either the tactical or strategic stages of cooperation. Across stages, firms support the defection of their rivals to move to the MF equilibrium. These findings show that cooperation is the main mechanism by which multi-market rivals move to the MF equilibrium and deterrence plays a role that is much more limited than the role that is ascribed to it by the current literature.

1.4 The Structure of the Dissertation

This dissertation is structured into six chapters, including this introductory chapter.

In Chapter 2, I explain and describe the evolution of the literature on MF in four sections. In the first section, I describe MF theory and elucidate that MF is a property of the relationship of rivals rather than a property of market structure. In the second section, I explain how studies conducted by industrial organization scholars progressively found support for MF theory and established not only boundary conditions for the MF theory but highlighted the relevance of

learning to MF. In the third section, I discuss the shape of the relationship between market overlap and MF, explain the limitations of the deterrence and familiarity as causal mechanisms of MF and dwell on the emergent nature of MF. In the fourth section, I explain the three gaps in the literature and the motivation for the research questions of this dissertation.

In Chapter 3, I develop the process model that explains the genesis of MF between a dyad of rivals. In general, the model postulates that MF is the result of a cooperative learning process that is motivated and triggered by the development of inter-organizational trust, which, in turn, is a by-product of rivalry. Hence prior to presenting the model, a discussion of the processes involved in rivalry and how they ultimately lay the groundwork for the formation of inter-organizational trust is required. This chapter is divided into four sections. In the first section, I relate the mutual recognition of rivalry between two multi-market firms and the resulting competitive interaction to the development of multi-market competition, reduction in performance, and norms of competition. In section two, I argue that multi-market competition, norms of competition and poor performance, in turn, result in inter-organizational trust. In section three, I introduce the model and develop the hypotheses. In the last section, I summarize the chapter.

In Chapter 4, I outline the sample and methodology that I will use to investigate the hypotheses of this dissertation. This chapter is divided into four sections. In the first section, I provide the criteria that I used to select the sample and explain the alternative samples considered and the actual sample that I selected. Second, I discuss the selection of time period and justify it. Third, I provide operational definitions of both theoretical and control variables used in each of the three models used to test the hypotheses. First, I define the variables of the first model and data sources that will be used to calculate these variables. Next, I define the

variables of the second and third models and their data sources. In the fourth section, I explain the reasons for the selection of the multi-level modeling and describe the method itself.

In Chapter 5, I explain the process by which I selected each of the “Final” models used to test the hypotheses, discuss and interpret their empirical results and finally investigate the robustness of the findings and carry out additional empirical analyses undertaken to ensure the accuracy of the statistical inferences. This chapter is divided into three sections. In the first section, I investigate the first set of hypotheses that theorizes about the formation of inter-organizational trust and its impact on cooperation. In the second section, I investigate Hypotheses 2, 3 and 4, which are related to tactical cooperation. In the last section, I investigate strategic cooperation and thus Hypotheses 5, 6 and 7.

Finally, in Chapter 6, I discuss the contributions of the dissertation to the literature and the implications of the findings for theory and practice and provide suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

In this chapter, I explain and describe the evolution of the literature pertaining to mutual forbearance (MF). This chapter is divided into four sections. In the first section, I define MF theory and explain that MF is a property of the relationship of rivals rather than a property of market structure. In the second section, I review the literature and primary findings from studies on MF from industrial organization (IO) literature. In the third section, I review the literature and primary findings from studies on MF from strategy research. I first summarize the “variance” studies and elaborate on the limitations of these studies and then review the literature on causal forces of MF. Finally, I review the literature that questions the deliberateness of MF as a strategy. In the last and fourth section, I summarize the main findings across the literatures on MF and identify the three gaps that exist in the literature that provide the motivation for the research questions addressed in this dissertation.

The literature review demonstrates the need to re-direct the research on MF to a new line of inquiry that studies the processes by which it originates. In a nutshell, the literature review shows that although we know that multi-market contact reduces the intensity of rivalry, that the relationship between multi-market contact and MF is curvilinear and that MF takes place especially in the primary and key markets of multi-market firms, we still lack a theory that explains: the causal forces that switch competition into cooperation across markets that are consistent with what we know about how managers and decision makers act, the process by which multi-market rivals move to the MF equilibrium, and the role of cooperation in this process.

2.1 Mutual Forbearance Theory

MF theory states that as a dyad of rivals increases the number of markets in which they jointly and simultaneously compete, they begin to forbear from competing in each other's key markets (spheres of influence) due to the threat of cross-market retaliation (Edwards, 1955). Multi-market competition results in MF because it provides both the familiarity required to collude and the ability to deter aggression in one's own spheres of influence through threat of retaliation in the spheres of influence of one's rivals (Jayachandran et al., 1999). Such retaliation is not only less costly for the responding focal firm, but also more detrimental to the aggressor (Karnani and Wernerfelt, 1985; Parker and Roller, 1997), which reduces the motivation of multimarket rivals to defect from forbearance (Gimeno, 1999). Rivals in these situations move toward the adoption of a tit-for-tat, "live and let live" MF strategy (Hughes and Oughton, 1993; Jayachandran et al., 1999).

MF is a feature of the relationship between a pair of rivals. "The theoretical construct of multi-market contact is fundamentally about the relationship that unfolds over time between two firms across the multiple markets in which they compete" (Baum and Korn, 1999, p: 272). Similar to conventional IO literature, MF theory assumes that cooperation is based on interdependence between direct rivals. However unlike traditional IO literature, MF theory proposes that the source of interdependence between rivals is the level of their multi-market contact rather than industry properties such as number of sellers, cost or demand conditions (Kantarelis and Veendorp, 1988). According to MF theory, it is the level of multi-market contact between firms that influence the level of their cooperation with one another and the conduct in a given market (Singal, 1996). Since a focal firm can choose (Child, 1972) to have different levels of contact with a given firm across markets, due its corporate and business level strategy and

change its existing level of contact with a given firm across time, multi-market contact varies not only across competitive dyads and from relationship to relationship at a given point in time, but also within the same competitive dyad across time (Barnett, 1993). Consequently, MF is a property of the relationship between a dyad of rivals (Baum and Korn, 1999) rather than a property of industry structure (Boeker et al., 1997; Haveman and Nonnemaker, 2000). The following quotation from Adams (1974) clarifies this point:

“Suppose a firm sells in ten distinct markets, with a share of ten percent in each. Suppose, further, that in every one of these markets, the firm has nine competitors, each also with a ten percent share. If the nine competitors in any one market have no positions in the other nine markets, the original firm has a total of ninety competitors. If, however, the nine competitors in any one market also have positions in each of the other nine markets, the original firm has a total of only nine competitors. While the intra-market fewness of sellers in these two examples is identical, the likelihood that sellers will recognize their interdependence in any given market is substantially greater in the latter case” (Adams, 1974, p: 1282).

Empirical evidence provides supporting evidence for the proposition that MF takes places between rivals. Barnett (1993) postulates rivalry as a boundary condition for MF because he finds that MF depends on the existence of strategic groups whose members identify one another as rivals. Likewise, Baum and Korn (1999) empirically demonstrate that the impact of a given level of multi-market contact on MF varies significantly from one competitive dyad to another and within the same dyads over time, and that dissimilar multi-market rivals, which are less likely to recognize one another as rivals (Baum and Mezias, 1992; Desarbo et al., 2006; Chen et al., 2007), do not forbear from competition.

Additional evidence that MF takes place between rivals comes from the studies that examine how CEO tenure moderates the relationship between multi-market contact and intensity of rivalry. CEO tenure facilitates the identification of rivalry because it increases the familiarity with the competitive environment. Hence if rival identification is critical to mutual forbearance strategy, predictions of the literature concerning the relationship between multi-market contact and intensity of rivalry should be more likely or valid for CEO's with greater tenure in the position. Such an expectation is supported empirically. Stephan et al., (2003) find that CEO tenure positively moderates the inverted U-relationship between multi-market contact and intensity of rivalry and suggest that long tenure facilitates identification of rivals due to an increase in familiarity with the competitive environment. Similarly, Boeker et al. (1997) find that organizations with a new CEO are more likely than others to exit markets that are required to maintain key footholds and Stephan et al. (2003) find that firms with new CEOs are more likely to enter markets as multi-market contact increases, contrary to predictions of MF theory.

The findings that demonstrate that MF is a property of the relationship between multi-market rivals explains why the MF research that measures rivalry through industry concentration, which has been used as an aggregate and coarse grained measure of rivalry, and examines the impact of its interaction with multi-market contact on firm performance, has mixed findings¹. This measure ignores the relational nature of MF.

¹ While Scott (1982, 1991), Whalen (1996), Jans and Rosenbaum (1996) and Haveman and Nonnemaker (2000) found that interaction of multi-market contact with industry concentration reduces rivalry in line with MF theory, Mester (1987) and Fernandez and Marin (1998) discovered that such interaction actually increases the intensity of rivalry and impairs MF. Others also found insignificant results (Baum and Korn, 1996; Fuentelsaz and Gomez, 2006).

MF theory has been developed in both the industrial organization literature and the strategy literature. Because MF was originally proposed and investigated by industrial organization economists (Golden and Ma, 2003). I review that literature in the next section.

2.2 Intellectual Foundations of MF Theory: The Industrial Organization Literature

There are four different streams of research that examine MF within the industrial organization tradition: Banking, non-banking, conceptual and empirical studies. Each stream is discussed in turn in the following sub-sections.

2.2.1 The First Stream: Banking Studies

Industrial organization economists were the first to examine MF theory and the rivalry dampening impact of multi-market contact. These initial studies were predominantly in the banking industry and were designed to test Solomon's (1970) argument that MF theory will not hold in the banking industry.

Despite their skeptical approach to MF theory, findings from this stream of research are inconclusive (Whalen, 1996); there are supporting, contradictory and insignificant findings. Some studies found empirical support for the MF theory. Heggstad and Rhoades (1978) found a positive relationship between multi-market contact and market share stability of banks in local areas through a longitudinal study. Ten years later, Gelfand and Spiller (1987) examined the MF theory in the Uruguayan banking sector and demonstrated that prior to the relaxation of entry barriers, domestic incumbent firms escalated rivalry in the key market of multi-nationals, the US\$ denominated market for commercial loans segment, in order to prevent those multi-nationals from expanding into their own key market, the New Peso lending market. In another empirical investigation of MF in the banking industry, Martinez (1990) empirically established that multi-market contact positively influenced market share stability of size rankings of the 100

largest U.S. bank holding companies between 1984 and 1989. Six years after Martinez's study, Whalen (1996) found a positive relationship between primary and secondary out-of-state linkages and dominant firm profitability in the banking industry. Finally, Pilloff (1999) discovered a positive relationship between multi-market contact and profitability in the banking industry.

Despite such empirical support for MF theory in the banking industry, other studies that examined MF theory through cross-sectional designs, predominantly within a state, discovered that multi-market contact increased the level of rivalry as captured by such industry specific performance measures as service charge ratio in deposits, interest rates on loans, market share stability or instability and return on assets. Whitehead (1978), for example, discovered that multi-market contact among Florida Bank Holding companies in 1976 intensified rivalry. Similarly, Mester (1987) found a negative relationship between multi-market contact and market share stability, service charges and return on assets for 171 California savings and loans firms that operated in 56 county markets in 1982.

In addition to these opposing but significant findings, there were also insignificant and mixed findings. For example Rhoades and Heggstad (1985) found that multi-market contact is not associated with the intensity of rivalry and thus does not have an impact on return on assets, service charges, loan rates and fees. Alexander (1985) found mixed results. He discovered a positive relationship between multi-market contact and service charges in the demand deposit market. However he did not find any impact of multi-market contact on interest rates in the short term business loan market.

While some suggest that the results of these banking studies are evidence that MF may not exist, others attribute the inconclusive findings to methodological artifacts. First, these studies measured multi-market contact through coarse-grained and aggregate market-level multi-market count measures. Specifically, the early measures computed the average number of multi-market contacts between a subset of dominant firms in a focal market (Gimeno and Jeong, 2001). Hence these measures of multi-market contact did not reflect the argument of MF theory that MF is relation specific.

Second, these studies assumed the existence of MF equilibrium and inferred its existence from high performance, predominantly through cross-sectional designs (Golden and Ma, 2003; Ma, 1998). However MF equilibrium is not self-enforcing and the process by which firms arrive at the MF equilibrium requires the escalation of rivalry, at least initially (Baum and Korn, 1999; Stephan and Boeker, 2001). The threat of retaliation and deterrence that is the core mechanism of MF in the literature requires that firms increase the level of multi-market contact between themselves and thus aggressive behavior. Therefore, if cross-sectional studies test MF theory before firms have moved to MF, they can find evidence that appears to contradict MF theory. This suggests that the selection of sample and time period may influence the empirical findings of the papers that used cross-sectional designs.

Third, circumstances unique to banking industry may have influenced the findings of these studies. In the banking industry, MF requires a very high level of multi-market contact because it is an institutionalized industry (Stephan and Boeker, 2001). In this industry, a positive relationship between multi-market contact and intensity of rivalry is expected until contact points among banks reach a very high threshold level. If and when firms reach this high threshold level, multi-market contact is expected to de-escalate rivalry. Because banking studies did not examine

a non-linear relationship between multi-market contact and intensity of rivalry, they were not likely to capture the rivalry dampening effect of multi-market contact. In addition, although clear market definition is crucial to test MF theory, products and markets are not clearly defined and identified in the banking industry. Several products are marketed not only within a given local market but also across state boundaries (Singal, 1996). Hence it is difficult to establish a clear linkage between performance and multi-market contact in the industry.

Work outside the banking industry avoided many of the conceptual and methodological weaknesses present in much of the banking industry work and found more consistent support for MF theory. These studies are discussed next.

2.2.2 The Second Stream: Studies outside Banking Industry

The second stream of research within the IO perspective examined MF theory in non-banking industries. Unlike the first stream, the empirical findings of this stream were more conclusive and provided support for MF theory in such diverse industries as the cement, hotel, airline, retail, cellular phone, automobile and various sectors of U.K. and U.S. manufacturing industries.

One set of studies examined MF theory in manufacturing industries. Scott (1982) was the first to test MF theory in manufacturing industries. He used the Federal Trade Commission's Line of Business data and found that multi-market contact coupled with high concentration increased the profitability of 437 U.S. manufacturing companies in 1974. This was after controlling for market share, which ruled out the possibility that efficiency or market power was the cause of profitability. Using the same data base, Feinberg (1985) confirmed Scott's findings. In particular, he found that multi-market contact at both the firm and industry levels increased price-cost margins in 1976, although the rivalry dampening effect of MF was stronger at the firm

level. Using a cross-sectional research design and industry-level measures of multi-market contact, Strickland (1985) found a negative relationship between multi-market contact and price-cost margins for 195 top U.S. manufacturers in 408 standard industrial classifications in 1963. Eight years after his initial study, Scott (1991) once more found that multi-market contact coupled with high concentration increased profits. He also re-interpreted Bain's observation about the relationship between profits, concentration and entry barriers and argued that high level of multi-market contact among studied firms was the main reason for the hypothesized and observed positive relationship between concentration and profits. In addition to these studies which examined MF theory within the context of U.S. manufacturing industries, Hughes and Oughton (1993) examined the relationship between multi-market contact and level of rivalry in the U.K. manufacturing industries. They discovered a positive relationship between multi-market contact and performance as captured by price cost margins and return on invested capital.

In addition to these manufacturing studies, a group of studies tested MF theory in the airline industry. The findings of these empirical studies are mixed. The majority of the studies that tested MF theory in the international and U.S. airline industry provided support for the MF theory. Evans and Kessides (1994), through a longitudinal design, found that multi-market contact increased fares in the U.S. airline industry for the 1000 largest city-pair routes between 1984 and 1988. Similarly, Miller (2010) found that even the consent decrees of the U.S. Department of Justice that aimed to limit the communication of ticket price changes among major carriers did not prevent multi-market contact from increasing fares. Likewise, Singal (1996) found a positive relationship between multi-market contact and performance, measured as yield per mile and change in yield per mile, in the airline industry. His results also indicated that

the impact of a change in multi-market contact on fares is higher than the impact of a change in concentration.

In addition, while Zou et al. (2012) established that multi-market contact increased airfares in the international air travel market, Zou et al. (2011) discovered that multi-market contact increased yield in the U.S. domestic market. Besides, Ciliberto and Williams (2012) found support for the hypothesis that multi-market contact leads to MF in the U.S. airline industry. Sandler (1988), who investigated the impact of multi-market contact on market share instability before and after deregulation in the U.S. airline industry, found mixed support for the MF theory. He found that multi-market contact intensified rivalry before deregulation but had a non-significant market share stabilizing impact after deregulation. These inconsistent findings might be due to the short duration of the study. His results show that after carriers switched from non-price competition to price competition, multi-market contact de-escalated rivalry albeit in an insignificant manner between 1978 and 1980. The insignificant rivalry de-escalating impact of multi-market contact may be due to the short time frame and might have been significant had the study investigated behavior over a longer period of time following deregulation.

Despite the prevalence of the empirical support for the MF hypothesis in the international and U.S. airline industry, studies that investigated the MF theory in the Chinese airline market provided evidence inconsistent with the MF hypothesis. Zhang and Round (2009) concluded that multi-market contact was negatively associated with airfares for China Southern airline market but the same effect was insignificant for the China Eastern market. Two years later, Zhang and Round (2011) found that multi-market contact actually did not have a significant impact on price wars and collusion in Chinese airline markets. The findings of these papers that are inconsistent with the MF hypothesis might stem from their sample and study period that do not contain the

conditions that are required for MF strategy to succeed. For example, since Chinese airline companies decentralize decision making (Zhang and Round, 2009), it is not possible to execute and implement MF strategy in the Chinese airline market (Golden and Ma, 2003; Jayachandran et al., 1999).

Industry specific studies of MF have been conducted in several industries besides airline. Using a structural model of firm behavior, Jans and Rosenbaum (1996) found that as multi-market contact increased, prices increased and diverged from marginal costs in the 25 regional cement markets in the U.S. Like Jans and Rosenbaum, Parker and Roller (1997) used a structural model and found a positive relationship between multi-market contact and prices in the cellular phone industry. Busse (2000) also examined MF theory in the cellular phone industry. Unlike Parker and Roller (1997), she was mainly interested in whether multi-market contact facilitates collusion by providing more opportunities to coordinate actions. She found that multi-market contact was associated with identical price schedules in different markets, which enabled firms to raise prices by approximately 7-10 %. Fernandez and Marin (1998) provided more support for the MF theory in their study of the Spanish hotel industry, which found that multi-market contact enabled firms to transfer their ability to control price from highly concentrated markets to less concentrated markets where it is much more difficult to collude. Likewise, Leheyda (2007) found evidence for the MF theory in the U.S. automobile industry. Cotterill and Haller (1992) used a direct measure of rivalry, market entry, to study the existence of MF for supermarket chains. In line with the findings of other industry specific studies, they found that multi-market contact de-escalated rivalry and entry rates were lower into markets populated by large chains. Despite such support for the MF theory, Waldfogel and Wulf (2006), who employed various empirical approaches to establish the robustness of their findings, found that multi-market

contact did not have a robust effect on advertising prices in the U.S. radio broadcast markets during the years surrounding the Telecommunications Act.

Having found predominantly supporting evidence for the MF theory in product markets, industrial organization scholars began to examine the impact of the number of contacts in innovation markets on the level of the intensity of rivalry in both innovation and product markets. For example Wegberg et al. (1994) demonstrated that multiple contacts across R&D projects can blunt the edge of competition in innovation markets. Vonortas (2000) showed that contacts across innovation and product markets can result in inferior technological standards which are enforced in product markets through collusive arrangements.

As the number of empirical studies that support MF in different industry contexts increased, industrial organization scholars began to conduct theoretical work in order to enrich and calibrate MF theory.

2.2.3 The Third Stream: Conceptual Studies

Initially, MF theory was based on the arguments of Edwards (1955) and Simmel (1950), which were later elaborated on by Adams (1974) and Mueller (1969). According to the logic of these arguments, multi-market contact blunts the edge of competition because in the face of defection, multi-market firms can retaliate not only in all of the contact markets but also selectively in markets where the cost of retaliation is low for them and high for the aggressor(s). Hence multi-market firms are expected to adopt a “live and let live” policy (Edwards, 1955) and carry out reciprocal “super-ordination and subordination” agreements (Simmel, 1950) due to the threat of deterrence.

Two sub-streams of research emerged in the conceptual stream that used mathematical modeling to enrich MF theory. The first sought to establish boundary conditions. Kantarelis and

Veendorp (1988) made the first contribution to this stream and demonstrated that MF requires demand fluctuations across markets. Two years later, Shaffer (1990) added another condition by demonstrating that firms do not mutually forbear from rivalry when marginal costs are constant. By incorporating the boundary conditions set by these two papers, Bernheim and Whinston (1990) argued that multi-market contacts themselves are not sufficient for MF since contacts across markets increase the cost and benefit of defection in equal proportions. They went on to demonstrate that in the case of perfect monitoring, constant returns to technology, and identical markets and firms, multi-market contact increases the cost and benefit of defection in equal proportions and thus just enlarges the payoff matrix of multi-market rivals without influencing their decision calculus and motive to cooperate. However they also showed that when markets or multi-market firms differ from one another, multi-market contact can enhance the possibility of cooperation between firms by relaxing the incentive constraints. Specifically, they argued that when there are differences across markets with respect to growth or concentration levels, multi-market firms can use contacts across markets to transfer slack in incentive constraints from less competitive markets to more competitive markets so as to sustain collusion in the more competitive market. Finally, they postulated that when there are differences across firms with respect to their cost structure and efficiency, multi-market firms can establish turfs or spheres of influence and refrain from escalating rivalry in their rivals' spheres of influence in return for similar treatment in their own spheres of influence.

Responding to the arguments of Bernheim and Whinston (1990), Spagnolo (1999) demonstrated that dissimilarity across markets or firms is not a requirement for the actualization of the rivalry dampening impact of multi-market contact as long as the objective functions of firms are concave. Hence he pinpointed the concavity of objective functions as a boundary

condition for MF. He argued that although multi-market contact increases the benefit and cost of deviation from forbearance in equal proportion in the absence of asymmetry across firms or markets, marginal losses weigh heavier than marginal gains when the objective functions of multi-market firms are concave. This in turn, he argued, motivates multi-market firms to cooperate with one another across markets.

The second sub-stream in the conceptual literature was developed by Thomas and Willig (2006) and Matsushima (2001) and investigated the role of imperfect monitoring on multi-market competition. Thomas and Willig (2006), through mathematical reasoning, demonstrated that multi-market contact is not conducive to firm performance when a firm's ability to detect defection varies across markets. They showed that when the ability to monitor differs across markets, firms should refrain from punishing defection that takes place in a given market that is susceptible to error-prone monitoring in another market so as not to unnecessarily escalate rivalry. That is because when monitoring is not perfect, multi-market rivals can detect non-existent defection and mistake an exogenous shock for aggression and trigger all-out war across markets. Thus the authors argue that firms should not link markets where the ability to detect defection varies.

Matsushima (2001) theorized about the role and relevance of imperfect monitoring of defection for MF strategy. He was particularly interested in situations in which firms are unable to sustain collusion in a market due to imperfect monitoring. Matsushima (2001) demonstrated that multi-market contact enables multi-market firms to distinguish exogenous shocks from defections. According to the logic provided by Matsushima (2001), contacts across markets enable firms to observe a bad signal several times and thus increase the accuracy with which the bad signal is correctly attributed to the aggressive intentions of rivals or the external conditions

beyond their control. Matsushima (2001), therefore, argued that multi-market contact improves the capacity of firms to cooperate and sustain collusion. This scholar's theoretical arguments were later translated into hypotheses by Greve (2008), a strategy scholar, and were tested in the Norwegian general insurance industry.

These conceptual studies paved the ground for experiments and the fourth stream. The fourth stream in the industrial organizational literature carried out experiments to test and better understand multi-market competition and MF.

2.2.4 The Fourth Stream: Experiments

Feinberg and Sherman (1985) carried out the first experimental study of MF. They investigated the conduct of multi-market firms that competed on quantity across identical markets. They found that choices and firm conduct are correlated in conglomerated markets, which provided the first empirical evidence that was consistent with the MF theory. Three years after their initial study, Feinberg and Sherman (1988) investigated the pricing conduct of multi-market firms across identical markets. They found out that facing the same sellers in many markets leads to higher prices than facing different sellers in different markets although price differential was not statistically significant. These scholars proposed that learning that derives from repeated interaction across markets helps firms carry out MF strategy, thereby underscoring the importance of learning to MF.

Following the groundbreaking theoretical work of Bernheim and Whinston (1990), Philips and Mason (1992) for the first time investigated multi-market competition across non-identical markets. These authors found support for the theoretical arguments of Bernheim and Whinston and empirically demonstrated for the first time that MF is not an “all or nothing” phenomenon; multi-market firms simultaneously compete in some of the jointly contested

markets while cooperating in others to maximize their total earnings. Four years later, Philips and Mason (1996) investigated the impact of stringent anti-trust laws on multi-market rivalry. They discovered that effective enforcement of anti-trust laws in a focal market brings about collusive behavior in other jointly contested markets where anti-trust enforcement is either lax or ineffective, underscoring the negative by-product of stringent anti-trust regulations targeting specific markets. In 2001, these authors studied heterogeneous rather than homogeneous conglomerates and discovered a new source of the extended interdependence of markets. In their 1996 study, they proposed that markets are strategically linked if the same rivals meet in these markets. In this initial conceptualization, competition across markets was the glue that linked these markets. In other words, multi-unit strategy was the main source of the linkage. However in their 2001 study, Philips and Mason discovered that markets can be also linked by the actions of a focal firm that is active in these markets but that faces different opponents in each of them. Under such condition, they argued, the focal multi-market firm can transfer its know-how and experiences that are formed in a given market to another market to achieve its aspirations and in the process can link markets. In this framework, it was intra-organizational learning rather than inter-firm competition across markets that link markets. In other words, multi-unit organization was the source of linkage. Hence like Feinberg and Sherman (1988), these scholars discovered the relevance and importance of learning to multi-market competition and MF. These two alternative sources of extended interdependence across markets, multi-unit firm and multi-market strategy, later became the two themes around which Baum and Greve (2001) prepared an edited book to advance the MF literature.

Guth et al. (2010) qualified the learning-based arguments of Philips and Mason (2001) and argued that learning is relevant to multi-market competition and MF as long as markets are

similar to one another because similarity across markets facilitates the effective transfer and application of what is learned in a given market to a similar issue in another market. These authors also discovered that cooperation in complement markets is higher than cooperation in substitute markets. In addition, they found that conglomerate firms cooperate less often than single firms because of their desire to compensate their low performance and loss in a given market through high performance in other markets. This finding implies that multi-market firms are not reluctant to partition markets and accept low performance in a given market in return for high performance in another.

Cason and Davis (1995) investigated the role of communication and especially “cheap talk” in triggering and sustaining collusion. Their empirical model was inspired from the rampant price communication that facilitates tacit collusion in the airline industry. These scholars discovered that it is difficult to develop an effective “language of communication” among multi-market rivals especially when communication is constrained to price offers. They also found that tacit cooperation stems from accommodating and supporting defection of rivals with or without communication. This finding underscores the importance of cooperation to forming tacit collusion.

2.2.5 Summary of the Industrial Organization Literature

While earlier work in the banking industry found mixed support for MF theory, later work using more sophisticated methods and studying other industries provided more conclusive evidence for MF theory. Additionally, both conceptual and empirical work enriched MF theory and established not only boundary conditions but also highlighted the relevance of learning and cooperation to MF and the dyad-specific and market-specific nature of MF.

As MF research was flourishing in the industrial organization domain and the empirical support for MF theory was building, it attracted the attention of strategy scholars, who were drawn to the performance enhancing effect of MF. That work is reviewed in the next section.

2.3 MF in the Strategy Literature

Observation of the rivalry dampening and performance enhancing impacts of multi-market contact found in contemporary work in industrial organization literature attracted the attention and interest of strategy researchers in MF theory. Contrary to industrial organization economists whose primary interest in MF was focused on its negative impact on social welfare, strategy researchers became interested in MF because of its theorized and observed positive impact on firm performance. While economists seek to maximize social welfare by fixing and weeding out market frictions, strategy scholars are interested in maximizing firm performance through the creation of market frictions (Porter, 1981). Since strategy as a field, especially its mechanistic perspective (Farjoun, 2002), seeks to explain the causes of superior firm performance and abnormal returns (Rumelt et al. 1991; Porter, 1991), strategy researchers began to examine whether firms can establish contact across markets for the purpose of creating market frictions and thereby increase their performance. Thus, strategy researchers conceptualized MF as a specific form of strategy that seeks to improve firm performance by sustaining cooperation between direct rivals across markets (Gimeno and Woo, 1999).

MF is a form of cooperative equilibrium that differs from the "market allocations" that result from economic forces. Although MF strategy and outright competition can both result in the dominance of one of the members of a competitive dyad in a given market and bring about differences in their markets shares, the way in which MF results in those outcomes differs from that of outright competition in three ways.

First, multi-market rivals that execute a MF strategy voluntarily divvy up markets. More specifically, they willingly reduce their level of participation in one of the jointly contested markets in return for increasing it in another market as a part of their MF strategies. Hence the observed level of differences in market share is an outcome of choice dictated by a MF strategy rather than an outcome of economic forces of competitive advantage. Economic forces of competitive advantage cannot explain the performance enhancing outcomes of MF because MF takes place among rivals that have similar level of competencies that result from extended competition in similar product and factor markets.

Second, unlike competitive forces, MF strategy requires a pair of multi-market rivals to maintain a sufficient level of overlapping markets in order to execute their MF strategies. Without maintaining footholds in a sufficient number of jointly contested markets, a dyad of multi-market rivals cannot deter defection and assure that their attempts to cooperate will not be exploited by its dyad member. Hence unlike outright competition that can motivate and result in market exit from jointly contested markets, MF strategy motivates the maintenance of overlapping markets and requires a pair of multi-market rivals to sustain a sufficient level of jointly contested markets. Thus, the assignment of markets to particular firms as a result of a MF strategy paradoxically requires reciprocal presence in one another's markets.

Third, in the case of actual defection of their rivals, multi-market firms that execute a MF strategy use their existing footholds in the key markets of their rivals to retaliate and punish defection. However the purpose of that punishment is not to escalate the level of rivalry but to restore competitive balance and maintain the existing super-ordination and subordination agreements that divvy up markets. Unlike competition that attacks the ability of a rival to dominate a market, MF strategy attacks the motive of a rival to be competitive to dominate a

market. Hence in the case of MF, the observed differences in market shares derive from impairing the will rather than ability of a rival.

2.3.1 Variance Studies

Much of the work on MF theory undertaken by strategy scholars used variance studies to discover the sign and shape of the relationship between multi-market contact and MF. There are two streams of variance studies.

The first stream predicts and tests a monotonic negative association between multi-market contact and level of rivalry. These studies were primarily longitudinal in design and predominantly used performance-based measures to capture the intensity of rivalry. This stream found supporting evidence for MF theory in the deregulated telephone industry (Barnett, 1993), in the U.S. airline industry (Baum and Korn, 1996, Gimeno and Woo, 1996; Gimeno, 1999; Prince and Simon, 2009), in the investment banking industry (Shipilov, 2009), in the Japanese shipbuilding industry (Greve and Mitsuhashi, 2004), in the Tokyo Banking industry as far as multi-market and single market bank rivalry is concerned (Greve, 2000), in the intra-European passenger airline industry (Fan, 2010), in the software industry through either such direct measures of rivalry as number of competitive moves and speed of countermoves (Young et al., 2000) or such indirect measures of rivalry as revenues from software licensing (Chellapa et al., 2010), in the U.S. computer related and manufacturing industry (Upson et al., 2012) and finally within the context of franchise organizations that regulate intra-organizational competition through multi-market contacts (Kalnins, 2004).

Despite such support, a group of studies found evidence that either contradicted the MF theory's main proposition that multi-market contact de-escalates rivalry or found consistent but insignificant results. For example Tanriverdi and Lee (2008) discovered that both multi-product

and multi-market competition escalated rivalry and thus had a negative impact on sales growth and their impact on market share was insignificant due to network externalities that exist in the software industry. Like Tanriverdi and Lee (2008), Gardner (2005) examined the software industry and discovered that product market overlap does not have a significant impact on both defensive and defensive-retaliatory action. Similar to Tanriverdi and Lee (2008) and Gardner (2005), Anand et al. (2009) scrutinized a knowledge-intensive industry and found that multi-market contact intensified the level of rivalry in the case of “exploration” and thus increased the likelihood of entry by firms that explore in the biopharmaceutical industry. Like Anand et al. (2009), Fuentelsaz and Gomez (2006) examined the relationship between multi-market contact and entry rate in the Spanish saving banks industry. These scholars were particularly interested in investigating a specific type of multi-market contact, called reciprocal contact, that is supposed to have the strongest impact on de-escalation of rivalry in line with the MF theory. Contrary to the main proposition of the MF theory, they discovered that reciprocal multi-market contact actually intensified rivalry and thus increased the rate of entry in the Spanish saving banks industry. Finally, Lazzarini (2007) investigated the role of multi-market contact as a control variable in the global airline industry and did not find a significant impact of multi-market contact on load factor.

Following the first stream, the second stream of MF research in strategy was inaugurated by the ground breaking research of Baum and Korn (1999). These scholars hypothesized, for the first time, a concave-down curvilinear relationship between multi-market competition and the intensity of rivalry by differentiating the creation of multimarket competition from its exploitation (Korn and Rock, 2001). They argued that at low levels of multi-market contact, multi-market firms intensify rivalry to establish deterrence but when the level of multi-market

contact reaches a high level, they begin to refrain from rivalry due to the threat of punishment resulting from aggressive conduct. This second stream did not infer the intensity of rivalry from outcome based performance measures, but rather used action-based measures, such as entry and exit (Anand et al., 2009; Baum and Korn, 1999; Fuentelsaz and Gomez, 2006; Haveman and Nonnemaker, 2000; Stephan et al., 2003; Jung, 2010), competitive aggressiveness (Yu et al., 2009) or level of participation in a market (Haveman and Nonnemaker, 2000) as proxies for intensity of rivalry. This sub-stream found support for the hypothesized curvilinear relationship in airline industry (Baum and Korn, 1999), Spanish saving banks industry (Fuentelsaz and Gomez, 2006), California savings and loan industry (Haveman and Nonnemaker, 2000), California hospital industry (Stephan et al., 2003), Korean hospital industry (Jung, 2010) and global automobile industry (Yu et al., 2009).

2.3.1.1 Empirical Limitations of the Variance Studies

Although the variance studies are useful to understand the sign and shape of the relationship between breadth and intensity of rivalry at the aggregate level, they have several limitations. First, this sub-stream, because of its nature, does not explain how multi-market rivals start and then learn to cooperate and coordinate their actions across markets to move to the MF equilibrium (Busse, 2000; Kang et al., 2010; Scott, 1991). The studies are silent on the process of multi-market competition but provide a useful starting point to build a process theory of MF.

Second, this stream's utilization of the level of multi-market contact as a proxy for multi-market competition, which is the main independent construct in the literature, results in two types of shortcomings. First, the construct of multi-market contact does not capture the actual competitive/cooperative actions and reactions of multi-market firms in their jointly contested markets by which MF is established. Capturing the content of multi-market competition is crucial because the competitive weapons employed to compete across markets can influence not

only the competitive dimensions on which firms forbear across markets, but also the stability of MF as an equilibrium because cooperation that is founded upon resource-intensive strategic moves are expected to be more stable than cooperation that is based on easily reversed tactical moves.

Second, the attempt to capture multi-market competition through multi-market contact spuriously inflates the level of competition across markets because multi-market contact cannot automatically evolve into multi-market competition due to cognitive limitations/biases of managers and the fragmented structure of markets. For multi-market contact to be transformed into multi-market competition, all firms with overlapping markets must identify one another as rivals. However like any firm, a multi-market firm is expected to identify only a small subset of firms with which it has contacts across markets as rivals because firms, in general, recognize only a handful of firms as rivals due to the cognitive limitations of managers (Bigne and Lopez, 2000; Clark and Montgomery, 1999; Porac and Thomas, 1994). Even if a multi-market firm identifies another multi-market firm as its rival, this is not sufficient to transform multi-market contact into multi-market competition because competition across markets requires multi-market firms to *mutually* recognize one another as multi-market rivals, without which intentional jockeying for positions across markets cannot be carried out. Given that recognition of rivalry is asymmetric (Desarbo et al., 2006), a multi-market firm will engage in multi-market competition only with those members of its rivalry set that also consider itself as rivals.

Once a group of multi-market firms mutually recognize one another as multi-market rivals, they are loath to identify other firms with which they have multi-market contact as multi-market rivals due to cognitive inertia in rival identification (Reger and Palmer, 1996; Hodgkinson, 1997), attenuating further the theoretical link between multi-market contact and

multi-market competition. Hence multi-market competition is a possibility solely for a subset of the subset of firms that have contact across markets. In addition, fragmented market structures might bar the transformation of multi-market contact into multi-market competition because firms with multi-market contact that target different niches in their overlapping markets do not necessarily compete with each other across their common markets. As a result of all of these factors, the empirical finding that multi-market contact reduces the level of rivalry may be spurious (Jacobson, 1992) if multi-market contact does not capture multi-market competition to begin with (Korn and Rock, 2001).

Third, the variance sub-stream considers MF as the inevitable and ultimate solution to the prisoner's dilemma type of cooperation problem faced by multi-market rivals and infers the existence of MF from stable market shares, high profitability or reduction in level of rivalry. However multi-market competition can result in alternative competing equilibriums such as limited war, all out war, or maintenance of the status quo (Karnani and Wernerfelt, 1985). Even if multi-market firms reach MF equilibrium at a point in time, such equilibrium is not self-reinforcing and is susceptible to defection-based breakdown at any time because of the classical problems associated with tacit collusion such as lack of focal points, imperfect monitoring, exogenous shocks etc. (Scherer and Ross, 1990). Hence the variance sub-stream exclusively studies only one type outcome of multi-market competition and rules out the equally likely alternative equilibriums and the breakdown of cooperation, which is a temporary but a natural component of multi-market competition. We need theories and models that can explain the natural progress and development of MF as it evolves.

Since both streams of variance research demonstrated that multi-market contact, most of the time, is conducive to firm performance and, at some period, reduces the intensity of rivalry, a

group of researchers started to investigate the causal forces of MF. These researchers focused predominantly on whether multi-market contact leads to MF through familiarity or deterrence.

2.3.2 Empirical Studies of Causal Forces of Mutual Forbearance

2.3.2.1 Familiarity

Familiarity and deterrence are considered to be key mechanisms in the transformation of multi-market competition into MF (Jayachandran et al., 1999). Familiarity is argued to be essential to MF (Barnett, 1993; Fuentelsaz and Gomez, 2006; Gimeno and Woo, 1996; Young et al., 2000) because it facilitates the exchange, collection and interpretation of information that is crucial to cooperation. Firms that are familiar with each other can not only coordinate their actions more effectively, which is key to cooperation, but also interpret one other's actions much more accurately than firms that are not familiar with each other. As such, familiar firms are better positioned to emit and recognize signals of cooperation. The literature argues that familiarity is a function of the number of common markets among firms. It is hypothesized that as the number of markets in which firms compete increases, familiarity between those firms increases due to deepened and extended interaction.

2.3.2.1.1 Boundaries and Limitations of the Familiarity Mechanism

Despite the attractiveness of the logic, the overall empirical findings of the studies that investigated the role of familiarity which is empirically captured through strategic/resource “similarity” or “norms”, do not support its proposed role as a primary causal mechanism for the formation of MF. First, empirical papers that examined the Caves and Porter (1977) hypothesis that familiarity reduces rivalry within the context of multi-market competition found mixed results. While Gimeno and Woo (1996) and Marcel et al. (2010) empirically demonstrated that familiarity escalates the intensity of rivalry among multi-market rivals, others discovered that familiarity actually either de-escalates rivalry (Fuentelsaz and Gomez, 2006; Young et al., 2000)

or does not have a significant impact on competition (Li and Greenwood, 2004). The study by Upson et al. (2012) encompassed these mixed findings as they found out that similarity reduces both foothold attack and foothold withdrawal in the computer-related and manufacturing industries. Second, the empirical investigation of the impact of the interaction of familiarity with multi-market contact on competition resulted in inconclusive findings. While Li and Greenwood (2004) found that such interaction led to a reduction in the level of rivalry, both Young et al. (2000) and Fuentelsaz and Gomez (2006) found that the very same interaction escalated rivalry. Once more, the findings of Upson et al. (2012) encompassed these contradictory impacts of such interaction in the computer related and manufacturing industries. They found that the interaction of similarity with market commonality increases both foothold attack and foothold withdrawal.

In light of such mixed evidence, further research into familiarity and its complex interaction with multi-market contact is warranted (Fuentelsaz and Gomez, 2006). We still do not know how these two forces, in isolation and in combination, shape and mold rivalry. In the extant literature, familiarity is perceived as the “enabler” of cooperation because it is hypothesized that it facilitates information collection, exchange and interpretation. However ability is necessary but not sufficient to instigate and maintain cooperation. To start the process of cooperation, rival firms must also be first motivated to cooperate. Having been exposed to an extended period of cut throat competition and conflict laden competitive histories, rivals firms cannot automatically and effortlessly develop the motive to cooperate. Rival firms can deepen and develop their cooperation by using their abilities to coordinate and communicate once they are motivated to cooperate. Therefore the literature must theorize about both the ability and motive (Chen, 1996) in order to cooperate to develop a comprehensive understanding and theory of cooperation between rival firms.

Because of the mixed findings of the aforementioned studies, subsequent research turned its attention to deterrence, the second mechanism hypothesized to switch competition into cooperation across markets.

2.3.2.2 Deterrence

The “deterrence stream” argues that market overlap deters rivalry because of the threat of cross-market retaliation in the face of defection (Barnett, 1993; Baum and Korn, 1996; Evans and Kessides, 1994; Gimeno 1999; Gimeno and Woo, 1999; Haveman and Nonnemaker, 2000; Li and Greenwood, 2004). According to this line of reasoning, the number of common markets between a dyad of rivals increases the cost of defection and intensification of rivalry due to the threat of expected simultaneous and spatial retaliation across common markets. Market overlap enables a focal firm to punish defection and aggression on the part of its multi-market rival not only in the focal market where aggression has initially taken place but also selectively in the primary markets of aggressor (Karnani and Wernerfelt, 1985) where retaliation is less costly for the responding focal firm and more detrimental to the aggressor. Hence market overlap broadens the competitive response portfolio of multi-market rivals and increases the effectiveness and efficiency of retaliation in response to aggression of a multi-market rival, thereby deterring the intensification of rivalry.

Empirical work in the “deterrence stream” examined asymmetries in multi-market rivals’ competitive advantage across markets, which is what makes multi-market competition relevant to MF (Bernheim and Whinston, 1990). Research in this area sought to tease out the deterrence and cost reducing effects of multi-market competition in order to disentangle the contribution of deterrence-based tacit collusion to performance from that of economies of scope (Hughes and Oughton, 1993). Results suggest that mutual contacts between rivals in one another’s turfs

(spheres of influence) are the only type of contact that attenuates rivalry (Evans and Kessides; 1994; Gimeno 1999; Li and Greenwood, 2004) and not having footholds in markets where rivals have cost advantages, and thus high market share, intensifies rivalry (Gimeno and Woo, 1999). Additionally, this stream showed that MF takes place predominantly in the primary and key markets of multi-market firms rather than in their all of the jointly contested markets (Barnett, 1993). Multi-market firms refrain from rivalry in the spheres of influence of their rivals in return for dominating their own spheres of influence.

While deterrence as a mechanism was gaining predominance in the literature as a causal force behind MF, some researchers were providing both empirical evidence and theoretical arguments that questioned the external validity of deterrence as the causal force and established the boundary conditions under which deterrence may be ineffective as a switch from competition to cooperation across markets.

2.3.2.2.1 Boundaries and Limitations of the Deterrence Mechanism

There is no direct empirical test of the deterrence mechanism and the evidence on the main proposition of “deterrence stream” is mixed. In the strategy literature, deterrence acquired predominance over familiarity as a mechanism to switch competition into rivalry across markets. However there is no empirical work that directly tests the causal relationship between deterrence and MF. The extant literature on deterrence does not go beyond delineating which type of markets and contacts are the most effective to establish deterrence and de-escalate rivalry. Even the empirical findings concerning the main proposition of the “deterrence stream” are inconclusive. The “deterrence stream” proposes that reciprocal contacts are more effective than non-reciprocal contacts to deter rivalry and finds empirical support for such a claim. Nevertheless, recent findings from Fuentelsaz and Gomez (2006) provide contrary evidence and

refute the main proposition of the “deterrence stream”. These scholars discovered that rather than de-escalating rivalry, reciprocal multi-market contact actually intensified rivalry and thus increased the rate of entry in the Spanish saving banks industry.

Empirical work that studies the retaliatory moves of multi-market firms to the defection of their multi-market rivals suggests that deterrence, and thus the threat of punishment, cannot alone trigger MF. For example, Smith and Wilson (1995) found that most of the time, multi-market firms do not respond to the entry of their multi-market rivals into their markets and if they do, they raise their prices upon entry rather than escalating rivalry. Likewise, contrary to premise of MF theory that requires immediate punishment of defection, Kang et al. (2010) found that multi-market firms do not respond to defection of their multi-market rivals with their own price reductions to discipline defectors. Shankar (1999) also found that when a multi-market firm launches a new product into the market of its multi-market rival, the defending multi-market firm actually lowers its marketing expenditures, rather than increases them. In addition, Jung (2010) uncovered that at low or moderate levels of multi-market contact, firms carry out compensatory exits rather than retaliatory entries even though the deterrence argument requires multi-market firms to establish footholds in each others’ market so as to build the ability to deter, especially when the level of multi-market contact is low to moderate. Finally, Gardner (2005) found out that product market overlap does not have a significant impact on defensive retaliatory actions in the software industry, demonstrating that multi-market rivals actually do not exercise deterrence and thus punish defection. These findings are not unexpected because firms in general do not respond to aggression (Steenkamp et al., 2005; Leeflang and Wittink, 1992), which reduces the effectiveness of the deterrence mechanism to discipline defectors and signal the intent to re-

establish collusion. In addition, the exercise of deterrence, and thus punishment of defection, is costly to the punisher, impairing its credibility (Sorenson, 2007).

Empirical work on the boundary conditions of MF also raises questions regarding the extent to which deterrence can act as a primary mechanism to trigger MF. Four boundary conditions have been laid out. First, the exercise of deterrence requires intra-firm coordination and cooperation (Golden and Ma, 2003; Jayachandran et al., 1999; Kalnins, 2004; Ma, 1998; Korn and Rock, 2001; Yu et al., 2009) that are not commonly found in multi-market firms. Deterrence as a mechanism calls for integration devices and incentives that reward firm-level performance rather than sub-unit performance. Without coordinating their actions across markets, providing the right competitive information to the right unit at the right time and intensifying rivalry in less competitive markets for the sake of reducing rivalry in more competitive markets, firms can not exercise deterrence across markets and rivalry can converge to market by market competition (Jayachandran et al., 1999). Deterrence across markets requires centralization of corporate-level and business-level strategic decisions (Kalnins, 2004) or incentives and integration devices at the lower subsidiary or divisional level that promote coordination and cooperation (Golden and Ma, 2003). Coordination and cooperation among markets allow units of an organization to share information that comes from diverse markets and to transfer enforcement power from less competitive to more competitive markets to exercise deterrence, a move that will hurt the performance of units competing in less competitive environments. That is why, for example, geographic or related diversifiers and firms that implement a global international strategy are in a better position to exercise deterrence (Golden and Ma, 2003; Ma, 1998) and multi-market rivals in the Chinese airline industry that lack

centralized decision making fail to execute MF strategy and escalate rivalry (Zhang and Round, 2009).

A second boundary condition for deterrence is uncertainty, which is a common trait in multi-market competition. Uncertainty impairs the effectiveness of deterrence as a mechanism. Under conditions of uncertainty, sociological arguments, which assert that firms take action to imitate one another in order to reduce uncertainty and establish legitimacy, replace game theoretic arguments, which propose that firms take actions in order to deter one another (Kalnins, 2004). Uncertainty impairs the effectiveness of deterrence to prevent the escalation of rivalry because it motivates multi-market firms to imitate one another (Dimaggio and Powell, 1983) and mimic one another's diversification moves (Fligstein, 1990) at the expense of intensifying rivalry due to cognitive and normative pressures. For example uncertainty motivated rival firms in the Portuguese banking industry to enter each others' markets, which were known to be unprofitable, and wittingly escalate the level of rivalry because normative rationality prevails over economic rationality under uncertainty (Barreto and Baden-Fuller, 2006). Even when economic rationality prevails over normative rationality, uncertainty prevents the rational calculation of the cost and benefit of defection. This in turn impairs the effectiveness of deterrence especially when would-be defectors overestimate the benefit of defection and underestimate the cost of defection. That is why the relationship between level of multi-market contact and entry is positive rather than negative in markets characterized by uncertainty (Anand et al., 2009), contrary to MF theory. Under uncertainty, even reciprocal contacts, which are the most effective contacts to deter rivalry, are associated with increased entry rates and thus the escalation of rivalry (Fuentelsaz and Gomez, 2006).

Imperfect observability is the third boundary condition; it reduces the effectiveness and importance of deterrence as a mechanism to trigger and promote cooperation. Deterrence as a capacity requires the ability to detect and observe defection (Greve, 2008). If multi-market rivals cannot observe defection, they cannot punish it. The ability to detect defection precedes the ability to punish defection. However competitive actions are not perfectly observable in all market segments and industries. For example in the insurance industry, it is difficult to detect defection precisely because price reduction by a firm can derive from its proprietary technology of risk assessment rather than its desire to increase market share (Li and Greenwood, 2004). When prices, quality and quantity are not perfectly observable, multi-market firms might detect non-existent defection or overlook existent defection, impairing the effectiveness of deterrence. Additionally, the ability to observe and detect defection hinges on the number of firms in the market where defection occurs rather than on the number of common markets that create the deterrence mechanism (Greve, 2008). Therefore, the threat of punishment, and thus deterrence, may not be a credible threat when a high level of multi-market contact does not coexist with a high number of firms in the market where defection has taken place. The likelihood of a given market to simultaneously meet these conditions is low. As the level of multi-market contact increases among firms in a given market, the overall size of these firms is expected to significantly increase. The increase in size, in turn, is expected to reduce the number of firms operating in a market given the carrying capacity of the market (Hannan and Freeman, 1977). Hence, deterrence is not as important as it is argued in the literature because it cannot help multi-market firms to successfully complete the first step in deterrence; the detection of defection.

The fourth and final boundary condition is the level of market concentration, which influences the effectiveness of deterrence. The effectiveness of deterrence as a mechanism of MF

depends on the level of concentration that exists in a market. When concentration is very high and prices are significantly above the competitive level, the expected benefit of defection can exceed the expected cost, reducing the usefulness of deterrence (Greve, 2008). When concentration is very low in a market, and thus competition is intense, exercise of punishment cannot be a credible threat because no firm by itself can shape the actions of other firms in a competitive environment (Jayachandran et al., 1999). The findings of Prince and Simon (2009) provide support for the changing role of concentration contingent upon its level. These scholars found that the positive impact of multi-market contact on delay in the airline industry diminishes in highly concentrated markets but the effect gets stronger in moderately concentrated markets.

The dual role played by concentration depending on its level explains why the findings concerning the impact of industry concentration on the strength of the relationship between multi-market competition and MF are inconclusive. While Scott (1982, 1991), Whalen (1996), Jans and Rosenbaum (1996) and Haveman and Nonnemaker (2000) found that the interaction of multi-market contact with industry concentration reduces rivalry in line with MF theory, Mester (1987) and Fernandez and Marin (1998) discovered that such interaction increases the intensity of rivalry and impairs MF. Others have found insignificant results (Baum and Korn, 1996; Fuentelsaz and Gomez, 2006).

In addition to the four boundaries that limit the external validity of deterrence as a trigger for MF, there are four limitations to the logic underlying the deterrence argument. First, the argument that it is the expectation and thus the threat of punishment that causes MF (Chen, 1996; Gimeno, 1999; Li and Greenwood, 2004) is inconsistent with what we know about how managers and firms make decisions. Managers cannot refrain from escalating rivalry by foreseeing that defection will be punished because boundedly rational managers are generally not

forward-looking (Korn and Rock, 2001; Meyer and Banks, 1997) and cannot carry out contingent decision making that requires looking more than two steps into the future and then reasoning backward (Deshpande and Gatignon, 1994; Hutchinson and Meyer, 1994; Montgomery et al., 2005; Moore and Urbany, 1994; Reibstein and Chussil, 1997; Urbany and Montgomery, 1998; Zajac and Bazerman, 1991).

Even if one assumes that managers can carry out contingent thinking and can refrain from rivalry due to the expected threat of retaliation, it remains difficult for them to correctly interpret the motive behind the escalation of rivalry intended to deter competition. The deterrence proposition assumes that managers can differentiate retaliation, which is an act of aggression that seeks to create collusion, from rivalry that is an act of aggression intended to out-compete rivals. This is not a plausible argument because managers do not always construe competitive signals accurately (Mezias and Starbuck, 2003), especially the competitive reactions of rivals (Clark and Montgomery, 1996a; Coyne and Horn, 2009; Montgomery et al., 2005). The inability to interpret the exercise of deterrence as a signal to cooperate is much more acute in the context of multi-market competition due to a rich history of competitive battle between multi-market firms. In addition, according to the well-established organizational learning literature, firm behavior and conduct is not based on future expectations, as suggested by the deterrence proposition, but on past experiences (Cyert and March, 1963). Firms learn from and live in the past (Greve, 2000). Accordingly, firms cannot learn to cooperate if they have not previously cooperated. Hence deterrence alone cannot promote MF because it requires cooperation among firms that lack a history of cooperation.

Second, the deterrence argument is logically flawed and probabilistically unlikely. There are two types of deterrence. Firms can deter either retaliation or aggression (Porter, 1980). The

extant literature on MF exclusively focuses on the latter type due to its argument that it is the threat of punishment of aggression that de-escalates rivalry. This results in logical inconsistency. For the threat of punishment to work and MF to be realized, it requires both members of a competitive dyad to fail to deter retaliation so that they, themselves, are not aggressive but succeed in deterring threatening moves so that their rivals are not aggressive. However since deterring both retaliation and threatening moves requires irreversible and binding commitment in the form of aggressive investments and actions that will escalate rivalry (Porter, 1980), it is logically inconsistent and impossible for both members of a dyad to jointly and simultaneously fail to deter retaliation while succeeding in deterring threatening moves.

Third, evidence that shows that MF is more likely to be an emergent rather than a deliberate strategy (Korn and Rock, 2001) reduces the possibility that it is deterrence that originates MF. The deterrence argument requires multi-market firms to intentionally enter into each other's markets in order to establish deterrence (Baum and Korn, 1999, Scott, 1982). However we know that multi-market contacts are predominantly established by chance and thus for reasons not akin to the *ex ante* desire to collude (Scott, 1982, Korn and Baum, 1999); one study found that the correlation between observed level of multi-market contact and chance-driven multi-market contact is 0.93 (Gimeno, 2002). These findings suggest that firms increase their level of multi-market contact for reasons not related to the deterrence of rivalry (Kalnins, 2004), suggesting that deterrence alone is not likely to originate MF.

Fourth and finally, the literature on deterrence does not recognize that the process of rivalry binds rivals and develops cooperation and that the resulting cooperation itself reduces the importance and relevance of deterrence to MF strategy. The deterrence mechanism assumes that the process of cooperation will not change the nature of subsequent cooperation and deterrence

will be always the main source of MF because the literature on MF takes a statistic perspective on the relationship between rivals. In its current form, MF theory assumes that rivals cooperate with one another because deterrence obviates the motive to defect and that the process of cooperation does not have any impact on subsequent relations between rivals. However rivalry is a dynamic phenomenon and repeated and continuous interaction between rivals binds them together and cross-fertilizes ties between them (Trapido, 2007). This in turn leads rivals to develop cooperative norms, reducing the importance of deterrence to cooperation and MF. For example, during World War I, opposing armies developed rules to cooperate with one another due to the static nature of their fighting and the resulting understanding that their needs and problems were identical. More specifically, armies of opposing states developed norms that prohibited them from striking and shooting when soldiers were eating and meeting their basic needs and incumbent soldiers indoctrinated incoming soldiers with the importance of such norms to sustain the cooperation (Axelrod, 1984). The source of such cooperation was not deterrence but fraternization with the enemy that derived from repeated interaction.

In addition to the binding nature of rivalry that brings about cooperation, once rival firms begin to cooperate, the process of cooperation itself has a self-reinforcing impact not only on subsequent cooperation but also on the nature and magnitude of trust formation between rivals. Deterrence provides the lowest level of trust between rivals (Shapiro et al., 1992). According to the logic of deterrence-based trust and cooperation that dominates the MF literature, trust and the motive to cooperate derive from the ability to deter defection and thus firms trust their ability to punish defection rather than trustworthiness of their rivals. However this literature ignores findings that suggest that once cooperation starts, deterrence-based trust gives way to knowledge-based and identification-based trust, which are higher forms of trust (Shapiro et al.,

1992). When rival firms decide to cooperate because of deterrence-based trust, they start to share critical knowledge about themselves and thus start to better understand each others' values and preferences. In addition, they gather evidence concerning the predictability, reliability and trustworthiness of their rivals and learn which rivals are trustworthy. They use the resulting information and understanding to selectively cooperate with rivals that are reliable and predictable (Peteraf and Shanley, 1997). At this stage of cooperation, firms trust the cooperative nature of their rivals and deterrence plays a limited role.

The process of cooperation with selected rivals has been associated with common framing of problems, mutual imitation and the development of routines to carry out cooperation (Peteraf and Shanley, 1997). All of this leads cooperating rivals to form a common identity and to identify themselves with one another (Livengood and Reger, 2010; Peteraf and Shanley, 1997). As a result of such identification process, firms categorize the rivals with which they cooperate as "we, the serious and fair actor" and the ones that they do not cooperate with as "them, the unserious and unfair actors" (Baldwin and Bengtsson, 2004). Once firms identify themselves with a group of rivals, their cooperation derives from that attachment and their common identity, but not deterrence. This in turn reduces the importance of deterrence to MF. Hence we need to explain what makes rival firms sustain cooperation and refine the role played by deterrence.

In its original formulation, deterrence (Edwards, 1955) and cooperation (Simmel, 1950) were positioned as the two main drivers of MF. However the deterrence mechanism gained pre-eminence in the extant literature. Yet, as noted in this discussion, much of the recent empirical and theoretical literature suggests that threat of punishment alone cannot trigger MF. This suggests that the impact of cooperation on MF and the process by which multi-market rivals

establish reciprocal super-ordination and subordination agreements by assigning their overlapping markets to one another may be a more fruitful avenue of research. In fact, the finding that multi-market firms respond to the aggressive moves of their rivals with moves that de-escalate rather than escalate rivalry (Cason and Davis, 1995; Jung, 2010; Kang et al., 2010; Smith and Wilson, 1995; Shankar, 1999) demonstrates the importance of cooperation as a trigger of MF. A more complete understanding of the roles deterrence and cooperation play in the emergence of MF requires returning to the intellectual roots of MF theory and investigating the role of cooperation in MF (Baum and Korn, 1999; Korn and Baum, 1999). Through such an investigation, it will be also possible to gain a better understanding of the role of deterrence that is consistent with the current empirical findings and theoretical arguments in different streams of research and to theorize about the interplay and dialectic interaction between cooperation and deterrence.

The third stream in strategy literature on MF investigates the intentionality and thus origins of MF strategy.

2.3.3 Deliberateness of MF Strategy

The MF literature does not explain what motivates multi-market firms to cooperate across markets because it argues that MF is a deliberate strategy and assumes that rivals establish contacts across markets with the intent to deter rivalry. A recent sub-stream of research has put these arguments and assumptions to the test. In particular, this sub-stream investigates whether firms establish contacts across markets with the ex ante motive to de-escalate rivalry. The empirical findings of this sub-stream demonstrate that multi-market contacts are predominantly established by chance (Gimeno, 2002; Korn and Baum, 1999) and thus for reasons not akin to the ex ante desire to collude (Greve, 2006; Scott, 1982, Korn and Baum, 1999). Following the

coincidental formation of multi-market contact, multi-market firms at a point in time do recognize the possibility of initiating a MF strategy and, contingent upon such recognition, purposefully and strategically begin to either exploit their existing level of multi-market contact (Gimeno, 2002) or continue to increase the existing level of multi-market contact so as to implement a MF strategy (Greve, 2006).

This suggests that MF is an emergent rather than a deliberate strategy (Korn and Rock, 2001) and calls for both empirical and theoretical work to investigate the motive behind MF. Investigating the motive behind MF is crucial because MF theory, in essence, is a motivational theory of competitive advantage. Unlike strategic group theory (Caves and Porter, 1977) and resource based view (Barney, 1991) that propose that the main way to establish competitive advantage is to harm the *ability* of rivals to compete by building either ex ante or ex-post limits to competition, MF theory suggests that the fundamental path to competitive advantage is to dilapidate and wilt the *motive* of rivals to compete aggressively (Gimeno, 1999). We need to develop theories that explain the genesis of MF given the recent evidence that demonstrates that MF is not a deliberate but an emergent strategy.

2.4. Summary

This literature review demonstrates that our understanding of MF has improved over the years. We know that multi-market rivals forbear from rivalry, that the relationship between multi-market contact and level of rivalry is curvilinear, that MF takes place primarily in the key markets of rivals and is a property of the relationship between a dyad of rivals, and that multi-market contacts are established for reasons unrelated to the motive to forbear from rivalry.

Though our understanding of MF has increased significantly as a result of research, this literature review shows that there are three crucial gaps in our understanding. First, we do not

know what motivates multi-market rivals to begin to mutually forbear. The theoretical arguments put forth in extant literature assume that MF is a deliberate strategy and that multi-market rivals are motivated to forbear from the beginning, despite the empirical evidence to the contrary. Hence we need to explain what motivates multi-market rivals to forbear from competition by leveraging their contacts across markets. More specifically, we need to provide a theoretical explanation for the *unintentional* formation of MF and the *causes* of the *switch* that transforms competition into cooperation.

Second, cooperation and its impact on MF are not studied in the extant literature even though cooperation was originally proposed as one of two mechanisms that trigger MF across markets. The literature review shows that firms' natural response to aggression and defection is cooperation. Hence we need to develop a better understanding of the role of cooperation in the development of MF especially since MF, in essence, is a strategy of cooperation. We have not yet identified the strategic effects of multi-market competition when rivalry involves cooperation (Kang et al., 2010).

Third, because the majority of the studies examine only the sign and functional form of the relationship between multi-market contact and mutual forbearance, we do not know how firms coordinate their actions to move to the MF equilibrium (Busse, 2000) rather than to competing equilibriums, such as limited war, all out war, or maintenance of the status quo. More specifically, we do not know how firms use contacts across markets to learn how to cooperate (Scott, 1991) and signal their intent to mutually forbear (Busse, 2000). In addition, we do not know how signals from multi-market firms to establish cooperation fail and the impact of such failures on the genesis of MF. Thus, we need theories that explain the process by which multi-market rivals move to the MF equilibrium.

In the next chapter, I develop a model that addresses each of these gaps in our understanding. The model as a whole seeks to bring cooperation back into our understanding of the development of MF. As noted above, investigation into the role of cooperation has been overshadowed by a focus on deterrence, even though theoretically both deterrence and cooperation are required for the development of MF. Therefore, the first research question to be addressed in this dissertation is: What is the role of cooperation in the development of MF?

I use theories of trust and learning as guiding perspectives in the development of the model. Trust, as a construct, is relevant to MF theory because it is associated with both cooperation and deterrence and it confirms to the prospective orientation of MF theory. I argue that trust is particularly relevant in the context of multi-market competition because the processes associated with multi-market competition are consistent with the formation of inter-organizational trust. Besides, the core of MF strategy requires firms to make themselves vulnerable to retaliation across markets (Greve, 2000). Such willingness to be vulnerable is the definition of trust for scholars that conceptualize trust as a social orientation towards others (Mayer et al., 1995; Malhotra, 2004; Rousseau et al., 1998). Thus, the second research question to be addressed in this dissertation is: Does trust enable a dyad of multi-market rivals move from rivalry to cooperation and, if so, how?

I take an organizational learning perspective to develop hypotheses about how cooperation evolves and how multi-market rivals coordinate their actions to move to mutual forbearance equilibrium rather than to competing equilibriums. Theories of organizational learning are relevant to MF theory because multi-market contact provides many opportunities to learn (Scott, 1991) and acts as information conduit that facilitates all types of learning (Wegberg and Witteloostuijn, 2001). “Facing the same other seller in different markets affords a learning

opportunity that is not present when a different rival is faced in every market” (Feinberg and Sherman, 1988, p: 986). In addition, an organizational learning perspective complements and enriches the prospective orientation of MF with an historical perspective that also shapes firm conduct. Examining MF through the lens of organizational learning provides a more realistic and comprehensive approach to the study of MF because it acknowledges that both the past and the future influence the cooperative and competitive actions of firms. Thus, the third research question to be addressed in this dissertation is: Does learning theory explain the process by which a dyad of multi-market rivals moves to MF?

CHAPTER 3

A THEORETICAL MODEL: ORIGINS OF MUTUAL FORBEARANCE

In this chapter, I develop a model of the evolution of mutual forbearance between a dyad of rivals across markets. The model is based on the theoretical foundations of mutual forbearance that were outlined in chapter two and it suggests that mutual forbearance across markets between a dyad of rivals is the result of a learning process. The development of inter-organizational trust, which results from extended multi-market rivalry between two firms, is proposed as the triggering mechanism that motivates the initiation of the learning process.

Prior to presenting the model, a discussion of the processes involved in rivalry and how they ultimately lay the groundwork for the formation of inter-organizational trust is required. Section one therefore links the mutual recognition of rivalry between two multi-market firms and the resulting competitive interaction to the development of multi-market competition, reduction in performance, and norms of competition. Section two relates multi-market competition, norms of competition, and poor performance to inter-organizational trust. Section three introduces the model and develops the hypotheses that are tested in this dissertation. The fourth and final section of this chapter summarizes the chapter.

3.1 Rivalry, Multi-market Competition, Poor Performance and Norms of Competition

Multi-market firms are more likely than single-market firms to recognize one another other as rivals because their market overlap, and possibly the resource overlap that paves the way for the market overlap in the first place, enables them to become aware of their extended interdependence across markets (Chen, 1996; Chen et al., 2007). Following the mutual recognition of rivalry, multi-market firms start to pay attention to, and interact extensively with,

one another. Extensive interaction between a dyad of multi-market rivals intensifies their level of rivalry, reduces their performance and facilitates the creation of shared norms of competition between them.

3.1.1 Recognition of Rivalry and Extended Interdependence

Multi-market firms are likely to recognize one another as rivals due to their market and resource overlap (Chen, 1996). Repetitive interaction not only in product but also in factor markets across time and space facilitates the recognition of rivalry. Once multi-market firms recognize each other as direct rivals, they focus their attention on each other (Porac et al., 1989), reciprocally monitor (Heil and Robertson, 1991; Porac and Thomas, 1994) and collect information about one another (Porac and Thomas, 1994; Peteraf and Shanley, 1997) and attend to competitive intelligence they gather due to threat bias (Dutton and Jackson, 1987). Managers are much more aware of their direct rivals than their potential and indirect rivals (Bergen and Peteraf, 2002; Clark and Montgomery, 1999). Through such reciprocal attention, multi-market rivals recognize their extended interdependence across markets and recognize that an action taken in a given market might lead to a response in one, some or all of the jointly contested markets (Pilloff, 1999).

3.1.2 Rivalry and Multi-Market Competition

Once multi-market rivals define each other as rivals and recognize their extended interdependence across jointly contested markets, multi-market competition supersedes market by market competition (Jayachandran et al., 1999; Singal, 1996). Under this condition, multi-market firms link their competitive response functions across markets and account for the would-be actions and reactions of their rivals in *all* of the jointly contested markets rather than in a given market when formulating their competitive actions and reactions (Pilloff, 1999). Additionally, they strive to maximize aggregate and overall performance across markets rather

than maximizing performance in a given market. For example multi-market firms intensify competition and reduce their prices in their concentrated markets so as to charge a higher price than they could otherwise charge in their less concentrated markets in order to maximize their overall profitability *across* markets (Bernheim and Whinston, 1990; Fernandez and Marin, 1998; Philips and Mason, 1992; Jans and Rosenbaum, 1996).

3.1.3 Rivalry and Firm Performance

As a dyad of multi-market rivals begins to orient toward one another, they direct their competitive activity (Smith, Grimm & Wally, 1997), action or response, toward each other and intensify the level of rivalry. Multi-market firms that mutually identify each other as rivals are more likely to direct a high percentage of their overall competitive activity towards each other and become more competitively aggressive (Ferrier, 2001) because perception of rivalry intensifies aggression towards firms that are recognized as rivals (Bogner and Thomas, 1993; Chen et al., 2007; Gripsrud and Gronhaug, 1985). Evidence that competition is much more intense within perceived competitive groups that are predominantly formed by firms with high multi-market contact than it is across them supports this contention (Bigne and Lopez, 2002; Borroi, Minoja, Sinatra, 1998; Porac and Thomas, 1990, 1994; Porac et al., 1995). This argument is also in line with studies that found an inverted U-shaped relationship between multi-market contact and intensity of rivalry (Anand et. al., 2009; Baum and Korn, 1999; Fuentelsaz and Gomez, 2006; Haveman and Nonnemaker, 2000; Stephan et al., 2003; Jung, 2010; Yu et al., 2009). These studies, as discussed in chapter two, demonstrate that multi-market rivals initially escalate the level of rivalry between them, especially when the level of multi-market contact between them is low to moderate.

Two opposing views are identified in the literature concerning the impact of competitive aggression on firm performance. On the one hand, rivalry is expected to improve firm performance (Jacobson, 1992; Young et al., 1996). According to this view, which is under the influence of the Austrian school, there is a positive relationship between firm performance and complex and broad repertoires of competitive actions (Miller and Chen, 1994; Miller and Chen, 1996; Ferrier et al., 1999), the speed with which competitive actions are executed (Lee et al., 2000; Ferrier, 2001), and the volume of competitive action (Young et al., 1996; Ferrier et al., 1999, Ferrier, 2001; Miller and Chen, 1994). On the other hand, a stream of research, under the influence of the industrial organization paradigm, asserts and demonstrates that competitive aggression impairs firm performance (Armstrong and Collopy, 1996; Barney, 1991; Scherer and Ross, 1990).

Despite the existence of these opposing views and evidence about the relationship between level of rivalry and performance, I argue that in the context of multi-market competition, rivalry ultimately impairs the performance of firms engaged in multi-market competition, for the following reasons. First, in addition to competing for customers in product markets, multi-market firms compete for similar types and levels of resources in factor markets (Chen, 1996). This in turn increases not only their expenditures to lure additional customers from each other in the product markets but also the prices of resources that they acquire in the factor markets. This increase in cost in both product and factor markets impairs the performance of multi-market firms. Second, the increase in spending and cost in both product and factor markets does not create a sustainable difference between multi-market rivals because they tap into similar resources, use similar levels of resources and create similar resources by competing in common product markets (Barney, 1991). Lack of differences in ability and competence in turn prevents

multi-market rivals from outcompeting one another despite their increase in expenditures and investment. Third, multi-market rivals can select each other's spheres of influence as main battlegrounds in order to impair each other's respective goals and to take effective and efficient competitive actions with asymmetrical profit consequences (Porter, 1980). By escalating rivalry in one another's key markets, multi-market rivals can inflict the greatest damage to one another with minimum expenditure of resources (Barnett, 1993; Gimeno, 1999; Parker and Roller, 1997).

3.1.4 Rivalry and the Development of Norms of Competition

Repeated and extended competition between two firms in a multimarket context results in those rivals learning how to compete with each other and developing shared norms of competition (Porac et al., 1989). Competitive interaction between a dyad of multi-market rivals leads to the development of rules that guide their competitive interaction (Thomas and Soldow, 1988) and define appropriate competitive conduct (Huff, 1982; Spender, 1989). Extended competitive interaction over time and across markets allows multi-market rivals to learn how to compete with one another, which in turn leads to the development of shared norms of competition that become legitimized over time (Porac et al., 1989; Panagiotou, 2006; Reger and Huff, 1993; Reger and Palmer, 1996; Nath and Gruca, 1997; Marcel et al., 2010; McNamara et al., 2003; Osborne et al., 2001; Cheng and Chang, 2009). As multi-market rivals interact across markets and time, they learn to limit the range of competitive weapons and breadth of strategies employed (Borroi et al., 1998; Daniels et al., 2002) by aligning their mental models of competition (Fiegenbaum, and Thomas, 1995). For example, in the airline industry, where competition takes place among multi-market rivals, members of the same strategic group are "prohibited" from carrying out price competition within their group but are "allowed" to engage in non-price competition (Peteraf, 1993). Thus, "over the long term, pairs of firms are more likely to interact competitively through the subset of action types that executives at both firms

subjectively label as important, rather than through those action types that they disagreed upon” (Marcel et al., 2010, p: 131).

3.2 Shared Norms, Multi-market Competition, Poor Performance and the Formation of Inter-Organizational Trust

The by-product of all of these aforementioned processes and events is the formation of trust between multi-market rivals in a competitive dyad. Shared norms, multi-market competition and poor performance activate the three antecedents of trust.

There are various definitions of trust in the literature depending on the perspective adopted. For example Robinson (1996) views trust as a psychological state and defines trust as a person’s “expectations, assumptions or beliefs about the likelihood that another’s future actions will be beneficial, favorable or at least not detrimental to one’s interests” (p: 576). Hardin (1992) approaches trust from a rational choice perspective and views trust as an encapsulated interest. He argues that “I trust you because it is in your interest to do what I trust you to do” (p: 153). By adopting a social psychological perspective and conceptualizing trust as a social orientation towards others rather than a calculative orientation, Mayer et al. (1995) define trust as the “willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the trustor irrespective of the ability to monitor or control the party” (p: 712). The common element in these and other definitions of trust is that trust is an expectation of trustworthiness due to either the positive intentions or the conduct of a trustee (Bhattacharya et al., 1998; Gulati, 1995; Hagen and Choe, 1998; Hosmer, 1995; Lewicki et al., 1998; Mayer et al., 1995; Ring and Van de Ven, 1992; Zaheer et al., 1998).

Trust is context specific and either calculative or relational considerations can be dominant in different contexts (Hardin, 1992; Kramer, 1999). In this dissertation, because I examine inter-organizational trust between two rivals, I will take a calculative, instrumental and strategic approach to trust and thus my conception of trust will not be based on benevolence. Accordingly, I will view trust as “an *expectancy* of positive outcomes that one can receive based on the *expected action* of another party in an interaction characterized by uncertainty” (Bhattacharya et al., 1998, p: 462, emphasis added).

Four constructs have been identified as antecedents of trust: Interdependence, deterrence, predictability, and risk taking. In the following subsections, it is argued that multi-market competition, shared norms of rivalry and reduction in performance activate these four antecedents of trust. While multi-market competition activates the interdependence/deterrence antecedent of trust, norms of rivalry actuate the predictability antecedent of trust. Declines in performance spark risk taking.

3.2.1 From Multi-Market Competition to Trust Formation through Interdependence and Deterrence

Interdependence is the first antecedent of trust (Rousseau et al., 1998; Shapiro et al., 1992). When interdependence is low, neither trust nor distrust is relevant (Lewicki et al., 1998). Under such conditions, organizations do not mutually influence one another’s payoffs through their conduct nor do they rely on each other to achieve their objectives (Kramer, 1999). However as interdependence increases among organizations, trust becomes an effective and efficient tool to manage such interdependence. Multi-market competition leads to the formation of trust between rivals by deepening the interdependence that exists in a single market and by extending that interdependence across markets (Lewicki et al., 1998; Sheppard and Sharman, 1998).

In addition to deepening interdependence, multi-market competition leads to a specific source of trust that is based on deterrence (Bhattacharya et al., 1998; Shapiro et al., 1992). Within the context of multi-market competition, the possibility of simultaneous punishment across multiple contact points as a response to defection and default from mutual forbearance reduces the return to defection. Repeated and multiple interactions across time and space and mutual hostage taking behavior (Shapiro et al., 1992) deters multi-market rivals from opportunistic behavior. Deterrence that derives from multi-market contact assures a trustor that its cooperation will not be exploited.

In the extant literature, there is an argument that deterrence-based trust is not trust at all (Boyle and Bonacich, 1970; Sitkin and Roth, 1993; Williamson 1993; Yamagashi and Yamagashi, 1994). This argument is based on the reasoning that trust exists when there is a temptation and an incentive to cheat since trust requires willingness to be vulnerable (Mayer et al., 1995; Malhotra, 2004; Rousseau et al., 1998). However these arguments are not strongly applicable to interactions among firms (Gulati, 1995), especially interactions among rivals in a competitive dyad. Because these rivals exist in a Hobbesian state of nature, cooperation based on a willingness to be vulnerable is not possible due to the threat of exploitation (Hardin, 1992). For example in Prisoners' Dilemma situations, defection is the dominant and cooperation is the dominated strategy. Deterrence and punishment of defection reduce the magnitude and likelihood of a sucker payoff, thereby reducing returns to defection. Deterrence tames and attenuates the competitive orientation of rivals to maximize performance differences among one another and thus their relative payoffs (Armstrong and Collopy, 1996; Bendor et al., 1991) and motivates them to increase their joint payoff through trust and cooperation. Deterrence, therefore, fosters (Hagen and Choe, 1998) and supplements (Das and Teng, 1998) trust among

rivals that cannot otherwise trust one another (Hardin, 1992; Shapiro et al., 1992). In line with a contingent view of trust (Kramer, 1999), in the case of rivalry, calculative and instrumental considerations are more influential than social and relational considerations to the establishment of trust.

3.2.2 From Norms of Rivalry to Trust Formation through Predictability

Interaction between rivals and the resulting norms of rivalry activate the third antecedent of trust, which is predictability (Adler, 2001; Rousseau et al., 1998; Shapiro et al., 1992). Competing through similar mechanisms over time enables rivals to become very familiar with the strategic repertoires of their rivals and allows them to correctly predict each other's actions and responses (Caves and Porter, 1977; Peteraf, 1993; Porter, 1979).

Predictability, in turn, motivates trust in three distinct ways. First, predictability is a source of trust because if firms can predict how their rivals will compete, they can exploit that knowledge to their advantage and thus expect a positive outcome from the competitive actions of its rivals. The predictability of uncooperative behavior can lead to an expectancy of positive outcome and trust (Shapiro et al., 1992). A “feint” stratagem that was implemented by Ralston Corporation is a case in point (McGrath et al., 1998). Ralston Corporation was the leader in the American pet food industry in the late 1980's and its main distribution channel was supermarkets. To consolidate its position in supermarkets, Ralston Corporation paradoxically developed and launched its Pro Plan line directly into pet shops, which were the main distribution channels of its rivals like Iams and Hill's Science Diet. The main motive for Ralston Corporation to attack the main distribution channel of its rivals was to compel them to divert their resources away from its main distribution channel: supermarkets (McGrath et al., 1998). Ralston Corporation predicted that its rivals would take a defensive response to its attack and

focus all of their resources on reinforcing their position in pet shops and in the process divert resources away from supermarkets. Based on that prediction, Ralston Corporation launched its attack and as a response, rival firms focused all of their resources on reinforcing their positions in pet shops and in the process helped Ralston Corporation dominate supermarkets. Hence Ralston Corporation managed to reinforce its position in supermarkets by exploiting the predictably uncooperative behavior of its rivals.

Second, predictability provides the knowledge required to determine whether a third party is trustworthy or can be guided to be trustworthy. For example being familiar with each others' interests, rivals in the biotech (Oliver, 2004) and mobile phone industries (Fjeldstad et. al., 2004) knew that it was in their mutual interest to be trustworthy and cooperate with one another to either legitimize their industry or establish common standards and ensure system compatibility respectively. Predicting that defection was not a rational possibility, rival firms in these two industries deemed one another trustworthy and did not hesitate to share their technological knowledge.

Third, predictability also allows a trustor to determine the ways in which a trustee can be guided to become trustworthy (Shapiro et al., 1992). With this knowledge, trustors can engage in actions that are likely to lead to trustworthy behaviors on the part of trustees, thereby providing the positive outcomes expected by trustors. For example in the U.S. scheduled passenger airline industry, carriers historically announced fare increases in a particular city-pair market to encourage their rivals to follow suit. In other words, they trusted their rivals with their price increases. Such trusting behavior in turn instigated trustworthy behavior in trustees as rivals responded with their own price increases. That is why Department of Justice was able to find phrases of the nature “(carrier name) is now on board for the (date) increase to (fare level) on

(city1) - (city2)” (Borenstein, 2004, p: 238) after analyzing the daily internal fare reports of airlines like Alaska, American, Continental, Delta, Northwest, Trans World United and USAir which are members of the sample of this study and accuse them of colluding across markets to raise fares.

3.2.3 From Performance Reduction to Trust Formation through Risk Taking

Risk taking is the third precondition of trust (Boyle and Bonacich, 1970; Das and Teng, 1998; Hardin, 1992; Macy and Skvoretz, 1998; Rousseau et al., 1998; Sheppard and Sherman, 1998). Trust entails positive expectations about the motives or conduct of a trustee (Bhattacharya et al., 1998; Gulati, 1995; Hagen and Choe, 1998; Hosmer, 1995; Lewicki et al., 1998; Mayer et al., 1995; Ring and Van de Ven, 1992; Zaheer et al., 1998). However, for various reasons, a trustee may not merit such positive expectations, making trust a risky endeavor and increasing the variance of the rate of return on trusting behavior (Hardin, 1992).

Trust entails risk because positive expectations of trustworthiness can significantly diverge from the actual conduct of a trustee as a result of three factors (Hardin, 1992). The first factor derives from errors on the part of the trustor. A trustor can misperceive a trustee due to erroneous conjectures, misunderstand the possible set of actions available to a trustee, misinterpret relations between actions, outcomes and consequences (Bhattacharya et al., 1998) or misjudge the cooperative moves of a trustee due to differences in values, cognitive understandings or imperfect monitoring (Kollock, 1993). Second, uncertainty due to external shocks, lack of perfect information and/or causal ambiguity (Bendor et al., 1991; 1996) can lead to errors in expectations about the trustworthiness of a trustee. Third, poor and incomplete execution of a cooperative strategy by a trustee, despite the willingness to cooperate, can lead to a discrepancy between trustor expectations and the actual behavior of the trustee. Noise in the

implementation of a cooperative move due to a mistake or an accident (Kollock, 1993) can lead to discrepancies between expected cooperative behavior and the observed behavior of a trustee. Due to these factors, expectations of trustworthiness may not be met and a trustor may be subject to risk either due to intentional or unintentional exploitation of trust.

Extended reduction in performance over time increases the propensity of rivals to take risks, thereby establishing this antecedent to trust formation between rivals. Theoretical arguments and accompanying empirical evidence indicate that there is a negative relationship between performance and risk taking at both individual and organizational level of analyses. At the individual level, prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) and escalation of commitment theory (Bazerman, 1984; Northcraft and Neale, 1986; Schaubroeck and Davis, 1994; Staw, 1976, 1981; Staw and Ross, 1987; Whyte, 1986) demonstrate and argue that low performance increases risk taking. At the level of the organization, prospect theory (Bowman, 1982, 1984; Gooding et al., 1996; Fiegenbaum, 1990; Fiegenbaum and Thomas, 1986, 1988; Lehner, 2000) and behavioral theory of the firm (Bromiley, 1991; Cyert and March, 1963; McNamara and Bromiley, 1997; McNamara and Bromiley, 1999; Miller and Chen, 2004; Palmer and Wiseman, 1999; Wiseman and Bromiley, 1991; Wiseman and Catanach, 1997) demonstrate that losses and performance below aspiration levels increase risk seeking. Because both individual and organizational level analyses indicate that reduction in performance increases risk taking, increase in risk taking behavior due to low performance at the organizational level cannot be attributed to managers who take uninformed

risks due to their inability to correctly perceive and understand the risks that they face² (Greve, 2003).

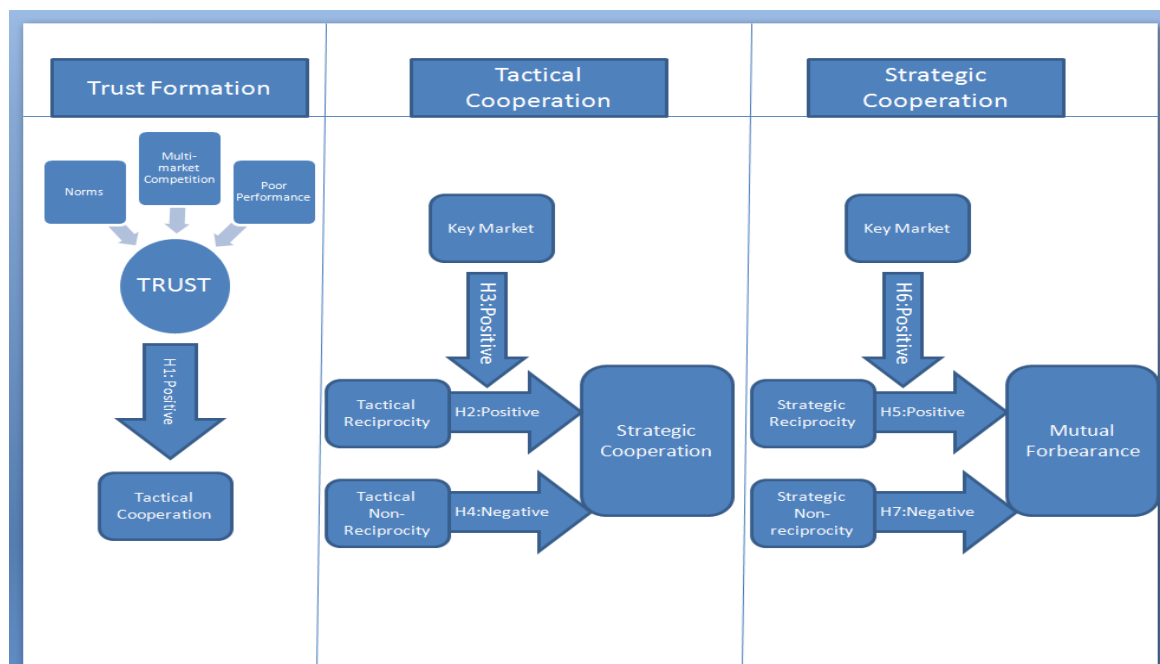
3.3 A Model of the Origins of Mutual Forbearance

In this section, I introduce a model of the origins of MF, which is illustrated in Figure 1. I argue that the development of inter-organizational trust leads to the motivation to attempt cooperation (Hardin, 1992; Smith et al., 1995). This motivation in turn triggers the start of a two-phased experimental learning process by which the firms develop an understanding of how to cooperate across markets. Multi-market rivals first attempt to cooperate at the tactical level (e.g., changes in price) in order to minimize the costs associated with a lack of reciprocity (exploitation). If the initial cooperative moves at the tactical level are reciprocated, they escalate their commitment to cooperation by cooperating at the strategic level (e.g., market exit). If attempts to cooperate succeed at both the tactical and strategic level, mutual forbearance is attained and the performance of both firms is expected to increase. The model also suggests that

² In spite of the theoretical and empirical evidence that suggests that low performance increases risk taking, it can be argued that threat rigidity theory provides an alternative explanation and thus sign for the relationship between performance and risk seeking. Threat rigidity theory may on the surface appear to argue that low performance results in risk aversion (George et al., 2006; Sitkin and Pablo, 1992). However this argument is incomplete because it is based on the assumption that newer alternatives are more risky than existing alternatives and, therefore, committing to an existing alternative demonstrates risk aversion. The main message of threat rigidity, however, is escalation of commitment to well-learned initial choices and responses due to constriction in control, restriction in information processing and efficiency orientation or resource conservation (Staw et al., 1981) regardless of the level of riskiness associated with existing alternatives. According to this perspective, firms act rigidly in the face of threat due to a mechanistic shift and fall back on well rehearsed routines (George et al., 2006) which might be more or less risky depending on the risk level of alternatives. Firms thus can commit themselves to more risk in the face of threat if well learned responses happen to be more risky than new alternatives. For example Chattopadhyay et al., (2001) found empirical support for their argument that in the face of control reducing threat, organizations that have a prior orientation to product innovation come up with more product innovations, which are risky behaviors by nature. Likewise, although not divesting a low performing unit is a risky behavior, Shimizu (2007) empirically demonstrated that an organization lacking divestiture experience retains the low performing unit and assumes risk in the face of threat. In addition, NBA coaches keep the playing time of a low performing player constant and assume risk (Staw and Hoang, 1995). NBA player's playing time is determined by their place in the draft rather than their performance due to escalation of commitment.

reciprocity is more likely if initial moves are made in the bread and butter markets of each multi-market rival because cooperation in those areas results in greater gains to the firms. Finally, the model offers a process explanation for the failure of MF in instances when it would be expected: If attempts at cooperation are not reciprocated at either the tactical or strategic level, rivalry will resume and MF will not be established. The details of these processes and resulting hypotheses are outlined in the following sections.

Figure 1: The Theoretical Model



3.3.1 How does trust enable a dyad of multi-market rivals to move from rivalry to cooperation?

In general, trust is a pre-condition of cooperation (Hardin, 1992) and often leads to cooperation (Smith et al., 1995). In the context of multi-market competition, I expect trust to lead to cooperation for three reasons. First, trust solves the iterated Prisoner's Dilemma posed by multi-market competition (Hughes and Oughton, 1993; Young et al., 2000) by changing the payoff matrix (Das and Teng, 1998; Lewicki et al., 1998) through predictability and deterrence. Through predictability and deterrence, members of a dyad not only know that mutual willingness

to cooperate is high due to low performance, but also that the mutual temptation to defect is low. Trust, in this sense, acts a focal point (Schelling, 1960) to converge the expectations of rivals towards the cooperative outcome. Second, as a focal point, trust facilitates cooperation among rivals without overt communication. Specifically, high levels of firm predictability reduce the importance of communication between rivals to coordinate their activities. Third, without an expectancy of positive outcome, the switch from competition to cooperation requires a lot of positive experience and trustworthy behavior that runs counter to conflict laden history of rivals (Hardin, 1992). However since trust in this context derives from both assurance and knowledge that cooperation is in the mutual interest of rivals, rival firms begin to trust even though they lack a rich history of cooperation.

Despite the intuitive link between trust and cooperation, an emerging stream of research questions the trust and cooperation linkage (Rindfleisch, 2000). Especially within the context of rivalry, the relationship between trust and cooperation is argued to be fuzzy and weak because vertical cooperation is much clearer than horizontal cooperation (Smith et al., 1995). Others argue that trust has a small impact on cooperation among rivals (Rindfleisch, 2000). These arguments are based on the perspective that trust is but one of many mechanisms that can foster cooperation. In addition to trust, coercion (Hardin, 1992; Rousseau et al., 1998) and control (Das and Teng, 1998; Gulati, 1995; Rousseau et al., 1998) are argued to pave the way for cooperation. According to this view, the willingness to cooperate due to sanctions and control do not mean that trust exists (Mayer et al., 1995; Yamagishi and Yamigishi, 1994) because cooperation, which is a behavior, can be triggered by coercion or control independent of trust.

These arguments against linking trust and cooperation are not applicable to the context studied here. Such arguments assume that coercion and control are substitutes for trust and

ignore the relationships that exist between trust and control and coercion (Das and Teng, 1998). As argued before, deterrence, as a type of sanction, is a source of trust and as such cannot be a substitute for trust. Sanctions³, or the potential for sanctions, promote trust (Hagen and Choe, 1998) by reducing the attractiveness of defection and non-cooperation (Das and Teng, 1998; Hardin, 1992; Shapiro et al., 1992). This is especially true for rivals that may be willing to trust and cooperate with one another but refrain from doing so due to the fear of being “suckered”. Likewise, trust and control are not substitutes. By providing an objective record of trustworthiness, control, particularly social rather than process and output control, reinforces trust (Das and Teng, 1998). In addition, control is thought to depend upon the existence of binding agreements and so is not applicable to the theory developed here because tacit collusion through mutual forbearance cannot rely on binding agreements

Once multi-market rivals decide to trust and cooperate, they are expected to initiate cooperation across markets through tactical competitive instruments due to two reasons. First, compared to strategic competitive actions, tactical competitive actions, such as changes in price, require fewer and more general resource commitments and are easier to execute and reverse (Connelly et al., 2010; Smith et al., 1992). Therefore, they not only effectively signal cooperation by escalating commitment to cooperation when a rival is cooperative, but also enable swift response should the rival respond to that signal with an aggressive response and thus minimize the cost of being exploited. Second, the reduction of intensity of rivalry through tactical actions not only limits the downside risk for the initiator (trustor), it provides substantial benefits to the trustee, thereby motivating reciprocation (Malhotra, 2004).

³ Institutional sanctions are not applicable to the theory developed here as tacit collusion through mutual forbearance cannot be enforced by institutional coercion. Actually, the purpose of such sanctions is to prevent collusion in the first place. Anti-trust law is a case in point.

Formation of inter-organizational trust among a dyad of rivals requires the activation of all of the four antecedents. Interdependence makes trust relevant to a dyad of rivals. Predictability enables rivals to foresee whether they can trust each other or can be guided to trust each other. Deterrence provides the assurance that exploitation of trust is costly and the propensity to take risks motivates rivals to trust one another as there is always the likelihood that expectation of trustworthiness may not be met. Because trust is expected to lead to cooperation, especially initially at the tactical level, and formation of inter-organizational trust requires the activation of all of its antecedents, I postulate that only the interaction of norms of competition, multi-market competition and low performance is expected to lead to tactical cooperation. This argument is also in line with the empirical findings of different streams of literature which demonstrate that predictability, by itself, can escalate or de-escalate rivalry either within the context of multi-market competition (Gimeno and Woo, 1996; Fuentelsaz and Gomez, 2006; Li and Greenwood, 2004; Marcel et al., 2010; Upson et al., 2012; Young et al., 2000) or strategic groups (Fiegenbaum and Thomas, 1995; McNamara et al., 2003) and that poor performance can either escalate (Young et al., 1996) or de-escalate (Scherer and Ross, 1990) rivalry. For trust to form, all of the antecedents of trust should be simultaneously activated. Hence:

Hypothesis 1a: The interaction of low performance, norms of competition and multi-market competition is positively associated with the commencement of tactical cooperation between a dyad of multi-market rivals.

Poor performance plays a particular role in the interaction because it reverses the negative impact of the interaction of norms of competition and multi-market competition on tactical experimental cooperation. Multi-market rivals that compete in a similar manner are much more aggressive than multi-market rivals that compete through dissimilar means (Fuentelsaz and

Gomez, 2006, Young et al., 2000). Multi-market rivals deploy their similarity to intensify rivalry (Gimeno and Woo, 1996). There are three main reasons for that.

First, competing similarly prevents differentiation and compels multi-market rivals to compete within a narrow band of action and engage in zero sum competition. Second, similarity in competitive actions across multi-market rivals intensifies rivalry because it increases the speed, likelihood, effectiveness and efficiency of responses (Porter, 1980; Marcel et al., 2010; Smith et al., 1992). Rivals easily detect moves similar to their own and do not need to take time to collect information in order to make accurate sense of them (Ferrier, 2001; MacMillan et al., 1985). Specifically, similarity in competitive actions reduces the size of blind spots (Chen, 1996; Desarbo et al., 2006; Moore and Urbany, 1994; Ng et al., 2009; Zajac and Bazerman, 1991; Zahra and Chaples, 1993) and competitive uncertainty. This in turn increases the intensity of rivalry because effective, efficient and speedy responses prevent multi-market rivals from building mobility (Caves and Ghemawat, 1992) and resource position barriers (Lippmann and Rumelt, 1982). Third, strategy and resources are two sides of the same coin (Wernerfelt, 1984), and so similar competitive actions lead to the development of similar resources, thereby intensifying rivalry. Lack of a unique core competence and unique resources intensifies rivalry among multi-market rivals (Barney, 1991; Bernheim and Whinston, 1990). Multi-market rivals use their knowledge of norms of competition to maximize performance differences among them rather than to increase absolute profitability (Armstrong and Collopy, 1996) until they recognize that they cannot out-compete their rivals.

Poor performance dampens and undermines the negative effect of the interaction of norms of competition and multi-market competition on tactical cooperation because it activates change and search processes in multi-market rivals that motivate them to cooperate. Poor

performance motivates multi-market firms to change their competitive routines (Cyert and March, 1963), strategies (Audia and Boeker, 2000) and actions (Miller and Chen, 1994, 1996; Ferrier et al., 1999). Poor performance that derives from competition makes it clear to rival firms that they cannot manage their interdependencies through competition (Bresser, 1988), urging them to manage their interdependencies through the alternative mechanism, cooperation, (Bresser and Harl, 1986) as exemplified by the formation of SEMATECH by the participants of the U.S. semi-conductor industry (Browing et al., 1995). In addition to motivating change, performance failure triggers problem-focused and local search (Miller and Chen, 1994), which is likely to portray multi-market rivals as the culprit of performance problems and mutual forbearance as the solution to the performance problem (Cyert and March, 1963).

Having faced a performance problem, a dyad of multi-market rivals initiates a simple minded search for solutions. To find the probable cause of their performance problems, they begin by initiating a local search in the neighborhood of problem symptoms. In this context, the neighborhood of problem symptoms is likely to be the key markets of each rival because aggression in these markets has a stronger impact on performance than aggression in secondary markets (Barnett, 1993). Therefore, multi-market firms in a competitive dyad are likely to begin their search for causes of performance problems in the terrain of the key markets. Because a given multi-market rival is the repeatedly observed common factor in markets where performance is low, firms are likely to identify the aggression and hostility of rivals in these markets as a potential cause of low performance.

Having spotted a probable cause of the performance problem, multi-market rivals look for solutions in the neighborhood of current alternatives. The most current alternative available to a dyad of multi-market rivals as a solution to their performance problem is to attack because

firms with multi-market contact initially escalate their level of rivalry (Anand et al., 2009; Baum and Korn, 1999; Fuentelsaz and Gomez, 2006; Haveman and Nonnemaker, 2000; Stephan et al., 2003; Jung, 2010). However because this alternative has already been identified as the main source of the performance problems and thus is unsatisfactory, multi-market firms are expected to change their aggressive stance in the key markets of their rivals, for actions that are unsatisfactory are altered (Cyert and March, 1963; Greve, 1998; Lant et al., 1992; Levinthal and March, 1981; Levitt and March, 1988; Nelson and Winter, 1982). Poor performance is expected to dampen the negative impact of the interaction of norms of competition and multi-market competition on tactical cooperation because it triggers search processes and change that promote cooperation.

Hypothesis 1b: Poor performance reverses the negative sign of the interaction of norms of competition and multi-market competition on the commencement of tactical cooperation between a dyad of multi-market rivals.

3.3.2 Learning to Cooperate

Once the motivation to cooperate at the tactical level has been created, firms are left with the task of moving from rivalry to cooperation and MF. Following a prolonged period of intense rivalry across markets, how does a dyad of multi-market rivals move to a more cooperative relationship and learn to mutually forbear? I argue that it is through a process of experimental learning. I expect that the development of cooperation in general (Gulati, 1995) and MF in particular, occurs through an experimental learning process because such a process offers five advantages to multi-market firms in a competitive dyad.

First, experimental learning, itself, increases the likelihood of cooperation among rivals because it lowers the constraining impact of a hostile history on future interactions by helping firms replace schema-driven information processing with data-driven information processing.

Experimental learning help firms switch from top-down information processing to bottom-up information processing and thus prevents them from going beyond the competitive intelligence collected by improving the efficiency and effectiveness with which they gather and process information (Prabhu and Stewart, 2001). Experimental learning reduces the cost of collecting competitive intelligence and increases the effectiveness of processing it due to its incremental nature (Huber, 1991) that diminishes not only the amount of required investments per experiment but also the complexity of collected information. This in turn empowers rival firms to give more weight to the actual content of competitive information that they collect than to their previous expectations and prior representations, which portray one another as aggressors when processing information (Moore, 1992). The resulting switch from top-down information processing to bottom-up information processing (Fiske and Taylor, 1991) dampens the restraining impact of a hostile competitive history on future interaction and thus facilitates cooperation among rivals.

Second, developing MF through experimentation reduces the magnitude of the cost of being exploited by a trustee. By unilaterally forbearing from rivalry, a focal firm exposes itself to the possibility of defection by a rival and accepts vulnerability. Small and gradual experimental investments to build and test the expected forbearance behavior of a rival minimize the magnitude of possible “sucker” payoff and thus diminish the size of such vulnerability.

Third, building and corroborating MF through incremental and experimental steps (Hardin, 1992) facilitates the discovery of those multi-market rivals that are willing to forbear from competition. Without incremental actions to build MF, the cost of misplaced expectation of cooperation across markets can be too high to bear. Under these conditions, multi-market firms might eschew from exercising MF and thus be unable to assess the extent to which its rivals are willing to cooperate. This would create a self-perpetuating cycle whereby initial hesitation to

cooperate across markets leads to more hesitation. Incremental investments in MF can provide the information required to accurately update and correct prior beliefs about the expected cooperation of a rival across markets.

Fourth, in addition to reducing the cost of being exploited by a defector, reinforcing satisfactory cooperative actions but dropping unsatisfactory ones by dint of a gradual experimental process prevents unnecessary wars, especially in noisy and uncertain environments. Tit for tat strategies, which prescribe initial cooperation followed by imitation of cooperative or defective choices of a rival, can trigger unnecessary escalation of conflict and cycles of recrimination because firms, under noise and uncertainty, can mistake a cooperative move for an uncooperative one (Bendor et al., 1991; Kollock, 1993). That is why, in line with the arguments of behavioral theory of the firm, repeating satisfactory moves that aim to establish MF and modifying unsatisfactory ones through “win-stay and lose-shift” strategies are more effective than “eye for eye” strategies that are based on imitating what a rival does in order to sustain cooperation (Nowak, 2006) across markets.

Fifth, incremental and gradual acts of forbearance from rivalry repeatedly signal cooperation and provide a longer time horizon over which actors can notice, recognize and interpret signals to mutually forbear. This increases the possibility of accurate interpretation of the signal, especially in the face of shared understanding. Incremental strategies lengthen the time horizon, making initial investments in MF seem more promising (Axelrod, 1984).

The process of experimental learning of a MF strategy is aided by the multiple contacts across markets that provide ample opportunities to learn how to cooperate (Scott, 1991). The key markets of multi-market rivals play a particularly crucial role in the experimental process for

several reasons. Multi-market firms are expected to initiate MF by incrementally reducing the intensity of competition in their rival's key markets, which generate a significant proportion of that rival's overall firm revenues and profits (Karnani and Wernerfelt, 1985). The reason for this is that signaling the desire to cooperate in the key markets of rivals is much more effective in reducing the intensity of rivalry than signaling that desire in other types of markets (Evans and Kessides, 1994; Gimeno, 1999; Li and Greenwood, 2004) because cooperation has the largest impact on performance when it occurs in the competitor's key markets.

Because learning is incremental in nature (Huber, 1991; Miner and Mezias, 1996) and cooperation passes through stages (Lewicki et al., 1998; Rousseau et al., 1998; Smith et al., 1995), multi-market rivals learn to mutually forbear from competition through a two-staged process whereby incremental learning occurs not only within, but also across stages. In each stage, multi-market firms carry out actions to test and verify their positive initial expectations about the potential cooperation of their rivals across markets. Through their actions and the resulting positive or negative feedback, rivals revise their prior expectations (Doz, 1996; Boyle and Bonacich, 1970) and adjust the level of MF accordingly. In the following subsections, I discuss each stage of the experimental learning process that leads to MF.

3.3.2.1 First Stage: Tactical Experimental Cooperation

As noted in the discussion of Hypothesis 1a, the formation of trust motivates the initial cooperative activity at the tactical level between members of a competitive dyad. If attempts of a member of a dyad to cooperate at the tactical level is reciprocated, the resulting positive experience (reciprocation) and satisfactory results motivate members of a dyad to gradually expand and increase their commitment to MF (Lui and Ngo, 2005; Ring and Van de Ven, 1992; 1994) since fairness, reciprocity and equitability reinforce expectations of positive outcomes

(Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999; Ring and Van de Ven, 1992). “Trust earned from prior engagement then serves as the evidence to justify a subsequent risky step beyond the accumulated evidence” (Das and Teng, 1998, p: 504). In other words, the resulting evidence of trustworthy behavior at the tactical level motivates members of a given dyad to escalate their commitment to cooperation and thus cooperate at the higher strategic level.

To start cooperation at the strategic level, multi-market firms need actual and historical evidence of cooperation at the tactical level because strategic cooperation requires multi-market firms to assume a higher level of risk than tactical cooperation requires them to assume. Since attempts to cooperate at the strategic level are more difficult to reverse and require a significant commitment of specific resources and thus time to execute (Connelly et al., 2010; Smith et al., 1991), multi-market firms analyze the outcomes of their historical tactical experiments of cooperation with the intent to learn whether they pay off and prefer to escalate their commitment to cooperation if they conclude that cooperation at the tactical level pays off (Doz, 1996; Ring and Van De Ven, 1992, 1994; Lui and Ngo, 2005). Hence strategic cooperation depends not so much on an expectancy of positive outcomes as it does on past cooperative behavior, bringing organizational learning to the fore in the process of cooperation. Multi-market firms need concrete and historical evidence of cooperation at the tactical level to escalate their commitment to cooperation and tactical reciprocity provides such evidence. Hence:

Hypothesis 2: Tactical reciprocity is positively associated with strategic cooperation between a dyad of multi-market rivals.

Cooperative moves that are sensitive to the differential territorial interests of multi-market firms are more effective at initiating and maintaining cooperation. Not all common contact points (markets) between rivals are equally effective targets for reducing the intensity of

competition. Signaling subordination in the key markets of rivals by de-escalating rivalry in these markets in return for similar treatment in one's own key markets is much more influential than signaling cooperation in peripheral markets of rivals because cooperation in key markets has the largest impact on performance (Evans and Kessides, 1994; Gimeno, 1999; Li and Greenwood, 2004). Therefore initiating moves designed to signal cooperation in the turfs and key markets of multi-market rivals are more likely to motivate trustee multi-market firms to reciprocate with their own cooperative moves in the trust-giving multi-market firm's key markets. In addition, refraining from aggression in the key markets of a rival reduces the likelihood of retaliation in the focal and/or non-focal markets (Chen, 1996). This in turn prevents the transformation of a local conflict into total warfare across markets and facilitates the maintenance of footholds in the key markets of rivals, which are essential to the implementation of MF strategy. Hence:

Hypothesis 3: The “keyness” of markets in which tactical cooperation is carried out positively moderates the positive relationship between tactical reciprocity and strategic cooperation between a dyad of multi-market rivals.

When a trustee does not reciprocate and instead exploits the forbearance moves of a trustor at the tactical level, the resulting negative feedback and unsatisfactory performance lead a trustor to reduce its commitment to MF because in the face of non-reciprocity and the resulting unacceptable outcomes, firms change their routines (Cyert and March, 1963; Levinthal and March, 1981; Levitt and March, 1988; Nelson and Winter, 1982), strategies (Audia and Boeker, 2000; Audia et al., 2000; Greve, 1998) and competitive actions (Miller and Chen, 1994, 1996; Ferrier et al., 1999). In the case of defection at the tactical level and non-reciprocity, a dyad of multi-market rivals is expected to de-escalate their commitment to cooperation at the deeper

strategic level. Thus, I expect a negative relationship between non-reciprocity at the tactical level and strategic cooperation.

Hypothesis 4: Tactical non-reciprocity is negatively associated with strategic cooperation between a dyad of multi-market rivals.

3.3.2.2 Second Stage: Strategic Experimental Cooperation

Following satisfactory tactical cooperation, a dyad of multi-market rivals starts to cooperate at the deeper strategic level. If the outcomes of strategic experimental learning at the second stage are satisfactory in the sense that a dyad of multi-market rivals positively reciprocates each other's strategic cooperative moves, they then escalate their commitment to cooperation and begin to mutually forbear from competition.

Successful strategic cooperation results in MF because cooperation at the second stage not only persuasively communicates trustworthiness, but also unequivocally demonstrates the commitment to not to harm one another. Cooperation among multi-market firms at the second stage is more binding and irreversible than cooperation at the first stage since multi-market rivals de-escalate the level of rivalry through strategic rather than tactical actions. By de-escalating rivalry through strategic actions at the second stage, multi-market firms give up the option to dominate particular markets in return for dominating others and thus “*demonstrably* take some diminution in their own performance that accrues to the benefit of competitors” (Porter, 1980; p: 105). The binding and difficult to reverse nature of cooperation at the strategic level reinforces and expands the scope of super-ordination and subordination agreements that are tentatively and rudimentarily ratified in the preceding first stage and marks the beginning of MF whereby multi-market rivals assign markets to one another (Doz, 1996; Ring and Van De Ven, 1992, 1994; Lui and Ngo, 2005). De-escalation of rivalry through strategic actions strongly verifies the trust-

based expectations of cooperation and thus provides evidence of commitment to cooperation that justifies the beginning of MF. Hence:

Hypothesis 5: Strategic reciprocity is positively associated with MF between a dyad of multi-market rivals

As is the case with tactical experimental cooperation, strategic experimental cooperation in key markets is much more visible and is a stronger signal of the intent to cooperate. Because key markets are the main revenue generators of multi-market firms, multi-market firms are expected to be not only much more sensitive, but also more responsive to the cooperative moves of their rivals in their key markets. Through strategic experimental cooperation in key markets, a dyad of multi-market rivals assigns some of their jointly contested markets to one another and reinforces and clarifies their subordination and super-ordination agreements. The “gambit” stratagem executed by Gillette to share markets with Bic illustrates this point. Gillette withdrew all of its resources from the key market of Bic, which was the “lighters” market in 1984, so as to motivate Bic to exit its own key market which was “razors” market. Because of the saliency and clarity of that cooperative move, Bic accepted the “gambit” and exited from the key market of Gillette. As a result of these reciprocal exits, Bic and Gillette “signed off” on a tacit agreement for cooperation and reinforced their position in their respective key markets (McGrath et al., 1998). Furthermore, attacking a rival in its key markets motivates a rival firm to retaliate (Chen, 1996). Hence being cooperative in the key markets of a rival prevents the escalation of rivalry and also enables the cooperating firm to maintain its footholds in the key markets of their rivals without fighting for them. I therefore postulate that carrying out strategic cooperative moves in key markets is much more effective in establishing spheres of influence and increasing market share in these turfs than carrying out such moves in peripheral markets.

Hypothesis 6: The keyness of markets in which strategic cooperation is carried out positively moderates the positive relationship between strategic reciprocity and MF between a dyad of multi-market rivals.

If the outcomes of actions undertaken to escalate commitment to MF through experimental cooperation at the strategic level are not satisfactory, multi-market rivals once more de-escalate their commitment to further cooperation. Observing that strategic cooperation does not pay off, multi-market firms are expected to refrain from MF.

Hypothesis 7: Strategic non-reciprocity is negatively associated with MF between a dyad of multi-market rivals.

3.4 Summary

In this chapter, I addressed the three research questions identified at the end of chapter 2 by introducing a model of the process by which MF evolves. I began by explaining how rivalry leads to formation of inter-organizational trust between a dyad of multi-market rivals by activating different antecedents of trust. I specifically argued that rivalry leads to formation of norms of rivalry and multi-market competition and results in low performance and all of the three, in return, activate the deterrence, interdependence, predictability and risk taking antecedents of trust and help form inter-organizational trust.

Inter-organizational trust in turn paves the way for cooperation between a dyad of multi-market rivals. Specifically, multi-market rivals start cooperation at the tactical level to reduce the cost of being exploited and have the option to escalate commitment to MF in the case of positive experience and thus reciprocity. If multi-market rivals do not positively reciprocate each other's cooperative moves at the tactical level, they refrain from cooperation at the strategic level. However in the face of positive reciprocity, they increase their commitment to MF and start to cooperate at the strategic level. If the experimental outcomes of strategic cooperation are not successful due to lack of positive reciprocity, multi-market rivals once more de-escalate their

commitment to cooperation. Nevertheless, if a dyad of multi-market rivals mutually reciprocates cooperative moves at the strategic level, they embark on MF. In the experimental process by which firms learn to mutually forbear and increase their commitment to cooperation, key markets play a significant role. I argued that signaling the intent to cooperate in key markets is much more conducive to escalating commitment to cooperation than signaling the intent to cooperate in non-key markets.

The seven hypotheses developed to test the model also address the three research questions that motivate this dissertation. The first question is: What is the role of cooperation in originating MF? In the extant literature, the threat of punishment and thus deterrence is portrayed as the primary means by which MF develops. However as argued in the literature review, the theoretical and empirical support for the deterrence mechanism is weak and studying the role of cooperation in originating MF may be a more fruitful avenue of research. To this end, I proposed Hypotheses 2, 3, 5 and 6 which suggest that cooperation is the primary mechanism by which MF evolves.

The second research question is: Does trust enable a dyad of multi-market rivals move from rivalry to cooperation and if so how? As argued in the literature review, MF is not a deliberate but rather an emergent strategy. Firms do not establish contacts across markets *ex ante* to mutually forbear. They leverage their contacts across markets *ex post* to mutually forbear. Because the theoretical arguments in the extant literature assume that MF is an intended strategy, they do not explain the reason for the re-deployment of resources and emergent formation of MF strategy. To address this gap, I argued that it is inter-organizational trust that motivates a dyad of rivals to leverage their contacts across markets to cooperate. To this end, I proposed Hypotheses 1a and 1b.

The third research question of the dissertation is: “How does a dyad of multi-market rivals learn to mutually forbear? The extant literature does not identify the process by which MF originates due to the dominance of variance studies and the dominant but empirically ungrounded assumption that MF is an intended strategy. To address this gap and explain how MF emerges and breaks down, I proposed a two-staged learning process by which multi-market rivals use their contacts across markets to learn to cooperate and to signal their intent to cooperate (Scott, 1991; Busse, 2000). This process is addressed by Hypotheses 2, 3, 4, 5, 6 and 7.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

In this chapter, I outline the sample and methods to be used to test the hypotheses. First, I discuss sample selection. Second, I discuss the selection of time period. Third, I define both theoretical and control variables in two different subsections. In the first sub-section, I define variables of the first model and the data sources used to calculate those variables. In the second sub-section, I provide the operational definitions of the variables of the second and third models and define the data sources for those variables. In the fourth and final section, I define the methodology used to test the hypotheses.

4.2 Sample Selection

The research questions and the resulting theoretical model guide the choice of sample selection criteria. In this dissertation, I examine the role of cooperation and inter-organizational trust in originating MF and the process by which a dyad of multi-market rivals learns to mutually forbear from competition. The specific components of the theoretical model and the related hypotheses suggested eight criteria that I use to select the population of interest and the final sample.

First, I argue that multi-market contact, norms of competition and low performance together activate the four antecedents of inter-organizational trust that eventually leads to MF between a dyad of firms in the face of positive reciprocity. This in turn calls for a population where these constructs jointly exist and can be empirically observed.

Second, I propose that a dyad of multi-market rivals learns to mutually forbear from competition. In the theoretical model, multi-market rivals learn to use their jointly contested

markets to cooperate ex post. Because the effectiveness of learning depends on frequent and prompt feedback, an ideal population consists of an industry that is characterized by frequent competitive actions-reactions and comprehensive and reliable data sources that record, and make available to incumbent firms, the outcomes of these actions.

Third, the effectiveness of reciprocity and signaling that are theorized to be the two main instruments by which a pair of rivals establishes MF depends on the causal clarity between a firm's performance and its rival's actions/reactions, which in turn depends on the level of the homogeneity of markets. Reciprocity requires causal clarity because causal clarity enables a member of a pair of multi-market rivals to clearly understand how the actions/reactions of its rival influence its own performance, enabling it to decide whether to ignore, or exploit its rival's actions/reactions. In addition, causal clarity enables multi-market firms to identify which specific action/reaction of which rival is the cause of their current performance, enabling them to direct their response to the correct target. Signaling also requires causal clarity because it reduces signal noise and thus is more likely to lead similar interpretations both by the receiver and sender. Homogenous markets are a pre-condition for causal clarity because these types of markets increase the correlation between the demand outcomes of rivals (Sudhir et al., 2005), enabling multi-market firms to correctly attribute a change in their own demand and performance to changes in the competitive actions/reaction of their rivals across markets. Hence an ideal population consists of an industry where markets are homogenous.

Fourth, I propose a two-stage process whereby a dyad of rivals gradually escalates their commitment to cooperation through signaling their intent to cooperate. Hence an ideal population consists of an industry where there are mechanisms and tools in place to signal the intent to cooperate.

Fifth, I contend that a dyad of multi-market rivals learns to mutually forbear from competition through a two-stage process that begins with de-escalation at the tactical level followed by de-escalation at the strategic level. Hence an ideal population consists of an industry where incumbent firms deploy both tactical and strategic competitive weapons.

Sixth, the empirical investigation of hypotheses requires that a dyad of multi-market rivals simultaneously compete and cooperate across markets. The dissertation hypotheses predict *changes over time in patterns* of competition and cooperation between firms within a competitive dyad across and within different markets. Therefore an appropriate population is composed of an industry that contains multi-market rivals that compete in some markets but cooperate in others.

Seventh, the overall intent of the dissertation is to examine the genesis of MF. Hence it is important to select an industry in which there is evidence that MF exists, especially at the competitive inter-organizational dyad level. Hence an ideal population consists of an industry where there is strong evidence that MF exists at the dyad level.

Finally, any empirical context in which MF is studied must exhibit certain characteristics. First, firms or markets must differ from one another (Bernheim and Whinston, 1990; Evans and Kessides, 1994). Second, markets should be clearly defined (Gimeno, 1999). Third, firms should be single or dominant business companies so that multi-market contacts outside the studied industry do not confound the form and sign of the relationship between multi-market contact and MF (Gimeno, 1999). Fourth, sampled multi-market rivals should be able to observe each others' competitive actions, firm specific demand and market share in order to detect defection and cooperation (Greve, 2008). Fifth, firm decision making should be centralized so that contacts

across markets and extended interdependence can be managed, replacing market-by-market competition with multi-market competition (Golden and Ma, 2003; Kalnins, 2004; Yu et al., 2009).

Utilizing these criteria, I considered several candidate populations that had been utilized in prior research on multi-market competition and mutual forbearance including the hospital, insurance, personal computer, hotel, software, automobile and airline industries. I considered the U.S. hospital industry but dropped it because insurance companies and governmental regulations shape and influence the competitive actions of hospitals. I also considered but dismissed the U.S. insurance industry because of lack of required data availability. The U.S. PC industry was eventually dropped from consideration due to its limited number of markets and a lack of diversity in recorded historical competitive actions. The hotel industry was found to be unsuitable because multi-market competition that exists at the national level can confound findings at the state level. I considered but dropped the U.S. software industry because the market-based network economies of this industry require participant firms to compete aggressively in all of the available markets. Finally, I scrutinized but later rejected the U.S. automobile industry because of the infrequency of competitive actions and heterogeneity of product markets due to differentiation, which can impair the effectiveness of cooperative signals.

The U.S. scheduled passenger airline industry met all of the selection criteria and so was selected as the population of interest. As noted in the literature review, the U.S. airline industry has been extensively used as an empirical context for the study of MF (Baum and Korn, 1996, 1999; Evans and Kessides, 1994; Gimeno and Woo, 1996, 1999; Gimeno, 1999, 2002; Korn and Baum, 1999; Zou et al., 2011; Marcel et al., 2010; Prince and Simon, 2009; Sandler, 1988; Smith

and Wilson, 1995; Singal, 1996) and so has the added advantage of providing a solid empirical base upon which this study can build.

In line with prior literature (Marcel et al., 2010; Prince and Simon, 2009; Smith and Wilson, 1995), the sample is composed of the 10 major U.S. domestic carriers with revenue exceeding \$1 billion in the beginning of the study period. This sample is appropriate for the current study because the theoretical model requires a sample of firms that mutually recognize one another as rivals and prior research suggests that a sample that is composed of carriers with a comparable scope and domain of competition ensures that the sampled firms compete against with one another (Miller and Chen, 1996) and mutually recognize one another as rivals (Desarbo et al., 2006). Literature on rival identification demonstrates that identification of rivals depends on perceived similarity (De Chernatony et al., 1993a; Panagiotou, 2006; Peteraf and Bergen, 2003; Porac et al., 1995; Porac and Thomas, 1990).

Size and market overlap are the most common dimensions of similarity that firms use to identify rivals (Chen et al., 2007). Large firms are more likely to be perceived as rivals (Gripsrud and Gronhaug, 1985; Walton, 1986) because they have more resources at their disposal, pose a greater threat (Porac et al., 1995) and are salient (Clark and Montgomery, 1996b). In addition, large firms are more likely to recognize other large firms as rivals due to their similarity with respect to their relative rather than absolute size (Clark and Montgomery, 1999). Market overlap is used by firms to identify their rivals (Chen et al., 2007; Cunningham and Culligan, 1988) because it provides the motive to carry out competitive actions or reactions and is much more visible than other types of overlap such as resource overlap (Chen, 1996). Once more, similarity with respect to markets and targeted customers leads to mutual recognition of rivalry

(Panagiotou, 2006). Hence a sample of firms with similar domains of competition is expected to mutually recognize one another as rivals.

Limiting the sample to a few firms is consistent with the finding that perceived markets are much more concentrated than markets assessed by conventional, objective measures (Gripsrud and Grønhaug, 1985). The empirical results of a set of exploratory studies show that managers, on average, do not recognize more than seven firms as their rivals (Bigne and Lopez, 2002; Boari et al., 2001; Borroi et al., 1998; Clark and Montgomery, 1996b, 1999; De Chernatony et al., 1993a, 1993b; Montgomery et al., 2005; Odorici and Lomi, 2001; Panagiotou, 2006; Porac and Thomas, 1990, 1994; Porac et al., 1995). Hence the selected sample size prevents either over-estimation or under-estimation of the scope of the competitive landscape from the perspective of firms.

The selected population and sample together ensure that the observed performance differences of a pair of rivals across markets derive from their MF strategies rather than their differences in their competitive competencies. In the last three decades, empirical studies of the U.S. airline industry have conclusively demonstrated that incumbent firms of the U.S. scheduled passenger airline industry do mutually forbear from competition (Baum and Korn, 1996, 1999; Bilotkach, 2011; Ciliberto and Williams, 2012; Evans and Kessides, 1994; Gimeno, 1999, 2002; Gimeno and Woo, 1996; Miller, 2010; Prince and Simon, 2009; Singal, 1996; Zou et al., 2012). More to the point, the study sample study is composed of carriers that are very similar to one another with respect to their size and that compete in same factor and product markets. Thus, there is competitive parity between sample members. As such, they cannot easily out-compete one another or manage their interdependencies through competition, increasing the likelihood that observed performance differences of sampled firms stem from their MF strategies.

All of the data on U.S. scheduled passenger airline industry to be used in this dissertation come from the different databases of Department of Transportation. They include the DB1B Market and Ticket tables of Origin and Destination Survey; the P-1(a), P-1.2, P-6 and P-7 Schedules of Air Carrier Financial Reports (Form 41 Financial Data); the T1: U.S. Air Carrier Traffic And Capacity Summary by Service Class; and the T-100 Domestic Market table of Air Carrier Statistics (Form 41 Traffic)- U.S. Carriers. These databases are available at <http://www.transtats.bts.gov/> and are detailed in the sections in which I define the data sources for each variable. I use SAS PROC SQL to prepare the data sets that are used to investigate the hypotheses.

4.3 Time Period

I selected January 1, 1993- December 31, 2000 as an appropriate time period for this study. Five characteristics of this time period guided this decision. First, the sample period excludes exogenous shocks that might confound the internal validity of the findings. The airline industry was disrupted by the 1990-1991 recession and the 1991 Gulf War, leading to record losses in 1990, 1991 and 1992 (Borenstein, 2004) and the terrorist strikes of September 11, 2001 (Marcel et al., 2010). The selected sample period excludes such exogenous shocks that resulted in extremely low firm performance independent of the level of rivalry and thus controls for their effect. In addition, extreme losses may reduce the propensity to take risk because firms are risk-averse when their performance falls below their survival level (March and Shapira, 1987) and thus the extreme losses that are observed in the initial years of 1990's and 2000's can make it much more difficult to investigate the formation of trust that requires risk taking behavior.

Second, over the sample period, two moderators of the relationship between multi-market contact and tactical cooperation, norms of rivalry and organizational performance, show great heterogeneity and variation. This makes the selected time period an appropriate temporal context

to empirically observe how different levels of norms of rivalry and organizational performance moderate the relationship between multi-market contact and tactical cooperation. Results of generalized linear model analysis and data collected to calculate performance failure and norms of rivalry indicate that performance failure differs not only within dyads across time but also across dyads at the $p < 0.0001$ level. Firm performance showed great variation over the sample period and across dyads due to the dual effects of general industry recovery and performance failures. For example, between 1993 and 2000, 30 airlines entered bankruptcy proceedings according to the U.S. Airline Bankruptcies and Service Cessations file of Air Transport Association, even though industry level total operating revenues was increasing as demonstrated by the “total operating revenues” variable of the Schedule P-1.2 of the Air Carrier Financial Reports of Department of Transportation, which provides quarterly loss and profit statements for airlines whose revenues exceed \$20 million. Norms also differed across dyads at the $p < 0.0001$ level. However norms did not significantly change within a dyad across time because in the initial years following de-regulation, airlines’ competitive actions converged in order to improve perceived legitimacy and thus organizational performance (Chen and Hambrick, 1995).

Third, the selected time period encompasses a period of shift in the assignment of markets to carriers, enabling the empirical observation of the creation of spheres of influence and genesis of MF with which this dissertation is concerned. Over the sample period, route networks and hub and spoke systems were stabilized, which resulted in the gradual formation of spheres of influence as carriers established hub-based networks and began to dominate routes that originate or terminate in their respective hubs (Oster and Strong 2001). The process of such stabilization within this period enables me to capture the genesis of MF.

The selected time period also provides the opportunity to observe whether carriers capitalized on their existing multi-market contacts to initiate and generate mutual forbearance in line with the theory that I develop. Unlike the second half of the 1980's, which was marked by a merger wave and thus a significant change in the level of multi-market contact (Evans and Kessides, 1994), the selected study period is characterized by a limited number of mergers, which keeps the level of multi-market contact among rivals relatively constant and allows me to observe how multi-market rivals leveraged their existing contacts across markets *ex post*.

Finally, it is more difficult to observe signaling commitment to MF through actual price increases, one of the main independent variables of this study, before 1992 than it is to observe them after 1992. Prior to 1992, carriers were able to signal their intention to cooperate through pre-announcements of fare increases and “cheap talk” without following through on the preannouncements and actually offering the pre-announced fare increases to the market (Borenstein, 2004). After 1992 however, the importance of actual price increases to signal the intent to cooperate in both a given market and across markets increased due to a settlement that was reached between two airlines, United Airlines and USAir, and Department of Justice in 1992 and the consent decree that prohibited eight members of the sample of this study to preannounce price increases to fix ticket prices and communicate linkages between fares on different routes.

All data used in the study is reported quarterly and there are 8 years of data and 45 dyads. There are two different data tables. The first data set that is prepared to test Hypothesis 1a and 1b has 1385 observations. The second data set that is prepared to test the remaining hypotheses contains 158831 observations.

4.4 Operational Definitions of Variables

In this section, I define the theoretical and control variables of this dissertation. I estimate three different empirical models as depicted by Figure 1. The first model investigates the formation of trust and thus Hypothesis 1a and 1b. The second model examines the process of tactical cooperation and thus Hypothesis 2, 3 and 4. Finally, the third model investigates the process of strategic cooperation and thus specifically examines Hypothesis 5, 6 and 7.

I also define the variables used in each of the three models, each of which will be estimated independently from the others. In the first sub-section, I define variables for the first model and identify the data sources that are used to compute those variables. In the second sub-section, I provide the operational definitions of the variables for the second and third models and identify their data sources.

4.4.1 Model One

4.4.1.1. Dependent Variable

Tactical Cooperation: I define tactical cooperation as the sum of the average fare (ticket price) charged by the members of a given dyad at time t . To calculate this variable, I first calculate the average fare at the firm-market-time level. I do this by multiplying the number of passengers flying market m with carrier i at time t with the market fare they paid and then take the sum of these products to get the total fare charged by carrier i in market m at time t . I then divide the resulting total fare by the number of total passengers served by carrier i in market m at time t to compute the average fare at the firm-market-time level. Following this, I move the average fare calculated at the firm-market-time level up to the firm-time level by calculating its mean across markets at time t . As the final step, I sum the resulting time-specific average ticket prices of members of a given dyad to calculate the dependent variable at the dyad-time level.

Three characteristics of the empirical context of this study support the use of the sum of the average ticket prices of a pair of rivals to calculate tactical cooperation. First, airlines compete in a Bertrand market where prices are strategic complements and quantities are strategic substitutes. Thus, matching the price moves of a rival is the profit maximizing response and summing the average fares captures that. Second, although price is dictated by the firm that prefers the lowest price, in the empirical context of this study, the firm that prefers the lowest price differs across markets due to the spheres of influence and hub and spoke operations. This in turn enables a pair of rivals to accept low prices in some markets in return for high ticket prices in others, which is the essence of a MF strategy. Since I expect such behavior to lead to an increase in average ticket prices, I sum the average ticket prices of a pair of rivals to capture it. Third, performance failure in line with the theoretical arguments of this dissertation transforms Prisoner's Dilemma into an assurance game where imitating the pricing behavior of rival is the profit maximizing response (Kollock, 1998). The outcome of such behavior can be captured by tracing the sum of the ticket prices of a pair of rivals over time.

Several factors support the use of ticket prices to calculate the dependent variable. First, pricing as a tactical competitive instrument provides a clear and strong stimulus (Hambrick et al., 1996; Heil and Robertson, 1991). Price moves reveal more information than that provided by other types of tactical moves (Chen and MacMillan, 1992) and the information is easier to interpret (Smith et al., 1991). Hence price increases are more likely than other types of moves to be attributed to the intention of the signaler to cooperate than to other factors such as insufficient capacity or increase in demand.

Second, pricing as a signaling instrument is highly visible (Chen and Miller, 1994; Chen and Hambrick, 1995; Chen et al., 2002). Consequently, firms are more likely to be aware of and recognize price increases and thus recognize the intention to cooperate and trust.

A third reason to use average fare as a proxy for tactical cooperation is that pricing decisions are frequent but not unique (Leeftang and Wittink, 1992), and so are more likely to quickly reduce the impact of hostile history that exists among rivals on their future interactions. Through frequent price increases, multi-market firms can not only repeatedly demonstrate to their multi-market rivals their intention to cooperate, but they can also reduce the negative impact of their conflict laden history on the effectiveness of their cooperative moves by triggering in their rivals, data-driven, bottom-up information processing, rather than history-driven top-down information processing, in decision making processes. Firms are hostages of their prior beliefs and use reputational beliefs about their rivals to guide their interactions with them (Prabhu and Stewart, 2001). It is therefore difficult for a dyad of rivals to cooperate in the face of historical interaction characterized by hostility. However pricing decisions provide frequent information and feedback and thus reduce the impact of the past on future interactions. Hence faced with frequent price increases, firms are expected to give more weight to the current cooperative moves of their rivals than to their past competitive actions. Thus, when taking actions, they will rely less on prior representations of their rivals (Moore, 1992) as hostile actors and work to update the negative reputational beliefs they held about them (Prabhu and Stewart, 2001).

A fourth reason to use average fares as a proxy for tactical cooperation is that frequency of price changes, coupled with the ability of price moves to affect bottom line results without

much delay (Chen and MacMillan, 1992; Steenkamp et al., 2005), make pricing an effective tool for developing trust.

Fifth, because they are tactical actions, price increases reduce not only the likelihood, but also the duration of being suckered. A trustee can defect and exploit a trust-giver in order to increase its market share and performance by not reciprocating with an increase in price in the trust-giver's markets. However price increases can easily be reversed in the face of defection because the implementation requirements of such actions are low (Chen et al., 1992). This in turn can make cheating less effective and reduces the duration of defection.

Sixth, firms that use pricing as a signal of cooperation are better positioned to foresee the likely responses of their rivals than are firms that use other forms of competitive action (Montgomery et al., 2005). Therefore firms that initiate cooperation through price increases can conjecture better about the likely responses of their rivals and can cooperate much more effectively.

Finally, the choice of ticket price as a proxy for tactical cooperation is driven by the fact that performance failure, which is one of the independent variables in my model, influences tactical competitive actions, particularly pricing actions, more than it influences strategic competitive actions, especially in the airline industry. More specifically, prior research suggests that initial responses to performance problems are almost exclusively changes in price (Miller and Chen, 1994). Managers of airlines modify and change prices in the face of performance failure because price changes require fewer and more general resources, are easier to reverse and are less challenging to the existing power base and status of decision makers compared to strategic actions (Chen et al., 1992; Connelly et al., 2010; Smith et al., 1991). Hence in this

context, multi-market firms that suffer from performance problems are expected to carry out tactical cooperation through pricing increases.

Market definition and the trip structure (e.g., route) offered to satisfy demand for a given market is crucial to the calculation of fare. I define a market as a non-directional city-pair. Since there is little or no cross elasticity of demand among city-pair markets (Gimeno, 1999), this demand-based definition ensures clear market delineation required by any study of MF. I also use non-directional rather than directional markets because carrier conduct in a given market (e.g., hub creation) and characteristics of a given market (e.g., market concentration, number of firms, keyness) or network structure of a carrier (e.g., hub economies) do not depend on which city is the origin or destination in a city-pair market.

With respect to trip structure, I look only at direct flights, which include non-stop and on-plane stop trips consistent with the definition of the Department of Transportation. Unlike non-direct flights that escalate rivalry, direct flights facilitate cooperation among carriers (Abramowitz and Brown, 1993; Borenstein, 1989, 1991, 1992). This characteristic of direct flights is essential for this study, which aims to explain the genesis of inter-organizational cooperation among multi-market rivals. In addition, the study of direct flights enables me to match different databases of Department of Transportation such as T-100 Domestic market data and DB1B Market table without losing observations and mixing different market definitions.

The data used to calculate average fare are from the DB1B Market table of the Airline Origin and Destination Survey (DB1B) which is a 10% sample of airline tickets from reporting carriers. The unit of observation of DB1B is at the itinerary level and the periodicity of the data is quarterly. I use the “market fare” variable of DB1B Market table as a basis to calculate average fare. In DB1B Market table, market fare is given for a directional market. However, as

discussed, I define a market as a non-directional city-pair market and thus I combine flights from point A to point B with flights from B to A before calculating the fare.

To calculate the total fare charged by a carrier in market m at time t reliably and consistently, I merge the DB1B Market table with the DB1B Ticket table by using the itinerary ID that is common to both tables and then filter the merged database in accordance with several data screening criteria as follows. First, I include only those itineraries that have one coupon⁴ in the market so that market fare is based on direct flights. To this end, I set “MktCoupons” variable equal to one in the DB1B Market. Second, I include only itineraries whose price information is reliable and that are not sold in bulk since unreliable price data and special discounts can confound the calculation of average ticket price (Orlov, 2011). I therefore eliminate tickets purchased by travel agencies for re-sale in packaged tours by using the “bulk fare indicator” of DB1B Market Table. In addition, I eliminate unreliable ticket prices by using the “dollar credibility indicator” variable of DB1B Ticket table. Third, I will include only domestic intra-line tickets (Evans and Kessides, 1994) and flights where the ticketing carrier is also the operating carrier. Without excluding inter-line itineraries and code sharing flights where the operating and ticketing carrier are different, it is difficult to know who is setting the price (Gerardi and Shapiro, 2009) and the manner in which ticket revenues are split through pro-rate agreements. Therefore, I keep only those itineraries that have a single operating carrier and where the reporting and operating carrier is the same airline company. To this end, I set the “Online” variable of DB1B Ticket table to one and equate “TkCarrier” variable to “OpCarrier” variable in DB1B Market table. Fourth, I delete observations from monopolized markets where there is only one incumbent firm because the level of analysis of this study is the inter-

⁴ Number of coupons refers the number of individual flight numbers (coupons) in an itinerary or market. For example, while a non-stop flight from Atlanta to Chicago requires one coupon, a flight from Atlanta to Chicago through a change-of plane stop at Boston requires two coupons.

organizational dyad. Fifth, I will delete open-jaw (e.g., ATL-BOS-NYC) and circle round trips (e.g., LAX-MIA-MSP-LAX) (Borenstein, 1989) since I am interested in non-directional city-pair markets. Following such filtering, I calculate the average fare charged by a carrier in market m at time t , and sum the average fares of the members of a given dyad to calculate the dependent variable.

The resulting “filtered DB1B Market table” is used to calculate other independent variables in other models as will be discussed.

4.4.1.2 Independent Variables

Multi-Market Contact (MMC): I use level of multi-market contact to capture the level of mutual interdependence and deterrence (threat of punishment) that exist between a given pair of rivals in a given quarter. My operational definition of multi-market contact is based on Baum and Korn’s multi-market contact measure (1999) and is given below:

$$\text{Multimarket contact}_{ijt} = \sum_{m \in M_{it}} [C_{imt} \times (D_{imt} \times D_{jmt})] + \sum_{m \in M_{jt}} [C_{jmt} \times (D_{imt} \times D_{jmt})]$$

For all $\sum_{m \in M_{it}} (D_{imt} \times D_{jmt}) > 1$, otherwise = 0

where m refers to a given market in the set of markets of M_{it} and M_{jt} served by rival airlines i and j at time t (a given quarter) and D_{imt} and D_{jmt} are dummy variables that are set to one if airlines i and j operate in market m at time t and zero otherwise. C_{imt} and C_{jmt} respectively reflect the dependence of airline i and airline j on market m for ticket revenue generation at time t . I define market dependence as the percentage of total ticket revenue generated in a given market by a given carrier at time t . This measure is equal to zero if a dyad of rivals have zero common markets and it is symmetric. The data to calculate this variable are from the “filtered DB1B Market table”.

This measure of multi-market contact reflects two important features of multi-market competition. First, the C_{imt} and C_{jmt} terms in the equation capture the perceived importance of a given level of multi-market contact and thus weighs the contacts between a pair of rivals by the importance of these contacts to the firms themselves, reflecting the finding that contacts that are in the key markets of rivals are more important than contacts in non-key markets (Barnett, 1993). Second, being at the dyad level, this measure captures mutual perception of a pair of rivals concerning the importance of their extended interdependence rather than their one-sided perception (Baum and Korn, 1999).

Norms of Rivalry: Norms of rivalry, as a measure at the level of inter-organizational dyad, capture the predictability antecedent of inter-organizational trust. The measure utilized in this study captures the multivariate Euclidean distance between a pair of rivals (Gimeno and Woo, 1996; Fuentelsaz and Gomez, 2006; Young et al., 2000) along seven dimensions of rivalry: average fare, number of market entries and exits, total advertising and publicity expense (AdExpense), total passenger service expenditures (PaxSvcExpense), available seat miles (AvailSeatMiles), and revenue aircraft departures performed (RADPerformed). These measures come from different databases of the U.S. Department of Transportation. Specifically, average fare and number of market exits and entries are from the “filtered DB1B Market table”; AdExpense and PaxSvcExpense are from the schedule P-7 of Air Carrier Financial Reports, which provide quarterly operating expense statements categorized into functions such as aircraft operating expense or traffic servicing expense for large air carriers; AvailSeatMiles and RADPerformed are from the T1: “U.S. Air Carrier Traffic and Capacity Summary by Service Class” which is a monthly summary of T-100 traffic data reported by U.S. air carriers and is compiled by carrier entities and service classes. In addition to reflecting significant aspects of

competition in the airline industry, the studied dimensions capture the most important competitive actions in any competitive context like pricing (average fare), marketing (advertising expenditure), product introduction (market entry) and withdrawal (market exit), capacity (available seat miles and flight frequency) and service actions (flight frequency and passenger service expenditures) (Ferrier et al., 2002; Ferrier and Lyon 2004).

To calculate norms of rivalry, I create a vector of seven variables based on these seven dimensions for each airline and time period and then measure the absolute value of the Euclidean distance between the vectors of two airlines that constitute a dyad at time t . Following this, I normalize this measure by dividing it by the maximum distance in the market (Young et al., 2000) and subtract the resulting value from one so that higher values reflect greater agreement on norms of rivalry between a pair of rivals and thus a better ability to predict action and reaction.

Operationally:

$$\text{Norms of rivalry}_{i,t;j,t} = 1 - \left[\frac{\sum_{d=1}^7 |D_{it} - D_{jt}|}{\max_{k,l} \sum_{d=1}^7 |D_{kt} - D_{lt}|} \right]$$

where D_{it} (D_{jt}) refers to airline i 's (j 's) score in strategic decision dimension d ($d=1$ (Fare); $d=2$ (Market entry); $d=3$ (Market exit); $d=4$ (Advertising Expense); $d=5$ (Passenger Service Expense); $d=6$ (Available Seat Miles); $d=7$ (Revenue Aircraft Departures Performed)) at time t and k and l are the firms in the market at maximum distance for dimension d at time t .

Performance Failure: This measure, which is at the dyad level, captures the risk taking antecedent of trust. Consistent with extant literature on aspiration level adaptation (Cyert and March, 1963; Lant and Mezias, 1992), which is aligned with the organizational learning perspective that I adopt to explain the origins of MF, I define performance failure or success with

respect to aspiration levels by deducting the aspiration level of firm i at time t from its performance at time t . Performance outcomes above aspiration level are framed as success and performance outcomes below aspiration level are framed as failure. Hence depending on their performance level relative to respective aspiration levels, members of an inter-organizational dyad can experience three distinct performance outcomes. First, both members of a dyad can experience success if both have performance levels above their respective aspiration levels. Second, one firm in the dyad can experience success while the other one experiences failure because its performance is below its aspiration level. Third, both members of the dyad can suffer from performance failure when the performance of both firms is below their respective aspiration levels. To capture these three states of performance at the dyad level at time t , I use a categorical variable that takes the value of 1 for the first state (success-success), 2 for the second state (success-failure or failure-success) and 3 for the third state (failure-failure).

Since I deduct the aspiration level of firm i at time t from its performance at time t to decide whether its performance outcome can be framed as success or failure, the first step is to define aspiration level. Following extant literature (Bromiley, 1991; Wiseman and Bromiley, 1996; Park, 2007), I define aspiration level as the weighted average of the social aspiration level (SA) and historical aspiration level (AS) using the following index function:

$$Aspiration_{it} = I(P_{i,t} < SA_{i,t}) * SA_{it} + I(P_{i,t} > SA_{it}) * (1.05) * HA_{it}$$

where $Aspiration_{it}$ is the aspiration level of firm i at time t , SA_{it} is the social aspiration level at time t , P_{it} is the performance level of firm i at time t and HA_{it} is the historical aspiration level of firm i at time t . SA_{it} is defined as the average performance of the other nine firms that form the

sample at time t and HA_{it} is defined as the performance of the focal firm i in the previous quarter, that is at time $t-1$.

According to this index function, at time t , when a focal firm's performance is below its social aspiration level, its aspiration level is equal to its social aspiration level. However when a firm's performance is above its social aspiration level, its aspiration level is 1.05 times its historical aspiration level.

Having defined aspiration level, the second step is to define performance since success or failure is defined by comparing performance to aspiration level. Consistent with the literature that studies rivalry within the context of U.S. scheduled passenger industry (Miller and Chen, 1994, 1996) I define firm performance as operating revenue (OpRevenues) per available seat mile (AvailSeatMiles). The data for this measure, which is called total revenue per available seat mile (TRASM), come from different databases of Department of Transportation. OpRevenues is from Schedule P-1.2 of the Air Carrier Financial Reports of Department of Transportation. Schedule P-1.2 provides quarterly profit and loss statements for carriers with annual operating revenues of \$20 million or more. AvailSeatMiles is from T1: U.S. Air Carrier Traffic and Capacity Summary by Service Class of Air Carrier Summary.

I use a market-based rather than a profit-based measure of performance for several reasons. First, competitive actions have a more direct impact on market based performance measures than they have on profit-based measures. Profit-based measures such as ROE or ROA are strongly influenced by internal operational decisions concerning depreciation, asset valuation, non-recurring income and expense items (Chen and Miller, 1994) and other factors such as tax rebates, tax anomalies and interest rates, which are not directly related to the level of

rivalry in the market place (Miller and Chen, 1996). Since I argue that a dyad of rivals commences cooperation when rivalry impairs their performance, I use operating revenue per available seat mile to define firm performance because this measure is directly impacted by rivalry. Second, in the airline industry, operating revenue per available seat mile is frequently used by managers to track and evaluate firm performance (Miller and Chen, 1994, 1996).

4.4.1.3 Control Variables

I control for production costs and quality in the first model because they can influence fare levels. In addition, I control for dependence across dyads. All of these controls are at the dyad-time level.

I use three variables to capture production costs. These are:

Cost per available seat mile (CASM): I control for cost per available seat mile (CASM), which is a measure of the sum of the unit costs of the members of dyad i at time t , because I expect the sum of the average fare charged by the members of dyad i to increase as their production costs increase. Unit cost is defined as the ratio of total operating expense (TotalOpExpense) to available seat miles (AvailSeatMiles). TotalOpExpense is reported in Schedule P-7 of the Air Carrier Financial Reports and provides quarterly operating expenses by functional grouping for large certified U.S. air carriers. AvailSeatmiles is reported in T1: U.S. Air Carrier Traffic and Capacity Summary by Service Class. To calculate CASM at the dyad-time level, I first calculate unit cost at the carrier-time level by dividing the total operating expense (TotalOpExpense) of a given carrier at the time t to its available seat miles (AvailSeatMiles) at time t . Next, I sum the unit costs of the members of dyad i at time t to calculate CASM at the dyad-time level.

Productivity: I control for productivity because I expect a negative relationship between total productivity of the members of dyad i at time t and the sum of their average prices at time t . Dyad members can pass their efficiency on to customers in the form of lower fares. To calculate productivity at the dyad-time level, I first calculate it at the firm-time level and then sum the productivity scores of members of dyad i at time t . To calculate productivity at the firm-time level, I take the ratio of the total operating revenues (OpRevenues) of a given carrier at time t to its number of full time equivalent employees (FTEEmployees) at time t . OpRevenues is reported in schedule P-1.2 of Air Carrier Financial Reports. This schedule is a quarterly profit and loss statement for carriers whose annual operating revenues exceed \$20 million and FTEEmployees is reported in Schedule P-1(a) Employees of Air Carrier Financial Reports, which is a monthly interim operations report of air carrier employment. After I calculate the individual productivity scores of the members of a given dyad at time t , I take their sum to compute productivity at the dyad-time level.

Stage Length: Stage length, which is the sum of the average distance flown by members of dyad i at time t , is expected to lead to higher ticket prices because distance has a positive impact on price (Borenstein, 1989). To calculate stage length at the dyad-time level, I will first calculate stage length at the firm-time level and then sum the stage length of the members of dyad i at time t . To calculate stage length at the firm-time level, I take the ratio of revenue miles flown (RevMilFlown) by a given carrier at time t to its revenue aircraft departures performed (RADPerformed) at time t . Both of these variables are reported in T1: U.S. Air Carrier Traffic and Capacity Summary by Service Class. After I calculate the stage length and thus the average length of all flights of the members of a given dyad at time t , I sum them to calculate stage length at the dyad-time level.

I also control for variables that influence both cost or service quality. To this end, I use the following variables:

Load Factor: Load factor, in general, reflects the proportion of airline output that is consumed and thus the percentage of filled seats. Airlines sell revenue passenger miles and produce available seat miles. Load factor is the ratio of the former to the latter and thus captures capacity utilization at the aircraft level. Since I define load factor at the dyad-time level, I sum the load factor levels of the members of dyad i at time t to calculate this control variable. Load factor influences fares in three ways (Borenstein, 1989), making its impact on fares indeterminate. First, it can reduce the sum of the average fare charged by the members of a given dyad because it reduces the per passenger cost of their flights. Members of a given dyad can pass on such cost savings to their passengers in the form of lower ticket prices. Second, load factor can increase the sum of the average fares charged by the members of a given dyad because it increases their opportunity cost of using their aircrafts due to demand peaking. Third, it can reduce the average fare level of a given dyad because of the reduction in perceived quality of their services due to their crowded planes.

To calculate load factor at the dyad-time level, I first compute load factor at the carrier-time level and then sum the load factor values of the members of dyad i at time t . To calculate load factor at the carrier-time level, I divide the revenue passenger miles flown (RevPaxMiles) by a given carrier at time t by its available seat miles (AvailSeatMiles) at time t . Both of these variables are available from T1: U.S. Air Carrier Traffic and Capacity Summary by Service Class. After I calculate the load factor at the carrier-time level, I sum the load factor values of the members of dyad i at time t .

Seating Density: Seating Density captures economies of density of the members of dyad i at time t . It is the sum of the average size of an aircraft on flights of the members of dyad i at time t . The sign of the impact of seating density on fare level is indeterminate due to its two opposing impacts (Borenstein, 1989). On the one hand, seating density is expected to reduce the sum of the average fare charged by the members of a given dyad by reducing their cost per-seat mile cost. On the other hand, seating density can have a positive impact on the sum of the average fares of the members of a given dyad by increasing the perceived quality of their products and value proposition as larger planes are perceived as more comfortable and safer. To calculate seating density at the dyad-time level, I first calculate it at the carrier-time level by dividing the available seat miles (AvailSeatMiles) of carrier i at time t by its revenue miles flown (RevMiles Flown) at time t . Both of these variables are available from T1: U.S. Air Carrier Traffic and Capacity Summary by Service Class. Next, I sum the respective seating density values of the members of dyad i at time t to capture seating density at the dyad-carrier level.

Frequency: Frequency is defined as the sum of the revenue aircraft departures performed (RADPerformed) by the members of dyad i at time t . This variable is reported in T1:U.S. Air Carrier Traffic and Capacity Summary by Service Class. The sign of the effect of frequency on the dependent variable is indeterminate due to its two opposing impacts (Borenstein, 1989). On the one hand, there is a positive relationship between frequency and aircraft utilization, lowering per flight costs of the members of dyad i , which can be passed on to passengers in the form of lower prices. On the other hand, greater flight frequency reduces the total number of delays of the members of a dyad. This in turn improves the perceived quality of their services, enabling them to increase their ticket prices.

I use network effect to control for the dependence across dyads.

Network Effect: Network effect is a dyad specific auto regressive term that controls for firm effects across dyads. Since level of analysis is unordered pairs of rivals, observations on dyads that have common members are not independent of one another, which leads to cross-sectional interdependence. A given airline may be a member of multiple dyads at any given time period and observations that come from dyads that have a common member are not independent. For example if firm *i* has an aggressive pricing policy, errors from dyads that have airline *i* as the common actor will be correlated due the general propensity of this firm to cut prices. Such cross-sectional interdependence is called common actor effect (Baum and Korn, 1999; Lincoln, 1984) and, if not corrected, can lead to inefficient parameter estimates and difficulty to rigorously examine the statistical significance of results (Gulati, 1995).

There are various solutions offered in the literature to control for this kind of unobserved heterogeneity. The first solution is to consider common actor effect as a model misspecification and include controls for all firm-level attributes that influence fare levels to eliminate all unmeasured effects of common firms (Gulati, 1996; Stuart, 1998). However it is difficult to identify and control for all of the relevant firm level variables, which limits the effectiveness of this solution, especially when the model is not completely specified (Korn and Baum, 1999). The second solution is to consider membership of a given firm in multiple dyads as an oversampling problem and discount oversampled cases in proportion to their extent of oversampling (Baum and Korn, 1996; Gulati, 1995). However this solution does not solve the problem of cross-sectional interdependence and the resulting correlation of errors from dyads that have common actors (Fuentelsaz and Gomez, 2006). The third solution is to use firm dummy variables and code them as one for each firm that is a member of a particular dyad in a particular time period (Stuart, 1998). However, this solution consumes too many degrees of freedom.

A fourth solution to control for unobserved heterogeneity and the method that I use in my empirical model is to include a network autocorrelation term (Lincoln, 1984; Lincoln et al., 1992; Park, 2007). I use the “network effect” as the dyad specific autoregressive term to control for biases that stem from unobserved similarities and dependence among dyads with a common firm (Lincoln et al., 1992; Park, 2007; Keister, 1999). “Network effect” is a variable that is defined for the ij th dyad and refers to the mean of the dependent variable across all dyads that include firm i or firm j (excluding ij) (Lincoln et al., 1992). The purpose of this variable is to capture within quarter firm effects that are not otherwise included in the model (Stuart, 1998). It cleans the coefficients on other independent variables of the unobserved propensities of the two airline companies in a dyad to charge a particular level of ticket price within each time period. Hence “network effect” is an additional control for unobserved heterogeneity and including it in the empirical model is similar to the mean differencing strategy that is used to control for cross-sectional and time specific interdependence in panel data analysis (Lincoln et al., 1992). “Network effect” is constructed by multiplying a W matrix by y_{ij} . W is a square matrix (45 by 45) with all potential dyads listed as rows and columns. For example, for three airlines, “the rows and columns are the dyads 1-2, 1-3, and 2-3. If the row and column dyads share a common node, then a 1 is entered in the matrix; otherwise a 0 is entered. The rows are then normalized by dividing each element by the sum of the row” (Wholey and Huonker, 1993, p: 360).

4.4.2 Model Two and Three

In this section, I provide operational definitions for the dependent, independent and control variables for model 2 and model 3 and specify the data sources. Data used to construct these variables are from the following databases of Department of Transportation: The T-100 Domestic Market table, which contains domestic market data about carrier, origin and service

classes for enplaned passengers; and the DB1B Market and DB1B Ticket tables of Origin and Destination Survey that provide information about fares, number of coupons, reliability and a bulk ticket indicator as previously discussed and the resulting “filtered DB1B market table”.

4.4.2.1 Dependent Variable and Independent Variables of Model Two

4.4.2.1.1 Dependent Variable of Model Two

Strategic Cooperation (SC): The dependent variable for the second model is strategic cooperation.

Unlike tactical actions, strategic actions refer to actions that require significant resource commitments, are difficult to implement and reverse and pay off over the long run (Connelly et al., 2010; Smith et al., 1991). In the airline industry, examples of strategic actions are initiation of frequent flier programs and new services, new airplane purchases, mergers and acquisitions, feeder and inter-industry alliances and hub creation (Miller and Chen, 1994). The theoretical model that this dissertation seeks to test is based on a learning approach, which requires that the strategic conduct used for testing be observable in market *m* at time *t* between a pair of rivals and occur frequently enough to act as feedback to learn and teach cooperation. Hub creation meets these two criteria and is used in this study as a measure of strategic action.

Different variables are used in the literature to define “hubness” including organizational share (Borenstein, 1989), hub share (Gimeno and Woo, 1996; Gimeno, 1999), airport share (Gimeno, 2002) and airport market share (Evans and Kessides, 1994). However all of these variables define “hubness” as the average of a carrier’s share of enplanements at both end cities of a city pair market, which captures the end result of hub creation rather than the process by which it was created. Hubs are created through a process of internal allocation decisions. Therefore, I define “hub creation” as the percentage of overall firm enplanements that take place

at both end cities of a city-pair market. Unlike the commonly accepted definition that considers hub creation by a focal carrier as a function of not only its own internal resource allocations decisions but also those of its rival, the measure that I use considers hub creation by a focal carrier exclusively a function of its own strategic investments and thus captures “firm share” rather than “market share”. Thus, this measure reflects the level of internal resource allocations of a given carrier with the purpose of creating a particular hub (Gimeno, 1999).

I define strategic cooperation as the ratio of the “hub creation” score of the member of a given dyad whose hub-creation score is higher than that of its rival in market m at time t to the “hub creation” score of its rival with the lower “hub creation” score. In other words, strategic cooperation is defined as the ratio of the high “hub creation” score to the low “hub creation” score of two rivals that constitute a dyad in market m at time. To calculate strategic cooperation, I rank the “hub creation” scores of the members of a given dyad from low to high and then divide the high “hub creation” score by the low “hub creation” score.

Strategic cooperation captures the purposeful creation of spheres of influence and thus the partitioning of the airline industry among rivals *ceteris paribus*. This measure is based on the assumption that a member of a dyad interprets the reduction in its rival’s level of investments to create a hub at either end point of a market as a signal of its intent to cooperate. Hence higher values of this variable refer to higher levels of cooperation.

The data to construct the strategic cooperation variable are taken from the T-100 Domestic Market table. I use the “passengers” variable from this table to calculate the total number of originating passengers from both end points of market m in a given quarter for each and every sampled carrier and use this figure as the basis to calculate “hub creation” at the

carrier-market-time level and then construct the strategic cooperation variable at the dyad-market-time level.

4.4.2.1.2 Independent Variables of Model Two

For the second model, which tests the hypotheses related to the relationship between tactical cooperation and strategic cooperation, there are three independent variables: tactical reciprocity, tactical non-reciprocity and “keyness”.

Tactical Reciprocity (TR) and Tactical Non-Reciprocity (TNR): In line with the hypothesis, I expect tactical reciprocity to have a positive slope and tactical non-reciprocity to have a negative slope in the strategic cooperation equation. Hence I expect jumps in the estimated values of strategic cooperation, which in turn calls for spline dummy variables (Greve, 1998) to operationalize tactical reciprocity and non-reciprocity. Consequently, I define tactical reciprocity as the absolute value of the sum of the average fare charged to a passenger flying the market by each of the dyad members in market m at time t when both members’ fares reflect a percentage increase from the previous quarter and zero otherwise. In a somewhat similar fashion, I define tactical non-reciprocity as the absolute value of the sum of the average fare charged to a passenger flying the market by each of the dyad members in market m at time t when only one of the dyad member’s fare reflect a percentage increase from the previous quarter and zero otherwise.

The data to construct these two variables are from the “filtered DB1B Market table”

Keyness: “Keyness” is a measure of the relative dependence of the members of dyad i on market m at time t for ticket revenue generation. To construct this variable, I first calculate the proportion of ticket revenues generated in a given market by each member of a dyad at time t . Next, I take the ratio of the higher proportion to lower proportion to calculate the “keyness” variable. Larger values of this ratio in a particular market indicate that dyad members’

dependence on the relevant market is moving in opposite directions, a sign of increasing “keyness” of the market for the dyad member with the higher percentage and decreasing “keyness” of the market for the dyad with the lower percentage.

To calculate ticket revenues, I multiply the “market fare” variable by the “number of passengers” variable from the “filtered DB1B Market table”.

4.4.2.2 Dependent Variable and Independent Variables of Model Three

4.4.2.2 .1 Dependent Variable of Model Three

Mutual Forbearance (MF): In the third model, I examine the impact of strategic reciprocity and non-reciprocity on mutual forbearance, making mutual forbearance the dependent variable. In the extant literature, different measures are used to capture mutual forbearance in the context of the airline industry such as frequency of flights (Bilotkach, 2011), yield (Gimeno, 1999; Gimeno and Woo, 1996; Zou et al., 2011), on-time performance (Prince and Simon, 2009), fare price (Evans and Kessides, 1994; Singal, 1996; Zhang and Round, 2009; 2011), Lerner index (Gimeno, 2002; Gimeno and Woo, 1999), geographic market entry and exit (Baum and Korn, 1996), market share instability (Sandler, 1988) and market share (Gimeno, 1999).

I capture mutual forbearance through market share since it reflects the final outcome of the theorized process of mutual forbearance creation that this dissertation seeks to explain. In the process of developing and forming mutual forbearance, firms constantly attempt to partition an industry and repeatedly assign and re-assign markets to each other. When such partitioning is satisfactory for all of the rivals, they commence to mutually forbear. Specifically, they allow their rivals to dominate particular markets in return for their own dominance in other markets and thus effectively sign off on tacit reciprocal super-ordination and subordination agreements.

Market share is a valid measure to capture such tacit agreements because market share reflects the extent to which a given firm dominates, or is allowed to dominate, a market.

I define mutual forbearance as the ratio of the market share of the member of a given dyad whose market share is higher than that of its rival in market m at time t to the market share of its rival with the lower market share. To calculate mutual forbearance, I rank the market share of the members of a dyad from high to low and then divide the high market share by low market share. As the value of this variable increases, one member of a given dyad becomes more dominant in the relevant market than its rival, capturing the tacit super-ordination and subordination agreements.

The population and sample of this study ensure that formation of spheres of influence and market share differences, which are the hypothesized outcomes of the two-staged experimental process of cooperation, derives from MF strategies of a pair of multi-market rivals rather than their outright competition. In the last three decades, empirical studies of the U.S. airline industry have conclusively demonstrated that multi-market rivals in the U.S. airline industry do mutually forbear from competition (Baum and Korn, 1996, 1999; Bilotkach, 2011; Ciliberto and Williams, 2012; Evans and Kessides, 1994; Gimeno, 1999, 2002; Gimeno and Woo, 1996; Miller, 2010; Prince and Simon, 2009; Singal, 1996; Zou et al., 2012). This in turn suggests that the dependent variables of the two-staged experimental processes of cooperation will capture the outcome of MF strategies of a pair of multi-market rivals rather than the ability of one of the dyad members to outcompete other dyad member. Similarly, the fact that the sample of this study is composed of carriers with similar size and market scope suggests that formation of spheres of influence and market share differences will derive from MF strategies of a pair of rivals. Lacking the ability to

outcompete one another, sampled carriers are expected to cooperate and divvy up markets to one another to maximize their overall firm profitability during the study period.

I use the T-100 Domestic Market table (U.S. Carriers) of the Air Carrier Statistics database to calculate market share at the carrier-market-time level and MF at the dyad-market-time level. The T-100 table provides domestic market data about carrier, origin, destination and service class for enplaned passengers. I use the “passenger” variable of this table to calculate the market shares of a pair of rivals, which is then used to construct the mutual forbearance variable. The “passenger” variable provides a count of passengers that enplane and de-plane between two specific points on the same flight. Hence the count is based on passengers that are on direct flights, which includes both non-stop flights and flights with on-plane stops where the flight number remains the same, in line with the definition of market used by the T-100 Domestic Market table of Air Carrier Statistics.

4.4.2.2 .2 Independent Variables of Model Three

The third model has three independent variables: strategic reciprocity, strategic non-reciprocity and “keyness”.

Strategic Reciprocity (SR) and Strategic Non-Reciprocity (SNR): I expect strategic reciprocity to have a positive slope and strategic non-reciprocity to have a negative slope in model three. Hence I expect jumps in the estimated values of mutual forbearance, which, once more, requires spline dummy variables (Greve, 1998) to operationalize these two constructs. As a result, I define strategic reciprocity as the absolute difference of the “hub creation” scores (percentage of overall firm enplanements that take place at either of the two cities of the city-pair market) of a pair of rivals at time t when percentage change from the previous quarter in hub creation score is positive for one dyad member and negative for the other dyad member and zero otherwise. A pair of rivals is expected to divert their resources away from each other’s hubs to

signal cooperation and concentrate their resources on their respective hubs so as to mark these hubs as their spheres of influence. The operational definition of strategic reciprocity captures such simultaneous resource diversion by one dyad member and concentration by the other member as an attempt to deepen cooperation and partition the airline industry.

Strategic non-reciprocity is equal to the absolute difference of the “hub creation” scores (percentage of overall firm enplanements that take place at either of the two cities of the city-pair market) of a pair of rivals at time t when percentage change from the previous quarter in hub creation score is positive for both members of a dyad and zero otherwise. This variable captures the escalation of rivalry by a dyad member when the other member is making clear, visible, and significant commitments to either end point of a market to signal its willingness to dominate flights that fly to/from each end points of a given market.

The data to construct the strategic reciprocity and non-reciprocity variables are from T-100 Domestic Market. The “passengers” variable of the T-100 Domestic market table is used to calculate the number of total originating passengers from both end points of market m at a given quarter for each and every sampled carrier. I then employ this figure as the basis to calculate strategic reciprocity and strategic non-reciprocity.

Keyness: This variable is common to both model two and model three, so I use the same operational definition of “keyness” provided for the second model.

4.4.2.3 Control Variables of Model Two and Three

I control for competition, demand and cost, which influence the dependent variables of model 2 and 3 to rule out alternative explanations.

I will use two variables that exist at the market level to control for actual competition: Market concentration and number of firms. To construct these variables, I use the information from the full census of carriers in the U.S. scheduled passenger industry.

Market Concentration (MC): I capture market concentration through the Herfindahl–Hirshman index. Thus market concentration is the sum of squared market shares of all carriers operating in market m . A carrier's market share is the ratio of the carrier's on-flight market passengers enplaned at time t to the total on-flight market passengers enplaned at time t .

Market concentration is expected to have a positive impact on strategic cooperation and mutual forbearance. I expect a positive relationship between market concentration and strategic cooperation because dominance of a market by a few carriers can lead to dominance over originations by the same carriers at both end cities of a market. I expect a positive relationship between market concentration and mutual forbearance because, in general, increase in concentration level facilitates collusion. As concentration level increases in a market, it becomes more effective and efficient to send signals and form a shared understanding, both of which then can be deployed by a handful of incumbent firms to assign markets to one another in return for similar treatment.

I use the “passengers” variable of T-100 Domestic Market table of Air Carrier Statistics to construct the market concentration variable.

Number of Firms (NF): Number of firms is the count of the number of firms that operate in market m at time t . As the number of carriers in a given market increases, the level of competition escalates. Consequently, I expect that number of firms will have a negative impact on both strategic cooperation and mutual forbearance.

The data source for this variable is the T-100 Domestic Market table of Air Carrier Statistics. I use this table to count the number of unique carriers that operate in market m at time t .

I use the variable, number of passengers, to control for the size of demand.

Number of Passengers (NP): As the name implies, this variable is the count of the number of passengers in market m at time t . It is used to control for the size of the market and thus the level of demand. An increase in the level of demand can have a positive, negative or zero impact (Sudhir et al., 2005) on strategic cooperation and mutual forbearance. The competing and alternative relationships between changes in demand and cooperation level are influenced by several pre-conditions. The most important for this research is the condition of observability of competitor prices and market share. This is particularly relevant to the empirical context of this dissertation because in the U.S. scheduled passenger airline industry, prices of rivals and market share are made available to incumbent firms through governmental agencies like Department of Transportation or Federal Aviation Administration, trade associations like Airlines for America and also Airline Tariff Publishing Company. The “observability” condition is therefore expected to lead to a negative relationship between aggregate demand level and strategic cooperation/mutual forbearance in a given market. The reason for this is that when market shares and prices of rivals are observable, firms that face high aggregate demand cut their prices to increase their market share at the expense of their rivals because they know that, on average, the level of future aggregate demand will be less than current level of demand, thereby reducing the credibility of threat of future punishments (Sudhir et al., 2005; Rotemberg and Saloner, 1986) and impairing strategic cooperation. Likewise, an increase in number of passengers reinforces the motive of air carriers to steal customers from one another and thus reduces the absolute difference in their respective market shares. Thus, I expect a negative relationship between number of passengers and mutual forbearance. This variable is constructed by using the “passengers” variable of T-100 the Domestic Market table of Air Carrier Statistics.

Finally, I control for variables that influence cost. These variables are hub economies and firm size, both of which are defined at the dyad-market-time level.

Hub Economies (HE): This variable is based on the average number of originating passengers at the end-points of a market of a carrier. To compute this variable, I first calculate the average number of originating passengers at the end-points of a market for both members of a dyad and then rank these numbers from high to low and divide the high average to low average. This measure is defined at the dyad-market-time level.

Hub economies reduce total costs through economies of scope because different flights share ground facilities and services, personnel and passengers that travel to different destinations. This variable is expected to have a positive impact on strategic cooperation and mutual forbearance because it improves the position of a dyad member vis-à-vis its rival with respect to end-point dominance and market share.

I use the “passengers” variable of T-100 Domestic market as a basis to calculate hub economies.

Firm Size (FS): Firm size is based on the number of passengers that are enplaned by members of a dyad in *other* markets. To compute this variable, I first calculate the number of passengers that are enplaned by members of a dyad in *other* markets and rank these two numbers from high to low and divide the high number of passengers by the low number of passengers. This measure is defined at the dyad-market-time level.

Firm size is expected to have a positive impact on strategic cooperation and mutual forbearance because it is expected to reduce average costs through economies of scale and learning by doing. The reduction in average costs is expected to be reflected in lower ticket prices, which strengthens the dominance of a carrier at the end points of a market and increases

its market share. This measure also reflects the increase in brand recognition of a member of a given dyad and thus is expected to have a positive impact on its reputation which in turn will have a positive impact on strategic cooperation and MF.

I use the “filtered DB1B Market table” to calculate this variable.

I include “network effect” as a control variable in both models two and three to control for dependence across dyads in a market at time t.

Network Effect: In both models two and three, I control for dependence across dyads that derives from having a common member by using the “network effect” control variable. Not controlling for cross-sectional interdependence results in inefficient parameter estimates and impairs statistical inference (Gulati, 1995). To control for the common actor effect and dependence of observations coming from dyads that have a common member, (Lincoln et al., 1992; Park, 2007; Keister, 1999), I include “network effect” as a control variable in the statistical equations of models two and three. “Network effect” refers to the mean of dependent variable over all dyads that include firm i or firm j (excluding ij) (Lincoln et al., 1992) and is defined at the dyad-market-time level. Hence the operational definition of “network effect” differs across the two models. For the second model, “network effect” is the mean of strategic cooperation across all dyads that include firm i or firm j (excluding ij) in market m at time t. For the third model, “network effect” is the mean of mutual forbearance across all dyads that include firm i or firm j (excluding ij) in market m at time t. The data source for this variable is T-100 Domestic Market table.

In addition to these control variables common to both model two and three, I will control for “tactical rivalry” in the second model and “strategic rivalry” in the third model.

Tactical Rivalry (TRivalry): Tactical rivalry is defined as the absolute value of the sum of the average fare charged by each of the dyad members in market m at time t when both dyad members' fares reflect a percentage reduction from the previous quarter and zero otherwise. I expect tactical rivalry to have a negative impact on strategic cooperation because tactical rivalry will reduce the absolute difference between hub creation scores of a pair of rivals in market m at time t . This control variable will ensure that the sign, magnitude and significance of the relationship between tactical reciprocity/non-reciprocity and strategic cooperation are clear of the impact of tactical rivalry on strategic cooperation.

To calculate tactical rivalry, I use the “filtered DB1B Market table”.

Strategic Withdrawal (SW): Strategic withdrawal is equal to the absolute difference of the “hub creation” scores (percentage of overall firm enplanements that take place at both end points of a city-pair market) of a pair of rivals at time t when percentage change in the hub creation score from the previous quarter is negative for both members of a dyad and zero otherwise. When both members of a dyad withdraw strategically from the end points of a market, their market share is expected to shrink. More importantly, such withdrawal demonstrates that flights flying to and from these points are of secondary importance for these firms and thus do not warrant a mutual forbearance strategy. This is a crucial control because it ensures that the sign, magnitude and significance of the hypothesized causal relationships are not confounded by the desire of a pair of rivals to withdraw from a given market.

I use the “passengers” variable of T-100 Domestic Market table to calculate this variable.

A summary of all dependent, independent and control variables categorized by the number of the model is provided in Tables 1, 2 and 3 respectively.

Table 1: Dependent Variable

Model 1	Model 2	Model 3
<p>Tactical Cooperation: Sum of average fare that dyad member i and j charge per passenger at time t</p>	<p>Strategic Cooperation: the ratio of the “hub creation” score (percentage of overall firm enplanements that take place at both end points of the city-pair market at time t) of the dyad member whose hub creation score is higher than that of the other member to the “hub creation” score of the other dyad member with the lower “hub creation” score.</p>	<p>Mutual Forbearance: the ratio of the market share (ratio of a firm’s on-flight market passengers enplaned at time t in market m to the total on-flight market passengers enplaned at time t in market m) of the dyad member whose market share is higher than that of the other member to the market share of the other dyad member with the lower market share</p>

Table 2: Independent Variables

Model 1	Model 2	Model 3
<p>Multimarket contact$_{ijt}$=</p> $\sum_{M \text{ it}} [C_{imt} \times (D_{imt} \times D_{jmt})] + \sum_{M \text{ jt}} [C_{jmt} \times (D_{imt} \times D_{jmt})]$ <p>For all $\sum_{M \text{ it}} (D_{imt} \times D_{jmt}) > 1$, otherwise = 0</p> <p>$C_{imt}$ and C_{jmt} respectively reflect the dependence of airline i and airline j on market m for revenue generation at time t. I define market dependence as the percentage of overall ticket revenue generated in a given market by a given carrier at time t</p>	<p>Tactical Reciprocity: absolute value of the sum of the average fare charged by each of the dyad members in market m at time t when both members’ fares reflect a percentage increase from the previous quarter and zero otherwise</p>	<p>Strategic Reciprocity: the absolute difference of the “hub creation” scores (percentage of overall firm enplanements that take place at both end points of the city-pair market at time t) of a pair of rivals at time t in market m when percentage change from the previous quarter in hub creation score in market m is positive for one dyad member and negative for the other dyad member and zero otherwise</p>
<p>Norms of rivalry$_{i,t,j,t}$</p> $= 1 - \left[\frac{\sum_{d=1}^7 D_{it} - D_{jt} }{\max k, l \sum_{d=1}^7 D_{kt} - D_{lt} } \right]$	<p>Tactical Non-reciprocity : the absolute value of the sum of the average fare charged by each of the dyad members in market m at time t when only one of the dyad member’s fare reflect a percentage increase from the previous quarter and zero</p>	<p>Strategic Non-Reciprocity: the absolute difference of the “hub creation” scores (percentage of overall firm enplanements that take place at both end points of the city-pair market at time t) of a pair of rivals at time t in market m when percentage change from the previous</p>

where D_{it} (D_{jt}) refers to airline i 's (j 's) score in strategic decision dimension d ($d=1$ (Fare); $d=2$ (Market entry); $d=3$ (Market exit); $d=4$ (Advertising Expense); $d=5$ (Passenger Service Expense); $d=6$ (Available Seat Miles); $d=7$ (Revenue Aircraft Departures Performed)) at time t and k and l are the firms in the market at maximum distance for dimension d at time t .	otherwise	quarter in hub creation score in market m is positive for both members of a dyad and zero otherwise
<p>Performance Failure: 1- As the first step, performance relative aspiration levels is calculated for each member of dyad at time.</p> <p>Aspiration level for firm I at time t is: $(I(P_{i,t} < SA_{i,t}) * SA_{i,t} + I(P_{i,t} > SA_{i,t})) * (1.05) * HA_{i,t}$ where P stands for performance, SA stands for social aspiration which is average performance of rivals of firm "i" at time t and HA is the historical aspiration which is equal to performance of firm "i" in the previous time period 2- This variable takes the value of 1 if performance of each of the dyad members is above their relative aspiration (success-success), takes the value of 2 when performance of only one dyad members is below its aspiration level (success-failure or failure-success) and takes the value of 3 when performance of the both members of a dyad is lower than their respective aspiration level (failure-failure).</p>	Keyness: the ratio of higher proportion of ticket revenues generated by a member of dyad " i " in a given market at time t to lower proportion of ticket revenues generated by the other member of dyad " i " in a given market at time t	Keyness: the ratio of higher proportion of ticket revenues generated by a member of dyad " i " in a given market at time t to lower proportion of ticket revenues generated by the other member of dyad " i " in a given market at time t

Table 3: Control Variables

Model 1	Model 2	Model 3
Cost available per seat: (Operating Expense of dyad member i at time t / Available Seat Miles of dyad member i at time t)+(Operating Expense of dyad member j at time t / Available Seat Miles of dyad member j at time t)	Market Concentration: the sum of squared market shares (ratio of a focal firm's on-flight market passengers enplaned at time t in market m to the total on-flight market passengers enplaned at time t in market m) of all carriers operating	Market Concentration: the sum of squared market shares (ratio of a focal firm's on-flight market passengers enplaned at time t in market m to the total on-flight market passengers enplaned at time t in market m) of all carriers operating

	in market m at time t	in market m at time t
Productivity: (Operating Revenues of dyad member i at time t/FTEEmployeess of dyad member i at time t)+(Operating Revenues of dyad member j at time t/FTEEmployeess of dyad member j at time t)	Number of Firms: count of the number of firms that operates in market m at time t	Number of Firms: count of the number of firms that operates in market m at time t
Stage Length: (Revenue Miles Flown by dyad member i at time t/Revenue Aircraft Departures Performed by dyad member i at time t)+(Revenue Miles Flown by dyad member j at time t /Revenue Aircraft Departures Performed by dyad member j at time t)	Number of Passengers: count of the number of passengers in market m at time t	Number of Passengers: count of the number of passengers in market m at time t
Load Factor: (Revenue Passenger Miles of dyad member i at time t/Available Seat Miles of dyad member i at time t)+(Revenue Passenger Miles of dyad member j at time t/Available Seat Miles of dyad member j at time t)	Hub Economies: the ratio of the number of originating passengers of a given dyad member with the higher number of originating passengers at the end-points of a market to the number of originating passengers of the other dyad member with the lower number of originating passengers at the end-points of the same market	Hub Economies: the ratio of the number of originating passengers of a given dyad member with the higher number of originating passengers at the end-points of a market to the number of originating passengers of the other dyad member with the lower number of originating passengers at the end-points of the same market
Seating Density: (Available Seat Miles of dyad member i at time t/Revenue Miles Flown of dyad member i at time t)+ (Available Seat Miles of dyad member j at time t/ Revenue Miles Flown of dyad member j at time t)	Firm Size: the ratio of higher number of passengers that are enplaned by a member of a dyad in other markets at time t to the lower number of passengers that are enplaned by the other member in other markets at time t	Firm Size: the ratio of higher number of passengers that are enplaned by a member of a dyad in other markets at time t to the lower number of passengers that are enplaned by the other member in other markets at time t
Frequency: (Revenue Aircraft Departures Performed by dyad member i at time t)+ Revenue Aircraft Departures Performed by dyad member j at time t)	Tactical Rivalry: the absolute value of the sum of the average fare charged by each of the dyad members in market m at time t when both dyad members' fares reflect a percentage reduction from the previous quarter and zero otherwise	Strategic Withdrawal : the absolute difference of the “hub creation” scores (percentage of overall firm enplanements that take place at both end points of the city-pair market) of a pair of rivals at time t in market m when percentage change in hub creation score in market m from the previous quarter is negative for both

		members of a dyad and zero otherwise
Network Effect: The mean of tactical cooperation across all dyads that include firm “i” or ” j” for the ijth dyad (excluding ij) at time t	Network Effect: The mean of strategic cooperation across all dyads that include firm “i” or ” j” for the ijth dyad (excluding ij) at time t in market m	Network Effect: The mean of mutual forbearance across all dyads that include firm “i” or ” j” for the ijth dyad (excluding ij) at time t in market m

4.5. Methodology

I use multi-level modeling⁵ to test the hypotheses for several reasons. First, multi-level modeling enables me to model unit heterogeneity that exists in the data sets not only in terms of variable intercepts but also variable slopes. Second, multi-level modeling can model not only co-variance of intercepts and slopes but also co-variance of slopes, enabling me to discover the sign and significance of a relationship that exists either between slopes and intercepts or between slopes in the data sets. Third, I can use this method to build statistical models and select the model that provides the “best”⁶ fit to the data at hand. Fourth, through multi-level modeling, I can produce precise estimates of coefficients and accurate statistical tests and thus can infer correctly. Fifth, I can employ this type of modeling to analyze unbalanced panel data sets of this study. Sixth, I can use multi-level modeling to study the underlying processes of cooperation through archival data and can shed light on the lower-level cooperative processes that lead to higher level outcomes.

4.5.1 Variable Intercepts and Slopes

Multi-level modeling can model unit heterogeneity in terms of variable intercepts and slopes (Singer and Willett, 2003), a capability which is sine quo non in the context of multi-market competition. Unlike the popular fixed-effects or random-effects models which can model

⁵ This method is also known as random coefficients or hierarchical modeling.

⁶ It is necessary to qualify this statement. As Box and Draper (1987) stated, all models are wrong and only some of them are useful. Hence the “best” model is a model that is useful given the purpose of a particular research project and is estimable.

unit heterogeneity merely through intercepts that vary across cross-sectional units (Bollen and Brand, 2010), multi-level modeling can capture unit heterogeneity not only through intercepts but also slopes that vary across units. The capability to model variable slopes is especially indispensable for this research, which theoretically and empirically investigates the process of the switch from rivalry to mutual forbearance between pairs of rivals. The nature of rivalry and mutual forbearance calls for variable intercepts and slopes.

Rivalry is a subject-specific phenomenon. In general, a given pair of rivals experiences a unique relationship due to the relation-specific nature of rivalry. Unlike competition whose definition evolved from different suppliers' *independent striving* for patronage to eventually their numbers in a given market, rivalry is the *conscious* act of striving for potentially incompatible positions (Scherer and Ross, 1990). Indeed rivalry takes place when “one firm orients towards another and considers the actions and characteristics of the other in business definition with the goal of achieving a commercial advantage over the other” (Porac et al., 1995, p: 204). Hence the content and level of rivalry differs from one relationship to another. The relation-specific nature of rivalry in general and MF in particular requires intercepts and slopes that vary randomly across the sampling units of this study.

The social construction of rivalry also requires the ability to model variable intercepts and slopes. In the population, members of a competitive dyad are expected to respond to their perception of the values of theoretically important predictors of this study such as tactical reciprocity or multi-market contact rather than to their “actual” values and in the process socially construct the nature, content and level of rivalry, requiring a statistical model that allows variable slopes. In general, firms perceive their competitive environment and act upon their perceptions of the environment rather than the environment itself. Firm conduct is a response to perceptions of

stimuli rather than to stimuli themselves because managerial cognition mediates the relationship between objective external stimuli and organizational action (Nadkarni and Barr, 2008). That is why firms assign different meanings to the very same competitive signals (Heil and Roberston, 1991) or significant events in the general environment (Barr et al., 1992), overlook the significance of competitive responses or fail to respond to them promptly (Zajac and Bazerman, 1991), asymmetrically define one another as rivals (Desarbo et al., 2006) and recognize only a handful of firms as rivals among a myriad of market participants (Panagiotou, 2006). Further, by acting upon their understanding of external stimuli, firms socially construct or, in other words, enact their competitive environment (Smircich and Stubbart, 1985). In the process of mutually enacting their competitive environment by *responding* to their understanding and perception of the competition, rivals socially construct the nature, content and level of rivalry (Porac et al., 1989, 1995). In a socially enacted competitive environment where bounded rationality and incomplete information replace supra-rationality and complete information respectively, ascending perception and awareness (Chen, 1996) to a preeminent role, pairs of rivals are expected to assign different meaning to the same stimulus and thus respond differently to the same stimulus. Capturing variation in response requires multi-level modeling that can model variable intercept and slopes.

Studies conducted in the U.S. airline industry, which is also the empirical context of this study, provide empirical support for the relevance of perception and enactment to rivalry and demonstrate the relevance of multi-level modeling to investigating the hypotheses of this dissertation. For example, Chen and his associates (2007) empirically demonstrate that in the U.S. airline industry, a pair of rival airline's volume of attack on one another is significantly influenced by the level of tension that is perceived to exist between them even after controlling

for the “actual” level of tension between them. Similarly, the findings of Tsai and his coauthors (2011) reveal that adopting the mindset of a rival and seeing the competitive environment through the lens of a rival increases the market share of a focal firm vis-à-vis its rival in a competitive dyad in the U.S. airline industry since socially constructed competition molds and shapes firm response and action. In light of the empirical evidence and theoretical arguments provided, I expect slopes to vary across competitive dyads. The mutually interacting interpretations of the members of a dyad are expected to create a unique response to what is observed in the sample data, adding low/moderate level of heterogeneity to the theorized data generation process explained in section three of this theoretical and empirical study. To capture such heterogeneity, I use multi-level modeling.

Like rivalry, mutual forbearance is a dyad-specific construct and should be modeled through a subject-specific model such as multi-level modeling that can model variable slopes rather than marginal or population averaged models such as generalized estimating equations, fixed-effects or random-effects models. “The theoretical construct of multi-market contact is fundamentally about the relationship that unfolds over time between two firms across the multiple markets in which they compete” (Baum and Korn, 1999, p: 272). Hence the strength and even sign of the relationship between dependent and independent variables can change from one dyad to another. That is why there is no theoretical ground for constraining the slopes to be equal across dyads in this study by using panel data methods such as fixed-effects or random-effects.

Further, multi-market competition is a strategic issue and its framing as an opportunity or threat can lead to divergent firm conduct, which can be captured by variable slopes. Multi-market competition is a strategic issue because it has the potential to influence organizational

performance and have an impact on a firm's present or future strategies (Dutton et al., 1983; Dutton and Webster, 1988; Dutton, 1993; Schneider and Meyer, 1991; Dutton and Duncan, 1987; Thomas et al., 1994; Ginsberg and Venkatraman, 1992). Like any other strategic issue, multi-market competition has to be diagnosed and ascribed a meaning so as to inform and guide firm conduct (Dutton et al., 1983; Dutton et al., 1990; Dutton and Duncon, 1987; Thomas and McDaniel, 1990). However, similar to any other issue, multi-market competition is ill-defined and ambiguous (Schneider and Meyer, 1991; Schneider, 1997). In the extant literature, it is defined as a double-edge sword because it has the potential to both intensify and de-escalate competition (Porter, 1980). Multi-market competition as a strategic issue, consequently, incorporates both threat and opportunity consistent attributes, making its organizational categorization arduous and daunting.

The categorization and framing of multi-market competition has important repercussions for the formulation and execution of mutual forbearance strategy as interpretations influence firm conduct and strategy (Dutton et al., 1983; Denison et al., 1996; Sharma, 2000; Dutton and Duncan, 1987; Dutton and Jackson, 1987; Dutton et al., 1990; Schneider and Meyer, 1991; Thomas and Daniel, 1990; Julian and Ofori-Dankwa, 2008; Ginsberg and Venkatraman, 1992; Schneider, 1997). The framing and interpretation of multi-market competition through organizational interpretive schemes as an opportunity is expected to result in cooperative or collusive behavior among behaviors, while the framing of multi-market competition as a threat is expected to intensify competition and such variance in interpretations which is expected to lead to variance in competitive behavior across markets should be modeled directly, requiring multi-level modeling.

4.5.2. Modeling Co-variance

I expect not only covariance of intercepts and slopes but also of slopes in this study. Therefore, I use multi-level modeling because it can model and test such covariance. The main purpose of this study is to explain the origins of mutual forbearance or, in general, explain how rivals start to cooperate. The relationship between intercepts and slopes can be crucial to understanding how firms move towards cooperation. For example, if a pair of rival carriers initiates cooperation from a low price level and thus has a low intercept, the slope of their cooperation can be higher than that of a pair of rivals that starts cooperation from a high price level and thus intercept if there is a “compensatory” relationship between intercepts and slopes. In addition to the covariance of intercepts and slopes, I expect slopes to co-vary in this study as well. For example, competing in a similar fashion may be associated with performance failure either positively if rival firms deploy their understanding of the norms of competition to escalate rivalry or negatively when rivals deploy their understanding of the norms of the competition to cooperate.

4.5.3 Model Building and Selection

Unlike fixed-effects or random-effects models that are widely used to examine longitudinal data, multi-level modeling can be used to build statistical models and select the “best” model among all theoretically feasible and empirically competing alternatives. With multi-level modeling, it is possible to specify the structure of between-subject random-effects and within-subject random errors and select the covariance structure that best fits the data through either likelihood ratio tests if compared models are nested or through information criteria such as Akaike’s Information Criterion (AIC) and Schwarz’s Bayesian Information Criterion (BIC) if compared models are not nested. This capability allows me to build the mean structure or the fixed component of a statistical model by using the theory that I develop and then

compare the goodness-of-fit of various covariance structures that have the identical but theoretically determined mean structure through log likelihood tests or the information criteria provided. For example, given a pre-determined mean structure that is guided by my theoretical model, I can model the within-subject correlation and thus dependence that stems from time through the most flexible “unstructured” variance-covariance structure that enables variance and covariance to be freely estimated from the data and then compare this covariance structure with the “compound symmetric” variance-covariance structure that constrains covariance to be constant among any two measurements and variance to be constant over time through a log-likelihood ratio test. In addition, with multi-level modeling, I can determine how much of the “explainable” variation in the outcome of interest is explained by the inclusion of additional time-varying predictors to the “Unconditional Means Model” through the Pseudo- R^2 statistic (Singer and Willett, 2003) and can gauge the relative contribution of each theoretical variable to the overall model.

4.5.4 Precision of estimates

One of the main benefits of using multi-level modeling is the precision of its estimates. By enabling a researcher to select the covariance structure that is the “best” fit for a model given data, multi-level modeling increases the precision of the estimates of fixed-effects and leads to the calculation of correct confidence intervals and p-values (Azuerro et al., 2010). Model-based estimates of the multi-level models are a weighted average of the ordinary least squares (OLS) and population average estimates. The weights are determined by the relative precision of OLS and population average estimates; when OLS estimates are more precise than population average estimates, they have a greater weight than population averages in the calculation of model-based estimates and vice-versa (Singer and Willett, 2003). Because of such weighting, units that have a high level of uncertainty in their estimates “borrow strength” from population average estimates

and their estimates shrink toward the grand mean, enabling a researcher to extract as much information as possible from a given data set. The precision of estimates, however, comes at the expense of biased estimates. The estimates of multi-level modeling are expected to have some degree of bias in them because in practice, at almost all times, unit effects are correlated with predictors.

Researchers need to use their judgment when selecting between precision and variance. The Hausman test, which is designed to test whether estimates are biased, is susceptible to false rejection. This test, which is widely used in strategic management literature, is designed solely to investigate whether the predictors are biased and thus is silent on the more important issue of whether the disadvantage of having some degree of bias in the parameter estimates is outweighed by a sufficient gain in efficiency⁷, making it neither a necessary nor sufficient statistic to decide between fixed and random effects (Clark and Linzer, 2012).

I believe that the benefits of precise estimates outweigh the disadvantages of biased estimates given the empirical context and hypotheses of my dissertation and thus I prefer narrow but biased estimates to unbiased but highly variant estimates (Singer and Willett, 2003). Empirical studies that study competition in the U.S. airline industry reveal that the general response of carriers to aggression is cooperation (Borenstein and Rose, 1995; Ciliberto and Schenone, 2010; Smith and Wilson, 1995). Since previous findings shows that carriers' response to aggression and cooperation is similar, I need very precise estimates to be able to capture the hypothesized effects if they exist and differentiate the hypothesized impact of reciprocity

⁷ An allegory of prescribing a drug can be used to articulate this point further. If and when a statistical test examines whether a drug has side effects, most of the time, it will discover that it has negative side effects and conclude that it should not be prescribed. That is why in practice the decision to prescribe a drug hinges on whether the overall benefit of using a given drug outweighs its disadvantages and is left to the discretion of experts rather than to a statistical test. That is why in this section, I provide several reasons for my preference for multi-level modeling, which is a type of random effect.

(cooperation) from the hypothesized impact of non-reciprocity (aggression) at both a tactical and a strategic level. Without precise estimates, I cannot tease out the fine-grained outcome differences of cooperation and defection and, as a result, I might inaccurately either reject or fail to reject the hypotheses. Besides, precise estimates are important to alleviate problems that might stem from measurement error such as endogeneity. This dissertation aims to redirect the literature on MF to a new path and develops new measures in the process. Since the measures are original, they might be susceptible to measurement error. Using precise estimates can facilitate the detection of the magnitude of measurement error and help future research refine these measurements.

4.5.5 Nature of measurements

Multi-level modeling can analyze a data set in which spacing and number of measurements vary across subjects. Multi-level modeling does not require measurements to take place at the same time for all subjects. In addition, multi-level modeling enables the number of observations to vary across subjects and thus allows the analysis of unbalanced panel data. This method can handle different types of missing data ranging from “missing completely at random” which has the most restrictive assumptions to “covariate dependent dropout” and “missing at random”, which has the least restrictive assumptions (Kwok et al., 2008). Hence multi-level modeling uses all of the information available in the data and thus missing observations do not create problems. The ability of this method to analyze missing data is an important capability for my research since the data sets that I use are unbalanced.

4.5.6 The ability to model underlying processes in panel data

Multi-level modeling is capable of examining longitudinal data at different levels and thus can explain how underlying *processes* that operate at a lower level combine and interact with one another to produce systematic behavior at a higher level. The ability to model

underlying processes is crucial for my research since I intend to explain the *process* of the genesis of MF.

In using this methodology, I use two levels to analyze the panel data sets that I prepared. At the first and lower level, I will model measurements as nested in either dyads or cross-classification of dyads and markets. These are observational units of my samples. At the second and higher level, I model the estimated intercepts and slopes of the theoretically important variables of the first-level model as outcomes and let slopes vary at the dyad level.

The capability to examine my data from different levels or vantage points will enable me to explain the change in cooperation that takes place within my data sets much more comprehensively. By using this method, I will be able to examine how actions of members of a given dyad first lead to MF at the dyad level and then average systematic behavior at the population level. For example, if I do not find a statistically *significant* and *systematic* fixed⁸ effect between a given dependent variable and independent variable on average at the population level, I can decide whether the insignificant aggregate relationship observed on the surface is due to lower level opposing forces that bring an aggregate net change of zero at the higher surface level (Engel and Reinecke, 1996).

By analyzing my data sets at different levels, I can also examine the change in cooperation not only within but also across subjects. The ability to model the first level intercepts and slopes as outcomes to be explained at the second level will allow me to vary intercepts and variables that are of theoretical interest across sampling units of this study and thus discover the inter-dyad differences in the theorized cooperative processes.

⁸ Fixed effects refer to effects that do not vary across units in multi-level modeling.

4.6 STATISTICAL MODELING AND ESTIMATION

I use three multi-level models to empirically examine all of the hypotheses of this dissertation because of the aforementioned advantages. The first multi-level model investigates the first set of hypotheses and thus the formation of inter-organizational trust. The second multi-level model tests the second, third and fourth hypotheses and thus sheds light on how cooperative actions at the tactical level deepen cooperation and lead to cooperation at a higher strategic level. The third and final multi-level model statistically investigates the remaining hypotheses of this study and examines the relationship between strategic cooperation and the genesis and formation of MF.

4.6.1 Model Building

In general, multi-level models are composed of two parts which are respectively the “structural” and the “stochastic” part (Singer and Willett, 2003). The structural part is composed of fixed effects that do not vary across sampling units. Fixed effects are, in essence, population specific estimates. They define the means for a population and thus can be considered as “pooled” or mean effects, which is why the “structural part” of a multi-level model can be construed as the mean model. The “stochastic” part of a multi-level model contains random effects that vary across sampling units and thus estimates subject-specific effects. Specifically, it estimates two types of random effects: between-subject random effects and within-subject random errors (Kwok et al., 2008). While between-subject random effects account for variance heterogeneity between responses from distinct sampling units and thus variable intercepts and slopes, within-subject random errors account for covariance patterns between responses coming from the same sampling unit and thus time-related dependence of observations (Cheng et al., 2010). Hence I will select the covariance structure that provides the best fit to data for each and every model in order to obtain valid inferences for the fixed effects and subject specific estimates

(Singer and Willett, 2003). I will not build up the fixed part of the models because this part is guided and developed by the theory that I develop.

To build the stochastic component of each of the three multi-level models and select the one that provides the best “fit” to data at hand, I follow the top-down method proposed by Bliese and Ployhart (2002) and Hox (2010). I first compare alternative covariance structures for between-subject random effects to select the “best” covariance structure. I start with the simplest covariance structure for between subject random effects and proceed by adding an additional random effect to this covariance structure step by step. To move from more simple to more complex covariance structures, I cumulatively include the theoretically grounded variables as random effects in the covariance structure for between subject random effects. For example, to investigate Hypotheses 1a and 1b, I examine the goodness-of-fit of four models with alternative covariance structures for between-subject random effects and each of the preceding covariance structures is nested in the subsequent covariance structure because the subsequent covariance structures include an additional random effect that the preceding covariance structure lacks. The first model allows the intercept to vary across sampling units; the second model lets the intercept and the effect of MMC to vary across dyads; the third model allows the intercept and the impact of MMC and norms to vary across dyads; the fourth model allows the intercept and the effects of norms, MMC and performance failure to vary across dyads. Since the covariance structures that I specify get successively more complex, I do not end up selecting an over-identified model. I model between-subject random effects through unstructured (UN) covariance structure, which models variances and co-variances of between-subject random effects, and banded main diagonal covariance structures (UN (1)), which solely models variances of between-subjects random effects and constrains its off-diagonal elements to zero.

Following the selection of the “best” covariance structure for between-subject random effects for a given model, I compare competing covariance structures for within-subject random errors and select the one that provides the “best” fit given the theoretically defined fixed effects and empirically determined between-subject random effects (Cheng et al., 2010; Bliese and Ployhart, 2002). Specifically, I investigate variance components (VC), compound symmetry (CS) and first-order autoregressive (AR (1)) covariance structures and compare their goodness-of-fit to select the structure that provides the best fit to the data (Bliese and Ployhart, 2002). I build the error covariance after determining the “best” covariance structure for between-subject random-effects because it is what remains after removing the effects of fixed and random variables in each and every model (Singer, 1998).

I compare alternative models with identical fixed effects but with different covariance structures through either log-likelihood ratio tests or information criteria. When models are nested within one another, I use the log-likelihood ratio (LR) test to select the winning model. “With L_j , the log likelihood for model j , the LR test statistic $T = -2 (L_1 - L_2)$ asymptotically follows and therefore is referred to as χ^2_d distribution, where d is the difference in the number of parameters between two models” (Cheng et al., 2010, p: 511). When models are not nested, I use the information criteria to select the covariance structure that provides a better fit. Specifically, I compare the AIC statistic and BIC statistic of different models that have identical fixed-effects but different covariance structures and prefer smaller AIC and BIC statistics to larger AIC and BIC statistics. I consider the AIC and BIC statistics of a given model to be “small enough” compared to the AIC and BIC statistics of an alternative model when its AIC and BIC statistics are at least two units lower than the corresponding AIC and BIC statistics of the alternative model (Singer and Willett, 2003).

After selecting the model with the stochastic component that provides the “best” fit, I check whether it meets the assumptions of multi-level modeling since a model’s estimates will be biased and inferences will be erroneous if it violates the assumptions of multi-level modeling. Multi-level model incorporates several assumptions. It presumes that level-1 and level-2 predictors are independent of corresponding level-1 and level-2 residuals respectively; that level-1 and level-2 errors are independent; that level-1 residuals are independent and normally distributed with a mean of zero and variance σ^2_{ϵ} ; that level-2 random effects are multivariate normal, each with a mean of zero and a variance of σ^2_{qq} and a covariance of σ^2_{qq} ; that estimates are linear in parameters (Singer and Willett, 2003). When I find that the selected model violates the assumptions of multi-level modeling, I carry out the necessary fixes to ensure that the violations do not impair inferences.

In addition to finding and estimating the model that provides the “best” fit, I also estimate an “Unconditional Means” model for the first, second and third model and a “Cross-Classified Unconditional Means” model for the second and third model in order to partition outcome variance into its components, calculate the intra-class correlation coefficient (ICC) and justify utilization of cross-classified random effect models to investigate Hypotheses two, three, four, five, six and seven. An “Unconditional Means” model, or a “Cross-classified Unconditional Means” model, can be considered a one-way random effects ANOVA model (Singer, 1998). It does not contain any predictors and thus forces all of the variance in the dependent variable to reside in the composite error term that is composed of between-subject random effects and within-subject random errors. Hence it partitions the outcome variation into its within-subject and between-subject variance components and thus estimates level-1 and level-2 residuals, enabling me to understand not only the level and source of variance, but also calculate ICC

(Singer and Willett, 2003). Calculating ICC enables me to test whether there is *significant* variation over time in cooperation within a sampling unit and whether sampling units *significantly* differ from one another with respect to their level of cooperation.

In addition to these models, I estimate a “control” model that contains only the control variables of a given multi-level model. I use the results of this model to understand the behavior of control variables when theoretical predictors are not included.

4.6.2 Estimation and Software

I use SAS PROC MIXED to analyze the empirical models of this study and use both SAS and MLwiN to investigate the robustness of the findings. I use SAS PROC MIXED to estimate all of the models because SAS offers flexible programming and is suitable to analyze large data sets due to its other procedures such as PROC SQL and PROC HP MIXED. I run SAS in batch mode to be able to tap into the speed and memory of IBM Power 7-755 high-performance computing cluster and IBM System x3850 X5 Server. I use the non-parametric bootstrapping capability of MLwiN to investigate the robustness of the findings.

With SAS PROC MIXED, I can estimate all of the proposed models with either full or restricted maximum likelihood. To compare models with identical fixed effects but different random variables, I use restricted maximum likelihood estimation, which maximizes the likelihood of sample *residuals* as the estimation method. Full maximum likelihood estimation can lead to biased estimates of variance components, especially when the number of subjects is few and/or a model has large number of predictors (Hand and Crowder, 1996), because of its failure to account for the degrees of freedom lost when estimating fixed effects (Hox, 2010; Singer and Willett, 2003). In general, full maximum likelihood estimation underestimates variance components. To attain unbiased estimates, I estimate all of the models with restricted

maximum likelihood estimation. I also calculate the goodness-of-fit statistics of the “Unconditional Means” model, “Cross-classified Unconditional Means” model, “Control” model and “Final” model that will be selected with full maximum likelihood estimation because I can compare the fitness of these models whose fixed-effects differ only with a full maximum likelihood estimation.

4.7 MODELS

I demonstrate all of the multi-level models that will be estimated with a level-1 and level-2 specification rather than a composite specification and thus write separate equations at two levels (i.e., observation nested in dyads for the first model, observations nested in the cross-classification of dyads and markets for the second and third model) to explain the multiple sources of variation that exist in data more effectively. The level-1 and level-2 specification can be converted into a composite specification that has one equation by substitution.

4.7.1 Model One

The first model investigates trust formation and, thus tests Hypotheses 1a and 1b, by investigating the conduct of 45 dyads across 32 quarters. The level of analysis for the first model is dyad-time. Hence the subscripts i and j refer to the i th occasion and j th dyad respectively in all of the equations in this subsection. To select the “Final” model that will be used to test hypotheses, I compare the goodness of fit of models with identical fixed effects but different covariance structures through log-likelihood ratio tests or AIC and BIC statistics.

To select the best covariance structure for between subject random effects, I build and compare four models with nested covariance structures. I build the covariance structure of each model in such a manner that each subsequent model’s covariance structure contains an additional random effect that the preceding model’s covariance structure lacks. This process ensures that

the preceding model is nested in the subsequent model. The first model lets the intercept vary across sampling units; the second model lets the intercept and the effect of MMC to vary across dyads; the third model lets the intercept and the impact of MMC and norms to vary across dyads; the fourth model includes the intercept, norms, MMC and performance failure in the Z matrix and thus lets their effects vary across dyads. Since I use unstructured covariance structure to model random effects, I also allow all of the variables included in the Z matrix to co-vary among themselves. All of these four alternative models contains the identical fixed effects since the “structural” part of these models is guided by the theory that I develop.

I provide the statistical equations of the first model that will be estimated below. This model serves as a baseline from which to build models 2, 3 and 4. As explained above, the covariance structure of the first model allows intercepts to vary across dyads. Hence the term μ_{0j} in the equation reflects the difference between grand mean and dyad-specific mean.

The level-1 equation for the first model is:

$$Y_{ij} = \beta_{0j} + \beta_{1j} \text{CASM}_{ij} + \beta_{2j} \text{Productivity}_{ij} + \beta_{3j} \text{Stage_Length}_{ij} + \beta_{4j} \text{Load_Factor}_{ij} + \beta_{5j} \text{Seating_Density}_{ij} + \beta_{6j} \text{Frequency}_{ij} + \beta_{7j} \text{Network_Effect}_{ij} + \beta_{8j} \text{MMC}_{ij} + \beta_{9j} \text{Norms}_{ij} + \beta_{10j} \text{Performance_Failure}_{ij} + \beta_{11j} \text{MMC}_{ij} * \text{Norms}_{ij} + \beta_{12j} \text{MMC}_{ij} * \text{Performance_Failure}_{ij} + \beta_{13j} \text{Norms}_{ij} * \text{Performance_failure}_{ij} + \beta_{14j} \text{MMC}_{ij} * \text{Norms}_{ij} * \text{Performance_failure}_{ij} + r_{ij}$$

The level-2 equations for the first model are:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

$$\beta_{4j} = \gamma_{40}$$

$$\beta_{5j} = \gamma_{50}$$

$$\beta_{6j} = \gamma_{60}$$

$$\beta_{7j} = \gamma_{70}$$

$$\beta_{8j} = \gamma_{80}$$

$$\beta_{9j} = \gamma_{90}$$

$$\beta_{10j} = \gamma_{10}$$

$$\beta_{11j} = \gamma_{11}$$

$$\beta_{12j} = \gamma_{12}$$

$$\beta_{13j} = \gamma_{13}$$

$$\beta_{14j} = \gamma_{14}$$

where $r_{ij} \sim N(0, \sigma^2)$ and $\mu_{0j} \sim N(0, \tau_{00})$

After comparing the four alternative models and selecting the covariance structure for between-subject random effects that provides the “best” fit, I examine alternative covariance structures for within-subject random errors and select the one that best fits the data as the “Final” model. To this end, I investigate variance components, compound symmetry, and first-order autoregressive covariance structures and compare their goodness-of-fit (Bliese and Ployhart, 2002).

I also estimate an “Unconditional Means” model to partition variance components (i.e., σ^2, τ_{00}) into their within-dyads (i.e., over time) and between-dyads components. Such specification expresses the dependent variable Y_{ij} using a pair of connected models since observations are nested within dyads: one at the observation level (level-1) and another at the dyad level (level-2). At level-1, I express dyad i ’s ticket price in occasion j as the sum of dyad-specific intercept that corresponds to dyad i ’s average ticket price (β_{0j}) and a random error (r_{ij})

associated with the i^{th} observation in the j^{th} dyad. At level 2 (the dyad level), I express the dyad specific intercepts as the sum of an overall mean (γ_{00}) and a sequence of random deviations from that overall mean (μ_{0j}). Hence this model postulates that the observed value of Y for dyad j on occasion i is composed of deviations about the dyad specific mean (β_{0j}) and the grand mean (γ_{00}). On occasion i , Y_{ij} deviates from dyad j 's true mean (β_{0j}) by r_{ij} . The level-1 residual thus can be considered a “within-dyad” deviation that measures the discrepancy or distance between Y_{ij} and β_{0j} (Singer and Willett, 2003). After that, dyad j 's true mean (β_{0j}) deviates from the grand mean or population average true mean (γ_{00}) by μ_{0j} . This level-2 residual can be considered a “between-dyad” deviation that measures the distance between β_{0j} and γ_{00} and allows variable intercepts across dyads (Singer and Willett, 2003).

The level-1 equation for “Unconditional Means” model is:

$$Y_{ij} = \beta_{0j} + r_{ij}$$

The level-2 equation for “Unconditional Means” model is:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

where $r_{ij} \sim N(0, \sigma^2)$ and $\mu_{0j} \sim N(0, \tau_{00})$

In addition, I use the resulting estimates of level-1 error variance (σ^2) and level-2 error variance (τ_{00}) to calculate the ICC that both demonstrates the proportion of total outcome variation that lies between subjects and summarizes the magnitude of residual autocorrelation. I will calculate the ICC by the following formula:

$$ICC = \frac{\tau_{00}}{\tau_{00} + \sigma^2}$$

I also use this model as a reference to explain how much of the within-subject variation in the dependent variable is explained by the time-varying variables of the “Control” and “Final” models. The “Unconditional Means” model estimates level-1 residual variance, which can be considered as an effective ceiling on the amount of variation in the dependent variable that can be explained by time-varying predictors (Singer, 1998). Hence I expect the time-varying variables of the “Control” and the “Final” model to explain some of the level-1 residual variance of the “Unconditional Means” model and thus fit the data better than the “Unconditional Means” model as far the level-1 residual variance is concerned. To capture such an increase in “fit”, I calculate the Pseudo R_e^2 statistics of the “Control” and “Final” model. The Pseudo R_e^2 statistics explains how much of the within-subject variation in the dependent variable is explained by the time-varying variables of both the “Control” and the “Final” model. To calculate the Pseudo R_e^2 statistics of the “Control” and “Final” model, I first deduct their respective residual variances from the residual variance of the “Unconditional Means” model that serves as a benchmark. The resulting difference will reflect the contribution of the respective time varying variables of the “Control” and the “Final” model to the reduction in the residual variance of the “Unconditional Means” model. To make the improvements in fit comparable across models, I divide the calculated differences by the estimated residual variance of the “Unconditional Means” model and thus calculate the Pseudo R_e^2 statistic of the “Control” and “Final” model. I provide the equations that are used to calculate Pseudo- R_e^2 statistics below.

Pseudo- R_e^2 statistic for the “Control” model will be calculated by the following equation:

$$Pseudo-R_e^2 = \frac{\sigma^2_{unconditional\ means\ model} - \sigma^2_{control\ model}}{\sigma^2_{unconditional\ means\ model}}$$

Pseudo- R_e^2 statistic for the “Final” model will be calculated by the following equation:

$$Pseudo-R^2 = \frac{\sigma^2_{unconditional\ means\ model} - \sigma^2_{final\ model}}{\sigma^2_{unconditional\ means\ model}}$$

4.7.2 Model Two

The second model investigates the process of tactical cooperation and thus Hypotheses 2, 3 and 4. In the second model, observations are nested within the cross-classification of dyads and market. To select the best covariance structure for between-subject random effects, I compare the goodness-of-fit of four models with alternative covariance structures. All models have identical fixed effects since the “structural” part of these models is guided by the theory that I develop. However their “stochastic” part will differ because each subsequent model will add an additional random effect to the covariance structure of the preceding model. Hence the first model will let the intercept vary across markets and dyads; the second model will allow the intercept to vary across markets and dyads and also let the effect of tactical-reciprocity vary across dyads; the third model will let the intercept vary across markets and dyads and also permit the impact of tactical-reciprocity and tactical-non-reciprocity to vary across dyads; the fourth model will permit the intercept vary across markets and dyads and let the impact of tactical-reciprocity, tactical-non-reciprocity and the interaction of tactical-reciprocity with keyness to vary across dyads. I use the UN (1) covariance structure to model the between-subject random effects.

The following level-1 and level-2 equations specify the first model that will be estimated. In the level-1 equation, $Y_{i(jk)}$ represents the strategic cooperation score of observation i nested within the cross-classification of dyad j and market k . The subscripts (jk) are written in parenthesis to show that they conceptually exist at the same level that is the (jk) th dyad and market combination in the cross-classifications of dyads and market.

The level-1 equation for the model that is first to be estimated is:

$$Y_{i(jk)} = \beta_{0(jk)} + \beta_{1(jk)} \text{Tactical_Rivalry}_{ijk} + \beta_{2(jk)} \text{Market_Concentration}_{ijk} + \beta_{3(jk)} \text{Number_of_Firms}_{ijk} + \beta_{4(jk)} \text{Number_of_Passengers}_{ijk} + \beta_{5(jk)} \text{Hub_Economies}_{ijk} + \beta_{6(jk)} \text{Firm_Size}_{ijk} + \beta_{7(jk)} \text{Network_Effect}_{ijk} + \beta_{8(jk)} \text{Tactical_Reciprocity}_{ijk} + \beta_{9(jk)} \text{Tactical_Nonreciprocity}_{ijk} + \beta_{10(jk)} \text{Keyness}_{ijk} + \beta_{11(jk)} \text{Tactical_Reciprocity}_{ijk}^* \text{Keyness}_{ijk} + r_{i(jk)}$$

The level-2 equations for the model that is first to be estimated are:

$$\beta_{0(jk)} = \gamma_{00} + \mu_{0j} + v_{0k}$$

$$\beta_{1(jk)} = \gamma_{10}$$

$$\beta_{2(jk)} = \gamma_{20}$$

$$\beta_{3(jk)} = \gamma_{30}$$

$$\beta_{4(jk)} = \gamma_{40}$$

$$\beta_{5(jk)} = \gamma_{50}$$

$$\beta_{6(jk)} = \gamma_{60}$$

$$\beta_{7(jk)} = \gamma_{70}$$

$$\beta_{8(jk)} = \gamma_{80}$$

$$\beta_{9(jk)} = \gamma_{90}$$

$$\beta_{10(jk)} = \gamma_{10}$$

$$\beta_{11(jk)} = \gamma_{11}$$

$$\text{where } r_{i(jk)} \sim N(0, \sigma^2) \text{ and } \begin{pmatrix} \mu_{0j} \\ v_{0k} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & 0 \\ 0 & \tau_{11} \end{pmatrix} \right]$$

Following the selection of the “best” covariance structure for between- subject random effects through log likelihood ratio tests, I investigate three different covariance structures, VC, CS and AR (1), to model the time-dependent dependence of observations. I compare the goodness-of-fit of the models with these three alternative covariance structures and select the one that provides the best fit by using either LR tests or the AIC and BIC statistics. The selection of

the best covariance structure to model time related dependence will finalize the specification of the model that will be estimated to test hypotheses 2, 3 and 4.

In addition to the estimation of the “Final” model that will be estimated, I estimate an “Unconditional Means” model and a “Cross-classified Unconditional Means” model and compare their goodness-of-fit with a LR test to justify the modeling of the hierarchical structure of data through a “cross-classified random effects” model. If the results of the LR test reveal that the latter model provides a better fit than the former model, then, I will be required to use a “cross-classified random effects” model to build the subsequent models and model observations as nested in the cross-classification of markets and dyads rather than within dyads.

To construct the “Unconditional Means” model, I model dyad j ’s strategic cooperation in occasion i as the sum of the dyad-specific intercept or mean (β_{0j}) and a random error (r_{ij}) associated with the i^{th} observation of j^{th} dyad at level-1. At level-2 (the dyad level), I model the dyad-specific intercept as the sum of an overall or grand mean (γ_{00}) and a series of random deviations from that overall mean (μ_{0j}). Overall, this model specifies that the observed value of Y for dyad j on occasion i is composed of deviations around the dyad-specific mean (β_{0j}) and the grand mean (γ_{00}). On occasion i , Y_{ij} deviates from dyad j ’s true mean (β_{0j}) by r_{ij} . The level-1 residual can thus be considered a “within-dyad” deviation that measures the discrepancy or distance between Y_{ij} and β_{0j} (Singer and Willett, 2003). Dyad j ’s true mean (β_{0j}) in turn deviates from the grand mean or population average true mean (γ_{00}) by μ_{0j} . This level-2 residual can be considered a “between-dyad” deviation that measures the distance between β_{0j} and γ_{00} and allows variable intercepts across dyad-markets (Singer and Willett, 2003).

The level-1 equation for “Unconditional Means” model is:

$$Y_{ij} = \beta_{0j} + r_{ij}$$

The level-2 equation for “Unconditional Means” model is:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

where $r_{ij} \sim N(0, \sigma^2)$ and $\mu_{0j} \sim N(0, \tau_{00})$

To construct the “Cross-Classified Unconditional Means” model, at the observation and, thus first level, I estimate an intercept only model which is:

$$Y_{i(jk)} = \beta_{0(jk)} + r_{i(jk)}$$

where strategic cooperation score of observation $Y_{i(jk)}$ of observation i within the cross-classification of dyad j and market k is modeled by the intercept $\beta_{0(jk)}$ and a residual error term $r_{i(jk)}$.

The subscripts (jk) reveal that the intercept $\beta_{0(jk)}$ varies independently across both dyads and markets. Hence I model the intercept using the following second-level equation:

$$\beta_{0(jk)} = \gamma_{00} + \mu_{0j} + v_{0k}$$

$$\text{where } r_{i(jk)} \sim N(0, \sigma^2) \text{ and } \begin{pmatrix} \mu_{0j} \\ v_{0k} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & 0 \\ 0 & \tau_{11} \end{pmatrix} \right]$$

In this equation, μ_{0j} is the residual error term for dyad and v_{0k} is the residual error term for market. Hence I model outcome variable with an overall intercept γ_{00} , with a residual error term μ_{0j} for dyad j and a residual error term v_{0k} for market k and the individual residual error term $r_{i(jk)}$ for observation i nested in the cross-classification of dyads and markets.

I calculate the ICC for dyad by the following formula:

$$ICC_{\text{dyad}} = \frac{\tau_{00}}{\tau_{00} + \tau_{11} + \sigma^2}$$

I calculate the ICC for market by the following formula:

$$ICC_{\text{market}} = \frac{\tau_{11}}{\tau_{00} + \tau_{11} + \sigma^2}$$

I also estimate a “control” model that exclusively includes the control variables (i.e., coefficients from β_{0j} to β_{7j}) to examine the significance and sign of the impact of control variables when theoretical predictors are not included.

4.7.3 Model Three

The third model investigates the process of strategic cooperation and thus tests Hypotheses 5, 6 and 7. In the third model, observations are nested within the cross-classification of dyads and market. To select the best covariance structure for between-subject random effects, I compare the goodness-of-fit of four models that contain alternative covariance structures. All models include identical fixed-effects because the theory that I develop guides the “structural” part of these models. Nevertheless, their “stochastic” components will be different as each subsequent model will add an additional random effect to the covariance structure of the preceding model. Hence the first model will let the intercept vary across markets and dyads; the second model will allow the intercept to vary across markets and dyads and also permit the effect of strategic-reciprocity to vary across dyads; the third model will let the intercept vary across markets and dyads and permit the impact of strategic-reciprocity and strategic-non-reciprocity to vary across dyads; the fourth model will allow the intercept to vary across markets and dyads and allow strategic-reciprocity, strategic-non-reciprocity and the interaction of strategic-reciprocity

with keyness to vary across dyads. I use the UN (1) covariance structure to model between-subject random effects

The following level-1 and level-2 equations specify the first model that is estimated. In the level-1 equation, $Y_{i(jk)}$ represents the mutual forbearance score of observation i nested within the cross-classification of dyad j and market k . The subscripts (jk) are written in parenthesis to show that they conceptually exist at the same level that is the (jk) th dyad and market combination in the cross-classifications of dyads and market.

The level-1 equation for the model that is first to be estimated is:

$$Y_{i(jk)} = \beta_{0(jk)} + \beta_{1(jk)} \text{Strategic_Withdrawal}_{ij} + \beta_{2(jk)} \text{Market_Concentration}_{ij} + \beta_{3(jk)} \text{Number_of_Firms}_{ij} + \beta_{4(jk)} \text{Number_of_Passengers}_{ij} + \beta_{5(jk)} \text{Hub_Economies}_{ij} + \beta_{6(jk)} \text{Firm_Size}_{ij} + \beta_{7(jk)} \text{Network_Effect}_{ij} + \beta_{8(jk)} \text{Strategic_Reciprocity}_{ij} + \beta_{9(jk)} \text{Strategic_Nonreciprocity}_{ij} + \beta_{10(jk)} \text{Keyness}_{ij} + \beta_{11(jk)} \text{Strategic_Reciprocity}_{ij}^* \text{Keyness}_{ij} + r_{i(jk)}$$

The level-2 equations for the model that is first to be estimated are:

$$\beta_{0(jk)} = \gamma_{00} + \mu_{0j} + v_{0k}$$

$$\beta_{1(jk)} = \gamma_{10}$$

$$\beta_{2(jk)} = \gamma_{20}$$

$$\beta_{3(jk)} = \gamma_{30}$$

$$\beta_{4(jk)} = \gamma_{40}$$

$$\beta_{5(jk)} = \gamma_{50}$$

$$\beta_{6(jk)} = \gamma_{60}$$

$$\beta_{7(jk)} = \gamma_{70}$$

$$\beta_{8(jk)} = \gamma_{80}$$

$$\beta_{9(jk)} = \gamma_{90}$$

$$\beta_{10(jk)} = \gamma_{10}$$

$$\beta_{11(jk)} = \gamma_{11}$$

$$\text{where } r_{i(jk)} \sim N(0, \sigma^2) \text{ and } \begin{pmatrix} \mu_{0j} \\ v_{0k} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & 0 \\ 0 & \tau_{11} \end{pmatrix} \right]$$

After the selection of the “best” covariance structure for between- subject random effects through log likelihood ratio tests, I examine alternative covariance structures to model the dependence that derives from time and select the best covariance structure. Specifically, I investigate three different covariance structures, VC, CS and AR (1), to model time-dependent dependence of observations. I conduct LR tests or use AIC and BIC statistics to select the best covariance structure for within-subject random errors and finalize the specification of the model to be estimated to test Hypotheses 5, 6 and 7.

In addition to the above-mentioned model, I will estimate an “Unconditional Means” model and a “Cross-classified Unconditional Means” model and compare the goodness-of-fit of the former model with that of the latter with the LR test for the sake of validating the modeling of the hierarchical structure of data through a “cross-classified random effects” model. If the result of the statistical test shows that “cross-classified random effects” model provides a better fit than the former model, I will use the “cross-classified random effects” model to model the competing models and thus model observations as nested in the cross-classification of dyads and markets.

To build the “Unconditional Means” model, I model the mutual forbearance of a given dyad in a given market in occasion i as the sum of dyad specific intercept (β_{0j}) and a random error (r_{ij}) associated with the i^{th} observation of the j^{th} dyad at level-1. At level-2 (the dyad level),

I model the dyad-specific intercepts as the sum of an overall or grand mean (γ_{00}) and a series of random deviations from that overall mean (μ_{0j}). Overall, this model specifies that the observed value of mutual forbearance for dyad j on occasion i is composed of deviations around the dyad-specific mean (β_{0j}) and the grand mean (γ_{00}). While the level-1 residual (r_{ij}) captures the distance between Y_{ij} and β_{0j} and thus “within-dyad” deviation, the level-2 residual (μ_{0j}) measures the distance between β_{0j} and γ_{00} and thus captures “between-dyad” deviation.

The level-1 equation for “Unconditional Means” model is:

$$Y_{ij} = \beta_{0j} + r_{ij}$$

The level-2 equation for “Unconditional Means” model is:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

where $r_{ij} \sim N(0, \sigma^2)$ and $\mu_{0j} \sim N(0, \tau_{00})$

To build the “Cross-classified Unconditional Means” model and partition variance into its components, at the observation and thus first level, I estimate an intercept only model which is:

$$Y_{i(jk)} = \beta_{0(jk)} + r_{i(jk)}$$

Where the mutual forbearance score of observation $Y_{i(jk)}$ of observation i within the cross classification of dyad j and market k is modeled by the intercept $\beta_{0(jk)}$ and a residual error term $r_{i(jk)}$.

The subscripts (jk) reveal that the intercept $\beta_{0(jk)}$ varies independently across both dyads and markets. Hence I model the intercept using the following second-level equation:

$$\beta_{0(jk)} = \gamma_{00} + \mu_{0j} + \nu_{0k}$$

where $r_{i(jk)} \sim N(0, \sigma^2)$ and $\begin{pmatrix} \mu_{0j} \\ v_{0k} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & 0 \\ 0 & \tau_{11} \end{pmatrix}\right]$

In this equation, μ_{0j} is the residual error term for dyad and v_{0k} is the residual error term for market. Hence I model the outcome variable with an overall intercept γ_{00} , with a residual error term μ_{0j} for dyad j and a residual error term v_{0k} for market k and the individual residual error term $r_{i(jk)}$ for observation i nested in the cross-classification of dyads and markets.

I calculate the ICC for dyad by the following formula:

$$ICC_{\text{dyad}} = \frac{\tau_{00}}{\tau_{00} + \tau_{11} + \sigma^2}$$

I calculate the ICC for market by the following formula:

$$ICC_{\text{market}} = \frac{\tau_{11}}{\tau_{00} + \tau_{11} + \sigma^2}$$

In addition to the “Unconditional Means” model, I estimate a “Control” model that exclusively has the control variables (i.e., coefficients from β_{0j} to β_{7j}) to examine the sign and significance of the effect of control variables when theoretical predictors are not included.

CHAPTER 5

EMPIRICAL FINDINGS

In this section, I discuss the empirical results of the three models and interpret the findings. I also investigate the robustness of the findings through additional empirical analysis.

In the first section, I will explain the process by which I selected the “Final” model that tests Hypotheses 1a and 1b and elaborate on its findings. In addition to discussing the findings of the “Final” model, I will also elaborate on the findings of the “Unconditional Means” and “Control” models that serve as yardsticks. I also ascertain the robustness of the findings of the “Final” model by investigating whether it meets the assumptions of multi-level modeling. I do this through non-parametric bootstrapping and compare the resulting bootstrap standard errors to the asymptotic standard errors of the “Final” model.

In the second section, I describe the process by which I selected the “Final” model that tests Hypotheses 2, 3 and 4 and elaborate on its findings and the findings of the associated “Cross-classified Unconditional Means” model and the “Control” model that serve as benchmarks. Next, I examine whether the “Final” model that is selected to test the relevant hypotheses meets the assumptions of multi-level modeling. To test the robustness of the findings of the “Final” model, I compare its asymptotic standard errors to the robust standard errors of the “Empirical” model.

In the third section, I once more explain the process of model selection and interpret the findings of the “Cross-classified Unconditional Means” model, “Control” model and the “Final” model selected to investigate Hypotheses 5, 6 and 7. Next, I examine whether the selected “Final” model meets the assumptions of multi-level modeling. To test the robustness of its

findings, I compare its asymptotic standard errors to the robust standard errors of the “empirical” model.

5.1 Model 1

As stated in the preceding chapter, I analyzed four competing models to select the best model to examine Hypotheses 1a and 1b. Before carrying out the analysis, I investigated the level of multicollinearity among variables. The results reported in Table 4, demonstrate that the variance inflation factor (tolerance) was significantly higher than 10 (lower than 0.1) for all of the main theoretical variables and their interactions. As a solution to multicollinearity, and especially non-essential multicollinearity, I centered the three theoretical variables on their group-means. I used group-mean centering instead of grand-mean centering because of several reasons. First, studying the genesis of MF, which is naturally a feature of the relationship between a pair of rivals, requires me to examine MF formation within dyads rather than across them. Group-mean centering eliminates confounding with between-dyad effects. Second, the first set of hypotheses is concerned with the interactions among level-1 variables. This in turn requires group-mean centering (Hox, 2010). As expected, group-mean centering eliminates multicollinearity. The results indicated that after centering, multicollinearity was no longer an issue. As reported in Table 5, the variance inflation factors of all variables are significantly lower than 10. Table 6 provides the correlation and descriptive statistics of the variables of the first model. Numbers in the parenthesis reflect the significance level of correlations.

Table 4: Tolerance and Variance Inflation Factor before Centering

Variable	Tolerance	Variance Inflation Factor
CASM	0.53846	1.85716
Productivity	0.49806	2.00781
Stage-length	0.30806	3.24617
Load-factor	0.50382	1.98482
Seating-density	0.37875	2.64027
Dyad-frequency	0.37542	2.66372
Network-effect	0.40107	2.49335
MMC	0.00187	533.56986
Norms	0.00192	521.24325
Performance-failure	0.01014	98.62078
MMC*Norms	0.00130	766.62445
MMC*Performance-failure	0.00179	557.96644
Norms*Performance-failure	0.00177	565.70766
MMC*Norms*Performance-failure	0.00133	754.10165

Table 5: Tolerance and Variance Inflation factor after Centering

Variable	Tolerance	Variance Inflation Factor
CASM	0.54443	1.83677
Productivity	0.52926	1.88944
Stage-length	0.39153	2.55410
Load-factor	0.52326	1.91109
Seating-density	0.40437	2.47295
Dyad-frequency	0.51216	1.95250
Network-effect	0.40043	2.49728
MMC	0.88889	1.12499
Norms	0.90022	1.11084
Performance-failure	0.92031	1.08659
MMC*Norms	0.84682	1.18088

MMC*Performance-failure	0.94649	1.05653
Norms*Performance-failure	0.80407	1.24367
MMC*Norms*Performance-failure	0.77986	1.28228

Table 6: Descriptive Statistics and Correlations of Model 1

Variable	Mean	S.D	1	2	3	4	5	6	7	8	9	10
1- Tactical Cooperation	333.24593	42.40344										
2- Cost Available Per Seat	0.0001891	0.0000245	0.49167 (<.0001)									
3- Productivity	25.34460	3.59410	-0.15790 (<.0001)	0.22719 (<.0001)								
4- Stage Length	1463	225.11664	0.70168 (<.0001)	0.12915 (<.0001)	-0.13277 (<.0001)							
5- Load Factor	1.35875	0.07747	0.23967 (<.0001)	0.21931 (<.0001)	0.52925 (<.0001)	0.34320 (<.0001)						
6- Seating Density	292.44198	17.48286	0.51740 (<.0001)	-0.14303 (<.0001)	-0.31047 (<.0001)	0.42496 (<.0001)	0.05329 (0.0474)					
7- Frequency	271483	86910	0.21162 (<.0001)	0.25386 (<.0001)	0.02644 (0.3254)	-0.13359 (<.0001)	0.06023 (0.0250)	0.42080 (<.0001)				
8- Network Effect	331.93787	23.88184	0.85957 (<.0001)	0.47853 (<.0001)	0.11211 (<.0001)	0.60864 (<.0001)	0.38522 (<.0001)	0.31392 (<.0001)	0.13296 (<.0001)			
9- Multi-market Contact	0	0.13216	-0.03030 (0.2599)	-0.08161 (0.0024)	-0.18419 (<.0001)	-0.09453 (0.0004)	-0.16248 (<.0001)	0.00646 (0.8103)	0.09323 (0.0005)	-0.10363 (0.0001)		
10- Norms of Rivalry	0	0.05115	0.01164 (0.6652)	0.02455 (0.3612)	-0.00041 (0.9878)	0.03704 (0.1683)	0.00562 (0.8343)	-0.04878 (0.0696)	-0.00808 (0.7640)	0.06609 (0.0139)	0.03313 (0.2179)	
11- Performance Failure	0	0.43413	-0.11618 (<.0001)	-0.07978 (0.0030)	-0.10650 (<.0001)	-0.02301 (0.3922)	-0.07751 (0.0039)	0.01760 (0.5129)	0.00681 (0.8001)	-0.17540 (<.0001)	-0.07105 (0.0082)	0.02049 (0.4461)

I analyzed four models with alternative stochastic components as indicated in Table 7 so in order to identify the model that provides the best fit to data and to test the first set of hypotheses. The algorithms of all of the models converged. However the estimated G matrix of model 4 was not positive definite, pointing out the over-specification of their stochastic components (Kiernan et al., 2012). This model's non-positive definite G matrix, which is the

variance/covariance matrix for between-subject random effects, indicates that its stochastic component is too complex given the information contained in the data set (Kiernan et al., 2012, Singer and Willett, 2003). Since the last model is over-specified, I discarded it⁹.

Table 7 describes the random variables, covariance structure, deviance statistic (-2 times the sample log-likelihood), AIC and BIC statistics and number of covariance parameters of each model. The note that “estimated G matrix is not positive definite” in the table denotes that the corresponding model, which is model four in this case, is too complex given data and will not be included in model comparison through LR tests.

Table 7: Models with Alternative Between-Subject Random Effects Covariance Structures

Model Number	Random Variables	Covariance Structure	Deviance Statistic	AIC Statistic	BIC Statistic	Number of Covariance Parameters
1	Intercept	UN	10523.4	10527.4	10531	2
2	Intercept, MMC	UN	10429	10437	10444.2	4
3	Intercept, MMC, Norms	UN	10387.4	10401.4	10414	7
4	Intercept, MMC, Norms, Performance Failure	UN	Estimated G matrix is not positive definite			11

⁹ It is possible to force a model to fit data by increasing the number of iterations and likelihood evaluations and providing starting values for covariance parameters. However I am not so much interested in forcing a model to fit a given data set as I am in finding a model that accurately reflects the complexity of the data generation process and amount of information contained in the data set by following identical procedure for all models that I estimate. This is especially the case given that the fixed component of the model reflects the theory that I develop in this dissertation.

As reported in Table 8, I carried out two LR tests and selected model 3 as the final model to be used to investigate the first set of hypotheses. The comparison of model one with model two shows that the difference in their deviance statistics, (ΔD), is $(10523.4 - 10429) = 94.4$ with $(4 - 2) = 2$ degrees of freedom (DF) and is statistically significant at the $p < .001$ level. This result indicates that model 2 provides a better fit than model 1 and provides evidence to reject the null hypothesis that the 2 parameters of model two, variance of MMC and covariance of MMC with the intercept, are simultaneously 0. However model 3 provides a better fit than model 2 because the corresponding delta deviance is significant at the $p < .001$ level. Hence I selected model 3 as the final model and treated the intercept, MMC and norms as random variables.

Table 8: Comparison of Nested Models

Models Compared	ΔD	ΔDF	Significance	Selected Model
1 versus 2	94.4	2	Yes	2
2 versus 3	41.6	3	Yes	3

Following the selection of model 3, I modeled the dependence of level-1 residuals through three alternative different covariance structures, VC, CS and AR (1), and selected the VC covariance structure. The results indicated that modeling the correlation of level-1 residuals through CS and AR (1) introduces too much unnecessary complexity into the model given the data set. The algorithm of the model with the CS covariance structure for within-subject random errors converged but its final Hessian matrix was not positive definite. I discredited this model because the resulting non-positive definite Hessian matrix, which is used to compute the standard errors of the covariance parameters, implies a non-optimal solution, unstable estimates and too much complexity due to linear dependencies in the parameters (Kiernan et al., 2012). The algorithm of the model with an AR (1) covariance structure converged but its estimated G matrix

was also not positive definite. The covariance parameter estimate for variance of MMC reached a boundary constraint and thus there was not sufficient variation left in the dependent variable that can be attributed to the variance of MMC after controlling for everything in the model. Since these covariance structures led to over-specification of the stochastic component of the model (Singer and Willett, 2003), I discarded them and modeled the correlation of level-1 residuals with the default VC covariance structure and estimated the following model, whose level-1 and level-2 equations are given below, to test the first set of hypotheses:

The level-1 equation is:

$$Y_{ij} = \beta_{0j} + \beta_{1j} \text{CASM}_{ij} + \beta_{2j} \text{Productivity}_{ij} + \beta_{3j} \text{Stage_Length}_{ij} + \beta_{4j} \text{Load_Factor}_{ij} + \beta_{5j} \text{Seating_Density}_{ij} + \beta_{6j} \text{Frequency}_{ij} + \beta_{7j} \text{Network_Effect}_{ij} + \beta_{8j} \text{MMC}_{ij} + \beta_{9j} \text{Norms}_{ij} + \beta_{10j} \text{Performance_Failure}_{ij} + \beta_{11j} \text{MMC}_{ij} * \text{Norms}_{ij} + \beta_{12j} \text{MMC}_{ij} * \text{Performance_Failure}_{ij} + \beta_{13j} \text{Norms}_{ij} * \text{Performance_failure}_{ij} + \beta_{14j} \text{MMC}_{ij} * \text{Norms}_{ij} * \text{Performance_failure}_{ij} + r_{ij}$$

The level-2 equations are:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

$$\beta_{4j} = \gamma_{40}$$

$$\beta_{5j} = \gamma_{50}$$

$$\beta_{6j} = \gamma_{60}$$

$$\beta_{7j} = \gamma_{70}$$

$$\beta_{8j} = \gamma_{80} + \mu_{8j}$$

$$\beta_{9j} = \gamma_{90} + \mu_{9j}$$

$$\beta_{10j} = \gamma_{10}$$

$$\beta_{11j} = \gamma_{11}$$

$$\beta_{12j} = \gamma_{12}$$

$$\beta_{13j} = \gamma_{13}$$

$$\beta_{14j} = \gamma_{14}$$

$$\text{where } r_{ij} \sim N(0, \sigma^2) \text{ and } \begin{pmatrix} \mu_{0j} \\ \mu_{8j} \\ \mu_{9j} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & \tau_{01} & \tau_{02} \\ \tau_{10} & \tau_{11} & \tau_{12} \\ \tau_{20} & \tau_{21} & \tau_{22} \end{pmatrix} \right]$$

In addition to this model, I also estimated an “Unconditional Means” model to partition variance in ticket prices into its within-dyad and between-dyad components and a “Control” model that only contains the control variables. In addition, I re-estimated the selected model with non-parametric bootstrapping to replace its asymptotic standard errors with bootstrap standard errors so that I can solve any inference-related problems that may derive from selected model’s violation of the normality assumption. The name of this model is “Bootstrap”.

Table 9 reports the results of the “Unconditional Means model”, “Control model”, “Final model” and the “Bootstrap” model and their Pseudo-R² and goodness-of-fit statistics. In Table 9, estimates of standard error are provided below the relevant coefficient estimates and are in parenthesis. For the “Bootstrap model”, I also provide the 2.5th and 97.5th percentiles of the bootstrap distribution of the last of the 75 bootstraps to establish confidence intervals for parameters and test whether they are equal to zero. Since I use the confidence intervals to test whether a parameter estimate is significant, I do not use the “asterisk” notation to denote the significance of the bootstrap estimates. It is important to note that although I estimate all of these models with restricted maximum likelihood estimation, I calculated their goodness-of-fit statistics with full maximum likelihood estimation since this estimation is the only estimation

that provides goodness-of-fit statistics that can be used to compare models whose fixed and random components differ. I use “(ML)” to denote that fit statistics (i.e., deviance, AIC, BIC) are estimated with maximum likelihood in Table 9. The restricted maximum likelihood estimates of goodness of fitness statistics of compared models are already provided in Table 7.

Table 9: Results of the First Model

	Unconditional Means Model	Control Model	Final Model	Bootstrap
Response	Tactical Cooperation	Tactical Cooperation	Tactical Cooperation	Tactical Cooperation
Fixed Part				
Intercept	333.10* (5.4308)	240.07*** (10.4054)	-22.6292 (22.9591)	-22.114 (22.194) Quantiles: 2.5% -66.6219, 97.5% 22.0524
Control Variables				
CASM		486475*** (19316)	-43687 (25996)	-45158.191 (28322.783) Quantiles: 2.5% -99519.75, 97.5% 11777.3662
Productivity		-1.8564*** (0.1327)	-0.1732 (0.1961)	-0.179 (0.025)

				Quantiles: 2.5% -0.6004, 97.5% 0.2115
Stage Length		0.04169*** (0.002482)	0.04961*** (0.005084)	0.0498 (0.0052) Quantiles: 2.5% 0.0396, 97.5% 0.0603
Load Factor		-20.7462*** (6.2281)	-32.5522*** (5.8928)	-32.5445 (5.786) Quantiles: 2.5% -44.3238, 97.5% -21.064
Seating Density		0.5947*** (0.03120)	00.08296 (0.07166)	0.0801 (0.069) Quantiles: 2.5% -0.054, 97.5% 0.2124
Frequency		2.852E-7 (5.55E-6)	-0.00001 (0.000019)	-0.00001321 (0.00001724) Quantiles: 2.5% - 0.00004555, 97.5% 0.00002256
Network Effect		0.9688*** (0.02270)	0.9629*** (0.01808)	0.9632 (0.0182)

				Quantiles: 2.5% 0.9258, 97.5% 0.9969
Independent Variables				
MMC			16.6450*** (4.2896)	16.602 (4.212) Quantiles: 2.5% 8.3896, 97.5% 24.5816
Norms			-25.2367~ (12.7330)	-24.781 (12.494) Quantiles: 2.5% -49.5519, 97.5% -0.0427
Performance Failure			-1.8038** (0.6260)	-1.819 (0.662) Quantiles: 2.5% -3.0645, 97.5% -0.464
MMC*Norms			-45.7474 (45.7974)	-45.141 (44.766) Quantiles: 2.5% -139.1409,

				97.5% 42.6018
MMC*Performance-failure			-5.0939 (4.7138)	-4.966 (4.332) Quantiles: 2.5% -13.2137, 97.5% 3.4721
Norms*Performance-failure			19.4596 (13.3565)	19.74 (14.344) Quantiles: 2.5% - 8.3896, 97.5% 47.8641
MMC*Norms*Performance-failure			272.98** (83.2996)	276.943 (85.607) Quantiles: 2.5% 109.7685, 97.5% 441.3023
Random Part				
Level: Dyad-number				
Intercept/Intercept	1310.50*** (282.95)		319.71*** (84.7154)	322.6165 (68.7436) Quantiles: 2.5% 172.92, 97.5% 440.6679
MMC/Intercept			95.2173 (78.2280)	95.3254 (77.2042)

				Quantiles: 2.5% -65.2156, 97.5% 235.6276
MMC/MMC			479.74** (173.79)	477.4997 (166.2753) Quantiles: 2.5% 104.0824, 97.5% 754.9072
Norms/Intercept			-99.0406 (227.57)	-101.9109 (214.0362) Quantiles: 2.5% -499.2288, 97.5% 346.3567
Norms/MMC			-168.19 (343.69)	-177.8003 (354.9661) Quantiles: 2.5% -885.2007, 97.5% 527.6012
Norms/Norms			4622.94** (1661.63)	4660.5068 (1494.1356) Quantiles: 2.5% 1319.0610, 97.5% 7162.3018
Level: Time				
Intercept/intercept	514.24*** (19.8669)	171.37*** (6.5310)	86.8646*** (0.001)	86.7269 (3.5807)

				Quantiles: 2.5% 79.3445, 97.5% 93.6266
Pseduo-R² Statistics and Goodness-of-fit				
Pseduo-R _{y,y} ²		0.90	0.8044	
Pseduo-R _e ²		0.66675	0.83108	
Deviance (ML)	12772.4	11046.6	10421.7	
AIC (ML)	12778.4	11064.6	10465.7	
BIC (ML)	12783.9	11111.7	10505.4	

~p <.10; * p<.05; **p<.01; ***p<.001

As shown in Table 9, the result of the “Unconditional Means” model indicates that the grand mean fare charged by a dyad is 333.10. In addition, the estimates of within-dyad variance (514.24) and between-dyad variance (1310.50) are significant at the $p<.001$ level. This indicates that average ticket price varies over time within a dyad and that dyads differ from one another with respect to their level of prices. The estimates of variance components show that the ICC is: $1310.50 / (1310.50 + 514.24) = .718184508$. This result demonstrates that the proportion of total outcome variation that lies between dyads is approximately .718. This suggests that 71.8 % of the variance in fares is between-dyad variation, while the remaining 28.2 % variation is within dyads. ICC also shows that the average relationship between any pair of ticket prices within a dyad, and thus the residual autocorrelation, is .718. Since 28.2 % variation in ticket prices is within dyads, I expect that the introduction of time-varying variables by subsequent models will explain some portion of that variation as will be reflected by Pseduo-R_e².

The second column of Table 9 shows the results of the “control” model that contains only the control variables. The findings indicate that all of the control variables apart from frequency are significant at the $p < .001$ level and the direction of the coefficient estimates are consistent with predictions. As expected, there is in general a positive relationship between cost and ticket prices as indicated by the signs of coefficient estimates on CASM, productivity and stage length. On the one hand, as cost per available seat miles of a dyad increases, such increase in cost is reflected in higher tickets prices. On the other hand, as members of a dyad become much more productive and generate more operating revenue per employee, they reflect these efficiency gains in their prices, leading to a reduction in the sum of their fares. Results indicate that a one unit increase in the productivity of dyads reduces their total ticket price by approximately 1.8 dollars. In addition, a dyad increases its ticket prices by 0.042 dollars on average for each additional revenue mile flown per revenue aircraft departures since distance has a positive impact on cost, which is expected to be reflected in higher prices.

The remaining variables, which are load factor, seating density and frequency, control for both cost and service quality. I offered competing predictions for their impact on fare levels in Chapter Four due to their dual but opposing impact on prices. I argued that they can either increase ticket prices through demand-side effects (i.e., increase in quality leads to higher prices) or reduce them through supply-side effects (i.e., reduction in cost is expected to reduce ticket prices). The results for this set of control variables generally indicate the prevalence of demand-side effects over supply-side effects. The overall evidence suggests that passengers assign an important role to perceived quality and are ready to pay high ticket prices to have access to such quality. This tendency is first reflected by the sign of the coefficient on load factor. Load factor has a negative impact on price and the opportunity cost of not being able to sell seats at a

premium price due to demand peaking does not increase ticket prices; actually, a one unit increase in the filled seats of a dyad reduces the sum of dyad members' average ticket price by 20.75 dollars. The negative relationship between load factor and ticket prices may stem from the reduction not only in the per passenger cost of the flight but also in perceived quality of the flight that can be attributed to more crowded airplanes. Consistent with the impact of load factor on ticket prices, seating density, which is a proxy for average aircraft size of dyads, has a positive impact on prices. As a pair of rivals' total value of the ratio of available seat miles to revenue miles seat flown increases by one unit, their total price goes up by 0.5947 dollars because passengers perceive large planes as safer and more comfortable than small planes and are ready to pay more for the perceived quality of the product (Borenstein, 1989). Among all of the control variables, frequency is the only one that does not have a statistically significant impact on prices. That being said, its positive impact on prices is consistent with the explanation that increase in flight frequency reduces the number of delays and enables passengers to select convenient flight departure times in line with their schedule. This in turn improves perceived quality and increases the reservation prices of customers. Despite its insignificance, as the frequency of flights increase, ticket price levels do not diminish as expected from a supply-side perspective that would argue that higher aircraft utilization reduces fare levels through lowering costs per flight.

The network effect which controls for unobserved dyad-heterogeneity is significant in the "Control" model. This variable controls for the unobserved general pricing tendency of the members of a dyad. The results indicate that there is a positive relationship between a focal dyad's ticket price and average ticket prices across all dyads that include only one member of the focal dyad.

The “Control” model is superior to the “Unconditional Means” model as demonstrated by its Pseduo- R^2 and Goodness-of-fit statistics. The model explains 90 percent of the variation in the dependent variable. In addition, it explains 66 % of “explainable” variation in level-1 residuals, which account for within-dyad variance in the level of ticket prices. In other words, the introduction of 7 time-varying predictors by the “Control” model explains 66 % of the variation in level-1 residuals as indicated by its Pseduo- R_e^2 statistic. The “Control” model also provides a better fit than the “Unconditional Means model” because its AIC statistic and BIC statistic are considerably lower than those of the “Unconditional Means” model.

Column three of Table 9 presents the findings of the “Final” model, which contains all of the predictors and model intercepts, MMC and norms as random effects. There are both differences and similarities between the “Final” model and the “Control” model. With respect to similarities, the sign and significance of the effects of stage length, load factor and network effect are identical across both models. In addition, the size of the coefficients for stage length (0.04169 versus 0.04961) and network effect (0.9688 versus 0.9629) is very similar for the “Control” and the “Final” model. Despite such similarities, there are some differences between these models as far as the sign and significance of the variables are concerned. The introduction of time-varying question predictors into the “Final” model changes the significance of the three supply-related variables. The effects of productivity and seating density become non-significant in the “Final” model. In addition, the positive and significant effect of CASM becomes negative and the positive but non-significant impact of frequency becomes negative in the “Final” model.

As far as goodness-of-fit statistics are concerned, the “Final” model explains 83% of the “explainable” variation in the level-1 residuals of the “Unconditional Means” model and 80 % of the variation in the dependent variable. However the Pseduo- $R_{y, \hat{y}}^2$ statistic of the “Final” model

should be interpreted with caution since most of the variation in the dependent variable is between-dyad variation. Under this condition, the inclusion of time-varying predictors results in a Pseudo- $R_{y, \hat{y}}^2$ statistic that is lower than that of the “Control” model. Although the introduction of time-varying variables reduces the residual variance by 83%, their inclusion in the model increases the residual variance at the second level, reducing the overall Pseudo- $R_{y, \hat{y}}^2$ statistic (Singer and Willett, 2003; Kwok et al., 2008). That is why the comparison of the Pseudo- $R_{y, \hat{y}}^2$ statistic of the “Control” model with that of the “Final” model appears to indicate that the “Control” model explains more variation in the dependent variable than the “Final” model, even though it contains fewer time-varying variables than the “Final” model. Nevertheless, the AIC statistic and BIC statistic of the “Final” model clearly show that it provides a better fit than the “Control” model.

The results for the main question predictors indicate that MMC de-escalates rivalry despite the rivalry-escalating impact of norms and performance failure. Results show that increasing the level of contact between members of a dyad reduces the intensity of rivalry between them; actually, a one unit increase in MMC increases dyad members’ total quarterly ticket price by 16.64 dollars at the $p < .001$ level when the value of norms of rivalry and performance failure variables is equal to their respective dyad-specific mean. The significance of this finding is important because recent studies on MMC in the airline industry do not find a significant impact of MMC on either ticket prices (Zhang and Round, 2011) or on the likelihood of retaliation and retaliation lag (Marcel et al., 2010). That being said, the finding that MMC reduces the level of rivalry in the airline industry is in line with the predominant finding of research papers that study MF in the airline industry. Scholars that study MF demonstrated that MMC has a positive impact on airfares (Evans and Kessides, 1994; Singal, 1996; Zou et al.,

2012), yield (Gimeno and Woo, 1996; Gimeno , 1999; Zou et al., 2011), Lerner index (Gimeno and Woo, 1999; Gimeno, 2002), delays (Prince and Simon, 2009) and negative impact on entry and exit rates (Baum and Korn, 1996; 1999) and frequency of flights (Bilotkach, 2011) in the airline industry. The finding that MMC increases fare levels reveals that the interdependence and deterrence effects of MMC prevail over its rivalry enhancing effects in this study. However such dominance is not automatic because MMC, as a double-edged sword, has the potential to escalate rivalry (Porter, 1980) and diminish fares in the airline industry (Zhang and Round, 2009). As argued in Chapter 3, MMC is initially expected to escalate rivalry. That may be why one of the original studies that studied the early years of the airline industry found that MMC intensified the level of rivalry among carriers and destabilized their market shares just before the deregulation between 1974 and 1976 and had an insignificant but market share stabilizing effect after the deregulation (Sandler, 1988). However it seems from the results of the present study that the continuous and repeated interaction among carriers led sampled carriers to conclude that cooperation is more conducive to their performance than price competition.

Norms of rivalry have a negative effect on the sum of ticket prices of members of dyad. Results indicate that a one unit increase in norms of rivalry reduces dyad member's total ticket prices by 25.23 dollars at the $p < .0537$ level when value of MMC and performance failure variables is equal to their dyad-specific mean. This is consistent with arguments made in Chapter 3 that competing similarly escalates rather than de-escalates rivalry. First, firms that compete similarly cannot differentiate their value proposition in the eyes of customers, forcing them to lure customers away from each other through price cuts and thus engage in zero-sum competition where costumers gain at the expense of firms. Second, similarity in competitive actions increases the speed, likelihood, effectiveness and efficiency of responses (Porter, 1980; Marcel et al.,

2010, Smith et al., 1992), for rivals can accurately and promptly detect, diagnose, understand and mimic moves similar to their own (Ferrier, 2001; MacMillan et al., 1985). Effective, efficient and quick responses in turn prevent the acting firms from gaining a competitive advantage over the responding firms by building mobility (Caves and Ghemawat, 1992) and resource position barriers (Lippman and Rumelt, 1982). Third, similar competitive actions result in the development of similar capabilities and impede the creation of competence differences between firms, which in turn intensifies rivalry (Barney, 1991, Bernheim and Whinston, 1990).

The observed positive relationship between norms and rivalry in the airline industry, which is also supported by recent findings (Norman et al., 2007), contradicts the Caves-Porter hypothesis (1977) which reflects the general stance of industrial organization economics. This hypothesis postulates that norms reduce the intensity of rivalry as they provide focal points for coordinating actions. However the evidence for this hypothesis is inconclusive among studies that study the impact of both norms and MMC on rivalry. While some found support for the Caves-Porter hypothesis (Fuentelsaz and Gomez, 2006; Young et al., 2000), others discovered that similarity has either a significant (Gimeno and Woo, 1996, Marcel et al., 2010) or non-significant (Li and Greenwood, 2004) positive impact on rivalry.

Despite such conflicting findings, the extant literature is silent on the potential causes. I think recognition of the dual role played by similarity can shed light on such mixed findings. In the extant literature, similarity is allowed to play a single role. In essence, Caves and Porter hypothesis considers norms as an “enabler” of cooperation. In this view, it is theorized that norms facilitate information collection, exchange and interpretation and thus provide the ability to cooperate. However ability is necessary but not sufficient to cooperate. Rival firms should have both the ability and the motive (Chen, 1996) to cooperate. Norms and the resulting

familiarity and predictability can be deployed to take advantage of the weakness of rivals and thus escalate rivalry or initiate, motivate and maintain cooperation. It is the motive that will determine whether norms are put to competitive or cooperative use and it is performance failure that provides the motive to cooperate. Poorly performing rivals will be motivated to deploy their familiarity to cooperate because of their experience that deploying familiarity to outcompete does not pay off. That is why, it is important to examine performance failure, norms and their interaction to understand whether norms are redeployed to initiate and maintain cooperation in the face of performance failure as I am doing in this dissertation.

The results show that performance failure intensifies rivalry. A one unit increase in performance failure reduces sum of ticket prices of members of a dyad by 1.80 dollars at the $p < .01$ level when the value of MMC and norms of rivalry variables is equal to their respective dyad-specific mean. Therefore when members of a dyad perform below their aspirations and experience failure, rivalry through price cuts escalates. This finding is in line with the research that found that bankrupt carriers initiate price wars (Borenstein and Rose, 1995, Busse, 2002). Failing carriers might escalate the level of rivalry, which can further aggravate their poor performance, because being in the “failure” state increases their willingness to take risks (March and Shapira, 1987). When firms’ performance is below their aspiration but above their survival point, their objective functions become convex (Spagnolo, 1999; Tversky and Kahneman, 1992) and opportunities for gain from fighting looms larger than retreating and being submissive. Hence the increase in propensity to take risks might explain the increase in the aggression that takes place among members of a dyad.

The impact of the interaction of MMC and norms on ticket prices is negative for a pair of rivals but insignificant. The sign of the effect is consistent with the expectation that multi-market

rivals that compete similarly compete much more fiercely than those that compete dissimilarly because norms enable multi-market firms to “hit” one another where it hurts the most and deploy predictability and familiarity that stem from commonly shared norms of competition to intensify rivalry. Norms and the resulting comprehensive understanding of rivalry enable multi-market rivals to selectively attack one another in their key markets to inflict the greatest damage. The findings of the extant literature on the observed relationship are mixed. While Li and Greenwood (2004) found that the interaction of MMC with similarity de-escalates rivalry, both Fuentelsaz and Gomez (2006) and Young et al. (2000) found that their interaction escalates rivalry. The findings of Upson et al. (2012) confirm the mixed findings of these scholars and demonstrate that interaction of similarity with market commonality increases both foothold attack and foothold withdrawal in the computer related and manufacturing industry. Omission of a moderator can be responsible for the inconclusive findings in the literature. As I argue in chapter 3 and formulated Hypothesis 1b, performance failure may moderate the impact of the interaction of norms and MMC on intensity of rivalry by providing the switch to shift competition into cooperation and activating all of required antecedents of trust which is expected to lead to cooperation. The results of the Hypothesis 1b are reported later in this chapter.

In the “Final” model, the interaction of MMC with performance failure has a negative but insignificant impact on fares. The negative sign might be due to the *inability* of dyads to trust one another despite their *motivation*. Poorly performing carriers that have contacts across markets may be motivated to trust one another with their price increases, but they may not know how to instigate, signal and motivate cooperation in their rivals due to the lack of norms that reduce competitive uncertainty and regulate rivalry.

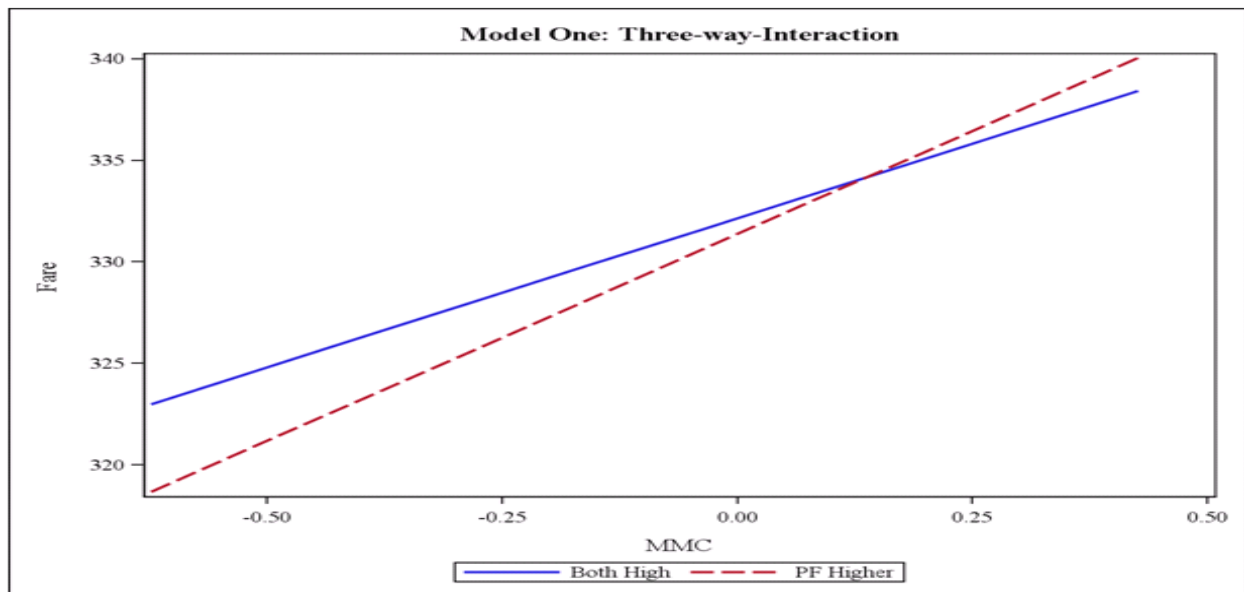
When norms and performance failure coexist between firms, they have not only the ability but also the motive to trust one another with their price increases across markets. However, as indicated by the positive but insignificant effect of the interaction of norms and performance failure, norms and performance failure may be necessary but not sufficient for the formation of trust. To establish trust, carriers need to recognize that their payoffs are interdependent, making trust relevant to them, and be assured that their trustworthiness will not be exploited by defecting rivals. Multi-market contact not only provides the assurance in the form of deterrence but also instills in rivals an understanding that their payoffs are mutually interdependent. Hence I expect the interaction of MMC, norms and performance failure to trigger trust as hypothesized in Hypothesis 1a.

The results provide support for Hypothesis 1a. The three-way interaction has a positive impact on the ticket prices at the $p < .001$ level. MMC, norms, and performance failure jointly trigger all of the antecedents of trust (interdependence, deterrence, predictability and risk taking) and result in trust formation between members of a given dyad. The results indicate that all of the two-way interactions are non-significant and two of them actually escalate the level of rivalry. This provides further support for Hypothesis 1a and demonstrates that all of the four triggers of trust must simultaneously exist for trust to be formed. When one of the triggers is missing, trust is not formed. The interaction of MMC with norms actually impairs trust and thus lowers prices because carriers deploy predictability and familiarity that stem from commonly shared norms of competition to intensify rivalry in the absence of performance failure. The deterrence and recognition of extended interdependence that stem from MMC might constrain the intensity of such rivalry and might explain the insignificance of the rivalry enhancing impact of the interaction of MMC and norms. Like the ability to cooperate that is provided by norms,

motivation by itself is not sufficient to trigger trust. Although performance failure may provide the switch from competition to cooperation, carriers that do not know how to cooperate due to their lack of understanding of the rules of competition cannot foresee whether the other party is trustworthy or can be motivated to be trustworthy. The insignificance of the rivalry enhancing impact of the interaction of MMC and performance failure may be due to unsuccessful attempts of carriers to establish trust that attenuate the level of rivalry to a certain extent. Then, it is only the three-way interaction that triggers trust by activating all four antecedents of trust.

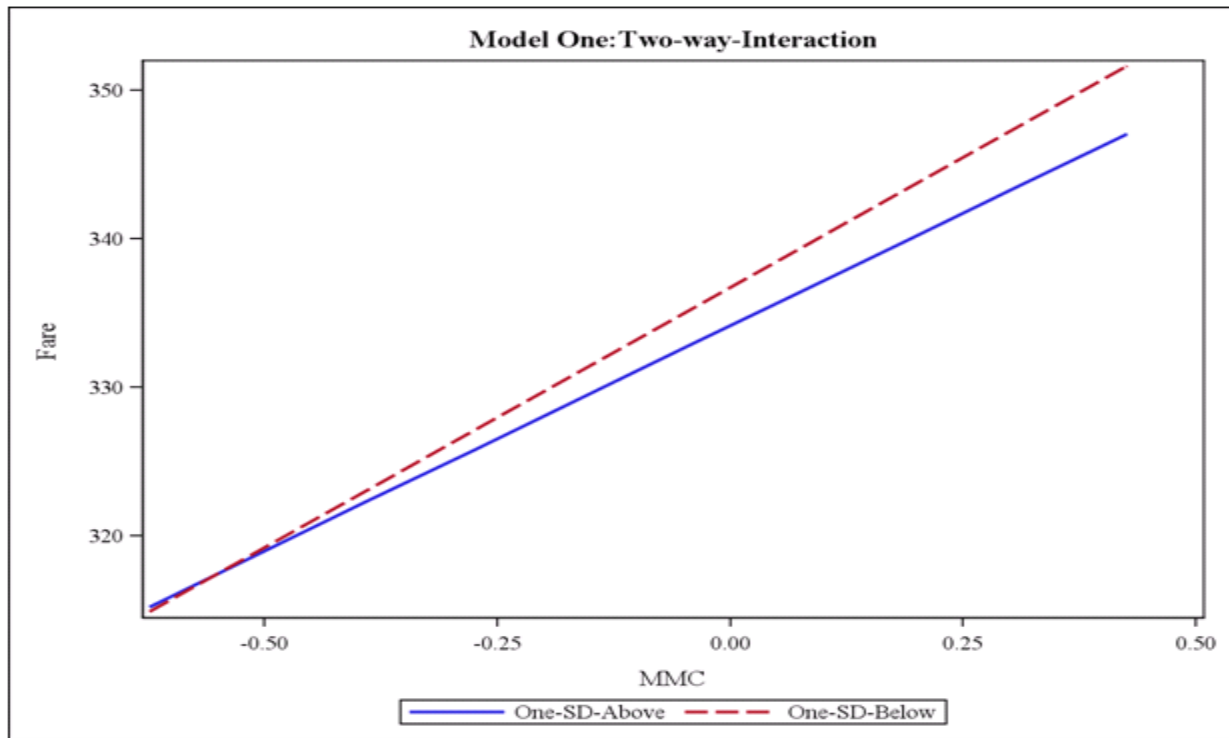
The Figure 2 shows the impact of the three-way interaction on trust after accounting for the effects of the control variables and provides a visual depiction of the observed significant relationship. The solid line shows the slope when both norms of competition and performance failure are one standard deviation above their respective mean and the dotted line represents the slope when norms of competition is one standard deviation above its respective mean and performance failure is two standard deviations above its respective mean. As performance failure becomes more severe, the slope becomes steeper, as represented by the slope of the dotted line, and the positive relationship between MMC and ticket prices becomes stronger. This supports the theoretical argument developed in Chapter 3. Performance failure not only provides the motive to trust but triggers search process that eventually transforms competition into cooperation.

Figure 2: Three-way Interaction



There is no support for Hypothesis 1b. However the evidence is consistent with the prediction that poor performance reverses the negative sign of the interaction of norms of competition and multi-market competition on the commencement of tactical cooperation between a dyad of multi-market rivals. As can be seen from Figure 3, norms negatively moderate the relationship between MMC and fares. The dotted line represents the slope when norms of competition are one standard deviation below its mean after controlling for everything else in the model. The solid line depicts the relationship between MMC and fares when norms of competition are one standard deviation above its mean after controlling for everything else in the model. Although increase in the level of norms of competition does not result in a negative slope, it weakens the positive relationship between MMC and ticket prices as reflected by the flatter slope of the straight line. However when poor performance is included as the third moderator of the relationship, the negative sign of the interaction of norms and competition is reversed indicating a significant and positive impact on the commencement of tactical cooperation, consistent with Hypothesis 1b.

Figure 3: Two-way Interaction



5.1.1 Robustness Check

The validity of my inferences and conclusions depends on whether the estimated “Final” model meets the assumptions of multi-level modeling. Therefore in this section, I test the assumed normality of the distribution of level-1 and level-2 residuals, homoscedasticity and linearity.

The following q-q plot demonstrates that the level-1 residuals are not normally distributed although the departure from normality does not appear substantive. As indicated in Table 10, the significance of the Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-Von Mises and Anderson-Darling statistics also support the conclusion that level-1 residuals are not normally distributed.

Figure 4: Q-Q Plot of Level-1 Residuals

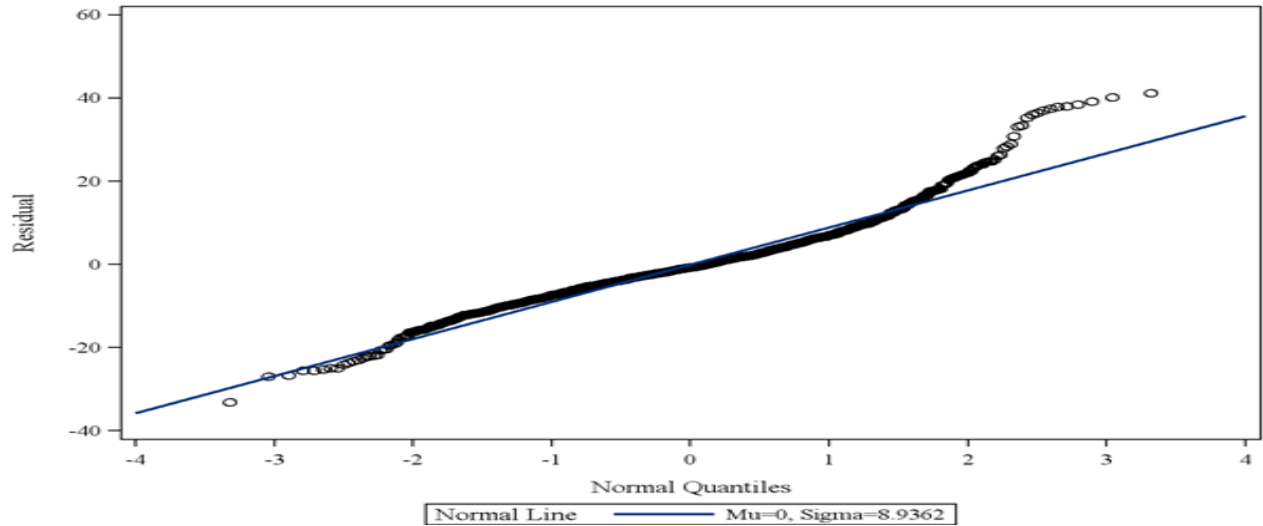


Table 10: Statistical Tests of the Normality of Level-1 Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.94875	<0.0001
Kolmogorov-Smirnov	0.07909	<0.0100
Cramer-von Mises	2.70413	<0.0050
Anderson-Darling	16.13410	<0.0050

Although level-1 residuals are not normally distributed, all of the level-2 residuals are normally distributed as indicated by Figures 5, 6 and 7 that depict the q-q plots of the intercepts, MMC and norms of competition respectively. This conclusion is also supported by the insignificant Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-Von Mises and Anderson-Darling statistics. Tables 11, 12 and 13 provide the results of these tests for all of the level-2 residuals.

Figure 5: Q-Q Plot of Level-2 Intercept Residuals

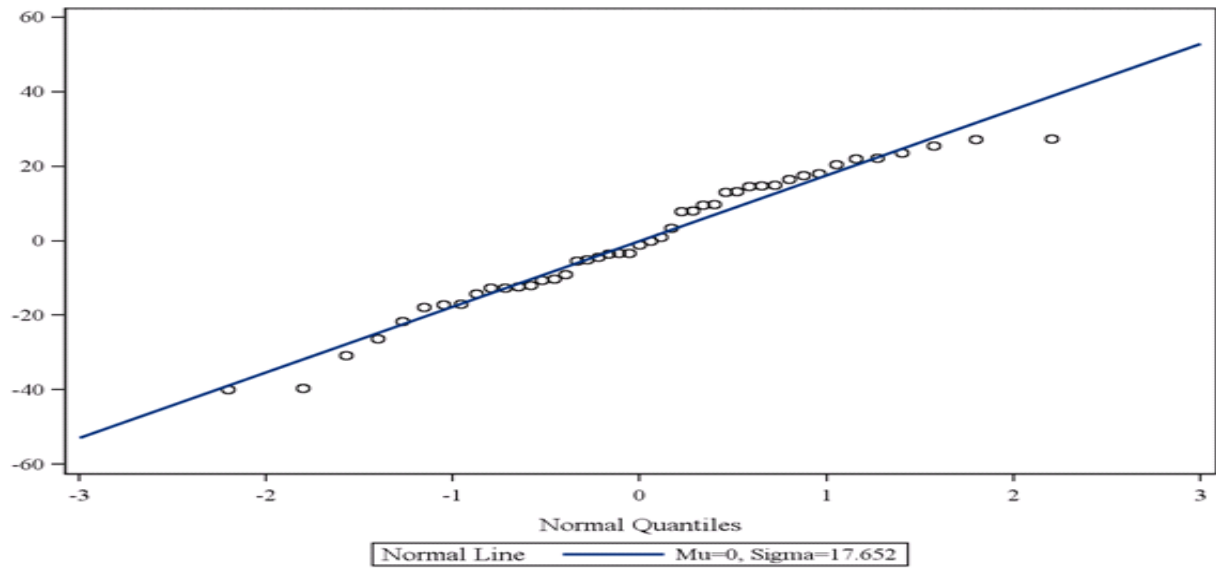


Table 11: Statistical Tests of the Normality of Level-2 Intercept Residual

Test	Statistic	P Value
Shapiro-Wilk	0.962664	0.1543
Kolmogorov-Smirnov	0.103925	>0.1500
Cramer-von Mises	0.065689	>0.2500
Anderson-Darling	0.447107	>0.2500

Figure 6: Q-Q Plot of Level-2 MMC Residuals

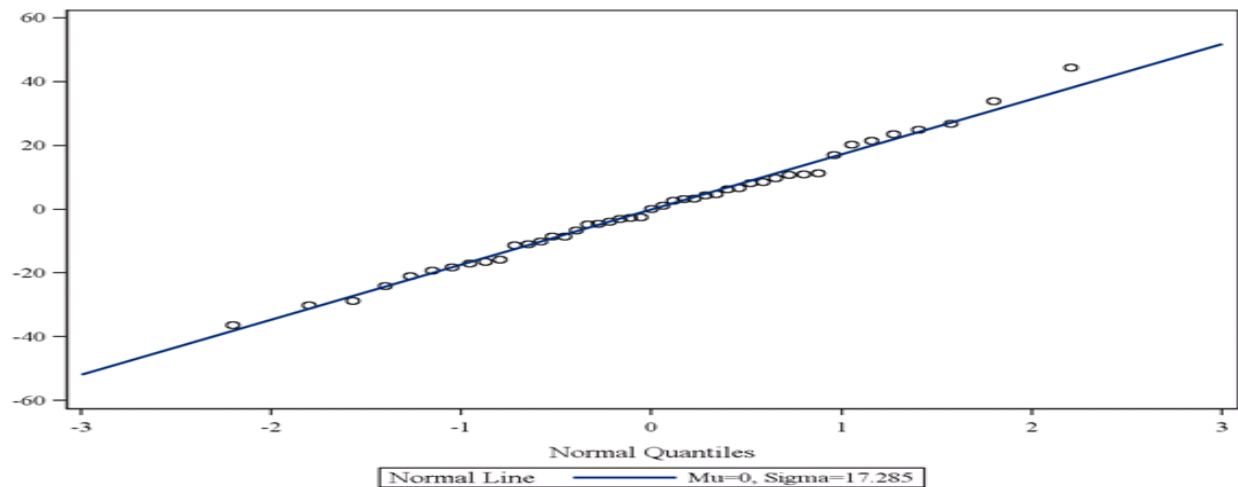


Table 12: Statistical Tests of the Normality of Level-2 MMC Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.991878	0.9866
Kolmogorov-Smirnov	0.079167	>0.1500
Cramer-von Mises	0.021161	>0.2500
Anderson-Darling	0.140264	>0.2500

Figure 7: Q-Q Plot of Level-2 Norms Residuals

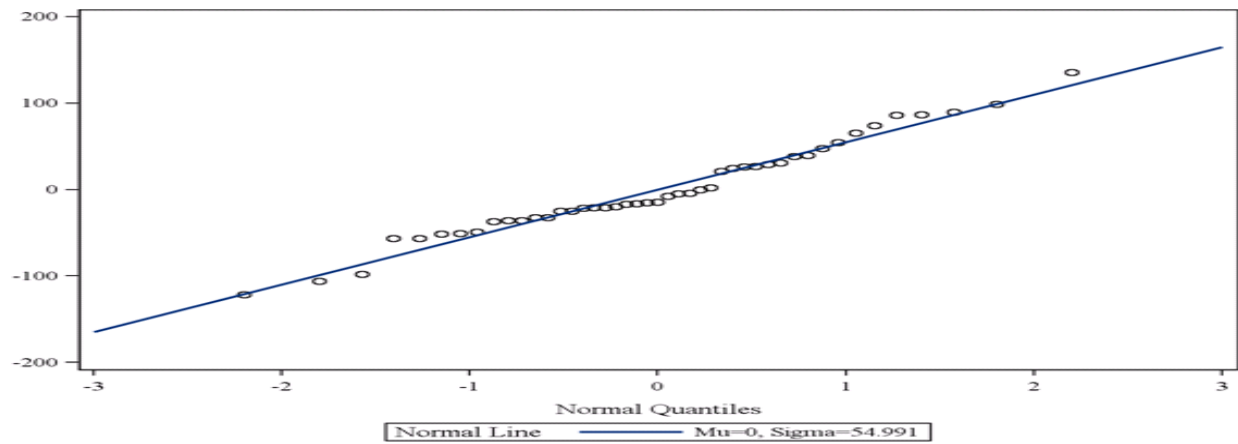


Table 13: Statistical Tests of the Normality of Level-2 Norms Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.975400	0.4467
Kolmogorov-Smirnov	0.116855	0.1244
Cramer-von Mises	0.098851	0.1156
Anderson-Darling	0.531674	0.1718

The variance of the level-1 variance is constant across dyads and prediction space as displayed in Figures 8 and 9. The dyads seem to have the same constant variance and the residuals do not show a pattern when they are plotted against the prediction space and dyads.

What is portrayed by the visual diagnostics is also supported by the insignificant F ratio produced by ANOVA that fails to reject the null hypothesis that variance of error is the same across dyads. The F ratio appears in the left corner of the Figure 8. In addition, Levene's test, O'Brien's Test and Brown and Forsythe's test failed to reject the null hypothesis that the residual variance is homogeneous. Figure 9, displays the scatter plot of the level-1 residuals against the predicted value with superimposed zero and Loess fit line, and provides support for the assumed linear relationship since the Loess fit line does not display any large deviations from the 0-line and it generally follows it (Cohen et al., 2003).

Figure 8: Residual versus Dyads

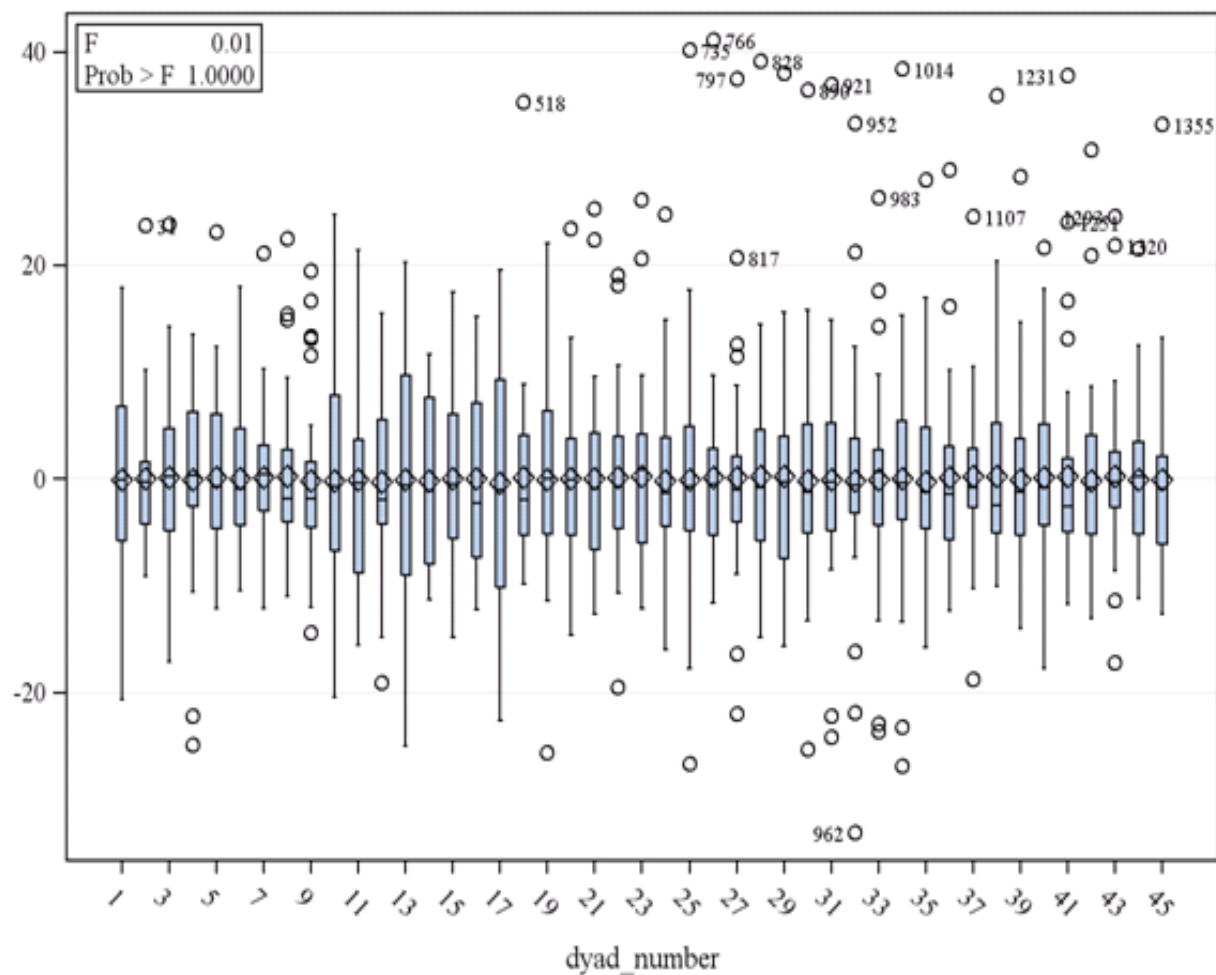
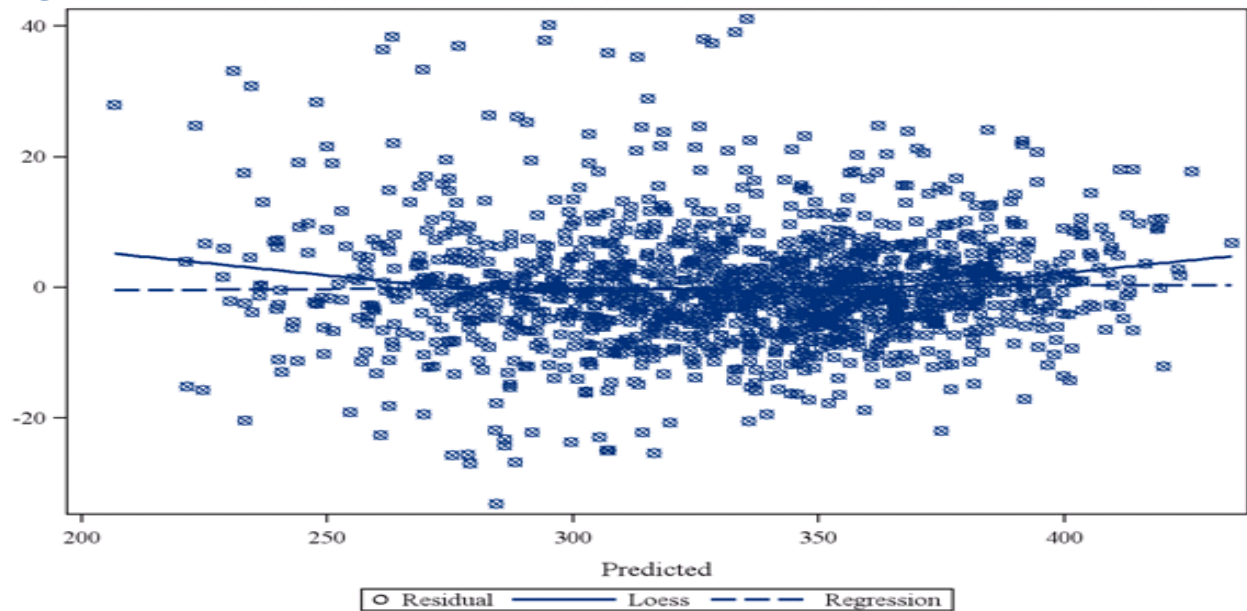


Figure 9: Residual versus Predicted Values



In sum, the post-hoc diagnosis shows that a linear model is the right specification and variance of the residuals is constant. Therefore I do not need to model heteroscedasticity directly or correct the standard errors. Nevertheless, the diagnosis shows that there is a departure from normality at level-1, which might bias asymptotic standard errors and result in incorrect inferences (Hox, 2010).

To assess the robustness of the conclusions and inferences that I drew from the restricted maximum likelihood estimation, I carried out non-parametric residual bootstrap using MLwiN. I preferred non-parametric bootstrap to parametric bootstrap because the former does not make any distributional assumption and thus enables me to record the nature and magnitude of bias in statistical inference that derives from the violation of the assumption of normality. I preferred non-parametric residual bootstrapping to non-parametric cases bootstrapping because variance of the residuals is constant in my data set. I used MLwiN to run the model and its iterative generalized least squares, which is equivalent to restricted maximum likelihood estimation.

By utilizing 75 iterated bootstrap runs of 1500 iterations, I obtained an approximated sampling distribution of the parameters and generated bias corrected estimates, estimated standard errors and constructed valid confidence intervals. The last column of Table 9 presents estimates and standard errors of the “Bootstrap” model. I also constructed the 95 % confidence intervals by taking the 2.5th and 97.5th percentiles of the bootstrap distribution of the last of the 75 bootstraps.

The results indicate that the violation of the assumption that level-1 residuals are normally distributed does not lead to inaccurate inferences. The parameter estimates and standard errors of the “Final” model are very similar to those of the “Bootstrap” model. In addition, t-tests of the “Final” model and the 95 % confidence interval estimates of the “Bootstrap” model lead to identical inferences. The similarity of the findings of the “Final” and “Bootstrap” model indicates that the results of the “Final” model estimated by restricted maximum likelihood estimation are robust. The violation of the normality assumption does not result in incorrect estimates because of the large sample size properties of restricted maximum likelihood estimation which provides asymptotically consistent, unbiased and efficient estimates (Singer and Willett, 2003). In the final analysis, there is no reason to suspect the asymptotic results of the “Final” model and the violation of the normality assumption does not bias inferences given the large sample size.

5.2 Model 2

I estimated the second model with using “cross-classified random effects” models to accurately reflect the structure of the data, which does not have an unambiguous hierarchy of observations nested within dyads nested within markets. In the data set, observations are nested within the cross-classification of markets and dyads because observations from a given dyad

belong to many markets and observations from a given market belong to many dyads. Hence strategic cooperation is influenced by both markets and dyads due to the cross-classified data structure. Therefore, I model both markets and dyads as sources of variation in strategic cooperation, but in such a manner that observations are nested within markets and dyads, with markets and dyads crossed. I took the logarithm of the dependent variable to normalize the distribution of residuals and also scaled the “number of passengers” and the “keyness” variables by dividing them by one and ten thousand respectively to reduce the processing time of estimated models. Table 14 provides the correlation and descriptive statistics of the variables of the second model. Numbers in the parenthesis reflect the significance level of correlations.

Table 14: Descriptive Statistics and Correlations of Model 2

Variable	Mean	S.D	1	2	3	4	5	6	7	8	9	10
1- Strategic Cooperation	1.13451	0.92304										
2- Tactical Rivalry	85.82881	150.66667	-0.01728 (<.0001)									
3- Market Concentration	0.58577	0.23010	0.17218 (<.0001)	0.00660 (0.0089)								
4- Number of Firms	5.79416	2.40486	-0.16814 (<.0001)	0.03021 (<.0001)	-0.42927 (<.0001)							
5- Number of Passengers	167.09092	277.04764	-0.01808 (<.0001)	-0.00658 (0.0091)	-0.31109 (<.0001)	0.48109 (<.0001)						
6- Hub Economies	4.86525	6.81726	0.46292 (<.0001)	0.00598 (0.0178)	0.19866 (<.0001)	-0.13713 (<.0001)	-0.02642 (<.0001)					

7- Firm Size	2.14836	1.27197	0.04691 (<.0001)	-0.03872 (<.0001)	-0.02710 (<.0001)	0.03746 (<.0001)	0.02994 (<.0001)	0.10458 (<.0001)				
8- Network Effect	3.00537	6.53414	0.12774 (<.0001)	-0.00554 (0.0281)	-0.03598 (<.0001)	0.07343 (<.0001)	0.06505 (<.0001)	0.04003 (<.0001)	0.03125 (<.0001)			
9- Tactical Reciprocity	105.42427	190.86193	-0.01931 (<.0001)	-0.31466 (<.0001)	0.01962 (<.0001)	-0.01286 (<.0001)	-0.04314 (<.0001)	0.00381 (0.1316)	-0.02742 (<.0001)	-0.0069 (0.0056)		
10- Tactical Non-Reciprocity	158.77325	196.44221	-0.01013 (<.0001)	-0.46043 (<.0001)	0.06412 (<.0001)	-0.01046 (<.0001)	-0.08374 (<.0001)	0.02744 (<.0001)	-0.03667 (<.0001)	-0.0217 (<.0001)	-0.4464 (<.0001)	
11- Keynes	0.05050	1.09245	0.05958 (<.0001)	-0.00052 (0.8366)	-0.00332 (0.1880)	0.00788 (0.0018)	0.03224 (<.0001)	0.01862 (<.0001)	0.00158 (0.5318)	0.03547 (<.0001)	-0.0147 (<.0001)	-0.01089 (<.0001)

I compared four different models with alternative variance-covariance structures to select the best model to investigate Hypotheses 2, 3 and 4. The first model allowed the intercept to vary across markets and dyads and the second model allowed not only intercept to vary across markets and dyads but also the effect of tactical-reciprocity to vary across dyads. The third model permitted the intercept to vary across markets and dyads and the impact of tactical-reciprocity and tactical-non-reciprocity to vary across dyads and the fourth model let the intercept vary across markets and dyads and the effect of tactical-reciprocity, tactical-non-reciprocity and the interaction of tactical-reciprocity with “keyness” to vary across dyads.

The results indicated that all models apart from the first model were too complex and poorly specified. The algorithms of Models 2, 3 and 4 did not converge since there was not sufficient information contained in the data set to let the effects of tactical-reciprocity, tactical-non-reciprocity and the interaction term to vary across dyads. Two main causes of non-

convergence are poorly specified model and insufficient data (Hox, 2010; Singer and Willett, 2003). Given the large number of observations, the main reason for the non-convergence of Models 2, 3 and 4 is their poor specification. Non-convergence derives from variance components whose estimates are too close to zero (Hox, 2010). In Model 2, the estimate of tactical reciprocity, which is a random effect, is 1.423E-8. In Model 3, the estimates of tactical reciprocity and tactical non-reciprocity, which are random effects, are 5.706E-8 and 6.397E-8 respectively. In Model 4, the estimates of the random effects, which are tactical reciprocity, tactical non-reciprocity and the interaction of tactical reciprocity with keyness, are 6.795E-8, 6.203E-8 and 6.39E-6 respectively. The variance component estimates of these models that were too close to zero show that these models are too complex given the amount of information contained in the data set. Therefore I discarded them and selected the first model that allowed the intercepts to vary not only across inter-organizational competitive dyads, but also markets, to test the hypotheses. The level-1 equation and level-2 equations of the selected model are given below.

In the level-1 equation, $Y_{i(jk)}$ represents the strategic cooperation score of observation i nested within the cross-classification of dyad j and market k . The subscripts (jk) are written in parenthesis to show that they conceptually exist at the same level that is the (jk) th dyad and market combination in the cross-classifications of dyads and market.

The level-1 equation for the selected model is:

$$Y_{i(jk)} = \beta_{0(jk)} + \beta_{1(jk)} \text{Tactical_Rivalry}_{ijk} + \beta_{2(jk)} \text{Market_Concentration}_{ijk} + \beta_{3(jk)} \text{Number_of_Firms}_{ijk} + \beta_{4(jk)} \text{Number_of_Passengers}_{ijk} + \beta_{5(jk)} \text{Hub_Economies}_{ijk} + \beta_{6(jk)} \text{Firm_Size}_{ijk} + \beta_{7(jk)} \text{Network_Effect}_{ijk} + \beta_{8(jk)} \text{Tactical_Reciprocity}_{ijk} + \beta_{9(jk)} \text{Tactical_Nonreciprocity}_{ijk} + \beta_{10(jk)} \text{Keyness}_{ijk} + \beta_{11(jk)} \text{Tactical_Reciprocity}_{ijk} * \text{Keyness}_{ijk} + r_{i(jk)}$$

The level-2 equations for the selected model are:

$$\beta_{0(jk)} = \gamma_{00} + \mu_{0j} + v_{0k}$$

$$\beta_{1(jk)} = \gamma_{10}$$

$$\beta_{2(jk)} = \gamma_{20}$$

$$\beta_{3(jk)} = \gamma_{30}$$

$$\beta_{4(jk)} = \gamma_{40}$$

$$\beta_{5(jk)} = \gamma_{50}$$

$$\beta_{6(jk)} = \gamma_{60}$$

$$\beta_{7(jk)} = \gamma_{70}$$

$$\beta_{8(jk)} = \gamma_{80}$$

$$\beta_{9(jk)} = \gamma_{90}$$

$$\beta_{10(jk)} = \gamma_{10}$$

$$\beta_{11(jk)} = \gamma_{11}$$

$$\text{where } r_{i(jk)} \sim N(0, \sigma^2) \text{ and } \begin{pmatrix} \mu_{0j} \\ v_{0k} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & 0 \\ 0 & \tau_{11} \end{pmatrix} \right]$$

Following the selection of Model 1, I modeled the dependence of level-1 residuals through three alternative different covariance structures (VC, CS and AR (1)) and selected the AR (1) covariance structure. Although the “cross-classified random effects” model that I estimate is normally estimated with two separate random statements with their unique subjects (i.e., random intercept/subject=market; random intercept/subject=dyad), I estimated all of these covariance structures with one random statement to be able to reduce not only memory problems and execution time but also request robust standard errors from SAS PROC MIXED. It is important to note that the results of such alternative parameterization are identical to those of the aforementioned conventional parameterization as far as the fixed component of the model that

tests the hypotheses of this dissertation is concerned. For example, I estimated the selected model, Model 1, using both the conventional approach and the proposed alternative and found that the results of these alternative parameterizations are identical. In the alternative specification, while I modeled market-specific intercept as a random effect and thus as component of the residual error term, I modeled dyad-specific intercept as a fixed-effect by creating dummy variables for each and every dyad in the fixed component of the model. I preferred to model the dyad-specific intercept rather than the market-specific intercept as a fixed-effect because the number of dyads is significantly lower than the number of markets. By using this alternative parameterization, I compared alternative covariance structures that model level-1 residuals and thus dependence that derives from time.

The model with the CS covariance structure provided a better fit than the model with the default VC covariance structure because the difference in their deviance statistics was $(307118.2 - (-13618.3)) = 320736.5$ with $(3-2) = 1$ DF and was statistically significant. However the model with the AR (1) covariance structure provided a better fit than the model with the CS covariance structure because the former model's AIC (-191049) and BIC (-191031) statistics were much smaller than the corresponding AIC (-13612.3) and BIC (-13594.6) statistics of the latter model. I did not carry out an LR test to compare these two covariance structures because the models that they belong to are not nested. I therefore modeled the dependence of observations that stem from time by using the AR (1) covariance structure and used this model to test the Hypotheses 2, 3 and 4.

In addition to this model, I estimated a "Cross-classified Unconditional Means" model to partition variance in strategic cooperation into its between-market, between-dyad and within-dyad-market components and also a "Control" model that only contains the control variables. To

verify that a “Cross-classified Unconditional Means” model is required by the structure of the data, I compared the fit of this model to the fit of an “Unconditional Means” model that partitions the variance in strategic cooperation to its between-dyad and within-dyad components via an LR test. The test results indicated that the “Cross-classified Unconditional Means” model provides a better fit than the alternative “Unconditional Means” model. The difference in the deviance statistics of these two types of “Unconditional Means” models was $(406084.5 - 349703) = 56381.5$ with $(3-2) = 1$ DF and was statistically significant at the $p < .001$ level. The result of the LR test indicated that the structure of the data requires me to model observations as nested in the cross-classification of markets and dyads.

Table 15 displays the results of these models and their Pseudo- R^2 and goodness-of-fit statistics. Although I estimated all of these models with restricted maximum likelihood estimation, I calculated their goodness-of-fit statistics with full maximum likelihood estimation because this estimation is the only estimation that provides goodness-of-fit statistics that can be deployed to compare models whose fixed and random components differ. The full maximum likelihood estimates of the goodness-of-fit statistics of all models are provided in Table 15 and are denoted by (ML). In Table 15, estimates of standard error are provided below the relevant coefficient estimates and are in parenthesis.

Table 15: Results of the Second Model

	Cross-Classified Unconditional Means Model	Control Model	Final Model^a	Empirical Model^a
Response	Strategic Cooperation	Strategic Cooperation	Strategic Cooperation	Strategic Cooperation

Fixed Part				
Intercept	1.6151*** (0.1297)	1.2747*** (0.1285)		
Control Variables				
Tactical Rivalry		-1.89E-6 (0.000011)	0.000012*** (3.652E-6)	0.000012* (4.832E-6)
Market Concentration		0.1123*** (0.01426)	-0.00376 (0.002918)	-0.00376 (0.005085)
Number of Firms		-0.00315* (0.001586)	-0.00245*** (0.000249)	-0.00245*** (0.000486)
Number of passengers/1000		-0.00022*** (0.000036)	-0.00024*** (6.133E-6)	-0.00024*** (0.000037)
Hub Economies		0.06058*** (0.000298)	0.04109*** (0.000272)	0.04109*** (0.001446)
Firm Size		-0.03519*** (0.005389)	-0.00932*** (0.001155)	-0.00932** (0.003081)
Network Effect		-0.00587*** (0.000430)	0.001593*** (0.000076)	0.001593*** (0.000316)
Independent Variables				
Tactical Reciprocity			0.000017*** (2.853E-6)	0.000017*** (4.004E-6)
Tactical Non-Reciprocity			0.000014*** (3.175E-6)	0.000014*** (4.298E-6)
Keyness/10000			-0.00032 (0.000222)	-0.00032 (0.000252)
Tactical Reciprocity*Keyness			0.000023** (9.099E-6)	0.000023* (9.363E-6)

Random Part				
Intercept/Dyad	0.7455*** (0.1606)	0.7215*** (0.1551)		
Intercept/Market	0.4976*** (0.01581)	0.2724*** (0.008926)	0.1290*** (0.006551)	0.1290*** (0.006551)
Level: Time				
Intercept/intercept	0.5031*** (0.001802)	0.4*** (0.001432)	0.5164*** (0.005402)	0.5164*** (0.005402)
AR(1)			0.9922*** (0.000087)	0.9922*** (0.000087)
Pseudo-R² Statistics and Goodness-of-fit				
Pseudo-R _{y,y} ²		0.2024	0.3142	0.3142
Deviance (ML)	349700.7	312398.7	-191445	-191445
AIC (ML)	349708.7	312420.7	-191327	-191327
BIC (ML)	349700.7	312398.7	-190977	-190977

~p <.10; * p<.05; **p<.01; ***p<.001 ^a Dyad-specific intercepts are not shown to improve readability. Besides, intercept is not shown since it is not comparable to the intercept of the first two models. For the “final” and “Empirical” model, intercept is the expected average strategic cooperation between the members of the 45th dyad.

As shown in Table 15, the result of the “Cross-classified Unconditional Means Model” shows that the grand mean strategic cooperation is 1.6151. In addition, the estimates of between-market variance (0.4976), between-dyad variance (0.7455) and within-dyad-market variance (0.5031) are significant at the $p<.001$ level, resulting in a total variance of 1.7462. These results point out that average strategic cooperation varies over time within the cross-classification of markets and dyads and that markets differ from one another and dyads differ from one another with respect to their level of cooperation. The intra-class correlation for the market level is $0.4976/1.7462=.285$ and the intra-class correlation for the dyad level is $0.7455/1.7462=.427$.

Therefore 28.5 % of the total variance is accounted for by markets and 42.7 % by dyads. In other words, while 28.5 % of total variation in strategic cooperation reflects mean strategic cooperation differences between markets, 42.7 % of the total variance reflects mean strategic cooperation differences between dyads. In addition, $0.5031/1.7462=28.8$ percent of the total variation in strategic cooperation is attributable to variation of strategic cooperation that is nested within the cross-classification of markets and dyads.

The second column of Table 15 shows the results of the “control” model that contains only the control variables. The results of this model indicate that all of the variables of this model, apart from tactical rivalry, are significant and the signs of the coefficient estimates are consistent with the arguments and predictions developed in Chapter Four for all variables except firm size. As argued in Chapter 4, tactical rivalry escalates the level of competition and thus has a negative impact on strategic cooperation, though its impact is not significant. Market concentration has a positive impact on strategic cooperation; a one unit increase in market concentration increases strategic cooperation by 11.88% at the $p<0.001$ level because market dominance by a handful of carriers makes it more effective to coordinate actions and signal cooperation, and facilitates the dominance of one member of a dyad over originations at both end points of city-pair market. The number of firms has a negative impact on cooperation; an additional firm reduces strategic cooperation by 0.31% at the $p<0.05$ level because an increase in the number of firms in a given market escalates the level of rivalry (Scherer and Ross, 1990). I pointed out the competing arguments for the impact of number of passengers in Chapter 4 and selected the argument that proposes a negative relationship. The “control” model shows that the number of passengers does have a negative impact on strategic cooperation. More specifically, an additional customer reduces strategic cooperation by 0.022 at the $p<0.001$ level. The primary

explanation for this result is that the observability of competitor prices and market share motivates carriers to cut prices to increase their market share when the level of demand is high. In the face of high demand for air travel, carriers know that the level of demand in the near future will be lower than its current level, especially due to the cyclical nature of industry. This in turn reduces the credibility of the threat of future punishment and motivates carriers to defect to maximize their current rate of return.

Hub economies have a positive impact on strategic cooperation as expected; a one unit increase in hub economies increases strategic cooperation by 6.24 % at the $p < 0.001$ level. Hub economies lead to economies of scope and thus reduce total cost. The relative reduction in total cost of a focal carrier vis-à-vis its rival in turn helps the focal carrier with the better cost structure to dominate the end points of a market, establishing the positive relationship between hub economies and strategic cooperation. Contrary to expectation, firm size has a negative impact on strategic cooperation; a one unit increase in firm size reduces strategic cooperation by 3.5 % at the $p < 0.001$ level. This suggests that superior cost structure and quality compared to a rival's are not sufficient to motivate the less capable rival to de-escalate rivalry. The less capable dyad member might be motivated to escalate its investments in the hubs of its rival to maintain its ability to launch counter-attacks. The observed negative sign might therefore be required by the dynamics of mutual forbearance, where carriers are expected to maintain footholds in their hubs and thus spheres of influence. Finally, in the "Control" model, "network effect" negatively influences strategic cooperation; a one unit increase in the "network effect" reduces strategic cooperation by 0.58 % at the $p < 0.001$ level.

The "Control" model provides a better fit than the "Cross-classified Unconditional Means" model. The values of the AIC (312420.7) and BIC (312398.7) statistics of the "Control"

model are considerably lower than the corresponding values of the AIC (349708.7) and BIC (349700.7) statistics of the “Cross-classified Unconditional Means” model. This attests that “Control” model is superior to the “Cross-classified Unconditional Means” model as far goodness-of-fit is concerned. In addition, the “Control” model explains approximately 20 % of the variation in the dependent variable as indicated by its Pseudo- $R_{y,\hat{y}}^2$ statistic. As explained previously, the Pseudo- $R_{y,\hat{y}}^2$ statistic should be interpreted with caution since most of the variation in the outcome variable is between-dyad variation (Singer and Willett, 2003). While markets account for 28.5 % of the total variance, dyads account for 42.7 % of the total variance in the outcome variable, a condition that requires a cautious interpretation of Pseudo- $R_{y,\hat{y}}^2$ statistic.

The “Final” model, which includes all of the independent variables and allows market and dyad-specific intercepts, is the next model in Table 15. The sign and significance of number of firms, number of passengers, hub economies and firm size are similar across the “Control” and “Final” models. These three variables are negative and significant at the $p < 0.001$ level in the “Final” model but only number of passengers and firm size are negative and significant at the $p < 0.001$ level in the “Control” model. In the “Final” model, a one unit increase in number of firms reduces strategic cooperation by 0.245 %; a one unit increase in the number of passengers reduces strategic cooperation by 0.024 %; a one unit increase in firm size reduces strategic cooperation by 0.93 %.

Nevertheless, there are also differences between the results of the “Control” and “Final” model. In the “Final” model, the sign of the tactical rivalry reverses and becomes positive and significant. A one unit increase in tactical rivalry increases strategic cooperation by 0.0012 %. In addition, the sign of market concentration becomes negative and non-significant in the “Final”

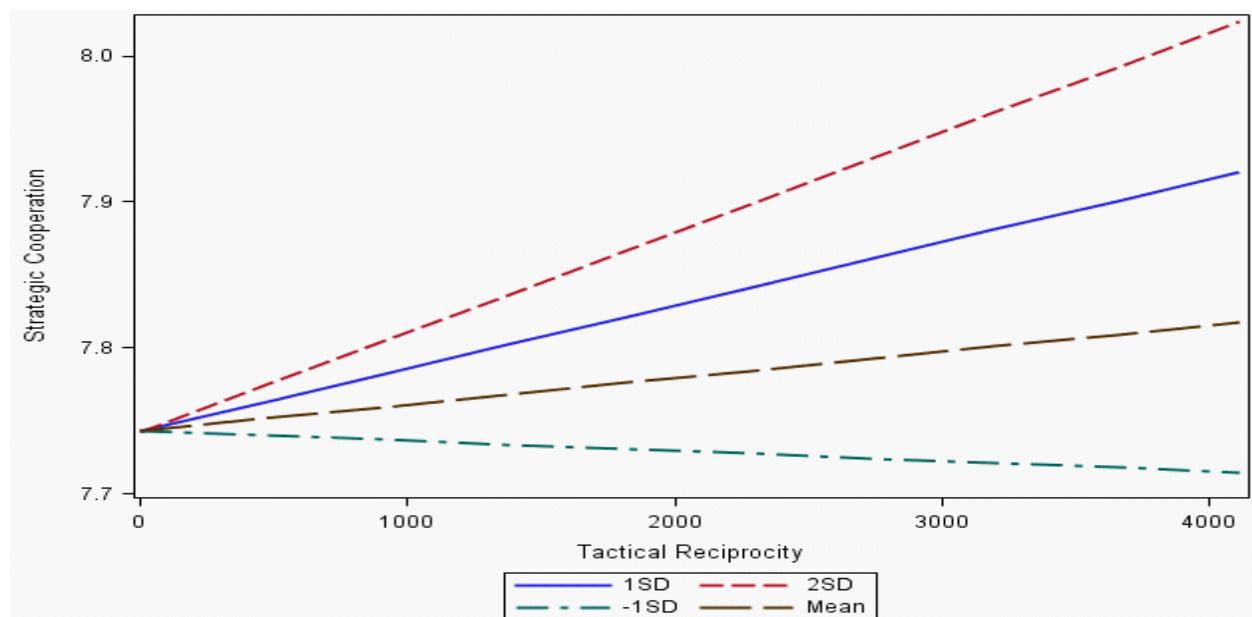
model. Finally, the sign of “network effect” becomes positive in the “Final” model; a one unit increase in “network effect” increases strategic cooperation by 0.159 %.

The first independent variable of the “Final” model is tactical reciprocity, which tests the second hypothesis. The significance and positive sign of the effect of this variable provides support for Hypothesis 2. A one unit increase in tactical reciprocity increases strategic cooperation by 0.0017 % at the $p < 0.001$ level when the value of “keyness” is equal to zero. When a pair of rivals responds to price increases with their own price increases, their cooperation at the strategic level intensifies. This is consistent with my argument that through price increases, members of a competitive dyad signal their commitment to cooperation and start to assign markets to another and enable the creation of spheres of influence.

There is also evidence to support Hypothesis 3; results show that the “keyness” of markets in which tactical cooperation is carried out positively moderates the relationship between tactical reciprocity and strategic cooperation at the $p < 0.01$ level. Although the impact of the “keyness” on strategic cooperation is negative and not significant, it amplifies the positive impact of tactical reciprocity on strategic cooperation as hypothesized. Signaling cooperation in key markets is much more conducive to strategic cooperation than signaling cooperation in non-key markets. For a one unit increase in the “keyness” of a market, the effect of tactical reciprocity increases strategic cooperation by 0.0023 %. Thus, for the markets with the highest value of “keyness”, 265.06914 in my data, tactical reciprocity is expected to increase the log of strategic cooperation by $0.000017 + 0.000023(265.06914) = 0.0061$. Figure 10 illustrates how “keyness” positively moderates the relationship between strategic cooperation and tactical reciprocity. The plot depicts the regression slopes of tactical cooperation at the mean level of “keyness” and minus 1 standard deviation and plus 1 and 2 standard deviations of the “keyness”

variable to facilitate interpretation. From Figure 10, it is clear that “keyness” is a positive moderator of the relationship between tactical reciprocity and strategic cooperation. As depicted by the dotted line, when rivals signal cooperation in markets whose level of “keyness” is one standard deviation below the mean value of “keyness”, the relationship between tactical reciprocity and strategic cooperation is negative. However as the level of “keyness” of a market, in which tactical cooperation takes place, increases, the slope not only becomes positive but also steeper, reinforcing the positive relationship between tactical reciprocity and strategic cooperation. Tactical reciprocity in markets whose “keyness” level is one standard deviation above the mean value of “keyness” transforms the negative slope into a positive one as shown by the solid line. The relationship between strategic cooperation and tactical reciprocity becomes much stronger as rival carriers respond to one another’s price increases with further price increases in markets whose level of “keyness” is two standard deviations above the mean value of “keyness” as depicted by the dotted line.

Figure 10: Two-way Interaction



Hypothesis 4 is not supported; the results contradict the expectation that tactical non-reciprocity intensifies rivalry and thus has a negative impact on strategic cooperation. The results indicate that a one unit increase in tactical non-reciprocity increases strategic cooperation by 0.0014 % at the $p < 0.001$ level. Thus, rather than impairing cooperation, defection appears to reinforce cooperation. To better understand this unexpected finding, I carried out a post hoc analysis to examine whether market “keyness” moderates this relationship as it does the relationship between tactical reciprocity and cooperation.

The results shows that tactical non-reciprocity increases strategic cooperation by 0.00085 percent at the $p < 0.05$ level for a one unit increase in the value of “keyness”. This finding suggests that the positive impact of tactical non-reciprocity on strategic cooperation strengthens as market keyness increases and provides further support for the argument that multi-market rivals support the defection of their rivals and escalate their commitment to cooperation even in the face of defection in markets where multi-market are not expected to tolerate defection.

Since the contribution of key markets to overall firm profitability is higher than that of peripheral markets (Gimeno, 1999), defection in key markets inflicts greater damage on cooperating firms than defection in peripheral markets. Thus, the fact that market keyness strengthens the positive impact of tactical non-reciprocity on strategic cooperation demonstrates that the more non-reciprocity hurts, the more multi-market rivals escalate their commitment to cooperation. Since multi-market firms escalate their commitment to cooperation as feedback becomes more negative, learning theory, which suggests that firms drop conduct that does not pay off (Cyert and March, 1963), may not explain how a pair of multi-market rivals moves towards MF equilibrium at the tactical level.

This finding is in line with empirical evidence that indicates that, in general, firms do not respond to aggression (Steenkamp et al., 2005; Leeflang and Wittink, 1992) and instead move towards cooperative equilibrium by supporting the defection of their rivals (Cason and Davis, 1995). This is especially true for multi-market firms in general and the airline industry in particular.

Other work has found that multi-market firms do not reduce their price to discipline defectors (Kang et al., 2010) and actually lower rather than increase their marketing expenditures as a response to the new product introduction moves of their rivals (Shankar, 1999). In addition, a group of studies conducted in the airline industry confirms the cooperative stance of carriers against market entry and undercutting and provides industry specific evidence for the “forgiveness” of carriers. Smith and Wilson (1995), for example, found that in general multi-market carriers do not respond to the entry of their multi-market rivals into their own markets and if they do respond, they increase rather than reduce their ticket prices. Similarly, carriers do not match the price cuts of their bankrupt rivals (Ciliberto and Schenone, 2010) and if they do, they respond with price increases (Borenstein and Rose, 1995).

The evidence shows that in general carriers prefer to ignore aggression and when they recognize aggression, they prefer to de-escalate rather than escalate rivalry. Although I do not find support for Hypothesis 4, the results are consistent with the empirical findings that postulate that carriers prefer to maintain cooperation in the face of defection and move towards cooperative equilibrium towards through cooperation. Sampled carriers respond to aggression and cooperation similarly in the sense that they prefer cooperation to punishment of defection to trigger and sustain cooperation since the magnitude of the impact of tactical reciprocity and tactical non-reciprocity on strategic cooperation is almost identical.

The finding that carriers prefer to cooperate with defecting rivals has important implications for the MF literature, which considers deterrence as the main mechanism to originate and sustain MF. Lack of punishment of defection at the tactical stage shows that rival carriers did not move to the MF equilibrium through the exercise of deterrence even though the sampling period and the sample itself meet all of the conditions required for the exercise of deterrence. In the U.S. domestic airline industry, carriers can establish spheres of influence due to their hub operations and exercise deterrence to protect them because markets are clearly defined and differ from one another with respect to growth rates and concentration levels. Also, the sampled carriers can coordinate their actions across markets and punish defection either in a focal or non-focal market because of their centralized decision making. Moreover, the studied firms can detect defection through their access to data bases that store competitive actions. Despite these conditions that are conducive to the exercise of deterrence in the U.S. scheduled airline industry, the results indicate that rival carriers did not exercise deterrence and punish defection at the tactical stage.

There are five factors that may motivate rival firms to prefer cooperation to competition in the face of non-reciprocity. First, it is costly to punish defection (Sorenson, 2007). Second, carriers may refrain from punishing defection because the act of punishment itself cannot unambiguously convey the desire to collude. It is difficult to differentiate the exercise of deterrence, which is an act of aggression that seeks to create collusion, from rivalry which is an act of aggression intended to out-compete rivals, and thus carriers may prefer to emit cooperative signals as a response to defection to reveal their commitment to cooperation.

Carriers' willingness to maintain cooperation in the face of defection may be due to their common identity, a third potential explanation for the preference for cooperation. It is likely that

the studied carriers established a strong group identity due to their common business model and history (Bluedorn and Denhardt, 1988), frequent and extended interaction across time and space (Trapido, 2007) and, the emergence of a common enemy during the study period. Studied carriers used the hub and spoke business model and interacted with one another across time and space during the study period. They also have similar historical experiences and thus constitute a cohort, which in turn creates a common identity (Bluedorn and Denhardt, 1988). Due to repeated interaction, common business model and history, it is likely that rival carriers developed an understanding that their preferences and values were similar, facilitating the formation of a common identity (Livengood and Reger, 2010; Peteraf and Shanley, 1997). In addition, the competition coming from the newly emerging low-cost carriers might have reinforced the common identity of sampled firms that follow a hub and spoke business model and led them to classify low-cost carriers that offer non-stop and no-frills flights as “them, the unserious and unfair actors” (Baldwin and Bengtsson, 2004). The resulting group identity in turn might have motivated the sampled firms to assess the reliability of other large carriers with whom they identify themselves through group norms rather than historical transactions (Peteraf and Shanley, 1997), providing the motive to cooperate even in the face of non-reciprocity.

A fourth explanation may be the size similarity of the sampled carriers (Mas-Ruiz and Ruiz-Moreno, 2011). Firms of similar size are reluctant to compete because they know that they cannot out-compete their rivals in an efficient and effective manner (Barney, 1991). Similarity of size implies similarity in the level of resources which in turn can deter rivals from escalating rivalry. Such reduction in the level of rivalry can explain the maintenance of cooperation even in the face of defection during the study period. A fifth explanation for why carriers tolerated defection and insisted on cooperation despite rivals’ defection may be because a tit-for-tat

strategy is not optimal for the airline industry given its cost structure and exit barriers. If a carrier punishes defection in the airline industry, this can trigger price warfare and can push ticket prices towards extremely low levels due to the cost structure of rivals. Fixed costs constitute an important portion of the overall costs of a carrier and the product that is offered, a seat, is a perishable item since it cannot be sold once a plane takes off. Moreover, the marginal cost of adding passengers to a flight is very low, approximately equal to the cost of a soft drink and a bag of peanuts on most flights and thus rival carriers can reduce their ticket prices till they are equal to the marginal cost of serving an additional passenger. The combination of high fixed costs with low marginal costs and the perishable nature of the product offered provide the incentive to chisel in the U.S. scheduled airline industry. For example, attempts by American Airlines to coordinate fares and collude on prices failed in both 1983 and 1992 due to the underlying cost structure of the industry that motivated defection (Pindyck and Rubinfeld, 2005) and eventually led to price warfare. Knowing that punishment of defection can trigger all-out-war due to the cost structure of the industry, carriers might have supported the defection of their rivals to signal their commitment to cooperation. This is especially true since carriers cannot exit the industry in the case of price wars to minimize their loss because of their contacts with labor unions and the industry specific nature of their resources, which cannot be effectively deployed in another industry.

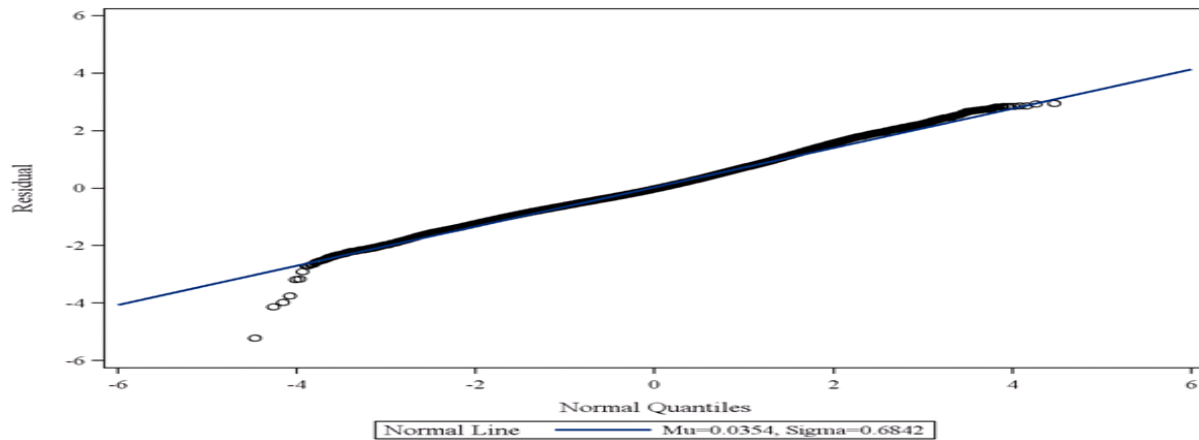
Since firms learn from and live in the past (Cyert and March, 1963; Greve, 2000), it seems that airlines seek to replace their competitive history with their rivals with a cooperative one and instill in their rivals past experiences replete with cooperative signals to motivate cooperation. Therefore, deterrence is not a viable force in the process of the formation of MF at the tactical stage of cooperation, although it starts the cooperative process by motivating at least

one of the members of a given dyad to trust the other member with its price increases. However once trust is formed, a pair of rivals moves to the MF equilibrium through cooperation rather than deterrence. The lack of support for the fourth hypothesis and the result of the post hoc analysis show that cooperation is the main causal driver of MF and is the main mechanism by which MF is formed. This finding addresses the call of researchers by revealing the relevance and importance of cooperation to the formation of MF (Baum and Korn, 1999; Kang et al., 2010; Korn and Baum, 1999) and reflects the validity of the limitations of the deterrence mechanism that I laid out in Chapter 2.

5.2.1 Robustness Check

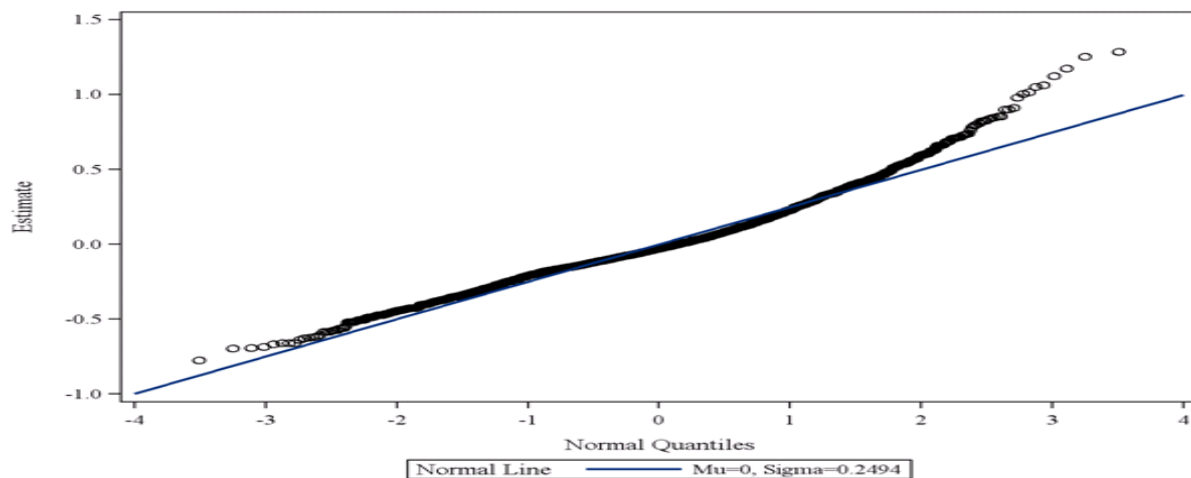
I checked whether the estimated model meets the assumptions of multi-level modeling. I first checked whether level-1 residuals are normally distributed. The results of the Kolmogorov-Smirnov ($p < 0.01$), Cramer-Von-Mises ($p < 0.005$) and Anderson Darling ($p < 0.005$) statistics are significant and thus there is statistical evidence to reject the claim that level-1 residuals are normally distributed. Since these tests are highly sensitive to departures from normality and cannot convey the nature and magnitude of the non-normality that is detected, I also visually examined the distribution of residuals. As depicted by the q-q plot of the level-1 residuals in Figure 11, level-1 residuals in general follow a normal distribution but there are some outliers. Because I checked the accuracy of data during the data collection stage, I do not have any reason to delete these outliers although the same data set without these outliers could result in stronger support for the hypotheses. Given the sample size and asymptotic properties of maximum likelihood estimation, I do not expect that this minor violation of normality will lead to incorrect inferences.

Figure 11: Q-Q Plot of Level-1 Residuals



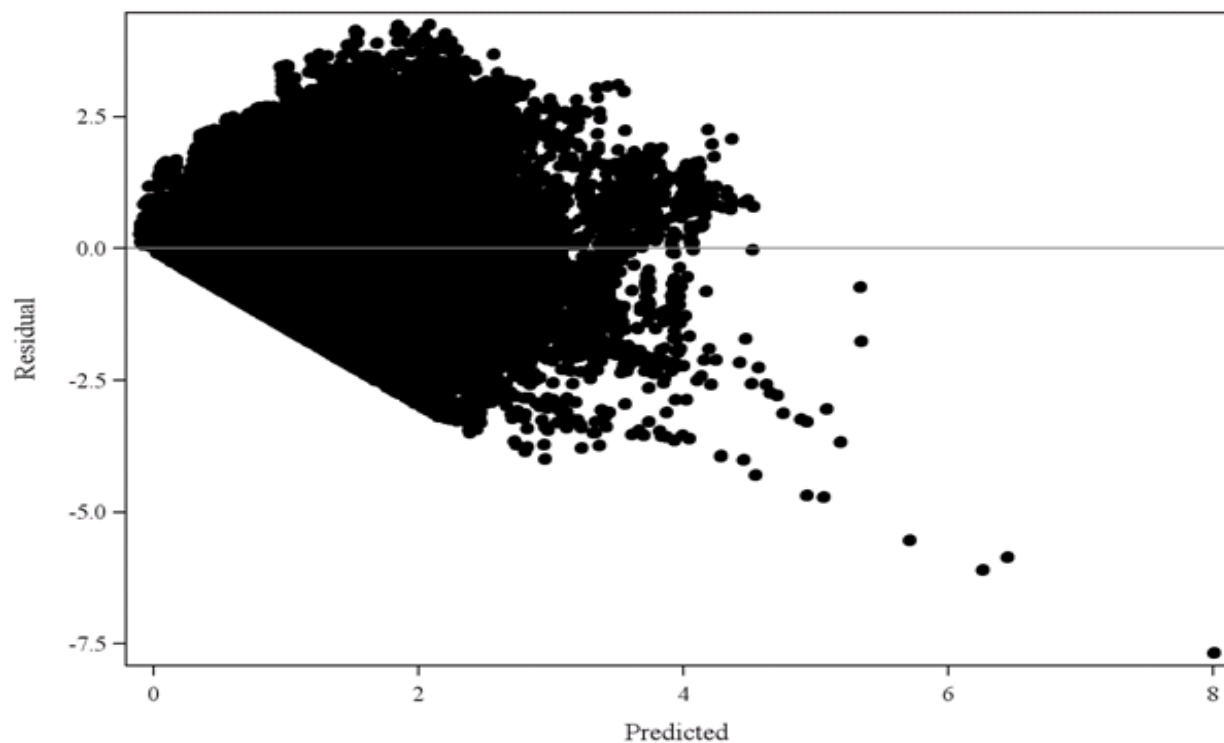
I also analyzed whether level-2 residuals are normally distributed. Once more, the Kolmogorov-Smirnov ($p < 0.01$), Cramer-Von-Mises ($p < 0.005$) and Anderson Darling ($p < 0.005$) statistics are significant and thus provide statistical evidence that the data distribution is non-normal. The graphical examination of the distribution of the level-2 residuals portrayed in Figure 12 illustrates that the distribution of level-2 residuals is slightly skewed to the right. The nature and magnitude of normality in the level-2 residuals as depicted by Figure 12 is not expected to bias results due to the large number of observations (2785) and the large sample properties of maximum likelihood estimation (Singer and Willett, 2003).

Figure 12: Q-Q Plot of Level-2 Residuals



The estimated model violates the homoscedasticity assumption as depicted in Figure 13. Figure 13 illustrates that the residuals do not have constant variance across the prediction space. Heteroscedasticity can bias the standard errors of the estimates and test statistics and thus can impair inference. To correct the standard errors and test statistics involving the fixed-effects parameters, I used the “sandwich” estimator. Since this estimator corrects standard errors, it also solves inference related problems that can derive from the violation of normality (Hox, 2010), though I do not expect such a violation to lead to incorrect inferences given its nature and magnitude, large sample size and the estimation method used.

Figure 13: Standardized Conditional Level-1 Residuals



The results of the model with robust standard errors, which is called “Empirical”, are provided in the last column of Table 15. The results of this model are identical to the model with asymptotic standard errors with two exceptions. The significance of the fixed effect of “firm

size” reduced to $p < .01$ from $p < .001$ and the significance of the impact of the interaction of tactical reciprocity with “keyness” reduced to $p < .05$ from $p < .01$. Hence the “sandwich” estimator reduces the statistical significance of only two terms and does not change the conclusions and statistical inferences about Hypotheses 2, 3 and 4.

5.3 Model 3

I estimated the third model with cross-classified random effects model to correctly reflect the structure of the data, which does not have an unequivocal hierarchy of observations nested within dyads nested within markets. In the data set, observations are nested within the cross-classification of markets and dyads since observations from a given dyad pertain to many markets and observations from a given market belong to many dyads. Due to the cross-classified data structure, both markets and dyads have an impact on strategic cooperation. Therefore, I model both markets and dyads as sources of variation in strategic cooperation, but in such a manner that observations are nested within markets and dyads, with markets and dyads crossed.

Table 16 provides the correlation and descriptive statistics of both control and theoretical variables. The level of the significance of correlations is indicated in parenthesis. I scaled number of passengers and keyness variables by dividing them by one thousand. Besides, I took the log of the dependent variable to normalize the distribution of the residuals.

Table 16: Descriptive Statistics and Correlations of Model 3

Variable	Mean	S.D	1	2	3	4	5	6	7	8	9	10
1- Mutual Forbearance	2.99375	2.46363										
2- Strategic Withdrawal	0.0003507	0.00104	0.10796 (<.0001)									
3- Market Concentration	0.58431	0.22935	0.20174 (<.0001)	-0.00041 (0.8729)								
4- Number of Firms	5.79869	2.40692	0.03183 (<.0001)	0.00539 (0.0353)	-0.42423 (<.0001)							
5- Number of Passengers	166.31562	275.8937	0.10628 (<.0001)	0.06684 (<.0001)	-0.30883 (<.0001)	0.48087 (<.0001)						
6- Firm Size	2.15331	1.27758	-0.03712 (<.0001)	0.12999 (<.0001)	-0.02570 (<.0001)	0.03643 (<.0001)	0.03017 (<.0001)					
7- Hub economies	4.85068	6.81620	0.42465 (<.0001)	0.07469 (<.0001)	0.20300 (<.0001)	-0.13757 (<.0001)	-0.02839 (<.0001)	0.10415 (<.0001)				
8- Network Effect	491.35496	3211	0.08848 (<.0001)	0.01362 (<.0001)	-0.02951 (<.0001)	0.08906 (<.0001)	0.13817 (<.0001)	-0.00196 (0.4438)	0.01377 (<.0001)			
9- Strategic Reciprocity	0.0005497	0.00139	0.13526 (<.0001)	-0.13239 (<.0001)	-0.00730 (0.0044)	0.01007 (<.0001)	0.09808 (<.0001)	0.17170 (<.0001)	0.10420 (<.0001)	0.02492 (<.0001)		
10- Strategic Non-Reciprocity	0.0003332	0.00104	0.13698 (<.0001)	-0.10744 (<.0001)	0.01345 (<.0001)	-0.00058 (0.8209)	0.06476 (<.0001)	0.08042 (<.0001)	0.10602 (<.0001)	0.01353 (<.0001)	-0.12606 (<.0001)	
11- Keynes	0.43495	9.15986	0.09591 (<.0001)	0.01999 (<.0001)	-0.00047 (0.8539)	0.00422 (0.0995)	0.02873 (<.0001)	0.00107 (0.6754)	0.02126 (<.0001)	0.01188 (<.0001)	0.04973 (<.0001)	0.02172 (<.0001)

As I discussed in section 4, I compared the goodness-of-fit of the “Cross-classified Unconditional Means” model that allows intercepts to vary across not only markets and dyads with that of the “Unconditional Means” model that permits only the intercepts to vary across dyads. The result of the comparison indicates that the difference in the deviance statistics of these two alternative models that force all variance to reside in the residuals is $(712804.1 - 683198.9) = 296052$ with $(3-2) = 1$ DF and is statistically significant. This indicates that modeling observations as nested in the cross-classification of markets and dyads provides a better fit than modeling them as nested in dyads. In light of this evidence, I used the cross-classified random effects model to build the four competing models that contain identical fixed-effects but alternative stochastic components.

I estimated these four alternative models with restricted maximum likelihood estimation in order to be able to report unbiased estimates and compare their deviance statistics with the LR tests. The algorithms of all of the models converged. Table 17 indicates the random variables, covariance structures for between-subject random effects, deviance statistics, AIC and BIC statistics and number of covariance parameters of these four alternative models. As it can be seen from the identity of the random variables of each and every model, models are nested within one another, enabling LR tests.

Table 17: Models with Alternative Between-Subject Random Effects Covariance Structures

Model Number	Random Variables	Covariance Structure	Deviance Statistic	AIC Statistic	BIC Statistic	Number of Covariance Parameters
1	<ul style="list-style-type: none"> Intercept/Dyad Intercept/Market 	UN(1)	631179.4	631185.4	631179.4	3
2	<ul style="list-style-type: none"> Intercept/Dyad Intercept/Market Strategic Reciprocity 	UN(1)	628813.7	628821.7	628813.7	4

3	<ul style="list-style-type: none"> • Intercept/Dyad • Intercept/Market • Strategic Reciprocity • Strategic Non-Reciprocity 	UN(1)	626250.5	626260.5	626250.5	5
4	<ul style="list-style-type: none"> • Intercept/Dyad • Intercept/Market • Strategic Reciprocity • Strategic Non-Reciprocity • Interaction 	UN(1)	624289.9	624301.9	624289.9	6

The results of the LR tests carried out to select the “best” covariance structure for between-subject random effects indicate that Model 4 provides the “best” fit of all of the alternative models estimated. Table 18 provides the number of nested models whose goodness-of-fitness is compared, the difference in their deviance statistics and their degrees of freedom, the statistical significance of the LR tests conducted and, finally, the model that is selected. Model 2 provides a better fit than Model 1 because the corresponding delta deviance, which is 2365.7, with 1 DF, is significant. The significant delta deviance provides evidence to reject the null hypothesis that variance of “strategic reciprocity” is equal to zero. Model 3, in turn, provides a better fit than Model 2 because the delta deviance of these models, which is 2563.2 with 1 DF, is statistically significant. The significance of the difference of their deviance statistics provides evidence to reject the null hypothesis that the variance of “strategic non-reciprocity” is equal to zero. Therefore I do not have any empirical and theoretical reason to constrain the slope of this variable to be equal across dyads. Finally, Model 4 provides a better fit than Model 3 because the difference in their deviance statistics, which is 1960.6 with $(3-2) = 1$ DF, is statistically significant, demonstrating that the variance of the interaction of “strategic reciprocity” with “keyness” is not equal to zero. Therefore I selected Model 4 as the model with the “best” covariance structure for between-subject random effects. I model market-specific intercept,

dyad-specific intercept, “strategic reciprocity”, “strategic non-reciprocity” and the interaction of “strategic reciprocity” with “keyness” as random effects.

Table 18: Comparison of Nested Models

Models Compared	ΔD	ΔDF	Significance	Selected Model
1 versus 2	2365.7	1	Yes	2
2 versus 3	2563.2	1	Yes	3
3 versus 4	1960.6	1	Yes	4

I provide the level-1 and level-2 equations of Model 4 below. In the level-1 equation, $Y_{i(jk)}$ represents the mutual forbearance score of observation i nested within the cross-classification of dyad j and market k . The subscripts (jk) are written in parentheses to show that they conceptually exist at the same level that is the (jk) th dyad and market combination in the cross-classifications of dyads and market.

The level-1 equation of the model 4 is:

$$Y_{i(jk)} = \beta_{0(jk)} + \beta_{1(jk)} \text{Strategic_Withdrawal}_{ij} + \beta_{2(jk)} \text{Market_Concentration}_{ij} + \beta_{3(jk)} \text{Number_of_Firms}_{ij} + \beta_{4(jk)} \text{Number_of_Passengers}_{ij} + \beta_{5(jk)} \text{Hub_Economies}_{ij} + \beta_{6(jk)} \text{Firm_Size}_{ij} + \beta_{7(jk)} \text{Network_Effect}_{ij} + \beta_{8(jk)} \text{Strategic_Reciprocity}_{ij} + \beta_{9(jk)} \text{Strategic_Nonreciprocity}_{ij} + \beta_{10(jk)} \text{Keyness}_{ij} + \beta_{11(jk)} \text{Strategic_Reciprocity}_{ij} * \text{Keyness}_{ij} + r_{i(jk)}$$

The level-2 equations of the model 4 are:

$$\beta_{0(jk)} = \gamma_{00} + \mu_{0j} + \nu_{0k}$$

$$\beta_{1(jk)} = \gamma_{10}$$

$$\beta_{2(jk)} = \gamma_{20}$$

$$\beta_{3(jk)} = \gamma_{30}$$

$$\beta_{4(jk)} = \gamma_{40}$$

$$\beta_{5(jk)} = \gamma_{50}$$

$$\beta_{6(jk)} = \gamma_{60}$$

$$\beta_{7(jk)} = \gamma_{70}$$

$$\beta_{8(jk)} = \gamma_{80} + \mu_{8j}$$

$$\beta_{9(jk)} = \gamma_{90} + \mu_{9j}$$

$$\beta_{10(jk)} = \gamma_{10}$$

$$\beta_{11(jk)} = \gamma_{11} + \mu_{11j}$$

$$\text{where } r_{i(jk)} \sim N(0, \sigma^2) \text{ and } \begin{pmatrix} \mu_{0j} \\ v_{0k} \\ \mu_{8j} \\ \mu_{9j} \\ \mu_{11j} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & 0 & 0 & 0 & 0 \\ 0 & \tau_{11} & 0 & 0 & 0 \\ 0 & 0 & \tau_{22} & 0 & 0 \\ 0 & 0 & 0 & \tau_{33} & 0 \\ 0 & 0 & 0 & 0 & \tau_{44} \end{pmatrix} \right]$$

Following the selection of Model 4, I modeled the dependence of level-1 residuals through three alternative different covariance structures, VC, CS and AR (1), and chose the AR (1) covariance structure to model within-subject random error. To reduce the processing time and memory requirements of these models, I used several different procedures and options available in SAS. I initially estimated the model with the AR (1) covariance structure through the HPMIXED procedure of SAS because this procedure is not only designed to overcome the estimation problems that I can face due to the large number of random effects and observations but it also supports the AR (1) covariance structure that I am interested in. After completing the HPMIXED procedure, I passed the covariance parameter estimates of this procedure to PROC MIXED to carry out additional analyses that PROC HPMIXED is not capable of and accelerate the subsequent analysis. The algorithms of all of the estimated models converged and thus I

evaluated their relative goodness of fit to select the best model. The comparison of the goodness-of-fit of the VC covariance structure with that of the CS covariance structure indicated that the latter covariance structure is superior to the former due to the difference in their deviance statistic, which is equal to $(624289.9 - 519857.3) = 104432.6$ with 1 DF, and is statistically significant. Following this, I compared the fitness of the CS covariance structure with AR (1) covariance structure and selected the AR (1) covariance structure as the “best” covariance structure because the values of the AIC (498467) and BIC (498453) statistics of the model with the AR (1) covariance structure are considerably lower than the values of the corresponding AIC (519871.3) and BIC (519857.3) statistics of the CS covariance structure. Therefore, I modeled the correlation of level-1 residuals with the AR (1) covariance structure and selected this model as the “Final” model to test Hypotheses 5, 6 and 7.

The cross-classified random effect model is a real resource hog and created estimation problems. First, the data set has 158,831 observations and thus requires extensive memory and processing power not only to run the analysis, but also to produce the supplementary tables used to carry out diagnostics. Second, I process the data by two different kinds of subjects because I simultaneously investigate two different subjects, markets and dyads. This in turn impairs the efficiency of the estimation logarithm, which is based on an iterative procedure. Third, the number of subjects is substantively high with 2803 markets and 45 dyads. In addition to examining too many random effects, the model contains 12 fixed effects. Finally, the analysis examines the dependence of observations that come from the same dyads with the AR (1) covariance structure, which contains two parameters, up to 32 time periods. Due to the complexity of the model, its algorithm is likely to stop due to too many likelihood evaluations, infinite likelihood or required resource limitations that might preventing the production of the

results within the maximum number of days that a program is allowed to run on the server used to conduct the analysis.

I took several steps to overcome these problems and improve the efficiency and performance of the estimation (Kiernan et al., 2012). First, I made several changes to my running environment which is UNIX. I tested several memory and CPU combinations to understand whether the model is memory or CPU intensive. After several attempts, I discovered that the estimation is resource intensive and increased the size of the memory to the allowed maximum, which in turn reduced the number of jobs that I could run in the batch mode. As usual, I ran the analysis in the batch mode to improve efficiency. In addition, I used several options available in SAS PROC MIXED that speed the processing of data and reduce the level of memory and CPU utilized. I also scaled variables such as number of passengers and “keyness” by dividing them by one thousand to reduce processing time. Finally, I used an alternative procedure, PROC HPMIXED, to speed the estimation of the “Final” model. PROC HPMIXED is designed to examine complex models, such as the present model, to estimate the covariance parameters. Once I attained these estimates, I passed them to PROC MIXED to accelerate the estimation and for further analyses that are not available in PROC HPMIXED. When I passed on these estimates to PROC MIXED, I used one subject rather than two as I did with the second model. This time, I modeled markets as fixed-effects through using dummy variables in the fixed component of the model although there are more markets than there are dyads. Since the “Final” model allows strategic reciprocity, strategic non-reciprocity and the interaction of strategic reciprocity with “keyness” to vary across dyads. I was compelled to model markets rather than dyads as fixed-effects. I used one subject rather than two so that I can request PROC MIXED to process the observations by subjects, which reduces resource requirements, and generates robust standard

errors, especially when the outcome of diagnostics invalidate asymptotic standard errors. I used the “noprofile” and “noiter” options to improve efficiency.

Table 19 displays the results of four models that are estimated to investigate Hypotheses 5, 6 and 7. The first model is the “Cross-classified Unconditional Means” model that partitions the variance in the outcome variable into its components. The second model is the “Control” model that contains only the control variables. The third model is the “Final” model that includes both the control variables and theoretical variables. Finally, the last model is the “Empirical” model that provides robust standard errors rather than asymptotic random errors. I estimated all of these models with restricted maximum likelihood estimation and provided their goodness-of-fit statistics in Table 17. However since these models have different fixed components, the comparison of the fitness of these models must be based on full maximum likelihood estimation. I therefore provide the maximum likelihood estimates of deviance, AIC and BIC statistics of these models, which are denoted by (ML), in Table 19. Moreover, in Table 19, the estimates of standard errors are provided below the relevant coefficient estimates and are in parentheses.

Table 19: Results of the Third Model

	Unconditional Cross-classified Means Model	Control Model	Final Model^b	Empirical Model^b
Response	Mutual Forbearance	Mutual Forbearance	Mutual Forbearance	Mutual Forbearance
Fixed Part				
Intercept	2.6050*** (0.08123)	-0.5861*** (0.1037)		
Control Variables				

Strategic Withdrawal		148.64*** (5.1354)	429.97*** (9.0638)	429.97*** (53.9115)
Market Concentration		2.4330*** (0.04387)	2.7390*** (0.03494)	2.7390*** (0.1408)
Number of Firms		0.09432*** (0.004876)	0.05066*** (0.003080)	0.05066*** (0.005034)
Number of passengers/1000		0.002003*** (0.000102)	0.000505*** (0.000078)	0.000505*** (0.000099)
Firm Size		0.01920 (0.01625)	-0.05138*** (0.01367)	-0.05138* (0.02159)
Hub Economies		0.1622*** (0.000927)	0.1135*** (0.001652)	0.1135*** (0.008725)
Network Effect		0.000032*** (1.656E-6)	0.000022 (0)	0.000022*** (2.859E-6)
Independent Variables				
Strategic Reciprocity			419.82*** (54.1684)	419.82*** (52.2392)
Strategic Non-Reciprocity			427.27*** (52.0809)	427.27*** (52.7250)
Keyness/1000			0.01639*** (0.000690)	0.01639*** (0.004893)
Strategic Reciprocity*Keyness/1000			31.7368~ (17.5354)	31.7368*** (8.7023)
Random Part				
Intercept/Dyad	0.2347*** (0.05606)	0.3144*** (0.07524)	1.0010*** (0.2553)	1.0010*** (0.2553)
Intercept/Market	2.3710***	1.0983***		

	(0.08155)	(0.04233)		
Strategic Reciprocity			128340*** (0)	128340*** (0)
Strategic Non-Reciprocity			118185*** (0)	118185*** (0)
Strategic Reciprocity*Keyness			13032*** (0)	13032*** (0)
Level: Time				
Intercept/intercept	4.7190*** (0.01714)	3.8229*** (0.01390)	3.8120*** (0.02473)	3.8120*** (0.02473)
AR(1)			0.8435 (0.001124)	0.8435 (0.001124)
Pseudo-R² Statistics and Goodness-of-fit				
Deviance (ML)	683195.7	648683.6	493090.1	493090.1
AIC (ML)	683203.7	648705.6	498640.1	498640.1
BIC (ML)	683195.7	648683.6	503653.6	503653.6

~ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$ ^b Market specific intercepts are not shown to improve readability and intercept is not shown since it is not comparable to the intercept of the first two models.

The first column of Table 19 displays the results of the “Unconditional Cross-classified Means Model” that partitions the variance in the dependent variable into its constituents. According to the results, the grand mean mutual forbearance is 2.6050 and is statistically significant at the $p < .001$ level. In addition, the estimates of between-market variance (2.3710), between-dyad variance (0.2347) and within-dyad-market variance (4.7190) are statistically significant at the $p < .001$ level, resulting in a total variance of 7.3247. These statistical findings indicate that average mutual forbearance varies over time within the cross-classification of markets and dyads and that markets differ from one another and dyads differ from one another as

far the level of mutual forbearance is concerned. The intra-class correlation for market is $2.3710/7.3247=.324$ and the intra-class correlation for dyad is $0.2347/7.3247=.032$. This means that markets and dyads account for 32.4 % and 3.2 % of the total variance in the outcome variable, respectively. In other words, while 32.4 % of total variance in mutual forbearance reflects mean mutual forbearance differences between markets, 3.2 % of the total variance reflects mean mutual forbearance differences between dyads. In addition, $64.4(4.7190/7.3247=0.644)$ percent of the total variation in mutual forbearance is attributable to variance of observations nested within the cross-classification of markets and dyads across time.

The second column of Table 19 contains the findings of the “Control” model that includes only the control variables. This model is superior to the “Unconditional Cross-classified Unconditional Means” model as indicated by the values of its AIC and BIC statistics, which are lower than those of the “Unconditional Cross-classified Unconditional Means” model. As can be seen from the table, strategic withdrawal has a positive and significant impact on the log of mutual forbearance at the $p<.001$ level. I used this variable to control for the alternative explanation that observed mutual forbearance and de-escalation of rivalry in a focal market might be due to the simultaneous withdrawal of a pair of rivals from the focal market rather than their intentional desire to partition the airline industry. As expected, market concentration has a positive and significant impact on mutual forbearance at the $p<.001$ level. A one unit increase in the Herfindahl–Hirschman Index increases mutual forbearance by 1039.3%. Market concentration and the resulting reduction in the number of firms can facilitate the signing off on tacit super-ordination and subordination agreements between a pair of rivals. An increase in the concentration level makes it much more effective and efficient to send signals and form a shared

understanding between a pair of rivals which in turn can be deployed to reciprocally assign markets to one another.

Contrary to expectations, number of firms has a positive and significant impact on mutual forbearance at the $p < .001$ level; the entry of a carrier into the focal market increases mutual forbearance by 9.89%. Number of passengers influences mutual forbearance positively and significantly at the $p < .001$ level although I argued in Chapter 4 for a negative relationship. An additional passenger increases the mutual forbearance between a pair of rivals by 0.2%. The positive relationship suggests that an increase in the level of demand for air travel augments the market share differences between a pair of rivals. Firm size has a positive impact on mutual forbearance, in line with expectations but its impact is not significant. The positive but non-significant impact of firm size may be due its positive influence on the cost and quality differences between a pair of rivals. The resulting divergence in cost and quality can augment the market share differences of a pair of rivals serving a given city-pair market and thus increase the observed level of mutual forbearance between them.

As expected, hub economies significantly contribute to mutual forbearance; a one unit increase in hub economies increases mutual forbearance by 17.6 % at the $p < .001$ level as expected. Network effect, which controls for the dependence of observations coming from dyads with common members, has a positive and significant effect on mutual forbearance; a one unit increase in the network effect increases the mutual forbearance between a pair of rivals by 0.32% at the $p < .001$ level. This suggests that the tendency of the members of the focal dyad to be cooperative is reflected by the other dyads to which they belong.

The next column in Table 19 contains the results of the “Final” model that was selected to test Hypotheses 5, 6 and 7. The standard errors of the variance estimates of the “Final” model for strategic reciprocity, strategic non-reciprocity and the interaction term are zero. This is not problematic due to three reasons.

First, I already tested the significance of the estimates of variance components in the process of comparing the goodness-of-fit of the models, which differ from one another only in terms of their stochastic components, by using the chi-square-based likelihood ratio tests and thus do not need to know their standard errors. To reiterate, I initially selected the “Final” model’s covariance structure for between-subject random effects by using the UN (1) covariance structure and the LR tests. The UN (1) covariance structure allowed me to investigate the significance of each of the covariance parameters individually by performing chi-square tests on the difference of the deviance of two nested models. The results of these tests revealed that the covariance structure for between-subject random effects of Model 4 provided the “best” fit. Following this, I performed a chi-square test on the difference of the deviance of two nested models with alternative covariance structures for within-subject random errors and selected the model with the CS covariance structure over the model with the VC covariance structure because of the resulting significant chi-square test. Finally, I used information criteria to compare the fit of the CV covariance structure to that of the AR (1) covariance structure and selected the AR (1) covariance structure since the values of the AIC and BIC statistics of the model with the AR (1) covariance structure were lower, by 21404.3, than the corresponding values of the AIC and BIC statistics of the model with the CV covariance structure. This difference is immense because a difference of 10 is sufficient to be considered a “very strong” evidence (Singer and Willett, 2003) of the superior fit of the AR (1) covariance structure, and clearly shows that the two

parameters of the AR (1) covariance structure are significant. Since I tested the goodness-of-fit of the models that differed from one another only in terms of their stochastic components via LR tests, I already tested the significance of the estimates of the variance components in the process of selecting the “best” model and thus do not need to know the estimates of the corresponding standard errors.

The second reason that standard errors of zero are not a problem is that the LR tests that I carried out to investigate the significance of the estimates of the variance components are superior to the alternative Wald test, which requires the estimates of the standard error of the variance components to determine whether estimates of covariance parameters are significant. SAS investigates the significance of the estimates of the variance components through the Wald test and provides Wald Z statistic. This test uses the estimate of the variance components and the corresponding standard errors to produce the Wald Z statistic, which is then compared with the standard normal distribution to determine whether the covariance parameter estimates are significant. However such comparison is problematic because the variance components do not have normal distributions; they have bounded and skewed distributions. Thus hypotheses about variances can be tested via a chi-square test. That is why this statistic is not reliable and inferior to chi-square tests (Hox, 2010; Singer and Willett, 2003). Due to these two statistical reasons, covariance parameter estimates of strategic-reciprocity, strategic non-reciprocity and the interaction term are significant at the $p < .001$ level and are displayed as such in Table 19.

Third, I am not so much interested in the statistical significance of the estimates of the covariance parameters as I am in the reliability of the estimates of the fixed effects used to test the various hypotheses. Modeling the data generation process as accurately as possible is essential to improving the efficiency of the estimates of fixed effects that I am interested in.

The first seven variables of the “Final” model, which is superior to the “Control” model as indicated by its smaller AIC and BIC statistics, control for and rule out alternative explanations that might stem from supply and demand side effects. The sign and significance of the control variables are identical between the “Control” and “Final” models with the exception of the “firm size” variable whose effect becomes not only significant but also negative in the “Final” model. In the “Final” model, all of the control variables are significant at the $p < .001$ level.

Strategic withdrawal, the first control variable in the “Final” model, seeks to rule out the alternative explanation that the observed MF between a pair of rivals is due to their withdrawal from a given market. According to the results, strategic withdrawal increases the log of mutual forbearance by 429.97. This suggests that a pair of rivals disproportionately reduces the amount of their investment to transform one end-point of a market into a hub and thus withdraw from a market at different rates. This in turn increases the difference between their market shares, leading to a positive impact of strategic withdrawal on mutual forbearance.

The second control variable of the “Final” model is market concentration, which controls for the level of competition. As expected, a one unit increase in market concentration increases mutual forbearance by 1447.15 %. The primary explanation for this result is that reduction in the level of competition facilitates cooperation between a pair of rivals by increasing the effectiveness and efficiency of signaling and reducing the competitive threat coming from other carriers that might disrupt the tacit agreements that are reached between the pair. For example American Airlines, which is known for its failed attempts to establish collusion in the U.S. domestic airline industry, attempted to fix prices in 1983, but this scheme was not successful due to the defection of Pan Am, who started a price war. On February 21, 1982, Robert Crandall,

who was president and CEO of American Airlines, called Howard Putnam, president and CEO of rival company, Braniff Airways, and proposed to fix prices and put an end to the fare warfare between their companies (Pindyck and Rubinfeld, 2005). However this attempt failed as this call was recorded and brought to the attention of anti-trust authorities. One year later, Robert Crandall made another step to establish collusion and proposed a uniform fare schedule based on mileage to fix prices. Initially, American Airlines was able to reach an agreement with TWA and Continental airlines. However Pan Am, unsatisfied with its market share, dropped its price. This in turn broke up the tacit agreements reached between major carriers and started a price war.

The third control variable of the “Final” model is the number of firms, which partials out the impact of increased competition on the theorized relationships. Contrary to expectations, number of firms has a positive impact on MF; the entry of an additional carrier into a given market increases mutual forbearance between a pair of rivals by 5.196 %. This unexpected effect may be due to five factors. First, as shown by prior empirical studies (Prince and Simon, 2009) and the settlement that was reached between the Department of Justice and 8 members of the sample that prohibited them from linking different fares with special codes and pre-announcing price increases (Borenstein, 2004), sampled carriers are experienced mutual forbearers that possess a shared understanding that entry into one another’s markets is an essential component of a purposeful MF strategy that calls for mutual footholds. This especially the case since the positive impact of the “number of firms” on mutual forbearance is only observed for carriers that cooperate at the strategic level and that are only one step away from establishing MF. The same variable has a negative impact on strategic cooperation in Model 2, which investigates the process of tactical cooperation.

The change in the sign of the number of firms variable might be due to the implementation of the lessons learned from the tactical cooperation phase. The model developed in this dissertation theorizes two types of learning outcomes from tactical cooperation. At the tactical level, carriers in general tend to be cooperative, as suggested by the findings of the second model. Through their repeated interaction across time and space, carriers are expected to learn from the cooperative moves of their rivals. The repeated cooperative attempts across time and space to establish MF provided many opportunities to learn how to carry out MF strategy (Feinberg and Sherman, 1988; Scott, 1991) effectively and efficiently and refine it. It may be that carriers developed a common understanding of the requirements of MF strategy and understood that they need to establish footholds in each other's markets in the course of their interaction. That is why, sampled carriers that cooperated at the strategic level were more likely to interpret an increase in the number of firms in a given market as an integral part of an intentional MF strategy than were carriers that cooperated only at the tactical level and thus were more likely to refrain from escalating the level of rivalry.

A second learning outcome from tactical cooperation that might explain the positive relationship between number of firms and MF is that the increase in the number of firms in a given market increases the likelihood of detecting defection and thus its punishment which in turn might reinforce cooperation (Greve, 2008). Another possibility may be tied to the sample which excludes carriers that have a single contact with a given carrier, referred to as single-market rivals. Empirical results indicate that single-market firms are aggressive and can disrupt cooperative arrangements between multi-market firms since single-market firms' aggression in the market of a rival cannot be immediately punished in their non-focal markets (Haveman and

Nonnemaker, 2000). The absence of such firms in the sample can explain why the increase in the number of firms, and thus entry, does not increase the level of competition.

A fourth explanation for the observed positive relationship between number of firms and mutual forbearance could be due to blocking of potential competition. By entering into each other's markets, sampled carriers can make it much more difficult for other firms to enter to a given market, escalate the level of rivalry and break up the cooperative arrangements that they have established. Finally, I think the contribution of the increase in competition to the mutual forbearance observed between a pair of rivals could be due to the differential impact of the resulting increase in competition on a pair of rivals that have varying levels of commitment to the focal market, which in turn determine the depth of market-specific capabilities. Escalation of rivalry might impose more harm on the less capable and committed member of a dyad than it might on the more capable and committed member due to differences in their ability to ward off competitive threats. This in turn can increase the difference in their market shares. Further, escalation of competition for the same passengers and resources can hone and develop the current capabilities of the more committed member of a dyad at a rate that is higher than the less capable member. This in turn can enable the more committed and capable member of a given dyad in a given market to increase its market share at the expense of the less capable member, which does not willingly assign the focal market to its more committed and capable dyad member.

Number of passengers also has a positive impact on cooperation and thus an increase in the level of demand contributes to MF. More specifically, one additional customer increases mutual forbearance by 0.05 %. This might be due to the preferences of passengers to fly with the dyad member that already has the higher market share in the focal city-pair market due to its

market specific investments. The observed positive relationship between number of passengers and mutual forbearance contradicts my prediction in Chapter 4.

In Chapter 4, I argued that demand level can either escalate or de-escalate the level of competition and opted for its rivalry escalating impact since competitor prices and market shares are observable in the U.S. domestic passenger airline industry due to the availability of databases that store competitive action data (Sudhir et al., 2005). However the result supports the alternative impact and explanation. It seems that an increase in the number of passengers, and thus level of aggregate demand for air travel, does not encourage cooperating rivals to defect at the strategic level to gain short-term profits, despite the cyclical nature of the industry that impairs the deterrence of future punishment and observability of prices and market shares of rivals that motivates rivalry. As the level of aggregate demand increases, carriers do not fight for market share at the expense of their rivals. Rather, they assign markets to one another.

In addition, the change in the sign of the effect of “number of passengers” from negative in the second model to positive in the third model not only captures the dual and opposing impact of this variable on competition but also underscores the changing impact of the level of demand on cooperation across stages of cooperation. Similar to the “number of firms” whose effect switches from being negative in the case of tactical cooperation to being positive in the case of strategic cooperation, “number of passengers” escalates competition during tactical cooperation but de-escalates it during strategic cooperation. The identical sign reversal of the impact of both “number of firms” and “number of passengers” variables across different forms and stages of cooperation reveals an empirical regularity that warrants further investigation by scholars interested in cooperation and competition.

Firm size controls for the differences in cost structures of a pair of rivals that stem from differences in their economies of scale and learning by doing. Although the impact of this variable is positive and not significant in the “control” model, it is negative and significant in the “Final” model; a one unit increase in this variable reduces mutual forbearance between a pair of rivals by 5 %. It seems that as the difference between the respective numbers of passengers of a pair of rivals in the non-focal markets widens, then, they seek to reduce the gap between their respective market shares in the focal market. The negative relationship between this variable and mutual forbearance is unexpected and suggests that as the difference between the respective numbers of passengers of a pair of rivals in the non-focal market widens, they reduce the gap between their respective market shares in the focal market.

The observed relationship may be due to efforts of the “weaker” carrier with the lower number of passengers in non-focal markets to minimize the aggregate performance difference between itself and its rival and to re-establish itself as a “mighty” competitor that is worth cooperating with. Experimental results indicate that rival firms strive to minimize overall performance differences between themselves (Armstrong and Collopy, 1996). Hence the dyad member that lags behind and whose performance is inferior can be motivated to equate its market share to that of its rival. This restoring behavior is especially relevant within the context of MF because overall competence similarity is required by the nature of MF strategy, an issue that is put on the sidelines by the current research on MF. Rival firms need to have similar capabilities and performance to mutually forbear from competition. Although firms need to have asymmetric competencies at the market level to carry out MF strategy (Bernheim and Whinston, 1990; Phillips and Mason, 1992), they need to retain similar or comparable competencies at the firm level so that they will recognize one another as rivals, (De Chernatony et al., 1993a;

Panagiotou, 2006; Peteraf and Bergen, 2003; Porac and Thomas, 1990; Porac et al., 1995) and will prefer cooperation to competition, knowing that they cannot outcompete one another through competition (Barney, 1991) and a potential “war” will last too long and will be detrimental to performance. The rivalry escalating impact of firm size might be capturing the attempts of a dyad member with the lower number of passengers to reestablish itself as a “mighty” actor in the focal market and a potential partner to cooperate with.

Hub economies is another control variable of the “Final” model and captures the ratio of the magnitude of the economies of scope of a pair of rivals serving a given city-pair market. As expected, this variable has a positive impact on mutual forbearance; a one unit increase in the number of hub economies increases mutual forbearance by 12 %. As this ratio increases, it becomes relatively “cheaper” for the dyad member with the higher value of hub economies to serve to the focal city-pair market. Its sharing of resources and passengers across different flights that either originate from or terminate in one end-point of a focal market reduces its total cost of serving the focal market and thus enables it to reinforce or improve its position in the market at the expense of the other member.

Network effect, the last control variable of the “Final” model, controls for the dependence of observations coming from dyads with a common member. It has a positive and significant impact on mutual forbearance; a one unit increase in the network effect increases mutual forbearance by 0.0022 %. The standard error of this variable is zero because of its current scale. Scaling this variable by dividing it by a constant can solve this problem. Such linear transformation will not have an effect on the statistical significance of this variable, its corresponding t value or the overall deviance of the estimated model because multi-level model is invariant under linear transformation as far as fixed effects are concerned (Hox, 2010).

Therefore I did not scale this variable and re-run the model. In addition, the “Empirical” model whose findings replace those of the “Final” provides the standard error and statistical significance of this variable.

The first independent variable of the “Final” model tests Hypothesis 5. The relevant statistic shows that a one unit increase in strategic reciprocity increases the log of mutual forbearance by 419.82 at the $p < .001$ level when the value of “keyness” variable is zero. The slope of strategic reciprocity is the predicted value for markets whose keyness is zero. This finding supports Hypothesis 5. Mutually reciprocating cooperative moves contributes to the mutual forbearance between a pair of rivals and rival firms assign markets to one another. When a pair of rivals’ ratio of originating passengers that they serve from both ends of a focal city-pair market to their total passengers moves in opposite directions, they are assigning markets to one another, leading to a positive association between strategic reciprocity and mutual forbearance.

“Keyness” is the second independent variable of the “Final” model. It captures the relative dependence of a pair of rivals on a given market for ticket revenue generation. As the value of this variable increases, dyad members’ dependence on the focal market for revenue generation moves in opposite directions, making the focal market more important for the dyad member with the higher market dependence. According to the results of Table 19, a one unit increase in the value of the “keyness” variable increases mutual forbearance by 1.65 % at the $p < .001$ level. Despite its positive impact and rivalry de-escalating impact in this model, “keyness” actually intensifies the level of rivalry between a pair of rivals in the second model albeit in a non-significant manner.

The difference in the sign of “keyness” variable across these two models points to the changing role played by this variable as firms move from tactical to strategic cooperation. When a pair of rivals cooperates at the tactical level, rival firms are likely to be wary of performance differences in a focal market due to their competitive history and thus are likely to compensate for the difference in the percentage of revenue that they generate from a focal market by increasing their investments at either or both ends of a city-pair market to restore the competitive balance between themselves. However this rebalancing act is not necessary when a pair of rivals cooperates at the deeper strategic level. The level of commitment to cooperation in the strategic phase of cooperation is higher than the corresponding level of commitment to cooperation in the tactical phase because carriers that cooperate at the strategic level signal their commitment to cooperation by reducing their level of participation in a focal market that is important to their rivals rather than increasing their prices, a signal that cannot be easily reversed.

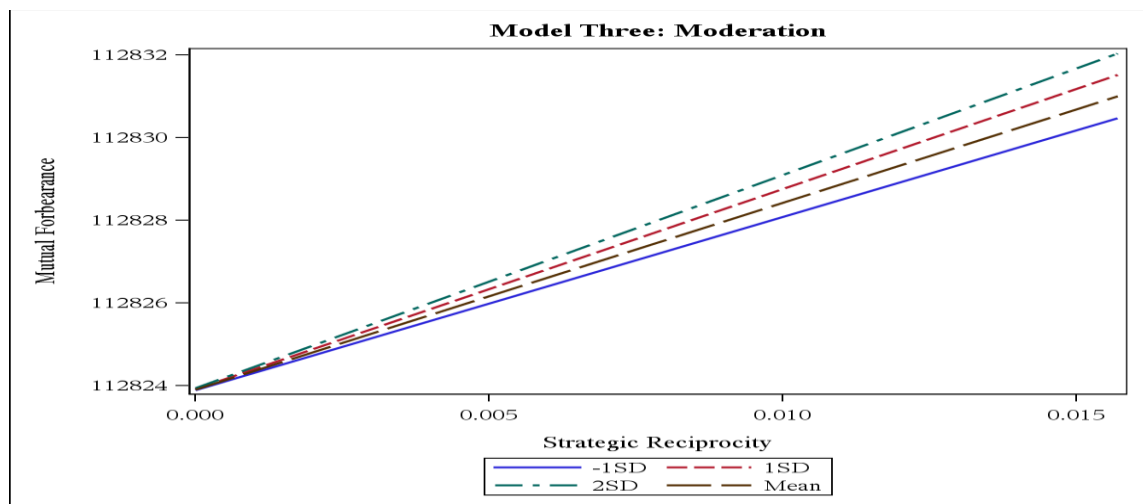
The purpose of cooperative signals at the strategic level is to partition the U.S domestic airline industry and the dependent variable of the third model was designed to capture such partitioning of the industry. Therefore in the model, the difference between “firm” shares of a pair of rivals in a focal market translates into a difference between their “market” shares as they move from tactical cooperation to strategic cooperation.

The interaction term of the “Final” model tests Hypothesis 6. The result of this model indicates that the interaction between strategic reciprocity and “keyness” increases the log of mutual forbearance by 31.7368 at the $p < 0.0663$ level. This provides moderate support for Hypothesis 6. For a one unit increase in the “keyness” of a market, the effect of strategic reciprocity increases the log of mutual forbearance by 31.7368. For the markets with the highest value of “keyness”, 34.35746 in my data, the expected effect of strategic reciprocity is

$419.82 + 31.7368 \times (34.35748) = 1510.216471$ on a log scale. Figure 14 displays a plot of the regression slopes of strategic reciprocity at the mean and plus/minus 1 standard deviation and plus 2 standard deviation of the “keyness” variable to facilitate interpretation of the interaction term.

It is clear from figure 14 that higher values of strategic reciprocity lead to higher values of mutual forbearance and that the difference is greater in markets with higher values of “keyness”. The figure depicts that the positive relationship between strategic reciprocity and mutual forbearance strengthening as the “keyness” of the focal market, where a pair of rivals positively reciprocates each other’s cooperative moves, increases. This is consistent with the argument I made in Chapter Three that the “keyness” of a market positively moderates the relationship between strategic reciprocity and mutual forbearance because signaling cooperation in the key or “bread and butter” markets of a rival significantly contributes to its performance (Barnett, 1993; Evans and Kessider, 1994; Gimeno, 1999, Li and Greenwood, 2004) and thus motivates it to reciprocate with its own cooperative moves in the signal sender’s key markets. In general, the greater dependence of a firm on a market, the higher the likelihood that it will not only respond but also match the action of the initiating firm (Chen, 1996; Smith and Wilson, 1995). The results confirm this expectation for cooperative relationships and shows that cooperative signals in key markets reinforce the positive relationship between strategic reciprocity and mutual forbearance. Further, signaling cooperation in the key markets of rivals does not bring about retaliation and thus enables the signal sender to retain its foothold in such markets, which is vital to the successful execution of a MF strategy.

Figure 14: Two-way Interaction



The final independent variable of the “Third” model is strategic non-reciprocity. The expected average effect of strategic non-reciprocity on mutual forbearance is positive and significant. A one unit increase in strategic non-reciprocity increases the log of mutual forbearance by 427.27 at the $p < 0.001$ level. Hence, there is no support for the seventh and final hypothesis. Similar to the effect of tactical non-reciprocity, strategic non-reciprocity does not impair the level of cooperation between a pair of rivals.

To gain better understanding of this finding, I conducted additional analyses to investigate whether “keyness” moderates the impact of strategic non-reciprocity on MF. The results indicate that strategic non-reciprocity decreases MF by 79 % for a one unit increase in the value of “keyness” at the $p < 0.14$ level¹⁰. This finding suggests that the “keyness” of markets in which defection occurs has no effect on the relationship between non-reciprocity at the strategic level and commitment to cooperation. As with the findings from the effect of tactical non-

¹⁰ The non-significant result is attained in the “empirical” model that provides robust estimates. In the “final” model, the impact of the interaction of strategic non-reciprocity with “keyness” on MF is highly significant at the $p < 0.0001$ level.

reciprocity, it appears that initiating firms continue to engage in cooperative behavior, even in the face of defection. This is inconsistent with expectations grounded in an experimental learning perspective.

As with the case of Hypothesis 4, the lack of support for Hypothesis 7 and the result of the post-hoc analysis suggest that carriers do not exercise deterrence and punish defection to move to the MF equilibrium, which highlights the limitations of deterrence mechanisms as an explanation for the development of MF, as discussed in Chapter 3.

The fact that the empirical context of this study meets all of the conditions that are required for the exercise of deterrence but does not find it provides further support for the argument that carriers do not exercise deterrence to form MF. First, as required by MF, there are differences across markets and carriers in the airline industry, enabling carriers to establish spheres of influences that are embodied by the hub and spoke system (Bernheim and Whinston, 1990). Second, the decision making of carriers is centralized so they can punish defection not only in the focal market where defection has taken place but across their jointly contested markets (Golden and Ma, 2003). Third, the exercise of deterrence requires detection of defection (Greve, 2008). The homogeneity of services offered by the firms and their ready access to data bases that store competitive information facilitate the detection of defection in the airline industry. Fourth, there is not much uncertainty (Anand et al., 2009) that can put pressures on carriers to imitate one another, even at the expense of intensifying rivalry in order to legitimize themselves, increasing the effectiveness of deterrence mechanisms to sustain cooperation.

As discussed previously, several characteristics of the sample industry and firm may explain why airlines do not exercise deterrence to establish MF. First, the cost structure of

airlines and the industry dynamics make incumbent firms more tolerant of aggression of their rivals and reduce the effectiveness of punishing defection to restore cooperation via a tit-for-fat strategy. Due to their high fixed cost to marginal cost ratio, perishable product offering, difficulty to exit the airline industry due to industry specific assets and contractual obligations and inability to increase volume of production gradually and in par with the increase in demand due to bulk purchasing of fleets, carriers are under intense pressure to be competitive and to sell as many revenue-passenger miles as possible. Being aware of such industry forces, carriers are not only more likely to attribute the aggression of their rivals to industry dynamics rather than to their predisposition and willingness to inflict harm, but also refrain from punishing defection to restore cooperation via a tit-for-tat strategy in order to prevent the eruption of a potentially devastating competitive warfare. Second, punishment of defection entails significant costs for the punisher (Sorenson, 2007). Third, the act of punishing defection may not be an effective signal to initiate cooperation. It may intensify the level of rivalry because the signal receiver cannot easily uncover and understand the intention behind the competitors' aggression. Fourth, sampled carriers are similar to one another in terms of their overall size and this similarity might deter them from escalating the level of rivalry (Barney, 1991; Mas-Ruiz and Ruiz Moreno, 2011).

5.3.1 Robustness Check

In this section, I check whether the estimated “Final” model meets the assumptions of multi-level modeling to ensure that my inferences and conclusions are valid. I test the normality of the distribution of level-1 and level-2 residuals, homoscedasticity and linearity and provide both visual diagnostics and related summary statistics.

Figure 15 and 16 provides visual diagnostics for the level-1 residuals. The graphical examination of the distribution of the residuals helps reveal the nature and magnitude of any

non-normality in the level-1 residuals which cannot be detected by statistical tests that will be also provided. Figure 15 displays a histogram of the level-1 residuals with an overlaid normal curve and demonstrates that the distribution of the level-1 residuals generally follows a normal distribution. Figure 16 displays a q-q plot which gives a much more precise picture of the distribution of level-1 residuals. The plot approximates a straight line and thus depicts that the level-1 residuals have a close to normal distribution. However the shape of the slight divergence of the plot from the straight line indicates that the level-1 residuals have heavy tails, a conclusion confirmed by the statistical tests. As pointed out in Table 20, the significance of the Kolmogorov-Smirnov, Cramer-Von Mises and Anderson Darling statistics support the conclusion that the level-1 residuals are not normally distributed. Although these statistical tests provide evidence to reject the claim that level-1 residuals are normally distributed, I do not expect that the observed violation of normality will result in incorrect inferences for two reasons. First, the nature and magnitude of the non-normality as depicted by Figure 15 and Figure 16 is not severe because level-1 residuals have close to a normal distribution. Second, given the large sample size and asymptotic properties of maximum likelihood estimation, I do not expect the observed normality to invalidate the statistical inferences.

Figure 15: Histogram of Level-1 Residuals

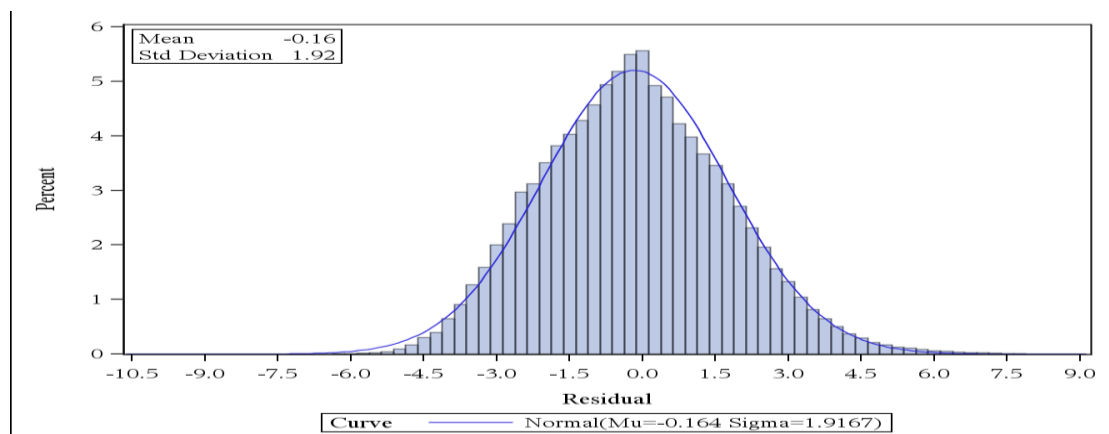


Figure 16: Q-Q Plot of Level-1 Residuals

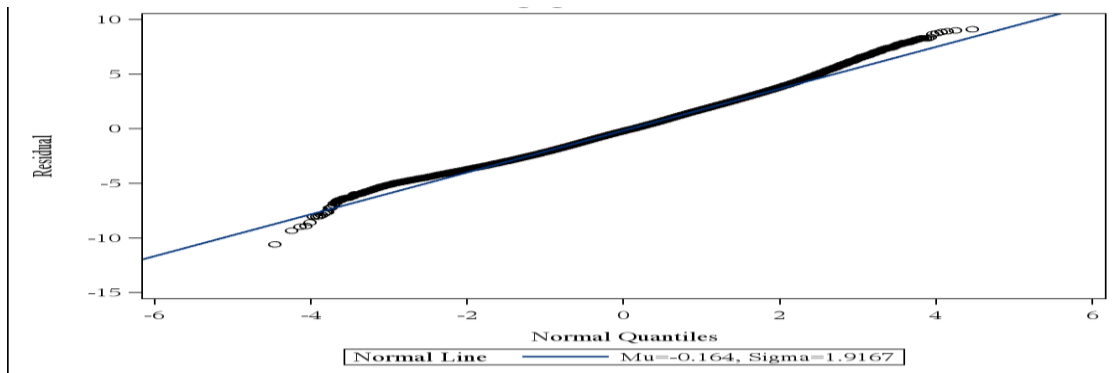


Table 20: Statistical Test of the Normality of Level-1 Residuals

Test	Statistic	P Value
Kolmogorov-Smirnov	0.01408	<0.0100
Cramer-von Mises	9.05326	<0.0050
Anderson-Darling	69.78122	<0.0050

I examined the distribution of the level-2 residuals with both visual diagnostic tools and statistical tests. Since the estimated “Final” model contains 4 random variables, the intercept, strategic reciprocity, strategic non-reciprocity and the interaction of strategic reciprocity with keyness, I analyzed the distribution of these four random variables in order. Figure 17 is a q-q plot of the level-2 residuals pertaining to the intercept term. The plot shows that the level-2 residuals of the intercept term do not follow a normal distribution. The significance of the Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-Von Mises and Anderson Darling statistics provide further evidence that level-2 residuals are not normally distributed as indicated by Table 21.

Figure 17: Level-2 Intercept Residuals

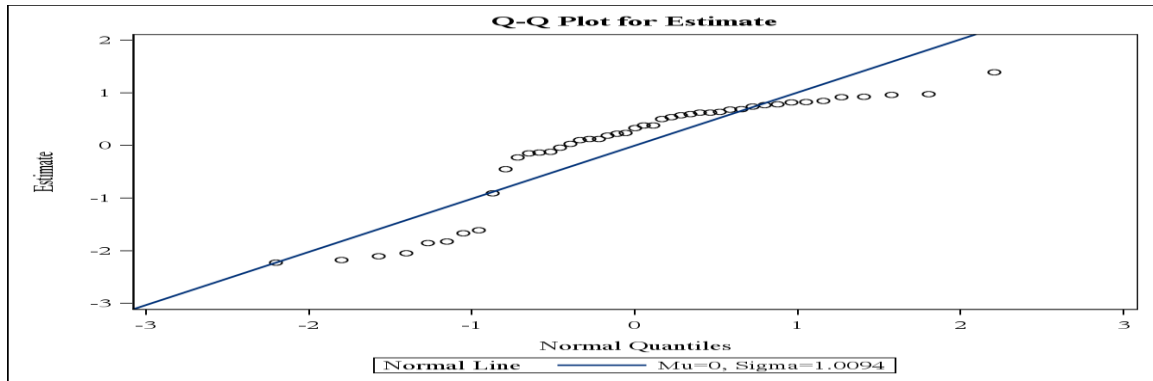


Table 21: Statistical Test of the Normality of Level-2 Intercept Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.827793	<0.0001
Kolmogorov-Smirnov	0.196697	<0.0100
Cramer-von Mises	0.518891	<0.0050
Anderson-Darling	3.078033	<0.0050

Unlike the distribution of the level-2 residuals pertaining to intercepts, the distribution of the level-2 residuals belonging to strategic reciprocity is normal. The q-q plot in Figure 18 shows that residuals follow the straight line, supporting the conclusion that the residuals have a normal distribution. Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-Von Mises and Anderson Darling tests fail to reject the claim that level-2 residuals are normally distributed as indicated by their non-significance in Table 22.

Figure 18: Level-2 Strategic Reciprocity Residuals

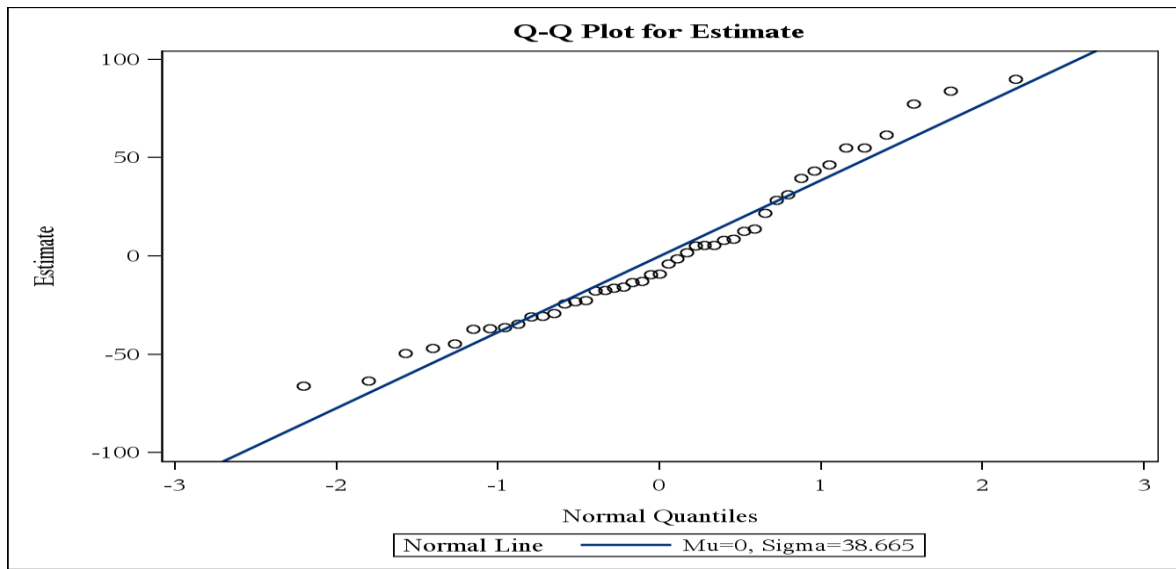


Table 22: Statistical Test of the Normality of Level-2 Strategic Reciprocity Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.958978	0.1117
Kolmogorov-Smirnov	0.105387	0.1500
Cramer-von Mises	0.103942	0.0975
Anderson-Darling	0.616737	0.1024

Similar to the distribution of the level-2 residuals pertaining to strategic reciprocity, the distribution of the level-2 residuals belonging to strategic non-reciprocity is normal. The q-q plot in Figure 19 reveals that the residuals have a normal distribution. The statistical insignificance of the Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-Von Mises and Anderson Darling test statistics provides further evidence for the normality of the level-2 residuals that belong to strategic reciprocity as indicated by Table 23.

Figure 19: Level-2 Strategic Non-Reciprocity Residuals

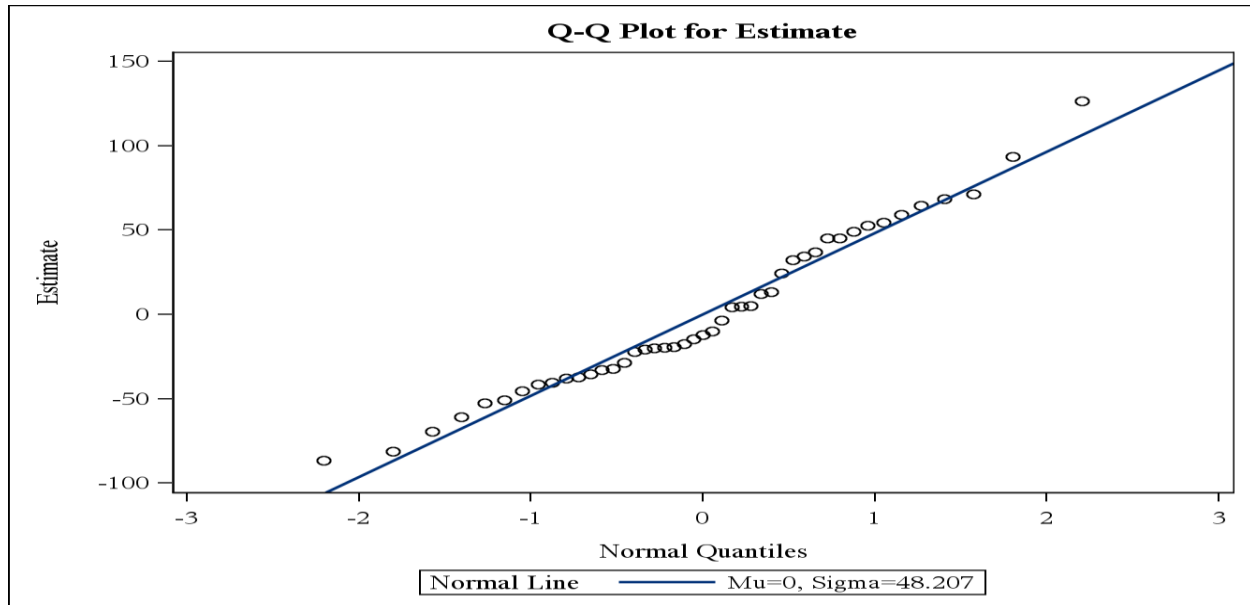


Table 23: Statistical Test of the Normality of Strategic Non-Reciprocity Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.971104	0.3173
Kolmogorov-Smirnov	0.117141	0.1222
Cramer-von Mises	0.101174	0.1065
Anderson-Darling	0.525575	0.1787

Similar to the distribution of the level-2 residuals pertaining to intercepts, the distribution of the level-2 residuals belonging to the interaction of strategic reciprocity and keyness variables is not normal. The q-q plot as depicted by Figure 20 displays the non-normality of the residuals pertaining to the interaction term. As indicated by Table 24, the significance of the Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-Von Mises and Anderson Darling tests confirms the non-

normality depicted by the q-q plot and provides further evidence for non-normality as noted in Table 20.

Figure 20: Level-2 Interaction Term Residuals

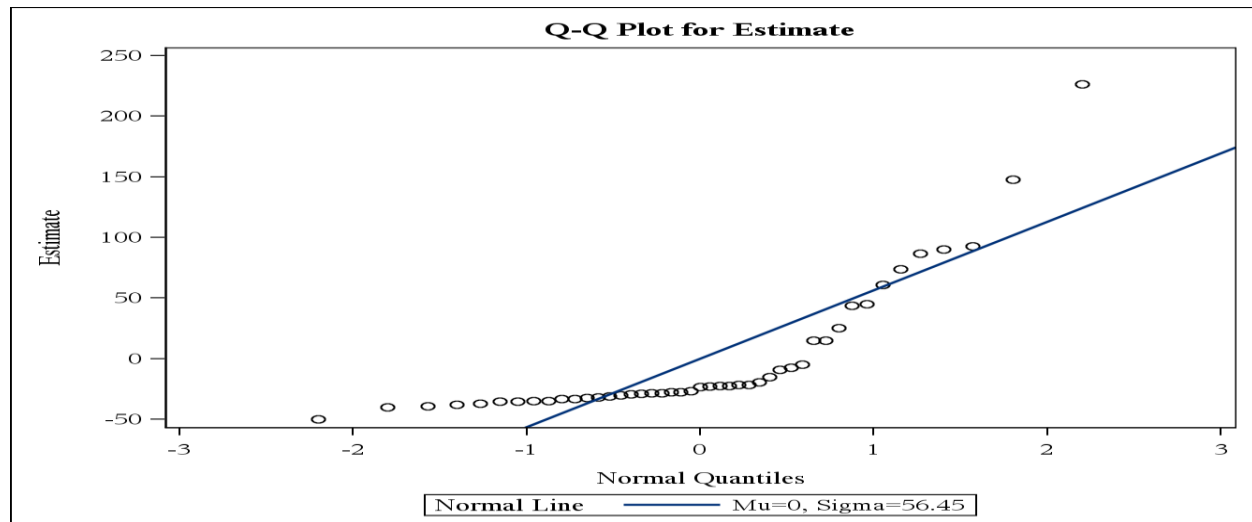


Table 24: Statistical Test of the Normality of Level-2 Interaction Term Residuals

Test	Statistic	P Value
Shapiro-Wilk	0.702405	<0.0001
Kolmogorov-Smirnov	0.278393	<0.0100
Cramer-von Mises	0.970966	<0.0050
Anderson-Darling	4.971452	<0.0050

The estimated model slightly violates the homoscedasticity assumption and the resulting heteroscedasticity can bias standard error of estimates and test statistics, impairing the accuracy of statistical inferences. As Figure 21, which plots the conditional standardized level-1 residuals against the predicted values, portrays, variance in the residuals increases as the predicted value

gets larger, leading to a right opening megaphone shape. Figure 22, which plots the conditional standardized level-1 residuals against dyads, indicates that the variance of the level-1 residuals is not constant across dyads. The result of the one-way ANOVA test confirms this conclusion through its significant F statistic as depicted in Figure 22. I also tested whether conditional standardized level-1 residuals have a constant variance across dyads by the Levene's test, O'Brien's test and Brown and Forsythe's test that, altogether, investigate different types of heteroscedasticity. All of these statistical tests are significant at the $p < .0001$ level, providing evidence for the existence of non-constant variance in the data set. In addition to portraying non-constant variance, the right opening megaphone shape of the plot in Figure 21 also shows that linear specification is the correct specification to investigate Hypotheses 5, 6 and 7.

Figure 21: Plot of Standardized Conditional Level-1 Residuals against Predicted Values

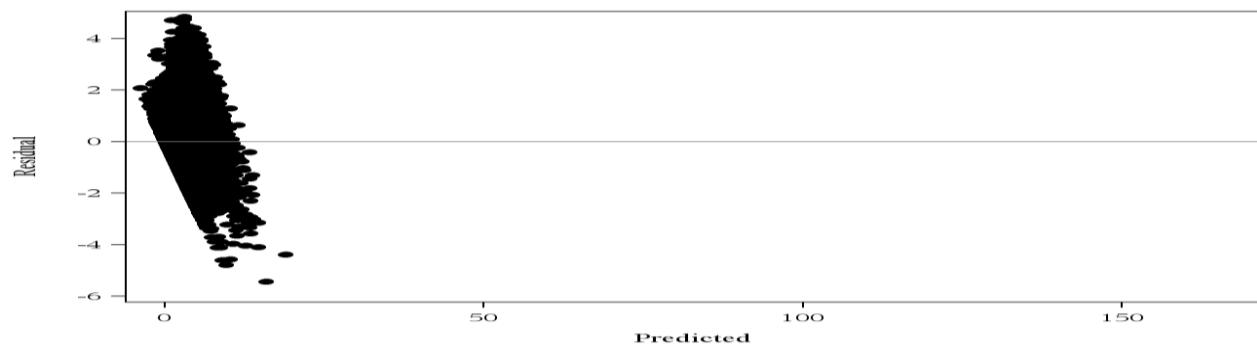
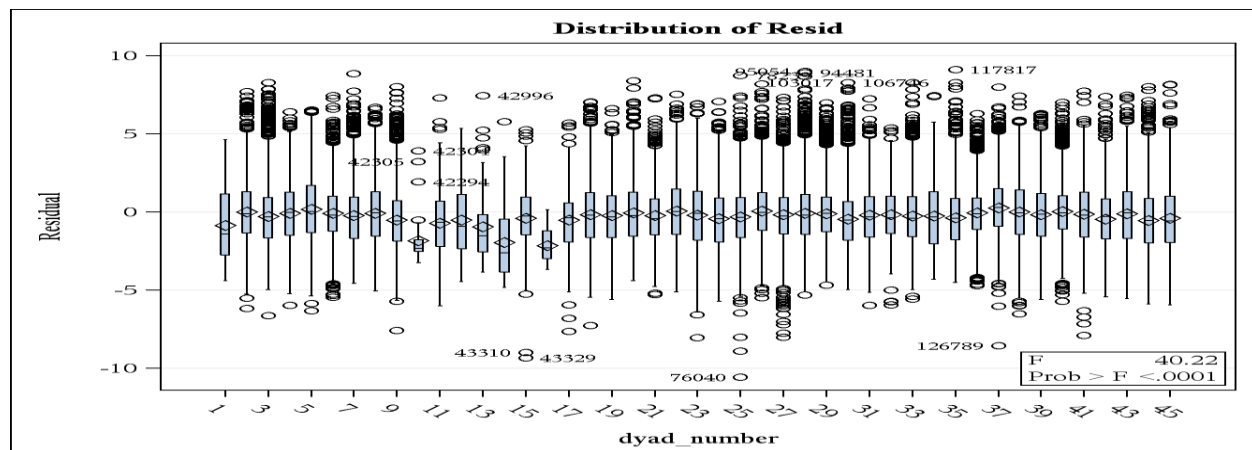


Figure 22: Plot of Standardized Conditional Level-2 Residuals against Predicted Values



In the final analysis, level-1 residuals in general follow a normal distribution. The visual diagnostics shows that the level-1 residuals of the estimated model have heavier tails than a normal distribution. However given the large sample size and asymptotic properties of maximum likelihood estimation that generates consistent, efficient and unbiased estimates in large samples and given that the level-1 residuals have close to a normal distribution, I do not expect that the observed non-normality impair statistical inference. At the higher level, while level-2 residuals pertaining to intercepts and interaction do not follow a normal distribution, the remaining level-2 residuals, which belong to strategic reciprocity and strategic non-reciprocity, follow a normal distribution. The observed non-normality at level-2 can bias inferences. Likewise, Figures 21 and 22 and the accompanying statistical tests show that variance is not constant across the prediction space and dyads. This in turn can bias standard errors and test statistics involving the fixed parameters. That is why I estimated robust standard errors to overcome the inference problems that could derive from non-constant variance and violation of normality. In particular, I used the “sandwich” estimator to produce robust errors for fixed effects. The results of this model, called “Empirical” are shown in Table 19.

The statistical significance and sign of the relationships remains the same across “Final” and “Empirical” models for 5 of the control variables and 3 independent variables and thus there are only three differences between the findings of the “Final” and “Empirical” model. The first difference is the reduction in the statistical significance of the “firm size” variable. This variable is significant at the $p < .001$ level in the “Final” model. However in the “Empirical” model, it is significant at the $p < .05$ level. The second difference across these two models is the availability of the standard error of the “network effect” in the “Empirical” model. Third, the statistical significance of the interaction term that investigates

Hypothesis 6 increases from $p < .1$ level to $p < .001$ level in the “Empirical” model. This finding provides very strong evidence that supports Hypothesis 6.

Chapter 6

Discussion and Conclusion

In this chapter, I summarize the findings of this dissertation and their contribution to the strategic management and multi-market competition literature. I also discuss the implications of the findings for practice and policy. Next, I discuss the limitations of the study. The chapter ends with a discussion of directions for future research and a summary conclusion

6.1 Overall Findings

Table 25 summarizes the findings of this dissertation and the level of support for each of the hypotheses. The data support five of the seven proposed theoretical relationships displayed in Figure 1 suggesting that these relationships may accurately depict and describe how multi-market rivals cooperate and establish MF. The data do not support Hypotheses 4 and 7 and the expected rivalry escalating impact of tactical non-reciprocity and strategic non-reciprocity. Contrary to expectations, the empirical results show that both tactical non-reciprocity and strategic non-reciprocity de-escalate rather than escalate the level of rivalry and contribute to cooperation between a pair of rivals.

Table 25: Empirical Findings

Hypothesis	Final Model	Empirical Model
<i>Hypothesis 1a: The interaction of low performance, norms of competition and multi-market competition is positively associated with the commencement of tactical cooperation between a dyad of multi-market rivals.</i>	Supported	Supported
<i>Hypothesis 1b: Poor performance reverses the negative sign of the</i>	Not Supported (Consistent)	Not Supported (Consistent)

<i>interaction of norms of competition and multi-market competition on the commencement of tactical cooperation between a dyad of multi-market rivals.</i>		
<i>Hypothesis 2: Tactical reciprocity is positively associated with strategic cooperation between a dyad of multi-market rivals.</i>	Supported	Supported
<i>Hypothesis 3: The “keyness” of markets in which tactical cooperation is carried out positively moderates the positive relationship between tactical reciprocity and strategic cooperation between a dyad of multi-market rivals.</i>	Supported	Supported
<i>Hypothesis 4: Tactical non-reciprocity is negatively associated with strategic cooperation between a dyad of multi-market rivals.</i>	Not Supported	Not Supported
<i>Hypothesis 5: Strategic reciprocity is positively associated with MF between a dyad of multi-market rivals</i>	Supported	Supported
<i>Hypothesis 6: The “keyness” of markets in which strategic cooperation is carried out positively moderates the positive relationship between strategic reciprocity and MF between a dyad of multi-market rivals.</i>	Moderate Support	Strong Support
<i>Hypothesis 7: Strategic non-reciprocity is negatively associated with MF between a dyad of multi-market rivals.</i>	Not Supported	Not Supported

Overall, the results suggest that the process of rivalry between a pair of rivals activates the four antecedents of trust which, in turn, motivates the firms to initiate a two-staged process of cooperation across markets. More specifically, multi-market competition activates the deterrence

and interdependence antecedents of trust, results in the formation of norms of competition and impairs firm performance. The resulting norms of competition and performance failure, in turn, activate the predictability and risk-taking antecedents of inter-organization trust respectively and complete the formation of inter-organizational trust. The existence of inter-organizational trust motivates a pair of rivals to cooperate across markets.

The process by which cooperation develops is partially consistent with a two-staged experimental learning process. Positive feedback from an experimental learning process in which one firm of the dyad pair initiates cooperative behavior in the key market(s) of its rival increases commitment to cooperation because it (i) increases the likelihood of cooperation, (ii) reduces the cost of cooperation (iii) facilitates the detection of trustworthy rivals, (iv) prevents unnecessary wars and (v) repeatedly signals the will to cooperate. Rivals that mutually cooperate at a tactical level deepen their cooperation and progress to strategic cooperation. Rivals that cooperate at the strategic level begin to assign markets to one another and mutually forbear, especially when they signal their intent to cooperate in the key markets of their rivals.

Contrary to expectations, the results suggest that multi-market firms tolerate and often support the defection of their rivals. A trustor maintains its cooperation even in the face of the defection of a trustee and even in key markets. These findings suggest a more complex process than was hypothesized and points to the potential influence of the temporal orientation of the firms (or firm management) and/or signal strength.

The validity of the findings rests on whether it is correct to conclude that the allocation of markets between firms in this study is the result of a MF strategy rather than the result of competition. Multi-market firms can voluntarily divvy up markets between one another as a

result of their MF strategy or be forced to reduce the level of their participation in a market due to the forces of competition. In other words, one could argue that the creation of spheres of influence and market share differences of rivals that are the hypothesized outcomes of tactical and strategic cooperation in this study are due to the superior competitiveness of one firm over the other rather than the adoption of a MF strategy.

Evidence from prior research in the U.S. scheduled passenger airline industry supports the position that the market allocations captured in this study are the result of MF. In the last three decades, empirical studies have consistently demonstrated that multi-market rivals in the U.S. airline industry mutually forbear from competition (Baum and Korn, 1996, 1999; Bilotkach, 2011; Ciliberto and Williams, 2012; Evans and Kessides, 1994; Gimeno, 1999, 2002; Gimeno and Woo, 1996; Miller, 2010; Prince and Simon, 2009; Singal, 1996; Zou et al., 2012). The sample and time frame in this study were selected to be consistent with these works and to capture a period of time prior to the establishment of MF in the industry but in which MF is expected to have begun to emerge.

The logic underlying the formation of MF also supports the interpretation of results as the formation of MF rather than the outcomes of market competition. MF strategy forms when multi-market rivals cannot out-compete one another and so are locked in a competitive battle that neither firm can win. The observed super-ordination and subordination of multi-market rivals across markets therefore stems from the motivation of those rivals to cooperate across markets; MF influences firm performance by reducing the *will*, rather than the *ability*, of rivals to out-compete one another (Gimeno, 1999). Knowing that they cannot out-compete each other without too much sacrifice due to their size and market scope similarity (Mas-Ruiz and Ruiz-Moreno, 2011), a pair of multi-market rivals begins to mutually forbear from competition and adopts a

“live and let live” policy. The findings of this dissertation are consistent with this line of logic; it was not until both firms in a competitive multi-market dyad experienced performance failure that they began to cooperate. As noted in Chapter 5, the firms in each dyad in the sample had very similar capabilities and resources, making competitive dominance by one firm across markets unlikely. Further, the finding that performance failure reverses the rivalry escalating impact of the interaction of multi-market contact and norms further supports this perspective and suggests that the partitioning of the airline industry is not an outcome of competition but rather derives from a MF strategy.

6.2 The Contributions of the Dissertation to the Literature

The results of this study make multiple contributions to our understanding of the emergence of MF in multi-market context and open up new lines of inquiry directed at better understanding the processes and outcomes associated with multi-market contact.

First, this study is the first to develop and test a process-based explanation of the emergence of MF. Variance models of MF have established that multi-market firms often refrain from competing with one another, but they do not explain how firms move from intense rivalry to cooperation (Van de Ven, 2007). Contemporary research has discussed the importance of studying the process of multi-market competition (Baum and Korn, 1999). However no theoretical model has been proposed to explain the process by which MF emerges. This dissertation takes up this task. The proposed theoretical model describes the progression of multi-market competition from rivalry to cooperation and provides insight into the processes by which multi-market firms either move to MF equilibrium (Busse, 2000) or escalate their rivalry. It also accounts for defection-based breakdown of cooperation between a dyad of multi-market rivals at different points in time.

Second, this dissertation provides insight into what motivates multi-market rivals to begin to cooperate as well as the emergent nature of that motive and MF strategy. Contrary to initial arguments in the literature that viewed multi-market contact as a conscious attempt to foster cooperation, contemporary empirical findings demonstrate that multi-market contacts are predominantly established by chance (Scott, 1982; Korn and Baum, 1999; Gimeno, 2002). This suggests that MF emerges *ex post* from competitive interaction across markets (Korn and Rock, 2001) and that it is not a planned, but rather an emergent strategy (Mintzberg and Waters, 1985). Despite such findings, no prior study has explained how MF emerges between rivals. By introducing inter-organizational trust as a pre-condition of cooperation, this dissertation provides a theoretical explanation for the emergence of the motive to cooperate from the competitive interactions of multi-market rivals and sheds light on the emergent nature of MF strategy. This is important because MF theory is, in essence, a motivational theory of competitive advantage. Unlike strategic group theory (Caves and Porter, 1977) and the resource based view (Barney, 1991) that propose that the main path to competitive advantage is to reduce the *ability* of rivals to compete by building either *ex ante* or *ex-post* limits to competition, MF theory proposes that the main way to establish competitive advantage is to reduce the *motive* of rivals to compete aggressively (Gimeno, 1999).

Third, this dissertation brings cooperation back into the core of the process by which multi-market rivals form MF (Scott, 1991; Busse, 2000; Kang et al., 2010) and theorizes about its interplay with deterrence in line with the recent call of MF researchers (Baum and Korn, 1999; Kang et al., 2010; Korn and Baum, 1999). This is important because although cooperation and deterrence were originally proposed as the two causes of MF (Baum and Korn, 1999), subsequent research has focused on deterrence as the main causal force of MF and thus has not

theorized about the impact of cooperation on MF and the nature of the relationship between deterrence and cooperation.

The empirical results from this study suggest that deterrence is one of many factors that together trigger the formation of inter-organizational trust. The results also suggest that rivals do not exercise deterrence (punish defection) to form MF as assumed by the current literature. Rather, this study finds that a pair of rivals moves to the MF equilibrium through a process in which firms (1) reciprocate one another's cooperative moves, especially in key markets (2) support defection in both key and peripheral markets. The finding that non-reciprocity escalates cooperative actions was unexpected and is inconsistent with an experimental learning perspective, which would predict a de-escalation of commitment in the face of negative response (non-reciprocity). These results, therefore, provide mixed support for experimental learning as the process by which firms initiate cooperation and move to an MF equilibrium. The findings highlight the need for further investigation into the processes that guide response in the face of defection as firms move toward MF and its implications for the validity of a learning perspective. Several potential avenues are discussed in section 6.5, Future Research Directions.

Fourth, the proposed theoretical model sheds light on the inconclusive findings from research on the impact of familiarity, and its interaction with multimarket contact, on the level of rivalry. Contemporary research in both the strategic group literature (Fiegenbaum and Thomas, 1995; McNamara et al., 2003) and the MF literature (Gimeno and Woo, 1996; Fuentelsaz and Gomez, 2006; Li and Greenwood, 2004; Young et al., 2000, Marcel et al., 2010) provide mixed and inconclusive findings about the relationship between familiarity and level of competition and the impact of its interaction with multi-market contact on the level of rivalry. The empirical findings of this dissertation reveal that it is only the three-way interaction of familiarity, multi-

market contact and low performance that de-escalates rivalry. This suggests that familiarity is a double-edged sword; the ability to predict behavior provided by familiarity can be used to either attack or cooperate. The decision to attack or cooperate depends on the motive of the firm (Chen, 1996) and the motivation to cooperate develops in the face of unsatisfactory performance. Therefore, the ability and the motive to cooperate require the interaction of familiarity and low performance. This interaction by itself is not, however, sufficient to de-escalate rivalry because rivals must also recognize that their performance outcomes are interdependent and that defection is costly. Multi-market contact increases the cost of defection and facilitates the recognition of mutual interdependence. In sum, the results provide a more complete explanation for the inconsistent findings of different streams of research by highlighting that multi-market contact, norms of rivalry and performance failure are each necessary, but not sufficient to motivate cooperation. All three must be present in order to activate the inter-organizational trust that triggers motivation to cooperate.

6.3 Policy and Managerial Implications of Findings

MF represents a special case of collusion because multi-market rivals collude across markets rather than within a given market to improve their overall firm profitability. Contact across markets enables multi-market rivals to transfer their ability to collude from less competitive markets to more competitive markets (Bernheim and Whinston, 1990). Multi-market competition and MF, therefore, have the potential to influence the relative size of the consumer and producer surplus, calling for a discussion of the anti-trust implications of mutual forbearance.

The findings suggest that low performing multi-market firms are more likely to not only initiate MF but also to accept overtures to cooperate. This suggests that anti-trust authorities may

wish to focus their attention on underperforming and unsuccessful firms that might be under their radar rather than on successful and cash-rich companies that might receive more attention due to their high producer surplus. If and when anti-trust authorities identify firms with low producer surplus as potential colluders, they might pre-empt the moves of such companies before they take action to collude.

There are also several implications for managers of multi-market firms. First, the results suggest that poor performance in both firms of a dyad of multi-market rivals is an important trigger for willingness to cooperate. This suggests that managers of multi-market firms suffering poor performance may wish to identify multi-market rivals that are suffering similar performance outcomes as targets for the initiation of more cooperative interactions with an eye toward establishing MF and attaining improved performance. Second if managers wish to establish cooperation with their multi-market rivals, they should signal their intent to cooperate in the key markets of their rivals because results suggest that signaling the intent to cooperate in the key markets of rivals is more conducive to cooperation than signaling it in peripheral markets. Third, managers may wish to respond to the non-reciprocal responses of their rivals to cooperative signals by increasing the strength of those signals. The results of this study demonstrate that non-reciprocity is positively related to the escalation of cooperation, suggesting that cooperation results from continued signaling of cooperation in the face of defection.

6.4 Limitations

The study design, data characteristics and context, while appropriate and necessary for this study, also result in several limitations.

First, the empirical model does not investigate the linkages across different stages of cooperation because the process by which MF emerges is investigated by testing three distinct

empirical models. More specifically, the empirical model does not capture the shape and sign of the relationship (1) among tactical reciprocity, strategic reciprocity and MF (2) among tactical non-reciprocity, strategic non-reciprocity and MF and (3) between the reciprocity and non-reciprocity related processes. Therefore the research does not examine the entire process as it naturally unfolds. In the future, I can empirically model the linkages across different stages of cooperation by using structural equation modeling. Alternatively, I can use multi-process models with multiple states if I do not have data that captures the variables of interest through reflective measures that are required for structural equation modeling.

Second, this dissertation does not investigate when and who initiates cooperation and who responds to whom because it examines undirected rather than directed dyads. Because the data set was constructed from secondary data sources, it does not longitudinally track and identify the specific actions and responses a pair of rivals directs toward one another. More granular data at the action-response level are needed (Chen, 1996) to empirically investigate the process of cooperation as it naturally unfolds between a pair of rivals and capture the target of a specific cooperative action and response. Thus, in the future, I intend to create a data set that captures the competitive and cooperative actions and responses of a pair of rivals in real time so that I can specify the temporal order of the actions/responses of a pair of rivals and the identity of the firms that not only take an action but also respond to a particular action. Such a data set can be prepared by collecting real-time data from the websites of carriers and online reservation systems. In addition newspapers and relevant journals can be content analyzed to capture the actions/reactions of a pair of rivals. Once prepared, a data set that captures competitive behavior at the action-response level can be investigated through event history analysis.

Third, the longitudinal design of the study and the focus of firm-market pairs required limiting the sample to firms within a single, well-defined industry, which limits the generalizability of the results. Several characteristics of the U.S. Scheduled Passenger Airline industry may have influenced the results. For example, the industry is structurally unattractive with low levels of profitability; bankruptcy is pervasive. In such an industry, the need for cooperation among rivals can be extremely high. Since fierce competition is extremely costly for all of the participants of the industry due to the realities of the industry discussed in Chapter 5, rival companies in the airline industry may be more strongly motivated to cooperate than would firms in other types of industries. Hence future research should test the theorized relationships in different empirical contexts to investigate the external validity of the findings.

6.5 Future Research Directions

The results of this research offer multiple implications for future research.

The lack of support for Hypotheses 4 and 7 highlights the opportunity for further inquiry into the factors that influence the emergence of cooperation. In particular, three different research streams seem particularly promising as avenues for such an inquiry.

First, the positive impact of tactical non-reciprocity and strategic non-reciprocity on cooperation suggests the need for additional research on the relative influence of prior experience and future expectation on cooperation. These findings imply that cooperative behavior in the face of defection may be guided more by future expectations than by historical experiences. The finding that defection leads to cooperation might be due to multi-market firms assigning greater weight to their expectations of cooperative behavior, a result of inter-organizational trust, than to their historical experiences of cooperation with their rivals.

Future research can tease out the respective influences of historical experiences of cooperation and positive expectations of cooperative behavior on the decision to cooperate and to determine if a dyad member supports the defection of its rival because of its expectation of a positive outcome from its interaction with that rival. If future evidence shows that future expectation is more important than past experiences in shaping and molding MF, additional research to investigate how long the expectation of positive outcome sustains the cooperation of a trustor in the face of a cheating trustee and to identify the organizational factors that influence a firm's positive expectations should be undertaken. The findings may suggest that the future orientation inherent in inter-organizational trust is a better theoretical tool for explaining the emergence of cooperation in the face of defection than organizational learning, which assigns a major role to past events, to explain firm cooperative conduct and decisions within the context of multi-market competition. Alternatively, the findings may provide insight into whether and how the experimental learning process itself differs under conditions of trust.

Second, future research can investigate whether common identity explains the support of cooperation in the face of non-reciprocity. An identity that is shared by a group of firms might lead them to support one another's defection because firms assess the reliability and trustworthiness of other firms with whom they identify through group norms rather than historical transactions (Livengood and Reger, 2010; Peteraf and Shanley, 1997). This in turn can motivate firms that share a common identity to cooperate even in the face of defection and non-reciprocity. Repeated interaction (Trapido, 2007), size similarity (Mas-Ruiz and Ruiz-Moreno, 2011), common business models and history (Bluedorn and Denhardt, 1988), and common enemy (Baldwin and Bengtsson, 2004) are factors associated with the formation of a common identity and would be an obvious set of initial variables with which to begin.

Third, it may be that the empirical observation that one of the members of a dyad supports the defection of the other dyad member is due to factors other than trust. Three potential explanations are: (1) the ability of the non-cooperating member of the dyad to deter the retaliation of its rivals, (2) the inability of the cooperating dyad member to deter the competitive aggression of its rival, or (3) the desire of the cooperative dyad member to use defection supporting behavior as a credible signal of its commitment to cooperation. Since the findings of this dissertation reveal that deterrence is not relevant to the process of cooperation, the next step is to explain *how* and *through which causal mechanism* deterrence is not akin to the process of cooperation. Each of these factors can shed light on why deterrence does not appear to play a role in the process of cooperation by which MF is formed in this study. Since cooperation is one of the two causal forces of MF, it is important to know whether the findings that appear to show support for non-reciprocity are due to the commitment of at least one of the members of a dyad to cooperation or rather to the inability of that member to effectively retaliate against or effectively deter the competitive aggressiveness of its rival.

The finding that performance failure is a relevant and important force in the formation of the motive to mutually forbear suggests the need for additional research on its impact on MF. In particular, future research is needed to better understand the boundary conditions of the effect of performance failure on the emergence of MF. Different levels of poor performance may have opposing impacts. Extreme losses have been found to reduce the propensity to take risks and thus make cooperation, which requires risk taking (March and Shapira, 1987), less likely. Extremely poor levels of performance have also been associated with threat rigidity behavior, which invokes established competitive routines, and therefore the continuation or escalation of rivalry,

and may be especially likely in a multi-market context because multi-market rivals have well established routines for competition and know how to compete (Shimizu, 2007).

In this dissertation, performance failure was categorized into three groups using aspiration levels and social competitive benchmarks. However the most severe form of performance failure, bankruptcy, was not included because bankruptcy was not expected to trigger cooperation. Bankruptcy is, however, a prevalent phenomenon in the airline industry; during the study period, 30 airlines entered bankruptcy proceedings according to the U.S. Airline Bankruptcies and Service Cessations File of Air Transport Association. This prevalence enables a quasi-experimental design to disentangle the effect of different levels of performance failure on the level of rivalry.

Finally, in a direct extension of the theoretical model proposed in this paper, future research can be undertaken to unravel the evolution of the relationship between multi-market contact and level of rivalry in tactical and strategic stages of MF formation and partition the observed inverted U shaped relationship into its tactical and strategic components. If future research finds that the shape of the relationship changes across different stages of cooperation, this can explain the reason for the inconsistent findings concerning the relationship between multi-market contact and level of rivalry in different empirical contexts.

6.6 Conclusion

The purpose of this dissertation was to provide a process-based explanation for the unintentional formation of MF. More specifically, I sought to understand and explain (i) the role of cooperation in motivating and initiating MF (ii) whether trust enables a dyad of multi-market rivals to move from rivalry to cooperation and, if so, how (iii) whether learning theory explains the process by which a dyad of multi-market rivals moves to MF.

I investigated these three sets of questions by adapting the theoretical lenses of inter-organizational trust and organizational learning. I used multi-level modeling, which is particularly suitable to analyze the research questions of this dissertation, to test the hypotheses in the U.S. scheduled passenger airline industry between 1993 and 2000.

Consistent with the proposed theoretical model, I found that (1) inter-organizational trust leads to tactical cooperation (2) tactical reciprocity leads to strategic cooperation (3) market “keyness” positively moderates the positive relationship between tactical reciprocity and strategic cooperation (4) strategic reciprocity leads to MF (5) market “keyness” positively moderates the positive relationship between strategic reciprocity and MF. These findings are consistent with a process model in which multi-market rivals move to the MF equilibrium through cooperation and the process of competition itself provides the motive to cooperate. Contrary to expectations, I found that (1) tactical non-reciprocity leads to increased strategic cooperation and (2) strategic non-reciprocity leads to increased MF.

These findings provide support for the argument that inter-organizational trust provides the motivation for a dyad of multi-market rivals to move from competition to cooperation and, eventually, MF. They do not, however, fully support experimental learning as the process through which firms develop cooperative strategies. The finding that non-reciprocity both in key and peripheral markets increases cooperative behavior rather than a return to competition suggests the need for further investigation and refinement of the theoretical model. Altogether the research undertaken in this dissertation paves the way for a new line of MF inquiry that investigates the process by which multi-market rivals establish MF and refines the role of cooperation within the context of multi-market competition and MF.

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