ESSAYS ON COMPETITION AND USER-GENERATED CONTENT

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by

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ABSTRACT

In recent years, research on the marketing impact of online user-generated content (such as blogs, twitter, forum postings etc.) has received attention from academics as well as practitioners. However, research on the role competition plays in the marketing impact of user-generated content has received relatively little attention. Specifically, there is no research on the dyadic impact of competitive user generated content (e.g., how do blog posts about firm A influence the performance of firm B and vice versa) Through this dissertation, I intend to contribute to the literature on the impact of user-generated content on firm performance by examining competitive interactions.

In essay 1, I carry out a comprehensive review of the competition literature in marketing, management, economics, sociology, and other related fields to enable me to identify the concepts and models critical to examining competitive interactions. In essay 2, I test for the existence of competitive interactions in the impact of blog posts about cable news shows on their daily viewership. I find that competitive interactions do exist and whether the competitive impact of user-generated content is positive or negative varies across different time slots of cable news programming. In essay 2, I found evidence for competitive interaction, but did not have a continuous measure for competition. In essay 3, set in the airline industry, I develop a continuous measure for the competition variable (asymmetric multi-market competition) and test the moderating effect of this competition variable on the impact of competitors’ negative user-generated content on stock returns. I find evidence for the existence of competitive interactions yet again, and find the direction as well as magnitude of these interactive effects to vary depending on the level of competition. Specifically, I find that airline firms benefit from negative online user-generated content.
about competitors at symmetric but moderate and asymmetric but advantageous levels of multi-market competition.
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Chapter 1

Competition and its Implications for Marketing Strategy

ABSTRACT

Competition plays a critical role in the formulation and effectiveness of marketing strategies, as researched extensively in marketing and related fields. This chapter provides an overview of the main themes of competition research in marketing and in related fields such as economics, industrial organization, management, and sociology. First, we elaborate on competitive market structure and competition; we discuss why market structure matters and describe the demand-based, supply-based, and environment-based perspectives on competitive market structures. We also integrate these three perspectives to provide guidelines for further research. Second, we discuss behavioral and structural approaches to understanding firms’ and managers’ responsiveness to competition, that is, the competitive interactions that influence firms’ marketing strategies. We discuss interfirm rivalry literature from marketing and management, structure-conduct-performance literature from industrial organization, and structural models from New Empirical Industrial Organization research. We also examine the issues in empirically and analytically modeling competitive interactions from both behavioral and structural perspectives. Finally, we suggest an agenda for further research, where we also integrate how the Internet and user-generated content are changing the nature of competition among firms.

When we look to the individuals of the same variety or sub-variety of our older cultivated plants and animals, one of the first points which strikes us, is, that they generally differ much more from each other, than do the individuals of any one species or variety in a state of nature.
When we reflect on the vast diversity of the plants and animals which have been cultivated, and which have varied during all ages under the most different climates and treatment, I think we are driven to conclude that this greater variability is simply due to our domestic productions having been raised under conditions of life not so uniform as, and somewhat different from, those to which the parent-species have been exposed under nature.

**Introduction**

In August 2009, at the World Athletic Championships in Germany, Tyson Gay clocked 9.71 seconds, his personal best, running the 100 meters faster than any man in previous editions of the tournament. However, it was not enough to make him the tournament record holder, nor did it win him the gold medal. Running in the same race, Usain Bolt, with a time of 9.58 seconds, captured the gold medal, the tournament record, the world record, and the news headlines. This example of a phenomenal athletic performance by Gay, overshadowed by Bolt’s, underlines a truism that is as applicable to business as it is to sports: Performance is always evaluated relative to competitors’.

Market share, a key performance metric of a firm’s marketing activities, measures the firm’s sales relative to those of its competitors. Reibstein and Wittink (2005) stress the importance of measuring firm performance in relative terms. That is, competition plays a role not only for measuring but also for determining performance. As Day and Reibstein (1997) recognize, the success of marketing activities depends on how a firm’s activities compare with those of its competitors. For example, whether customers respond to a firm’s sales promotions and buy the firm’s product often depends on the sales promotions offered by the firm’s competitors. Managers thus are mindful of competitors’ present and possible future actions when they devise and execute their marketing strategies (Leeflang and Wittink 1996). In this sense,
competition affects almost every aspect of firm strategy—from devising and executing strategies, to the success of those strategies, to the evaluation of firm performance, and also critically influences a firm’s allocation of resources (Shankar 2011).

The objective of this essay is to conduct a review of the competition literature and marketing and allied fields in a way that is useful for academics as well as practitioners. For academics, this essay will summarize the theoretical frameworks, research approaches, data sources, and modeling issues, and lay out an agenda for further research. For practitioners, this essay provides a concise but detailed summary of the research on competition that will serve as a useful reference in devising competitive strategies.

Competition has received ample attention from academics, in both business research and allied social sciences. Competitor analysis and competitive analysis have been extensively examined by marketing scholars (e.g., Czepiel and Kerin 2011; Shankar 2010a, b). In this chapter, we take a detailed look at extant literature on competition in marketing and in related disciplines, such as strategic management, industrial organization (IO), economics, and sociology. Researchers in these disciplines have studied various questions related to competition in depth, which we broadly classify into two categories: competitive market structures and competitive interactions. Market structure reflects the configuration of competing firms in an industry with respect to some key dimensions. Diverse perspectives serve to investigate market structures, including a demand-based perspective (in marketing), supply-based perspective (IO and strategic management), and environment-based perspective (IO and sociology). In the next section, we discuss these three perspectives to offer an integrated perspective and lay out an agenda for further research.

Competitive interactions, which we then outline, entail dynamic managerial strategic decision making that accounts for competitors’ actions. We end by elaborating on the emerging topics that researchers should consider to understand competition.
Market structure and competition

Market structure refers to the configuration of competing firms in an industry, generally with regard to who competes with whom at a given level of the value chain. The study of competitive market structures started with a regulatory policy perspective (Demsetz 1973), according to which governments use market structure information to formulate public policy to protect the interests of stakeholders, including customers. One of the basic tenets of capitalist societies is that competition benefits the customer by spurring firms to improve quality and keep prices low. Governments, keen to protect this tenet, consider the market structure to ensure that competition is not stifled by the unfair practices of a few dominant players. Such research provides details about different types of market structures (e.g., monopoly, duopoly, oligopoly, monopsony) and their relative advantages and disadvantages (e.g., Perry 1984; Posner 1975).

From a managerial perspective, market structures influence important decisions related to advertising, branding, promotions, innovation, and R&D. These market structures are asymmetric (e.g., Amit and Schoemaker 1993; Carpenter et al. 1988; DeSarbo et al. 2006; Shankar et al. 1998, 1999), such that the degree to which one firm competes with another is not the same as the degree to which the second firm competes with the first. Such asymmetries may arise from supply-based factors, such as differences in firm resource endowments or geographic scope of operations, as well as demand-based perspectives, such as differences in customer loyalty. Managers clearly must take such asymmetries into consideration when devising and executing marketing strategies.
**Demand-based perspective of competition**

The demand-based perspective on market structure assumes that competitive market structures rest in the minds and hearts of customers, and customers end up deciding which firms compete with one another. Not surprisingly, with its focus on customers, the demand-based perspective has received significant attention from marketing researchers (e.g., Blattberg and Wisniewski 1989; Cooper and Inoue 1996; DeSarbo et al. 2006).

From a demand-based perspective, market structures are “a set of products judged to be substitutes within those usage situations in which similar patterns of benefit are sought, and the customers for whom such usages are relevant” (Day et al. 1979, p. 10, emphasis in original). The complexity of the process by which consumers decide which products or brands to purchase provides myriad customer data that can uncover market structures, including but not limited to perceived brand similarities (e.g., DeSarbo and Manrai 1992), brand-switching probabilities (e.g., Carpenter and Lehmann 1985), panel data on purchase choices (e.g., Hansen and Singh 2009), customer knowledge structures (e.g., Alba and Chattopadhyay 1985), and price elasticity (e.g., Blattberg and Wisniewski 1989). Depending on the nature of the data, their granularity, and the stage of the customers’ decision-making process, assessments of market structure can and often do vary.

Through a review of literature that contains a demand-based perspective on competition, we have identified three broad research approaches that identify market structure according to customers’ attitudes and behaviors: (1) knowledge structure approach, (2) consideration set approach, and (3) purchase decision approach. These approaches differ in terms of the stage of the purchase process the respondents are at when the data are collected: (1) no immediate purchase intended, (2) purchase intended in the near future, and (3) purchase concluded, respectively.
Knowledge structure approach

Consider consumers who own a laptop or have used one in the past. Their knowledge about laptop brands likely is an outcome of their past purchase and usage, the opinions and experiences of their friends and family, their exposure to laptop advertising, and what they have read or heard about laptops in the media, such as reviews and descriptions. However, these customers do not have an immediate need for a laptop. Data collected from them—by asking them to imagine a hypothetical purchase scenario and respond with their perceptions of brand similarities, brand preferences, price sensitivity, and so on—will give researchers a picture of the market structure according to the knowledge structure of customers (e.g., Sinha and DeSarbo 1998). Therefore, in this knowledge structure approach, market structure represents the composition of a set of products, according to customers’ perceptions of the competing players in the market (e.g., Alba and Chattopadhyay 1985).

Consideration set approach

When customers have an active need for a laptop, the set of products in their consideration set likely differs from those they perceive in the absence of an active need. For example, customers who otherwise would consider Windows-based, Mac-based, and Linux-based laptops as substitutes may limit their consideration set when faced with an actual decision to, say, just Windows-based laptops. This alteration in the consideration set could have manifold reasons, such as switching costs, recent advertising, or budget constraints. The resulting market structure provides information about competition based on the consideration sets of potential customers (e.g., Urban, Johnson, and Hauser 1984). The consideration set approach thus is based on data collected from customers who have an expressed intention to purchase in the near future.
DeSarbo and Jedidi (1995), for example, use personal interviews with customers who intend to purchase an automobile within six months to measure consideration sets.

*Purchase decision approach*

Consumers think differently in the initial stage of their decision-making process versus the final stage, when they make the purchase (e.g., Grewal et al. 2003). Thus, if customers have eliminated Apple from their consideration set, they may consider Lenovo, HP, Toshiba, and Acer laptops, but their final choice may focus on HP versus Acer. Their final purchase features only one brand, of course. Thus, customers’ perceptions about the set of products in the initial stage of the purchasing process differ from those in the final stage (Shocker et al. 1991). Research on customer structure from a demand-perspective based on data about final purchases, such as panel data, brand-switching in repeat purchase setting, and so on, therefore indicates a competitive market structure based on the purchase decision, which we call the *purchase decision approach* (e.g., Hansen and Singh 2009).

Each of these three approaches can offer useful insights for researchers, managers, and policymakers, depending on the stage of the customer purchase cycle. The demand-based perspective is particularly useful for high-velocity industries, whose market composition and patterns change rapidly. Assessing the nature of competition, including the make-up of asymmetry, on the basis of what customers think can lead to insights that otherwise might not be salient. We therefore encourage researchers who examine competition from a demand-based perspective to consider the pros and cons of these three approaches to data collection carefully and study the interdependencies among them from a market structure perspective. Perhaps triangulating across these methodologies would also be useful in capturing a more complete
picture of the market structure by incorporating more facets of consumer decision-making than just one methodology would reveal.

**Supply-based perspective of competition**

The supply-based perspective assumes that competitive market structures reflect the minds of managers, who run the firms, and the collective structure results from how firms view one another as competitors, which determines the final competitive market structure in an industry (DeSarbo et al. 2006). Scholars from the domains of industrial organization (IO) and strategic management primarily view the competitive market structure of an industry through the lens of firms’ and managers’ perceptions of whom they compete with, and who competes with them.

This supply-based perspective has its roots in the IO school of economics (Mason 1939), which stresses the importance of industry structure and observes that firm profitability depends directly on competitive market structure factors, such as industry concentration (e.g., Scherer and Ross 1990) and the oligopolistic/monopolistic nature of competition (e.g., Stigler 1964). However, IO scholars view the composition of the market as purely structural, in that just by existing in the same industry, all firms compete. Strategic management scholars (e.g., Barney 1986) have drawn heavily from the IO view but also questioned the assumption that all firms in an industry are *de facto* competitors. Instead, competitive market structures may arise from managerial perceptions, which requires the incorporation of managers’ demographic and psychological factors into any competitor identification or analysis (e.g., Porac and Thomas 1990; Zajac and Bazerman 1991). Thus, the supply-based perspective identifies and analyzes competitive market structures on the basis of the perceptions of managers pertaining to which firms are their competitors and which are not. Scholars identify competitive market structures
primarily through perceptual cognitive data obtained from managers and textual analyses of company reports and shareholder letters, as well as strategic firm variables (e.g., available from financial databases), with the assumption that these variables reflect managerial cognitions.

Industrial competition is dyadic (i.e., the struggle between two firms for customers and resources), but because the supply-based perspective charts market structure according to the firm-level perceptions of managers, there could be a mismatch in how two firms view each other. Managers from Firm A might view Firm B as a competitor, whereas managers from Firm B do not consider Firm A competition, which leads to asymmetric competition (e.g., DeSarbo et al. 2006). In the 1960s and 1970s, U.S. automobile and electronics firms did not view Japanese firms as competitive threats, but Japanese firms considered U.S. firms as their primary competitors. Thus, competitive market structures derived from managerial perceptions can provide insights into the asymmetric nature of competition in the market.

Asymmetry in managers’ views of competition suggests that not all firms in an industry compete equally; rather, there are subsets of firms that compete more intensely with each other than firms in other subsets. These subsets within an industry are called strategic groups, a phrase first used by Hunt (1972) and adopted by many others (e.g., Ketchen et al. 1997; McGee and Thomas 1986). Strategic groups consist of firms in an industry that are similar in factors such as their product portfolio or cost structure, so they adopt similar strategies. Firms in a strategic group compete more intensely than firms across strategic groups, and strategic groups help explain performance differences across firms (e.g., Cool and Schendel 1987; Dranove et al. 1998).

Although strategic groups help analyze market structure, growing recognition notes heterogeneity in the degree to which firms comply with the strategic recipes of their groups (e.g., Ketchen et al. 1993). Scholars studying market structures from a supply-based perspective recently have sought to understand the complexities of strategic group compositions, as well as within-group differences in strategies and performance outcomes. For example, McNamara et al.
(2003) study differences within strategic groups and find variations in the way core and secondary members perform. DeSarbo and Grewal (2008) propose the notion of hybrid strategic groups that consist of firms that blend strategies from two or more groups. Similarly, a recent focus has been to study the dynamics of strategic groups (e.g., Fiegenbaum et al. 2001; Mascarenhas 1989), using models for evolutionary paths of strategic groups (DeSarbo et al. 2009) and hidden Markov models to reflect firm switching across strategic groups (Ebbes et al. 2010).

**Environment-based perspective of competition**

The competitive market structure may evolve as a result of environmental factors, such as government regulations, legal environment, infrastructure, institutions, and technological advancements. Apart from strategic management, two disciplines have also examined the role of the environment: the political economy (PE) school of economics (e.g., Bresnahan and Reiss 1991) and organizational sociology (e.g., White 1981).

The PE school draws from theories in economics, law, and political science to explain how political institutions in an environment influence economic activity (e.g., Gaynor and Vogt 2000; Neven and Röller 2005). With regard to competition, PE scholars examine how aspects of the environment, shaped by political institutions such as public policy, regulations, and the legal system, affect the competitive market structure of an industry. The most well-known and conspicuous element of the environment (as related to political institutions) that influences competitive market structure is anti-trust legislation. Anti-trust legislations (such as the US anti-trust law and the European Union competition law) are enacted by governments to protect their citizens’ interest by maintaining market competition and regulating or curbing what governments view as “anti-competitive conduct.” The rationale behind such legislation is that if a certain firm grows in size and uses its relative size advantage to undermine its competitors, the overall level of
competition in the market declines, leaving consumers vulnerable to undesirable outcomes such as price gouging and poorer quality of products or services. Anti-trust legislation is the tool governmental regulatory bodies use to stop companies from engaging in or penalize them for conduct that could suppress robust competition.

Anti-trust legislation can play several influential roles in shaping market structure. As a direct influence, the government might step in and force a firm it deems too big and powerful to break up into smaller firms, which changes the market structure radically. Perhaps the most famous example of this exertion of government force was the breakup of “Ma Bell” (AT&T) in the 1980s, which by U.S. government mandate became several smaller firms popularly referred to as “Baby Bells,” transforming the market structure of the telephone industry from a monopoly to an oligopoly. Regulatory bodies also can use anti-trust laws to prevent a change to the existing market structure by stopping mergers if regulators believe the resulting market concentration will harm competition and thus consumers.

The legal environment influences market structure beyond just anti-trust legislation though. In economies in which the legal environment provides relatively easy recourse for firms that are victims of unethical or illegal practices (e.g., patent violations, intellectual property disputes, misleading advertising), it is difficult for dominant firms to engage in predatory practices or increase their power. A well-functioning legal system can stop the market structure from being held hostage by dominant firms. However, in economies whose legal system is not as robust, dominant firms often shape the market structure to their benefit by engaging in rent-seeking behaviors and moral hazard (e.g., Hainz 2003).

Other aspects of the external environment that can influence market structure include the infrastructure and technological advancements. Technological advancements and the related intellectual property can shape the market structure, depending on, for example, whether the advances are driven by dominant big players or newcomers. The cellular phone industry’s
competing technological standards—GSM (developed by existing dominant players) versus CDMA (developed by newer firms)—have prompted several studies on the resulting market structure evolution (e.g., Bekkers et al. 2002).

Infrastructure, such as roads, freight, airports, electricity, telecommunications, and financial systems, also influence competitive market structures. In economies with a well-developed infrastructure, companies of varying sizes can compete, leading to a market structure that is amenable to greater competition. However in economies with poor infrastructures, big companies with access to capital have an advantage. For example, in India, the power infrastructure falls short of meeting demand, so firms often build power plants within their manufacturing units to ensure reliable power supplies, which requires significant access to capital and thus erects barriers to entry.

Organizational sociologist argue that market structure results from as well as reflects the position of the relevant industrial actors (firms, suppliers, regulators…) in the social structure that connects these industrial actors. Sociologists view economic activity and the resultant market structure as determined primarily by socially defined positions in the market context (e.g., Granovetter 1985; White 1981). Thus, market structure is socially constructed, as perceived by all market participants, and influenced by factors related to the participants’ position in the social structure, their roles, and their status (e.g., Podolny 1993). Sociologists regard competition among firms as relationships, the resulting competitive market structure as a network of relationships, and the market structure as an evolving entity that reflects levels of embeddedness in the network (e.g., Uzzi 1996), including structural holes (e.g., Burt 1995) or cliques (e.g., White 1981). A full understanding of the structural aspects of the network of relationships among market participants can reveal the nature of the market structure, its antecedents, and its consequences for all the participants.
Integrating the three perspectives

Thus far, we have discussed three broad perspectives on competitive market structure: consumers’, managers’, and the environmental perspective. Although market structure has been studied in detail by scholars in several fields, each producing its own perspective, we believe that the way forward is to integrate these three perspectives.

As DeSarbo et al. (2006) argue, there are shortfalls in the demand- and supply-based perspectives, and it would be beneficial to view them as complements. The supply-based perspective, which relies only on managerial perceptions, likely reflects asymmetry in competition and ignores some firms that consumers might view as competitors; thus, its picture of the precise nature of the market structure is incomplete. The demand-based perspective relies only on consumer perceptions and thus likely excludes newcomers that eventually will become potent forces in the competitive market structure but are not yet on equal footing with other firms. DeSarbo et al. (2006) integrate these two approaches to conceptualize asymmetric market structures.

We stress the need for more integrative work that combines not only the supply- and demand-based perspectives but also the environment-based approach. The study of competitive market structures should not be a choice among the influences of managers, consumers, or the environment; rather, it should treat all these perspectives as complementary and draw from phenomena suggested by all of them to develop a complete picture of the market structure.

The market structure in a given industry can and should be regarded as the interplay among the actions of managers, consumers, and the environment. For example, in the cellular phone industry, the market structure clearly has been shaped by managers, consumers, and the environment. From a supply-based perspective, the exclusive agreements between phone manufacturers and service providers (e.g., Apple and AT&T for the iPhone) determine who
competes with whom. From a demand-based perspective, consumers appear to perceive the Blackberry as a functional phone primarily used by professionals, whereas the iPhone and Android phones are “cool toys” used by nonprofessionals, such that the latter two phones appear closer to in the perceptual space than does the Blackberry. Finally, from an environment-based perspective, technological advances such as 3G and 4G services have drastically changed the landscape, allowing a new entrant such as Apple to achieve a strong position quickly.

Any approach that studies an industry from only one of the three perspectives will fail to recognize the impact of the other two perspectives. However, the observations from these three perspectives clearly are related. For example, the technological advancements allowed Apple to enter the cellular phone industry with the iPhone, and consumers who previously used other Apple products such as iPods and Macs viewed it as a desirable product, unlike existing Blackberry phones, which enabled AT&T to attract this significant chunk of Apple fans by entering into an exclusive agreement with it. Integrating the three perspectives should provide a richer understanding of competitive market structures than does focusing on just one of them.

**Agenda for further research on competitive market structures**

Research on competitive market structures, in both marketing and related fields, has been plentiful and insightful, but several areas show promise for ongoing research. Although every aspect of market structure can benefit from further research, we focus on a few areas we consider most important for marketing scholars and practitioners, given the state of extant literature.

As we noted previously, integrating the three perspectives of market structure can lead to new insights. However, the integration of all three perspectives poses several challenges, conceptually (e.g., integrating the differing theories on which the three perspectives rely), methodologically (e.g., developing models that can capture phenomena from all three
perspectives and their interactions), and in terms of the data (e.g., gathering data on managerial perceptions, consumer perceptions, and environmental constructs). Tackling these challenges will be difficult but also will lead to insights regarding the identification, antecedents, and consequences of market structure that hitherto have been unknowable.

In our review of market structure literature across various fields, we have noticed that empirical studies overwhelmingly are cross-sectional (although notable exceptions exist e.g., Ebbes et al. 2010). Although cross-sectional studies can identify the market structure and related phenomena in the short run, they cannot capture the evolution of the market structure over time. We call for studies that investigate the temporal aspects of market structure, using longitudinal data and appropriate time-dynamic models. Most industries undergo structural breaks or shocks (e.g., radical innovation, regulatory changes, recession) that shake up the market structure; we argue for the need to incorporate these structural breaks into longitudinal studies of market structure. Such longitudinal studies can provide insights into how market structures evolve over time and why. For example, a longitudinal study of changes in the airline industry’s market structure over the past three decades, driven by antecedents such as oil price fluctuations, Internet booking, the entry of budget airlines, regulatory changes, the 9/11 attacks, mergers, and so on, could clarify how that market structure evolved and reveal the relative impact of the various antecedents.

**Competitive interactions**

Research on competitive interactions addresses questions that fit under the broad question that Weitz (1985) articulates as follows: “How do competitive actions affect the firm’s market decisions?” This stream of research considers how firms react to the actions of their competitors, the extent of their responsiveness to competitors, and the efficacy of these competitive reactions.
We classify research on competitive reactions into three broad categories, based on their conceptual and methodological approaches: behavioral, structural, and game theoretic approaches. The behavioral approach, as used primarily in strategic management literature (e.g., Chen 1996) and frequently in marketing literature (e.g., Bowman and Gatignon 1995), attempts to predict the competitive reactions of firms on the basis of their characteristics and those of their competitors. The structural approach, from IO but also gaining ground in marketing, uses economic models of the competitive strategy choices of firms, according to profit maximization goals. Finally, the game theoretic approach models the optimum competitive reactions of firms with an equilibrium analysis (as explained in greater detail in Moorthy 1985; Rao 2011). In the following sections, we focus on the behavioral and structural approaches to competition and their main themes, using research from marketing, IO, and strategic management.

**Behavioral approach to competitive reactions (interfirm rivalry)**

The dominant approach in strategic management literature (e.g., Chen 1996), which also appears frequently in marketing literature (e.g., Gatignon et al. 1989), draws from organizational theory to predict the strategic behavior of firms that react to competitive actions, as well as the results of their interfirm rivalry. The underlying principle is the structure-conduct-performance (SCP) paradigm (Bain 1951), which holds that a firm, in the interest of sustaining its performance, reacts to its competitors’ actions in the form of an action–response dyad (Chen et al. 1992) or a series of moves and countermoves (e.g., Porter 1980). Strategic reactions to competitive actions depend on antecedents specific to the competitor who employed the competitive attack, the firm that reacts, and the market conditions. Management scholars typically analyze competitive reactions using firm- or industry-level antecedents; marketing scholars typically study brand-level antecedents (Chen 1996).
A firm’s competitive behavior is motivated by its goal of capturing market share from competitors (in the case of a firm undertaking a competitive attack) or defending or improving existing market share (in the case of a firm responding to a competitor’s action). The perceived utility of strategically attacking competitors to capture market share has been demonstrated through strategies such as garnering the first-mover advantage by introducing a new product first, price cuts and discounts, aggressive promotions, increased advertising budgets, and so on. Although such competitive attacks seem to work in the short run, evidence for their long-term utility is mixed. For example, Young et al. (1996) find that firm performance increases with more competitive attacks, but Pauwels et al. (2002) uncover virtually no long-term effects of aggressive price promotions introduced to capture market share. Evidence is similarly mixed about the efficacy of a swift competitive response, such that some studies show that early and aggressive responses to competitive attacks benefit the reacting firms (e.g., Chen and MacMillan 1992), whereas others indicate competitive responses harm retaliating firms (e.g., Steenkamp et al. 2005). Yet competitive attacks and responses seem permanent phenomena that show no signs of declining.

In marketing literature, a behavioral approach to competitive reactions typically uses market share as the dependent variable, with marketing mix variables such as price, advertising, and innovation as explanatory variables (e.g., Blattberg and Wisniewski 1989; Eckard Jr 1987; Lynch Jr and Ariely 2000). Descriptive studies attempt to determine the nature of competitive reactions and their antecedents (e.g., Gatignon et al. 1989), and normative studies use tactics such as decision calculus models to suggest the best course of action for firms in a given situation (e.g., Hauser and Shugan 1983). Most such studies use firm-level factors and model reactions in terms of those factors. Some marketing scholars also attempt to identify and demonstrate behavioral underpinnings for why firms (i.e., managers) react as they do to competitive actions or what the strategic competitive reasoning might be (e.g., Montgomery et al. 2005). Marketing managers’
behavioral responses do not appear to include the heterogeneity of the situation, often because of the difficulty of obtaining necessary information and the uncertainty of predicting competitor outcomes.

Strategic management literature examines the antecedents of competitive reactions and their effectiveness at a higher level of abstraction than in marketing. The primary theoretical basis has been the resource-based view (Barney 1991), which scholars have used to derive constructs related to firms’ resources as antecedents of competitive reactions. Other theoretical bases include firms’ conceptualization of competitors (e.g., Porac and Thomas 1990), awareness of the interdependence among competitors (e.g., Amit et al. 1988), the relational nature of their competition (e.g., Barnett 1993), and recently the dynamic capabilities perspective (e.g., Teece et al. 1997).

Strategic management scholars also conceptualize constructs that help them predict competitive reactions. For example, Chen (1996, p. 107) defines resource similarity as “the extent to which a given competitor possesses strategic endowments comparable, in terms of both type and amount, to those of the focal firm.” Typically, competitive actions and responses by firms with high levels of resource similarity will be similar and constrained, such that the firms have similar competitive vulnerabilities. In contrast, firms with low resource similarity should exhibit greater variety in the competitive strategies they use, because of their unique strategic resources. Resource similarity is a construct useful for predicting competitive reactions.

A construct used to predict patterns of competitive interaction that has gained popularity in recent years with management and marketing scholars is multimarket or multipoint competition. Karnani and Wernerfelt (1985) describe multimarket or multipoint competition as a situation in which firms compete simultaneously in several markets. The airline industry is the most common example; all airlines do not compete on all routes, and there is a difference in the degree to which how many markets they have in common. The degree of multimarket competition, also termed
market commonality (e.g., Chen 1996), reveals competitive reactions in strategic management literature (e.g., Anand et al. 2009) and marketing literature (e.g., Kang et al. 2010). Studies across industries show that greater multimarket competition actually deters aggressive competitive actions, a phenomenon referred to as mutual forbearance. Such forbearance is driven by the awareness that greater multimarket competition leaves the attacker open to counterattacks in multiple markets. Firms that compete in a majority of their markets tend not to attack each other but instead pursue competitors with whom they have a moderate degree of multimarket contact. The dominant view of the behavioral approach to competitive reactions relies on the school through from IO known as SCP. This SCP-based view assumes that engaging in aggressive competitive behavior or rivalry is counterproductive, and over the long term, firms engaged in multimarket competition should eschew aggressive competitive behavior. However, most industries also are becoming dynamic, seeing shorter business cycles, and confronting a new kind of competition known as “hypercompetition” (D'Aveni 1995). This concept of hypercompetition extends the idea of Schumpeterian competition, which is characterized by “creative destruction” (Schumpeter 1934). That is, businesses are in a state of flux, and the only way for firms to grow and keep growing is to destroy old technologies and products and develop new ones. A sustainable competitive advantage that might have been enough to help firms stave off competitive attacks in the past cannot really be sustained. Thus, an aggressive competitive action does not necessarily suppress performance, as suggested by the SCP model, but rather spurs growth, and continuous aggressive hypercompetition helps firms. The hypercompetition view also implies that competition is not varying but rather something that firms should accept as a given, and then function accordingly. Demonstrations of hypercompetition mainly appear in “high velocity” (Eisenhardt 1989) environments such as software and computer technology among others. Scholars such as Illich et al. (1996) and Wiggins and Ruefli (2005) demonstrate
though that an increasing number of industries display high velocity and dynamic characteristics, such that hypercompetition extends beyond high-tech industries.

Finally, the behavioral approach focuses mainly on a firm’s behavior, treating the firm or a specific industry as the unit of analysis. However, the decisions a firm makes essentially are decisions by its managers, so some scholars have tried to study competitive reactions using managers as the unit of analysis (e.g., Montgomery et al. 2005). These studies investigate how competitive reactions might be determined by characteristics specific to individual managers. Competitive actions and responses undertaken by firms thus result from the way managers perceive the competition and what they believe is the best course of action. Theories to predict managerial behavior in competitive scenarios include regulatory focus theory (e.g., McMullen et al. 2009), competitive reasoning (e.g., Montgomery et al. 2005), the awareness-motivation-capability perspective (e.g., Chen et al. 2007), and the upper echelons perspective (e.g., Hambrick et al. 1996), among others. These studies indicate that heterogeneity among managers influences the kind of competitive moves firms make. For example, Hambrick et al. (1996) find that managerial teams that are diverse in terms of education, background, and experience are more prone to make competitive attacks but slower to react to them than are homogenous teams. Similar studies that link competitive reactions to managerial heterogeneity could shed further light on the nature of the process that drives competition.

**Structural Approach to Competitive Reactions (NEIO Model)**

The structural approach from IO has gained considerable ground in marketing as a means for studying competitive reactions. This approach relies on the New Empirical Industrial Organization (NEIO) framework and uses structural economic models to consider the competitive
strategy choices of firms, according to some kind of optimizing behavior, typically profit maximization (e.g., Chintagunta et al. 2006; Kadiyali et al. 2001).

In particular, NEIO scholars (for reviews see Ackering et al. 2007; Bresnahan 1989; Reiss and Wolak 2007) address several limitations of the SCP paradigm, such as its inability to capture heterogeneity in the structural characteristics across firms and industries, and thus marketing strategies, fully. Studies using the SCP paradigm also tend to pool data across industries and, even if the analysis is limited to one industry, fail to account for heterogeneity across firms. Some studies run separate regressions (e.g., Prescott et al. 1986) or allow for fixed effects in panel data (e.g., Boulding and Staelin 1993), but as Kadiyali et al. (2001) point out, differences across and within industries, and their impact on performance, run deeper than the SCP variables. The SCP paradigm also suffers from the issue of endogeneity arising from simultaneity (Wind and Lilien 1993); though conduct influences performance, there also is ample evidence of performance influencing conduct too (e.g., sales affecting advertising). Thus, the endogeneity inherent to the SCP paradigm creates a problem with regard to studying competitive reactions. Furthermore, the SCP paradigm considers cost data only in terms of accounting costs and resulting profits, which do not give a complete picture of costs compared with economic profits.

The structural approach, i.e., the NEIO model seeks to overcome these limitations of the SCP paradigm by estimating effects at the industry level and then, within industries, at the firm level. The NEIO model consists of three main specifications: (1) a demand specification that expresses the relationship of demand with strategic variables; (2) a cost specification that
expresses economic costs (not just accounting costs\textsuperscript{1}) that the firm incurs by undertaking the available strategies; and (3) a specification for competitive reactions, which shows how competing firms react to one another. Using these three specifications, the model derives first-order conditions from different equilibriums, according to the context. To estimate the model, researchers can use approaches that allow for simultaneous equation estimation to account for endogeneity, such as 3SLS, GMM, or the instrumental variable approach (e.g., Kadiyali et al. 2001; Shankar 1997). With such rich, robust, and flexible models to specify the demand, cost, and competitive interaction functions, as well as appropriate models to account for endogeneity, the NEIO approach provides relatively unbiased, more complete findings about competitive reactions than does the SCP paradigm.

Moreover, NEIO models provide other benefits compared with the SCP paradigm (see Chintagunta et al. 2006; Kadiyali et al. 2001). Researchers using NEIO models compare empirically alternative theoretical frameworks and select the most appropriate framework according to model fit (e.g., Knittel and Stango 2003; Porter 1983). The variables in NEIO models, such as demand, cost, and strategy variables, link to existing theories on firm behavior and lend themselves to simple interpretation. Because the NEIO models account for industry and firm effects, the estimated parameters are independent of the changes in the levels of strategic variables and can be used for managers’ “what-if” analyses (e.g., Dunne et al. 2009; Goolsbee and Petrin 2004). Finally, NEIO models allow for a fine-grained analysis of the antecedents of firm profitability, which makes it possible to determine the proportion of profit that came from each strategic action.

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\textsuperscript{1} As Kadiyali et al. (2001, p 165) argue, accounting costs are simply average costs, and thus suspect for predicting profitability, for which economic (marginal) costs would be more relevant. Hence, using economic costs in addition to accounting costs results in better conclusions related to profitability.
In recent years, NEIO models have appeared in marketing literature as means to study competitive reactions and optimum competitive strategies in diverse contexts, focusing on not only marketing mix variables such as price, advertising, and promotions (e.g., Shankar 1997; Sun 2005; Vilcassim et al. 1999) but other strategic variables as well. For example, Shankar and Bayus (2003) apply the NEIO framework to the video game industry and find that consumer network strength effects decrease with greater consumer network size, such that firms in small networks can overtake the sales of firms in large networks.

**Agenda for Further Research on Competitive Interactions**

Through this summary of the extensive work done on competitive reactions in marketing and allied fields such as strategic management and industrial organization, we identify promising avenues for further research that can contribute significantly to the field. We arrange these suggestions into two categories, conceptual and methodological.

Conceptually, as Chen (1996) has noted, the greatest promise for research likely involves building a solid theoretical basis for understanding what drives competitive actions and reactions, as well as why some competitive strategies work better than others. Although well-regarded theoretical frameworks such as the SCP paradigm and the resource-based view provide insights into the processes that drive competitive behavior, we argue that a complete, if not comprehensive, theory of competitive behavior has not yet been formulated. The need for a comprehensive theory can be gauged from the diversity of empirical findings related to the desirability and efficacy of competitive strategies across contexts and industries. The path to stronger theoretical frameworks should be paved by incremental contributions that describe phenomena related to competitive behaviors at increasing levels of abstraction compared with empirical findings. For example, multimarket competition research has helped explain
competitive phenomena in terms of market commonality. Such theoretical contributions will add to our understanding of competitive behavior and competition in general.

Methodologically, the advances in the structural approach using NEIO models have been promising and should be extended by incorporating newer variables and interaction effects. Specifically, robust functional forms for the cost and competitive interaction specifications in NEIO models might increase insights into how competitors react and interact. The importance of better functional forms for the specifications involved extends beyond NEIO modeling and into game theoretic and empirical modeling as well (for a review and assessment, see Leeflang 2008). Our understanding of competitive reactions and behavior also might benefit from the use of longitudinal data with dynamic models, which allow for convincing analyses of causality and can address the issue of endogeneity.

The ubiquity of the Internet has fundamentally changed the way business is done. Not surprisingly, the Internet has changed the nature of competition, in terms of both market structure and competitive reactions (Vardarajan, Yadav, and Shankar 2008). In particular, the phenomenon of asymmetric competition, as we described in Section 2, denotes a difference in the degree to which two firms view each other as competitors, arising from factors such as firm size and market reach. However, the Internet, by fundamentally changing market reach, has reduced asymmetric competition in several industries. Barnes & Noble, a firm more than a century old and still the largest book retailer in the United States, would not have considered smaller players as direct competitors prior to the 1990s, and certainly did not worry about Amazon.com, an online company that started in 1994 out of a tiny office with minimal funding. Yet the expansion of the Internet reduced market reach and access barriers, such that consumers could buy books from Amazon.com more easily than by driving over to a Barnes & Noble store. Asymmetry declined because of the Internet, and Amazon.com is now Barnes & Noble’s biggest competitor. The
market structure of the book industry changed fundamentally and in a relatively short period of
time. This market structure in an Internet-enabled environment deserves further research.

Although market reach is the strongest driver of changing market structures, it is by no
means the only one resulting from the Internet. The explosion of user-generated content (e.g.,
blogs, YouTube, twitter) has created a new arena for firm competition, in which user involvement
reaches unprecedented levels. Reviews of products and services in blogs or consumer forums
hold as nearly much weight as, if not more than, reviews posted in newspapers and magazines.
These reviews force firms that never competed with others to do so, undermining the market
leader and first-mover advantages. For example, Microsoft’s and Yahoo’s search engines existed
well before Google’s, but Google, mainly through word of mouth on online forums, quickly
became the market leader. More research on late mover and first mover advantages in the
Internet-enabled environment is desired (e.g., Lieberman and Montgomery 2011; Shankar and
Carpenter 2011; Varadarajan et al. 2008).

The Internet also has introduced new challenges and avenues for competitive actions and
reactions. The reduced costs for distribution and marketing communication give firms new ways
to attack their competitors, and competitors have newer ways to respond. For example, firms
recognize the importance of appearing on the first page of relevant results on search engines,
which has led to the burgeoning field of search engine optimization (in 2008, worth US$15
billion) for firms that must improve their search engine visibility relative to their competitors.
Firms also encourage user-generated content to involve loyal consumers in attacks on the
competition, as evidenced by the pitched battles in the blogosphere between users of Apple’s
Macintosh computers and PCs running Microsoft’s Windows. Such phenomena are clearly
worthy of greater and ongoing scrutiny.
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<td></td>
<td>- Asymmetric competition</td>
<td></td>
<td>DeSarbo et al. (2006)</td>
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<td></td>
<td>- Strategic groups</td>
<td></td>
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<td>Market Share Battle</td>
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<td>Chen and Macmillan (1992)</td>
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<td>Hypercompetition</td>
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<tr>
<th>- Government regulations</th>
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<tr>
<td>- Legal and technological environment</td>
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- Competitive structure reflects social structure
- Competitive structure is shaped by anti-trust legislation and policies
- Competitive structure reflects the impact of legal and technological environment on firms.

- Environmental factors.
Chapter 2

Cable News Wars and the Internet: Modeling Competitive Interactions for Primetime Viewership and User-Generated Content

ABSTRACT

Academics and practitioners alike recognize that user-generated content (UGC) about products, such as blog posts, help not only predict but also boost product performance (e.g., sales). Building on extant research pertaining to the UGC–performance relationship, this study models the competitive effects of the relationship between the daily viewership share of cable news shows and the daily volume of content-coded blog posts, using a multivariate mixed distribution model (mixture of Dirichlet-lognormal and Poisson-lognormal). Data from a 30-week period describe viewership of competing cable news shows on Fox News, CNN, and MSNBC during the 7:00, 8:00, and 9:00 p.m. time slots. Although blog posts of different valences (positive, negative, neutral, and co-mentions) have a positive effect on daily viewership for a show, the strength and temporal prevalence of this positive effect varies across time slots. Blog posts of different valences related to a show’s competitors have a statistically significant effect on viewership, but whether the effect is positive or negative varies across time slots. These findings demonstrate the importance of competitive effects when formulating and assessing UGC-related marketing strategies.

1. Introduction

In recent years, the growing influence of cable news networks and their opinionated hosts (e.g., Bill O’Reilly, Rachel Maddow) has caught the attention of viewers, online users, politicians, and advertisers alike. In 2008, the combined advertising revenue of the “big three”
cable news networks, Fox News, CNN, and MSNBC, stood at US$1.3 billion, a growth of 80% since 2003.\(^2\) This revenue growth comes primarily from advertising during primetime slots, when the three networks air one-hour, opinion-based commentary shows (Dagnes 2010) that attracted an average daily combined viewership of 4.6 million in 2009.\(^3\) The primetime slots that provide the context for our study, during May–November 2009, featured at 7:00 p.m. *The Fox Report with Shepard Smith* on Fox News, *Lou Dobbs Tonight* on CNN, and *Hardball with Chris Matthews* on MSNBC; at 8:00 p.m., these networks aired, respectively, *The O’Reilly Factor*, *Campbell Brown*, and *Countdown with Keith Olbermann*; and at 9:00 p.m., *Hannity, Larry King Live*, and *The Rachel Maddow Show*.

Every day, the hosts of primetime cable news shows (with the exception of King’s interview-based show) express their opinions about topical political events; their opinions reflect their position on the conservative–liberal spectrum of political ideologies and are usually quite strident (Dagnes 2010). The ideological nature of the competition among cable news networks, often characterized as the “cable news war,” also has helped boost the influence and commercial success of all the shows (Harris 2009).

This ideological competition is also reflected in user-generated content (UGC) related to the shows, including blog posts, YouTube videos, Twitter updates, message board posts, and so on. Viewers post their opinions and participate in online conversations, often about controversial points raised by the hosts, run-ins with politicians, or their ideological positions (Boehlert 2009). Extant research reveals that UGC positively influences the viewership of newly released films (e.g., Duan et al. 2008) and new entertainment television shows (e.g., Godes and Mayzlin 2004); we build on this research to model competitive interactions in the UGC–viewership relationship.


\(^3\) Source: Nielsen Media Research.
for cable news shows. With this research, we therefore aim to model the relationship between a show’s UGC and its viewership, as well as incorporate endogenous competitive interactions as a means to examine how a show’s viewership may be influenced by its competitors’ UGC.

To model competitive interactions for any performance metric (e.g., viewership), we must differentiate between the influence of growth in the overall size of the market and the influence of changes in the market shares of competitors (e.g., Nguyen and Shi 2006, Soberman and Gatignon 2005). In the context of primetime cable news shows, we therefore recognize the difference between changes in a cable news show’s viewership due to a general trend in which primetime viewers move from entertainment to news programming, or vice versa, and changes in viewership due to a corresponding change in a competing cable news show’s viewership. We further note that though advertising revenues have grown steadily (compounded annual growth rate of 10.2% in the past seven years), cable news viewership has demonstrated no discernible trends. Total daily primetime cable news viewership has fluctuated around 3 to 5 million viewers, including 3.7 million in 2003, 4.6 million in 2009, a low of 3.0 million in 2006, and a high of 5.0 million in 2008 (a year marked by a lengthy Democratic Party primary race and a historic presidential election). Primetime cable news viewership as a proportion of total primetime cable viewership also has fluctuated, from 4.9% in 2003 to 5.5% in 2009 to a low of 3.7% in 2006, and a high of 6.2% in 2008. This lack of consistent up- or downward trend suggests that changes in a typical cable news show’s viewership primarily reflect market share effects, not market size effects. Therefore, we focus on modeling the market share effects for the daily viewership for the set of competing cable news shows.

To model the competitive interaction for UGC–viewership relationships, we gathered data about daily viewership and daily volumes of blog posts for cable news shows that air on the “big three” cable networks in three consecutive weeknight primetime slots (7:00, 8:00, and 9:00 p.m. Eastern Time), for a period of 30 consecutive weeks (150 weeknights) during May–
November 2009. We coded the blog posts by content into four mutually exclusive and exhaustive categories: co-mentions (mentioning a show or host and competitors), positive blogs (agree with or praise the show or host), negative blogs (disagree with or criticize the show or host), and neutral blogs (posts without an opinion about the show or host that merely report on what was said or shown). To model the endogenous relationships among viewership and UGC for competing cable news channels, we allow for within-show endogeneity, which reflects the relationships between a show’s own UGC and its viewership; competitive effects, or the influence of the competition’s UGC and viewership on the focal show’s UGC and viewership; state dependence to control for the carryover effects of viewership from the previous day and previous time slot; and unobserved heterogeneity in the shows’ inherent propensities to drive UGC or viewership. Because the UGC data are count data, we adopt a Poisson specification and express viewership as a percentage share of total television viewership, and for the viewership share measures for all the cable news shows we turn to a Dirichlet specification. Our multivariate mixed distribution model features Dirichlet-lognormal and Poisson-lognormal mixtures for the endogenous relationships among the UGC and viewership variables related to competing shows that air during the three time slots.

We find that although a show’s UGC positively influences its viewership, this positive relationship varies in strength and prevalence (in lags) across time slots, and the time slots with the most ideological programming exhibit the strongest effects. We also find that competitors’ UGC can have a negative or positive effect on a show’s viewership, depending on the nature of the time slot. At 7:00 p.m., the programming is mainly news and analysis based, and the effect of competitors’ UGC on the show’s viewership is largely negative, but in the 8:00 and 9:00 p.m.

4 The overlap between co-mentions and other categories was 6% on an average. Thus, to avoid counting the blog posts twice, we coded all posts mentioning two or more hosts as co-mentions.
time slots, when the shows’ emphasis is on ideological commentary, the effect becomes positive. Our results, though specific to a cable news context, underline the broader imperative to take competition into account when assessing the relationship between UGC and performance.

We organize the remainder of this article as follows: In § 2, we elaborate on our data and their sources. In § 3, we discuss the modeling issues pertinent to our context of television viewership and UGC, and in § 4, we develop the model specification. We discuss the model estimation and selection procedures in § 5, followed by the results of our empirical analysis in § 6. Finally, in § 7, we discuss the theoretical and managerial implications of our findings and conclude with some directions for further research.

2. Data

2.1. Data Context

We collected data about the three major 24-hour cable news networks in the United States, Fox News, CNN, and MSNBC, which account for more than 80% of cable news viewership. For every weeknight (Monday–Friday) for a 30-week period beginning in May 2009, we collected data about the three consecutive three timeslots (7:00, 8:00, and 9:00 p.m. Eastern Time) that attract the highest viewership ratings for the three networks. The networks air one-hour shows in each slot, hosted by solitary anchors who directly compete for viewers. During our study period, at 7:00 p.m., Fox News aired The Fox Report with Shepard Smith, CNN

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6 Although there are two other cable news networks, Headline News and CNBC, the former’s primetime programming (assessed December 2010) focuses more on human interest stories than politics, and the latter’s coverage is related exclusively to the financial sector. These two networks are thus not direct competitors of Fox News, CNN, and MSNBC for the segment of politically savvy viewers.
showed *Lou Dobbs Tonight*, and MSNBC aired *Hardball with Chris Matthews*. At 8:00 p.m., these networks aired, respectively, *The O’Reilly Factor, Campbell Brown*, and *Countdown with Keith Olbermann*. At 9:00 p.m., *Sean Hannity* (Fox News), *Larry King Live* (CNN), and *The Rachel Maddow Show* (MSNBC) aired.

The three time slots that make up our data context are different in terms of the content and slant of programming as well as the nature of competition. At 7:00 p.m. (Smith, Dobbs, Matthews), the shows’ focus is on analysis of the news, whereas at 8:00 p.m. (O’Reilly, Brown, Olbermann), the emphasis is on opinion and strident commentary, including frequent criticism of the competitor hosts and networks. At 9:00 p.m., two of the shows (Hannity on Fox and Maddow on MSNBC) are opinion and commentary based, whereas the third show (Larry King) is devoid of opinion or commentary from the hosts and is composed of interviews. Thus, the three time slots offer three different sets of competitors with distinct variations in the programming content. Our data consist of daily viewership figures as a performance measure and blog posts as the UGC measure over this 30-week period (150 weeknights) for all nine shows (for descriptive statistics, see Table 2-1).

<table>
<thead>
<tr>
<th>Time Slot</th>
<th>Network</th>
<th>Host</th>
<th>Viewership Share (%)</th>
<th>Blog Posts (Std. Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7 PM</td>
<td>Fox News</td>
<td>Shepard Smith</td>
<td>1.59</td>
<td>0.28 10.69 21.27</td>
</tr>
<tr>
<td>7 PM</td>
<td>CNN</td>
<td>Lou Dobbs</td>
<td>0.62</td>
<td>0.28 38.53 39.55</td>
</tr>
<tr>
<td>7 PM</td>
<td>MSNBC</td>
<td>Chris Matthews</td>
<td>0.58</td>
<td>0.11 42.51 20.00</td>
</tr>
<tr>
<td>8 PM</td>
<td>Fox News</td>
<td>Bill O’Reilly</td>
<td>2.82</td>
<td>0.43 49.42 32.91</td>
</tr>
<tr>
<td>8 PM</td>
<td>CNN</td>
<td>Campbell Brown</td>
<td>0.70</td>
<td>0.38 13.87 8.95</td>
</tr>
<tr>
<td>8 PM</td>
<td>MSNBC</td>
<td>Keith Olbermann</td>
<td>0.97</td>
<td>0.20 69.04 37.91</td>
</tr>
<tr>
<td>9 PM</td>
<td>Fox News</td>
<td>Sean Hannity</td>
<td>2.14</td>
<td>0.45 76.77 35.58</td>
</tr>
<tr>
<td>9 PM</td>
<td>CNN</td>
<td>Larry King</td>
<td>0.96</td>
<td>0.38 119.61 68.15</td>
</tr>
<tr>
<td>9 PM</td>
<td>MSNBC</td>
<td>Rachel Maddow</td>
<td>0.84</td>
<td>0.19 72.05 35.41</td>
</tr>
</tbody>
</table>
2.2. Data Description

Viewership Data

We obtained daily viewership ratings from Nielsen Media Research. Nielsen provides a variety of television viewership measures, such as viewership data on a minute-by-minute basis (as frequently used to conduct research on television advertising; e.g., Wilbur 2008), the number of viewers who watched a show in the time slot in which it was telecast, viewership numbers in different age groups (e.g., adults 18–49 years), and regional market shares, among others. For the purpose of our investigation of the relationship between a show’s viewership and UGC, we chose a time unit that allowed for robust longitudinal analysis, contained enough instances of UGC to make the longitudinal analysis possible, and allowed for a meaningful substantive interpretation of the results. Thus, we chose a day as the time unit, allowing us to use daily viewership measures as well as daily blog post volumes.

We used what Nielsen classifies as Live + Same Day (Live+SD) ratings, which estimate the viewership for a show when it airs live, as well as viewership on the same day of recordings of the show (e.g., DVR, TiVo), based on a sample of more than 9,000 households. We converted the Live+SD ratings to the percentage of total viewership by dividing the number of estimated viewers of each show by the number of total television viewers. Thus, our measure for viewership of a cable news show for a given day reflects the percentage of television viewers who watched the show when it was aired live, plus those who recorded the show and watched it on the same day. In Figure 2-1, we depict the daily viewership percentages for the three time slots during our 30-week study period.

---

7 Nielsen collects data by observing a statistically selected sample of more than 9,000 households spread across 210 television markets. Details are available at http://en-us.nielsen.com/tab/product_families/nielsen_tv_audience.
Figure 2-1 Daily Viewership Percentages

a. 7:00 p.m. Time Slot

b. 8:00 p.m. Time Slot

c. 9:00 p.m. Time Slot

Notes: The graphs represent the daily viewership percentages for the three time slots, and the three shows within each time slot, for the 30 weeks that our data cover.
As Figure 2-1 makes evident, Fox News earns the highest viewership among the three networks in all three time slots. A visual inspection reveals no discernible trend in the viewership percentages of any of the shows. We also conducted unit root tests to confirm that the data series were indeed stationary. We found the occasional spikes in viewership percentages to be related to important news stories that were in focus on those days. For example, near the end of the data period, spikes in the viewership percentages of all the nine news shows paralleled the timing of the Fort Hood shooting, an incident in which a U.S. army officer gunned down 13 people inside a military base on November 5, 2009. Similarly, other spikes were associated with noteworthy news stories, such as the death of Senator Edward Kennedy and major developments in the healthcare reform debate.

**UGC Data**

We used the daily number of blog posts mentioning a specific television show or its host as our measure for blog post volume, collected by running keyword-based search database queries on the Application Program interface (API) of three blog-tracking services: Google BlogSearch (http://blogsearch.google.com), Technorati (http://www.technorati.com), and Nielsen Blogpulse service (http://www.blogpulse.com).

Prior research has shown that the volume of UGC has significant predictive power for performance (e.g., Liu 2006); we expect the content of blog posts to play an important role too. The viewership influence of a positive blog post that praises the cable news show host differs from that of a negative posting, as well as that of one that is merely descriptive. We thus coded blog posts as positive, negative, or neutral in their content. Considering our interest in examining competitive dynamics, we also wanted to determine the impact of blog posts that mentioned more than one cable news show host, usually in a comparative context. Therefore, we also measured
the number of blog posts mentioning two or more competing cable news show hosts (e.g., mentioning Lou Dobbs on CNN at 7:00 p.m. together with Shepard Smith on Fox or Chris Matthews on MSNBC). For any given show, the number of blog posts that also mentioned at least one of the competitor shows or hosts in the same time slot represented our co-mentions measure. The overlap between co-mentions and blog-posts with positive and negative valence was 6%. Thus, if a blog post mentioned two or more competing hosts, we classified it under co-mentions, regardless of the valence, thus coding the blog posts into mutually exclusive categories.

The descriptive statistics for the content-coded blog posts for all nine shows appear in Table 2-2.

**Table 2-2 Descriptive Statistics for Blog Data**

<table>
<thead>
<tr>
<th>Time Slot</th>
<th>Network</th>
<th>Host</th>
<th>Positive Blogs</th>
<th>Negative Blogs</th>
<th>Neutral Blogs</th>
<th>Co-Mentions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>7:00 PM</td>
<td>Fox</td>
<td>Shepard Smith</td>
<td>2.22</td>
<td>5.86</td>
<td>0.69</td>
<td>1.66</td>
</tr>
<tr>
<td>7:00 PM</td>
<td>CNN</td>
<td>Lou Dobbs</td>
<td>6.46</td>
<td>5.72</td>
<td>8.56</td>
<td>9.38</td>
</tr>
<tr>
<td>7:00 PM</td>
<td>MSNBC/</td>
<td>Chris Matthews</td>
<td>12.96</td>
<td>7.18</td>
<td>1.85</td>
<td>1.95</td>
</tr>
<tr>
<td></td>
<td>Fox</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:00 PM</td>
<td>CNN</td>
<td>Bill O'Reilly</td>
<td>10.32</td>
<td>7.67</td>
<td>9.97</td>
<td>8.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Campbell</td>
<td>2.98</td>
<td>2.06</td>
<td>2.41</td>
<td>1.75</td>
</tr>
<tr>
<td>8:00 PM</td>
<td>MSNBC/</td>
<td>Olbermann</td>
<td>13.07</td>
<td>8.64</td>
<td>12.65</td>
<td>8.26</td>
</tr>
<tr>
<td></td>
<td>Fox</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:00 PM</td>
<td>CNN</td>
<td>Larry King</td>
<td>11.51</td>
<td>6.19</td>
<td>12.17</td>
<td>5.98</td>
</tr>
<tr>
<td>9:00 PM</td>
<td>MSNBC/</td>
<td>Rachel Maddow</td>
<td>2.89</td>
<td>3.52</td>
<td>0.43</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Fox</td>
<td></td>
<td>10.71</td>
<td>5.55</td>
<td>10.15</td>
<td>5.33</td>
</tr>
</tbody>
</table>

The content coding process used a combination of textual software analysis and human evaluation. On the basis of textual software analysis of a sample of 200 cable news show–related blog posts, from a period outside our data window, we derived a list of 65 adjectives and phrases commonly used to describe a show or host, including both positive (e.g., “brilliant,” “insightful,” “gets it right”) and negative (e.g., “wrong,” “loony,” “off the rails”) comments. We used this directory to create guidelines for classifying blog posts into valence categories. Two independent raters read and classified the blog posts into one of the categories, with inter-rater reliability of
Figure 2-2 Blog Valence and Co-Mention Percentages

Legend: ■ Comentions | Neutral Blogs | Negative Blogs | Positive Blogs

a. 7:00 p.m. Time Slot

b. 8:00 p.m. Time Slot

c. 9:00 p.m. Time Slot

Notes: The graphs represent the percentages of total blog posts with co-mentions (black), neutral posts (horizontal lines), negative posts (slanted lines), and positive posts (vertical lines).
Thus, each blog post that did not have co-mentions was classified as being either positive or negative (i.e., appreciative or critical of the host’s opinion or political analysis or ideology) or neutral (i.e., merely describing something from the news show, without offering a concrete positive or negative opinion). The valence-wise composition of blog posts for each cable news show is also depicted in Figure 2-2 (positive – vertical lines, neutral – slanted lines, negative – horizontal lines).\(^8\)

The difference in the nature of the competition across the three time slots is evident in the valence composition in Figure 2-2. At 7:00 p.m. (top panel), almost two-thirds of the blog posts offer no opinion but instead are neutral (66% Fox, 56% MSNBC, and 61% CNN). Positive blog posts heavily outnumber negative ones for two shows (Smith: 21% positive, 6% negative, Matthews: 30% positive, 4% negative), though negative (22%) outnumber positive (17%) statements for Dobbs. In contrast, at 8:00 p.m. (middle panel), only one-third of the blog posts express a neutral opinion of the shows, and the proportions of positive and negative blog posts combined are higher than the neutral posts for all three shows (O’Reilly: 21% positive, 20% negative; Brown: 22% positive, 17% negative; Olbermann: 19% positive, 18% negative). This pattern of blog valence suggests that most bloggers who write about 7:00 p.m. shows describe something they have seen and found noteworthy, and those who do express opinions usually praise the show or host. In contrast, at 8:00 p.m., most bloggers express an opinion, and roughly as many bloggers criticize the show or host as praise them. At 9:00 p.m., King’s show again stands out from not only Hannity and Maddow, with whom he competes in the same time slot, but also the rest of the cable news shows. Blog posts about King’s show are overwhelmingly

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\(^8\) Each blog post was classified into only one category, with no overlap in the classification. The number of blog posts in each category thus sums to the total number of blog posts.
neutral (96%) and feature comments about the interviews, without opinions about the show or Larry King. The small percentage of blog posts that express an opinion are favorable (positive 3%, negative .3%).

The differences in the percentages of co-mentions across the three panels of Figure 2-2 also confirm that the nature of competition varies across the three time slots. At 7:00 p.m., as the top panel of Figure 2 shows, co-mentions as a percentage of total blog posts were 6.8%, 3.7%, and 4.4%, for Fox, MSNBC, and CNN, such that overall, only around 5% of the blog posts about a 7:00 p.m. cable news show mention direct competitors. In contrast, at 8:00 p.m. (middle panel), co-mentions occur in 34.9%, 25.4%, and 28.9% of the blogs about Fox, MSNBC, and CNN. Thus, we see that roughly a third of total blog posts for 8:00 p.m. are co-mentions. Thus bloggers writing about the 8:00 p.m. shows hosted by O’Reilly, Olbermann, and Brown mention the competition in their posts significantly more frequently than those writing about the shows hosted by Smith, Matthews, and Dobbs. It follows then that readers of blogs about their preferred cable news receive exposure to at least mentions of, if not comparisons with, cable news shows that compete for the same time slot. At 9:00 p.m. (bottom panel), the co-mentions for Hannity (Fox) and Maddow (MSNBC), who host ideological opinion/commentary shows, reveal similar levels to those of the 8:00 p.m. shows, whereas the co-mentions for King’s nonpartisan, non-ideological interview are the lowest in the entire sample, at 1.6%. Thus, co-mentions appear connected to the nature of the shows, including their ideological slant and opinion content.

These statistics on co-mentions and valence of blog posts gives us insights into the differing nature of competition across the three time slots and bloggers’ responses. The most competition-aware and opinionated blogging takes place in reference to the 8:00 p.m. time slot, featuring the highest proportion of co-mentions and positive or negative comments. The number of positive and negative blog posts is approximately evenly matched, suggesting that each show has comparable numbers of supporters and detractors in the blogging world. At 7:00 p.m.
however, the salience of competing news shows is low in bloggers’ minds; only about 5% of the blog posts mention other shows or hosts. Furthermore, though most of the blog posts about 7:00 p.m. shows are neutral, a significant proportion represent opinionated blog posts, most of them positive. Thus, most users who take to their blogs to write opinionated posts about 7:00 p.m. shows, do so in praise. At 9:00 p.m., Hannity’s and Maddow’s programming, the competition, and bloggers’ approach to writing about them is similar to those features aligned with the 8:00 p.m. shows, with roughly equal positive and negative responses. King’s programming is of a different nature, as reflected by blog posts that include barely any co-mentions or opinions.

Because the shows air on weeknights, viewership numbers are available for five days per week, whereas new blog posts appear on all seven days. To ensure the UGC and viewership time series were of the same length, and for ease of longitudinal analysis, we added Saturday posts and videos to the Friday numbers and Sunday posts and videos to the Monday numbers.9

3. Modeling Television Viewership and User-Generated Content

There is a long history of models being used to study television viewership (e.g., Danaher and Mawhinney 2001; Liu et al. 2004; Wilbur 2008), and recently, researchers also have modeled the relationships between UGC and performance by entertainment or media products such as films (e.g., Rangaswamy and Gupta 2000), books (e.g., Chevalier and Mayzlin 2006), and television shows (e.g., Godes and Mayzlin 2004). We build on modeling issues addressed in the extant research related to television viewership and to UGC, with the objective of modeling competitive interactions in the UGC-viewership relationship among primetime cable news shows.

9 We tried other ways to combine the data, and the results did not change in terms of statistical significance.
3.1. Modeling Issues Specific to Television Viewership

Although our primary research objective is to study the relationship between UGC and television viewership, we recognize that our model must account for structural phenomenon identified in extant research on determinants of television viewership. We now discuss the relevant modeling issues. In particular, viewers’ choices about which television show to watch is significantly influenced by state dependence characteristics, i.e. their viewing habits in the recent past (e.g., Rust and Eechambadi 1989; Shachar and Emerson 2000; Wilbur 2008). According to Moshkin and Shachar (2002, p. 436), “65% of the viewers continue to watch the same network when a show ends and a new show starts.” The influence of viewing the show that airs immediately previous to the focal show is the lead-in effect (e.g., Rust and Eechambadi 1989). Because the primetime shows on a given cable news network tend to have similar ideological slants (e.g., Fox News is primarily conservative, MSNBC is primarily liberal), it is all the more important for us to account for the lead-in effect. Godes and Mayzlin (2004) also find that viewership for a given episode of a show is significantly influenced by the previous episode’s viewership. Therefore, we account for two distinct sources of state dependence: (1) the lead-in effect, or the influence of viewership of a show on the same network during the previous time slot, and (2) daily continuity, which is the influence of viewership of the show’s episodes on previous days.

Goettler and Shachar (2001) found that show characteristics such as heterogeneity in their content and appeal, have a significant effect on viewership. In the context of primetime cable news shows, which are strongly tied to the personalities and opinions of their hosts, show characteristics should be significant predictors of viewership. Because we are interested in the relationship between viewership and UGC, we must control for each show’s and host’s unique appeal and content and their effects on viewership. We therefore include an
unobserved heterogeneity component that is show and cable network specific. In summary, our model accounts for (1) lead-in effect state dependence, (2) daily continuity state dependence, and (3) unobserved heterogeneity across shows.

3.2. Modeling Issues Specific to User-Generated Content

If UGC represents an online form of word-of-mouth communication, the concepts and frameworks from word-of-mouth literature should extend to UGC (e.g., Dellarocas 2003). This approach assumes that UGC, much like traditional or offline word of mouth, is “a precursor as well as an outcome of consumer actions” (Godes and Mayzlin 2004, p. 547). Thus, UGC can be an outcome when it is produced by a user posting about the experience of consuming a product, i.e., a review of some sort. However, this outcome itself can serve as a precursor for the actions of other consumers. For example, Chevalier and Mayzlin (2006) find that consumer reviews on Amazon.com and Barnesandnoble.com both influence and are influenced by book sales. Thus, even as we argue for causality between UGC and viewership, we acknowledge the need for our model to estimate whether UGC is driving viewership, whether viewership is driving UGC, or both.

One of our primary objectives is to model competitive interactions in the context of UGC and viewership. We are not aware of any study that has modeled competitive interactions for UGC, and we address some possible relevant modeling issues. For example, UGC may drive viewership, and the shows in a given time slot compete for a stable segment of viewers, so our model must account for the effect that an increase in the UGC related to a show’s competitors has on the viewership of that show. Furthermore, differences in the nature of the competition and its resultant effect on UGC can vary across time slots. Our model therefore includes how the nature
of competition in a time slot influences UGC creation and content, as well as the competitive interactions between UGC and viewership.

To address UGC’s dual role as an antecedent as well as outcome of viewership, and to model competitive interactions in the UGC–viewership relationship, as well as variations in the relationship that reflect the nature of the competition, our model (1) treats each show’s daily UGC and viewership measures as multivariate dependent variables, and (2) uses lagged values of the focal show’s and competing shows’ UGC and viewership measures as explanatory variables.

4. Model Development

To model the competitive interactions for the relationship between UCG and viewership, we need a fully endogenous system that allows daily viewership and the volumes of positive, negative, neutral, and co-mentioning blogs to be functions of one another. Viewership is a proportion variable that indicates the viewer share of each show and thus suggests a Dirichlet distribution (e.g., Fader and Schmittlein 1993). In contrast, the UGC variables are count data, which suggest an underlying Poisson distribution (e.g., Wedel et al. 1993). All the variables relate to a common underlying phenomenon, namely, the show, and thus cannot be independent of one another. With five covarying variables, the model should have a multivariate specification. Furthermore, the viewership and volume of UGC for a show depends on its unique appeal, including but not limited to the host’s personality, the variety and popularity of guests, the political ideology espoused, and the quality of the content in terms of information and entertainment. This unique appeal suggests the need for show-specific effects. To account for the influence of the unique appeal of each show, our model features show-specific unobserved heterogeneity. Thus, taking into account the multivariate nature of our data, the underlying Dirichlet (for viewership) and Poisson (for UGC) distributions, and the need to account for
unobserved heterogeneity, we develop a multivariate model with Dirichlet-lognormal and Poisson-lognormal mixtures, in line with prior literature that describes the multivariate Poisson log-normal distribution (e.g., Aitchison and Ho 1989, Karlis and Meligkotsidou 2007) and the bivariate Poisson log-normal model (e.g., Cameron and Trivedi 1998, Srinivasan et al. 2007). We extend these previous models by allowing for one of the variables to be a Dirichlet and using a Dirichlet-lognormal mixture.

As Chib and Winkelmann (2001) demonstrate, if \( Y = (Y_1, \ldots, Y_k)' \) is a vector of discrete random variables with marginal Poisson distributions, and the parameter vector \( \Lambda = (\Lambda_1, \ldots, \Lambda_k)' \), then \( Y \) follows a multivariate Poisson log-normal distribution if \( \log(\Lambda) = \Omega + M \), such that the vector \( \Omega = (\Omega_1, \ldots, \Omega_k)' \) is distributed multivariate (i.e., \( k \)-variate) normal, and the vector components of \( M = (M_1, \ldots, M_k) \) are independent of one another. Specifying \( M_i = \beta_i'X_i \), where \( \beta_i \) and \( X_i \) are the parameter and covariate vectors for \( Y_i (i = 1, \ldots, k) \), respectively, it is possible to estimate the relationships between the variables \( Y \) and the covariates \( X \), where \( \Omega \) accounts for unobserved heterogeneity.

If \( Y_1, Y_2, \) and \( Y_3 \) are continuous proportion share variables, with \( Y_0 = 1 - Y_1 - Y_2 - Y_3 \) being the outside option, (in our case, these are viewership shares), they can be specified as Dirichlet distributed, with the parameters \( \alpha_0, \alpha_1, \alpha_2, \) and \( \alpha_3 \) for \( Y_0, Y_1, Y_2, \) and \( Y_3 \) respectively. Then the Dirichlet parameter can be defined as \( \log(\alpha_k) = \Omega_k + M_k \), which supports the estimation of the relationships between the dependent variable \( Y_k \) and covariates by specifying \( M_k = \beta_k X_k \), where \( \beta_k \) and \( X_k \) are the parameter and covariate vectors for \( Y_k \). Then \( \Omega_k \) is part of the multivariate normal vector \( \Omega \), which makes the Dirichlet- and Poisson-specified variables multivariate with a lognormal mixture.

Thus, if \( Y_{\text{j smwd}}^j \) is the value of a variable of type \( j \) (1 = viewership, 2 = positive blogs, 3 = negative blogs, 4 = neutral blogs, 5 = co-mentions) on day \( d \) (1 = Monday to 5 = Friday) of week \( w \) (1–30) for a show on network \( n \) (1 = Fox News, 2 = CNN, 3 = MSNBC) during time slot \( s \) (1 =
7:00, 2 = 8:00, 3 = 9:00), for viewership share (i.e., \( j = 1 \)), for a given time slot, the variables \( Y_{s1wd}^1, Y_{s2wd}^1, Y_{s3wd}^1 \) (viewership shares of the three cable news shows at the time slot) and \( Y_{s0wd}^1 \) = \( 1 - (Y_{s1wd}^1 + Y_{s2wd}^1 + Y_{s3wd}^1) \), i.e. the viewership share of all other TV shows at that time slot are distributed Dirichlet such that,

\[
\text{Pr}(Y_{s0wd}^1, Y_{s1wd}^1, Y_{s2wd}^1, Y_{s3wd}^1 | \alpha_{s0wd}, \alpha_{s1wd}, \alpha_{s2wd}, \alpha_{s3wd}) =
\]

\[
\frac{\Gamma(\alpha_{s0wd} + \alpha_{s1wd} + \alpha_{s2wd} + \alpha_{s3wd})}{\Gamma(\alpha_{s0wd})\Gamma(\alpha_{s1wd})\Gamma(\alpha_{s2wd})\Gamma(\alpha_{s3wd})} Y_{s0wd}^{\alpha_{s0wd}-1} Y_{s1wd}^{\alpha_{s1wd}-1} Y_{s2wd}^{\alpha_{s2wd}-1} Y_{s3wd}^{\alpha_{s3wd}-1}
\]

\[\ldots(1)\]

And for \( n = 1 \) to 3,

\[
\log(\alpha_{s0wd}) = \Omega_{s0wd}^1 + M_{s0wd}^1
\]  

(2)

For \( n = 0 \), i.e., the viewership of all other shows, we specify \( \log(\alpha_{s0wd}) = \Phi_{s0wd}^1 + H_{s0wd}^1 \) with \( \Phi_{sd}^1 \) being an intercept specific to each time slot and weekday and \( H_{s0wd}^1 \) being a product of time slot-weekday-level parameters and state dependence variables for each day.

For UGC variables \( j = 2–5 \), \( Y_{s0wd}^j, \sim \text{Poisson}(\lambda_{s0wd}^j) \), which implies that

\[
\text{Pr}(Y_{s0wd}^j | \lambda_{s0wd}^j) = \frac{\exp(\lambda_{s0wd}^j) \lambda_{s0wd}^{jY_{s0wd}^j}}{Y_{s0wd}^j!}
\]

(3)

\[
\log(\lambda_{s0wd}^j) = \Omega_{s0wd}^j + M_{s0wd}^j
\]  

(4)

where,

\( \lambda_{s0wd}^j \) is the parameter of the Poisson distribution;

\( \alpha_{s0wd}, \alpha_{s1wd}, \alpha_{s2wd}, \alpha_{s3wd} \) are the parameters of the Dirichlet distribution;

\( \Omega_{s0wd}^j \) is the multivariate normal intercept for variable \( j \) on weekday \( d \) for a show that airs at time slot \( s \) on network \( n \); and
\( M^j_{snwd} \) is the sum of the products of all parameters and the corresponding covariates, \( \beta'X \), which is independent for \( j = 1, 2, 3 \).

Thus, to examine the influences among and across a show’s UGC and viewership and its competitors’ UGC and viewership, we model \( \alpha_{snwd} \) for viewership and \( \lambda^j_{snwd} \) for each of the four UGC variables. In so doing, we account for the following effects: (1) within-show endogeneity \( (W^j_{snwd}) \), which refers to the effects of a show’s own viewership and UGC variables on one another; (2) competitive cross-effects \( (C^j_{snwd}) \) across the competition’s viewership and UGC variables and a show’s own viewership and UGC variables; (3) state dependence in the form of the daily continuity \( (D^j_{snwd}) \) of the effect of the variable’s values from recent days; (4) state dependence in the form of the lead-in effect \( (L^j_{snwd}) \), or the carryover of viewership of shows in the previous time slot to the focal show (modeled only for the viewership variable); and (5) unobserved heterogeneity \( (\Omega^j_{snwd}) \), that encompasses the show-specific multivariate intercepts that account for viewer preferences for the show’s content and host. Thus, we can rewrite Equations (2) and (4) as

\[
\begin{align*}
\log(\alpha_{snwd}) &= W^1_{snwd} + C^1_{snwd} + D^1_{snwd} + L^1_{snwd} + \Omega^1_{snwd} \quad \forall \ n = 1 \ to \ 3 \quad (2a) \\
\log(\lambda^j_{snwd}) &= W^j_{snwd} + C^j_{snwd} + D^j_{snwd} + L^j_{snwd} + \Omega^j_{snwd} \quad \forall \ j = 2 \ to \ 5. \quad (4a)
\end{align*}
\]

4.1. Within-Show Endogeneity

Extant UGC research indicates that UGC is a precursor and consequence of consumer actions (e.g., Chevalier and Mayzlin 2006; Liu 2006). In addition, the volume of blog posts that are positive, negative, neutral, and co-mentions should be interdependent. For example, positive blog posts read by users who disagree with the assessment could lead to negative blog posts in response. These blog posts can then drive viewership, and vice versa. To model this complex
structure, we specify that the value of a variable depends on the values of the other two variables for the current and two prior days. Thus, we specify within-show endogeneity for endogenous variable of type J as (where \( j = 1, \ldots, 5 \); \( 1 = \) viewership, \( 2 = \) positive blogs, \( 3 = \) negative blogs, \( 4 = \) neutral blogs, \( 5 = \) co-mentions; \( k = 0,1,2 \) are the lags; and \( \beta_{1j} \) are corresponding show- and weekday-specific parameters):

\[
W_{snw}^{j=1} = \sum_{j \neq 1}^{5} \sum_{k=0}^{2} \beta_{1j}^{1j} Y_{snw(d-k)}^{j} \cdot
\]

(5)

For Mondays and Tuesdays, the previous days include the Thursday and Friday of the previous week. These equations constitute a component of the regression equations that make up our model. We expect our findings to be consistent with extant research that suggests positive effects between a show’s UGC and its viewership. We also allow the effect to vary in magnitude across the three time slots.

### 4.2. Competitive Cross-Effects

Research on marketing communication strategies shows that product performance depends not only on its own marketing communication strategies but also those of its competitors (e.g., Dube and Manchanda 2005; Naik et al. 2005). We expect competitive cross-effects to be similarly manifest in UGC–viewership relationships. The effect of competitors’ UGC on a show’s UGC and viewership might be positive or negative. For example, an increase in UGC about Rachel Maddow’s show is likely an indicator of the buzz about her show among viewers and might increase viewership of her show, which may come at the expense of Larry King’s or Sean Hannity’s viewership. An increase in Keith Olbermann’s viewership may relate to a controversial

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10 We estimated the model for lags ranging from 1 to 5; the coefficients stopped being statistically significant after a lag of two days.
opinion he expressed about a political issue that prompts bloggers to post their opinions about him rather than about Bill O’Reilly or Campbell Brown. In contrast, if the bloggers disagree with Olbermann and write about contrasting opinions expressed by O’Reilly and Brown, the increase may appear in blogs about the latter hosts. Thus, consistent with extant research on comparative advertising (e.g., Barry 1993; Pechmann and Stewart 1990), we find compelling reasons to expect competitive cross-effects between the shows’ UGC and viewership, whether positive or negative.

To capture these possible cross-effects, we model each variable for a show as dependent on the UGC and viewership of both competing shows. In addition to the values for the same day, we include values for the preceding two days to allow for lagged effects. Thus, we specify competitive cross-effects for a particular endogenous variable of type J as (where $j = 1, \ldots, 5$; $1 =$ viewership, $2 =$ positive blogs, $3 =$ negative blogs, $4 =$ neutral blogs, $5 =$ co-mentions; $k = 0, 1, 2$ are the lags; $n = 1, 2, 3$ are the networks; and $\beta_{2;\ldots}$ are the corresponding show- and weekday-specific parameters):

$$C_{sNwd}^J = \sum_{j=1}^5 \sum_{k=0}^2 \beta_{2j}^{(n\neq N)(d-k)} y_s^j (n\neq N) w(d-k).$$  \hspace{1cm} (6)

4.3. State Dependence: Daily Continuity

The longitudinal nature of our data requires that we account for the likelihood that the value of a variable on a given day depends on the past values of the variable (as in Godes and Mayzlin 2004). Cable news shows often follow up on stories or segments on subsequent days. Thus, viewers who watched a show on day $d - 1$ may watch the show again on day $d$ to follow the story. We recognize daily continuity as a state dependence factor that determines viewership on any given day. Allowing for this state dependence enables us to identify the effect of prior viewership and prevent past viewership from confounding the results of other variables.
Furthermore, users who publish blogs tend to be connected through feeds and subscriptions and often react to other blogs and videos they have read. The interconnections among UGC users lead to a diffusion of messages over several days, such that the volumes of blog posts are likely influenced by their volumes in the recent past. To account for this state dependence, we empirically determine the appropriate lag to be 2, and assume the value of a variable on day $d$ is influenced by the previous two days, $d-1$ and $d-2$.

Many cable news shows contain specific segments that they air every week (e.g., O’Reilly runs a culture quiz every Monday and a conversation with comedian Dennis Miller every Wednesday). Viewers may tune in weekly to follow up on those segments from the previous week, as well as the blog posts related to those segments. To account for this effect, we specify the value of a variable on a given day as dependent on its value on the same weekday in the previous week, so for example, for $wd$, the weekly lag effect would come from $(w-1)d$. The daily continuity state dependence equations for the three variables (where $j = 1, ..., 5$; $1 =$ viewership, $2 = $ positive blogs, $3 = $ negative blogs, $4 = $ neutral blogs, $5 = $ co-mentions; and $\beta_2$) are the corresponding show- and weekday-specific parameters, that is:

$$D_{snwd}^j = \beta_3^j Y_{sn(w-1)d}^j + \beta_3^j Y_{sn(d-1)}^j Y_{snw(d-1)}^j + \beta_3^j Y_{sn(d-2)}^j Y_{snw(d-2)}^j$$  (7)

4.4. State Dependence: Lead-in Effects

Researchers studying television viewing habits reveal that viewership is influenced by a lead-in effect, such that viewers watching a given show on a network tend to keep watching that network (Rust and Eechambadi 1989, Shachar and Emerson 2000). The state dependence associated with the lead-in effect should play a role in the context of cable news too. For example, viewers who watch the self-described liberal Ed Schultz on MSNBC at 6:00 p.m. are likely to persist with the network and watch the liberal Chris Matthews at 7:00 p.m., whereas
viewers who watch the self-described conservative Bill O’Reilly at 8:00 p.m. are likely to remain with Fox News and watch the conservative Sean Hannity at 9:00 pm. Cable news networks are aware of this lead-in effect and try to benefit from it with “hand-offs,” or introductions in which hosts make a short appearance on the preceding show to give the audience a preview of their topics for discussion.

Although lead-in effects suggest that greater viewership of preceding shows on competing networks should have a negative effect on a focal show’s viewership, switching behaviors are possible, especially among viewers who are not strongly connected to any ideology. Viewers who watch cable news on a given night and want to hear all sides of a debate about a certain issue, for example, may watch MSNBC at 7:00 p.m., CNN at 8:00 p.m., and Fox News at 9:00 p.m. Thus, the show’s aggregate viewership could benefit from lead-in effects or suffer from switching effects in relation to preceding shows on its own network and competing networks. To capture this relationship, our model accounts for the effects of viewership of preceding shows on all three networks.  

We specify the lead-in effects state dependence equation as, where $s = 1, 2, 3$ is the time slot:

$$I_{snw}^1 = \sum_{n=1}^{3} \beta_{(s-1)nd} Y_{(s-1)nd}$$  

(8)

### 4.5. Unobserved Heterogeneity

To account for unobserved heterogeneity across shows, we use $\Omega_{snw}$ to represent the intercept levels of viewership, positive blogs, negative blogs, neutral blogs, and co-mentions that result from the unique appeal of a show, namely, its content and the personality of its host. We

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11 To estimate this effect for the 7:00 p.m. time slot, we obtained Nielsen viewership data for the 6:00 p.m. shows: Special Report with Bret Baier (Fox News), The Situation Room with Wolf Blitzer (CNN), and The Ed Show (MSNBC).
also expect the levels to vary with the day of the week. Because the intercept levels of viewership and blog posts relate to a common construct, we expect \( \Omega_{snd}^j \) to covary. Thus, we define the vector \( \Omega_{snd}^j \) as multivariate normal:

\[
\Omega_{snd}^j \sim \text{MVN}(\Omega^j, \Sigma) \quad \forall \ j = 1, \ldots, 5
\] (9)

5. Model Estimation

To estimate the multivariate mixture model specified in Equations (1)–(9), we use Markov chain Monte Carlo methods (e.g., Gilks et al. 1998, Rossi and Allenby 2003). The model will give us parameters for the effects of within-show endogeneity, competitive cross-effects, state dependence effects, and unobserved heterogeneity.

The multivariate normal intercept \( \Omega_{snd}^j \) captures unobserved heterogeneity, and the multivariate specification accounts for covariance among viewership and the UGC variables. We assume that \( \Omega_{snd}^j \) for all shows is drawn from a common non-informative multivariate normal distribution with a diagonal Wishart distribution for the precision matrix (see Appendix A for details).

We use conjugate and noninformative priors for all parameters. The parameter vectors \( \beta_{k_{snd}}^j \) (where \( k = 1, \ldots, 4 \) represent the four effects being estimated) which we will express cumulatively as \( \beta_{snd}^j \) in this section for ease of notation, are indexed by time slot, network, and weekday, such that they are specified for each show on each of the five weekdays. We specify the parameter vectors as distributed multivariate normal with a diagonal Wishart distribution for the precision matrix.

The underlying effects we estimate could be driven by different phenomena, such as popularity of the network, the time slot, or the weekday. Within the cable news industry, there are
three dominant networks – Fox News, CNN, and MSNBC. Each network has shows on the five weekdays at the three time slots of 7:00 p.m., 8:00 p.m., and 9:00 p.m., with different total viewerships. These shows have a base viewership that is largely stationary across our data window, but there should be systematic fluctuations in the viewership depending on which day of the week it is. For example, NFL Monday Night Football could influence the shows’ viewership on Mondays, whereas Thursday night sitcoms could influence viewership on Thursdays. Thus, the dynamics of the cable news industry suggest a hierarchy of effects that is: cable news industry \(\rightarrow\) network \(\rightarrow\) time slot \(\rightarrow\) weekday.

Thus, we specified the parameter distribution with three levels of hierarchy: The parameter vectors \(\beta_{snd}^j\) for dependent variable \(j\) for a show in time slot \(s\) on network \(n\) on weekday \(d\) can be drawn from show-specific multivariate normal distributions with means \(\beta_{s|n}^j\), which result from time slot-specific multivariate normal distributions with means \(\beta_s^j\), which in turn are drawn from a common multivariate normal distribution. In other words, \(\beta_{s|n}^j \sim MVN_k(\beta_{s|n}^j, V_{s|n}^j)\), \(\beta_s^j \sim MVN_k(\beta_s^j, V_s^j)\), and \(\beta^j \sim MVN_k(\beta_0^j, V_0^j)\), where \(\beta_0^j\) is a vector of zeros, and \(V_0^j\) is a diagonal matrix with large values (1000) for variances that reflects a lack of knowledge about the means of the parameters (see Appendix A for details).

We used standard Markov chain Monte Carlo procedures with three concurrent chains (Bolstad 2007). The first 5,000 iterations per chain are burn-in values; the next 40,000 iterations provide the samples for parameter estimation. To assess model convergence, we used Gelman-Rubin statistics, which showed that the model specification converged.

Thus, we present the results from the time slot specification of our model. To test the significance of the parameter values, we checked whether the 95% central posterior intervals contained 0 (as is the norm in Bayesian estimation; e.g., Rossi and Allenby 2003) to verify if the estimated parameter is different from 0.
6. Results

6.1. Within-Show Endogeneity and State Dependence Effects

In Table 2-3, we present the results for the within-show endogenous effects for the three time slots, with lagged effects of the show-related blog posts published on the same day, the previous day, and two days prior. Positive significant parameters (i.e., parameters for which the mean was positive and the 95% central posterior interval did not contain 0) are formatted bold. Negative significant parameters (i.e., parameters for which the mean was negative and the 95% central posterior interval did not contain 0) are formatted underlined and in italics. Non-significant parameters (i.e., parameters where 0 fell within the 95% central posterior interval) are expressed as "NS". Consistent with extant research on UGC, we find evidence for a positive effect of blog posts on viewership. This positive effect is statistically significant at the aggregate but varies in magnitude across time slots, as well as with the valence of blog posts. The changes in the UGC–performance relationship with the nature of the competition become evident in the same-day, and lagged (up to two days) parameters for the shows in the three time slots.

For the 7:00 p.m. time slot (Smith, Dobbs, Matthews), we see from the top panel of Table 2-3 that the effect of positive valence blog posts on viewership is positive and significant for six of nine parameters. The lagged coefficients for the effect of neutral blogs on viewership are also positive for all three shows at the 7:00 p.m. time slot. However, negative blog posts have an adverse effect on viewership, such that four coefficients are significant and negative, whereas only one is positive and significant. Five of the nine coefficients for the effect of co-mentions on viewership are not significant, three are positive and significant, and one is negative and significant. These results suggest that for the 7:00 p.m. time slot, positive or neutral blog posts
### Table 2-3 Model Results for Within-Show Endogeneity: Influence of the Shows’ Blog Posts on the Viewership for Three Time Slots

<table>
<thead>
<tr>
<th>Time Slot</th>
<th>Host (Network)</th>
<th>Day</th>
<th>Positive Blogs</th>
<th>Negative Blogs</th>
<th>Neutral Blogs</th>
<th>Co-Mentions</th>
</tr>
</thead>
<tbody>
<tr>
<td>7 p.m.</td>
<td>Smith (Fox News)</td>
<td>Day t</td>
<td>2.1E-04</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>1.3E-04</td>
<td>1.0E-04</td>
<td>2.3E-04</td>
<td>1.2E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>NS</td>
<td>1.4E-04</td>
<td>NS</td>
</tr>
<tr>
<td>Dobbs (CNN)</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>1.5E-04</td>
<td>-1.6E-04</td>
<td>3.3E-04</td>
<td>-5.2E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>1.2E-04</td>
<td>-1.2E-04</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Matthews (MSNBC)</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>3.8E-04</td>
<td>-1.5E-04</td>
<td>1.8E-04</td>
<td>2.2E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>3.3E-04</td>
<td>-1.1E-04</td>
<td>NS</td>
<td>1.8E-04</td>
</tr>
<tr>
<td>O'Reilly (Fox News)</td>
<td>Day t</td>
<td>2.3E-04</td>
<td>4.1E-04</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>7.6E-04</td>
<td>5.6E-04</td>
<td>3.1E-04</td>
<td>3.6E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>8.2E-04</td>
<td>6.2E-04</td>
<td>1.8E-04</td>
</tr>
<tr>
<td>8 p.m.</td>
<td>Brown (CNN)</td>
<td>Day t</td>
<td>2.1E-04</td>
<td>NS</td>
<td>1.1E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>4.3E-04</td>
<td>2.4E-04</td>
<td>2.6E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>1.3E-04</td>
<td>NS</td>
<td>-1.1E-04</td>
<td>2.9E-04</td>
</tr>
<tr>
<td>Olbermann (MSNBC)</td>
<td>Day t</td>
<td>2.7E-04</td>
<td>1.9E-04</td>
<td>1.8E-04</td>
<td>1.3E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>4.6E-04</td>
<td>2.3E-04</td>
<td>2.2E-04</td>
<td>2.4E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>3.8E-04</td>
<td>1.6E-04</td>
<td>2.9E-04</td>
<td>NS</td>
</tr>
<tr>
<td>Hannity (Fox News)</td>
<td>Day t</td>
<td>2.0E-04</td>
<td>NS</td>
<td>NS</td>
<td>2.4E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>3.8E-04</td>
<td>1.1E-04</td>
<td>4.5E-04</td>
<td>3.1E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>1.0E-04</td>
<td>-1.0E-04</td>
<td>NS</td>
</tr>
<tr>
<td>9 p.m.</td>
<td>King (CNN)</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>5.6E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>NS</td>
<td>NS</td>
<td>4.2E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>NS</td>
<td>3.6E-04</td>
<td>-1.0E-04</td>
</tr>
<tr>
<td>Maddow (MSNC)</td>
<td>Day t</td>
<td>2.4E-04</td>
<td>NS</td>
<td>NS</td>
<td>1.8E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>3.4E-04</td>
<td>2.2E-04</td>
<td>3.2E-04</td>
<td>2.2E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>1.0E-04</td>
<td>2.0E-04</td>
<td>-1.0E-04</td>
</tr>
</tbody>
</table>

**Notes:** Mean values of parameters obtained from the Markov chain Monte Carlo simulation. All coefficients in bold are positive and significant at $p < .05$. All coefficients formatted with italics and underlined are negative and significant at $p < .05$. Cells with values that are not significant at $p < 0.05$ contain the abbreviation “NS.”

help increase viewership, blogs that are negative lower viewership, and the effect of co-mentions is weak and varied.
For the 8:00 p.m. time slot (O’Reilly, Brown, Olbermann; middle panel, Table 2-3), blog posts have a largely positive effect, regardless of their valence or content. Eight of the nine coefficients are positive and significant for positive blogs, seven are positive and significant for negative blogs, and seven are positive and significant for the neutral blogs. The five coefficients that are statistically significant for the co-mentions are all positive. The ubiquity of positive, significant coefficients for the effect of blog posts on viewership across different categories of blog posts suggests that at 8:00 p.m., viewership is positively influenced by blog posts, regardless of what they say; Unlike 7:00 p.m. where negative blogs seem to have a negative effect, at 8:00 p.m. even the viewership effect of negative blogs is positive. Thus the difference in the nature of programming across 7:00 p.m. and 8:00 p.m. time slots is also borne out in the within show endogeneity effect of blog posts on viewership.

Finally, the 9:00 p.m. time slot features Hannity and Maddow—ideological commentators, similar to the hosts at 8:00 p.m.—and King, a non-political interviewer. This difference in the nature of King’s programming as compared to Hannity and Maddow is evident from the bottom panel of Table 2-3. The coefficients for the influence of the blog posts on viewership are largely positive and significant for Hannity and Maddow, regardless of the valence of those posts, similar to results from the 8:00 p.m. time slot. However, for King, only neutral blog posts have a positive, significant effect, whereas the coefficients for positive and negative blog posts are statistically insignificant. Thus, while Hannity and Maddow’s viewership benefits from blog posts written about them regardless of their valence, for King, only neutral blog posts are beneficial for viewership.

In sum, the results for within-show endogeneity from Table 2-3 thus reveal that a show’s own blog posts generally help its viewership, but the prevalence of the effect varies across time slots. There is also variation across time slots with regard to whether negative blog posts help or hurt viewership. The results for daily continuity state dependence, or the influence of
viewership on recent days, also largely support our expectations: The shows’ daily viewership measures are positively influenced by values on the previous two days and on the same weekday of the previous week. These effects are the strongest for Fox News and weakest for CNN. Similarly, the results for the lead-in effect’s state dependence i.e., the influence of the viewership of the show airing on the same network on the preceding time slot, largely conform to our expectations. The shows’ daily viewership measures are positively influenced by viewership of shows that air immediately prior on the same network. Again, these state dependence effects are strongest for Fox News in all time slots and weakest for CNN.

6.2. Competitive Cross-Effects

Table 2-4 contains the parameters for the competitive cross-effects of UGC on shows’ viewership. We present the show-level parameter values for the influence of positive, negative, neutral, and co-mention blog posts on viewership for each of the three networks at each of the time slots. Columns represent the viewership dependent variable for the three networks, being influenced by their competitors' blog posts classified as positive, negative, neutral and co-mentions. The rows represent the competitors, whose blog posts published on days t, t-1, and t-2, serve as the explanatory variables. Positive significant parameters are in displayed against a white background. Negative significant parameters are displayed against a gray background. Non-significant parameters are expressed as "NS" and displayed against a dark background.

At the 7:00 p.m. top slot, as is evident from the top panel of Table 2-4, the influence of competitors’ blog posts on a focal show’s viewership is more negative (28 coefficients) than positive (7 coefficients). Positive blog posts about the competition constitute 15 of these negative effects of competitors’ blog posts in viewership; Smith, all 6 negative, Dobbs 4/6 negative, Matthews, 5/6 negative. Negative blog, neutral blogs, and co-mentions are largely
Table 2-4 Model Results for Competitive Cross-Effects: Influence of Competitor Shows’ Blog Posts on Shows’ Viewership

<table>
<thead>
<tr>
<th>Time Slot</th>
<th>Network</th>
<th>Day</th>
<th>DV: Fox News Viewership</th>
<th>DV: CNN Viewership</th>
<th>DV: MSNBC Viewership</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Positive Blogs</td>
<td>Negative Blogs</td>
<td>Neutral Blogs</td>
</tr>
<tr>
<td>7 p.m.</td>
<td>Fox News</td>
<td>Day t</td>
<td>-3.4E-04</td>
<td>-1.0E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>-1.0E-04</td>
<td>NS</td>
<td>-1.3E-04</td>
</tr>
<tr>
<td></td>
<td>CNN</td>
<td>Day t</td>
<td>-2.2E-04</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>-3.2E-04</td>
<td>1.0E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>-1.7E-04</td>
<td>NS</td>
<td>-1.1E-04</td>
</tr>
<tr>
<td></td>
<td>MSNBC</td>
<td>Day t</td>
<td>-5.4E-04</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>-3.6E-04</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>-7.2E-04</td>
<td>1.3E-04</td>
<td>-2.1E-04</td>
</tr>
<tr>
<td>8 p.m.</td>
<td>Fox News</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>NS</td>
<td>1.0E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>-1.1E-04</td>
<td>2.1E-04</td>
<td>-1.5E-04</td>
</tr>
<tr>
<td></td>
<td>CNN</td>
<td>Day t</td>
<td>NS</td>
<td>6.4E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>-1.1E-04</td>
<td>1.1E-04</td>
<td>-2.2E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>-1.1E-04</td>
<td>4.2E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>MSNBC</td>
<td>Day t</td>
<td>-1.1E-04</td>
<td>4.2E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>1.1E-04</td>
<td>5.3E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>1.2E-04</td>
<td>1.4E-04</td>
<td>-1.1E-04</td>
</tr>
<tr>
<td>9 p.m.</td>
<td>Fox News</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>-2.1E-04</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>CNN</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>NS</td>
<td>NS</td>
<td>-2.2E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>NS</td>
<td>NS</td>
<td>-1.9E-04</td>
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<td></td>
<td>MSNBC</td>
<td>Day t</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-1</td>
<td>2.1E-04</td>
<td>3.4E-04</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Day t-2</td>
<td>-3.3E-04</td>
<td>4.1E-04</td>
<td>-1.1E-04</td>
</tr>
</tbody>
</table>

Notes: Columns represent the four types of blog posts for each of the three networks. Rows represent the competitor networks whose UGC measures provide explanatory variables for the dependent variables (DVs) specified in the columns. The mean values of the parameters came from the Markov chain Monte Carlo
simulation. All coefficients that are positive and significant at $p < .05$ appear in regular font with a white background; coefficients that are negative and significant at $p < .05$ appear in italics with a gray background. Cells with values that are not significant at $p < .05$ use the abbreviation “NS” against a dark background.
significant (34 coefficients out of 54 are non-significant). When the negative blogs, neutral blogs, and co-mentions are statistically significant, more of them are negative (13 coefficients) than positive (7 coefficients). Thus, at the 7 p.m. slot, posts about competitors have a largely negative effect on a focal show’s viewership.

However, as seen in the middle panel of Table 2-4, the pattern of results for the 8:00 p.m. time slot is the opposite of that at 7:00 p.m. The influence of competitors’ blog posts on a focal show’s viewership is considerably more positive (28 coefficients) than negative (10 coefficients). Most of these 28 positive significant coefficients are seen in the influence of competitors’ negative blogs (13 coefficients) and co-mentions (11 coefficients) on the focal show’s viewership. Thus, a show’s viewership is positively influenced by the negative blog posts about its competitors, as well as when there are co-mentions with the competitors.

We also see that positive effects of competitors’ blog posts are primarily evident for O’Reilly on Fox News (12 positive significant coefficients) and Olbermann on MSNBC (10 positive significant coefficients) than for Brown on CNN (6 positive significant coefficients). Furthermore, the positive effects on viewership for O’Reilly and Olbermann come primarily from each other (16 coefficients) as opposed to coming from Brown (6 coefficients). These results suggest that in contrast to the 7 p.m. time slot, the 8 p.m. time slot sees beneficial effects on viewership of competitors’ blog posts, and these benefits are reaped more by O’Reilly and Olbermann than by Brown.

At the 9:00 p.m. time slot seen in the bottom panel of Table 2-4, evidence for whether competitors’ blog posts help or hurt a focal show’s viewership is more ambiguous than at the 7:00 p.m. time slot (where it appears to hurt) and the 8:00 p.m. time slot (where it appears to help). At 9:00 p.m. there are 12 positive significant coefficients and 16 negative significant coefficients, with 26 coefficients non-significant. However, a closer look at the results reveals that all the positive coefficients for the 9:00 p.m. time slot are for the effects of Maddow’s blog posts on Hannity’s viewership (6 positive significant coefficients) and Hannity’s blog posts on Maddow’s viewership (6 positive significant coefficients).
Of the 16 negative significant coefficients, 9 come from the influence of King’s blog posts on Hannity’s and Maddow’s viewership levels, and 4 come from Hannity’s and Maddow’s blog posts on King’s viewership. Thus viewership numbers for Hannity and Maddow are helped by blog posts about each other but hurt by blog posts about King, and King’s viewership is hurt by blog posts about Maddow and Hannity. Hannity and Maddow are also vocally conservative and liberal, respectively, whereas King’s show is non-opinionated and composed entirely of interviews.

In summary, competitors’ blog posts have positive and significant impacts on a focal show’s viewership, and whether the effect is positive or negative varies across time slots.

6.3. Predictive Validity

We assessed the accuracy of our model by testing how well the model predicted viewership in a time frame outside of our sample period. We chose three weeks in December 2009 and collected viewership and blog post data about the nine shows. Following the Bayesian approach used by Neelamegham and Chintagunta (1999), we included only explanatory variables in the model and treated the dependent variable of viewership as a missing variable. This model predicted daily values for the three weeks based on the four blog post variables available for those days. We plotted the predicted values against the actual values in Figure 2-3. The root mean square error difference between the predicted and actual values is given in parentheses after each show host’s name.

The root mean square error values (from .008 for O’Reilly to .081 for King) and plots indicate that our model predicts viewership reasonably well. The actual and predicted values are close on normal days, and the difference is significant only on days when an unusual event led to a spike in viewership. For example, the spikes in viewership observed toward the end of the data period occurred across shows and coincided with the bombing attempt on a Northwestern Airlines flight from Amsterdam to Detroit.
Figure 2-3 Predictive Validity: Actual versus Predicted Values of Viewership for a Three-Week Hold-Out Sample

--- Actual Viewership
--- Predicted Viewership

a. 7 PM Smith (RMSE = 0.016) Dobbs (RMSE = 0.044) Matthews (RMSE = 0.027)

b. 8 PM O’Reilly (RMSE = 0.008) Brown (RMSE = 0.050) Olbermann (RMSE = 0.017)

c. 9 PM Hannity (RMSE = 0.025) King (RMSE = 0.081) Maddow (RMSE = 0.012)

Note: The actual viewership shares of the nine shows for three weeks are plotted against the values predicted by our model when we treat the viewership dependent variable as a missing value. The root mean square errors (RMSE) between the two values are depicted in parentheses after each host’s name.
On this day, the predicted value was far from the actual value, but for the other days, without international news events, our model performs well.

7. Discussion

The results from the multivariate model with Dirichlet-lognormal and Poisson-lognormal mixtures provide evidence for the influence of competition in the UGC–viewership relationship in the cable news industry. Competitors’ UGC, in the form of blog posts, influences the viewership of focal cable news shows. The direction of the effect (positive or negative) and its prevalence (over lagged periods), according to the content of the blog posts, varies across the three time slots. This variation indicates that though the effect of competitors’ UGC on viewership is statistically significant, the precise nature of the effect depends on the nature of the programming and competition across cable news shows.

The results for within-show endogeneity (Table 2-3) summarize the influence of a show’s own blog posts on its viewership and indicate that UGC, regardless of its valence, generally helps viewership. The influence of negative blog posts about a show on viewership was negative for only two of the nine shows and positive for six. Unlike traditional product or services, for which favorable UGC helps and unfavorable UGC hurts sales, in the cable news context, both negative and positive UGC have beneficial effects on viewership. The reason for this counterintuitive effect could reflect the very nature of the cable news industry, which puts mostly ideological, opinionated, and strident programming on during primetime, hosted by famous hosts who self-identify as liberal, conservative, or independent. Such programming creates an underlying narrative of conflict among shows that, in the era of UGC, spills over onto the Internet. Thus, the conflict might drive viewers to watch shows whose hosts they like and agree with, as well as shows whose hosts they disagree with, to gain fodder for discussions. For example, O’Reilly’s programming largely caters to conservative audiences, but frequent criticism and rebuttal of his views appears in liberal blogs, which indicates these viewers follow his show, at least when it contains
something controversial. This observation could explain why even negative posts about O’Reilly help his viewership.

Blog posts that are neutral and those with co-mentions of several competing shows also have a largely positive effect on a show’s viewership. Taken together with the results for positive and negative blogs, these results indicate that for cable news shows, no UGC is bad UGC. Regardless of what is said, UGC generally helps viewership—with the notable exception of Larry King’s interview show. For this show, only neutral blog posts have a statistically significant and positive effect. Therefore, if a cable news show is not part of the ideological conflict narrative, it appears that blog posts with polarized opinions or comparisons with competition do not influence viewership. Thus, prima facie, our results indicate that the ideological slant to programming is a necessary condition for deriving benefits from all UGC, regardless of its valence.

The results for competitive cross-effects (Table 2-4), i.e., the influence that competitors’ UGC has on a focal show’s viewership, are more mixed. At the 7:00 p.m. time slot, competitors’ UGC had a largely negative effect on the focal show’s viewership, whereas at 8:00 p.m. time slot, the effects were largely positive. At 9:00 p.m., the results for Hannity and Maddow, the ideological hosts, are similar to 8:00 p.m., mutually beneficial, but for Larry King were non-significant or negative. These results indicate that while competitive UGC has a statistically significant effect on cable news show viewership, whether the effect is positive or negative depends on the nature of the programming and competition.

It is interesting to note that competitive UGC was mutually beneficial for shows that were ideological and opinion-driven and low on actual news delivery (e.g. O’Reilly, Olbermann, Hannity, and Maddow). These results indicate that the narrative of conservative-liberal conflict that underlines cable news shows and spills over onto the internet among followers of cable news, could lead to beneficial effects of competitors’ UGC. Thus, if something noteworthy, be it positive or negative, is said about an opinion expressed by a conservative host, it could cause viewers to also tune into the liberal host to hear the contrary view and vice versa. The mutual benefits of competitors’ UGC seem sparse at the
more news and analysis driven 7:00 p.m. time slot, where there are usually few opposing viewpoints to keep abreast of. Whether competitors’ UGC helps or hurts a focal show’s viewership, it is clearly statistically significant. Thus, network executives should keep an eye on the UGC of not only their own shows, but their competitors’ shows, to better predict viewership.

The broader theoretical implications of our research are based on the need to account for competitive interactions while examining the performance implications of UGC. The UGC about any product shares the online space with its competitors. Even when the nature of the competition is not as acrimonious as in the cable news industry, we expect competition to play a role in shaping the UGC content, and in determining whether and to what extent UGC helps a product’s sales. Further research can benefit from modeling competitive interactions in the creation of UGC, as well as in the relationship between UGC and performance.

Our findings, by identifying the role of competition in the UGC-viewership context, can also pave the way for extending the research in marketing concerning the role of UGC in the television industry. For example, UGC measures of competing networks and shows can serve as additional metrics for optimizing television programming schedules (e.g., Liu et al. 2004, Reddy et al. 1998). Our analysis is at the aggregate level of daily viewership and UGC. Future research could examine the competitive interactions of UGC at play in time-shifted viewership (e.g., Live+7 Day ratings) as well as on minute-to-minute competitive switching behavior available from household panel data. Furthermore, measures about individual viewers’ posting and consumption of online UGC, in conjunction with panel data measures of television viewing (as collected by Nielsen Media Research), could also help extend behavioral research of television viewing habits (e.g., Woltman Elpers et al. 2003, Rust and Alpert 1984).

Research on UGC remains in an incipient stage, and with this article, we hope to have shed some light on how the nature of competition influences the effectiveness of UGC on firm performance. Because competition, whether among television shows or rival brands, can provide impetus for users to create and consume online content, academics as well as managers can benefit from understanding the role that
competition plays in determining the effectiveness of online marketing strategies. The avenues for impactful further research are thus manifold and promising.
Chapter 3
The Impact of Asymmetric Multi-Market Competition on Competitive Interactions of User-Generated Content

ABSTRACT

In this dissertation essay, I extend the findings from my previous dissertation essay by examining how a continuous measure of competition between two firms moderates the competitive interactions in the UGC-performance relationship. Specifically, I use the airline industry to examine how asymmetric multi-market competition (the number of focal airline routes that the competitor flies on) between dyads of airlines moderate the impact of negative user-generated content (NUGC) about competitors on one another’s abnormal stock returns. I collect data on nine biggest airlines in the United States for a period of 60 months spanning December 2003 to November 2008. I use a spatio-temporal model to measure the moderating effect of asymmetric multi-market competition on the role that competitors’ NUGC plays in influencing the focal airline’s stock returns. I find that an airline accrues the maximum stock returns benefits from a competitor’s NUGC if the focal airline flies on a higher percentage of the competitor’s routes than the competitor flies on the focal firm’s routes. I also find that airlines engaged in symmetric multi-market competition flying on approximately half of one another’s routes will both benefit from one another’s NUGC. I also find that stock return benefits of competitor’s NUGC are the lowest or negative when the multi-market competition among firms is mutually symmetric but high or mutually symmetric but low. These findings provide evidence of competitive interactions in the impact of UGC on financial performance, demonstrate the nature of the relationship as moderated by a measure of competition, and provide insights to academics and practitioners for shaping online marketing strategies with the competition in mind to maximize the return on marketing investment.
1. Introduction

In recent years, practitioners as well as academics have taken note of the impact of online user-generated content (such as blog posts) about firms/brands on their performance. In my previous essay (Sabnis and Grewal 2011), I demonstrated the existence of competitive interactions in user-generated content’s impact on performance in the cable news industry. My findings showed that a firm’s performance is affected not only by UGC about the focal firm, but also by UGC about its competing firms. I found this effect to be positive or negative across three competitive contexts.

I now take a step further and ask, can the impact of a firm’s UGC on its competitor’s performance be expressed as a function of the competition between them? Consider two airlines – Delta and Southwest. Both airlines operate in Boston and Los Angeles. However, only Delta operates in State College, Pennsylvania. If there is an increase in negative user generated content (hereafter NUGC) about Delta arising from online complaints, Southwest could benefit by attracting wary Delta customers in Boston or Los Angeles, but not in State College. How much Southwest can increase its revenues and consequently stock returns as a result of NUGC about Delta will depend on how many routes the two airlines have in common. Thus, the degree to which NUGC about Delta impacts Southwest will depend on the level of multi-market competition between the two airlines.

In this article, I model competitive interactions between airlines’ NUGC and financial performance as moderated by a continuous measure of competition between the airlines – multi-market competition. Airlines do not operate on all possible routes. I define the percentage of total Delta routes that Southwest flies on as the multi-market competition that Delta faces from Southwest. The multi-market competition that Southwest faces from Delta as a percentage of total Southwest routes will clearly be different from the multi-market competition that Delta faces from Southwest. Thus, the competition between two airlines yields measures of asymmetric multi-market competition between them.

Extant research has demonstrated the impact of online content on firms’ financial performance measures such as stock returns (e.g., Tirunillai and Tellis 2011). I examine if NUGC about a firm
influence its competitors’ stock returns as well. While testing for competitive interactions in NUGC’s impact on stock returns, I recognize the need to not only account for correlation in stock returns over time (temporal autocorrelation), but also correlation among stock returns of firms such as airlines operating in the same industry and thus facing similar environmental conditions. I account for the correlation among stock’s firms by adding a spatial autocorrelation component (where asymmetric multi-market competition serves as a proxy for space) to my model, thus making it a spatio-temporal model (e.g., Waller et al. 1997).

I use the spatio-temporal model to measure the moderating effect of asymmetric multi-market competition on competitive effects of NUGC on stock returns for the nine biggest airlines in the United States (listed in Table 1) in a 60 month period from December 2003 to November 2008. The explanatory variables are (1) NUGC, i.e., postings on blogs and complaint websites about each of the nine airlines each month, and (2) asymmetric multi-market competition, i.e., a 9X9 matrix expressing the percentage of focal firm routes that a competitor flies on for the nine airlines. The dependent variables are airlines’ abnormal stock returns (calculated using the Fama-French Three Factor Model) on a monthly basis.

I find evidence for statistically significant effects of competitors’ NUGC on a firm’s stock returns. Charting these effects as a function of asymmetric multi-market competition, I find that a firm benefits the most from NUGC about a competitor if the percentage of the competitor’s routes that the focal firm flies on is higher than the percentage of the focal firm’s routes the competitor flies on. I also find that firms who fly on roughly equal and moderate (40-70%) percentage of one other’s routes, can also benefit from NUGC about one another. However, if mutual competition is roughly equal but low (<30%) or high (>70%), then the focal firm’s stock returns are negatively impacted by negative UGC about the competitor.

The rest of the article is organized as follows. In § 2, I discuss existing literature on UGC, multi-market competition, and lay out a conceptual case for the competitive interactions. In § 3, I elaborate on the data and its sources. In § 4, I detail the model motivation and model specification. In § 5, I discuss the
results yielded by the model. Finally in § 6, I discuss the theoretical and managerial implications of the results, and conclude with some avenues for further research.

2. Conceptual Development

2.1. Impact of UGC on Competition’s Financial Performance

Marketing Impact of UGC

Research in marketing in recent years has provided evidence for the impact of UGC on market outcomes such as sales and adoption in contexts as diverse as online book sales (e.g., Chevalier and Mayzlin 2006), television shows (e.g., Godes and Mayzlin 2004), and newly released films (e.g., Duan et al. 2008), among others. Academics and practitioners alike recognize the marketing impact made by UGC on firms’ sales and revenues. Most firms now consider UGC as an invaluable component of the marketing communication strategy (Kliatchko 2009). In fact, some research in recent years (e.g., Trusov et al. 2009, Oestreicher-Singer and Sundarajan 2010) suggests that UGC, due to the enhanced peer-influence component and greater credibility (as the content is generated by users not marketers or advertisers) could have a stronger and more long-lasting impact than traditional marketing components.

UGC’s Role as Leading Indicator of Stock Returns

After the seminal paper by Srivastava et al. (1998) on the influence of market-based assets in creating shareholder value, a rich stream of literature has demonstrated the impact of various marketing activities such as advertising (Joshi and Hanssens 2009), brand equity (e.g., Madden at al. 2006), and product innovations (Srinivasan et al. 2009) on firm’s financial performance. It follows that UGC, a
critical element of marketing strategy, should influence financial performance. I now discuss how UGC could impact firms’ stock returns.

According to the efficient market hypothesis (Fama 1970), stock prices reflect the expectations about a firm’s future earning potential, based on publicly available information about the firm. Investor decisions about which firm’s stocks to buy are made after an analysis of public information such as the firm’s fundamentals (from the balance sheet), marketing strategy decisions such as advertising and R&D expenditures (from firms’ SEC reports) and earning expectations (issued by firms as well as market analysts). Additionally, investors are also interested in market-based assets that reflect consumers’ opinions about the firm that influence decisions about buying the firm’s products and thus impact financial performance (e.g., brand equity, reputation, customer satisfaction).

For information on these market-based assets, investors have traditionally relied on sources such as BusinessWeek Top Brands survey, Forbes’ ranking of firms based on reputation, and the American Customer Satisfaction Index (ACSI). However, these rankings and surveys are released infrequently (BusinessWeek and Forbes rankings are annual) and are usually lagged indicators of what consumers are thinking (ACSI index is released after a month’s delay). On the other hand, UGC is an instantly available expression of consumers’ experiences, brand perceptions, and word-of-mouth, and is thus a leading indicator. Investors can track UGC, get a sense of unexpected change in consumers’ opinions about firms, and use it to predict unexpected fluctuations in future earnings.

A 2009 survey by the Brunswick group of 455 analysts and investors in United States and Europe revealed that 30% of the respondents considered blogs and message boards as important sources of investment information, and 58% respondents believed “new media” will become increasingly important to them for investment decisions in the future. In a recent paper, Bollen et al. (2011) found

that data from Twitter feeds helped predict up-or-down movements in the Dow Jones Industrial Average with 87.6% accuracy.

In the marketing literature, a recent study by Tirunillai and Tellis (2011) showed evidence for impact of UGC on abnormal stock returns in an empirical study spanning six product markets and twelve brands. The authors argue that UGC can impact stock returns in two ways. Firstly, UGC by consumers (which expresses their satisfaction with recent purchase/consumption, their perceptions about brands, and occasionally their intentions about what they intend to purchase, etc.) can provide the latest information about the firm’s future performance at a greater temporal frequency than was previously available to investors in the pre-UGC world. Secondly, consumers who are undecided about which brand to buy frequently consult UGC for more information from peers, and UGC could thus influence their purchase decisions. At the aggregate level, both these processes indicate that UGC could provide investors with clues about future sales and cash flows, and could thus influence abnormal stock returns. The findings of Tirunillai and Tellis (2011) are in line with Luo (2007) who found that negative word of mouth could “signal lackluster future prospects of the companies’ stocks to financial analysts” (page 77) and thus harming airline firms’ abnormal stock returns. Thus, extant research in academia as well as industry trend has shown UGC to influence not only adoption, sales, and revenues, but also stock returns of firms.

**Focus on NUGC**

The valence of UGC can be positive or negative, depending on whether the user is praising or criticizing the firm. As Tirunillai and Tellis (2011) note, investors view negative information as being more diagnostic than positive information. They put forth three complementary explanations for the relative importance of NUGC. Firstly, due to negativity bias, negative information elicits a stronger response than positive information (Baumeister et al. 2001), and thus investors may overlook or discount positive information as being unreliable. Secondly, following loss aversion (Tversky and Kahnemann
1981), investors will be more mindful of avoiding losses than acquiring gains. Thirdly positive information about products or services (in the airline context, special discounts, free check-in luggage, sophisticated entertainment system etc.) tends to be actively communicated by firms through advertisements or press releases, and is largely well known and anticipated; however negative information is an outcome of experience of consumers, and is thus unanticipated, and likely to have a stronger impact on abnormal stock returns. Thus, given that the dependent variable of interest is abnormal stock returns, I focus on NUGC.\textsuperscript{13}

The value of NUGC to analysts could serve as a real time signal of service failures by airlines that could harm purchases by consumers in the future, and thus influence revenues and cash flows. Analysts have another source of information about airline service failures. Under US law, airlines are required to report incidents of service failure (flight delays, baggage problems, oversales etc.) to the Department of Transportation (DoT) on a monthly basis. However, the DoT releases these data publicly only after a 2 month delay. Thus, analysts get this information with a delay, whereas NUGC could convey similar information in real time, making NUGC an attractive metric for making investment decisions.\textsuperscript{14}

As NUGC indicates negative experiences and opinions of consumers, and could signal a reduction in future sales to investors, I expect a firm’s NUGC to have a negative impact on its own abnormal stock returns.

\textit{Competitive Impact of NUGC on Stock Returns}

What does the impact of a focal firm’s NUGC on its abnormal stock returns mean for competitors? If the assessment of UGC suggests a decline in consumer opinion about a firm and thus in

\textsuperscript{13} In a pilot analysis of blog posts about airline experiences in six months from January-June 2008, I found that 92.5\% of the posts were negative.

\textsuperscript{14} I also collected data on service failure incidents reported by the airlines to the DoT and found them to be positively correlated to NUGC (r = .424, p < .05).
the firm’s sales in the future, investors are likely to divest the firm’s stocks and invest elsewhere. If investors expect decline in a focal firm’s sales to result in an increase in a competitor’s sales, they could buy the competitor’s stocks instead. The decision by investors to switch from the focal firm to its competitor will be driven by whether investors expect the competitor to benefit from the decline in the focal firm’s sales.

In academia, an addition to the growing body of evidence about the performance impact of UGC for focal firms or brands, there is nascent research on how UGC influences competitors. Libai et al. (2009) found evidence for cross-brand influences of online word-of-mouth in the growth of the cellular industry. Netzer et al. (2011) suggest that mining UGC content for consumer perceptions of brands as compared to competitors can lead to insights about market structure that can improve performance. The previous essay in this dissertation (Sabnis and Grewal 2011) found support for existence of competitive interactions in the impact of UGC on cable news show ratings.

To the best of my knowledge, there is no academic research so far on competitive interactions in the impact of UGC on financial performance. However, there is some anecdotal evidence about investors using UGC to assess how competitive actions influence stock returns. For example, in 2009, with an eye on Starbucks customers, McDonald’s introduced a line of coffee beverages titled McCafe (accompanied by a USD100 million advertising campaign). A financial analyst, interested in assessing the impact of this move on Starbucks, requested the popular blog StarbucksGossip to post a question asking readers to weigh in with their opinions.¹⁵

Combining the evidence for competitive interactions in the UGC-performance relationship by the aforementioned scholars with the support for the impact of UGC on stock returns (e.g., Tirunillai and Tellis 2011), I argue for the existence of competitive interactions in the impact of UGC on stock returns of airlines. Tirunillai and Tellis (2011) also found negative UGC to have a significantly

¹⁵ http://starbucksgossip.typepad.com/_/2009/06/do-you-sense-that-mcds-mccafe-launch-has-affected-starbucks/comments/page/1/#comments
higher impact on stock returns than positive UGC. In the context of airlines, Luo (2007) demonstrated that (offline) negative word-of-mouth has a negative impact on the focal airlines’ stock returns. Thus, I argue that negative UGC, i.e., NUGC, will impact not only the stock returns of the firm the NUGC is about, but also the stock returns of competitors. A competitor’s stock returns can benefit from a focal firm’s UGC only if investors feel that the competitor can lure customers away from the focal firm. Whether a competitor can and will lure away customers from the focal firm will depend on the nature of competition between them, which I will now elaborate on the factors that determine the nature of the impact of a focal firm’s UGC on its competitors’ abnormal stock returns.

2.2. Role of Asymmetric Multi-Market Competition in Competitive Interactions

An airline facing NUGC should expect negative impact on its own stock returns as a result of customers and stock analysts responding negatively to the online criticism. If the NUGC makes customers move from the focal airline to its competitor, then competitive impact should be positive. However, if the competitor is viewed by the customers and stock analysts as being too similar to the errant airline, the competitive impact could be negative. Furthermore, the competitive impact will be positive, i.e., a competitor will benefit from the focal firm’s NUGC only if the competitor is able and willing to employ proactive strategies (such as targeted discounts, promotional campaigns) aimed at luring customers away. I propose that the direction (positive or negative) of the impact of NUGC on stock returns, as well as its relative magnitude, will be moderated by the degree of competition between the firms.

According to Karnani and Wernerfelt (1985), in industries such as airlines where firms compete simultaneously in several markets (but not in all of them), multi-market competition is a useful measure to study competitive interactions. The impact of competitors’ actions on a focal firm and the efficacy of responding to these actions are determined by the degree of multi-market competition, also termed as market commonality (e.g., Chen 1996).
Multi-market competition can be asymmetric when there is a difference in the degree to which two firms face competition from one another in their markets. For example, Delta flies on 79% of all JetBlue routes, but JetBlue only flies on 32% of all Delta routes, leading to asymmetry in the competition that Delta and JetBlue face from one another. As a result of this asymmetry, Delta would be in a better position to benefit from the change in the opinions of customers and stock analysts as a result of NUGC about JetBlue, than JetBlue would be to benefit from Delta’s NUGC. I thus argue that the NUGC of an airline will have a positive impact on the stock returns of competitors in whose favor the asymmetric competition is skewed relative to the focal airline.

If two airlines face roughly equal competition from each other, i.e., their market commonality is approximately symmetric, we can rely on existing literature to guide us on the expected outcomes. Studies across industries have demonstrated that greater multi-market commonality reduces the efficacy of attacking (or responding to) the competition, resulting in firms engaging in mutual forbearance (Edwards 1955). If there is high commonality in the markets that firms operate in, then a competitive attack in one set of markets can lead to a response in another set of markets. Firms engaged in high multimarket contact thus do not face one another’s attacks and do not benefit from one another’s failings. The mutual forbearance hypotheses have been supporting in competitive studies of marketing strategies such as product innovation, pricing (Kang et al. 2010) and advertising (Gimeno and Woo 1999) among others. Extending this argument, I argue that when two airlines have a high degree of market commonality, they will not benefit from increase in negative UGC about one another. In fact, the impact in such a scenario can be mutually negative, as a result of the perceived similarity between the two firms.

When two firms have a moderate level of symmetric market commonality, the competition they face from one another is not high enough to induce mutual forbearance, but is still high enough for them to benefit from one another’s failings. For example, Southwest and Delta fly on roughly half of one another’s routes. Thus, if there is NUGC about Southwest, Delta can benefit in half the markets without worrying about retaliatory attacks from Southwest in the other half, and vice versa. Thus,
I argue that the effect of airlines’ UGC on one another’s stock returns will be positive and significant when the market commonality between them is symmetric but moderate.

Another scenario is where the market commonality is symmetric but low. For example, AirTran flies only 15% of all the routes that Southwest flies on, and Southwest flies only 22% of all the routes that Airtran flies on. In such a scenario, I argue that the commonality of markets will be too low for NUGC about these airlines to have a significant impact on one another’s stock returns.

To summarize, the impact of an airline’s NUGC on its competitor’s stock returns will be positive and significant when a) the percentage of the focal airlines routes that the competitor flies is asymmetrically higher than the percentage of the competitor airline’s routes that the focal airline flies on, or b) when both airlines are indulged in moderate but symmetric level of multi-market competition. The impact will be negative for firms engaged in high level of symmetric multi-market competition.

3. Data

3.1. Data Context

The nine airline firms (listed in Table 3-1) that I chose to collect data about are the largest airline firms in the United States in terms of market capitalization, capacity, as well as passengers flown. Together, they accounted for 85% of the market share in the 2000-2010 decade. All nine airlines are single-brand airlines\(^\text{16}\), thus making it valid to connect NUGC about their names to their stock returns.

The selection for the time window for data collection had to satisfy the following criteria. Firstly, the time window had to be in a period when users were actively posting complaints online on websites and blogs. Secondly, the time window could not include a merger between any of the airlines,

---

\(^{16}\) Local carriers affiliated with national airlines, such as United Express for United Airlines and Delta Connection for Delta Airlines are owned and operated by separate entities, such as SkyWest Inc.
thus avoiding confounding effects of the merger on stock returns. Thirdly, the number of time units (months) had to be sufficiently high to provide degrees of freedom for estimation. Fourthly, the time window had to be short enough for the patterns of asymmetric multi-market competition to be largely constant. With these criteria in mind, I chose the 60 month time window from December 2003 (when NUGC about airlines was being regularly posted) to November 2008 (when Delta and Northwest merged). Thus the data context consists of the nine biggest airlines in the United States for a period of 60 months.

3.2. Data description

**Dependent Variable – Abnormal Stock Returns**

To assess the impact on financial performance of airline firms, I use abnormal returns, ubiquitous in prior research to assess the stock market’s valuation of the firm and expectations of investors regarding future earnings (e.g., Chakravarty and Grewal 2011, Sood and Tellis 2009). Specifically, I use abnormal returns for each airline in each month using the Fama-French 3-Factor model (Fama and French 1993), additionally including Carhart’s momentum factor (Carhart 1997). The Fama-French 3-factor model enhances the traditional asset pricing model approach of using the market portfolio (S&P500) as the benchmark for normal returns by adding a size factor of the stock and a book-to-market factor. Additionally, Carhart’s momentum factor accounts for persistence effects. Thus the combined Fama-French-Momentum 4-Factor model (FFM4) I use to estimate the abnormal stock return in a given month is as follows:

\[ R_{it} - R_{ft} = \alpha_{it} + \beta_{im}(R_{mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{ic}UMD_t + \epsilon_{it} \]  (1)

where

\[ R_{it} \] is the return of airline i (i: 1,...,9) in month t (t: 1,...,60);
$R_{ft}$ is the risk-free return on a one-month treasury bill;

$R_{mt}$ is the return from the value-weighted S&P500 portfolio;

$SMB_t$ is the Fama-French size factor for month t;

$HML_t$ is the Fama-French book-to-market factor for month t;

$UMD_t$ is the Carhart momentum factor;

$e_{it}$ is the error term;

$\alpha_{it}, \beta_{im}, \beta_{is}, \beta_{ih}, \text{and} \beta_{ic}$ are the parameters of the model to be estimated.

I use $E(R_{it})$, the expected monthly return from the estimation of this model to estimate the abnormal stock returns in each month as:

$$Y_{it} = R_{it} - E(R_{it})$$

(2)

These abnormal stock returns for each of the nine airlines for the 60 months are the dependent variables on which the effects of the explanatory variables are tested. The mean monthly abnormal returns for the airlines are given in Table 3-1. The mean monthly abnormal returns ranged from -.039% for US Airways to .055% for Continental Airlines.

**Table 3-1 Monthly Mean Values of Abnormal Returns and Negative User-generated Content for December 2003- November 2008**

<table>
<thead>
<tr>
<th>Airline</th>
<th>Mean Abnormal Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>AirTran Airways</td>
<td>-0.037%</td>
</tr>
<tr>
<td>American Airlines</td>
<td>0.020%</td>
</tr>
<tr>
<td>Delta Airlines</td>
<td>-0.014%</td>
</tr>
<tr>
<td>JetBlue</td>
<td>0.039%</td>
</tr>
<tr>
<td>Northwest Airlines</td>
<td>-0.027%</td>
</tr>
<tr>
<td>Southwest Airlines</td>
<td>0.024%</td>
</tr>
<tr>
<td>Continental Airlines</td>
<td>0.055%</td>
</tr>
<tr>
<td>United Airlines</td>
<td>-0.026%</td>
</tr>
<tr>
<td>US Airways</td>
<td>-0.039%</td>
</tr>
</tbody>
</table>
Independent variable – Unanticipated negative user-generated content (NUGC)

The NUGC, i.e., the negative user-generated content came from two primary sources: (1) Six complaint websites and travel forums where consumers can make posts expressing dissatisfaction about their experiences in detail, and (2) posts on individual blogs describing negative experiences while flying. I collected these data for each of the nine airlines for each of the 60 months by running API (application programming interface) queries on the websites and on Google BlogSearch. The mean monthly NUGC posts ranged from 17.83 for JetBlue to 65.50 for Delta Airlines.

Because the dependent variable is abnormal stock returns, it should reflect changes based on new information. However, airlines are likely to have an average level of NUGC based on customer dissatisfaction. There are also likely to be trends and seasonal factors are play in determining the level of NUGC that analysts would be aware of (for example, Thanksgiving or Christmas are times when the number of passengers flying is higher than usual, and thus, the NUGC could also be higher). To test the impact on abnormal stock returns, a robust measure of NUGC would be one that discounts trends, base levels of UGC, and expected seasonal fluctuations.

Thus, I operationalize NUGC as unanticipated NUGC, adapting the technique used by other scholars studying the relationship between marketing strategy and abnormal returns (e.g., Chakravarty and Grewal 2011, Mizik 2010). Following Dinner et al. (2009), I assessed the unanticipated component of NUGC with a regression of NUGC in month $t$ on the NUGC in month $t-12$ (i.e., the same month of the previous year, thus accounting for seasonality) and dummy variables for year (to account for trends in the growth of UGC level over time).

I used the residuals from the following equation as the measure of unanticipated NUGC:

$$X_{f,t} = \phi_f + \alpha X_{f,t-12} + \sum \delta_i \text{Yearn}_t + \epsilon_{f,t}$$

(3)

where $f = 1,2,\ldots,9$ airlines; $t = 1,2,\ldots,60$ are the months; $X_{f,t}$ is the UGC of airline $f$ in month $t$; $\phi_f$ is the airline-specific intercept; $\epsilon_{f,t}$ measures the unanticipated component of NUGC for airline $f$ at
time \( t \); \( Year_t \) is a set of dummy variable for the year that month \( t \) is in (ranging from 2003 to 2008); and \( \alpha \) is the estimate of seasonal persistence.

**Moderating variable – Asymmetric Multi-Market Competition**

I define the multimarket competition that airline A faces from airline B as the proportion of A’s routes that B flies on, and vice versa. Thus,

\[
\text{Comp}(A,B) = \frac{\text{Number of A’s routes that B flies on}}{\text{Total number of A’s routes}}
\]

\[
\text{Comp}(B,A) = \frac{\text{Number of B’s routes that A flies on}}{\text{Total number of B’s routes}}
\]

Even though the numerators in both the above expressions are equal, the denominators are different, given that the total number of routes each airline flies is different. So clearly \( \text{Comp}(A,B) \neq \text{Comp}(B,A) \), resulting in asymmetric dyadic measures of competition between two airlines. I express the asymmetric multi-market competition among all nine airlines as a competition matrix in Table 3-2.

**Table 3-2 Competition Matrix for the Nine Airlines**

<table>
<thead>
<tr>
<th></th>
<th>AirTran</th>
<th>AmerAir</th>
<th>Delta</th>
<th>JetBlue</th>
<th>Nwest</th>
<th>Swest</th>
<th>Conti</th>
<th>United</th>
<th>USAir</th>
</tr>
</thead>
<tbody>
<tr>
<td>AirTran</td>
<td>1.00</td>
<td>0.44</td>
<td>0.50</td>
<td>0.43</td>
<td>0.40</td>
<td>0.15</td>
<td>0.38</td>
<td>0.25</td>
<td>0.31</td>
</tr>
<tr>
<td>AmerAir</td>
<td>0.75</td>
<td>1.00</td>
<td>0.66</td>
<td>0.82</td>
<td>0.68</td>
<td>0.67</td>
<td>0.74</td>
<td>0.71</td>
<td>0.64</td>
</tr>
<tr>
<td>Delta</td>
<td>0.94</td>
<td>0.73</td>
<td>1.00</td>
<td>0.79</td>
<td>0.81</td>
<td>0.60</td>
<td>0.72</td>
<td>0.72</td>
<td>0.75</td>
</tr>
<tr>
<td>JetBlue</td>
<td>0.33</td>
<td>0.73</td>
<td>1.00</td>
<td>0.79</td>
<td>0.81</td>
<td>0.60</td>
<td>0.72</td>
<td>0.72</td>
<td>0.75</td>
</tr>
<tr>
<td>Nwest</td>
<td>0.69</td>
<td>0.69</td>
<td>0.75</td>
<td>0.82</td>
<td>1.00</td>
<td>0.65</td>
<td>0.72</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>Swest</td>
<td>0.22</td>
<td>0.57</td>
<td>0.46</td>
<td>0.39</td>
<td>0.54</td>
<td>1.00</td>
<td>0.52</td>
<td>0.69</td>
<td>0.60</td>
</tr>
<tr>
<td>Conti</td>
<td>0.53</td>
<td>0.60</td>
<td>0.53</td>
<td>0.79</td>
<td>0.57</td>
<td>0.50</td>
<td>1.00</td>
<td>0.52</td>
<td>0.49</td>
</tr>
<tr>
<td>United</td>
<td>0.44</td>
<td>0.74</td>
<td>0.69</td>
<td>0.71</td>
<td>0.75</td>
<td>0.87</td>
<td>0.68</td>
<td>1.00</td>
<td>0.85</td>
</tr>
<tr>
<td>USAir</td>
<td>0.64</td>
<td>0.77</td>
<td>0.82</td>
<td>0.82</td>
<td>0.86</td>
<td>0.87</td>
<td>0.74</td>
<td>0.98</td>
<td>1.00</td>
</tr>
</tbody>
</table>

**Note:** Airlines listed in the columns are the focal airlines (whose total routes form the denominator) and airlines listed in the rows are the competitors (whose common routes with the focal airline form the numerator). Thus, 0.75 in the 2nd row, 1st column indicates that American Airlines flies on 75% of AirTran’s routes.

I first calculated the competition matrix for May 2005, which was the 30th month in the 60 month time window. For the purposes of model identification, the competition matrix has to be treated as unchanged throughout the time window. To verify that the levels of competition did not change
significantly during the time window, I also calculated the competition matrices for December 2003 (the first month in the time window) and November 2008 (the last month in the sample). Pair-wise comparisons of the competition measure showed that for all the values, fluctuations in competition levels were fewer than 2%.

**Control Variables**

I identified three potentially significant confounding variables that could influence abnormal returns and controlled for them: (1) *Monthly average crude oil price* to control for the influence of oil price fluctuations on abnormal returns, (2) *monthly total passenger car miles* to control for the change in airline revenues as a result of fluctuations in the population’s driving habits, and (3) *monthly number of news articles* about each airline so that the impact of NUGC is not confounded by media coverage of airlines.

### 4. Model

#### 4.1. Model Motivation

The primary objective of this essay is to test the moderating effect that asymmetric multimarket competition has on the competitive interactions of UGC on stock returns. The model development is motivated by three main phenomena that the model needs to account for – (1) temporal autocorrelation and lagged effects, (2) direct impact of competitors’ stock returns in the same time period, and (3) parsimonious modeling of the interaction effect of dyadic asymmetric competition and NUGC on abnormal stock returns.
A time series model with autocorrelated errors can account for temporal autocorrelation and introducing coefficients for lagged values of the explanatory variables can account for lagged effects. However, accounting for the impact of competitors’ stock returns on the focal firm’s stock returns in the same time period requires a model that treats observations not as independent and identically distributed, but correlated. As Bradlow et al. (2005) noted, spatial statistics can be used in contexts where units of analysis (and their outcomes) are correlated with each other, by regarding space not only as geographic, but as any type of map (such as demographic or psychometric) that describes the relationship among the units. Bradlow et al. further say, “by generalizing the notion of a map, we can define a spatial model as a stochastic model which uses known or unknown (latent) relationships among individuals (consumers, managers, retailer etc.) to predict outcomes”.

Thus, if we consider the competitive market structure as being analogous to space, and asymmetric multi-market competition among two airlines as being analogous to the “distance” in space, then a model with a spatial component can account for the correlation among stock returns of the airlines as determined by their mutual competition. This phenomenon, of individual or firm outcomes being directly affected by outcomes of other individuals or firm is called spatial lag (e.g., Bell and Song 2004). Furthermore, spatial models also allow for spatial autocorrelation by allowing spatially correlated errors, the idea being that proximity/distance on the map can account for latent variables that drive outcomes.

Spatial models also allow for spatial drift, the idea that model parameters are a function of an individual/firm’s location on the map (e.g., Brunsdon et al. 1998, Fotheringham et al. 2002). In my context, a model with spatial drift will allow me to test the moderating effect of asymmetric multi-market competition (the spatial component) on the competitive interaction effects of NUGC on stock returns.

Combining the benefits of spatial lag, spatial autocorrelation, and spatial drift for estimating the interdependence among firms, and the temporal auto-correlation element to capture dependence across time, I develop a spatio-temporal model (e.g., Waller et al. 1997). This model will
allow me to capture temporal autocorrelation, lagged effects in time and competitive space, as well as allow me to treat the model parameters as being dependent on asymmetric multi-market competition.

4.2. Model Development

I now develop a model to estimate the competitive interactions of NUGC on stock returns of nine airline firms across a time period spanning 60 months. Let \([Y_i, \ldots, Y_9]\) be a 1 x 9 vector composed of \(Y_{it}\), the stock return of airline \(i (i = 1, \ldots, 9)\) in month \(t (t = 1, \ldots, 60)\). Let \([W]\) be an asymmetric 9 x 9 matrix such that \(W_{jk}\) equals the competition that airline \(j\) faces from airline \(k\), i.e., the proportion of all \(j\)’s routes that \(k\) flies on \((W_{jk} \neq W_{kj})\). All diagonal elements of \([W]\) are 1. I will now add effects to the model specification one by one.

* Spatial lag

The spatial lag in airlines’ stock returns, i.e., the direct impact of the stock returns of competitors’ stock returns can be modeled as,

\[
[Y_t] = \lambda[W][Y_t] + [e_t] \tag{4}
\]

where the scalar \(\lambda\) is spatial lag coefficient. The expression \(\lambda[W][Y_t]\) represents the impact of the stock returns and the asymmetric multi-market competition acting together to impact stock returns. Thus \(\lambda\) will indicate whether the cumulative direct impact of competitors’ stock returns on an airline’s stock returns is statistically significant, and whether it is negative or positive.
b) Spatial autocorrelation

Stock returns of an airline should be autocorrelated over the competitive space. Thus the error component in equation (4), \( [e_t] \), will be distributed multivariate normal such that,

\[
[e_t] \sim MVN([0], \Sigma(W))
\]  

(5)

c) Spatial drift and time-lagged coefficients

Spatial drift allows the model parameters to be functions of the location of the airlines on the space, i.e., their asymmetric multi-market competition with all other airlines. Thus, I can specify a spatial drift component such that the stock returns are dependent on an interaction between the explanatory variable (NUGC) measures of all airlines and the competitive matrix. It is important to note that there could be a delay in the impact of UGC on stock returns as analysts may need time to collect UGC data and analyze it before making investment decisions (e.g., Tirunillai and Tellis 2011). Hence, I also allow for a 1 month lag in the coefficients. Thus I rewrite equation (4) as

\[
\mathbf{Y}_t = \lambda \mathbf{W} \mathbf{Y}_{t-1} + [\beta] \mathbf{W} \mathbf{X}_t + [\beta 1] \mathbf{W} \mathbf{X}_{t-1} + [\eta_t] + [e_t]
\]  

(6)

where \([\beta]\) and \([\beta 1]\) are 9 \( \times \) 9 matrices of dyadic parameters such that \( \beta_{jk} \) is the parameter corresponding to moderating effect of the competition that airline \( j \) faces from airline \( k \) on the effect of NUGC about airline \( k \) on the stock returns of airline \( j \).

d) Temporal autocorrelation

The model also needs to account for the temporal autocorrelation, i.e., the correlation between stock returns at time \( t \) with stock returns in the past. I model temporal autocorrelation by including a term that is dependent on the stock returns in the previous month. Thus equation (6) can be rewritten as:

\[
\mathbf{Y}_t = \lambda \mathbf{W} \mathbf{Y}_t + [\beta] \mathbf{W} \mathbf{X}_t + [\beta 1] \mathbf{W} \mathbf{X}_{t-1} + [\eta_t] + [e_t]
\]  

(7)
where \([\eta_t] \sim MN([\eta_t], \Sigma_\eta)\), \(\Sigma_\eta\) is a covariance matrix drawn from a vague Wishart prior and \(\eta_0 = 0\).

To summarize, equation (6) represents my final spatio-temporal model with spatial lag, spatial autocorrelation, spatial drift, time-lagged coefficients, and temporal autocorrelation.

4.3. Model Estimation

I estimated the spatio-temporal model in equation (7) using Markov Chain Monte Carlo methods (e.g., Gilks et al. 1998, Rossi and Allenby 2003). The estimation yielded parameters for the spatial lag at an aggregate level and the spatial drift for the two monthly lags at an asymmetric dyadic level. I used standard Markov chain Monte Carlo procedures with three concurrent chains (Bolstad 2007). The first 5,000 iterations per chain are burn-in values; the next 60,000 iterations provide the samples for parameter estimation. To assess model convergence, I used Gelman-Rubin statistics, which showed that the model specification converged. To test the significance of the parameter values, I checked whether the 95% and 90% central posterior intervals contained 0 (as is the norm in Bayesian estimation; e.g., Rossi and Allenby 2003) to verify if the estimated parameters were different from 0.

5. Results

5.1. Spatial lag results

The term \(\lambda [W][Y_t]\) represents spatial lag, i.e., the direct impact of competitors’ stock returns on a focal firm’s stock returns. The spatial lag parameter \(\lambda = -0.643\) was statistically significant at 95% confidence level. The parameter being negative significant indicates that an increase in the abnormal returns of competitors has an aggregate negative effect on a firm’s stock returns.
5.2. Impact of Airline’s own NUGC on its Stock Returns

Table 3-3 Impact of an Airline’s Own NUGC on its Abnormal Stock Returns

<table>
<thead>
<tr>
<th>Airline</th>
<th>NUGC in Same Month</th>
<th>NUGC in Month t-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>AirTran</td>
<td>-0.011</td>
<td>-0.017</td>
</tr>
<tr>
<td>AmerAir</td>
<td>-0.013</td>
<td>-0.019</td>
</tr>
<tr>
<td>Delta</td>
<td>-0.013</td>
<td>NS</td>
</tr>
<tr>
<td>JetBlue</td>
<td>-0.010</td>
<td>-0.014</td>
</tr>
<tr>
<td>Nwest</td>
<td>NS</td>
<td>-0.035</td>
</tr>
<tr>
<td>Swest</td>
<td>-0.009</td>
<td>-0.018</td>
</tr>
<tr>
<td>Conti</td>
<td>NS</td>
<td>-0.049</td>
</tr>
<tr>
<td>United</td>
<td>NS</td>
<td>-.016</td>
</tr>
<tr>
<td>USAir</td>
<td>-0.028</td>
<td>NS</td>
</tr>
</tbody>
</table>

Note: All parameters expressed in numbers are significant at the 95% confidence level. Non-significant parameters are expressed as NS.

Table 3-3 presents the results for the diagonal elements of the parameter matrices, i.e., the impact of unanticipated NUGC about an airline on its stock returns for the current month and with a 1-month lag. As the table shows, six of the nine airlines have negative significant parameters for unanticipated NUGC for the same month and seven of the nine airlines have negative significant parameters for unanticipated NUGC with a 1-month lag. The airlines with both lagged parameters statistically significant are AirTran, American, JetBlue, and Southwest. The prevalence of negative parameters suggests that a firm’s abnormal stock returns are impacted negatively by its own unanticipated negative UGC.

5.3. Competitive Interactions in NUGC’s Impact on Stock Returns

Table 3-4 presents the results for the non-diagonal elements of the parameter matrices, i.e., the impact of competitors’ unanticipated NUGC on a focal firm’s abnormal stock returns. The airlines whose stock returns are the dependent variables are listed in the columns, and the airlines whose unanticipated NUGC are the explanatory variables are listed in the rows. The parameters are significant at the 95% confidence interval.
Table 3-4 Competitive Interaction Effects of NUGC on Abnormal Stock Returns

<table>
<thead>
<tr>
<th>DV ----&gt;</th>
<th>AirTran</th>
<th>AmerAir</th>
<th>Delta</th>
<th>JetBlue</th>
<th>Nwest</th>
<th>Swest</th>
<th>Conti</th>
<th>United</th>
<th>USAir</th>
</tr>
</thead>
<tbody>
<tr>
<td>IV</td>
<td>t</td>
<td>t-1</td>
<td>t</td>
<td>t-1</td>
<td>t</td>
<td>t-1</td>
<td>t</td>
<td>t-1</td>
<td>t-1</td>
</tr>
<tr>
<td>AirTran</td>
<td>-0.024</td>
<td>-0.039</td>
<td>0.014</td>
<td>0.032</td>
<td>-0.011</td>
<td>0.012</td>
<td>0.022</td>
<td>0.024</td>
<td>NS</td>
</tr>
<tr>
<td>AmerAir</td>
<td>NS</td>
<td>0.011</td>
<td></td>
<td></td>
<td>0.044</td>
<td>0.083</td>
<td>-0.019</td>
<td>-0.033</td>
<td>0.028</td>
</tr>
<tr>
<td>Delta</td>
<td>-0.021</td>
<td>-0.047</td>
<td>-0.022</td>
<td>-0.034</td>
<td></td>
<td></td>
<td>-0.004</td>
<td>-0.016</td>
<td>-0.021</td>
</tr>
<tr>
<td>JetBlue</td>
<td>0.011</td>
<td>0.016</td>
<td>NS</td>
<td>-0.007</td>
<td>0.004</td>
<td>0.009</td>
<td></td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td>Nwest</td>
<td>-0.018</td>
<td>-0.021</td>
<td>0.019</td>
<td>0.023</td>
<td>-0.045</td>
<td>-0.072</td>
<td>-0.015</td>
<td>-0.032</td>
<td></td>
</tr>
<tr>
<td>Swest</td>
<td>0.004</td>
<td>0.002</td>
<td>0.022</td>
<td>0.025</td>
<td>0.009</td>
<td>0.018</td>
<td>NS</td>
<td>0.009</td>
<td>0.043</td>
</tr>
<tr>
<td>Conti</td>
<td>0.009</td>
<td>0.015</td>
<td>-0.013</td>
<td>-0.017</td>
<td>0.031</td>
<td>0.081</td>
<td>-0.008</td>
<td>-0.022</td>
<td>0.008</td>
</tr>
<tr>
<td>United</td>
<td>-0.023</td>
<td>-0.07</td>
<td>NS</td>
<td>-0.011</td>
<td>0.016</td>
<td>0.015</td>
<td>-0.012</td>
<td>0.008</td>
<td>-0.009</td>
</tr>
<tr>
<td>USAir</td>
<td>-0.008</td>
<td>-0.013</td>
<td>0.065</td>
<td>0.091</td>
<td>-0.019</td>
<td>-0.022</td>
<td>0.081</td>
<td>-0.041</td>
<td>-0.021</td>
</tr>
</tbody>
</table>

Note: All parameters expressed in numbers are significant at the 95% confidence level. Non-significant parameters are expressed as NS. The airline whose stock returns are the dependent variables is in the columns and the airlines who’s NUGC are the explanatory variables are in the rows. The t column contains parameters for the same month and the t-1 column contains parameters for the 1-month lag.
Out of the 144 parameters for competitive interaction as moderated by asymmetric multi-market competition, 131 are statistically significant, of which 76 are positive and 55 are negative, suggesting that in most dyads, the impact of competitors’ unanticipated NUGC on a focal firm’s abnormal stock returns is positive.

The 144 parameters came from two different lags – 72 for the same month and 72 for month t-1. For the same month, out of the 72 parameters, 36 are positive and 26 are negative, and for month t-1, 40 are positive and 29 are negative. These findings suggest that the sign of the competitive interaction effect largely persists across the lags, and there is no significant difference in terms of polarity among the two lagged coefficients. Indeed, the sign of the interaction parameter flipped from positive to negative going from the previous month to same month only for three airlines dyads (AirTran’s impact on JetBlue, JetBlue’s impact on Northwest, and United’s impact on Northwest).

There is considerable variation across the airlines in terms of whether the impact of competitive unanticipated NUGC on their stock returns is positive or negative. For JetBlue, out of 16 parameters, 15 are statistically significant of which 4 are positive and 11 are negative, suggesting on the whole, JetBlue’s stock returns are hurt more than they are helped by competitors’ unanticipated NUGC. On the other hand, for United, out of 16 parameters, 14 are statistically significant, out of which 12 are positive and 2 are negative. As the competition matrix in Table 3-2 indicates, the competition that other airlines face from United is noticeably higher than the competition that other airlines face from JetBlue, partially supporting my initial conjectures about positive returns on competitive unanticipated NUGC being linked to the asymmetric advantage that an airline has in terms of competing on routes.

I now examine a few airline dyads with their asymmetric multi-market competition in mind. Consider Northwest and Southwest airlines. Northwest faces competition from Southwest on 54% of its routes, whereas Southwest faces competition from Northwest on 65% of its routes, thus giving Northwest the asymmetric advantage in competing on routes. The effect of Southwest’s unanticipated NUGC on Northwest’s stock returns is positive significant for the same month and 1-month lag, whereas the effect
of Northwest’s unanticipated NUGC on Southwest’s stock returns in negative significant for the same month and 1-month lag.

Now consider United and Continental airlines. United faces competition from Continental on 52% of its routes, whereas Continental faces competition from United on 68% of its routes. Prima facie, these asymmetric multi-market competition measures appear to be similar to the previous example of Northwest and Southwest. In terms of results, indeed, United, which has the asymmetric advantage in competing on routes, observes a positive effect on stock returns from Continental’s unanticipated NUGC. However, Continental also experiences a positive effect from United’s unanticipated UGC.

Thus, although these findings provide evidence for significant competitive interaction effects of unanticipated NUGC on stock returns, and show most of these effects to be positive, the precise nature of the role that asymmetric multi-market competition plays in shaping these effects is not fully clear. I will now express the results in a way that can help understand the relationship of the interaction effect with the asymmetric multi-market competition.

5.4. Impact of Asymmetric Multi-Market Competition on Competitive Interaction Effects of UGC on Stock Returns

As I discussed in the previous section, a majority of the interaction effects are positive significant, suggesting that unanticipated NUGC about competition generally helps a focal firm’s stock returns. However, there were also a number of negative parameters, suggesting that in some scenarios, competition’s unanticipated NUGC could actually hurt a focal firm’s stock returns.

In § 2.2, I argued that the interaction effect of competition and unanticipated negative UGC will depend on the asymmetric multi-market competition in the dyad, i.e., the extent to which two airlines in a dyad compete with each other. To estimate this relationship, I plotted the interaction parameters as polynomial functions of the two competition measures in a dyad (X axis: competition that
Figure 3-1 Surface Plots for Competitive Interaction Parameters against Asymmetric Multi-Market Competition

Note: The vertical axis in both graphs represent the interaction parameter value – L0 for same month and L1 for 1 month lag. In both figures, X axis is the proportion of focal firm’s routes that the competitor flies on, and the Y axis is the proportion of competitor firm’s routes that the focal firm flies on.
Figure 3-2 Contour Plots for Competitive Interaction Parameters against Asymmetric Multi-Market Competition

**Same Month**

Note: In both figures, X axis is the proportion of focal firm’s routes that the competitor flies on, and the Y axis is the proportion of competitor firm’s routes that the focal firm flies on. Contour values represent the interaction parameter.

**2 Month Lag**
focal firm faces from competitor, Y axis: competition that competitor faces from focal firm). I used response surface modeling methods (e.g., Lenth 2009, Myers et al. 2009) R for this purpose.

I ran linear, quadratic, cubic, and higher order models with the data. The best regression fit was with the quadratic function for the same month ($R^2 = 0.156$) as well as the 1-month lag ($R^2 = 0.249$). The 3D surface plots for each of the two coefficients are given in Figure 3-1, with contours in Figure 3-2.

Examining the surface plots and the contours indicate a common pattern in the results for both sets of lagged coefficients. The parameters values are the highest (in the 0.005-0.01 range) when Y is between 0.5 and 0.8, and X is between 0 and 0.4. Thus, a firm gets the maximum possible benefit about a competitor’s NUGC when it competes on half or more of its competitor’s routes, but faces competition from the competitor on 40% or less of its own routes. The parameter values are also moderately high (in the 0.002-0.005 range) when both firms compete with each other on roughly half of their own routes. Finally, parameter values are their lowest (even negative) when mutual competition between the airlines is symmetrically low or symmetrically high.

5.5. Robustness and External Validity Checks

To check that these results are robust, I first carried out a predictive validity test (as suggested by Neelamegham and Chintagunta 1999) on an extra year’s observations for all the nine airlines using the full model and compared it with a base model (without the NUGC data, but with spatial lag, spatio-temporal autocorrelation, and control variables). The root mean square error (RMSE) for abnormal stock returns was 0.181 for the full model as compared to 0.96 for the base model, indicating strong predictive validity. The DIC values also indicated a better fit with the full model.

My model uses unanticipated NUGC as the explanatory variable. To test for the robustness of the results, I also estimated three other specifications in terms of how NUGC was
operationalized – (1) a delta model (i.e., NUGC at time t minus NUGC at time t-1), (2) an ARIMA(1,1,1) model to account for moving averages integrated to the order 1, and (3) simply using levels of NUGC in each month, with lagged coefficient up to 2 months. The pattern of interaction parameters being positive or negative depending on the asymmetric multi-market competition was consistent across all three models, and the unanticipated returns model (RMSE = 0.181) outperformed the levels model with lags (RMSE = 0.231), ARIMA model RMSE = 0.234), and the delta model (RMSE = 0.262).

To check if the results were being driven by service failure incident reports that the DoT releases after a 2 month delay, I also ran a model using the incident values for all airlines, with same-month specification as well as with a 2-month lag (as that is when the data would be available to investors). I found that the incident reports data for the same month (RMSE = 0.434) as well as with a 2-month lag (RMSE = 0.376) underperformed the unanticipated UGC model. All these tests indicate that the results are robust to changes in data specification and the external validity of the results is boosted by testing against the alternative explanation of service failure reports driving abnormal stock returns.

6. Discussion

6.1. Theoretical Implications

The research objective of this essay was to test for the moderating effect of a continuous measure of competition (asymmetric multi-market competition) on the competitive interaction effects of negative user-generated content on airlines’ stock returns. The results support the existence of such a moderating effect and show it to be more positive than negative across the airlines. Examining the interaction parameters against dyadic competition measures also reveals that the impact of competitive NUGC on stock returns is the highest either when the firm holds an asymmetric competitive advantage over its competitor or when both airlines compete with each other on roughly half their routes.
These results provide useful insights for further research on the performance impact of user-generated content. Prior research had shown that competition plays a role in offline negative word-of-mouth’s impact on financial performance (Luo 2007) and that online UGC impacts financial performance (Tirunillai and Tellis 2011). In my previous dissertation essay (Sabnis and Grewal 2011), I had found support for competitive interactions in the impact of UGC on cable news show viewership. My results extend prior research by showing that competitive interactions play a role not only in influencing direct firm outcomes such as sales or viewership, but also on financial measures such as stock returns. Thus, the impact of UGC is not restricted to the purchase or adoption decision-making by customers but also extends to reactions of the stock market.

Treating competition as a continuous variable moderating the competitive interaction effects of UGC on stock returns allowed me to examine how competitive interactions vary based on competition. My findings are consistent with prior research on multi-market competition which suggests that a firm can benefit from attacking its competitors only if the market commonality between them isn’t too high, resulting in mutual forbearance (e.g., Chen 1996). Mutual forbearance has been demonstrated in traditional strategic maneuvering in the airline industry before. My findings extend this research to the domain of UGC by showing that firms can benefit from online negative word-of-mouth about one another, but only in certain competitive conditions. The stock market benefits accrued are the strongest when a firm flies on a higher percentage of its competitor’s routes than the competitor flies on its routes. These effects of asymmetric advantage in competition impacting the benefits of competitor’s NUGC are understandable. If Northwest flies in a higher proportion of Southwest’s routes, it can benefit by attracting customers on those routes who are impacted by NUGC. Northwest can then target Southwest’s customers by offering price discounts or stepping up advertising in select markets. If Southwest does not compete on a high proportion of Northwest’s routes, then Northwest can launch competitive attacks to benefit from NUGC without fearing retaliation from Southwest on other routes.
My findings also suggest that moderately high (50-70%) but roughly equal level of competition between two airlines leads to both of them benefiting from one another’s NUGC. Thus, airlines who are engaged in a moderate symmetric level of competition can see their stock returns increase if their competitor’s NUGC increases, but will also see the same competitor’s stock returns increase if their own NUGC increases. Recalling that the spatial lag coefficient (impact of competitors’ stock returns in the same time period) was negative and significant, the negative impact of an airline’s own UGC on its stock returns will be further compounded by the indirect effect of the benefits accrued to competitor’s stock returns as a result of its own negative UGC.

My research also has theoretical implications from a modeling standpoint. The spatio-temporal model I used was appropriate for the scenario, given that my observations were impacted not only by their past values (temporal autocorrelation), but also by other observations (spatial autocorrelation and spatial lag). As Bradlow et al. (2005) note, such dual correlations occur frequently in marketing questions. I propose that using spatio-temporal modeling will permit marketing researchers to better capture the underlying effects resulting from spatial and temporal dependencies.

6.2. Managerial Implications

My research provides guidelines for airline managers looking to improve their financial performance in these troubled times for the airline industry. Firstly, my research confirms the negative impact of the airline’s own UGC on its stock returns. In line with prior research on UGC, this finding underlines the importance of managers keeping an eye on the online buzz about their airline. Customers and markets are responding to negative UGC online, so airlines should consider hiring people to respond to complaints online in real time. Whenever a customer posts a complaint on a website or on their blog, if airlines are able to respond with an explanation or an apology (and perhaps compensation), it could ameliorate the negative impact of the NUGC on the customers’ and the stock market.
Findings for the moderating effect of asymmetric multi-market competition on the competitive interactions of UGC on stock returns can offer managers guidelines on how to use NUGC to chart competitive strategies, and which competitors to target. Managers can track NUGC online on complaint websites and blogs, and see which airlines are getting higher NUGC than usual. Then, depending on the nature of competition with that airline, my findings indicate whether it would be a good idea to act on the competitor’s NUGC or not. If the airline has an asymmetric competitive advantage, then they should try to attract the competitor’s customers with targeted discounts and advertising campaigns in markets where they compete with the airline. These targeted investments in discounts and advertising with an eye on competitors’ NUGC can improve the ROI on airlines’ marketing spending.

Conversely, airline managers tracking their own NUGC can get an idea of which competitor is likely to attack them with discounts or advertising campaigns, and on which routes. Managers can take a look at the market commonality they have with other firms and prepare for competitive attacks accordingly. My findings indicate that managers need not react to all competitive attacks in the wake of increase in their own UGC, only those that can impact their stock returns. Thus, my findings are useful for managers taking cognizance of the impact of UGC and new media on competitive marketing strategy.

6.3. Limitations and Further Research

In this research, I have focused on a limited number of variables - negative UGC, primarily on blogs and complaint websites, and abnormal stock returns. The relationship between UGC and financial performance can differ depending on the measures used. The competitive interaction effects I found may play out differently in the case of other rapidly growing online social media such as Facebook postings and twitter. Inability to mine archival data from those two websites prevented me from
including those variables in my analysis. However, further research should look into the different ways that different types of UGC display competitive interactions.

Prior research has demonstrated the impact of UGC on direct firm outcomes such as sales or viewership. My dependent variable was abnormal stock returns, following in the tradition of the stream of research on the financial impact of marketing. Although I found results in line with my expectations, further research should examine the competitive interactions of UGC’s effect on other performance variables such as volatility, risk, earnings projections, and so on. Additionally, UGC’s impact on market-based assets such as reputation or brand equity (which have been linked to financial performance in recent years) should also pave a new way for research on marketing impact of UGC.

I chose the airline context with an intention to demonstrate dyadic competitive in a traditional industry with multi-market competition. However, one of the limitations of my study is the plausible lack of generalizability. Although I have found competitive interactions to play a statistically significant role on firm performance in the airline context and in the cable news industry (in the previous essay), a multi-industry study is necessary to establish the validity of my findings across industries. One promising avenue of further research is modeling competitive interactions of UGC in multiple industries.

Despite these limitations, this essay has found evidence for the moderating effect of competition on competitive interactions of UGC. In addition to the findings from the first essay, I hope this dissertation provides a direction for further research that studies important phenomenon related to competition and UGC. Such research can give managers insights into devising competitive strategy in a way that could maximize the return on investment on their marketing budgets.
References


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