Marketing Networks 2.0

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Submitted in partial fulfillment of the requirements for
the degree of Doctor of Philosophy
under the Executive Committee of the Graduate School of
Arts and Sciences

COLUMBIA UNIVERSITY

2009
UMI Number: 3373532

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Online social networking, so-called social media and user-generated media, and consumer-driven marketplaces (e.g., eBay where individuals can be sellers) are interesting phenomena that can have important marketing implications. This dissertation comprises four essays related to these marketplace phenomena. Four research questions are asked and addressed, each considering social interactions between individuals in marketplaces: (1) how can network-based interactions between consumers generate economic value for firms and for other marketplace participants, (2) what drives the formation and evolution of these interactions and network relationships in a marketplace context, (3) what drives the activation of consumers' network relationships with respect to the transmission of information via word-of-mouth (WOM) from one consumer to another, and (4) what affects the reception of information via WOM and how can impact of WOM on consumers' attitudes and behaviors be measured and modeled? Each of these questions is addressed by a separate essay.

Essay 1 examines the economic value implications of social interactions between sellers in online marketplaces where sellers can form links to other sellers and customers can use these links (Internet hyperlinks) to browse between shops in a marketplace. This interesting phenomenon where potential competitors can link and send customers to each other is called "social commerce." Using data from a large social commerce marketplace in France, empirical findings suggest that seller networks can be beneficial, although not
all links are value-creating and it depends on whether links improve the network's browsability. Although allowing sellers to connect does increase total marketplace sales, how the structure of the marketplace network evolves can either help or hurt marketplace-level performance. At the individual seller (or shop) level, being part of the network can help make shops more accessible to customers, which in turn increases shops' sales.

Essay 2 examines the same social commerce network and addresses the issue of how this network structure formed and evolved over time. Given that the network does have some economic value, as found in essay 1, it is necessary to understand the evolution dynamics of this network. Although the network studied has a power-law degree distribution, its evolution is not well explained by preferential attachment or triadic and cyclic closure (common link formation mechanisms in extant literature). Instead, the evolution of the network and the emergence of its power-law degree distribution are found to be well explained by a network evolution mechanism that relies on shop attributes that are not directly related to the network: shops prefer to connect to shops with more diverse assortments. Thus, product assortment decisions made by sellers affect their ability to attract links to their shops from other shops, which in turn influences how accessible they are made by their position in the network.

Essay 3 explores the nature of consumers' social interactions with respect to the transmission of information via WOM. In this essay consumers' reasons for transmitting WOM and the drivers of their selections of recipients are studied with three experiments. Across three studies it is found that the main reasons for transmitting WOM are predominantly transmitter-focused and associated with transmitters using social capital.
embedded in their social relationships, the importance placed on these reasons by transmitters is related to the types of recipients that they actually choose to talk to, characteristics of recipients and the relationships they have with transmitters are strong drivers of transmitters’ decisions of who to (and who not to) transmit information to, and the underlying reasons for transmitting WOM, and hence the types of recipients that comprise one’s preferred “audience,” lie in transmitters wanting to use (but not build) social capital, but the type of use depends on whether people are sharing their own opinions (“initial transmission”) or passing on others’ opinions (“retransmission”).

Essay 4 also concentrates on WOM, but instead on the reception or “listening” side. In this essay, with two experiments, the characteristics of transmitters who are listened to are examined, and the drivers of WOM impact on recipients’ attitudes (and subsequent behaviors) are modeled. Importantly, here impact is captured as how much WOM messages from transmitters change two components of recipients’ attitudes toward the topic of the message (i.e., a brand or a product): disposition (e.g., perceived quality of the product, liking of the brand), and the certainty with which the disposition is held. Two studies demonstrate that WOM impacts disposition and certainty differently, changes in both disposition and certainty affect consumers’ intentions to purchase a talked-about brand, WOM from strangers in some cases can be as impactful as WOM from friends and acquaintances, and the relatively strong influence of strangers under some conditions seems to be the result of perceptions of the credibility of strangers as sources of information. Overall, the results illustrate that WOM reception is multiply-determined and, above all, the outcome of a complex set of processes.
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Acknowledgements

This dissertation has benefitted greatly from the support, guidance, and advice of many people, to whom I will always be professionally and personally indebted.

First, I thank my mentors and co-sponsors, Donald Lehmann and Olivier Toubia. The time, energy, enthusiasm and guidance I have been lucky to receive from Don and Olivier has been amazing. Working with them has been and continues to be a privilege and, more than anything else, a lot of fun.

Second, I thank the other members of my dissertation committee: Kamel Jedidi, Jacob Goldenberg, and Duncan Watts. Along with Don Lehmann, Kamel brought me to Columbia and encouraged my academic development from day one. I will always appreciate the support that Kamel has given me. Jacob and Duncan are responsible for getting me interested in social networks, word-of-mouth, and the other related topics upon which this dissertation is based. I continue to be influenced by their work.

Third, I thank the entire Columbia marketing faculty for their ongoing support, and in particular highlight Michel Tuan Pham, Leonard Lee, Oded Koenigsberg, Oded Netzer, Asim Ansari, and Rajeev Kohli for investing some of their valuable time in my academic development over the years. I also acknowledge Jonah Berger, Eric Bradlow, and Christophe Van den Bulte (all at Wharton) for their advice on various parts of this dissertation.

Fourth, I thank Jeremie Berrebi, David Levy, and Ilan Abhassera for providing data used in the first two essays of this dissertation.
Fifth, I thank my doctoral student colleagues at Columbia and my extended network of colleagues at other schools for their collective support and friendship. In particular, this process would not have been as enjoyable as it has been had I not been going through it with Peter Jarnebrant, Jeffrey Parker, Eric Hamerman, Isaac Dinner, Jeff Galak, Keith Wilcox, and Jonathan Zhang. I am lucky to have a group of colleagues who are also my good friends and who, I hope, will be colleagues, co-authors and friends (and drinking buddies) for decades to come.

Sixth, I thank my family. My mother Sandra Stephen, for supporting her son’s goals and dreams unconditionally since February 4, 1981. She has always been there for me, has always put my education first, and even if it made her life more difficult she has always gone out of her way to help me take advantage of opportunities in life. I look forward to repaying her for all she has done. I also thank my grandparents, Harry and Eileen Watt, who, along with my mother, have always been there for me, have always cheered me on, and instilled in me a sense of pride in my work and a belief that hard work, even from humble beginnings, always pays off.

Finally, and more than anyone else, I thank my fiancée (soon to be wife), Fiona Lazar. It is difficult to put in words how much all the amount of support, strength, and happiness that Fiona has provided over all these years has meant to me. I am deeply grateful to have her by my side. She followed me to the other side of the world on this adventure and made sure that we had everything we needed to pursue our goals and dreams in New York. Her support means the world to me, and sharing this experience and moving into new chapters of our lives together is priceless.
Dedication

For Fiona, Eileen, Harry and Sandra.
1

Introduction
1.1 Overview

The Internet and “Web 2.0” allow people to be more “socially connected” than ever. Online social networking, so-called social media and consumer-generated media, and consumer-driven marketplaces (e.g., eBay where individuals can be sellers, or so-called “social commerce” marketplaces that combine e-commerce with social networking) are phenomena of interest to both marketing academics and practitioners, and can have important marketing implications (e.g., consumer-generated media such as online product reviews can influence sales; cf. Chevalier and Mayzlin 2006). While some aspects of these phenomena have been studied and are at least somewhat understood, such as the marketing consequences of online word-of-mouth (WOM) or the role played by social network links in facilitating new product diffusion, many important questions remain unanswered, particularly in relation to understanding consumers in this context, and whether economic value can be derived from social networking and emerging marketplace trends that combine networking and e-commerce (i.e., “social commerce”).

In contributing to the growing body of literature that attempts to address some or both of these unanswered questions, this dissertation considers four research questions that consider social types of interactions between individuals in marketplaces: (1) how can network-based interactions between consumers generate economic value for firms and for other marketplace participants, (2) what drives the formation and evolution of these interactions and network relationships in a marketplace context, (3) what drives the activation of consumers’ network relationships with respect to the transmission of information via WOM from one consumer to another, and (4) what affects the reception
of information via WOM and how can impact of WOM on consumers’ attitudes and behaviors be measured and modeled? Each of these questions is addressed by a separate chapter of this dissertation.

1.2 Past Research

Provided here is a brief and general overview of past research in marketing and related fields that has examined social networks and associated issues (e.g., WOM, social contagion). Detailed reviews of extant literature are provided within each chapter.

Extant research on networks in marketing mostly centers on two issues: (1) describing consumers’ networks, often in terms of word-of-mouth (WOM) or product referrals (e.g., Brown and Reingen 1987; Reingen and Kernan 1986), or (2) on the aggregate effects of networks in relation to diffusion of innovations (e.g., Nair, Manchanda, and Bhatia 2006; Narayan and Yang 2008; Van den Bulte and Joshi 2007; Van den Bulte and Lilien 2001). Some very recent work also uses network models to understand online phenomena such as advertising links between websites (Katona and Sarvary 2008), links between blogs (Mayzlin and Yonagarasimhan 2006), individuals’ membership of online social networks (Katona, Zubcsek, and Sarvary 2008; Trusov, Bucklin, and Pauwels 2009), and how networks and product characteristics jointly affect ongoing consumption of products (Stephen and Berger 2009).

The social processes that underlie marketing decisions and actions have been of interest to academics and marketers for decades. Some early marketing studies addressed issues such as the spread of word-of-mouth (WOM) between consumers (e.g., Arndt
1967; Brooks 1957), the roles of social processes (e.g., WOM, referrals) in the diffusion of new products (e.g., Bass 1969; Czepiel 1974; Martilla 1971; Reingen and Kernan 1986), and interpersonal social influences on consumption behaviors (e.g., Bearden and Etzel 1982; Brown and Reingen 1987; Reingen et al. 1984; Ward and Reingen 1990). Work immediately following these early studies also addressed a similar set of issues, particularly social peer influence on consumption behaviors and WOM (e.g., Childers and Rao 1992; Frenzen and Nakamoto 1993; Frenzen and Davis 1990).

Around the same time that marketing academics were beginning to study social processes and their roles in contexts of interest to marketers, the literature on social networks in sociology was growing. Social networks are comprised of nodes (actors: consumers, managers or firms) and ties (social relationships, interactions, referrals), with ties connecting nodes. For example, a tie between two people, $i$ and $j$, could indicate that $i$ and $j$ are friends (or acquaintances). In WOM and referral networks a directed tie from $i$ to $j$ usually means that person $i$ referred or recommended a product to person $j$.

Interestingly, social network models of marketing phenomena such as WOM and consumer-to-consumer referrals existed as early as research by Reingen and colleagues’ (1984; 1986) attempts to map consumers’ social referral networks. In one classic application of descriptive social network analysis, Reingen and Kernan (1986) mapped the social network of customers of a piano tuner, and found that a lot of this person’s business appeared to come through WOM-based referrals among his customers. The early work, however, was mostly descriptive and focused on mapping the structure of networks of consumers. Related work in the business-to-business marketing literature
also emerged around the same time, using social network analysis techniques and more sophisticated statistical models to understand industry/market structure and competition (Iacobucci and Hopkins 1992).

The early social networks research in marketing tended to be methodologically straightforward and descriptive; that is, the network was the focus of inquiry, not factors influencing the network (i.e., network as the dependent variable), or consequences of the network (i.e., network as predictor or independent variable). Although understanding network structure and describing it using established descriptive measures can be useful, it is unlikely sufficient to address more complex research questions. Since adopting a network perspective (as opposed to a monadic or individual perspective, or even a dyadic perspective) is usually done in order to capture some of the inherent complexity in marketing contexts that cannot be addressed by simpler frameworks, more complex approaches are necessary (cf. Stephen and Berger 2009). Some examples that have been used recently include those used in studies of the diffusion of innovations, new products, or WOM, and have generally been along the lines of statistical models that use a known network structure (e.g., defining the social and professional relationships between doctors) as a predictor (along with other node-level covariates) of node-level outcomes (e.g., whether a doctor prescribes a new drug to a patient or not) (e.g., Van den Bulte and Lilien 2001), or agent-based simulations of diffusion or WOM processes (e.g., Goldenberg et al. 2001; Goldenberg et al. 2000; Stephen and Berger 2009; Watts and Dodds 2007).
Very recent work in marketing and consumer research has examined WOM, social contagion, diffusion of innovations, and consumer interdependence. Much of this work has involved empirical models and interesting, often Internet-derived, datasets.

Chevalier and Mayzlin (2006), Godes and Mayzlin (2004), Liu (2006), and Narayan and Yang (2008) have studied online WOM (e.g., product reviews on websites) and the influence of consumer-generated media on business outcomes. Models of consumers’ interdependent choices and preference have also been suggested (Yang and Allenby 2003; Zhang and Netzer 2009). Other work has modeled joining online social networks as a product adoption process, focusing on decisions to join such websites (Katona, Zubcsek, and Sarvary 2008) and how WOM influences the growth in such websites’ memberships (Trusov, Bucklin, and Pauwels 2009). Finally, game-theoretic and analytical work, building on related work in economics (Bala and Goyal 2000; Bramoullé et al. 2004; Hanaki et al. 2007; Jackson 2004; Jackson and Wolinsky 1996) has studied network formation in specific contexts, such as links between Internet websites for online advertising (Katona and Sarvary 2008), and links between blogs (Mayzlin and Yonagarasimhan 2006).

In studying networks of consumers, the focus is often on new product diffusion with WOM purportedly facilitated by network ties (e.g., Goldenberg et al. 2001). Related research considers the impacts of WOM and “buzz” on outcomes such as sales (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004, 2008; Liu 2006). Despite research on the outcomes of WOM and its role in diffusion processes, surprisingly little is known about individuals’ WOM transmission (“talking”) behaviors. In other words, the
underlying processes associated with WOM are not well understood. Accordingly, one issue addressed in this dissertation considers the drivers of sending word-of-mouth (WOM) in a social network of consumers, focusing on how people decide who to transmit WOM to in their social networks (chapter 5, essay 3). Another issue considered is the reception side of WOM, which has received virtually no attention in extant research. In chapter 6 (essay 4) the drivers of “listening” to product-related WOM from other consumers are examined, along with ways to measure and model the impact that received WOM has on consumers’ product attitudes and purchase intentions.

While networks of consumers are common, networks of consumers-as-sellers are also common and potentially interesting. Networks of sellers in online marketplaces such as eBay, for example, may have important and interesting impacts on key marketing outcomes, including sales. This type of network has received virtually no attention from researchers, although understanding how network links between online sellers affects sales (for example) is an ideal way not only to see how networks can affect sales, but also to develop an understanding of more general value implications of networks.

This is particularly relevant given that networking in online environments has become a cornerstone feature of social media and Web 2.0. Merging e-commerce, individual-driven marketplaces (e.g., eBay, Craigslist) and social networking (e.g., Facebook, MySpace) is a “hot” topic, and managers are trying to develop revenue models that are not just based on Internet advertising. For example, eBay is experimenting with social networking between its sellers (where the network links can be clicked on by browsing customers), MySpace has recently added a Craigslist-style classifieds feature,
and Facebook is working on a payment and marketplace system that will allow its 200 million users\(^1\) to become online sellers and turn Facebook into a massive online marketplace. Networks between sellers are also potentially intriguing since the links can include connecting with current or potential competitors. Thus, the implications of allowing online sellers to form network links ("social commerce") are not obvious. The economic value implications of social commerce networks are empirically examined in chapter 2 (essay 1). Building on this, the link formation dynamics of such networks involving sellers are modeled in chapter 3 (essay 2) by focusing on empirically comparing various theoretically motivated drivers of link formation.

In general, the networks research in marketing has evolved from descriptive mapping of referral ties and simple descriptive network analysis of consumer networks to sophisticated empirical research using cutting-edge statistical models to understand how consumers’ or firms’ network connections influence certain marketing outcomes. Nonetheless, much of this work has been based on modeling new product diffusion processes or product adoptions influenced by interdependent preferences or more direct social influence and WOM. With the increased "connectedness" of consumers in online and offline marketplaces, and firms’ moves to "monetize" web-based social networking applications such as Facebook.com and Myspace.com, the study of social networks in marketing contexts becomes more fundamental and has wider-ranging implications than simply using networks in empirical models of new product diffusion. Accordingly, many important issues that tie together social networks, marketing, retailing, and new forms of

\(^1\) As of late March 2009.
e-commerce such as "social commerce" and "social shopping" are currently unaddressed by extant marketing research.

Overall, this dissertation attempts to understand network-related interactions between marketplace participants (consumers, sellers), moving beyond the previous work on networks in marketing to (1) understand familiar phenomena in greater detail (i.e., WOM), and (2) explore and evaluate the potential value implications of new, emerging phenomena (i.e., seller networking in online marketplaces).

1.3 Abstracts of Essays

1.3.1 Essay 1 (Chapter 2)

This essay is titled "Deriving Value from Social Commerce Networks." Social commerce is an emerging trend in which sellers are connected in online social networks, and where sellers are individuals instead of firms. This essay examines the economic value implications of a social network between sellers in a large online social commerce marketplace. In this marketplace each seller creates his or her own shop, and network ties between sellers are directed hyperlinks between their shops. Three questions are addressed: (1) Does allowing sellers to connect to one another create value (i.e., increase sales), (2) what are the mechanisms through which this value is created, (3) how is this value distributed across sellers in the network and how does the position of a seller in the network (e.g., its centrality) influence how much it benefits or suffers from the network?

The findings are (1) allowing sellers to connect generates considerable economic value; (2) the network’s value lies primarily in making shops more accessible to
customers browsing the marketplace (the network creates a “virtual shopping mall”); and (3) the sellers that benefit the most from the network are not necessarily those that are central to the network, but rather those whose accessibility is most enhanced by the network.

1.3.2 Essay 2 (Chapter 3)

This essay is titled “Explaining the Power-Law Degree Distribution in a Social Commerce Network.” Here we study the evolution of a large social network in a social commerce community in which individuals create their own personal online “shops” and are allowed to create referral hyperlinks between each other’s shops. The dataset starts before the birth of the network (at which points shops were independent) and includes the birth of the network. Although the network studied has a power-law degree distribution, its evolution is not well explained by preferential attachment or triadic and cyclic closure. Instead, the evolution of the network and the emergence of its power-law degree distribution are found to be well explained by a network evolution mechanism that relies on vertex attributes that are not directly related to the network, whereby shops prefer to connect to shops with more diverse assortments and where assortment diversity follows a power-law distribution.

1.3.3 Essay 3 (Chapter 4)

This essay is titled “Why Do People Transmit Word-of-Mouth? The Effects of Recipient and Relationship Characteristics on Transmission Behaviors.” Despite the large
amount of research on WOM and social contagion in marketing, sociology, and other disciplines, surprisingly little is known about the drivers of individuals’ WOM transmission behaviors. This essay seeks to better understand why and to whom consumers transmit WOM about products.

Across three studies we find that (1) the main reasons for transmitting WOM are predominantly transmitter-focused and associated with transmitters using social capital embedded in their social relationships, (2) the importance placed on these reasons by transmitters is related to the types of recipients that they actually choose to talk to, (3) characteristics of recipients and the relationships they have with transmitters are strong drivers of transmitters’ decisions of who to (and who not to) transmit information to, and (4) the underlying reasons for transmitting WOM, and hence the types of recipients that comprise one’s preferred “audience,” lie in transmitters wanting to use (but not build) social capital, but the type of use depends on whether people are sharing their own opinions (“initial transmission”) or passing on others’ opinions (“retransmission”).

Specifically, initial transmitters use their social capital to give themselves a receptive audience for them to air their opinions with a high chance of being listened to. Retransmitters instead use social capital to obtain (but not contribute) new information from recipients and recipients’ social networks. Thus, initial transmitters appear to talk for the sake of talking (and try to avoid being ignored), and retransmitters talk in order to get fresh information in return.
1.3.4 Essay 4 (Chapter 5)

This essay is titled “Is Anyone Listening? Modeling the Impact of Word-of-Mouth at the Individual Level.” Most studies of word-of-mouth (WOM) in marketing have concentrated either on aggregate outcomes (e.g., new product diffusion) or on the transmission process (i.e., “talking” or “sending” information). This essay instead focuses on the reception process at the individual level (i.e., “listening” to information), and addresses two questions: what makes people listen to WOM, and what are the drivers of the type and extent of WOM impact on recipients’ brand attitudes and purchase intentions? Transmitter, message, and transmitter—recipient relationship characteristics are examined as potential drivers of reception/listening and WOM’s impact on the disposition recipients have toward focal brands and the certainty or confidence with which these dispositions are held.

Two studies demonstrate that (1) WOM impacts disposition and certainty differently, (2) changes in both disposition and certainty affect consumers’ intentions to purchase a focal talked-about brand, (3) WOM from strangers in some cases can be as impactful as WOM from friends and acquaintances, and (4) the relatively strong influence of strangers under some conditions seems to be the result of perceptions of the credibility of strangers as sources of information. Overall, the results illustrate that WOM reception is multiply-determined and, above all, the outcome of a complex set of processes.
2

Deriving Value from Social Commerce Networks
2.1 Introduction

Social commerce and social shopping communities are growing in number and in size. Broadly defined, social commerce and social shopping are forms of Internet-based “social media” that allow people to actively participate in the marketing and selling of products and services in online marketplaces and communities. One way to think of these applications is that they merge online shopping and social networking (Tedeschi 2006). The distinction between social shopping and social commerce is that while social shopping connects customers, social commerce connects sellers. The roles played by consumers vary across websites or platforms, and can range from generating content (e.g., product reviews and recommendations, known as “consumer-generated media,” on websites like Epinions.com, ThisNext.com, and Yelp.com) to being sellers and curators of online stores (e.g., eBay MyWorld/Neighborhoods, Squidoo.com, and Zlio.com). The Financial Times reported that Internet traffic to social commerce and social shopping websites grew by more than 500% between early 2007 and early 2008 (Palmer 2008), the New York Times reported that a number of social commerce firms are attracting substantial venture capital financing (Tedeschi 2006), and further growth and investment in this online retailing segment is expected.

Social shopping revolves around online word-of-mouth, and has recently been studied academically. For example, Chevalier and Mayzlin (2006) and Godes and Mayzlin (2004) studied word-of-mouth and the influence of consumer-generated media on business outcomes, and Watts and Dodds (2007) studied some marketing-related implications of social contagion from a social networks perspective. Recent research in
marketing has also examined related issues, such as consumer interdependence in choice and spatial models (Yang and Allenby 2003), and other issues related to social networks in marketing contexts (Iyengar, Valente, and Van den Bulte 2008; Katona and Sarvary 2008; Nair, Manchanda, and Bhatia 2006; Trusov, Bucklin, and Pauwels 2008; Van den Bulte and Joshi 2007; Van den Bulte and Lilien 2001).

Social commerce, on the other hand, is a more recent phenomenon and has not been studied as extensively. Social commerce marketplaces have four defining characteristics: (i) sellers (or shopkeepers) are individuals instead of firms, (ii) sellers create product assortments organized as personalized online shops, (iii) sellers’ can create hyperlinks between their personalized shops, and (iv) sellers’ incentives are based on being paid commissions on sales made by their shops. What emerges is a consumer-driven online marketplace of personalized, individual-curated shops that are connected in a network. Links between sellers’ shops in this network are directed, clickable hyperlinks that customers can use to move from shop to shop. In the specific marketplace that we study, which is a large and typical social commerce marketplace created in Europe, the products that sellers add to their shops come from vendors (e.g., Amazon, Apple, Gap) based on arrangements made by the marketplace owner. As a result, sellers do not own any inventory and do not set prices; they only manage the product mix.

Our aim is to understand social commerce as a new business concept, focusing on whether and how it generates economic value for marketplace-owning firms and for the individuals who participate as sellers in these marketplaces (by increasing sales). Issues related to connecting sellers have not been studied extensively (one exception is the
shopping center literature that we review below). The value implications of networks have been studied in other contexts, such as inter- and intra-firm networks of a formal or an informal nature (e.g., Rindfleisch and Moorman 2001; Tsai and Ghoshal 1998; Wuyts et al. 2004), and collaborative group networks (e.g., Freeman, Roeder, and Mulholland 1980; Grewal, Lilien, and Mallapragada 2006). The economic implications of social structure have also been discussed recently in economics and sociology (e.g., Goyal 2007; Greif 2006). However, very little is understood about whether networks provide some economic value in marketing and retailing contexts. We consider the following questions in relation to social commerce: (i) does allowing sellers to connect to one another create economic value (i.e., increase sales), (ii) what are the mechanisms through which this value is created, (iii) how is this value distributed across sellers in the network and how does the position of a seller in the network (e.g., its centrality) influence how much it benefits or suffers from the network?

We address these questions using a novel dataset from an online marketplace which, after hosting a set of independent, consumer-generated online shops for about 18 months, became a social commerce marketplace by allowing its sellers to connect their shops and form a shop network (a connection from shop A to shop B is represented by a directed hyperlink to shop B on shop A’s website). Our dataset covers both a pre-network and a post-network period (therefore allowing us to study the effect of the introduction of the networking feature), and it contains detailed information on the characteristics and performance of each shop (therefore allowing us to explore how the value created by the network is shared across members). We use multiple methods and analyze these data at
the marketplace level (using time series analysis) and at the shop level (using Bayesian statistical analysis). The essay is organized as follows. First, we review relevant literatures on shopping centers and social networks. Second, we describe our dataset. Third, we report the results of our marketplace-level analysis. Fourth, we report the results of our shop-level analysis. Finally, we conclude with a general discussion of the results, and suggestions for future research.

2.2 Background and Theory

Network ties between sellers in social commerce marketplaces are links between sellers’ shops that customers can use to browse between shops, akin to browsing through a virtual shopping center. For the individuals who participate as sellers in social commerce marketplaces and who earn commissions on sales that they make, the network can make their shops more accessible and more likely to be discovered by a browsing customer.

Bricks-and-mortar shopping centers are possible analogs to online social commerce marketplaces. Whereas social commerce shops are connected by directed hyperlinks, in offline shopping centers shops are linked by spatial proximities (although these offline “links” are not inherently social and are usually determined by retail planners). The literature on shopping centers in real estate economics has considered relevant issues such as tenant mixes and locations, rent setting, customer traffic generation, co-location, and spatial dependence between grouped shops (e.g., Eppli and Benjamin 1994; Lee and Pace 2005). Marketing researchers have also contributed to this
literature (e.g., Nevin and Houston 1980), including recent work examining retailers’ decisions to enter shopping centers (Vitorino 2008), and work on spatial dependence between marketing variables (e.g., market shares) at the geographic region level (e.g., Bronnenberg and Mahajan 2001).

An important concept in the shopping center literature is that of “retail demand externalities.” A positive retail demand externality exists when customers are drawn to a shopping center due to the presence of attractive “anchor” tenants, such as department stores, supermarkets, or super-stores (Eppli and Benjamin 1994). Smaller shops benefit from being in the same center as an anchor, because anchors increase customer traffic, and thus increase smaller shops’ chances of attracting customers and making sales (Ingene and Ghosh 1990). The benefits to customers include reduced travel costs and the convenience of multi-purpose or “one stop” shopping (Eppli and Benjamin 1994). These effects are generally empirically well supported (e.g., Eppli and Benjamin 1994; Nevin and Houston 1980). The spatial dependence stream of the shopping center literature (e.g., Lee and Pace 2005) suggests that shops’ locations within offline shopping centers can influence their sales (e.g., being next-door to an anchor may boost sales), although any shop in a shopping center is more accessible than a standalone shop outside of the center in most cases.²

Therefore, bricks-and-mortar shopping centers generate value primarily by making stores more accessible to customers. We argue that social commerce networks

² Similar logic applies to retailer co-location in local districts or zones (e.g., the diamond district in midtown Manhattan, second-hand book stores lining the Seine in Paris) More generally, retailer co-location is a micro type of the concept of industrial districts introduced by Marshall (1890/1961).
act as “virtual shopping centers” that create economic value through the same basic concept of accessibility. For individual sellers in large social commerce marketplaces, being found by customers can be challenging. Hence, being part of a network and, importantly, being accessible and reachable in that network, has a benefit comparable to the benefit offered by bricks-and-mortar shopping centers. Increasing the overall accessibility of the shops in the network makes the marketplace more “sticky”, i.e., helps retain customers within the marketplace for longer. In other words, the network has the potential to affect the number of visitors to any given shop, which has a direct impact on sales since the number of sales is simply equal to the number of visitors multiplied by the shop’s conversion rate.

However, while similar to offline shopping centers at a basic level, social commerce marketplaces are not merely online equivalents of shopping centers, thus making social commerce a theoretically and substantively interesting context to study. In particular, the drivers of accessibility are likely to differ between social commerce networks and bricks-and-mortar shopping centers for at least four reasons. First, links between shops in a social commerce network are directed, that is, a hyperlink is from shop A to shop B, and not necessarily the reverse. In bricks-and-mortar shopping centers, “links” (physical proximities) between shops are obviously undirected and customers’ browsing paths are not as structurally constrained as in an online shop network. Second, when a customer browses in a shopping center they do not visit (i.e., go into) every shop that they pass on their way from one shop to another. In the online context, however, browsing requires that the customer visit every shop along a path. For example, on a path
A → B → C, going from A to C requires visiting B. Third, traveling costs are lower online (relative to the goods being purchased). As mentioned earlier, one key benefit of grouping bricks-and-mortar retailers to form a shopping center is convenience, i.e., reduced traveling costs for customers. This benefit is likely to be less critical online. Fourth, while the number of neighbors of a bricks-and-mortar shop in a shopping mall is physically constrained, the number of links to and from any given shop in a social commerce network is not constrained.

As a result, while we use the shopping center literature to motivate the concept of accessibility, we turn to the social networks literature to study the drivers of accessibility in social commerce networks. At the marketplace level, networks that are more connected (i.e., with a larger number of links) generally tend to better improve the overall accessibility of their members. However, simply increasing the number of links may not always be beneficial. Improvements in accessibility depend on the browsability of the network, and not all links equally contribute to a network’s browsability. In particular, creating new links sometimes actually hurts the browsability of the network. For instance, in Figure 1 a simple network evolves from time 1 to time 2 with the addition of a new link. In time 2 shop D is brought into the network by shop A with the creation of the A→D link. This makes shop D accessible from shop A, but this also makes D a “dead-end” (i.e., a shop with at least one incoming link, but no outgoing links). If a customer browses to D (starting at A) then he or she will not be able to access shop B or

---

3 Nodes with incoming links but zero outgoing links are called “sinks” in graph theory and network analysis (de Nooy, Mrvar, and Batagelj 2005). Note that there is a possibility that a browsing customer could simply click their web browser’s “back” button to back-track out of a dead-end shop. Therefore the effect of dead ends found in our dataset is conservative.
C. Although the network at time 2 is more connected, the creation of a dead-end makes it less browsable (at least from B’s and C’s perspective).

Figure 1: Illustration of Dead-Ends

The accessibility of a website (in our case a shop) is influenced by the structure of the network to which it belongs and its position in this network relative to other sites (Vázquez 2003). Specifically, shops with higher indegree centrality (number of incoming links) should benefit more from the network compared to shops with lower indegree centrality because more incoming links equates to a higher chance of customer traffic in one’s shop. We also expect that shops with higher incoming proximity (can be reached
from more shops in fewer steps) will benefit more from the network compared to shops with lower incoming proximity, because shops that are accessible from fewer other shops and that lie further down browsing paths are less likely to be visited. Conversely, shops that provide many opportunities for customers to leave, by having a higher outdegree centrality (many outgoing links) or a higher outgoing proximity (can lead to more shops in fewer steps), should themselves benefit less from the network. Also, shops that are connected to by shops that are themselves highly interconnected will be less accessible since the likelihood of browsing customers reaching such a shop will be low unless their browsing path starts in its ego-network. We therefore anticipate that shops with lower incoming clustering coefficients tend to benefit more from the network. The concepts of indegree centrality, outdegree centrality, incoming proximity, outgoing proximity, incoming clustering coefficients and outgoing clustering coefficients are defined formally in Table 1. (Note that hub centrality and authority centrality, also defined in Table 1, are addressed later in the essay.)
Table 1: Network Position Measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Formula</th>
<th>Definition and Intuition</th>
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<tbody>
<tr>
<td>The shop network is comprised of $N$ shops. A directed link from shop $i$ to shop $j$ is denoted by $x_{ij}$. The network is represented as an $N \times N$ adjacency matrix, $X$, with diagonal elements $x_{ii} = 0$ (for all $i = 1, \ldots, N$), and off-diagonal elements $x_{ij} = 1$ if there is a link from $i$ to $j$ (and 0 otherwise).</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality</td>
<td>$(X \cdot 1)_i = k_i^\text{in}$ where 1 is an $N$-dimensional vector of ones.</td>
<td>The number of links from other shops that go to shop $i$.</td>
</tr>
<tr>
<td>Outdegree centrality</td>
<td>$(X \cdot 1)_i = k_i^\text{out}$ where 1 is an $N$-dimensional vector of ones.</td>
<td>The number of links from shop $i$ that go to other shops.</td>
</tr>
<tr>
<td>Incoming proximity</td>
<td>$[n_i^\text{in} / (N - 1)] \cdot [n_i^\text{in} / \sum_{j \in \text{in}} d(j, i)]$, where $\text{in}_i$ is the set of shops from which shop $i$ can be reached in a finite number of steps, $n_i^\text{in}$ is the number of shops in that set (indomain), and $d(j, i)$ is the geodesic distance (shortest path length) from shop $j$ to shop $i$.</td>
<td>Shop $i$'s incoming proximity is proportional to the proportion of shops in the network other than $i$ that can reach $i$ in a finite number of steps, and inversely proportional to the mean geodesic distance (shortest path length) from these shops to $i$.</td>
</tr>
<tr>
<td>Outgoing proximity</td>
<td>$[n_i^\text{out} / (N - 1)] \cdot [n_i^\text{out} / \sum_{j \in \text{out}} d(i, j)]$, where $\text{out}_i$ is the set of shops that can be reached from shop $i$ in a finite number of steps, $n_i^\text{out}$ is the number of shops in that set (outdomain), and $d(i, j)$ is the geodesic distance (shortest path length) from shop $i$ to shop $j$.</td>
<td>Shop $i$'s outgoing proximity is proportional to the proportion of shops in the network other than $i$ that can be reached from $i$ in a finite number of steps, and inversely proportional to the mean geodesic distance (shortest path length) from shop $i$ to these shops.</td>
</tr>
<tr>
<td>Incoming clustering coefficient</td>
<td>$e_i^\text{in} / k_i^\text{in}(k_i^\text{in} - 1)$ where $e_i^\text{in}$ is the number of directed links between shops that connect to shop $i$ directly (excluding $i$), and $k_i^\text{in}$ is the indegree of shop $i$.</td>
<td>The proportion of possible links that exist among the shops in shop $i$'s incoming ego-network. A shop with a higher incoming clustering coefficient is connected to by more clustered (as opposed to more dispersed) shops.</td>
</tr>
<tr>
<td>Outgoing clustering coefficient</td>
<td>$e_i^\text{out} / k_i^\text{out}(k_i^\text{out} - 1)$ where $e_i^\text{out}$ is the number of directed links between shops that shop $i$ connects to directly (excluding $i$), and $k_i^\text{out}$ is the outdegree of shop $i$.</td>
<td>The proportion of possible links that exist among the shops in shop $i$'s outgoing ego-network. A shop with a higher outgoing clustering coefficient connects to more clustered (as opposed to more dispersed) shops.</td>
</tr>
<tr>
<td>Hub centrality</td>
<td>The hub score for shop $i$ is the $i^{th}$ component of the eigenvector corresponding to the largest eigenvalue of $XX^T$.</td>
<td>These are both directed network versions of eigenvector centrality, which is an indicator of position-related status (i.e., being well connected to other well connected shops). Good hubs connect to many good authorities, and good authorities connect to many good hubs.</td>
</tr>
<tr>
<td>Authority centrality</td>
<td>The authority score for shop $i$ is the $i^{th}$ component of the eigenvector corresponding to the largest eigenvalue of $X^TX$.</td>
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</tbody>
</table>
Of course, other features will influence a shop’s likelihood of generating sales, which can generally be referred to as a shop’s “attractiveness” to customers. In this context, a shop’s attractiveness may be related to its product assortment (e.g., number of products, and uniqueness of its products vis-à-vis other shops in the marketplace) and the general ability or skill of the shopkeeper in creating an appealing product assortment. Finally, note that allowing sellers to connect to other shops could also have the effect of intensifying competition. However, because sellers typically do not set prices in such marketplaces (e.g., sellers select merchandise for their shops but do not set prices; vendors who provide the products set prices), intensified competition between sellers cannot force them to lower prices.4

2.3 Data

Our data come from a company that runs popular and rapidly growing social commerce marketplaces in France, Germany, the United Kingdom, and the United States. Our dataset covers the French marketplace, which is the largest and was the first that this company launched. The company leverages online retailers’ “affiliate” selling programs whereby websites that refer purchases to these retailers are paid commissions. Individuals (“sellers”) join this marketplace and are given tools to create their own online personalized stores or “shops” (each shop has its own URL). Sellers add products to their shops from a database of over 4 million products across many categories, with these

4 Sellers may however under-invest in service quality (e.g., visual attractiveness of their shops) in response to increased competition (Stern, El-Ansary, and Coughlan 1996).
products coming from over 100 vendor retailers such as Amazon.fr, Apple, Dell, and the Gap. Each seller has complete control over their shop’s product assortment. Importantly, sellers are individual people, as opposed to companies.

The purchasing process in this marketplace is as follows. When a customer selects a product from a shop, he or she is referred to the corresponding vendor who processes the transaction and ships the product (i.e., the marketplace owner and its members hold no inventory). The vendor then pays the marketplace owner a commission for each transaction generated by one of the marketplace’s shops, and this commission is shared with the seller whose shop generated the sale. For example, suppose that Mark visits Roger’s shop in this marketplace where Roger lists a range of books on Bayesian estimation. If Mark purchases a particular book, he is taken to the corresponding vendor’s website (say Amazon), pays the vendor with his credit card, and a few days later receives the book shipped from (or through) Amazon. Since Mark purchased a book from Roger’s shop, Amazon pays the marketplace a commission on that sale, and Roger in turn earns a portion of this commission. In summary, sellers are individual shopkeepers who do not own any inventory but create online shops that direct customers to online vendors, and who earn commissions on the sales made by their shops.

In June 2007, approximately 18 months after the marketplace had been established, the firm introduced a new feature that allowed members to link their shops to other shops (at that time the marketplace had 74,291 shops). Shops were independent (all disconnected) prior to the introduction of this feature. This feature gave birth to a network with shops as nodes and directed hyperlinks as ties. A link from shop A to shop
B means that shop A’s owner placed a hyperlink to shop B on shop A’s homepage. Shop B’s owner cannot reject the incoming link, but is not required to reciprocate this link (shop B’s owner is notified of the incoming link by email). Therefore, this network is directed.

Our dataset includes the entire French population of shops that were created anytime between the first day and the 781st day of this marketplace’s life (the last day of our dataset). The network was created (i.e., sellers were given the ability to link their shops to other sellers’ shops) on the 583rd day of the marketplace’s life; therefore our data cover approximately the first seven months of the network’s life. After 781 days of this marketplace’s life in France, 136,774 shops had been created, and 21,373 of these shops (15.6%) were part of the network (i.e., had at least one incoming or outgoing link). By this time the network had 82,810 directed links (network density, or the proportion of possible directed links that exist, was $1.21 \times 10^{-5}$). The marketplace and the network within it were growing quickly: an average of 180 new shops had been created in the marketplace each day, and once the network was born an average of 107 shops had joined the network each day, with an average of 421 new links created each day. Shops in this marketplace are generally small and have limited product assortments (the average shop features nine products). While the average commission revenue generated by each shop was modest (€2.84; although shops that made at least one sale had a higher average commission of €8.36), the aggregate revenue generated by the entire marketplace was nontrivial: 2.3 million transactions and €388,970 in commission revenues (from vendors) had been generated by the end of the observation window.
Note that our focus is on the network that lies within the overall marketplace. By the end of our dataset 15.6% of the shops in the marketplace were also part of the network (i.e., they had indegree > 0 or outdegree > 0 or both). This of course means that the vast majority of shops were not part of the network. We do not model individual sellers’ decisions to enter the network here (in the next chapter we consider the related issue of link formation, however). Thus, the network and the set of shops that are part of the network at any given point in time is taken as exogenous. Generally, the shops that were in the network made more sales and earned higher commissions than the shops that were not in the network. In fact, approximately 82% of the commission revenues earned since the birth of the network came from connected shops. Thus, given our aim of understanding financial outcomes in this marketplace, it makes sense to focus on the network since the connected shops accounted for the majority of revenue. Nevertheless, in the shop-level analysis (section 2.5) the set of shops in the data include shops without any connections.

We first analyze the data at the marketplace level to assess the economic value created by allowing sellers to link their shops to other sellers’ shops in a manner observable to customers. We use time series models to examine the value created by the network and the relation between this value and some aggregate characteristics of the network. We then analyze the data at the individual shop level to address the issue of how the economic value created by the network is distributed across its members, using a hierarchical Bayesian Tobit model with latent variables.
2.4  Marketplace-Level Analysis

2.4.1 Variables Used in Analysis

We first introduce the variables that will be the focus of our time series analysis. Our analysis of marketplace-level data uses autoregression with exogenous variables (ARX) time series models. Data are available on each of these variables for each of the 781 days in our dataset, covering both pre- and post-network birth periods:

- Commission\_revenues\_t: the commissions in € paid to the marketplace owner by the vendors for the sales made by the shops on day \( t \).
- Network\_t: a dummy variable indicating whether the network existed on day \( t \) or not;
- Marketplace\_size\_t: total number of shops in the marketplace at the end of day \( t \) (includes shops that are in the marketplace but do not have any network links);
- Network\_links\_t: total number of links in the shop network on day \( t \);
- Dead\_ends\_t: the total number of dead-end shops in the network on day \( t \). See Figure 1.

2.4.2 Impact of Allowing Sellers to Form a Network

Before investigating more specific issues related to network connectivity and marketplace commission revenues, we performed an initial test to address whether adding the networking feature had a positive effect on the commission revenues earned by the marketplace. In other words, did changing the disconnected online marketplace into a social commerce marketplace improve commission revenues? We addressed this question using a regime shift model, as introducing the shop network feature on the 583rd day of


the marketplace’s life was a “regime shift” for this marketplace. The impact of this regime shift can be modeled with the following ARX model:

\[
Commission_{revenues_t} = \beta_0 + \sum_{i=1}^{p} \phi_i \cdot Commission_{revenues_{t-i}} + \lambda_0 \cdot Network_t + \lambda_1 \cdot \Delta Marketplace_{size_t} + \epsilon_t
\]  
(2.1)

The best-fitting model (i.e., with the lowest BIC) had autoregressive lag of \(p = 6\).\(^5\)

\(Commission_{revenues_t}\), which we defined in its daily (differenced) form, was found to be stable and not evolving using an augmented Dickey-Fuller (ADF) unit root test (with a null hypothesis of non-stationarity; \(p < .001\)). \(Marketplace_{size_t}\), defined above in its total or cumulative form was found non-stationary based on an ADF test (\(p = .99\), however when differenced (i.e., the daily change in the number of shops in the marketplace) it was stationary (\(p < .001\)). Thus, we use the difference in \(Marketplace_{size_t}\) (i.e., the daily change) and not the cumulative level in our model (Dekimpe and Hanssens 2004). Indeed, it would be unreasonable to model a stationary series as a function of a non-stationary one. A Stock and Watson common trend test for cointegration found that these series were not cointegrated. The use of an ARX model instead of a VAR model was supported by a series of Granger causality tests (Granger 1969; Hanssens et al. 2001; Trusov et al. 2008) which confirmed the exogeneity of \(\Delta Marketplace_{size_t}\) and \(Network_t\). Since an incorrect choice of the AR lag \(p\) can erroneously conclude the absence of Granger causality, we selected a high lag (\(AR p = 30\)) to be more sure that the results apply at any lag and not just the best-fitting lag for the

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\(^5\) We considered adding a time trend and monthly seasonality effects in Equations (2.1) and (2.2), however in both cases Wald tests could not reject the null hypothesis that the time trend and all month effects were zero, thus suggesting that time and seasonality effects were not needed.
model (Hanssens 1980; Trusov et al. 2008). \( \Delta Marketplace\_size \) was not "Granger caused" by either \( Commission\_revenues \) or \( Network \) (\( \chi^2[60] = 65.19, p = .30 \)), and \( Network \) was not Granger caused by either \( \Delta Marketplace\_size \) or \( Commission\_revenues \) (\( \chi^2[60] = 40.07, p = .98 \)).

The regime shift model appeared to fit the actual series well (\( R^2 = .72 \), BIC = 11.77, median absolute deviation [MAD] = \( \epsilon59.78 \), median absolute percentage error [MAPE] = 17.94\%). The parameter for the network indicator was positive and significant (\( \lambda_0 = 112.54, t = 2.06, p < .05 \)), suggesting that shifting to a networked marketplace was a revenue-boosting decision on the marketplace owner's part.\(^6\) The effect of increasing marketplace size was also positive and significant (\( \lambda_1 = .36, t = 4.45, p < .01 \)). Overall, these results indicate that, after controlling for marketplace size, allowing sellers to network their shops permanently increased the mean daily commission revenues (i.e., the network effect can be interpreted as a small discontinuity or "jump").

2.4.3 Effects of Marketplace and Network Characteristics on Commission Revenues

Given this preliminary evidence indicating that the network's effect on commission revenues is positive, we next examined the influence of the marketplace's

\(^6\) Alternatively, visitor traffic might have increased between the pre- and post-network-birth periods. In the two months on either side of the network's birth the marketplace received 80,000 unique visitors/day, which decreased over the seven months following the network's birth to 65,000 visitors/day. Thus it cannot be that increased traffic caused the positive effect of the network's presence on revenues.
and the network’s aggregate properties on daily commission revenues with the following model:

\[
Commission\_revenues_t = \beta_0 + \sum_{i=1}^{p} \phi_i \cdot Commission\_revenues_{t-i} + \sum_{j=0}^{r} \Lambda_j \begin{bmatrix} \Delta Market\_size_{t-j} \\ \Delta Network\_links_{t-j} \\ \Delta Dead\_ends_{t-j} \end{bmatrix} + \epsilon_t
\]

(2.2)

All 781 days in the dataset were used to estimate this model.

In this model we examine more directly the effects of evolution in the marketplace’s size and network structure on marketplace commission revenues. As before, \(\Delta Market\_size_t\) is the number of new shops to join the marketplace on day \(t\). \(\Delta Network\_links_t\) and \(\Delta Dead\_ends_t\) capture daily evolution of the network. If the network adds value at the marketplace level by making shops more accessible and by facilitating customer browsing, we should expect new links to have a positive effect on marketplace commission revenues since new links increase browsing opportunities. However, if the network’s browsability is adversely affected by dead-end shops, we should expect an increase in the number of dead-end shops in the network to have a negative effect on marketplace commission revenues.

An alternative specification of these variables would of course be to use cumulative levels (e.g., cumulative number of links created by the end of day \(t\) for \(Network\_links_t\)). Although conceptually plausible, cumulative versions of these variables pose problems because they are all non-stationary (even after controlling for a time trend; all Dickey-Fuller tests \(p < .95\), whereas all Dickey-Fuller tests on daily/differenced series \(p < .001\)). This suggests that differences are appropriate. The autoregressive lags
of the dependent variable contain information about previous days’ levels of each of the exogenous variables, thus ensuring that these variables’ histories are accounted for. Note that we also found no evidence of cointegration for the daily series, making a VAR or ARX model in differences appropriate (instead of, for example, an error-correction model; cf. Dekimpe and Hanssens 2004). The ARX specification in (2) (and not a VAR model) was confirmed by Granger causality tests: (1) $\Delta \text{Marketplace\_size}$ was not Granger caused by $\Delta \text{Commission\_revenues}$, $\Delta \text{Network\_links}$, or $\Delta \text{Dead\_ends}$ ($\chi^2[90] = 60.49, p = .99$), (2) $\Delta \text{Network\_links}$ was not Granger caused by $\Delta \text{Commission\_revenues}$, $\Delta \text{Marketplace\_size}$, or $\Delta \text{Dead\_ends}$ ($\chi^2[90] = 88.34, p = .53$), and (3) $\Delta \text{Dead\_ends}$ was not Granger caused by $\Delta \text{Commission\_revenues}$, $\Delta \text{Marketplace\_size}$, or $\Delta \text{Network\_links}$ ($\chi^2[90] = 81.20, p = .74$).

The best-fitting model (i.e., with the lowest BIC) had $p = 7$ and $r = 0$ (i.e., the effects of the exogenous variables appear to be contemporaneous). The model has reasonable fit ($R^2 = .72$, BIC = 11.77, MAD = €49.73, MAPE = 15.73%). A Wald test for the joint hypothesis that $\Lambda = 0$ (i.e., all exogenous variables’ effects are zero) was significant ($\chi^2[3] = 27.44, p < .001$), indicating that the exogenous variables have an impact on commission revenues. A Wald test for the joint hypothesis that $\lambda_2 = \lambda_3 = 0$ (i.e., the network-related exogenous variables) was also significant ($\chi^2[2] = 6.77, p < .05$). Results are reported in Table 2, and Figure 2 plots the actual and fitted daily commission revenues time series to illustrate the model’s fit.
Table 2: Effects of Aggregate Marketplace and Network Characteristics on Marketplace Commission Revenues

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimated Effect (t-value) on Marketplace Commission Revenues</th>
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<tbody>
<tr>
<td>Intercept ($\beta_0$)</td>
<td>15.36 (.90)</td>
</tr>
<tr>
<td>Commission Revenues$_{t-1}$ ($\phi_1$)</td>
<td>.15 (4.34)**</td>
</tr>
<tr>
<td>Commission Revenues$_{t-2}$ ($\phi_2$)</td>
<td>.10 (2.70)**</td>
</tr>
<tr>
<td>Commission Revenues$_{t-3}$ ($\phi_3$)</td>
<td>.20 (5.61)**</td>
</tr>
<tr>
<td>Commission Revenues$_{t-4}$ ($\phi_4$)</td>
<td>.02 (.44)</td>
</tr>
<tr>
<td>Commission Revenues$_{t-5}$ ($\phi_5$)</td>
<td>.08 (2.10)*</td>
</tr>
<tr>
<td>Commission Revenues$_{t-6}$ ($\phi_6$)</td>
<td>.15 (4.31)**</td>
</tr>
<tr>
<td>Commission Revenues$_{t-7}$ ($\phi_7$)</td>
<td>.15 (4.18)**</td>
</tr>
<tr>
<td>Daily increase in marketplace size ($\lambda_1$)</td>
<td>.35 (4.31)**</td>
</tr>
<tr>
<td>Daily increase in number of “normal” network links ($\lambda_2$)</td>
<td>.25 (2.03)*</td>
</tr>
<tr>
<td>Daily increase in number of “dead-end” links ($\lambda_3$)</td>
<td>-3.10 (-2.54)*</td>
</tr>
</tbody>
</table>

* $p < .05$, ** $p < .01$, *** $p < .001$. $R^2 = .72$, BIC = 11.77, MAD = €49.73, MAPE = 15.73%.
Note: the solid black line is the actual daily marketplace commission revenues, and the broken grey line is the fitted daily commission revenues using the model in Equation (2.2). The solid vertical line indicates the birth of the network. The model tracks daily marketplace commission revenues well. Marketplace commission revenue is the total commissions paid to the marketplace owner on day \( t \) for all sales that are made by shops in the marketplace on day \( t \).
There is a positive and significant effect of growth in marketplace size ($\lambda_1 = .35$, $t = 4.31, p < .001$), meaning that daily marketplace revenues receive a boost from each new shop added. Likewise, growth in the number of links in the network has a positive and significant effect ($\lambda_2 = .25$, $t = 2.03, p < .05$), consistent with the idea that more connected networks tend to improve the overall accessibility of their members. Also as predicted, growth in the number of dead-end shops has a negative effect on marketplace performance ($\lambda_3 = -3.10$, $t = -2.54, p < .05$). All autoregressive parameters (effects of lagged daily commission revenues) were also positive and significant (except for the fourth day lag).

2.4.4 Impulse-Response Functions and Long-Run Impacts

We used impulse-response functions (IRFs) to quantify how much commission revenue is generated by a punctual increase of one unit in each of the exogenous variables and how this “shock” impacts the system over time (see below for details). Adding an extra shop to the marketplace generates €2.22 of additional revenues. Adding an extra new link to the network generates €1.59 of additional revenues. Adding an extra dead-end to the network, however, costs €19.54 in lost revenues to the marketplace owner. For each of these impacts, 95% of the total impact is realized by 70 days after the shock. The size of the dead-end effect is surprisingly large; for example, approximately nine new shops in the marketplace, or 13 new links in the network would be needed to offset the cost of a net gain of one new dead-end shop in the network. Interestingly, holding the number of dead-ends constant, one new link has approximately 72% of the
value of one new shop. Acquiring new sellers is likely to be more costly than encouraging existing sellers to create new links, thus the value of a link compares favorably with the value of a shop.

Persistence modeling can be used to examine the long-run effects of the exogenous variables in Equation (2.2). This approach estimates how a "shock" in an "impulse" variable (e.g., adding a new link) affects a "response" variable over time (e.g., daily commission revenue). This approach has been used in the marketing literature to study the long-run impact of changes in marketing variables on performance variables such as sales (e.g., Dekimpe and Hanssens 2004, 2005) or service adoptions (e.g., Trusov et al. 2008). Specifically, we use impulse-response functions (IRFs). An IRF simulates the impact over time of a change in one variable (in our case one of the exogenous variables) on the full dynamic system (Bronnenberg, Mahajan, and Vanhonacker 2000). Readers are referred to Dekimpe and Hanssens (2004, 2005) for a more detailed explanation of impulse-response functions, and Pauwels (2004) for an example of their use in modeling the impact of marketing actions or changes in marketing variables on dynamic systems. More typical uses of IRFs in marketing (e.g., stock return models) attempt to quantify long-run effects of marketing mix variables that last for months or even years. In our case, given the rapid growth of this marketplace and its social network, our time frame is much shorter.

The cumulative IRFs (sometimes referred to as total short-run effects) based on the estimated coefficients from the ARX model in (2.2) are plotted in Figure 3. These plots show how much commission revenue is generated by a punctual increase of one
unit in each of the exogenous variables and how this “shock” impacts the system over time (the effect propagates through the lags of the dependent variable).

**Figure 3: Cumulative Impulse-Response Functions**

2.4.5 Discussion of Marketplace-Level Results

The time series modeling in this section demonstrates the generally positive effect of the shop networking feature on aggregate marketplace performance: the presence of the network adds economic value, after controlling for the growth of the marketplace.
itself. These marketplace-level findings also provide initial support for our hypothesis that this value is generated by making shops more accessible. Having a network structure that provides customers with opportunities to move from shop to shop, by having a more connected network with few “dead-ends,” is valuable as it helps customers browse and find appealing shops and products before abandoning the marketplace.

The negative effect that increasing numbers of dead-end shops has on marketplace performance is strikingly large and surprising. This result suggests that one of the possible ways for the network to grow (i.e., existing connected shops sending links to shops that are not connected in the network; see Figure 1) can be extremely costly to the marketplace owner. The logic behind the negative impact of dead-ends is that while a dead-end shop is accessible from other shops, other shops are not accessible and customers who browse to them are “stuck” and are more inclined to abandon the marketplace. Unless a dead-end shop has something that a customer wants to purchase, the customer will want to move to another shop but the network structure does not allow for this. Hence, dead-ends can result in lost sales because the network structure constrains (and in this case prevents) further browsing behavior. Dead-ends make shops overall less accessible and this, it appears, can be very costly compared to the positive value of additional shops in the marketplace or additional links.

Further analysis checked that this effect was indeed correct and not just, for example, due to a statistical anomaly or bias. For example, time trend and seasonality effects were entered into the model in equation 2.2 since the dead-end effect might have just been picking up a time trend as the network grew (e.g., the number of dead-ends
increases with time as the size of the network increases). The dead-end effect was robust to the addition of these additional control variables in the time series model. Also, we ran an analysis where the change in dead-ends regressor was split into separate increase and decrease in dead-ends variables so that asymmetric effects of increasing and decreasing the prevalence of dead-ends could be estimated. This showed that increasing dead-ends had a strong negative effect and decreasing dead-ends had a similarly-sized positive effect on marketplace commission revenues. In other words, as the overall accessibility of networked shops increased (decreasing dead-ends), performance improved, and the opposite occurred as the overall accessibility decreased (increasing dead-ends). This further supports the dead-end effect reported above and is additional evidence that the network's potential value at the aggregate marketplace level lies in how the structure makes improves or damages shops' overall accessibility.

Note that dead-ends in this online network are similar to dead-ends in physical spaces and networks. For example, in a bricks-and-mortar shopping mall, shops that lie at the end of a long hall or at located as "satellites" across a carpark and away from the main complex of shops probably make customers who go to them less likely to want to go back to the other shops. Similarly, in a transportation network (e.g., a network of public commuter bus routes), a bus route that takes passengers to a place but does not have connecting routes to take them away from that place (either at all or at convenient times) is less valuable because these passengers who want to keep going have to find other means of transportation (e.g., a competing bus company, taxis, etc). Thus, the bus route to a "dead-end" destination can result in passengers abandoning that bus company
and not using other routes or visiting other destinations because they got stuck at the dead-end. Thus, the concept of dead-end nodes in a network hurting the overall value of the network not only applies in this social commerce marketplace but also is relevant to other types of networks in very different contexts.

We now turn to a shop-level analysis of the marketplace, in order to further investigate the role of accessibility, and to assess how the value created by the network is distributed across its members.

2.5 Shop-Level Analysis

2.5.1 Model

In this section we examine the effect of the network at the level of the individual seller (shop). Our aims here are to further test the role of accessibility as a mechanism through which the network enhances economic value in this marketplace, to further explore similarities and differences between social commerce marketplaces and bricks-and-mortar shopping centers, and to address our question of how the value generated by the network is distributed across its members. We measure Performance, as shop i’s total commissions earned during the last month of our dataset (i.e., seventh month after the network’s birth). Performance is modeled as a function of network- and assortment-related variables. All independent variables are measured at the end of the second-to-last month of this period (i.e., sixth month after the network’s birth).

We examine how a shop’s position in the network relative to other shops at the end of the sixth month influences its performance in the seventh month. We use several
network-related measures to describe a shop’s network position relative to other shops. Specifically, we use various traditional measures of a shop’s centrality in the network, computed based on the state of the network at the end of the second-to-last (sixth) month of data. The measures included are mostly based on those outlined by Faust and Wasserman (1992), Freeman (1979), de Nooy, Mrvar, and Batagelj (2005), and Van den Bulte and Wuyts (2007), and come from sociology and graph theory. In addition to centrality measures (e.g., degree) we use other node-level measures that help to describe a node’s (shop’s) position in the network relative to others. Each measure is listed in Table 1 and defined as follows:

- **Indegree centrality**: number of incoming links received by a shop from other shops;
- **Outdegree centrality**: number of outgoing links from a shop to other shops;
- **Incoming proximity** (Faust and Wasserman 1992; de Nooy et al. 2005): this measures the reachability of shop $i$ from other shops in the network. Incoming proximity is proportional to the proportion of shops in the network other than $i$ that can reach $i$ in a finite number of steps (shop $i$’s “indomain”), and inversely proportional to the mean geodesic distance (shortest path length) from these shops to $i$. Thus, incoming proximity is highest for shops that are accessible from a large number of shops in the network in only few steps. Note that this is a directed graph analog of Freeman’s (1979) standard “closeness” metric for undirected graphs;
• **Outgoing proximity** (Faust and Wasserman 1992; de Nooy et al. 2005): this measures the reachability of other shops in the network from shop $i$. Outgoing proximity is proportional to the proportion of shops in the network other than $i$ that can be reached from $i$ in a finite number of steps (shop $i$’s “outdomain”), and inversely proportional to the mean geodesic distance (shortest path length) from shop $i$ to these shops. Thus, outcoming proximity is highest for shops from which a large number of shops in the network are accessible in only few steps.

• **Incoming clustering coefficient** (Watts and Strogatz 1998; Zhou 2002): the incoming clustering coefficient of shop $i$ is the degree of interconnectedness among the shops that link to shop $i$. Specifically, it is the proportion of possible links that exist among the shops in shop $i$’s incoming ego-network. The higher a shop’s incoming clustering coefficient, the more densely interconnected its incoming ego-network is, i.e., that shop is connected to by other shops that are themselves highly interconnected (as opposed to being connected to by shops that are more dispersed throughout the network). Note that clustering is not a centrality measure, but rather a measure of how dense each shop’s ego-network is;

• **Outgoing clustering coefficient** (Watts and Strogatz 1998; Zhou 2002): the outgoing clustering coefficient of shop $i$ is the degree of interconnectedness among the shops that shop $i$ links to, and thus is the proportion of possible links that exist among the shops in shop $i$’s outgoing ego-network. The higher a shop’s outgoing clustering coefficient, the more densely interconnected its outgoing ego-
network is, i.e., that shop connects to other shops that are themselves highly interconnected;

- **Hub centrality** and **authority centrality** (Kleinberg 1999): these measures of centrality are directed graph analogs of eigenvector centrality (Bonacich 1987) for outgoing links (hub) and incoming links (authority). The basic concept of eigenvector centrality is that a shop is more prominent in the network if it is well-connected to other well-connected shops. A shop with a high hub score links to many shops with high authority scores, and a shop with a high authority score is linked to by many shops with high hub scores (these metrics are based on eigenvector decompositions of the network’s adjacency matrix; see Kleinberg 1999 for derivations). Because these centrality measures are not directly related to accessibility, we do not expect them to have a significant impact on shop performance.

We use two variables to describe a shop’s product assortment (as control variables), also computed at the end of the sixth (second-to-last) month of the dataset: (1) number of products listed by shop \( i \); and, (2) Average popularity of the products listed in shop \( i \), based on how many other shops in the marketplace feature the same products.\(^7\) In addition to these product assortment control variables, we also control for shop \( i \)’s age (the number of days between the time the shop was created in the marketplace and the last day of the sixth month of data), include in the model quadratic terms for indegree and

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\(^7\) The popularity variable is measured by first taking a count of the number of times each product is listed in shops in the marketplace (e.g., product X might appear on shops A and B, thus giving it a count of 2). The mean of this count within each shop and over all of the shop’s products is then taken as the measure of average popularity.
outdegree to allow nonlinear effects on performance, and allow for interactions between the network position variables and the number of products listed in a shop (shop assortment size).

A potential problem, however, is that a shop’s network position, its assortment, and its performance may all be influenced by a common latent variable. This endogeneity could be due to, for instance, a seller’s overall unobserved ability, which makes them a better seller in the marketplace as well as helps them get into a better position in the network and have a better assortment (e.g., akin to a general seller-specific “skill” effect). This type of endogeneity is an important issue when modeling social network-related variables (cf. Hartmann et al. 2008), because many social network properties may be driven by either unobserved attributes or endogenous attributes that are related to network structure or network position (Handcock, Raftery, and Tantrum 2007; Wasserman and Faust 1994). We control for this using latent variables. We allow each network position and product assortment variable to be a function of a shop’s latent ability. Our approach is similar to the data augmentation approach used by Hui, Bradlow, and Fader (2007) to model “category attractiveness” in their shopping path model for the movements of customers around grocery stores. The model is as follows:

\[(2.3) \quad \text{Network Position} \quad _{i,j} = \gamma_{0,j} + \gamma_{1,j} \text{Ability} + \delta_{i,j} \]

\[(2.4) \quad \text{Product Assortment} \quad _{i,k} = \alpha_{0,k} + \alpha_{1,k} \text{Ability} + \zeta_{i,k} \]

\[(2.5) \quad \text{Performance}^*_{i} = \beta_{0} + \beta_{1} \text{Ability}_i + \beta_{2} \text{Age}_i + \sum_{j=1}^{J} \beta_{3,j} \delta_{i,j} + \sum_{k=1}^{K} \beta_{4,k} \zeta_{i,k} + \sum_{l=1}^{L} \beta_{5,l} \delta_{i,l}^{2} + \sum_{j,k}^{J,K} \beta_{6,j,k} \delta_{i,j} \zeta_{i,k} + \varepsilon_i \]

\[(2.6) \quad \text{Performance}_i = \begin{cases} 0 & \text{if Performance}_i^* = 0 \\ \text{Performance}_i^* & \text{if Performance}_i^* > 0 \end{cases} \]
Where $j$ indexes the network position measures ($j = 1, \ldots, J$) taken at the end of the sixth month, $k$ indexes the product assortment measures ($k = 1, \ldots, K$) (in our case $J = 8$ and $K = 2$) taken at the end of the sixth month, $l$ indexes the quadratic terms (in our case $L = 2$), $j'$ and $k'$ index the position and assortment size interaction components (in our case $j' = 1, \ldots, 8$ and $k' = 1$), the $\gamma$'s are the network equation parameters, the $\alpha$'s are the assortment equation parameters, $[\delta, \zeta] \sim N(0, \Lambda)$ ($\Lambda$ is unconstrained, allowing nonzero covariances between the residuals), the $\beta$'s are the performance equation parameters, $\varepsilon$ is a random i.i.d. error with $\varepsilon_i \sim N(0, \sigma^2)$, and $\text{Performance}_i$ is the observed performance (i.e., commission revenues) of shop $i$ in the last (seventh) month. We use a Tobit specification (2.6) because commission revenues in this marketplace cannot be negative.

In addition to influencing shop performance, our model allows the $\text{Ability}$ latent variable to influence each shop’s network measures and assortment characteristics. Directly entering the network and assortment variables into the performance equation (2.5) would be inappropriate as it would give rise to biased and inconsistent network- and assortment-related estimates.\footnote{This is correct only under the assumption that there actually is a genuine underlying causal variable at work (ability), and that the ability variable is not simply a latent factor common to the genuinely causal variables of network position and product assortment.} Instead, the residuals from the network (2.3) and assortment (2.4) equations ($\delta_i$ and $\zeta_i$, respectively) are used as regressors in the performance equation (2.5). These residuals are ability-adjusted network- and assortment-related variables. Our latent variable approach appears to be an appropriate,
and relatively straightforward, technique for dealing with endogeneity issues in these
types of models.

This specification may also help us deal with some potential collinearity between
the network position measures that may be induced by a common latent variable.
However, this approach may not fully address collinearity between these measures
following from the fact that they are definitionally linked. The largest correlation
between unstandardized regressors is .60 among those based on incoming links, .55
among those based on outgoing links, and .92 among pairs of in- versus out-link versions
of the same measure. The mean correlation is otherwise low (.24). The largest correlation
was between authority and hub centrality (.92), both of which did not affect
Performance. We re-estimated the model without hub centrality, yielding similar results
(details available from the author). The next-largest correlation was between indegree and
outdegree (.80). Since both have large effects on commission revenues it is not
meaningful to remove them from the model. Instead, we decomposed indegree and
outdegree into unreciprocated indegree (number of in-links that shop i has not
reciprocated), unreciprocated outdegree (number of out-links that have not been
reciprocated), and reciprocated degree (number of two-way links). The highest
correlation between these variables was .56. The re-estimated the model with these three
variables replacing indegree and outdegree (but leaving all other regressors as previously
specified) found significant positive unreciprocated indegree (posterior mean = .46) and

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9 The large number of observations used to estimate our model, however, makes collinearity less of a
reciprocated degree effects (posterior mean = .26) with the unreciprocated outdegree effect marginally significant (posterior mean = -.08).

A hierarchical Bayesian procedure was used to estimate the parameters in this model. Technical details are provided in Appendix I. The prior on latent ability was $\text{Ability}_i \sim N(-1, \eta^2)$; diffuse priors were used for $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \alpha_0, \alpha_1, \gamma_0$ and $\gamma_1$; the priors on $\sigma$, $\eta$, and $\Lambda$ were $\sigma^2 \sim \text{InverseGamma}\left(\frac{r_0}{2}, \frac{s_0}{2}\right)$, where $r_0 = s_0 = 1$, $\eta^2 \sim \text{InverseGamma}\left(\frac{r_0}{2}, \frac{s_0}{2}\right)$, where $r_0 = s_0 = 1$, and $\Lambda \sim \text{InverseWishart}(n_0, n_0 \Lambda_0)$, $n_0 = J + K + 3$, and $\Lambda_0 = I$.

All network position- and product assortment-related variables were standardized (mean = 0, standard deviation = 1) before running the model. All shops in the dataset with at least one product at the end of the sixth month of the network's life (i.e., at the time the independent variables were computed) were included in the shop-level analysis. These criteria resulted in a set of 85,708 shops for estimating this model. Means, standard deviations, and correlations for the unstandardized variables are reported in Table 3. Estimation was based on 20,000 MCMC iterations with the first 10,000 as burn-in. All parameters mixed well and convergence was fast.
Table 3: Means, Standard Deviations, and Correlation Coefficients of the Network Position Measures

<table>
<thead>
<tr>
<th></th>
<th>Mean (st. dev.)</th>
<th>Correlations (between unstandardized variables)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indegree centrality</td>
<td>.76 (3.40)</td>
<td></td>
</tr>
<tr>
<td>Outdegree centrality</td>
<td>.76 (4.41)</td>
<td>.80</td>
</tr>
<tr>
<td>Incoming clustering</td>
<td>.04 (.15)</td>
<td>.39 .29</td>
</tr>
<tr>
<td>coefficient</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outgoing clustering</td>
<td>.04 (.16)</td>
<td>.40 .28 .74</td>
</tr>
<tr>
<td>coefficient</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Authority</td>
<td>.0002 (.003)</td>
<td>.54 .51 .10 .07</td>
</tr>
<tr>
<td>(in eigenvector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>centrality</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hub</td>
<td>.0002 (.003)</td>
<td>.49 .54 .09 .06 .92</td>
</tr>
<tr>
<td>(out eigenvector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>centrality</td>
<td>.01 (.03)</td>
<td>.60 .45 .48 .45 .21 .17</td>
</tr>
<tr>
<td>Inproximity centrality</td>
<td>.01 (.04)</td>
<td>.57 .55 .41 .40 .23 .22 .73</td>
</tr>
<tr>
<td>Outproximity centrality</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of products</td>
<td>43.00 (102.0)</td>
<td>.08 .07 .05 .05 .01 .01 .12 .09</td>
</tr>
<tr>
<td>Average product</td>
<td>315.39 (673.9)</td>
<td>-.08 -.06 -.08 -.08 -.02 -.02 -.12 -.10 -.11</td>
</tr>
<tr>
<td>popularity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commission revenues</td>
<td>.18 (3.30)</td>
<td>.12 .06 .04 .06 .03 .02 .11 .07 .02 -.02</td>
</tr>
</tbody>
</table>

2.5.2 Results

Parameter estimates are reported in Tables 4, 5 and 6. Note that only one of the interaction terms between the network position measures and shop product assortment size was statistically significant. Therefore we focus on the main effects and quadratic terms in our discussion, and mention the significant interaction where appropriate. Before discussing these results, however, we give details of model fit and model validation.
Table 4: Full Latent Variable Tobit Model, Effects of Network Position, Product Assortment, and Latent Ability on Shop-Level Commission Revenues (Equation 2.5)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Posterior Mean</th>
<th>Posterior Standard Deviation</th>
<th>95% Credible Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\beta_0$)</td>
<td>.175</td>
<td>.67</td>
<td>-1.18, 1.34</td>
</tr>
<tr>
<td>Latent ability ($\beta_1$)</td>
<td>.015</td>
<td>.67</td>
<td>-1.14, 1.37</td>
</tr>
<tr>
<td>Shop age ($\beta_2$)</td>
<td>.015</td>
<td>.02</td>
<td>-.02, .05</td>
</tr>
</tbody>
</table>

**Network effects**

- Indegree centrality ($\beta_{3,1}$)  
  $$.923^{***}$$  
<table>
<thead>
<tr>
<th>Posterior Standard Deviation</th>
<th>.06</th>
<th>95% Credible Interval</th>
</tr>
</thead>
</table>
  | Outdegree centrality ($\beta_{3,2}$)  
  | $-.503^{***}$ | .06 | -.62, -.39 |
  | Incoming clustering coefficient ($\beta_{3,3}$)  
  | $-.155^{***}$ | .03 | -.22, -.10 |
  | Outgoing clustering coefficient ($\beta_{3,4}$)  
  | $.049^*$ | .03 | -.01, .11 |
  | Authority (in eigenvector centrality) ($\beta_{3,5}$)  
  | -.087 | .09 | -.27, .09 |
  | Hub (out eigenvector centrality) ($\beta_{3,6}$)  
  | .039 | .09 | -.14, .22 |
  | Inproximity (incloseness) centrality ($\beta_{3,7}$)  
  | $.176^{***}$ | .04 | .10, .24 |
  | Outproximity (outcloseness) centrality ($\beta_{3,8}$)  
  | $-.072^{**}$ | .03 | -.14, -.01 |

**Product assortment effects**

- Number of products ($\beta_{4,1}$)  
  | .012 | .02 | -.02, .04 |
- Average product popularity ($\beta_{4,2}$)  
  | -.019 | .02 | -.05, .01 |

**Quadratic and significant interaction effects$^a$**

- Indegree$^2$ ($\beta_{5,1}$)  
  | $-.017^{***}$ | .002 | -.02, -.01 |
- Outdegree$^2$ ($\beta_{5,2}$)  
  | $-.007^{***}$ | .002 | .003, .01 |
- Authority $\times$ number of products ($\beta_{6,5}$)  
  | $.094^*$ | .06 | -.03, .20 |
- Inproximity $\times$ number of products ($\beta_{6,7}$)  
  | $-.041^{**}$ | .02 | -.09, -.002 |

* The 90% credible interval does not contain zero (two-sided).
** The 95% credible interval does not contain zero (two-sided).
*** The 99% credible interval does not contain zero (two-sided).
$^a$ None of the other interaction effects are close to being significantly different from zero.

Notes: (1) the error standard deviation (\( \sigma \)) has posterior mean = 3.226, posterior standard deviation = .04, and 95% credible interval (3.10, 3.27). (2) All network position- and product assortment-related variables were standardized (mean = 0, standard deviation = 1) before running the model.
Table 5: Full Latent Variable Tobit Model, Effects of Latent Ability on Network Position Measures (Equation 2.3)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Posterior Mean ($\times 10^{-3}$)</th>
<th>Posterior Standard Deviation</th>
<th>95% Credible Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network effects: intercepts $\gamma_{0,j}$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality ($\gamma_{0,1}$)</td>
<td>-0.491</td>
<td>0.03</td>
<td>-0.07, 0.06</td>
</tr>
<tr>
<td>Outdegree centrality ($\gamma_{0,2}$)</td>
<td>-0.422</td>
<td>0.03</td>
<td>-0.07, 0.06</td>
</tr>
<tr>
<td>Incoming clustering coefficient ($\gamma_{0,3}$)</td>
<td>-0.504</td>
<td>0.03</td>
<td>-0.07, 0.06</td>
</tr>
<tr>
<td>Outgoing clustering coefficient ($\gamma_{0,4}$)</td>
<td>-0.498</td>
<td>0.03</td>
<td>-0.07, 0.07</td>
</tr>
<tr>
<td>Authority (in eigenvector centrality) ($\gamma_{0,5}$)</td>
<td>-0.493</td>
<td>0.03</td>
<td>-0.07, 0.06</td>
</tr>
<tr>
<td>Hub (out eigenvector centrality) ($\gamma_{0,6}$)</td>
<td>-0.515</td>
<td>0.03</td>
<td>-0.07, 0.07</td>
</tr>
<tr>
<td>Inproximity (incloseness) centrality ($\gamma_{0,7}$)</td>
<td>-0.437</td>
<td>0.03</td>
<td>-0.06, 0.06</td>
</tr>
<tr>
<td>Outproximity (outcloseness) centrality ($\gamma_{0,8}$)</td>
<td>-0.614</td>
<td>0.03</td>
<td>-0.07, 0.07</td>
</tr>
<tr>
<td><strong>Network effects: slopes $\gamma_{1,j}$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality ($\gamma_{1,1}$)</td>
<td>0.505</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
<tr>
<td>Outdegree centrality ($\gamma_{1,2}$)</td>
<td>0.447</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
<tr>
<td>Incoming clustering coefficient ($\gamma_{1,3}$)</td>
<td>0.422</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
<tr>
<td>Outgoing clustering coefficient ($\gamma_{1,4}$)</td>
<td>0.496</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
<tr>
<td>Authority (in eigenvector centrality) ($\gamma_{1,5}$)</td>
<td>0.524</td>
<td>0.03</td>
<td>-0.07, 0.06</td>
</tr>
<tr>
<td>Hub (out eigenvector centrality) ($\gamma_{1,6}$)</td>
<td>0.565</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
<tr>
<td>Inproximity (incloseness) centrality ($\gamma_{1,7}$)</td>
<td>0.404</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
<tr>
<td>Outproximity (outcloseness) centrality ($\gamma_{1,8}$)</td>
<td>0.573</td>
<td>0.03</td>
<td>-0.06, 0.07</td>
</tr>
</tbody>
</table>
Table 6: Full Latent Variable Tobit Model, Effects of Latent Ability on Product Assortment Measures (Equation 2.4)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Posterior Mean ($\times 10^{-3}$)</th>
<th>Posterior Standard Deviation</th>
<th>95% Credible Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Product assortment effects: intercepts $a_{0,k}$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of products ($a_{0,1}$)</td>
<td>-.448</td>
<td>.03</td>
<td>-.07, .06</td>
</tr>
<tr>
<td>Average product popularity ($a_{0,2}$)</td>
<td>-.415</td>
<td>.03</td>
<td>-.07, .06</td>
</tr>
<tr>
<td><strong>Product assortment effects: slopes $a_{1,k}$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of products ($a_{1,1}$)</td>
<td>.505</td>
<td>.03</td>
<td>-.06, .07</td>
</tr>
<tr>
<td>Average product popularity ($a_{1,2}$)</td>
<td>.412</td>
<td>.03</td>
<td>-.06, .06</td>
</tr>
</tbody>
</table>

**In-Sample Model Fit and Validation.** In-sample fit was checked by comparing shops’ actual commission revenues with those predicted by the model. For each of the 10,000 post-burn-in MCMC draws we computed the predicted values for the shop performance dependent variable for each shop in the dataset. Fit may be assessed using posterior checks. In Figure 4 we plot the distribution across MCMC draws of the mean (across shops) predicted performance. In this figure, the histogram shows the posterior distribution of the fitted mean commission revenues, the solid vertical line represents the actual value. The average across MCMC draws of the mean predicted performance is €0.1782, extremely close to the actual value of €0.1783. For each draw we also computed the median (across shops) of the absolute deviation (MAD) between actual and predicted performance. The mean MAD over all draws was reasonably small (€0.056), keeping in mind that our dependent variable is a financial performance variable, which are typically
difficult to predict with extremely high accuracy. The mean over the MCMC draws of the correlation between the shops’ actual and predicted commissions was .22.

Figure 4: Posterior Distribution of Predicted Mean Commission Revenues

Nested Model Comparisons. We also performed a series of nested model comparisons which provided support for the introduction of network position effects and latent ability into the model. We first compared the full model in equations 2.3 to 2.6 to a nested model without network position effects; i.e., in equation 2.5 restricting $\beta_3 = \beta_5 = \beta_6 = 0$. Following Newton and Raftery (1994) and Rossi, Allenby, and McCulloch (2005)
we computed the log marginal densities for the two models using the harmonic means of the respective models’ likelihoods across posterior draws (every tenth draw after burn-in, for computational reasons).

The full model had a better fit ($-2 \log \hat{p}(y \mid M_{\text{product-only}}) = 2.334 \times 10^{-5}$ versus $-2 \log \hat{p}(y \mid M_{\text{full}}) = 2.308 \times 10^{-5}$; smaller is better), and a large log Bayes factor based on these log marginal densities ($\log BF_{\text{full vs product-only}} = 1289$; note that $\log BF_{A vs B} > 5$ is “strong evidence” in favoring model A over model B), which provided very strong evidence in favor of the full model over the product-only restricted model. The mean correlation between actual and predicted commissions (over MCMC draws) for this restricted model was clearly inferior to the full model (.07 versus .22). Note that because some of our priors were improper, special care should be taken when computing marginal densities and Bayes factors (Rossi and Allenby 2003). As a prior sensitivity analysis we used diffuse but proper priors and obtained very similar results.

We then performed another nested model comparison, this time comparing the full model in (2.3) to (2.6) to a restricted model with $\alpha = 0$, $\gamma = 0$ and $\beta_1 = 0$, which was a simpler Tobit model without the latent ability variable and entering the network position and product assortment variables directly as regressors instead of their ability-adjusted residuals. This simpler model’s fit and log Bayes factor were worse ($-2 \log \hat{p}(y \mid M_{\text{simple}}) = 2.311 \times 10^{-5}$ versus $-2 \log \hat{p}(y \mid M_{\text{full}}) = 2.308 \times 10^{-5}$; $\log BF_{\text{full vs simple}} = 139$), and the correlation between actual and predicted commissions was also worse than for the full model (.15 versus .22). We therefore base our findings on the full model with the latent “ability” specification.
Parameter estimates for the simpler Tobit model are reported in Table 7 for the sake of comparison and as a robustness check. All effects that are significant in the full model are confirmed by this simpler specification, and the magnitudes of the effects are very comparable. A few effects, such as that of outgoing clustering coefficient and authority, are not significant in the full model but are significant in the simpler model. Since the former fits better than the latter we do not focus heavily on these points of difference. Indeed, basing our substantive findings on the full model with fewer significant effects is conservative.
Table 7: Simpler Tobit Model, Effects of Network Position and Product Assortment on Shop-Level Commission Revenues

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Posterior Mean</th>
<th>Posterior Standard Deviation</th>
<th>95% Credible Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\beta_0$)</td>
<td>.189***</td>
<td>.01</td>
<td>.17, .21</td>
</tr>
<tr>
<td>Latent ability ($\beta_1$)</td>
<td>$0^a$</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Shop age ($\beta_2$)</td>
<td>.018</td>
<td>.02</td>
<td>-.004, .04</td>
</tr>
<tr>
<td><strong>Network effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality ($\beta_{3,1}$)</td>
<td>.914***</td>
<td>.04</td>
<td>.84, .98</td>
</tr>
<tr>
<td>Outdegree centrality ($\beta_{3,2}$)</td>
<td>-.498***</td>
<td>.05</td>
<td>-.59, -.41</td>
</tr>
<tr>
<td>Incoming clustering coefficient ($\beta_{3,3}$)</td>
<td>-.152***</td>
<td>.02</td>
<td>-.19, -.12</td>
</tr>
<tr>
<td>Outgoing clustering coefficient ($\beta_{3,4}$)</td>
<td>.050***</td>
<td>.02</td>
<td>.02, .09</td>
</tr>
<tr>
<td>Authority (in eigenvector centrality) ($\beta_{3,5}$)</td>
<td>-.084***</td>
<td>.03</td>
<td>-.15, -.02</td>
</tr>
<tr>
<td>Hub (out eigenvector centrality) ($\beta_{3,6}$)</td>
<td>.038</td>
<td>.05</td>
<td>-.02, .10</td>
</tr>
<tr>
<td>Inproximity (incloseness) centrality ($\beta_{3,7}$)</td>
<td>.178***</td>
<td>.02</td>
<td>.14, .22</td>
</tr>
<tr>
<td>Outproximity (outcloseness) centrality ($\beta_{3,8}$)</td>
<td>-.071***</td>
<td>.02</td>
<td>-.11, -.03</td>
</tr>
<tr>
<td><strong>Product assortment effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of products ($\beta_{4,1}$)</td>
<td>.013</td>
<td>.01</td>
<td>-.01, .04</td>
</tr>
<tr>
<td>Average product popularity ($\beta_{4,2}$)</td>
<td>-.015</td>
<td>.02</td>
<td>-.04, .01</td>
</tr>
<tr>
<td><strong>Quadratic and significant interaction effect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree$^2$ ($\beta_{5,1}$)</td>
<td>-.017***</td>
<td>.001</td>
<td>-.02, -.01</td>
</tr>
<tr>
<td>Outdegree$^2$ ($\beta_{5,2}$)</td>
<td>.007***</td>
<td>.002</td>
<td>.003, .01</td>
</tr>
<tr>
<td>Authority $\times$ number of products ($\beta_{6,5}$)</td>
<td>.100**</td>
<td>.04</td>
<td>.02, .18</td>
</tr>
<tr>
<td>Inproximity $\times$ number of products ($\beta_{6,7}$)</td>
<td>-.036**</td>
<td>.02</td>
<td>-.07, -.01</td>
</tr>
<tr>
<td>Outproximity $\times$ number of products ($\beta_{6,8}$)</td>
<td>.021*</td>
<td>.01</td>
<td>-.004, .05</td>
</tr>
</tbody>
</table>

* The 90% credible interval does not contain zero (two-sided).
** The 95% credible interval does not contain zero (two-sided).
*** The 99% credible interval does not contain zero (two-sided).
$a$ Fixed to zero.
$b$ None of the other interaction effects are close to being significantly different from zero.

Notes: (1) These estimates are based on a non-hierarchical Tobit model without a latent ability variable. Estimation involved 20,000 MCMC draws (10,000 burn-in). The model mixed well and converged quickly.
(2) The error standard deviation ($\sigma$) has posterior mean = 3.260, standard deviation = .01, and 95% credible interval (3.24, 3.28). All network position- and product assortment-related variables were standardized (mean = 0, standard deviation = 1) before running the model. Thus, posterior means in this table can be compared as "standardized" coefficients.
**Out-of-Sample Fit.** Out-of-sample fit was also assessed and found to be reasonable, albeit slightly worse than in-sample fit. The common approach of randomly splitting the data into an estimation sample and a hold-out validation sample is inappropriate here since our latent ability variable needs to be estimated for each shop, and predicting shop performance in a validation sample would require estimating latent ability for each shop in that sample, which would require using the validation data for estimation. Instead, we re-estimated the model with the network and product assortment variables measured at the end of month 5 (instead of the end of month 6) and the commission revenues measured during month 6 (instead of during month 7; i.e., "month 5/6" data instead of "month 6/7" data). As an indicator of robustness we found no qualitative differences between the results reported below from analysis of the month 6/7 data and the results from this month 5/6 data (details available from the author).

We then assessed out-of-sample fit by using these month 5/6 parameter estimates (including shop-level latent ability estimates) to predict the commission revenues earned during month 7 as a function of the network and assortment variables at the end of month 6 (i.e., using the month 5/6 data for calibration and the month 6/7 data for validation). The average predicted month 7 commission (mean taken across MCMC draws of the parameter estimates) was €0.1947, close to the actual mean month 7 commission of €0.1783 (and the actual mean lied well within the distribution of the predicted means from the MCMC draws). The MAD across draws was €0.077, which was slightly larger than for in-sample fit but still reasonable, and the mean correlation between actual and predicted commissions was .21.
Latent Ability Effects. We now describe the effects reported in Tables 4, 5 and 6 in detail, starting with the latent ability effects. The effect of a shop's latent ability on its performance was not significant, and the parameters (intercepts and slopes) in each of the network position and product assortment equations (2.3, 2.4) were not significant either. Hence, the residuals ($\delta, \zeta$) in the performance equation (2.5) are very similar to the original standardized independent variables. Note that the fact that the full latent variable model was favored over a simpler non-latent model based on the Bayes factor (see above) suggests that modeling latent ability is the more appropriate specification, despite the non-significance of these effects.

Degree Centrality Effects. A shop's position in this network affects its commission revenues. The largest effects on shop's commissions were associated with degree centrality, that is, the number of ties going into and out of each shop. Indegree centrality had a positive effect on commissions, and outdegree centrality had a (smaller) negative effect. This suggests that shops with more links going into them from other shops, and fewer links going out of them to other shops tend to perform better in terms of generating commission revenues for themselves. Both the indegree and outdegree effects are nonlinear given the significant quadratic terms (negative for indegree, positive for outdegree). Thus, the positive (negative) impact of a new incoming (outcoming) link diminishes as the number of existing links increases.\(^\text{10}\)

\(^{10}\) The maxima for the quadratic indegree effect is approximately 27 standard deviations above the mean indegree (indegree of about 93, which is less than the maximum observed indegree of 184), and the minima for the quadratic outdegree effect is approximately 36 standard deviations above the mean outdegree (outdegree of about 159, which is above the maximum observed outdegree of 100).
These results support our argument that the value of the network at the individual shop level lies in how the network makes shops more or less accessible to browsing customers. A higher indegree means that a shop is more likely to be found by a browsing customer. A shop with a higher outdegree, on the other hand, makes it easier for customers to leave that shop, which hurts performance. The asymmetry between incoming and outcoming links highlights one key difference between bricks-and-mortar shopping centers and social commerce marketplaces: such asymmetries are not possible in the former since links in bricks-and-mortar shopping centers are undirected.

These effects also raise some interesting game theoretic issues because they imply that sellers have an incentive to try to attract others to connect to their shops, but have a disincentive to connect their shops to others’ shops. This also raises the interesting issue of how the marketplace owner could incentivize its sellers to create network links that facilitate browsing. Note that because the absolute effect size of indegree centrality is greater than that of outdegree centrality, shop A may still benefit from linking to shop B as long as shop B reciprocates this link (in which case shop A would increase both its indegree and outdegree by 1, leading to a positive net effect). The posterior means for the standardized effects of indegree and outdegree centrality are .923 and -.503, respectively. The corresponding unstandardized effects are .272 and -.114, and the proportion of links that were reciprocated in our dataset is 61.7%. Supposing that when a shop creates an outgoing link to another shop there is a 61.7% chance of receiving a reciprocal

\[ \text{To convert a standardized estimate into an unstandardized estimate (which is required for this comparison) the posterior mean can be divided by the unstandardized variable's standard deviation. The unstandardized standard deviations are 3.40 and 4.41 for indegree and outdegree centrality, respectively.} \]
incoming link, the expected net effect (unstandardized) on the performance of the shop that created the outgoing link is 

\[-.114 + .617 \times .272 = .0538\].

In other words, given the tendency for reciprocity in this network, creating links to other shops is not costly in expectation.

**Proximity Centrality Effects.** The inproximity and outproximity effects were significant, and respectively positive and negative. The positive effect of inproximity means that shops that can be reached from a greater proportion of other shops in the network in fewer steps (i.e., with the customer having to pass through fewer other shops) benefit more from the network compared to shops that are less easily reached. It also shows that not only direct incoming links are important; rather, direct and indirect paths into a shop are value-relevant. This directly supports our accessibility argument. It also suggests that being closer to the start of potential browsing paths through the network is important. The comparatively weaker, negative effect of outproximity complements this, and indicates that being positioned in the network such that many other shops can be reached from one’s shop in relatively few steps hurts a shop’s performance. The inproximity \(\times\) number of products interaction was negative, suggesting that the positive effect of a shop’s incloseness centrality on its performance decreases as its assortment size becomes larger.

**Clustering Effects.** A shop’s incoming clustering coefficient had a negative effect on commissions, as expected. It appears to be better for a shop not to be connected to by shops that are themselves highly interconnected. Shops that are connected to by shops that are themselves highly interconnected have relatively poor accessibility from other
shops in the network that are not in their ego-network. For instance, if most of shop A’s incoming links come from a set of shops that are themselves highly interconnected then the chance that a customer entering the network at a randomly chosen shop in the network will browse to shop A is smaller than if shop A’s incoming links come from a more dispersed, less interconnected set of shops. This result contrasts with bricks-and-mortar shopping centers, where clustering provides the benefit of reduced customers’ traveling costs. Stores in bricks-and-mortar shopping centers are generally at least moderately clustered, and this clustering or grouping does not appear to have negative effects in the offline context (Eppli and Benjamin 1994). The effect of outgoing clustering, on the other hand, was not strong (it was marginally significant and positive). Indeed, outgoing clustering only has a weak and indirect effect on the accessibility of other shops outside of a shop’s ego-network.

**Hub and Authority Effects.** The prominence (eigenvector centrality) effects—hub and authority—were both non-significant, as expected. The finding that being in a more prominent position in the network does not affect commission revenues confirms that accessibility, not prominence or “prestige,” is the primary driver of how the value created by the network is distributed across shops. Note that we did however find a weak positive interaction between authority and the number of products in a shop, indicating that larger shops may benefit from being linked into by so-called “authority” shops. It is interesting that there are not eigenvector centrality effects when there are degree centrality effects, given that these centrality measures are typically positively correlated. While intuitively it might be good to be accessible from other accessible shops, this
intuition is not supported in these data. It seems that just a shop’s own accessibility matters in this regard (degree centrality), and not also how accessible its neighbors are (eigenvector centrality). Being “well connected” is sufficient; being “well connected” to other “well connected” shops is not necessary for additional performance improvements. Being accessible from any shop in terms of those shops’ degrees is equally valuable to a shop (but of course, as reported above, other clustering- and proximity-related aspects of those shops do matter).

2.5.3 Discussion of Shop-Level Results

These results provide further support for the importance of networks in social commerce marketplaces, and specifically highlight the critical role played by the network in making shops more accessible to customers browsing the marketplace. The economic value of the network is distributed across shops according to how accessible they are made by the network. Shops that are more accessible from other shops in the network generally enjoy higher commission revenues, after controlling for potential product assortment, shop age, and latent ability effects.

Importantly, depending on how centrality is defined, it may help or hurt accessibility. The shops that benefit the most from the existence of the network are those with many incoming ties (positive effect of indegree centrality), few outgoing ties (negative effect of outdegree centrality), are easily reachable from other shops (positive effect of inproximity centrality), cannot easily reach other shops (negative effect of
outproximity centrality), and are connected to by shops that are not densely interconnected (negative effect of incoming clustering).

Our findings are broadly consistent with discussions of shop accessibility in the offline shopping center literature, although the drivers of accessibility in this social commerce network differ substantially from bricks-and-mortar shopping centers. The directed nature of the links between shops in this marketplace creates asymmetries (between indegree and outdegree, inproximity centrality and outproximity centrality, and incoming clustering and outgoing clustering) that do not exist in offline shopping centers. Moreover, clustering has a different effect in social commerce networks compared to bricks-and-mortar shopping centers. Interestingly, the non-significant prominence and product assortment size effects suggest that it is not necessary to be prominently positioned in a social commerce network in order to benefit from the network, and that having a larger shop is not necessarily helpful.

We considered an extended version of this shop-level model, adding a one-month lag of the dependent variable as an additional regressor (i.e., the commission revenues earned by each shop during the sixth month after the network’s birth). The substantive results reported above and in Tables 4A-C were unchanged. Not surprisingly, the addition of the lagged dependent variable regressor improved the model’s fit. For example, the mean MAD over all draws decreased (€0.033 versus €0.056), and the mean over the MCMC draws of the correlation between the shops’ actual and predicted commissions increased (.61 versus .22). Details are available from the author.
Finally, it should be noted that an alternative way to analyze these data and examine how network position affects shop performance would be to construct a quasi-experiment by taking pairs of shops that are identical at time $t$ on all but one characteristic (e.g., indegree) and comparing their commission revenues at time $t + m$ (where $m > 0$).\textsuperscript{12} While a more sophisticated statistical model was used, this type of approach would also be reasonable and is worth considering for future research.

2.6 General Discussion

Despite the rapid growth in online social networks, and the recent emergence of online social commerce marketplaces where opportunities for social interactions in online retailing and e-commerce contexts are provided, extremely little is known about social networks between sellers. The findings reported here represent a first step in understanding the role that social networks play in e-commerce and online retailing. Critically, this essay shows how networks can help to generate economic value for social commerce marketplace owners and for the individuals who participate in such marketplaces.

Overall, our findings suggest that social commerce networks between sellers can play an important, economic value-creating role. A key issue for shops (or individual sellers) in large, online marketplaces is simply being accessible to customers. Social networks between sellers act as “virtual shopping centers” by helping customers browse between shops, therefore improving the accessibility of the network’s shops. A more

\textsuperscript{12} Thank you to Duncan Watts for this suggestion.
connected network tends to improve the overall accessibility of its members, especially if it is structured in a way that minimizes the number of "dead-ends" that customers cannot browse away from. The shops that benefit the most from the network are not necessarily those that are central to the network, but rather those whose accessibility is most enhanced by the network. Network-based notions of centrality need to be carefully considered when examining the relationship between network position and performance outcome (or more generally, any node-level dependent variable), because different measures of a node's centrality can have opposite effects.

The marketplace- and shop-level results suggest some measures that social commerce firms (marketplace owners) and sellers (individual members of this marketplace) could take to enhance their performance. For instance, sellers may wish to improve their network position so that they receive more incoming links from shops that are dispersed (i.e., not locally clustered). Given the strong effect of reciprocity, this could involve connecting to shops that are many steps away from one's shop (i.e., a path-shortening effect, similar to the cross-cutting paths that are discussed in the "small-world" network model; Watts and Strogatz 1998), instead of connecting to nearby shops. At the marketplace level it may be possible for the marketplace owner to develop mechanisms to encourage sellers to create links (thus improving overall accessibility) while discouraging the creation of dead-ends. Note that while these kinds of interventions are possible, we caution that "strategic" attempts to alter a social network's structure can lead to unintended consequences, given the inherent complexity of such systems. We leave more detailed considerations of these issues to future research.
These results also shed light on how network dynamics, which are driven by inherently social processes, influence economic value outcomes. Some of the drivers of network evolution that are typical in directed social networks may not be ideal for driving network-derived economic value. For example, while social networks naturally tend to evolve towards clustered groups (e.g., if A\(\rightarrow\)B and A\(\rightarrow\)C then it is more likely than chance that the B\(\rightarrow\)C link will form), we find that the clustering of shops hurts their performance in this marketplace. This is particularly relevant as online social networks that have relatively high levels of clustering (e.g., Facebook.com, MySpace.com) start introducing e-commerce “marketplace” features. Such social networks are possibly not structurally well-suited to being networks of sellers. Although clustering is problematic for sellers, reciprocity, on the other hand, appears to help here as receiving an incoming link as a result of reciprocity appears to offset the “cost” of the corresponding outgoing link. Reciprocity is also a common driver of link formation in social networks. We encourage further research that explores the appropriateness of different types of network structures and the corresponding network evolution processes for facilitating commercial operations.

This research is not without its limitations. First, our findings come from the study of a single online social commerce marketplace. Notwithstanding, the marketplace we studied is a pioneer in social commerce, and is large and established. Future research might explore variations on this business model, and consider other marketplaces with different retailing concepts (e.g., regular shops versus auction sellers). Second, while our shop-level model captures interdependence between shops through a set of node-level
network position measures, future research may also capture interdependence through the error structure, based for example on the work by Hoff (2003) in statistics or on spatial econometrics models, or by examining dynamic spillover effects across shops (e.g., network autoregressive models). For example, future research may explore how shops’ commission revenues and product assortments influence the commission revenues earned by shops that either link to them or to whom they link (preliminary analysis on this found that assortment overlap at either the product or the category levels did not significantly affect shop-level commission revenues). Third, we did not capture network dynamics in our shop-level model (Snijders 2006), in part for tractability reasons. We hope that future research will lead to the development of statistical models that are compatible with today’s large network datasets, and that allow capturing a wide range of effects such as strategic behavior, interdependence between nodes, and time dynamics.
3

Explaining the Power-Law Degree Distribution

in a Social Commerce Network
3.1 Introduction

One of the most documented aggregate network properties is the so-called “scale free” property, which is satisfied when vertices’ numbers of edges (degrees) are power-law distributed: i.e., few vertices have many edges and many vertices have few edges (Barabási and Albert 1999). This property has been found to describe networks in fields as diverse as Internet servers, pages on the World Wide Web, and scientific collaborations. The most common network evolution mechanism used to explain the emergence of a power-law degree distribution is preferential attachment, whereby members of the network prefer to connect to other members with many existing connections. This mechanism has been shown theoretically and empirically to give rise to power-law degree distributions. More recently, Vázquez (2003) showed both analytically and numerically that preferential attachment may be viewed as a consequence of local rules such as triadic closure, whereby members of the network prefer to connect to other members with whom they have “friends” in common, and cyclic closure.

A number of studies have found evidence of preferential attachment and triadic and cyclic closure in the evolution of real social networks across diverse domains. For example, Kossinets and Watts (2006) study email transmissions over a year at an Ivy League university and find some evidence for triadic closure and cyclic closure (although not preferential attachment). Newman (2001) studies the co-authorship relationships between scientists and finds some support for triadic closure and preferential attachment.

13 The term “scale-free” comes from the fact that the power-law distribution is independent of the size (scale) of the network.

Despite these studies showing that these mechanisms do affect the evolution of real social networks, very little is known about the magnitude of this influence and how it compares to that of other mechanisms. In particular, preferential attachment and triadic closure are edge formation mechanisms that are based on the network’s structure; that is, they capture how the current structure of a network influences the creation of new edges. Other mechanisms that are not directly related to the network’s structure may also influence edge formation. For example, Kossinets and Watts (2006) find some evidence to suggest that focal closure is a driver of network evolution, which in their case implies that being in the same group or class (in a university setting) makes people more likely to be connected, irrespective of their positions in the network (this is effectively homophily, and this effect of course could also go the other way: being connected might make people more likely to be members of the same group; cf. McPherson, Smith-Lovin, and Cook 2001). Although statistical models are available to capture such mechanisms (e.g., exponential random graph models, and the SIENA model [Snijders 1997, 2001a, 2001b, 2005], which allows for co-evolution of network structure and vertex-level covariates), there has been only little empirical work on how vertex attributes that are not directly related to the network structure influence the evolution of large networks.
It is important to note that preferential attachment and triadic closure have not necessarily been proposed as descriptors of the actual mechanisms through which edges are formed, but rather as phenomenological mechanisms that give rise to common aggregate structural network properties. One of our goals is to investigate the extent to which these mechanisms also have some descriptive validity and appropriately capture the actual underlying mechanisms of edge formation in social networks.

We study the evolution of a large social network with a power-law degree distribution in a social commerce community. Social commerce is an emerging trend in which sellers are connected in online social networks, and where sellers are individuals instead of firms (see chapter 2; Stephen and Toubia 2009). In particular, individuals create their own personal online “shops” and are allowed to create hyperlinks between each other’s shops (i.e., vertices in this network are individual members’ shops, and edges are directed hyperlinks between shops that members create over time). Stephen and Toubia (2009; and chapter 2) study the implications of allowing networks between individuals-as-sellers, taking the network as given and studying how its structure impacts profits in these emerging, inherently social, and user-generated marketplaces. The present essay studies the formation and evolution of a social commerce network, and in particular the emergence of its power-law degree distribution. We develop a tractable (given our large dataset) dynamic statistical model that allows quantifying the influences of multiple network evolution (edge formation) mechanisms that may explain the emergence of the network’s power-law degree distribution. We find that preferential attachment and triadic closure do not appear to explain well the evolution of this social network. Instead, the
evolution of this network and the emergence of its power-law degree distribution are more consistent with a simple mechanism whereby members prefer to connect their shops to shops that have more diverse assortments, where assortment diversity follows a power-law distribution (over shops).

While these findings may not apply for all kinds of networks (social, commercial, or other kinds), the findings in this essay serve as a kind of "proof of existence" that power-law degree distributions in networks (or just heavily skewed, long-tail distributions that are close to power-law) need not always come from mechanisms such as preferential attachment or triadic and cyclic closure. Of course no claims of broad generalizability are made; rather, the aim of this essay is to provide an empirical demonstration of how vertex/node characteristics that are exogenous to the structure of the network can not only play key roles in network formation per se, but also lead to aggregate network structures that have familiar, empirically generalizable properties (e.g., skewed, long-tail degree distributions).

This essay is organized as follows. We first describe the context of social commerce and our specific dataset. Following that we show that the network has a power-law degree distribution. We then discuss and formalize a set of social network evolution mechanisms that may explain the emergence of the network's power-law degree distribution. Next we quantify the impact of these mechanisms on the evolution of the social network, and finally conclude the chapter with discussion of the findings and considerations for future research.
3.2 Data and Context

Social commerce is an emerging and fast growing trend in which individuals are empowered to create their own personal online shops and to connect with other shops in an online social network (e.g., Shopit.com, Squidoo.com, Zlio.com, EBay neighborhoods). Our data come from a social commerce community that leverages the “affiliate” programs offered by online retailers (i.e., commissions offered to web sites that refer customers to the retailers). Members of the community (“sellers”) create personalized shops (each shop has its own URL) and add products to their shops from a database of over 4 million products. These products are actually sold by over 100 partner online retailers (who act as vendors/wholesalers). Sellers may add or remove products from their shops at any time. Sellers are individual people, not companies, and they do not hold inventory, set prices, or advertise directly. Instead, when a customer purchases a product from a shop, he or she is directed to a checkout page on the vendor’s website. The vendor processes the transaction and pays a commission to the company that hosts the social commerce community. The company in turn redistributes part of this commission to the seller whose shop generated the sale.

The way product assortments are organized in this marketplace will be important in our analysis. Each time a seller adds a new product to his or her shop, he or she has to assign this product to a category. Possible categories include a set of generic categories proposed by the company hosting the community (e.g., “apparel,” “books”), and seller-created categories (e.g., “My favorite books on social networks”). A given shop’s front page consists of $K$ equal-sized “boxes,” one for each of the shop’s $K$ categories. The size
of each box is common across all shops in the community. Each box contains a short
description of at most three products listed in the corresponding category, and a
thumbnail picture of the first product listed in that category. If more than three products
are offered in a given category, the box corresponding to that category contains a “view
all products in that category” link. See Figure 5 for an illustration. This is the standard
layout for every shop, and members can control only the products and their categories
(prices are set by vendors, not members; webpage layout is set by the marketplace
owner). The page layout interestingly makes the number of categories a shop has very
salient, even at first glance.
Approximately 18 months after this marketplace was established, the company introduced a new “social” or “community” feature that allowed sellers to post hyperlinks from their shops to any other shop in the marketplace. This turned the user-generated
marketplace into a social commerce community, and a social network was thus born with shops as vertices, and hyperlinks between them as directed edges. Prior to this feature being introduced, sellers' shops were independent. Links are publicly displayed on each shop's homepage, participation in this network is not compulsory, and links are permanent (i.e., they cannot be removed, which means for example that members cannot threaten link-removal as a strategic device against other members). The links here act as referrals in the sense that a link posted on shop $i$ pointing to shop $j$ allows the seller who owns shop $i$ to refer customers who visit shop $i$ to shop $j$. These links are simply internet hyperlinks and they carry no additional information other than the name of the to-shop. When shop $i$ creates a link to shop $j$, shop $j$ is made aware of this link by an email that contains a hyperlink to $i$, offering $j$ an easy opportunity to reciprocate $i$'s link. Reciprocating links is optional, therefore the edges are directed. The fact that the network was born after the marketplace was already well established implies that we have access to a set of relevant measures that describe a given shop before it entered the network. These measures are completely exogenous to the network (i.e., the network had no influence on them).

Our dataset covers two years of activity in this marketplace from its inception, beginning 18 months before and ending 24 weeks after the birth of the network. It includes network-relevant information as well as information on shops, with the network-relevant information starting at the birth of the network and the information on shops starting 18 months before the birth of the network. Over the observation window, 72,294 links were created. The number of shops in the community grew to 136,774 by the end of
the observation window (the community contained 74,291 shops when the network was born). In terms of the network, by the end of our 24-week observation window 19,125 shops either sent or received at least one link.\textsuperscript{14}

Though most sellers would likely want to earn commissions and therefore make money to compensate them for their efforts in creating their shops, it appears that the commissions earned by sellers are typically modest and likely not a significant source of income for these individuals. Indeed, although the profits of the marketplace as a whole are significant (2.3 million transactions and €388,970 earned by the marketplace owner in commission revenues over the observation period), each shop made on average 16.56 sales and earned on average €1.62 in commission revenues (shops who made at least one sale made on average 78.23 sales and earned on average €7.64 in commissions and the top 10\% of shops (by commission earnings) made on average 159.97 sales and earned on average €15.85 in commissions). Therefore, sellers in this marketplace appear to derive some non-monetary satisfaction from the commission revenues earned by their shops. In particular, creating, owning and managing a successful shop is a source of various non-monetary utility. For example, it may give bragging rights to its owner. It is also a validation that the seller’s tastes, which are reflected in his or her assortment choices, have been well received by other consumers. In other words, it provides a “revealed

\textsuperscript{14} Consistent with our argument below, shops with fewer categories are more likely to be disconnected (they are less attractive to other shops). At the end of the observation window, the average number of categories covered by the shops with neither in- nor out-links was 15.90, versus 23.75 for shops with at least one link (in or out). Connected shops are also “larger” in terms of the average number of products they feature (214.85 versus 53.36 for disconnected shops). Finally, the connected shops made more transactions on average (87.98 versus 5.08) and earned higher commissions (€8.61 versus €0.50).
preference” validation of his or her tastes, as the customers who purchase products from a shop implicitly endorse that shop and the seller who owns the shop. Therefore, although the commission revenues achieved by shops in our dataset are modest, it seems reasonable to assume that sellers will take actions to increase their shops’ revenues, as the utility that they derive from it seems larger than suggested by the actual amounts of money. One of the primary ways to increase the commission revenues of one’s shop, beyond the choice of product assortment, is to increase customer traffic by making the shop more accessible to customers.\footnote{Note that this phenomenon of seeking to make something one has created more accessible for the purposes of achieving recognition and the associated non-monetary utility occurs in many other contexts. For example, most bloggers or online product reviewers (e.g., on Amazon.com or Yelp.com) seek social validation of their ideas and opinions, which comes with increased recognition and traffic.}

Stephen and Toubia (2009) show that a key effect of creating a network between sellers in a social commerce marketplace is making shops more accessible to browsing customers. These links serve the purpose of allowing customers to move more easily throughout this online marketplace, like in a virtual shopping mall. Stephen and Toubia (2009) show that the presence of a network increases the revenues of a social commerce marketplace, and that the shops that benefit the most from the presence of the network (i.e., whose commission revenues are increased the most) are those whose accessibility is most enhanced by the network.

Given our argument that sellers should be expected to take actions that increase the commission revenues of their shop, we expect sellers to create links that they believe are likely to improve the accessibility of their shops. One apparent contradiction is that links are directed hyperlinks that direct customers from one’s shop to another shop.
Therefore the primary effect of links is to drive customers away from one's shop and to make other shops more accessible. The accessibility of a shop is increased when other shops create incoming links to that shop. Stephen and Toubia (2009) show that although outgoing links have a negative effect on commission revenue and incoming links have a positive effect, the net effect of creating a link is positive, for the following two reasons. First, the magnitude of the positive effect of an incoming link is larger than that of the negative effect of an outgoing link. Second, a large proportion of links are reciprocated. As a result, although creating a link has an immediate negative impact, it is likely to result in a reciprocated incoming link which will have a larger positive effect, making the decision to create a link consistent with profit maximizing objectives. This implies that reciprocity is likely to play a key role in the evolution of such a network.

3.3 Power-Law Degree Distribution

A network is said to have a power-law degree distribution when for degree $k$, the probability distribution of $k$ follows a power-law: i.e., $p(k) \propto k^{-\gamma}$, where $\gamma \geq 1$ is the power-law parameter. Figure 6 shows histograms of the indegree distribution in our network at various points in time, as well log-log plots of the same distribution. The histograms show a characteristic “long tail”, and all log-log plots are close to linear, suggesting that our network appears to have a power-law degree distribution.
Figure 6: Indegree Distributions

Note: Indegree distributions (histograms) at weeks 6 (top-left), 12 (top-right), 18 (bottom-left), and 24 (bottom-right). Insets are log-log plots of the histograms.

One standard way to quantify whether an empirical degree distribution is power-law is to fit a linear regression to the log-log plots. Linear regressions for the log-log plots in Figure 6 gave $R^2$ values of .924, .936, .926, .942, for the week 6, 12, 18, and 24 degree distributions, respectively. This suggests that power-laws fit the distributions in
Figure 6 well. Given the shortcomings of this approach (see, for example, Jones and Handcock 2003), more appropriate approaches for estimating the power-law parameter ($\gamma$) have been proposed, based on maximum likelihood. In particular, we used the approach proposed by Clauset, Shalizi, and Newman (2007), and estimated the $\gamma$ parameters to be 1.73, 1.72, 1.75, and 1.74 for the indegree distributions at weeks 6, 12, 18, and 24, respectively. This is consistent with previous empirical studies of power-law degree distributions, where this parameter was usually around 2 for the network to be called “scale-free” (Barabási and Albert 1999). Note that additional analysis suggests that the power-law degree distribution in our network emerged and stabilized five weeks after the network’s birth (i.e., the parameter value after five weeks post-birth did not significantly vary). Hence, this aggregate property seems to be fairly stable and persistent in this network.

We recognize that degree distributions that appear to be power-law are sometimes not, and instead have other distributions that look like power-law distributions (e.g., lognormal, most commonly; cf. Clauset et al. 2007). The tests reported above and the log-log degree histograms in Figure 5 all suggest that the degree distribution (at various points in time) is power-law. Since the limiting distribution of a lognormal random variable that has a finite lower bound (such as degree) is power-law (Champernowne 1953; Gabaix 1999; Mitzenmacher 2004), whether these distributions are in fact perfectly

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16 Clauset et al. (2007) show that their procedure provides consistent estimates of $\gamma$. In addition to estimating $\gamma$ this procedure also estimates a minimum degree ($k_{min}$) that sets a truncation point for the distribution. The parameter $k_{min}$ is such that the fitted power-law distribution has support $[k_{min}, \infty)$. In our case, we set $k_{min} = 1$, i.e., the distribution is not truncated. See Perline (2005) for issues related to truncated degree distributions.
power-law or instead better fit by lognormal (a close candidate) is largely inconsequential in this particular case. Rather, the key question is which mechanism (or set of mechanisms) can best explain the formation of this network and, hence, produce the observed, heavily skewed "long-tail" degree distributions over time. We examine these in the next section.

Notwithstanding the fact that whether the distribution is power-law or lognormal (for instance) does not matter a great deal here, it is still worth checking the goodness-of-fit of a power-law versus a lognormal to the weekly indegree distributions for this network. In the Clauset et al. (2007) procedure for estimating the power-law parameters (on the indegree distribution each week) fit can be determined based on a distribution deviance statistic, $D$ (in this case, a Kolmogorov-Smirnov fit statistic; see Clauset et al. [2007] for details). For a perfect power-law fit, $D = 0$. In practice, as long as $D$ is relatively small this indicates very good fit. With few exceptions, $D$ was always in the .04 to .05 range (exceptions were .13 in week 2, and .06 in weeks 4 and 10).\(^{17}\) Also, we formally compared lognormal and power-law fits using maximum likelihood estimators for the power-law and lognormal distributions’ parameters and then comparing fits using the Bayesian Information Criterion (BIC; smaller indicates better fit). The power-law distribution was found to fit better than a lognormal distribution for each of the weekly indegree distributions.

\(^{17}\) Note that in statistical tests the null hypothesis of $D = 0$ was usually rejected. This, however, simply indicates that power-law was not a perfect fit (which is arguably a near-impossible standard to meet with real network data). The small magnitudes of $D$ (in most cases), suggest that it was at worst a reasonable fit and at best a very good close fit. This is supported by the plots in Figure 5 and the conventional linear-fit statistics for the log-log distributions.
3.4 Mechanisms of Social Network Evolution that Could Explain the Power-Law Degree Distribution

We now discuss and formalize a set of network evolution mechanisms that are plausible drivers of the evolution of this network, and in particular of the emergence of its power-law degree distribution. We introduce these mechanisms formally in this section and compare them empirically in the next section. We start with preferential attachment, which is the most common explanation for the emergence of power-law degree distributions (Barabási and Albert 1999). Next we consider triadic closure and cyclic closure, which have been shown recently to be possible explanations for power-law degree distributions (Vázquez 2003). We argue that neither preferential attachment nor triadic closure (and cyclic closure) are likely to explain the evolution of this social network. Third, we consider a network evolution mechanism that is consistent with the hypothesis that sellers create links to other shops in order to increase the accessibility of their own shops. This mechanism is based on shop assortment diversity, a vertex attribute that is not directly related to the network’s structure. Finally, we argue that reciprocity is likely to play a critical role in the evolution of this network, and briefly discuss a random attachment mechanism.

3.4.1 Preferential Attachment

The mechanism of preferential attachment assumes that a vertex’s probability of receiving a new edge is proportional to the number of edges it already has. Barabási and
Albert (1999) showed that preferential attachment provides an explanation for the emergence of power-law degree distributions.

Formally, Barabási and Albert (1999) model the probability that vertex $i$ connects to vertex $j$ given that $i$ creates the $t^{th}$ edge in the network as $p_{ijt} = \frac{k_{jt}}{\sum_{k \in \tilde{N}_i} k_{kt}}$, where $k_{jt}$ is vertex $j$'s degree before the creation of edge $t$ and $\tilde{N}_i$ is the set of vertices to which $i$ is not already connected before the creation of edge $t$ (i.e., vertices that $i$ has not previously created an edge to). In directed graphs, preferential attachment may be further refined into in- and outdegree effects, with $p_{ijt,\text{indegree}} = \frac{k_{jt}^{in}}{\sum_{k \in \tilde{N}_i} k_{kt}^{in}}$ and $p_{ijt,\text{outdegree}} = \frac{k_{jt}^{out}}{\sum_{k \in \tilde{N}_i} k_{kt}^{out}}$, where $k_{jt}^{in}$ and $k_{jt}^{out}$ are vertex $j$'s indegree (number of edges to $j$ before the creation of edge $t$) and outdegree (number of edges from $j$ before the creation of edge $t$) respectively. Note that $p_{ijt}$ here, and in the subsequent sections, are choice probabilities (specifically, Luce choice probabilities).

In order to assess the relative prominence of various edge formation mechanisms, we will develop similar probabilities for each of the other mechanisms below. In other words, for each mechanism we model the probability that a vertex $i$ would choose to connect to vertex $j$ given that vertex $i$ creates edge $t$, and assuming that the formation of this new edge is motivated by this mechanism.

As mentioned above, we expect link formation in our context to be motivated by the objective of increasing one's shop accessibility. Shops with a large number of incoming links are likely to receive more traffic, as they are more likely to be found by customers browsing the marketplace. Indeed, Stephen and Toubia (2009) found a positive
effect of the number of incoming links on commission revenue. Therefore one may think that connecting to a shop $j$ that has a large indegree is attractive. We argue that it is not, and that although shop $j$ is likely to receive more traffic, linking to such a shop is not likely to be a great source of additional traffic for a shop $i$ that would create such a link.

Suppose first that shop $j$ has been reciprocating a large proportion of its incoming links (i.e., thus giving it a large outdegree). In that case, even if shop $j$ were to reciprocate a new incoming link from shop $i$, shop $i$ would have to share the traffic out of shop $j$ with a large number of other shops. Therefore shop $i$ would be likely to be left with little additional traffic (i.e., a relatively small share of shop $j$'s outgoing traffic), making linking to shop $j$ less attractive to shop $i$. Suppose instead that shop $j$ has not been reciprocating a large proportion of its incoming links. In that case shop $i$ would benefit more from a reciprocating link from $j$ to $i$. However, the very fact that shop $j$ has not been reciprocating a large proportion of its incoming links suggests that shop $i$ is also unlikely to receive a reciprocating link from shop $j$. Therefore shop $j$ is not attractive to shop $i$, whether $j$ has or has not reciprocated a large proportion of its incoming links. As a result, we do not expect indegree preferential attachment to be a key mechanism of edge formation in our context. Likewise, we do not expect outdegree preferential attachment to be a key edge formation mechanism either, for the simple reason that the more out-links a shop has, the more other shops there are to share that shop’s outgoing traffic with. Hence, being one more of these out-links should not be appealing to a shop that is trying to increase its accessibility and incoming traffic.
3.4.2 Triadic and Cyclic Closure

A commonly found characteristic in social networks is that vertices tend to be clustered, meaning that groups of vertices are densely interconnected between themselves (within-cluster). Relatively high clustering, for instance, is a key characteristic in small-world networks (Watts and Strogatz 1998). The notion of clustering is based on the sociological concepts of triadic closure and transitivity, which refer to the tendency for two individuals who are both tied to a common third person to become tied to each other (Davis 1963; Feld 1981; Holland and Leinhardt 1971). In other words, if there is at least one edge between vertices \( i \) and \( z \), and at least one edge between vertices \( j \) and \( z \), then there is a higher probability that an edge between \( i \) and \( j \) will be created. In undirected graphs, the triadic closure-based probability that vertex \( i \) chooses vertex \( j \) to create edge \( t \) may be modeled as

\[
p_{ijt} = \frac{c_{ijt}}{\sum_{h \in N_i} c_{iht}}
\]

where \( c_{ijt} \) is the number of common neighbors to which both \( i \) and \( j \) connect before the creation of edge \( t \).\(^{18}\)

In directed networks, different types of triadic closures are possible because of the combinations of directed edges that are possible in a triad of vertices. One noteworthy type of triadic closure in directed graphs is the "path-shortening" edge. This corresponds to a situation where before the creation of edge \( t \) vertex \( i \) connects to vertex \( z \) and vertex \( z \) connects to vertex \( j \); hence there is a two step path from \( i \) to \( j \): \( i \rightarrow z \rightarrow j \). If an edge from \( i \) to \( j \) is then formed there is now a direct, one step path from \( i \) to \( j \). Probabilities may be

\(^{18}\)In our empirical analysis we set \( p_{ijt} = 0 \) if \( \sum_{h \in N_i} c_{iht} = 0 \).
defined for each type of triadic closures using the same specification as in the undirected case, with the only difference being that \( c_{ijt} \) is limited to one type of triadic closure:

- \( p_{ij, \text{path-2}} = c_{ijt} / \sum_{h \in \tilde{N}_i} c_{ih} \), where \( c_{ijt} \) is the number of paths of length 2 that connect \( i \) to \( j \) before the creation of edge \( t \);
- \( p_{ij, \text{triadic}_a} = c_{ijt}^a / \sum_{h \in \tilde{N}_i} c_{ih}^a \), where \( c_{ijt}^a \) is the number of common neighbors to which both \( i \) and \( j \) connect before the creation of edge \( t \);
- \( p_{ij, \text{triadic}_b} = c_{ijt}^b / \sum_{h \in \tilde{N}_i} c_{ih}^b \), where \( c_{ijt}^b \) is the number of common neighbors that connect to both \( i \) and \( j \) before the creation of edge \( t \); and,
- \( p_{ij, \text{triadic}_c} = c_{ijt}^c / \sum_{h \in \tilde{N}_i} c_{ih}^c \), where \( c_{ijt}^c \) is the number of common neighbors that connect to \( i \) and to which \( j \) connects before the creation of edge \( t \).

Triadic closure may be generalized to higher-order path-shortening effects, also called cyclic closure, where paths of length \( l \) between two vertices are shortened by the formation of a direct edge between the vertices at the two ends of the path. In particular, we model the probabilities corresponding to \( l = 3 \) and \( l = 4 \) as follows (we do not find any empirical evidence for \( l > 4 \) in our dataset):

- \( p_{ij, \text{path-3}} = d_{ijt} / \sum_{h \in \tilde{N}_i} d_{ih} \), where \( d_{ijt} \) is the number of paths of length 3 that connect \( i \) to \( j \) before the creation of edge \( t \); and,
- \( p_{ij, \text{path-4}} \) is computed similarly based on the number of paths of length 4 that connect \( i \) to \( j \) before the creation of edge \( t \).

Note that the mechanisms of preferential attachment and triadic/cyclic closure are not necessarily independent. For example, Feld and Elmore (1982) suggest that the
formation of triads in friendship networks are in part a consequence of inequality of popularity among individuals (i.e., as implied by preferential attachment). Recently, Vázquez (2003) showed both analytically and numerically that degree-based preferential attachment may be viewed as a consequence of triadic and/or cyclic closure. Consider for example a vertex $i$ with one current edge with vertex $z$, which itself is connected to one other vertex. If $i$ chooses which vertex to connect to based on triadic closure, the probability that $i$ will connect to a randomly selected vertex $j$ is equal to the probability that there already exists an edge between $z$ and $j$, which itself is proportional to $j$’s degree. Therefore, triadic closure is another candidate for explaining the emergence of the power-law degree distribution in this network.

In our context, however, we argue that triadic closure is unlikely to be a key driver of edge formation, as it has at best no specific positive impact on accessibility. The impact on accessibility is in fact worse than average in the case of path shortening triadic closure. In particular, closing a $i \rightarrow z \rightarrow j$ triad by creating a link from $i$ to $j$ only creates a shortcut between $i$ and $j$. While this may have a positive impact on the traffic from $i$ to $j$, customers were already able to access $j$ from $i$ (through $z$) before the creation of this shortcut. Therefore the increase in $j$’s accessibility is on average less than that of a link from another shop $w$ to $j$, where no path existed between $w$ and $j$ before the creation of the link. Further, the problem with clusters in this type of network where customer traffic flows are critical is that customers can become “trapped” within a cluster of shops (i.e., cycling around the same set of shops and returning to already-visited shops). This is analogous to Granovetter’s (1973) strength of weak ties argument (because weak ties that...
bridge between clusters of strong-tied vertices can potentially bring fresh resources or information into those clusters). Indeed, Stephen and Toubia (2009) find that being part of a set of tightly clustered shops has a negative effect on a shop’s commission revenues.

### 3.4.3 Shop Assortment Diversity

The mechanisms of social network evolution reviewed above capture how the network’s current structure influences its evolution. These mechanisms ignore the influence that vertex attributes that are not related to the network may have on its evolution. In our social commerce network, we argue that shops with more diverse assortments, in particular, should be more likely to receive links, irrespective of their position in the network.

In this marketplace, as with many online marketplaces, there are several ways in which customers can find shops, besides using the network to browse the marketplace. These include search engines (e.g., Google) and directories (e.g., this marketplace has its own directory that lists shops by category). Hence, shops that come up in more search results and in more directory listings should be more accessible (externally) and therefore have a higher probability of receiving higher incoming traffic. Indeed, any given keyword search or directory search that a potential customer enters is more likely to overlap with a category offered by a shop that has more categories.\(^\text{19}\) The effect of assortment diversity

\(^\text{19}\) This is a familiar concept in the offline world as well. Bricks-and-mortar superstores or hypermarkets such as Wal-Mart in the United States and Carrefour in Europe, and traditional department stores such as Macy’s, are examples of shops with high levels of assortment diversity. A random customer with her own set of category preferences is more likely to find categories of interest to her if she visits one of these shops,
on incoming traffic is likely to be further enhanced if consumer demand is characterized by "long tails," where a large number of niche categories each appeal to a relatively small number of customers (Anderson 2006). (While we measure assortment diversity by the number of product categories featured by a shop, other measures of assortment diversity are available in our dataset. We show later that our results still hold if assortment diversity is measured by the total number of products offered by a shop, although the stronger effect is for number of categories.)

Therefore, shops in this marketplace are likely to want to receive links from shops with diverse assortments, in order to improve their own accessibility. While members do not have control over the incoming links that are formed to their shops, one approach is to create an outgoing link to such an attractive shop and hope to receive a reciprocating link back from that shop. (We discuss reciprocity next.) Hence, we consider an edge formation mechanism whereby shops prefer to connect to other shops with more diverse assortments. Note that an alternative way of thinking about this mechanism is that each product category in the "universe" of categories has an equal appeal, and that probability of linking to a shop is proportional to the appeal of its categories. Thus, a shop with five categories, for example, will have five times the appeal of a shop with one category, and therefore a higher probability of being linked to.\(^{20}\)

One interesting feature of this edge formation mechanism is that it is based on a vertex attribute that is not directly related to the network. In our statistical analysis, in

\(^{20}\) Thank you to Duncan Watts for pointing out this alternative interpretation.
order to disentangle this mechanism from the other mechanisms based on the network’s structure, we use a measure of shop assortment diversity that is completely exogenous to the network. In particular, once a shop enters the network its product assortment (and hence the product categories it features) is not completely independent from the structure of the network anymore. For example, receiving more links (i.e., increasing indegree) may provide positive reinforcing feedback to a seller and motivate him or her to increase the assortment of his or her shop. In that case at least part of the effect of shop assortment diversity on edge formation would be an indirect effect of preferential attachment: higher indegree would lead to more diverse assortments which in turn would make a shop more likely to receive new edges. Using a measure of shop assortment diversity that is exogenous to the structure of the network allows filtering out such indirect effects. Because our dataset starts before the creation of the network (at which point all shops in the marketplace were disconnected), we have access to such a measure. We use number of categories computed on the day the shop joined the network (i.e., either received or sent its first edge).

Formally, we model the effect of shop assortment diversity on network edge formation with the following probability: 

\[ p_{ij, \text{diversity}} = q_j / \sum_{h} q_h \],

where \( q_j \) is our measure for shop \( j \)'s assortment diversity.

Even if this network evolution mechanism does explain the evolution of this network, it remains to be proven how it can give rise to a power-law degree distribution. This mechanism would give rise to a power-law degree distribution if shop assortment diversity were itself power-law distributed (i.e., “power-law in, power-law out” or “PLI-
We find that this is indeed the case. Figure 7 shows a histogram and a log-log plot of the distribution of our measure of assortment diversity, which appears to be power-law distributed (i.e., few shops have very diverse assortments and many shops have very narrow assortments). The estimation procedure of Clauset et al. (2007) gives $\gamma = 1.37$ (and a linear regression of the log-log plot in Figure 7 gives $R^2 = .941$).

Figure 7: Shop Assortment Diversity Distribution

Note: Inset is the log-log plots of the histogram.
To illustrate the relationship between the distribution of assortment diversity and the distribution of indegree when assortment diversity is a driver of edge formation, we simulated the evolution of a network in which new edges were created only according to a vertex’s assortment diversity and in which assortment diversity followed a power-law distribution. We generated ten independent networks, each with 1,000 vertices and 10,000 edges, and with vertex assortment diversity drawn from a power-law distribution with $\gamma = 1.5$ at the start of each simulation (i.e., prior to each network’s birth). Each network started with no edges, and one edge was created per iteration. The following steps were performed at each iteration: (1) select a random vertex $i$ (we used a uniform distribution on the set of vertices), (2) compute the selection probabilities for each vertex $j$ to which $i$ is currently not connected, where the probability $p_{ij}$ that vertex $i$ chooses to connect to vertex $j$ at iteration $t$ is given by $p_{ij,\text{diversity}}$, and (3) draw vertex $j$ according to the probabilities computed in step 2 and create a directed edge between $i$ and $j$ (note: duplicate edges were not allowed). This simulation generated networks with power-law indegree distributions: $\bar{\gamma} = 1.638$ (averaged across the ten runs, standard deviation = 0.052), and an average goodness-of-fit of $R^2 = .91$ (standard deviation = .038). Therefore, power-law degree distributions emerge if edge formation is driven by an exogenous factor that is power-law distributed (shop assortment diversity in our case).\footnote{This simulation’s purpose was to generally illustrate that a power-law distributed input variable that is exogenous to the network structure can give rise to network with a power-law degree distribution. We replicated this simulation with properties that closely matched those of our data (i.e., $\gamma = 1.37$ matching the assortment diversity distribution in Figure 7) and generating 10,000 edges over 7,113 vertices (to give a density matching the final network density at the end of our observation window, .000198). The general}
3.4.4 Reciprocity

In social networks where edges are directed, vertex \( i \) has the option to reciprocate a \((j,i)\) edge by creating a new edge \((i,j)\). Formally, if vertex \( i \) creates edge \( t \) by choosing whom to connect to based solely on reciprocity, the probability that \( i \) chooses to connect to \( j \) may be modeled as being uniform on \( i \)'s unreciprocated edges: \( p_{ij,reciprocity} = r_t^{-1} \) if the edge \((j,i)\) already exists, and 0 otherwise, where \( r_t \) is the number of unreciprocated incoming edges that vertex \( i \) has before creating edge \( t \).

As mentioned above, the value of the network under study hinges on reciprocity, and shop \( i \) benefits from linking to shop \( j \) if shop \( j \) reciprocates this link. Therefore, while reciprocity in itself is not an explanation for the emergence of the network’s power-law degree distribution, we expect reciprocity to be an important driver of edge formation in our dataset.

3.4.5 Random attachment

Finally, it is also possible that vertices may randomly select whom to connect to. When an edge is randomly formed, the probability that vertex \( i \) chooses vertex \( j \) to form link \( t \) may be simply modeled as a uniform draw over all available vertices:

\[
p_{ij,random} = \left( \frac{1}{|\tilde{N}_u|} \right)^{-1}
\]

where \( \tilde{N}_u \) is again the set of vertices to which \( i \) is not already connected before the creation of link \( t \).

---

simulation result was replicated (mean \( y \) for indegree distribution = 1.93, st. dev. = .041, 10 simulation runs).

\(^{22}\) In our empirical analysis we set \( p_{ij} = 0 \) if \( r_t = 0 \).
3.5 Statistical Analysis

We now develop a statistical model that allows us to empirically compare how well the network evolution mechanisms introduced in the previous section explain the evolution of this social commerce network.

3.5.1 Model

We estimate a dynamic model in which network evolution is driven by a weighted combination of the network evolution mechanisms introduced in the previous section. Our model captures the evolution of the network, and not only its final structure. Each new edge (link) between two vertices (shops) provides us with one observation. At each new link, the shop from which the link is created makes a choice of a to-shop from all shops in the community to which it is not already connected. The equation below models the probability that shop \( j \) will be the recipient of the \( t \)th link in the dataset formed by shop \( i \), conditional on \( i \) forming the \( t \)th link. This probability is written as a mixture of probabilities capturing the social network evolution mechanisms introduced above:

\[
p_{ijt} = \left(1 - \sum_{l=1}^{9} \theta_l - \phi_l \right) p_{ijt,\text{random}} + \theta_1 \cdot p_{ijt,\text{indegree}} + \theta_2 \cdot p_{ijt,\text{outdegree}} + \theta_3 \cdot p_{ijt,\text{path-2}}
\]

\[
+ \theta_4 \cdot p_{ijt,\text{path-3}} + \theta_5 \cdot p_{ijt,\text{path-4}} + \theta_6 \cdot p_{ijt,\text{triadic-c}} + \theta_7 \cdot p_{ijt,\text{triadic-s}} + \theta_8 \cdot p_{ijt,\text{triadic-c}} + \phi_1 \cdot p_{ijt,\text{diversity}}
\]

(3.1)

Where the positive coefficients \( \theta_1 \) to \( \theta_9 \) are the relative importance weights of the different versions of preferential attachment, reciprocity, triadic closure and cyclic closure, and the positive coefficient \( \phi_1 \) is the relative importance weight of the assortment diversity mechanism. Each probability in the mixture assumes that the \( t \)th edge from vertex \( i \) to vertex \( j \) is driven by the corresponding mechanism, and the weights indicate
the relative magnitude of each mechanism as a driver of edge formation. We do not model the existence or absence of a link between \( i \) and \( j \) by the end of the observation window (like many extant statistical models of networks), but rather focus on what drives \( i \) to choose \( j \) among all possible shops, given that \( i \) creates the \( t \)th link. The weights indicate how consistent these observed decisions are with each mechanism.

Note that the probabilities corresponding to the preferential attachment, reciprocity, triadic and cyclic closure mechanisms are functions of \( t \); that is, of the structure of the network at the time of the creation of link \( t \). In contrast, the probability corresponding to shop assortment diversity is defined based on a measure that is independent from the structure of the network, and therefore does not depend on \( t \). Note also that our specification ensures that \( p_{ij} \) is bounded between 0 and 1, as it is a weighted combination (with the weights summing to 1) of probabilities, which are themselves bounded between 0 and 1.\(^{23}\) Finally, note that we do not aggregate any data in this analysis. Importantly, this model is tractable for our large dataset (72,294 links created between shops in a community that contained 136,774 shops at the end of our observation window; with slightly less than 19 billion links possible).

An alternative approach would have been to use a logit or probit choice model specification that would model the attractiveness of each possible to-vertex as a weighted average of its various characteristics (indegree, outdegree, shop assortment diversity, etc) (cf. Snijders 2001b). However, computing the edge formation probabilities in these

\(^{23}\) Relaxing the positivity constraints on the weights did not affect the results.
models would require computing the attractiveness of all possible to-vertices for each edge and for each candidate set of parameters, which would be a challenge given the large number of shops in the marketplace.\(^{24}\) In contrast, our specification allows computing the probabilities in the mixture only once, as these probabilities do not depend on the parameters of the model. Another approach would have been to use the SIENA model (Snijders 1997, 2001a, 2001b, 2005), which we briefly mentioned above. This program allows estimation from panel data, where not all changes in the network are individually recorded. In contrast, the data set analyzed here has a full record of all changes, and therefore a maximum likelihood approach was deemed more appropriate. Other approaches, such as exponential random graph models (ERGMs) of the kind implemented in the Statnet package (Handcock et al. 2008) were also considered but not pursued, as they do not make use of the longitudinal nature of our dataset.

### 3.5.2 Parameter Estimates

The parameters of our model are the positive weights \(\theta_1\) to \(\theta_9\) and \(\phi\). We maximize the natural logarithm of our likelihood function over these parameters, defined as the product of all \(p_{ij}\)'s over all \(T = 72,294\) links created during our observation.

---

\(^{24}\) Note also that there were almost 140,000 shops in this marketplace by the end of our dataset. Even though just under 20,000 shops ended up being connected in the network, the remaining shops must be included in the model, and treated as isolates/disconnected vertices.
window: \( L = \prod_{t=1}^{T} p_{ijt} \). Conditioning of the covariates on which \( p_{ijt} \) depends, we assume that the \( p_{ijt} \)'s are statistically independent (note that this assumption is common in extant statistical network models). Parameter estimates are reported in Table 8. The simple mechanism based on assortment diversity is prominent, with the largest weight of .657 (recall that the parameters sum to 1). Reciprocity is also strongly supported with an estimated weight of .240. All other parameters are very small. The combined weights on the preferential attachment mechanisms is .001, and the combined weights on the triadic closure and cyclic closure mechanisms is .094. The very small weight on preferential attachment is partly due to the fact that we also allow for triadic and cyclic closure effects (see argument at the end of section 3.4.2). We use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC; Raftery 1995) for model comparisons (Handcock and Jones 2004). Our model has an AIC of \( 4.956 \times 10^5 \) and a BIC of \( 4.957 \times 10^5 \). When the triadic and cyclic closure effects are removed from the model, indegree preferential attachment becomes slightly larger (.005 versus .001). However the AIC and BIC for that model are higher (both \( 5.07 \times 10^5 \)), suggesting that it is more appropriate to include triadic and cyclic closure effects in addition to preferential attachment.

---

25 The optimization algorithm was Newton-Rapson (with line search). Identical estimates were achieved using quasi-Newton methods, Newton-Rapson (with ridging), and trust-region methods.

26 The process based on shop assortment diversity remains the dominant effect in this specification.
Table 8: Empirical Comparison of Network Formation Mechanisms

<table>
<thead>
<tr>
<th>Effects</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_{\text{random}} ) : random attachment</td>
<td>.006</td>
</tr>
<tr>
<td>( \theta_1 ) : indegree preferential attachment</td>
<td>.001</td>
</tr>
<tr>
<td>( \theta_2 ) : outdegree preferential attachment</td>
<td>0&lt;sup&gt;ns&lt;/sup&gt;</td>
</tr>
<tr>
<td>( \theta_3 ) : path-2</td>
<td>0&lt;sup&gt;ns&lt;/sup&gt;</td>
</tr>
<tr>
<td>( \theta_4 ) : path-3</td>
<td>.002</td>
</tr>
<tr>
<td>( \theta_5 ) : path-4</td>
<td>0&lt;sup&gt;ns&lt;/sup&gt;</td>
</tr>
<tr>
<td>( \theta_6 ) : triadic (a)</td>
<td>.002</td>
</tr>
<tr>
<td>( \theta_7 ) : triadic (b)</td>
<td>.087</td>
</tr>
<tr>
<td>( \theta_8 ) : triadic (c)</td>
<td>.003</td>
</tr>
<tr>
<td>( \theta_9 ) : reciprocity</td>
<td>.240</td>
</tr>
<tr>
<td>( \phi_1 ) : shop assortment diversity</td>
<td>.657</td>
</tr>
</tbody>
</table>

Log-likelihood                  -247,797
Number of observations          72,294  
Number of free parameters       10       
AIC \((\times 10^5)\)            4.956
BIC \((\times 10^5)\)            4.957

Note: "ns" means nonsignificant; otherwise effects are significant at \( p < .001 \). The 95% confidence intervals for significant effects were all narrow (upper and lower bounds were equal when rounded to three decimal places); none overlapped.

### 3.5.3 Model Comparisons

In order to assess the validity of our model, we compare a series of nested models using AICs and BICs (a smaller AIC/BIC indicates superior fit). See Table 9. Our nested models include (a) a null model with random attachment only, and (b) a model with random attachment and all preferential attachment, reciprocity, triadic closure and cyclic closure mechanisms (but no assortment diversity mechanism). Both models have a higher AIC and BIC compared to the full model and thus achieve worse fit.
Table 9: Model Comparisons

<table>
<thead>
<tr>
<th>Fit Statistics</th>
<th>Full</th>
<th>Random Only (a)</th>
<th>Preferential attachment, reciprocity, triadic/cyclic closure (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-likelihood</td>
<td>-247,797</td>
<td>-820,203</td>
<td>-457,806</td>
</tr>
<tr>
<td>Number of observations</td>
<td>72,294</td>
<td>72,294</td>
<td>72,294</td>
</tr>
<tr>
<td>Number of free parameters</td>
<td>10</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>AIC ($ \times 10^5 $)</td>
<td>4.956</td>
<td>16.404</td>
<td>9.156</td>
</tr>
<tr>
<td>BIC ($ \times 10^5 $)</td>
<td>4.957</td>
<td>16.404</td>
<td>9.157</td>
</tr>
</tbody>
</table>

3.5.4 Robustness to Alternative Measures of Assortment Diversity

Our main measure of assortment diversity, as discussed above, was the total number of categories in a shop, measured just before a given shop entered the network so that the measure is completely exogenous to the network. To check the robustness of this measure we estimated the model in equation 3.1 using two alternative measures of a shop's assortment diversity (also computed on the day a shop entered the network): (1) the number of products listed on its front page (recall that at most three products per category are listed on a shop's front page in this community; see Figure 5), and (2) the total number of products offered by the shop. Estimates for the models using these alternative measures are reported in Table 10. Importantly, in both alternative models the assortment diversity effect is the largest effect, and reciprocity remains the second-largest effect. This suggests that our findings are robust to changes in the measurement of
assortment diversity. Moreover, using the number of categories as the measure of the assortment diversity gives the best AIC and BIC.\textsuperscript{27}

Table 10: Alternative Measures of Shop Assortment Diversity

<table>
<thead>
<tr>
<th>Effects</th>
<th>All Products</th>
<th>Products on Front page</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{\text{random}}$ :</td>
<td>.040</td>
<td>.041</td>
</tr>
<tr>
<td>$\theta_1$ :</td>
<td>.027</td>
<td>.022</td>
</tr>
<tr>
<td>$\theta_2$ :</td>
<td>.002</td>
<td>.001</td>
</tr>
<tr>
<td>$\theta_3$ :</td>
<td>.002</td>
<td>.001</td>
</tr>
<tr>
<td>$\theta_4$ :</td>
<td>.050</td>
<td>.027</td>
</tr>
<tr>
<td>$\theta_5$ :</td>
<td>.001</td>
<td>.001</td>
</tr>
<tr>
<td>$\theta_6$ :</td>
<td>.029</td>
<td>.012</td>
</tr>
<tr>
<td>$\theta_7$ :</td>
<td>.143</td>
<td>.095</td>
</tr>
<tr>
<td>$\theta_8$ :</td>
<td>.043</td>
<td>.018</td>
</tr>
<tr>
<td>$\theta_9$ :</td>
<td>.263</td>
<td>.227</td>
</tr>
<tr>
<td>$\phi_1$ : shop assortment diversity</td>
<td>.401</td>
<td>.558</td>
</tr>
</tbody>
</table>

Log-likelihood                -357,273     -280,858
Number of observations        72,294       72,294
Number of free parameters     10           10
AIC ($\times 10^5$)           7.146        5.617
BIC ($\times 10^5$)           7.147        5.618

Note: "ns" means nonsignificant; otherwise effects are significant at $p < .001$. The 95\% confidence intervals for significant effects were all narrow (upper and lower bounds were equal when rounded to three decimal places); none overlapped.

\textsuperscript{27} We also considered a mechanism whereby shops prefer to connect to other shops with more transactions (instead of more diverse assortment). A model using that mechanism instead of the shop assortment diversity mechanism has much poorer fit (AIC and BIC of $8.8 \times 10^5$) compared to the model reported in Table 8.
3.5.5 Robustness to Time

The estimates reported in Table 8 are not time-varying; that is, they are the average weights over all 24 weeks of data. There may, however, have been some time variation in the weights of the respective formation mechanisms. To examine this we estimated the model in equation 3.1 on a weekly basis (i.e., for week \( w \) only using the data for the links formed in that week). The estimated weights by mechanism type (preferential attachment, triadic and cyclic closure, shop assortment diversity, reciprocity, random) over time are plotted in Figure 8. The top line is for assortment diversity, and clearly this mechanism is the one dominant every week, despite minor fluctuations.

Figure 8: Estimated Parameters by Week

![Figure 8: Estimated Parameters by Week](image-url)
3.5.6 Discussion of Empirical Results

These results suggest that the emergence of the power-law degree distribution in the present network appears not to have been driven by preferential attachment or triadic closure, but rather is well-explained by a mechanism whereby shops prefer to connect to other shops that have more diverse assortments, where assortment diversity follows a power-law distribution.

This suggests that while preferential attachment, in particular, is a phenomenological mechanism that explains the aggregate properties of many networks, it may not always have good descriptive validity. Power-law degree distributions may also emerge when new edges are formed based on vertex attributes that do not directly depend on the network’s structure and that follow a power-law distribution. Such situations may be common, as power-law distributions have been found empirically in a wide range of domains. For instance, the power-law has been found to describe the population of cities (Rosen and Resnick 1980; Zipf 1949), the sizes of tax-paying firms in the United States (Axtell 2001), the distribution of the market shares of brands (Kohli and Sah 2006), and the number of pages of WWW sites (Huberman and Adamic 1999).

Future research may explore further the relation between the distribution of such vertex attributes and power-law degree distributions. For example, it may not be a coincidence that the WWW has been found to have a power-law degree distribution (Barabási and Albert 1999; Huberman and Adamic 1999; Vázquez 2003), and that the number of pages per site has been shown to be power-law distributed (Huberman and Adamic 1999). In particular, our findings suggest that a power-law degree distribution
would emerge if WWW sites were simply more likely to connect to larger sites (i.e., to
sites with more pages). Along similar lines, in an online dating community we find the
number of date requests received by members to be power-law distributed (based on a re-
analysis of the data studied in Lee et al. 2008). Following a similar argument as the one
in the present work, future research may explore whether date requests are influenced by
the physical attractiveness of the community’s members, and whether physical
attractiveness follows a power-law distribution.

3.6 General Discussion

We studied the evolution of a large social network in a social commerce
community in which individuals create their own personal online “shops” and are
allowed to create referral hyperlinks between each other’s shops. We found that the
evolution of the network is well explained by a combination of reciprocity and of a
mechanism whereby shops prefer to connect to shops with more diverse assortments.
Moreover this mechanism, and not preferential attachment, triadic closure or cyclic
closure, appears to have driven the network’s power-law degree distribution.

The current work is not without its limitations. First, our statistical model is
conditional on the \( t \)th edge being formed by vertex \( i \), which means that we do not model
the probability that the \( t \)th edge will be formed by vertex \( i \). Although an interesting
question in itself, the network evolution mechanisms that we study in this essay are

\[ ^{28} \text{The authors thank Leonard Lee for providing access to this dataset.} \]
almost entirely silent on how the from-vertex is determined for each edge that is created, therefore we did not incorporate that aspect of edge formation in our model. Second, there may be other mechanisms of edge formation not considered here. However, the mechanisms we considered appeared to account for much of the observed data (i.e., the weight on random attachment, which proxies a residual in our model, was very small), suggesting that our set of mechanisms, while not exhaustive, was sufficiently comprehensive. Finally, our efforts were focused on a single social network in the specific context of social commerce, and thus claims of generality of our results are only speculative. More work is needed, in different types of networks and different contexts, to fully understand both the dynamics of network structures and the micro-level forces that drive these dynamics.
Why Do People Transmit Word-of-Mouth? The Effects of Recipient and Relationship Characteristics on Transmission Behaviors
4.1 Introduction

Consumer-to-consumer word-of-mouth (WOM) communications are important parts of marketing, are major drivers of product success (or failure) in the marketplace, are lie at the core of currently popular buzz and viral marketing strategies. As consumers become increasingly “connected” (e.g., via online social networks such as Facebook.com) opportunities for transmitting WOM increase and, critically, it becomes easier to do this. Despite the importance and centrality of WOM to marketing practice, and the large amounts of WOM (or social contagion) research in marketing and in other fields (e.g., sociology, physics, economics), surprisingly little is known about the drivers of individuals’ WOM transmission behaviors.

Issues such as why consumers talk to some people but not to others and to whom they talk are not well understood. Extant research has instead focused on the aggregate outcomes of WOM (e.g., on product adoptions or sales), and in doing so has failed to consider why WOM gets generated and why certain people are talked to but not others (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004). Put simply, while past research has demonstrated some of the important aggregate outcomes of WOM in marketing contexts, surprisingly little is known about what determines who consumers decide to share product-related information with (i.e., choice of WOM recipient) and, perhaps more critically, what underlying reasons or motivations drive consumers’ WOM transmission behaviors.

This essay attempts to address these shortcomings of past literature by exploring (1) transmitters’ underlying reasons or motivations for spreading WOM, and (2) how
these transmission reasons are associated with who transmitters choose as their recipients. Given the ongoing growth in new technologies that make it very easy for consumers to share product- and brand-related information with each other (e.g., user-generated content, social media, and social commerce; cf. Chevalier and Mayzlin 2006; Godes and Mayzlin 2004, 2008; Stephen and Toubia 2009), understanding the process of WOM transmission in greater detail at the individual level is worthwhile.

Consumers are assumed to be selective transmitters of WOM. That is, a consumer with information about a product will rarely tell everyone they know about the product, even when given the opportunity. For example, even though Roger might love the latest U2 album he will not necessarily go out and tell this to everyone he knows (even when given the opportunity to easily tell many people). Instead, he might tell a handful of people. This being the case, Roger has presumably been selective in this WOM transmission. This is common and in each of the empirical studies we report in this essay we find evidence of selective transmission behaviors.

If transmitters are selective of their recipients then we can think of WOM transmissions in probabilistic terms: e.g., Roger (person i) will tell his friend Mark (person j) about his love for the new U2 album with some “transmission probability,” $p_{ij}$. The probability of transmission $p_{ij}$ is a critical parameter in quantitative diffusion and contagion models (including recent work by Watts and Dodds 2007), yet it is often set arbitrarily or drawn from a diffuse probability distribution. Alternatively, $p_{ij}$ is modeled as a function of transmitter characteristics (e.g., Castellano, Fortunato, and Loreto 2007; Goldenberg, Libai, and Muller 2001, 2004), such as transmitters’ internal propensities to
talk. While this is true to some extent (e.g., “opinion leaders” or “market mavens” may have higher baseline transmission probabilities than regular consumers), it disregards the possibility that transmitters’ behaviors are driven by other factors, such as characteristics of the recipient(s) and the nature of the relationship between the transmitter and potential recipient(s). Here we focus on determinants of WOM transmission behaviors that are functions of these additional factors.

We theorize that consumers’ “tell” versus “not tell” transmission decisions, or who they decide to transmit WOM to (and equally importantly who they decide not to transmit to), are driven by the anticipation of deriving social benefits from the WOM transmission. In other words, the decision of with whom to have a conversation about a product, for instance, will at least partly be made with certain social benefits or social consequences of the conversation in mind. Thus, recipients’ abilities to deliver desired benefits to transmitters will influence transmitters’ behaviors. Consumers’ social relationships (i.e., ties in their social networks) are resources and thus contain social capital (Bourdieu 1986; Coleman 1988, 1990). Various social needs (e.g., attention from others, obtaining useful information from others, strengthening friendships, and feeling that one’s opinions have been “heard” by others) can be fulfilled by transmitting WOM. In this sense, WOM transmissions either use existing social capital contained within social ties or build new social capital. For example, a consumer with a need for attention may prefer to transmit WOM to a friend who they believe will be interested in, and thus pay attention to, what they have to say. Thus, characteristics of the potential recipients and the relationships that transmitters have with these recipients should play a role.
Specifically, transmitters’ reasons for transmitting WOM to certain people but not to others should be related to the social benefits that they expect some people, but not others, to be able to provide (in terms of using-versus-building social capital).

Based on this general theoretical claim, this essay addresses two main questions: (1) what are the types of reasons that people have for transmitting WOM and how are these reasons or motives related to recipient selection, and (2) how do characteristics of recipients and the relationship between transmitters and recipients affect recipient selection? We thus, respectively, explore why people transmit WOM, and attempt to determine the drivers of decisions of to whom to transmit WOM.

We attempt to address these questions with three studies. In Study 1 we first document and categorize reasons behind real WOM transmissions that people made, and then link these different transmission reasons or motivations to recipient and relationship characteristics. Study 2 examines the link between these characteristics and recipient selection (i.e., who to talk to) and the effect of different types of transmission situations, specifically “initial transmission” versus “retransmission.” Finally, Study 3 links recipient and relationship characteristics to transmitters’ expectations of the potential social capital-related “benefits” that given recipients would provide (e.g., giving them attention, providing good information in return). This study helps to further uncover the

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29 Throughout this essay (and the following essay in chapter 4) we refer to two types of transmitters: initial transmitters and retransmitters. Initial transmitters have direct experience with the product that they are talking about and are sharing their own opinion with others (for example, someone who had purchased and used an MP3 player). Retransmitters, on the other hand, have not directly experienced the product but have instead heard about it from someone else. Thus when they talk about a product, they are passing on another person’s opinion (or others’ collective opinion). Note a person can be in both roles. Rather, the distinction applies to different transmission occasions that a person might be in.
motivational processes that drive WOM transmission behaviors, which, we find, are neither straightforward nor singly-determined.

Across these three studies we find that (1) the main reasons for transmitting WOM are predominantly transmitter-focused and associated with transmitters using social capital embedded in their social relationships, (2) the importance placed on these reasons by transmitters is related to the types of recipients that they actually choose to talk to, (3) characteristics of recipients and the relationships they have with transmitters are strong drivers of transmitters’ decisions of who to (and who not to) transmit information to, and (4) the underlying reasons for transmitting WOM, and hence the types of recipients that comprise one’s preferred “audience,” lie in transmitters wanting to use (but not necessarily build) social capital, but the type of use depends on whether people are sharing their own opinions (“initial transmission”) or passing on others’ opinions (“retransmission”). Initial transmitters use their social capital to give themselves a receptive audience for them to air their opinions with a high chance of being listened to. Retransmitters instead use social capital to obtain (but not contribute) new information from recipients and recipients’ social networks. Thus, initial transmitters appear to talk for the sake of talking (and try to avoid being ignored), and retransmitters talk in order to get fresh information in return.

The essay proceeds as follows. First, we review relevant literature and consider how selective transmission is related to consumers’ needs for using and/or building social capital in their social networks. Second, we describe the transmission process, social capital-related motivations, and potential drivers of transmitters’ recipient selections in
detail. Third, we present the results from three studies. Finally, we discuss implications of the results.

4.2 **Background**

4.2.1 **Previous Research on Word-of-Mouth**

Often WOM is studied in relation to its consequences rather than its determinants. Previous research has established the importance of WOM as a driver of new product diffusion (e.g., Arndt 1967; Brooks 1957; Czepiel 1974), examined the influence of referrals and recommendations on consumption (e.g., Brown and Reingen 1987; Reingen and Kernan 1986), and modeled WOM as a driver of innovation diffusion processes (e.g., Goldenberg, Libai, and Muller 2001). WOM is an important component in sociologists’ models of social contagion (Coleman, Katz, and Menzel 1957; Katz and Lazarsfeld 1955; Watts 2002), and facilitates the flow of information in social networks (Frenzen and Nakamoto 1993). Some research has also suggested that WOM—or social contagion—effects have been overstated (Van den Bulte and Lilien 2001). Recently, researchers have examined Internet-based WOM and its effects on product success (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004, 2008), the role of WOM in spreading public opinion over social networks (Stephen and Berger 2009; Watts and Dodds 2007), consumers’ susceptibility to social persuasion (Zemborain and Johar 2007), recipients’ evaluations of WOM transmitters (Gershoff, Mukherjee, and Mukhopadhyay 2007), and factors that influence how much recipients are impacted by WOM (Stephen and Lehmann 2009). Our focus, however, is on determinants—not consequences—of WOM.
transmission. Further, unlike much of the previous work, we study WOM at the individual level.

### 4.2.2 Selective Transmission

A number of factors could affect the probability that person i transmits a message to person j, \( p_{ij} \). First, it may be costly to transmit WOM, which would reduce \( p_{ij} \). Here we do not consider transmission costs since they are often negligible (e.g., it is relatively easy and costless to, for example, send an email or a text message to someone, or to have a conversation in a social setting). Second, external factors might encourage or discourage information sharing. For example, if a piece of information has negative externalities such that the utility a consumer derives from it declines as the number of other consumers who possess it increases, telling others about it is not in one’s self-interest (Frenzen and Nakamoto 1993). Third, the possibility of deriving social benefits (or incurring social costs) could motivate or demotivate WOM transmission. As briefly described above, social benefits are associated with a consumer’s social capital, the resources embedded in social ties (Bourdieu 1986). These ties can facilitate individual and group actions (Coleman 1990), and can be seen as investments in social relations with expected future returns (Lin 2001). If information is valuable, sharing it with others can strengthen relationships and build social capital. Sharing worthless or questionable information, however, may deplete social capital.

While transmitting WOM can lead to potential social benefits, it can also involve some risks (e.g., if the information is unwanted, irritating, or incorrect). Whether or not
these risks turn into negative consequences largely rest upon the recipient (e.g., a negative consequence of spreading WOM could be that a recipient does not listen or does not find the message interesting). Thus, consumers’ WOM transmission behaviors likely involve a consideration of associated benefits and risks with potential recipients in mind, since recipients’ responses to a transmission determine whether the transmitter receives a social benefit or incurs a social cost from sharing information. As such, unless all potential recipients are identical, this should, in most cases, result in selective transmission.

Taking selectivity one step further, work on WOM and social learning in economics assumes that individuals’ WOM behaviors are deliberate (Banerjee and Fudenberg 2004; Ellison and Fudenberg 1995) and linked to utility functions (López-Pintado and Watts 2008). Further, Burt’s (1992) theory of structural holes describes how social capital is a function of individuals’ “brokerage” opportunities in a social network (e.g., brokering the flow of information between others). If social capital is built by taking advantage of such opportunities, then WOM transmission decisions can possibly be construed as strategic. Notwithstanding, we do not take a strong position on whether transmitters are simply selective or socially strategic.

4.2.3 Transmissions over Social Ties

A social network is a set of individuals (“nodes”) and relationships between them (“ties”). Social ties vary in terms of their strength (e.g., “strong” for friends and “weak” for acquaintances), and are opportunities for information to be shared or exchanged
(Sahlins 1972). When a consumer transmits product information to another person, the social tie between them is *activated*; whether they transmit is represented by the probability $p_{ij}$.

Consider Figure 8. Person 1 is the *initial transmitter*. Suppose that person 1 just saw a new movie and really liked it (the *information* or opinion). Person 1 is connected to persons 2, 3, ..., $N$, and thus has $N - 1$ opportunities for sharing this information with members of his or her immediate social network (ego-network). Person 1 therefore selects whom he or she will transmit the information to (i.e., *who to tell*). Suppose that person 1 believes that only person 4 will satisfy their social needs, and thus only activates the person 1—person 4 tie. Assuming that they have not seen the movie, person 4 then becomes a potential *retransmitter* who can choose which friends and acquaintances to *retransmit* (i.e., pass on) person 1’s information to. This process continues until people stop retransmitting. Transmission decisions are thus important to flows of information.

**Figure 9: Word-of-Mouth Transmission over a Social Network**
Past research in consumer behavior and marketing has studied tie activation in social networks (e.g., De Bruyn and Lilien 2007; Frenzen and Nakamoto 1993). For instance, Brown and Reingen (1987) and Reingen and Kernan (1986) found that while strong social ties are more likely to be used, weak ties are important for bridging gaps in a social network. Studies based on cellular automata simulations of WOM over strong and weak ties find similar results (Goldenberg et al. 2001), as does the “strength of weak ties” literature in sociology (Granovetter 1973, 1983). In general, it seems that people have a preference for talking to strong tied friends (“strong tie bias”) when sharing information (Frenzen and Nakamoto 1993). Whether this is because people have more frequent contact with strong-tied friends than with weak-tied acquaintances or because friends are explicitly preferred is not clear.

Past individual-level WOM research on tie activation has neither experimentally examined consumers’ interrelated decisions to transmit to multiple people, nor associated observed transmission behaviors with social network tie characteristics. The related literature in sociology on social contagion, social influence, and information cascades (e.g., Coleman et al. 1957; Katz and Lazarsfeld 1955; Watts 2002) tends to mostly focus on the relationships between social structure and aggregate contagion or diffusion outcomes, placing less emphasis on individuals’ motivations to transmit information to others. Some work in marketing has examined the role of the social context on consumer behavior, although not from a social networks perspective (Fisher and Price 1992).
4.2.4 Social Capital and Social Needs as a Motivation to Transmit

Transmitting information or opinions (i.e., activating social ties) depends on the transmitter’s motivation to talk about or share information (Frenzen and Nakamoto 1993; Granovetter 1973). Sahlins (1972) sees WOM transmissions as social exchanges that require that the transmitter receive something in return for sharing information with a recipient, and WOM exchanges likely involve at least some self-interest-seeking on the transmitter’s part (Frenzen and Nakamoto 1993; Homans 1961). If this is the case, then WOM transmission amounts to using existing relationships for some gain or personal benefit. Further, to the extent that a transmitter’s social capital is embedded in these relationships, transmitting WOM then effectively involves using or leveraging social capital in the pursuit of some social benefits.

What kinds of benefits do transmitters hope to receive in consideration for them sharing information or opinions with recipients? We consider three types of social capital-related benefits that, in theory, could motivate transmission behavior: using transmissions to (1) get attention from others (e.g., being listened to, feeling like others are taking notice of one’s opinion), (2) solicit or seek information from others (e.g., to obtain “fresh” information on a topic, to validate existing, but uncertain, information), and (3) build upon one’s existing social capital (e.g., strengthening relationships, doing favors, increasing the span of one’s social influence or reputation). Of course, WOM transmissions could also be purely altruistic, though the altruistic act of sharing valuable information with someone still could positively affect the relationship and therefore have a social capital-building benefit.
4.3 Conceptual Framework and Overview of Studies

Recall that our primary goals are to understand why people transmit WOM (i.e., underlying motivations and reasons), and to whom they are more likely to transmit WOM under certain transmission situations (i.e., initial transmission versus retransmission). These research questions are addressed with three studies that touch on different aspects of these questions. A summary of our conceptual framework and the parts of it addressed by each study is in Figure 9.

Figure 10: Conceptual Framework

Based on the preceding theoretical discussion, particularly about social capital and motivations for WOM transmission, we focus on characteristics of recipients and the relationships between transmitters and recipients as key determinants of WOM
transmission behaviors. Basically, if transmitters are hypothesized to be driven by the possibility of deriving various social needs or benefits then recipients should play a major role, since it is the recipients who provide these benefits (whether or not they realize it—that is, that whether or not recipients’ responses are deliberate—is not important here).

4.3.1 Recipient and Relationship Characteristics

Fit and Receptivity. We now describe the characteristics of interest: fit, receptivity, connectivity, and tie strength. First, recipients must be open and receptive to information from the transmitter. A receptive recipient is a “likely listener.” We consider two dimensions of a recipient’s receptiveness: how well the information fits with or is aligned with the recipient’s interests (fit, from good to poor), and how receptive the recipient is expected to be to the transmitter’s information based on past experiences with that recipient (receptivity, from high to low). While receptive recipients are probably always desired by transmitters, we hypothesize that they will be particularly important for transmitters who are trying to use their social capital simply in order to express their opinions and receive attention (e.g., if you want to stand on a soap box you had better have a receptive audience). While it is always unpleasant to not be listened to, it is particularly unpleasant to have one’s own opinion ignored.

Connectivity. Second, we consider the transmitter’s perception of how well connected (many versus few ties) potential recipient are (connectivity from well connected to poorly connected). The connectivity can be important when transmissions are done in order to get information back from recipients. People with many connections
(and ideally outside of one’s own network of associates; i.e., “bridges” or “boundary spanners” or “brokers” in network parlance) should, on average, have access to more and—importantly—“fresher” information than people with few connections. Spreading information within one’s own immediate social neighborhood has limited benefits, and information can become stale in such situations (Granovetter 1973). Hence, if a transmitter’s goal is obtain new or validating (or both) information from recipients reciprocally then recipient connectivity could be important. We hypothesize that this will be particularly important for some retransmitters because the information they currently possess and are transmitting is not based on their own experiences and therefore they might want to use the WOM exchange as a way to qualify or elaborate on this information.

*Tie Strength.* Finally, the strength of the relationship between a transmitter and each potential recipient (*tie strength*, from strong to weak) may also play a role in driving transmission behaviors and choices of recipients. Tie strength is a common social network characteristic that has been studied extensively in previous work on WOM in marketing (e.g., Brown and Reingen 1987; De Bruyn and Lilien 2007; Frenzen and Nakamoto 1993; Goldenberg et al. 2001; Stephen and Lehmann 2009). Previous research has documented a “strong tie bias” where people tend to concentrate more on their closer friends when sharing information (Frenzen and Nakamoto 1993), even though the benefits of having weak ties have been extensively studied (cf. Granovetter 1973, 1983). From a social capital perspective, and in particularly when considering how transmitters might stand to benefit from WOM transmissions, talking to friends (strong ties) could be
beneficial because friends are more likely to listen and more likely to reciprocate by
giving information to the transmitter.

In terms of social capital, assuming that tie strength and the amount of embedded
social capital in the tie are positively correlated, a reason for transmitting over strong ties
is that if one wants to leverage their social capital then there is simply more capital built
up when the tie is stronger. Thus, a preference for transmitting over stronger ties is
consistent with intentions to use social capital. Conversely, preferring to transmit over
weaker ties is consistent with an intention to instead build social capital (e.g., giving
valuable information to an acquaintance is one way to strengthen the relationship). In a
consumer setting, however, this is less likely. For example, Frenzen and Nakamoto
(1993) showed that consumers were willing to share valuable information about limited
(scarce) deals with friends, but not with acquaintances. Thus, we hypothesize a general
“strong tie bias” among transmitters of product-related information, which further implies
a preference for using rather than building social capital in consumer settings.

Other Factors. We also consider whether the information being transmitted is
either favorable or unfavorable (valence). Although information characteristics can effect
consequences or impacts of WOM (e.g., Chevalier and Mayzlin 2006; Stephen and
Lehmann 2009), it is not clear what effect, if any, they have on transmission. Moreover,
there is an ongoing debate over the nature of message valence effects on WOM (see East,
Hammond, and Lomax's [2008] meta-analysis). We control for valence in our studies in
case it does have an effect, but it is not of theoretical interest to us.
4.3.2 Overview of Studies

In each study we look at the role of recipients in the transmission decision process. In Study 1, using participants’ recollections of actual WOM transmissions that they did and their reasons for doing so, we develop a general typology of reasons for transmitting WOM. We then examine the links between transmission reasons and recipient and relationship characteristics; that is, we see how the importance placed by transmitters on various reasons for transmission affect the characteristics of chosen recipients. Note that in Study 1, recipient and relationship characteristics are measured, not manipulated (they are the dependent variables of interest).

In Study 2 we look at the link between these characteristics and recipient selection; that is, how does the probability of transmission vary as a function of recipient and relationship characteristics. We are particularly interested in whether or not these effects vary between initial transmission and retransmission. This should help us see whether different motives are at play. In Study 2 we manipulate recipient and relationship characteristics and use a hypothetical WOM transmission scenario instead of having participants recall actual transmissions.

Finally, in Study 3 we look at transmitters’ perceptions of how recipients with different characteristics will respond when they receive information via WOM. Specifically, we see what social benefits transmitters expect different recipients to provide if talked to (e.g., likelihood of paying attention, likelihood of offering valuable/useful information in return). This study builds on Study 2 by examining the
underlying link between recipient and relationship characteristics (which we again manipulate) and the various social benefits discussed above.

4.4 **Study 1: Transmission Reasons**

4.4.1 **Design and Procedure**

One hundred ten students participated in this study as part of a larger laboratory session. We manipulated between-subjects type of transmitter (initial transmitter or retransmitter), and randomly assigned participants to one of these two conditions. Participants were asked to recall and describe a recent time that they transmitted WOM about a movie.\(^{30}\) Initial transmitters thought of when they had talked about a movie that they had personally seen, and retransmitters thought of when they had talked about a movie they had not seen and only had heard about from others. Participants gave details of the movie (title, lead actors) and described the conversation (including writing the first name of the recipient to make this recall task more concrete and vivid). Only one participant failed to provide sufficient details (e.g., the actors named were not in the stated movie), and was dropped. We are confident that the other 110 participants were involved in the task. Importantly, participants reported on *real* movies and *actual* WOM transmissions between themselves and their own friends or acquaintances (i.e., we used a “critical incident” approach).

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\(^{30}\) Throughout this essay we use movies because participants are very familiar with them and they are a common conversation topic (thus making it easier for participants to place themselves in the various scenarios used). Movies (and television shows) have also been used in previous WOM research (e.g., Godes and Mayzlin 2004; Liu 2006).
4.4.2 Measurement

This study’s main purpose was to identify reasons or motives for transmitting WOM. We gathered data on reasons in two ways. First, we used an open-ended item where we asked participants why they told this particular person about this movie and what motivated them to do this. Second, later in the study after some intervening questions, we presented participants with 14 possible reasons for transmitting WOM and had them rate how important each reason was in motivating them to talk to the given recipient about the particular movie on five-point scales (1 = “not at all important” to 5 = “extremely important”). We generated these 14 items based on the previously discussed social capital-related motivations, as well as by thinking of any other reasons that were not necessarily theory-based but might have been plausible (e.g., transmitting WOM to make “small talk”).

We content-analyzed the open-ended responses and found extremely high correspondence between the types of reasons written down and our scale items. We therefore used the data on the scale items in our analysis (see Table 11 for the items, and below for factor analysis details). Only one of the original 14 items was not represented in the open-ended responses (“To surprise them”), and was therefore dropped from subsequent analysis.
Table 11: Measures of Transmission Reasons

<table>
<thead>
<tr>
<th>Reason (Factor)</th>
<th>Items</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seeking Information</td>
<td>1. I wanted to see what this person thought about this movie.</td>
<td>.78</td>
</tr>
<tr>
<td></td>
<td>2. I wanted to see if they agreed with my opinion about this movie.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. I hoped that they would then share their knowledge about movies with me.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4. I wanted to impress this person with my taste in movies.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5. I wanted to tell them so that I could say that I had talked about this movie.</td>
<td></td>
</tr>
<tr>
<td>Giving Information</td>
<td>6. They gave me some information previously, so I was returning the favor.</td>
<td>.64</td>
</tr>
<tr>
<td></td>
<td>7. To help them choose a movie to watch/see.</td>
<td></td>
</tr>
<tr>
<td>Socially Expressing Strong Opinion</td>
<td>8. I just had to tell someone about this movie.</td>
<td>.65</td>
</tr>
<tr>
<td></td>
<td>9. I had a strong opinion about this movie, so I talked about it.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10. I wanted to let this person know that I had seen this movie.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>11. I thought they would be interested in my opinion about this movie</td>
<td></td>
</tr>
<tr>
<td>Making Small Talk</td>
<td>12. I wanted an excuse to start a conversation with them.</td>
<td>.90</td>
</tr>
<tr>
<td></td>
<td>13. To make small talk.</td>
<td></td>
</tr>
</tbody>
</table>

We measured characteristics of the recipients and of the transmitter’s relationship with their recipient (as dependent variables). Our items were designed to capture recipient/relationship characteristics (fit, receptivity, connectivity, tie strength). We measured fit by having participants rate their actual recipient on six five-point Likert scales (1 = “strongly disagree” to 5 = “strongly agree”) with items such as “This person has good taste in movies” and “This person is interested in movies.” The items were designed to capture recipient expertise and interest in movies, and they loaded on a single
factor (variance explained = 67%, $\alpha = .85$; we took the mean as a a single measure of recipient fit). Receptivity, which is more straightforwardly defined than fit, required just one five-point Likert-scaled item ("This person usually listens to what I have to say about movies."). Likewise, connectivity was also straightforward and required just one five-point Likert-scaled item ("This person talks to lots of other people."). For tie strength, following Marsden and Campbell (1984), we used three five-point items for relationship type (one item: increasing in personal intimacy from stranger to spouse/partner) and frequency of discussion (two items: about movies, and about general topics). All three items loaded on a single factor (variance explained = 68%, $\alpha = .75$).

4.4.3 Results

Typology of Transmission Reasons. We factor-analyzed the 13 reason items and recovered four factors that accounted for 65% of the variance. The groups of items under each factor, along with reliability statistics are reported in Table 11.\textsuperscript{31} The four factors reflect the following reasons for transmitting WOM: (1) to seek information from others ("seeking information"), (2) to give information to others ("giving information"), (3) to express one’s opinion on a product or topic for social self-presentation purposes ("socially expressing opinions"), and (4) to make small talk ("making small talk").\textsuperscript{32} We

\textsuperscript{31} The factor analysis was performed over all 110 observations, not by between-subjects condition. When checked for each condition no differences were found in the factor structures across conditions.

\textsuperscript{32} Although making small talk is not theoretically interesting, we included the small talk items to mitigate potential demand effects that could arise had we only given participants reasons with deliberate motivations (e.g., to give information to others). The open-ended question and the correspondence between our items and the responses to the open-ended question also help to mitigate demand concerns.
took means of the items in each factor to create single items for each reason. The scores ranged between 1 and 5 and a higher score on a reason means that, according to that transmitter, the reason was a more important or stronger reason for their reported WOM transmission. The means for these reasons across the four conditions are reported in Table 12. A multivariate analysis of variance to compare the means on these four reasons across the between-subjects conditions found no significant differences ($F(4, 103) < 1, p = .76$).

Table 12: Means for Strength of Transmission Reason

<table>
<thead>
<tr>
<th>WOM Transmission Reason Factor</th>
<th>Seeking Information</th>
<th>Giving Information</th>
<th>Socially Expressing Strong Opinion</th>
<th>Making Small Talk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transmission, Unsolicited</td>
<td>2.41</td>
<td>2.90</td>
<td>3.46</td>
<td>2.44</td>
</tr>
<tr>
<td>Retransmission, Unsolicited</td>
<td>2.26</td>
<td>2.52</td>
<td>2.72</td>
<td>2.09</td>
</tr>
<tr>
<td>Initial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transmission, Solicited</td>
<td>2.41</td>
<td>2.52</td>
<td>3.04</td>
<td>2.05</td>
</tr>
<tr>
<td>Retransmission, Solicited</td>
<td>2.50</td>
<td>2.78</td>
<td>3.19</td>
<td>2.31</td>
</tr>
</tbody>
</table>

*Linking Reasons to Recipient and Relationship Characteristics.* We next examined whether the strengths of different transmission reasons were associated with different recipient and relationship characteristics (per our conceptual framework in
Figure 9). The four measured recipient/relationship characteristics (fit, receptivity, connectivity, tie strength) were regressed on the reason importance scores (factors) in a multivariate (seemingly unrelated) regression. In separate regressions (estimated simultaneously with the primary regressions of characteristics on reasons) we specified reverse-causality effects (i.e., regressing the reasons on the characteristics), which helped to reduce estimation bias due to endogeneity. This approach substantially improved the fit of the model over a model that did not control for such reverse effects.

We summarize our results in Table 13. The main finding, irrespective of the specific nature of the effects, is that there are links between transmission reasons and recipient/relationship characteristics. This indicates that reasons for spreading WOM do shape the kinds of recipients that transmitters select, and supports our claim that transmitters are at least somewhat selective. The effects of reasons on recipient/relationship characteristics differed across between-subjects conditions, so for ease of presentation in Table 13 results from separate regressions, one for each condition, are reported.

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33 A multivariate model was used because of potential endogeneity among the regressors, particularly reverse-causality (i.e., just as reasons can influence characteristics of recipients, characteristics of recipients might have influenced reasons, particularly since we only observe transmissions that occurred and not all transmissions that could have also occurred but did not). Thus, a system of regression equations allowed us to control for these potential sources of endogeneity that could bias parameter estimates. See Hartmann et al. (2008) for a discussion the use of multivariate models for handling endogeneity.

34 For the sake of brevity, parameter estimates are not in Table 3. They are available upon request from the authors.
Table 13: Effects of Strength of Transmission Reasons on Recipient Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variables: Recipient, Relationship Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recipient fit with the topic</td>
</tr>
<tr>
<td>Initial Transmission (system $R^2 = .22$)</td>
<td>Give (-)</td>
</tr>
<tr>
<td>Retransmission (system $R^2 = .49$)</td>
<td>Seek (+)</td>
</tr>
</tbody>
</table>

Notes: (1) Seek = seek information, Give = give information, Opinion = socially express opinion. (2) All effects are significant at $p < .05$. In each regression (column) effects of Seek, Give and Opinion were estimated. If not listed it means that the effect was not significant in that regression. (3) The signs of the effects are in parentheses.

For initial transmission we found that the less importance placed on giving information, the better the chosen recipient’s fit with the movies topic ($b = -.20, t = -2.14, p < .05$) and the better connected there were ($b = -.32, t = -2.79, p < .01$). We also found that the less importance placed on seeking information, the higher the recipient’s receptivity was ($b = -.40, t = -2.82, p < .01$), and the more importance placed on expressing one’s opinion, the stronger the transmitter—recipient tie was ($b = .28, t = 2.28, p < .05$). Thus, when initial transmitters select recipients who are “likely listeners” (good fit or high receptivity or strong tie, or a combination of these attributes), the underlying reasons seem to be more about wanting to express one’s opinions and not wanting to give information to, or obtain information from, the recipient.

For retransmitters the pattern of results was quite different. We found that the more importance placed on both seeking information and expressing one’s opinions, the more likely it was that recipients were a good fit (seek: $b = .28, t = 1.97, p = .05$; opinion:
\( b = 0.22, t = 3.11, p < 0.01 \), and that their ties to the transmitters were stronger (seek: \( b = 0.48, t = 4.02, p < 0.001 \); opinion: \( b = 0.29, t = 4.62, p < 0.001 \)). Thus, when retransmitters select recipients who possess “likely listener” characteristics (here, good fit or strong tie), they seem to be doing so because they are seeking information and wanting to socially express their own opinions.

### 4.4.4 Discussion

The main purpose of this study was to identify some general types of reasons for transmitting WOM, which we found to be the following: (1) giving information, (2) seeking information, (3) socially expressing opinions, and (4) making small talk. Although unlikely exhaustive, the combination of open-ended data and scale data suggests that these reasons are fairly comprehensive and representative (and they have face validity). Clearly, WOM transmission is not only about giving information to others, but it also includes giving information in order to obtain information and using transmission simply as a “soap box” upon which to stand when wanting to socially express one’s opinions.

These reasons relate to social capital. Seeking information uses the social capital embedded in existing ties to get information or to check existing information with others. Giving information is a way to build social capital (e.g., by increasing the chances of the recipient reciprocating later by providing the transmitter with information) or to maintain/reinforce existing social capital (e.g., giving information to a friend is a way to keep that friendship alive). Social expressions of opinions is associated with using social
capital to secure an audience. Finally, although less important, making small talk also has social capital implications: not making at least some attempt to have a conversation with someone can damage the health of that relationship.

A particularly interesting finding from this study is that initial transmitters' recipients' characteristics seem to be affected by wanting to express opinions and explicitly not wanting to give or seek information, whereas retransmitters' recipients' characteristics are related to seeking information and wanting to express opinions. In light of our previous discussion on social capital-related drivers of WOM transmissions, it seems that initial transmitters just want to express their opinions (e.g., in order to get attention), whereas retransmitters express their opinions to help them get information from recipients (i.e., hoping for reciprocity). It appears that both initial transmitters and retransmitters use their social capital, but in different ways.

Note that these findings, although they have face validity, might only apply for WOM about movies. We chose movies for this study because they are something that people tend to talk about, thus making this recall task easier for participants. However, this of course means that the findings might not generalize to other product categories. A potential downside of using movies is that a lot of movie-related WOM occurs prior to a movie's release, and largely depends on the pre-release advertising budget for a given movie. While none of the movies that our participants reported transmitting WOM were pre-release (i.e., all were movies that had already been widely released; some were even in home video/DVD release when the study was conducted), it is possible that movies with more upfront advertising are talked about for different reasons to movies with less
upfront advertising (e.g., highly-publicized blockbusters might get talked about for different reasons to indie or art-house films with little to no advertising or publicity). Unfortunately, all but very few of the movies our participants listed talking about were “studio” films that had pre-release advertising and publicity, which does not permit an empirical comparison between these types of movies. This in itself is an interesting additional result: at least in this sample of individuals, talked-about movies tend to be well-known studio films. Had people talked about lesser-known films the “give information to others” transmission reason would have likely been more prevalent. At least in this study and for movies, it seems that people are more likely to pick topics that their recipients already know about, rather than talk about things that their recipients have not heard about. A possible reason for this is found in the next study: people like to talk to people who they think will listen to them. Selecting a topic that already has awareness among potential recipients is one way to increase the likelihood of being listened to.

4.5  Study 2: Drivers of Recipient Selection

4.5.1 Design and Procedure

The previous study showed that the types of recipients selected varied based on transmitters’ reasons for sharing information, and that the relative importance of these reasons varied depending on whether own information (initial transmission) or others’ information (retransmission) was being shared. In particular, initial transmitters and retransmitters were found to differ in how they used their social capital to fulfill certain personal needs. Study 1 therefore established a link between motivations for transmission
and recipient characteristics. However, only transmissions that took place were sampled and thus our data cannot speak to the characteristics of recipients and relationships that were not chosen by our participants. In this study we directly examine how characteristics of recipients and relationships affect choices of recipients from a set of potential recipients; hence, we see both chosen and not chosen recipients.

Two hundred students participated in exchange for either course credit or a nominal cash payment. Participants were randomly assigned to either an initial transmission or a retransmission condition. In this study we did not manipulate whether WOM was solicited or unsolicited to reduce the complexity of the experiment. Participants, assuming the role of a transmitter, were presented with a scenario that described a prerelease movie and asked participants to imagine having either seen this movie very recently at a preview screening (initial transmission) or heard about but not seen this movie (retransmission). Participants were told that their opinion of the movie was either positive or negative (valence; also manipulated between-subjects with random assignment). In the retransmitter condition a second nested factor was manipulated between-subjects: whether the opinion that participants received (and could then retransmit) is consistent with others’ opinions (consensus) or not (mixed).  

This “variance” (consensus vs. mixed opinions) factor was primarily introduced within the retransmitter condition for realism purposes. Since retransmitters are in possession of information received from other people, it could be the case that their tendency to pass-on this information depends on how certain they are in the information (see Dubois, Rucker, and Tormala 2009 and Stephen and Lehmann 2009 for discussions of certainty in attitudes and WOM). Directly manipulating this variance factor (instead of letting participants infer it) allowed us to control for this. As it turned out, this factor did not affect participants’ retransmission behaviors in this experiment.
factorial. Irrespective of whether participants were initial transmitters or retransmitters, they had to imagine themselves in a social situation (e.g., at a social gathering, or at the office) potentially transmitting WOM about this movie to people who they know (i.e., friends or acquaintances, but not strangers).

They were asked to imagine themselves in a scenario describing WOM transmission in a marketing context (i.e., sharing product information or opinions with friends or acquaintances in social settings such as at school, work, or a party). The scenario described a new movie that the participants were told to imagine having seen recently at a preview screening (initial transmitter condition) or a new movie that they had not seen but had heard about from friends/acquaintances (retransmitter condition). This general scenario is also used in Study 2. In a pretest, a separate group of respondents found this scenario believable and easy to relate to.

Participants were then presented with a list of 16 potential recipients (presented in randomized order), generated by a $2^4$ full factorial of recipient and relationship characteristics: (1) fit (good “likes movies” or poor “dislikes movies”), (2) receptivity (high “typically listens to your opinions” or low “does not typically listen to your opinions”), (3) connectivity (high “knows a lot of people” or low “knows few people”), and (4) tie strength (strong “close friend” or weak “acquaintance”). Participants were told that they know these 16 people, and were asked to imagine a real person from their own life who fit each description to “make the task easier.”

36 A few participants wrote peoples’ names next to each profile; suggesting that the scenario was realistic and participants were involved. We neither asked nor encouraged participants to associated profiles with real people.
Participants then completed a conjoint-type repeated choice task. For each potential recipient, participants indicated whether they would “tell this person about the movie” or “not tell this person about the movie” (i.e., they made 16 binary WOM transmission decisions). Participants could select anywhere between zero and 16 potential recipients and making these choices involved no costs. This conjoint-type task is similar to the experiment used by Wuyts et al. (2004) to study managers’ preferences for business-to-business relationship ties.

4.5.2 Results

Evidence of Selective Transmission. We first examined how selective participants were as transmitters by looking at the number of the 16 potential recipients each participant decided to transmit to. Although obviously not a measure of true selectivity since this was a hypothetical experimental task, this nevertheless gives an indication of how selective participants were in this experiment. Initial transmitters selected an average of 8.1 out of 16 recipients to transmit to (51%; SD = 3.15).

Retransmitters selected an average 7.7 out of 16 potential recipients (48%, SD = 3.2; no difference between transmitter types, p = .40). Further, selectivity was not explained by transmitter characteristics (age, gender, propensity to talk about movies) or by manipulated message characteristics. While selectivity would be expected if transmissions were costly, participants faced no costs in this experiment.³⁷

³⁷ We expected that, in the experimental setting, the number of chosen recipients would be biased downwards since some participants might have felt that it would be inappropriate to select all (or almost
Recipient Selection: Initial Transmission. Consistent with Study 1, we find a number of differences between initial transmission and retransmission here. Accordingly, we report results for each type separately. Table 14 lists each potential recipient's profile and the percentage of participants who chose to transmit to each one (for both initial transmission and retransmission). Across all initial transmitters, 65% (36%) of strong (weak) tie targets, 71% (30%) of good (poor) message fit targets, 63% (38%) of high (low) receptivity targets, and 53% (48%) of high (low) connectivity targets were selected. Good fit, high receptivity, and strong tie strength significantly enhanced transmission likelihood, and connectivity also had a smaller impact. This result is consistent with classic social influence theory where transmitters select targets based on who they think will find their messages more relevant (suggesting a preference for good fit recipients; Festinger, Schachter, and Back 1963), and with past WOM transmission research that shows a preference for sharing information over strong ties (Frenzen and Nakamoto 1993).

_Recipients Selected:_

- Strong tie targets: 65% (36%)
- Good message fit targets: 71% (30%)
- High receptivity targets: 63% (38%)
- High connectivity targets: 53% (48%)

The fact that the mean number of recipients chosen is so far away from the maximum possible does suggest selective transmission.
Table 14: Average Initial Transmission and Retransmission Probabilities

<table>
<thead>
<tr>
<th>Tie Strength</th>
<th>Recipient Message fit</th>
<th>Recipient Receptivity</th>
<th>Recipient Connectivity</th>
<th>Initial Transmission</th>
<th>Retransmission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong</td>
<td>Good fit</td>
<td>High</td>
<td>High</td>
<td>100.0</td>
<td>97.6</td>
</tr>
<tr>
<td>Strong</td>
<td>Good fit</td>
<td>High</td>
<td>Low</td>
<td>97.3</td>
<td>94.4</td>
</tr>
<tr>
<td>Strong</td>
<td>Good fit</td>
<td>Low</td>
<td>High</td>
<td>78.1</td>
<td>69.8</td>
</tr>
<tr>
<td>Strong</td>
<td>Good fit</td>
<td>Low</td>
<td>Low</td>
<td>75.3</td>
<td>68.3</td>
</tr>
<tr>
<td>Strong</td>
<td>Poor fit</td>
<td>High</td>
<td>High</td>
<td>56.2</td>
<td>37.8</td>
</tr>
<tr>
<td>Strong</td>
<td>Poor fit</td>
<td>High</td>
<td>Low</td>
<td>53.4</td>
<td>43.3</td>
</tr>
<tr>
<td>Strong</td>
<td>Poor fit</td>
<td>Low</td>
<td>High</td>
<td>32.9</td>
<td>22.8</td>
</tr>
<tr>
<td>Strong</td>
<td>Poor fit</td>
<td>Low</td>
<td>Low</td>
<td>26.0</td>
<td>27.0</td>
</tr>
<tr>
<td>Weak</td>
<td>Good fit</td>
<td>High</td>
<td>High</td>
<td>71.2</td>
<td>80.3</td>
</tr>
<tr>
<td>Weak</td>
<td>Good fit</td>
<td>High</td>
<td>Low</td>
<td>69.9</td>
<td>11.1</td>
</tr>
<tr>
<td>Weak</td>
<td>Good fit</td>
<td>Low</td>
<td>High</td>
<td>42.5</td>
<td>43.7</td>
</tr>
<tr>
<td>Weak</td>
<td>Good fit</td>
<td>Low</td>
<td>Low</td>
<td>34.3</td>
<td>44.9</td>
</tr>
<tr>
<td>Weak</td>
<td>Poor fit</td>
<td>High</td>
<td>High</td>
<td>31.5</td>
<td>26.2</td>
</tr>
<tr>
<td>Weak</td>
<td>Poor fit</td>
<td>High</td>
<td>Low</td>
<td>23.3</td>
<td>19.7</td>
</tr>
<tr>
<td>Weak</td>
<td>Poor fit</td>
<td>Low</td>
<td>High</td>
<td>11.0</td>
<td>75.4</td>
</tr>
<tr>
<td>Weak</td>
<td>Poor fit</td>
<td>Low</td>
<td>Low</td>
<td>5.5</td>
<td>11.8</td>
</tr>
</tbody>
</table>

To further examine the data, participants’ 16 “tell” versus “not tell” choices were modeled with a repeated measures (random effects) binary logit model. The model estimated the effects of the four factors and their two- and three-way interactions on recipient choices, accounting for unobserved heterogeneity and correlated within-subject
choices (through a random, participant-specific intercept). The factors were effects-coded (-1, +1). The model fit the data well (hit rate = 81.6%), and parameter estimates are reported in Table 15.

All four main effects of recipient characteristics are significant and positive (as suggested in Table 14), and the effect of connectivity is much smaller than the others. Neither of the two significant interactions (fit × tie strength, fit × tie strength × receptivity) included connectivity, further indicating its limited importance to initial transmitters' selections of recipients. An initial transmitter is most likely to transmit to recipients for whom the information is a good fit, who have been receptive in the past, and who are friends rather than acquaintances. Initial transmitters seem to mostly want to talk to people who are "likely listeners." We also find a tie strength × fit interaction.

From Table 4, initial transmitters have an average transmission probability of 94.7% to "likely listener" (good fit, high receptivity) friends compared to a 70.6% probability for "likely listener" acquaintances. Initial transmitters are extremely likely to talk to people who are almost guaranteed to listen: friends who have an interest in the topic and have a track record of receptivity.

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38 A four-way interaction was also tested, but was non-significant and removed from the model reported here.

39 An alternative model is a random coefficients binary logit model with participant-specific parameters (from a normal heterogeneity distribution). This was explored using a hierarchical Bayes model (see Rossi, Allenby, and McCulloch 2005). We found relatively low levels of heterogeneity among participants at the parameter level. Moreover, we got results that were qualitatively identical to those found with the simpler random effects binary logit model. Accordingly, we report results from, and base our findings on, the simpler random effects model.
**Table 15: Drivers of Initial Transmission and Retransmission**

<table>
<thead>
<tr>
<th>Effects</th>
<th>Initial Transmission (A)</th>
<th>Retransmission (B)</th>
<th>Comparison of (A) with (B)*</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Main Effects:</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall intercept</td>
<td>.21 (.251)</td>
<td>.22 (.221)</td>
<td>n/a</td>
</tr>
<tr>
<td>Tie strength (strong/weak)</td>
<td><strong>1.14</strong> (.122)</td>
<td>.93** (.089)</td>
<td>Not different</td>
</tr>
<tr>
<td>Fit (good/poor)</td>
<td><strong>1.47</strong> (.123)</td>
<td><strong>1.22</strong> (.087)</td>
<td>Not different</td>
</tr>
<tr>
<td>Receptivity (high/low)</td>
<td><strong>1.02</strong> (.122)</td>
<td>.55** (.087)</td>
<td>A stronger**</td>
</tr>
<tr>
<td>Connectivity (high/low)</td>
<td>.23** (.107)</td>
<td>.81** (.082)</td>
<td>B stronger**</td>
</tr>
<tr>
<td>Valence (positive/negative)</td>
<td>-.04 (.329)</td>
<td>-.05 (.250)</td>
<td>Not different</td>
</tr>
<tr>
<td>Consensus/mixed opinions</td>
<td>n/a</td>
<td>.08 (.250)</td>
<td>n/a</td>
</tr>
<tr>
<td><em>Two- and Three-Way Interaction Effects:</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tie strength × Fit</td>
<td><strong>.29</strong> (.118)</td>
<td>.89** (.087)</td>
<td>B stronger**</td>
</tr>
<tr>
<td>Tie strength × Receptivity</td>
<td>.15 (.118)</td>
<td>.82** (.086)</td>
<td>B stronger**</td>
</tr>
<tr>
<td>Tie strength × Connectivity</td>
<td>-.03 (.091)</td>
<td><strong>-.20</strong> (.074)</td>
<td>B stronger</td>
</tr>
<tr>
<td>Fit × Receptivity</td>
<td>.23 (.118)</td>
<td>.59** (.083)</td>
<td>B stronger**</td>
</tr>
<tr>
<td>Fit × Connectivity</td>
<td>-.03 (.093)</td>
<td>.35** (.082)</td>
<td>B stronger**</td>
</tr>
<tr>
<td>Receptivity × Connectivity</td>
<td>-.03 (.089)</td>
<td><strong>.38</strong> (.078)</td>
<td>B stronger**</td>
</tr>
<tr>
<td>Tie strength × Fit × Receptivity</td>
<td><strong>.28</strong> (.121)</td>
<td>.36** (.089)</td>
<td>Not different</td>
</tr>
<tr>
<td>Tie strength × Fit × Connectivity</td>
<td>.10 (.107)</td>
<td><strong>.38</strong> (.078)</td>
<td>B stronger</td>
</tr>
<tr>
<td>Tie strength × Receptivity × Connectivity</td>
<td>.09 (.107)</td>
<td><strong>.26</strong> (.080)</td>
<td>B stronger</td>
</tr>
<tr>
<td>Fit × Receptivity × Connectivity</td>
<td>.04 (.107)</td>
<td><strong>.77</strong> (.084)</td>
<td>B stronger**</td>
</tr>
</tbody>
</table>

*Random Effects Variance Components:*

| Var(Intercept) (between-subject variance) | **1.53** (.38) | **1.14** (.24) | **1.48** (.22) |

*Model Fit Statistics:*

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of transmitters</td>
<td>73</td>
<td>127</td>
<td>200</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-3,084</td>
<td>-5,764</td>
<td>-8,846</td>
</tr>
<tr>
<td>Percentage of choices correct</td>
<td>81.6%</td>
<td>81.4%</td>
<td>n/a</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01. Statistically significant estimates are in **bold**. Significance tests are based on F-tests of partial fixed effects, df num = 1, df den = 1080 for initial transmitter and df den = 1882 for retransmitter. Variables having fixed effects are effects-coded (-1, +1).

a Parameter estimates reported with standard errors in parentheses.

b Comparison based on estimating the model on the pooled dataset with a dummy variable (1 = initial transmission, 0 = retransmission) and estimating additional interaction terms for all of the fixed effects crossed with this indicator. Fit reported for this model. Overall test for model difference: $\chi^2(14) = 158.32, p < .001$. 
Additional insights can be gained by examining recipient-specific transmission probabilities. The estimated transmission probability is 96% when the recipient is a friend and a good fit. When the recipient is only a good fit or a friend but not both, the probabilities fall to 57% and 41%, respectively (both not significantly different from the 51% base rate). By comparison, the transmission probability for a recipient that is an acquaintance and a poor fit is 11%. High receptivity further strengthens the message fit effect to the point where adding high receptivity to a strong tie and good fit results in near-certain (99%) selection. Interestingly, we also find “interchangeable” effects between tie strength and receptivity, conditional on fit being good: as long as there is good fit, either a strong tie or a high receptivity recipient will be associated with a high transmission probability. Regardless, it seems that the most important factor driving initial transmission probabilities, good fit, must be present for initial transmission.

**Recipient Selection: Retransmission.** The estimates for the random effects binary logit for retransmission recipient selection choices are also reported in Table 15 alongside the initial transmission model (reception model hit rate = 81.4%). As mentioned above, the drivers of retransmission differ from the drivers of initial transmission (overall Wald test for difference: $\chi^2(14) = 158.32, p < .001$). On average, 58% (39%) of strong-tied (weak-tied) targets, 64% (33%) of good (poor) fit targets, 51% (45%) of targets with high (low) receptivity, and 56% (40%) of well (poorly) connected targets were selected for

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40 Since we estimated initial transmission and reception models separately in the interests of simplicity, to determine if an effect was significantly different between these two models we used a single (pooled) logit model and added a “transmission type” factor which we interacted with every other effect. For each effect that this interaction was significant we concluded that the effects differed across transmission type. The overall difference test reported here is a Wald test of the null hypothesis that all effects are the same between transmission types. This was clearly rejected.
retransmission. Here fit and tie strength have the strongest effects. The effect of fit, however, is slightly weaker here than for initial transmission, and likewise for the effect of receptivity. Hence, the two characteristics most associated with driving initial transmission are less dominant for retransmission.

The most interesting effects on retransmission compared with initial transmission are related to the greatly increased effect of recipient connectivity under retransmission (as a main effect and through interactions. Comparing the average transmission probabilities in Table 14 helps to highlight the role of connectivity here. Consider two recipient profiles that are acquaintances (weak tie), are a poor fit, and have low receptivity (the bottom two rows of Table 14). They only differ in terms of their connectivity (high versus low). For initial transmission, neither of these potential recipients were frequently selected (11% selection for the high connectivity profile, 5.5% selection for the low connectivity profile). However, 75.4% of retransmitters selected the high connectivity person versus only 11.8% for the low connectivity person. It appears that simply being well connected made an otherwise unappealing recipient worth talking to for the majority of retransmitters.

A similar contrast is seen even when the recipient is a “likely listener” (good fit, high connectivity) but is an acquaintance (weak tie) rather than a friend (strong tie). When this type of person has low connectivity the retransmission probability is low (11.1%), but when they have high connectivity the retransmission probability is high (80.3%). Such a large difference is not observed for these recipients under initial transmission, however (69.9% versus 71.2% initial transmission probabilities). These two
contrasts underscores the importance of recipient connectivity to retransmitters, since a similar pattern was not observed for initial transmitters.

### 4.5.3 Discussion

Two main findings come from this study. First, initial transmitters seem to want to transmit only to those people who are “likely listeners,” and are largely unconcerned with how socially connected their potential recipients are. Second, retransmitters, while also having a preference for transmitting to “likely listeners” (albeit weaker), appear to consider potential recipients’ connections and prefer to transmit to people who are more socially embedded.

These tendencies are consistent with the patterns of transmission reasons found in Study 1. If a transmitter is mostly concerned with having their opinions listened to, probably because they are seeking social attention, then they will want to transmit to “likely listeners,” who seem to be people who have good fit, high receptivity and/or are a strong tie. Initial transmitters were most likely to select recipients with these characteristics in this study. In Study 1 we saw that, for initial transmitters, these characteristics (and these particular levels) were associated with strong desires to express one’s opinions and strong desires to not give or seek information. Combining these results, initial transmitters seem to be using social capital just to get their voices heard.

Retransmitters, however, are different. If a transmitter is also concerned with recipient connectivity and prefers to talk to recipients who are well connected in their social networks (i.e., have many friends) then reasons for transmission are not only about
fulfilling a need for attention and being listened to. Transmitting to well connected recipients could be for two reasons: to attempt to build social capital (and reputation) by hoping that one's opinions will spread more widely through the recipient to his or her associates; or to use social capital not to have a convenient and receptive audience but rather to seek or obtain information. This latter possibility is about seeking information from people who are likely to have valuable and “fresh” information. Well connected people, by virtue of having many associates, are exposed to (on average) more sources of information and therefore might be seen as information “hubs” who, if your aim is to get new information (or validate existing information), you will want to talk to.

Clearly, since connectivity appears to be important to retransmitters’ recipient choices, one of these two possible explanations is likely. The results of the current study cannot disentangle the building versus using social capital mechanisms, but the results of Study 1 offer some guidance. For retransmitters in Study 1 we found that “likely listener” recipients were closely associated with a strong dual desire to express one’s opinions and to seek information. This more closely aligns with retransmitters using their social capital and sharing opinions with well connected recipients, hoping they will reciprocate by giving the retransmitter new information. Hence, it appears that people retransmit to people who will listen to them and who are well connected because these people (1) are likely knowledgeable on the topic, and (2) are likely to have access to various information sources and therefore are well positioned to provide information. Note that it is essential that retransmitters still want to express their opinions because something is needed to trigger the reciprocal flow of information from the recipient.
4.6 Study 3: Expected Social Benefits from Transmission

4.6.1 Design and Procedure

A key assumption of the above discussion is that people, when in the role of transmitter, consider recipients’ characteristics and, at least indirectly, are selective of targets. Both previous studies support this. However, if these transmitters are selective then it must be the case that they expect transmitting to certain recipients—conditional on recipient and relationship characteristics—to allow them to derive benefits, or help them to fulfill certain needs. We examine this in relation to previously-discussed social needs. Specifically, we try to link recipient/relationship characteristics to of the fulfillment of different social capital-related needs.

Twenty-eight students participated in this study as part of a larger laboratory session. These participants were from the same population used in the previous two studies. Participants were randomly assigned to either an initial transmitter or a retransmitter condition, and were presented with ostensibly the same scenario about WOM transmission and movies that we used in Study 2. However, instead of choosing who they would talk to about this movie, participants completed the conjoint-type task (2^4 recipient profiles, same as in Study 2) by rating expected outcomes of transmissions to each of the 16 potential recipients. Four types of expected outcomes (benefits) were considered, framed as how a recipient would likely react if transmitted to: (1) “they would pay attention,” (2) “they would give an informed response,” (3) “the existing relationship would improve,” and (4) “they would spread this information broadly.”
These expectations of what recipients would do map (respectively) to needs for attention, seeking information, and building social capital (3 and 4).

We used only eight items to measure these four outcomes since the rating task was burdensome. "Would pay attention" was measured by agreement with two five-point Likert-scaled items: “This person would listen to me,” and “I would influence this person’s opinion about this movie” (1 = “strongly disagree” to 5 = “strongly agree”). These items’ correlation was .70 (p < .001). "Would give an informed response” was also assessed by agreement with two five-point Likert-scaled items: “This person would have an informative response,” and “This person would in return give me good information” (1 = “strongly disagree” to 5 = “strongly agree”). The correlation between these items was .77 (p < .001). "Would improve the existing relationship” was measured by agreement with a single five-point Likert-scaled item: “Telling this person would improve our friendship” (1 = “strongly disagree” to 5 = “strongly agree”). And "Would spread information broadly” was measured by agreement with two five-point Likert-scaled items “This person would pass-on my opinion to many others,” and “Telling this person would improve my reputation as a source of information about movies” (1 = “strongly disagree” to 5 = “strongly agree”), and by one seven-point item “If you were trying to have your [this] opinion spread beyond your friends and acquaintances and out to people who you do not know, how effective would this person be to help start the process?” (1 = “very ineffective” to 7 = “very effective”). The Cronbach’s alpha for these three items was .84. The measurement structure was confirmed by a factor analysis, and we created measures for the expected transmission outcomes by averaging the appropriate items.
4.6.2 Results

The four expected outcomes were regressed on the four experimentally manipulated recipient and relationship characteristics. Since we had 16 ratings on each outcome for each participant we used a random effects model to account for the panel structure of the data (we estimated one model per outcome; i.e., dependent variables were treated separately). We estimated main effects of fit, receptivity, connectivity, tie strength and transmission type (initial vs. retransmission), and the four transmission type × recipient characteristics interactions.

The main effects of fit and receptivity were positive and significant for all expected outcomes ($ps < .01$). For example, good fit recipients were expected to pay more attention than poor fit recipients, and high receptivity recipients were expected to provide more information in return than low receptivity recipients. This is not surprising since good fit and high receptivity were consistently important drivers of recipient choice in Study 2. Also, well connected recipients are expected to be better than poorly connected recipients at spreading information broadly ($p < .01$), as it obviously should (but connectivity does not affect the other three expected outcomes). Interestingly, increased tie strength seems to only matter for increasing relationship strength under initial transmission (type × tie strength interaction, $p < .05$).

We are particularly interested in the interactions between transmitter type and the “likely listener” characteristics (fit and receptivity). Given the results already reported, it seems that initial transmitters are users of the social capital embedded in their existing relationships because they want to be listened to; that is for receiving attention from
others. Retransmitters, on the other hand, are social capital users in the sense that they transmit in order to get information from the recipient in return. If this is the case then in the current study we should expect the effects of fit and/or receptivity on expectations of receiving attention to be more strongly positive in the initial transmitter condition, and the effects of fit and/or receptivity on expectations of receiving an informed response to be more strongly positive in the retransmitter condition. These interactions were indeed found (type × receptivity interaction for attention, \( p < .01 \); type × fit interaction for information, \( p < .05 \)).

4.6.3 Discussion

The results of this third study provide conceptual replications of the importance of recipient fit and receptivity in driving WOM transmissions or, specifically here, expectations of desirable social capital-related benefits that recipients can provide transmitters. More critically, these results support our distinction between initial transmitters and retransmitters in terms of their underlying motivations. Interestingly, while both initial transmitters and retransmitters appear to be selective in their recipient choices (as demonstrated here by differences in expected outcomes as a function of recipient characteristics, and as demonstrated more directly in studies 1 and 2), and both seem to want to use their social capital, why they use their social capital appears to differ depending on whether they are sharing their own opinions or passing on someone else's opinions.
4.7 General Discussion

4.7.1 Theoretical Contributions

This essay's aim was to better understand why and to whom consumers transmit WOM about products. Despite the prevalence of WOM, its increasing importance with the emergence of online social networking, user-generated content and social media, and the rich body of extant literature on WOM in marketing and on social contagion in sociology, there have been few studies that have looked at the underlying processes that drive transmission behaviors.

Across the three studies we found that (1) the main reasons for transmitting WOM are predominantly transmitter-focused and associated with transmitters using social capital embedded in their social relationships, (2) the importance placed on these reasons by transmitters is related to the types of recipients that they actually choose to talk to, (3) characteristics of recipients and the relationships they have with transmitters are strong drivers of transmitters’ decisions of who to (and who not to) transmit information to, and (4) the underlying reasons for transmitting WOM, and hence the types of recipients that comprise one’s preferred “audience,” lie in transmitters wanting to use (but not build) social capital, but the type of use depends on whether people are sharing their own opinions (“initial transmission”) or passing on others’ opinions (“retransmission”).

Theoretically most interesting is this motivational and behavioral distinction between initial transmitters and retransmitters. Despite both types of transmitter using the social capital embedded in their existing social relationships to derive some social benefits for themselves, the nature of these benefits was very different. Initial transmitters
use their social capital to give themselves a receptive audience for them to air their opinions with a high chance of being listened to. Retransmitters instead use social capital to obtain (but not contribute) new information from recipients and recipients’ social networks.

In general, this finding and the related findings here demonstrate that the underlying processes that drive consumers’ WOM transmission behaviors are neither simple, straightforward, nor necessarily singly-determined. Rather, as we show, the underlying processes or drivers of WOM transmission differ according to the specific type of transmission and, in particular, whether own opinions are being shared or others’ opinions are being passed on. Direct versus indirect product experience, therefore, turns out to be a critical moderator of the WOM transmission process. Interestingly, we found very little (if any) evidence to suggest that transmitters have altruistic intentions; instead it seems that transmitters are largely self-focused.

Also interesting is the finding that initial transmitters—people who are telling others about their own, direct experiences with a product—do this just to be listened to or to get their opinions “off their chests” and not, for instance, to try to spread influence or impact others’ attitudes and behaviors. In fact, the impact of WOM on consumers’ attitudes and behaviors may be merely a side-effect of self-indulgent transmission behaviors. This is intriguing when considered in light of phenomena such user-generated content and social media, where regular consumers contribute ratings and reviews (and related content) to websites such as Amazon.com and Yelp.com. Based on our findings it
seems that such actions are driven by consumers wanting to help themselves rather than wanting to provide information to benefit others.

Finally, an important aspect of this essay is the conceptualization of WOM transmissions as deliberate decisions where transmission probabilities vary within-transmitter based on recipient characteristics, and are driven by social needs associated with either using or creating social capital. We do not claim that consumers always engage in deliberate, conscious decision processes as WOM transmitters. In fact, using WOM transmissions to fulfill social needs may be an instinctive, unconscious process (and one that warrants further research).

4.7.2 Limitations and Future Research

The current work is of course not without its limitations. First, in two out of three studies we used experimental data on hypothetical conversations about a hypothetical movie. Given our research questions, in particular our focus on the role of recipient characteristics in driving WOM transmission, experiments where we could exogenously determine these key variables were necessary and appropriate. We did, however, have one study (Study 1) where actual transmissions between real people formed the basis of our data, and the findings in that study were compatible with the other two studies’ findings. Also, the comparative lack of external validity in these studies was tolerable given that our scenarios depicted realistic and relatable situations. Similar scenario-based conjoint experiments have been used in the marketing literature with success (e.g., Wathne et al. 2001; Wuyts et al. 2004). Nonetheless, obviously it would be desirable to
unobtrusively examine actual WOM in a real context. An observational study that examines peoples’ WOM transmissions in both offline and online contexts would be a very interesting direction for future research to take.

Second, we only considered one-shot transmissions. It would be interesting to see what happens when information can be repeatedly transmitted to the same set of people; that is, studying the dynamics of WOM transmissions and social capital.

Finally, the focus was on what motivates consumers to activate network ties for WOM transmission, controlling for opportunity (participants were effectively structurally equivalent with the same ego-networks), ability (participants had the same information), and information content (messages were fixed). Future work should allow some or all of these to vary. Hopefully this work will encourage work on these and other related topics.
Is Anyone Listening? Modeling the Impact of Word-of-Mouth at the Individual Level
5.1 Introduction

Understanding the drivers and consequences of WOM has become a major research stream in marketing (e.g., Chen and Xie 2008; Chevalier and Mayzlin 2006; Frenzen and Nakamoto 1993; Godes and Mayzlin 2004, 2008; Goldenberg, Libai, and Muller 2001; Liu 2006; Stephen and Berger 2009; Watts and Dodds 2007). This research is closely related to current work on viral marketing and buzz marketing campaigns, which rely on consumers spreading information via WOM, increasingly through electronic means (e.g., De Bruyn and Lilien 2007; Godes and Mayzlin 2008), as well as the burgeoning stream of research on social networks in marketing contexts (e.g., Goldenberg, Han, Lehmann, and Hong 2009; Iyengar, Valente, and Van den Bulte 2008; Katona and Sarvary 2008; Nair, Manchanda, and Bhatia 2006; Stephen and Toubia 2009; Trusov, Bucklin, and Pauwels 2007; Van den Bulte and Joshi 2007).

Much of the extant marketing literature on WOM focuses on aggregate impacts of WOM on diffusion, new product adoption, or product sales (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Goldenberg, Libai, and Muller 2001). This literature, however, sheds less light on the underlying processes that drive consumers’ WOM transmission and reception behaviors, or how WOM impacts individual consumers’ attitudes and behaviors. Although these processes are likely to be complex and probably are multiply-determined, an individual- and process-level understanding of WOM impact is necessary given the increasing prevalence of WOM and related phenomena (e.g., user-generated media and social media) in the marketplace. This essay attempts to address
these issues and aims to gain a greater understanding of the processes through which product-related WOM affects consumers’ attitudes and behaviors.

While WOM transmission is obviously a necessary condition for potential impact, whether or not that information impacts those individuals who are exposed to it is more important. Surprisingly, much of the individual-level WOM research in marketing focuses almost exclusively on transmission (e.g., Dubois, Rucker, and Tormala 2009; Frenzen and Nakamoto 1993). This research examines, for example, factors that make people more or less likely to pass information on to their friends or more or less likely to give advice or recommendations to others. A similar disproportionate focus on transmission is found in related literatures on contagion models in fields such as biology, epidemiology, physics, and sociology (cf. Castellano, Fortunato, and Loreto 2007; Dodds and Watts 2004; Watts 2002), and is implied in agent-based and cellular automata models for diffusion of innovations and new products in marketing (e.g., Goldenberg et al. 2001; Watts and Dodds 2007).

This essay takes a different approach. We consider the drivers of WOM reception and, consequently, the impact that WOM has on recipients. The impact of WOM on recipients’ attitudes and purchase intentions is modeled as a function of transmitter (“source;” e.g., credibility, experience), message (e.g., valence, tone), and transmitter—recipient relationship (e.g., tie strength) characteristics. In addition to considering relationships where recipients and transmitters are friends or acquaintances, we also consider the case where the transmitter and recipient are strangers. People are frequently exposed to WOM from strangers (and sometimes in fact seek WOM from strangers),
partly due to the abundance of user-generated content and social media on the Internet (e.g., online product reviews on Amazon.com). Additionally, we consider not only the dispositional component of attitude (e.g., perceived product quality, liking of a product) but also the certainty with which this disposition or opinion is held (as a second—but not necessarily secondary—component of attitude).

Our overarching goal is twofold. First, we seek to understand the potentially complex drivers of WOM impact, which include several transmitter, transmitter—recipient relationship, and message characteristics. Second, we aim to develop a model of WOM impact where impact is a consequence of an attitude updating process. With these goals in mind, we address the following three research questions: (1) what makes people more or less likely to listen to WOM from others (i.e., WOM reception as a necessary precondition for WOM impacting a person’s attitudes), (2) what are the main drivers of WOM impact on recipients’ attitudes and subsequent behaviors, and finally, (3) which combinations of transmitter, relationship, and message characteristics have stronger versus weaker impacts on recipients’ attitudes and behaviors?

To preview our findings, two studies demonstrate that (1) how WOM changes disposition and certainty (as different attitude components) is not the same and depends on a relatively complex pattern of determinants, (2) changes in both disposition and certainty affect consumers’ intentions to purchase a product, and (3) intriguingly, WOM from strangers in some cases can be as impactful as WOM from friends and acquaintances. More generally, in the same spirit as recent (and controversial) work challenging the long-held belief that a small number of “opinion leaders” or “key
influentials” are responsible for causing social epidemics and new products “taking off” (Watts and Dodds 2007), our findings suggest that under the right conditions it may be possible for almost anyone to have at least a moderately impactful influence as a transmitter. The key lies in how WOM impacts recipients’ certainty: even if a transmitter cannot directly change a recipient’s opinion on a product (disposition), they might be able to change the certainty that a recipient has in their existing opinion (and this can be enough to impact purchase intentions). Thus, looking at WOM impact in terms of changes in both disposition and certainty is essential.

This essay is organized as follows. In section 5.2 we define WOM reception, delineate potential drivers of reception, and discuss issues associated with measuring and modeling WOM impact. We then present the results of two studies. First, in section 5.3 we examine whether individuals would be willing to listen to different WOM sources of information (i.e., receive information), which is a necessary condition for WOM impact. Second, in section 5.4 we model WOM impact as an attitude-updating process and test this with a study in which attitudes before and after being exposed to information via WOM are measured and then related the transmitter, message, and relationship characteristics. Finally, in section 5.5 we conclude with a discussion of our findings, their implications, and directions for future research.

5.2 Word-of-Mouth Reception versus Word-of-Mouth Impact

In many diffusion and contagion models, a person adopts a product with some nonzero probability after being exposed to another person who already has adopted the
product or who is talking about it (e.g., Goldenberg et al. 2001). Does mere exposure to a social source of information, however, constitute WOM reception? Such a view of reception is likely problematic because it assumes that exposure to information is sufficient for reception.

A different way to think about WOM reception is in terms of the extent to which the transmitted information impacts the target. In this case, a target is said to have received a message if the information impacts or changes their attitudes (e.g., toward a particular brand or product). While exposure is a necessary condition, it is not sufficient. We assume that once a message has been transmitted to a target, there are two parts to the target's reaction: first, a binary reception decision (i.e., do I listen to this person or not?), and second, conditional on “listening,” attitude updating.41

The amount that a recipient’s attitude toward a brand or a product is changed or updated is related to how much they believe in the message; i.e., its overall credibility. This, we argue, is likely to be a function of characteristics of the transmitter (e.g., source credibility), the message itself (e.g., how it is delivered), and the nature of the social tie between the transmitter and the recipient (if there is one). Importantly, a message may, instead of changing a recipient’s disposition, change the certainty with which that disposition is held. This is consistent with the “mean-variance” approach in utility theory and financial decision-making. The inclusion of the certainty component also relates to

41 A change in a target’s attitudes may also induce changes in their behavior as another part of their reaction; for now we focus on attitude change, and consider behaviors later.
the important role of confidence in consumer decision-making and behavior featured in
the Howard and Sheth (1969) model of buyer behavior.

5.2.1 Impact as Attitude Updating

Attitude updating and change has been studied by social psychologists for
decades, with persuasive communication cast as a major driver of attitude change (e.g.,
Hovland, Janis, and Kelley 1953; Hovland, Harvey, and Sherif 1957; Petty and Cacioppo
1986). In this literature the effectiveness of a communication is measured by how much
attitude change it induces. Our approach to WOM reception extends this perspective by
explicitly considering two components of an attitude: the dispositional part and the
certainty (or confidence) with which this disposition is held (see also Dubois, Rucker,
and Tormala 2009).

Both disposition and certainty can change over time, either in response to explicit
“communication” such as WOM, or without outside stimulation (e.g., attitudes might
diminish in strength over time, or regression-to-the-mean effects might change attitudes;
we do not consider such causes here). A person’s attitude toward a brand at time $t - 1$ is
their “prior” attitude. This attitude consists of disposition toward the brand (e.g., how
much they like it, how high quality they think it is) and certainty with which disposition
is held (e.g., how sure they are in liking the brand, or how confident they are in their
perception of quality).
Suppose that at time $t$ this person is exposed to information about a brand via WOM. What will their attitude be at time $t+1$? There are four possibilities or "classes" of impact:

- **Class 1.** No impact: disposition and certainty do not change;
- **Class 2.** Disposition changes, but certainty does not;
- **Class 3.** Disposition does not change, but certainty does; and,
- **Class 4.** Both disposition and certainty change.

A main focus of the empirical work in this essay lies in understanding which class a given message from a given transmitter is likely to fall into. We also examine how the amount of WOM impact differs across these classes.

### 5.2.2 Drivers of Word-of-Mouth Impact

Recipient (target), transmitter (source), message, and transmitter—recipient relationship characteristics are potential drivers of attitude change. An obvious transmitter characteristic is credibility as a source of information about a given product (for a review see Pornpitakpan 2004). Sources that are perceived to be more credible, not surprisingly, have been found to be more persuasive. In a WOM context, greater persuasive ability could translate into WOM having greater impact on attitudes. Experts, for example, may have a stronger impact on recipients' attitudes than novices. Similarly, WOM from people who have used a product may have a stronger impact on recipients' attitudes toward that product than WOM from people who have not used it.
In terms of message characteristics, we consider two that may influence WOM impact: the valence of the message, i.e., whether it is positive or negative, and whether the tone of the message is emotional or impassioned versus being more matter-of-fact. Tone may impact attitudes which have an affective basis, and many product-related attitudes tend to have affective content (cf. Agarwal and Malhotra 2005; Allen, Machleit, Kleine, and Notani 2005; Breckler 1984; Lavine, Thomsen, Zanna, and Borgida 1998; Ostrom 1969). Interestingly, valence, an obvious message characteristic, has produced mixed findings on its effect in the WOM literature (see, for example, East, Hammond, and Lomax [2008] and Godes and Mayzlin [2004]).

Lastly, we consider the strength of the relationship between the transmitter and the recipient. Typically only WOM from known transmitters is considered. Such individuals can be either “strong” ties (e.g., close friends) or “weak” ties (e.g., acquaintances), consistent with definitions in the social networks literature (Granovetter 1973; Marsden and Campbell 1984). Strangers, or “ambiguous sources” (Naylor, Norton, and Poynor 2008), as we argued above, are also worth examining. Thus, we include them in Study 2.

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42 Note that the difference between the message and a recipient’s prior attitude is also a plausible message characteristic (e.g., messages that are very similar to one’s prior might not have as much impact as messages that are very different). Though plausible, in this paper we only use situations where potential recipient’s attitude priors are relatively neutral, corresponding to cases where consumers are exposed to WOM about products for which they hold no meaningful prior attitudes (e.g., really new products).
5.3 Study 1: Word-of-Mouth Reception

5.3.1 Overview

Before directly examining how the previously described factors influence WOM impact in Study 2, we first consider the simple—but often overlooked and often implicit—binary reception or “listening” choices that recipients make as a necessary (but not sufficient) condition for impact on recipients’ attitudes.

We focus on transmitter characteristics as signals of source credibility since more credible transmitters are more likely to be listened to, which in turn should make their messages more impactful (Katz and Lazarsfeld 1955). Whether a message is received or not depends on how valuable a recipient finds the message, with this perception of value being positively related to transmitter credibility.

If person $i$ transmits information about a brand to person $j$, then we define the probability that person $j$ in fact listens to this message as $q_{ij}$. In this study we model $q_{ij}$ as a function of transmitter, message and relationship characteristics. We experimentally manipulated transmitter credibility using three factors (different signals of credibility): whether or not the transmitter has first-hand experience with the focal product category (experience/expertise), whether or not the transmitter is a good judge of product quality in that category (taste), and how socially “well connected” the transmitter is (which may signal credibility because being more connected should, on average, mean that the transmitter has access to more sources of information). For message characteristics we manipulated valence (positive versus negative sentiment expressed by the transmitter
about the product). For relationship characteristics, we manipulated whether the transmitter and recipient strongly ("friends") or weakly ("acquaintances") connected.

5.3.2 Procedure and Design

We used a conjoint-style repeated choice experiment, similar to those used previously to study WOM- and network-related choices in marketing (e.g., Frenzen and Nakamoto 1993; Wathne, Biong, and Heide 2001; Wuyts et al. 2004). Transmitter and relationship characteristics were manipulated within-subject, and message characteristics were manipulated between-subjects. One hundred twenty-seven students participated in this study.

Participants were given a scenario based on a pre-release fictitious movie that they had neither heard about nor seen (lack of knowledge of this movie was confirmed by a pretest in which no one reported knowledge of it). The participants were told to imagine themselves in a social situation (e.g., at a party or at the office socializing with colleagues) and were then presented with 16 distinct profiles of transmitters whom participants were told had talked about this movie to them. The transmitters were described on four characteristics: tie strength (strong/"close friend" or weak/"acquaintance"), experience ("seen the new movie themselves" [at a preview] or "heard about the new movie" indirectly from someone else), taste in movies ("good" or

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43 Pretests of the scenario suggested that it was reasonable and believable. We selected movies because consumers are both familiar with them and tend to discuss them with others. Previous WOM studies have examined movies and television shows for similar reasons (e.g., Godes and Mayzlin 2004; Liu 2006). Subjects reported that they found it easy to place themselves into the scenario that was presented to them.
bad), and social connectivity ("knows many people" or "knows few people"). For each of these profiles, participants were asked whether they would "listen to" or "not listen to" what that person had to say about the movie. Between-subjects message valence (positive or negative) was varied. Since participants, as recipients, were hypothetically exposed to WOM from sixteen transmitters we additionally varied, also between-subjects, whether the transmitters' opinions about this movie were largely consistent or were diverse/mixed.

Thus, our experiment was a mixed design with a 2 (valence) x 2 (consistency) between-subjects factorial. Nested within each of these conditions was a 2 (tie strength) x 2 (connectivity) x 2 (taste) x 2 (experience) within-subject full factorial. The dependent variable was the binary "listen" or "not listen" choice for each transmitter. We analyzed these data with a random effects logit model, with participant random effects controlling for repeated choices within-subject.

5.3.3 Results

Participants listened to an average of 7.3 out of 16 transmitters (46%; s.d. = 2.8). Overall, 53% (39%) of the transmitters who were strong (weak) ties, 57% (35%) of experienced (inexperienced) transmitters, 72% (20%) of transmitters with good (poor) taste in the movies category, and 49% (43%) of well (poorly) connected transmitters would be listened to (see Table 11). All the differences except for connectivity were significant at the .05 level.
Table 16: Average Reception Probabilities (Study 1)

<table>
<thead>
<tr>
<th>Tie Strength</th>
<th>Transmitter Experience</th>
<th>Transmitter Taste</th>
<th>Transmitter Connectivity</th>
<th>Percentage of Subjects Receiving (“Listen”)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong</td>
<td>Direct</td>
<td>Good</td>
<td>High</td>
<td>99.2</td>
</tr>
<tr>
<td>Strong</td>
<td>Direct</td>
<td>Good</td>
<td>Low</td>
<td>93.7</td>
</tr>
<tr>
<td>Strong</td>
<td>Direct</td>
<td>Poor</td>
<td>High</td>
<td>36.2</td>
</tr>
<tr>
<td>Strong</td>
<td>Direct</td>
<td>Poor</td>
<td>Low</td>
<td>34.9</td>
</tr>
<tr>
<td>Strong</td>
<td>Indirect</td>
<td>Good</td>
<td>High</td>
<td>68.5</td>
</tr>
<tr>
<td>Strong</td>
<td>Indirect</td>
<td>Good</td>
<td>Low</td>
<td>59.8</td>
</tr>
<tr>
<td>Strong</td>
<td>Indirect</td>
<td>Poor</td>
<td>High</td>
<td>21.3</td>
</tr>
<tr>
<td>Strong</td>
<td>Indirect</td>
<td>Poor</td>
<td>Low</td>
<td>13.4</td>
</tr>
<tr>
<td>Weak</td>
<td>Direct</td>
<td>Good</td>
<td>High</td>
<td>78.0</td>
</tr>
<tr>
<td>Weak</td>
<td>Direct</td>
<td>Good</td>
<td>Low</td>
<td>74.8</td>
</tr>
<tr>
<td>Weak</td>
<td>Direct</td>
<td>Poor</td>
<td>High</td>
<td>22.8</td>
</tr>
<tr>
<td>Weak</td>
<td>Direct</td>
<td>Poor</td>
<td>Low</td>
<td>13.4</td>
</tr>
<tr>
<td>Weak</td>
<td>Indirect</td>
<td>Good</td>
<td>High</td>
<td>56.7</td>
</tr>
<tr>
<td>Weak</td>
<td>Indirect</td>
<td>Good</td>
<td>Low</td>
<td>41.7</td>
</tr>
<tr>
<td>Weak</td>
<td>Indirect</td>
<td>Poor</td>
<td>High</td>
<td>12.6</td>
</tr>
<tr>
<td>Weak</td>
<td>Indirect</td>
<td>Poor</td>
<td>Low</td>
<td>8.7</td>
</tr>
</tbody>
</table>

Table 12 reports the parameter estimates from a logit model designed to predict which transmitters would be listened to. Transmitters with better taste and direct experience with the category were more likely to be listened to. Taste had a somewhat stronger effect than experience, meaning that one need not have direct experience with a product (i.e., in this case having seen the movie) to be perceived as credible. In addition,
experience and taste interacted with each other: experienced transmitters with good taste had a 93% chance of being listened to whereas inexperienced transmitters with good taste had a 59% chance (which is still greater than the base rate of 46%; \( p < .05 \)).

Table 17: Drivers of Reception (Study 1)

<table>
<thead>
<tr>
<th>Effects</th>
<th>Standardized Coefficient (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Main Fixed Effects:</strong></td>
<td></td>
</tr>
<tr>
<td>Overall intercept</td>
<td>-.13 (.12)</td>
</tr>
<tr>
<td>Tie strength</td>
<td>27.65** (3.76)</td>
</tr>
<tr>
<td>Transmitter experience</td>
<td>35.95** (3.78)</td>
</tr>
<tr>
<td>Transmitter taste</td>
<td>71.58** (5.33)</td>
</tr>
<tr>
<td>Connectivity</td>
<td>12.12** (2.57)</td>
</tr>
<tr>
<td>Valence of message(^a)</td>
<td>.21 (.23)</td>
</tr>
<tr>
<td>Consensus/mixed opinions(^a)</td>
<td>.39 (.22)</td>
</tr>
<tr>
<td><strong>Two- and Three-Way Interaction Fixed Effects:</strong></td>
<td></td>
</tr>
<tr>
<td>Tie strength ( \times ) Transmitter experience</td>
<td>11.41** (2.44)</td>
</tr>
<tr>
<td>Tie strength ( \times ) Transmitter taste</td>
<td>7.35** (2.75)</td>
</tr>
<tr>
<td>Tie strength ( \times ) Connectivity</td>
<td>-1.12 (2.08)</td>
</tr>
<tr>
<td>Transmitter experience ( \times ) Transmitter taste</td>
<td>14.36** (3.05)</td>
</tr>
<tr>
<td>Transmitter experience ( \times ) Connectivity</td>
<td>-1.60 (2.11)</td>
</tr>
<tr>
<td>Transmitter taste ( \times ) Connectivity</td>
<td>.76 (2.52)</td>
</tr>
<tr>
<td>Tie strength ( \times ) Transmitter experience ( \times ) Transmitter taste</td>
<td>7.14* (2.62)</td>
</tr>
<tr>
<td>Tie strength ( \times ) Transmitter experience ( \times ) Connectivity</td>
<td>1.49 (2.21)</td>
</tr>
<tr>
<td>Tie strength ( \times ) Transmitter taste ( \times ) Connectivity</td>
<td>3.18 (2.34)</td>
</tr>
<tr>
<td>Transmitter experience ( \times ) Transmitter taste ( \times ) Connectivity</td>
<td>1.41 (2.10)</td>
</tr>
</tbody>
</table>

**Random Effects Variance Components:**

| Var(Intercept) (between-individual variance) | .96** (.24) |
| Var(\( e_{oi} \)) (error variance)          | .90** (.03)  |

**Model Fit Statistics:**

| Number of individual actors | 127          |
| -2 Log-Likelihood           | 10373.29     |
| Percentage of choices correctly predicted | 83.3%        |

\(^* \ p < .05; ** \ p < .01\). Statistically significant estimates are in bold. Significance tests are based on \( F \)-tests of partial fixed effects, \( df_{num} = 1, df_{den} = 1890 \). Variables having fixed effects are effects-coded (-1, +1).\(^a\) These effects were dropped given their non-significance (their variances across individuals were also small, indicating minimal heterogeneity due to these attributes ).
The significant three-way interaction between tie strength, experience and taste suggests that a strong relationship (i.e., being friends) does not compensate for a lack of experience or taste. This further emphasizes the importance of transmitter credibility for reception; even friends tend to be ignored when they appear to lack credibility on the topic.

Finally, message consistency and valence did not significantly influence the probability of reception. Whether they influence the extent of WOM impact—given that reception occurs—is examined in the next study. Overall, this study suggests that transmitter and relationship characteristics indeed play an important role in determining the likelihood that a recipient will even listen to what a transmitter has to say.

5.4 Study 2: The Impact of Word-of-Mouth on Attitudes

5.4.1 Procedure and Design

In this study we examine how transmitter, message and relationship characteristics affect changes in a recipient’s disposition toward a brand and their certainty in this disposition. We hope to understand how the type of WOM impact (i.e., classes 1 to 4 outlined previously) varies as a function of these factors. Two hundred seventy-six subjects from a large online survey panel of undergraduate and graduate students (73% aged 18-25, 25% aged 26-34, and 2% above 35) participated in this study over the internet in return for entry in a cash lottery.

We again used a hypothetical but realistic WOM exposure situation. Participants were asked to imagine themselves shopping for an external hard drive for their computer.
We selected external hard drives because they are relatively important devices (e.g., for storing computer files, music and photo collections, and work) and should be subject to reasonably involved purchase decision making. Also, we did not want the majority of participants to have substantial expertise in the product category, since this could make it difficult to create attitude changes.

The scenario told participants that they were thinking about buying an external hard drive in order to store their important media and work files, and that when shopping one day they came across a display of them in a store. They were told to imagine that on this shopping occasion they were accompanied by two people: a strong tie “close friend” and a weak tie “acquaintance.” They were also told that the store had other customers—strangers—present. Participants were given information on two hard drive products, “Brand X” and “Brand Y.” While they were unfamiliar with these particular products, the products were in-stock, and apparently were suitable for their purposes. Each product was described on four apparently key attributes (storage capacity of 80 gigabytes, access time of 5,400 milliseconds, magazine endorsement as “editor’s choice”, and typical time to perform a full system backup of 60 minutes). They were identical on these attributes as well as price. No other information about these products was provided.

*Prior Attitude Measurement before Exposure to Word-of-Mouth.* The dispositional component of attitudes toward these products was operationalized as expected overall product quality. Quality is an appropriate basis for attitude in this category given the product’s utilitarian nature and purpose (i.e., to store and back-up

\[44\] The acquaintance was described to them as someone who they know but not very well.
computer data; Consumer Reports 2006). After reading the scenario and the basic (and intentionally uninformative) product information, participants rated the perceived quality of each brand on seven-point scales (1 = “very low quality” to 7 = “very high quality”). They also rated how certain they were about these quality ratings on seven-point scales (1 = “very uncertain” to 7 = “very certain”). As hoped, these priors were near the midpoint of the scales (mean = 4.71 for both measures). Purchase intent, measured on a seven-point bipolar scale (1 = “definitely buy X” and 7 = “definitely buy Y”), was also near the midpoint (mean = 3.95). Thus, as planned, the information used for forming prior attitudes and behavioral intentions was uninformative and non-discriminating between products and primed neutral attitudes toward, and indifference between, the products.

Exposure to Word-of-Mouth. We next exposed participants to WOM about brand X (and not brand Y). Between-subjects we manipulated transmitter, message and relationship characteristics through our description of from whom the message came and what they said.

For transmitter characteristics we used a single factor for credibility, expertise, with the message purportedly coming from either a computer science major (expected to have more category expertise) or a philosophy major (expected to have less category expertise). It is not uncommon for real transmitters to include some credibility information such as this about themselves in their messages, even if they are strangers to the recipient. We pretested this credibility manipulation on a sample of 34 people drawn
from a similar population (another online survey panel that had similar characteristics to
the one used in the main study) and found that the manipulation operated as intended.45

As a message characteristic we again varied valence. The message delivered was
“Brand X is good” (positive valence) or “Brand X is bad” (negative valence). Although
we did not find a valence effect on binary reception choices in Study 1, we are interested
in seeing whether message valence influences impact on attitudes. The tone of the
message was also varied. Messages were either emotional/impassioned or matter-of-fact.
Since subjects completed this task online in a text-based form (which is common for
WOM in online contexts), manipulating the tone of the message was a challenge. We
employed a subtle punctuation-based manipulation and held the text of the message
constant. For an emotional/impassioned tone, we ended the sentence with two
exclamation points (i.e., “Brand X is good!!” and “Brand X is bad!!”). For a more matter-
of-fact and less emotional tone we ended the sentence with a period (i.e., “Brand X is
good.” and “Brand X is bad.”). We expected this subtle tone manipulation would be
detected by our participants (mostly aged between 18 and 25, and all heavy Internet
users) because they tend to be sophisticated users of text messaging where punctuation
marks are known to profoundly change a message’s tone. This tone manipulation was
pretested alongside the transmitter credibility manipulation and operated as expected.46

45 The credibility manipulation was checked by asking “Who is likely to know more about computers, a
person with a college major in computer science or a person with a college major in philosophy?” (1 =
“computer science knows more” to 5 = “philosophy knows more”). The mean response was was 1.77 (s.d.
= .99), consistent with the desired effect of this manipulation.

46 Pretest participants were presented with a passage (supposedly text from an online product review) that
said that two products are good and liked (holding the actual text constant), but ended the statements about
For a transmitter—recipient relationship characteristic, as in Study 1, we used tie strength. However, unlike in study 1, in addition to “friends” (strong tie) and “acquaintances” (weak tie) we introduced a third level, “strangers” (no tie). When participants were given the message we told them it was from either their friend who was shopping with them, their acquaintance who was shopping with them, or another customer in the store who they did not know (not a salesperson).

To summarize, this study used a 3 (tie strength: stranger, weak, strong) × 2 (transmitter credibility: expert, novice) × 2 (message valence: positive, negative) × 2 (message tone: emotional/impassioned, matter-of-fact) between-subjects design. Participants were randomly assigned to one of the 24 conditions and the number of participants per condition was approximately equal.

**Attitudes after Exposure to Word-of-Mouth.** Participants’ post-WOM attitudes were measured using the same scales as before. We also again measured purchase intentions (1 = “definitely buy X” to 7 = “definitely buy Y”). Nothing other than the WOM exposure and manipulations of the factors of interest occurred between the prior attitude measurements and these attitude measurements. Thus, differences in reported attitudes can be attributed to the WOM manipulation.

---

one with two exclamation points instead of a period. Participants rated, on five-point Likert scales (1 = “strongly disagree to 5 = “strongly agree”), whether the person making the statements (“the reviewer”) was “passionate and excited about [the product].” The transmitter/reviewer was perceived as more passionate and excited about the product with the exclamation points than with the period (passionate mean = 3.38 for exclamation points versus 2.35 for period, \(t = 4.07, p < .001\); excited mean = 3.47 for exclamation point versus 2.27 for period, \(t = 4.86, p < .001\)). This was consistent with the planned effect of this subtle manipulation of message tone.
Attitude updating was computed accounting for the limitations of the interval measurement scales (see Appendix II). The results we report may be sensitive to the scale width, and we considered a number of options when designing this study. We ultimately decided to use seven-point measurement scales because they are commonly used in marketing practice to measure constructs such as brand attitudes and product perceptions, wide enough to allow for sufficient variation in responses, but not so wide that observed within-participant across-time changes in measures could be spurious and just due to random participant (response) error.47

5.4.2 Analysis Method

We did not use a simple regression model for four reasons. First, the dependent variables (changes in disposition and certainty), were represented as the proportion of a 0—1 scale (see Appendix II). We handled this by using conditional beta distributions on dependent variables.

Second, we have two dependent variables (changes in disposition and certainty) that are correlated \( r = .23, p < .001 \) and therefore should be modeled jointly. To deal with this we used a bivariate model, estimated endogenous effects (i.e., disposition

47 Consider the following example. Suppose we measured disposition and certainty on 0 to 100 scales, before WOM exposure a participant had a disposition score for Brand X of 55, and then after WOM exposure their disposition score for Brand X changed to 57. Is this two-point change diagnostic of a true change in their disposition (presumably attributable to WOM) or just some measurement error or noise? The wider the scale, the more difficult it is to determine whether small changes are true changes (a one point change on a 101-point scale is a movement along 1% of the scale). On narrower scales a change is more diagnostic: e.g., on a seven-point scale going from \( x \) to \( x+1 \) is a movement along 16.7% of the scale (one-sixth). Thus we had to balance competing needs of having a wide-enough scale to mitigate the potential for floor and ceiling effects and to allow for sufficient variation in responses, with having a narrow-enough scale to avoid this issue of small and potentially non-diagnostic, meaningless changes.
change affecting certainty change and vice versa), and also allowed for heteroskedasticity to be an explicit function of these endogenous effects (i.e., the beta dispersion parameters varied as a function of these dependent variables).

Third, there is a possibility of "excess zeros" (i.e., zero-inflation on one or both of the dependent variables, corresponding to no change in the respective attitude component). Zero changes could be caused by two different latent processes: (1) receiving the WOM but not being affected by it, and (2) not receiving the WOM (i.e., "tuning out" or ignoring the transmitter). We do not know which process occurs in each case, so we allow for zero-inflation by overlaying a mixture (latent class) model, similar to the zero-inflated Poisson or negative binomial models used for count data.\footnote{Note that if a variable is beta distributed then it theoretically can never equal 0. Empirically, this means that these two zero processes described here are identifiable because an observed zero change cannot technically be from a beta distribution. Conceptually, however, since we use a measurement scale an observed zero change really means that either there was actually perfectly zero change or a change that was too small to be detected by the scale (in some sense an infinitesimally small change).}

Fourth, we wanted to model the probability of each WOM impact class that we outlined above as a function of the experimental factors. To do this we specified link functions for the class probabilities that allowed these probabilities to vary as a function of covariates. An alternative would be to use a multinomial logit model (i.e., generalized logit) or discriminant analysis where the class probability (relative to a baseline class, e.g., the no impact class) is modeled as a function of covariates corresponding to the
transmitter, relationship and message factors. This would not, however, jointly model the
impact class and amount of impact, which is desirable.\footnote{Nevertheless, this simpler
approach should yield results about determinants of relative impact class
probabilities that are consistent with the integrated model. In additional analysis this was
indeed the case.}

Overall, this led to the development of a specialized bivariate zero-inflated beta (BZIB)
regression model for jointly modeling the class of WOM impact and the amount
of impact on two attitude dimensions. Although beta regressions, mixture models, and
zero-inflated models are commonly used, a generalized linear model that incorporates all
of these elements is less standard. Technical details are provided in appendices II and III.
This model allows us to estimate, simultaneously, the effects of the four experimental
factors (all 0/1 dummy variables) on (1) the WOM impact class probabilities, and (2) the
extent of updating of disposition and certainty. It also controls for endogeneity and
heteroskedasticity. Thus, this model allows us to identify the effects of interest and
consistently and robustly estimate the effects. Because preliminary OLS regressions
suggested that only main and two-way interaction effects existed, in the BZIB model we
estimated only main and two-way interaction effects. We also explored several different
specifications (and nested model fit comparisons).

5.4.3 Results

\textit{Preliminary Analysis.} Descriptive statistics are reported in Table 13. The average
absolute amount of updating of disposition toward brand X on the [0,1] scale was .19
(s.d. = .18). Approximately one-third of subjects did not update disposition at all, while
the maximum updating was .83. A very similar pattern was observed for updating of certainty in disposition toward brand X (mean = .19, s.d. = .21, 39% of cases with no certainty updating, maximum = .83). Interestingly, there was also significant (although less) updating for brand Y in the same direction even through it was never mentioned in the WOM, suggestive of a spillover effect.

Table 18: Descriptive Statistics (Study 2)

<table>
<thead>
<tr>
<th>Updating of Disposition ($y_{1i,2}$)</th>
<th>Brand X (focal product)</th>
<th>Brand Y (other product)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (standard deviation) on (0,1) scale</td>
<td>.19 (.18)</td>
<td>.10 (.13)</td>
</tr>
<tr>
<td>Percent of cases at 0</td>
<td>32.6%</td>
<td>54.4%</td>
</tr>
<tr>
<td>Maximum on (0,1) scale</td>
<td>.83</td>
<td>.67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Updating of Certainty in Disposition ($y_{2i,2}$)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (standard deviation) on (0,1) scale</td>
<td>.19 (.21)</td>
</tr>
<tr>
<td>Percent of cases at 0</td>
<td>39.1%</td>
</tr>
<tr>
<td>Maximum on (0,1) scale</td>
<td>.83</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Distribution of Word-of-Mouth Reception Cases ($c_{i,2}$)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1, no reception: $y_{1i,2} = 0, y_{2i,2} = 0$</td>
<td>17.7%</td>
</tr>
<tr>
<td>Case 2, only disposition changes: $0 &lt; y_{1i,2} &lt; 1, y_{2i,2} = 0$</td>
<td>21.4%</td>
</tr>
<tr>
<td>Case 3, only certainty changes: $y_{1i,2} = 0, 0 &lt; y_{2i,2} &lt; 1$</td>
<td>14.9%</td>
</tr>
<tr>
<td>Case 4, both change: $0 &lt; y_{1i,2}, y_{2i,2} &lt; 1$</td>
<td>46.0%</td>
</tr>
</tbody>
</table>
Almost half (46%) the participants updated both attitude components after being exposed to the message (class 4; see Table 13). Just over one-third (36.3%) of the participants fell into class 2 or 3, where only one attitude component was updated, and the remaining participants (17.7%) were in class 1 where there was no updating at all. This distribution of participants over these four classes suggests that using a mixture model is indeed appropriate and even necessary. Moreover, in approximately 45% of the cases where no disposition change is observed (classes 1 and 2), a certainty change was observed. Had we only observed disposition change (as is often the done in practice) and assumed that a zero change indicated no impact, then we would have been wrong almost half the time. This highlights the importance of examining not only direct attitudinal responses to WOM (i.e., disposition change) but also second-order or “meta-attitudinal” responses (i.e., certainty change).

**Model Fit.** We estimated the BZIB regression model using maximum likelihood techniques (see Appendix III for the likelihood function and other technical details). Despite model complexity (the full model had 85 estimable parameters), maximum likelihood estimation appeared to work well. Although not used here, Bayesian procedures would also be appropriate for estimating the parameters of this model. Model fit was examined on several dimensions.

The model, unsurprisingly, recovered the empirical distribution (i.e., $p_k$ for $k = 1, 2, 3$ and 4) of WOM impact classes almost perfectly. The predicted class sizes as proportions of participants (standard deviations) were for classes 1 to 4, respectively,
17.8% (10.6), 21.4% (10.4), 14.8% (12.0), and 46.1% (15.7), basically identical to the actual $p_k$'s of 17.7%, 21.4%, 14.9%, and 46.0%.

The mean absolute error (MAE) for change in each attitude component was small (for disposition updating MAE was .047, and for certainty updating it was .044). These compare favorably to MAEs of .122 and .113, respectively, for separate univariate OLS regressions, and MAEs of .122 and .114 for a bivariate seemingly unrelated regression. The mixture model structure that accounted for the four classes seems to be responsible for much of this substantially better fit. Clearly there is heterogeneity in how recipients' attitudes are impacted by WOM messages, and modeling this heterogeneity improves model fit.

We also compared the full model's fit to the fits of two restricted models: a null beta model, and a homoskedastic beta model based on -2 Log-Likelihood, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). Fit statistics are reported in Table 14. The full model is clearly better than these restricted models, and allowing for heteroskedasticity appears to be helpful here.

**Determinants of Word-of-Mouth Impact Class.** Parameter estimates for the effects of transmitter, message and relationship characteristics (and their interactions) on the impact class probabilities are reported in Table 15. To illustrate these effects, we report the estimated empirical distributions of impact classes at each level of the four factors in Table 16 for main effects and Table 17 for selected interactions (computed at the means of the other factors).
Table 19: Model Comparisons (Study 2)

<table>
<thead>
<tr>
<th>Model</th>
<th>Impact Class Effects&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Amount of Impact Effects&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Variance in Amount of Impact Effects&lt;sup&gt;a&lt;/sup&gt;</th>
<th>-2 Log-Likelihood&lt;sup&gt;b&lt;/sup&gt;</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null</td>
<td>Intercepts</td>
<td>Intercepts</td>
<td>Intercepts</td>
<td>428.7</td>
<td>442.7</td>
<td>468.1</td>
</tr>
<tr>
<td>Heteroskedastic</td>
<td>Intercepts Main effects Two-way interactions</td>
<td>Intercepts Two-way interactions Endogenous effects Other product effects</td>
<td>Intercepts Endogenous effects</td>
<td>-40.5</td>
<td>129.5</td>
<td>437.2</td>
</tr>
<tr>
<td>(Full model)&lt;sup&gt;d&lt;/sup&gt;</td>
<td>Intercepts Main effects Two-way interactions</td>
<td>Intercepts Two-way interactions Endogenous effects Other product effects</td>
<td>Intercepts Endogenous effects</td>
<td>218.1</td>
<td>384.1</td>
<td>684.6</td>
</tr>
</tbody>
</table>

Sample size: N = 276 for all models.

<sup>a</sup> Main effects are for the experimental factors (tie strength, credibility, valence, tone). Two-way interactions are all possible interactions between pairs of the experimental factors. Endogenous effects are the effects of the other attitude component (i.e., effect of certainty on disposition, effect of disposition on certainty). Other product effects are the effects of attitude components of the other product (disposition and certainty changes for Brand Y) on the focal product that is the dependent variable (Brand X).

<sup>b</sup> The maximized log-likelihood is used; smaller -2 Log-Likelihood indicates better model fit.

<sup>c</sup> AIC is the Akaike Information Criterion and BIC is the Bayesian Information Criterion; smaller AIC and BIC indicate better model fit.

<sup>d</sup> This is the model upon which the findings are based.
### Effect

<table>
<thead>
<tr>
<th>Class 2 Disposition Change</th>
<th>Class 3 Certainty Change</th>
<th>Class 4 Disposition, Certainty Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>Std. error</td>
<td>Estimate</td>
</tr>
<tr>
<td>1.43</td>
<td>.97</td>
<td>.98</td>
</tr>
</tbody>
</table>

**Intercepts: case k vs. case 1**

Main and two-way interaction effects: case k vs. case 1

- Strong tie transmitter (vs. stranger)
  - Estimate: -0.68, Std. error: 1.13
- Weak tie transmitter (vs. stranger)
  - Estimate: -1.18, Std. error: 1.07
- Expert transmitter (vs. novice)
  - Estimate: -0.93, Std. error: 1.04
- Positive message (vs. negative)
  - Estimate: 0.15, Std. error: 1.12
- Impassioned message (vs. matter-of-fact)
  - Estimate: -1.36, Std. error: 1.04
- Strong tie × Expert
  - Estimate: 0.60, Std. error: 1.22
- Strong tie × Positive message
  - Estimate: -1.63, Std. error: 1.24
- Strong tie × Impassioned tone
  - Estimate: 0.91, Std. error: 1.16
- Weak tie × Expert
  - Estimate: 1.98*, Std. error: 1.13
- Weak tie × Positive message
  - Estimate: -0.85, Std. error: 1.07
- Weak tie × Impassioned tone
  - Estimate: 0.61, Std. error: 1.09
- Expert × Positive message
  - Estimate: -2.17**, Std. error: 0.97
- Expert × Impassioned tone
  - Estimate: 1.81*, Std. error: 0.96
- Positive message × Impassioned tone
  - Estimate: 1.23, Std. error: 0.88

Four classes were possible. Class 1 has no disposition change and no certainty change. Class 2 has disposition change but no certainty change. Class 3 has certainty change but no disposition change. Class 4 has disposition and certainty change.

The baseline class is class 1.

* $p < .10$, ** $p < .05$, *** $p < .01$
<table>
<thead>
<tr>
<th>Effect</th>
<th>Class 1 No Reception</th>
<th>Class 2 Disposition Change</th>
<th>Class 3 Certainty Change</th>
<th>Class 4 Disposition, Certainty Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( P_1 )</td>
<td>( P_2 )</td>
<td>( P_3 )</td>
<td>( P_4 )</td>
</tr>
<tr>
<td><strong>Empirical Distribution</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Main effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tie strength:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strong tie friend</td>
<td>.18</td>
<td>.21</td>
<td>.15</td>
<td>.46</td>
</tr>
<tr>
<td>Weak tie acquaintance</td>
<td>.15</td>
<td>.11</td>
<td>.09</td>
<td>.65</td>
</tr>
<tr>
<td>No tie stranger</td>
<td>.17</td>
<td>.16</td>
<td>.12</td>
<td>.55</td>
</tr>
<tr>
<td>Transmitter credibility:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expert</td>
<td>.10</td>
<td>.11</td>
<td>.11</td>
<td>.68</td>
</tr>
<tr>
<td>Novice</td>
<td>.24</td>
<td>.24</td>
<td>.12</td>
<td>.40</td>
</tr>
<tr>
<td>Message valence:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
<td>.19</td>
<td>.09</td>
<td>.22</td>
<td>.50</td>
</tr>
<tr>
<td>Negative</td>
<td>.12</td>
<td>.28</td>
<td>.06</td>
<td>.54</td>
</tr>
<tr>
<td>Message tone:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotional/impassioned</td>
<td>.12</td>
<td>.20</td>
<td>.11</td>
<td>.58</td>
</tr>
</tbody>
</table>

\( ^a \) Computed at the means of all other variables.

\( ^b \) Probabilities across rows should sum to 1, although may not exactly due to rounding.
<table>
<thead>
<tr>
<th>Effect</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Reception</td>
<td>Disposition Change</td>
<td>Certainty Change</td>
<td>Disposition, Certainty Changes</td>
</tr>
<tr>
<td></td>
<td>$p_1$</td>
<td>$p_2$</td>
<td>$p_3$</td>
<td>$p_4$</td>
</tr>
</tbody>
</table>

**Empirical Distribution**

$Transmitter credibility \times Tie strength interaction^{a}$

| Strong tie friend: | Expert | .05 | .05 | .08 | .82 |
| Novice | .33 | .19 | .09 | .39 |

| Weak tie acquaintance: | Expert | .06 | .09 | .13 | .71 |
| Novice | .39 | .20 | .08 | .33 |

| No tie stranger: | Expert | .24 | .24 | .10 | .42 |
| Novice | .09 | .29 | .20 | .42 |

$Transmitter credibility \times Message valence interaction^{a}$

| Positive message: | Expert | .14 | .04 | .27 | .55 |
| Novice | .24 | .18 | .16 | .42 |

| Negative message: | Expert | .05 | .24 | .04 | .67 |
| Novice | .24 | .29 | .09 | .38 |

$Transmitter credibility \times Message tone interaction^{a}$

| Emotional message: | Expert | .08 | .22 | .08 | .62 |
| Novice | .17 | .16 | .14 | .53 |

| Matter-of-fact message: | Expert | .17 | .08 | .12 | .63 |
| Novice | .25 | .24 | .14 | .37 |

$^{a}$ Computed at the means of the other variables.
The probability of having no impact \(p_1\), i.e., zero change in disposition and
certainty (class 1), is somewhat analogous to the "not listen" responses in study 1
(assuming that if a recipient "listens" or receives WOM their attitudes will be impacted).
The statistically significant effects reported in Table 5, particularly the interactions,
mostly involved transmitter credibility and tie strength. Consistent with the first study,
message characteristics play a minor role in determining \(p_1\). More generally, the results of
Study 1 are conceptually replicated here.

Unlike in Study 1, however, message characteristics do affect the specific type of
WOM impact. Interestingly, Table 6 shows that while negative messages lead to more
changes in disposition than positive ones \((.28 + .54 = .82 \text{ for negative versus } .09 + .50 =
.59 \text{ for positive})\), positive messages were more likely to lead to changes in certainty \((.22 +
.50 = .72 \text{ for positive versus } .06 + .54 = .60 \text{ for negative})\).

Table 16 also highlights the key role of transmitter credibility: there is a 90%
chance of some impact \((1 - p_1|_{\text{expert}} = .90)\) when the transmitter is an expert versus a 76%
chance of some impact \((1 - p_1|_{\text{novice}} = .76)\) when the transmitter is a novice, similar to the
transmitter credibility effects found in Study 1. This is not surprising (it serves as a kind
of manipulation check). It is interesting, though, to see moderators of this effect in Table
17. The probability of having some impact is substantially lower for novice transmitters
irrespective of message valence and message tone, or whether the transmitter is a friend
or an acquaintance. Surprisingly, though, when the transmitter is a stranger and a novice,
recipients are more likely to be impacted by whatever that stranger has to say (.91) than
when the transmitter is a stranger and an expert (.76). Note that this is a reversal of the
main effect of transmitter credibility, and not simply a case of novices becoming more impactful when they are strangers (experts appear to simultaneously become less impactful when they are strangers). This result is consistent with the phenomenon of people being influenced by what amateur, inexperienced “reviewers” have to say about products and services on the internet (i.e., user-generated content), and may be due to inferences made about transmitter credibility, which we consider more in the general discussion.

Amount of Word-of-Mouth Impact. There is strong evidence of endogenous effects between the two attitude components (see Table 18). The amount of disposition change was positively affected by the amount of certainty change, and vice versa. This again reinforces the importance of jointly measuring and modeling both attitude components.\textsuperscript{50} The more a target’s disposition toward the focal product is enhanced after being exposed to WOM, the more their certainty is likely to increase (and vice versa). These two effects are not significantly different in terms of their size (contrast: $F(1, 276) < 1, p = .55$), suggesting symmetric endogenous effects.

\textsuperscript{50} These endogenous effects may alternatively be caused by method bias or a halo effect. If this is the case it is still necessary to control for these effects in the model.
### Effects

**Intercept**

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disposition change</td>
<td>-.85***</td>
<td>.16</td>
</tr>
<tr>
<td>Certainty change</td>
<td>2.92***</td>
<td>.83</td>
</tr>
</tbody>
</table>

**Endogenous effects:**

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disposition change</td>
<td>--------</td>
<td>----------</td>
</tr>
<tr>
<td>Certainty change</td>
<td>3.87***</td>
<td>.84</td>
</tr>
</tbody>
</table>

**Other product effects:**

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disposition change</td>
<td>1.36***</td>
<td>.34</td>
</tr>
<tr>
<td>Certainty change</td>
<td>.34</td>
<td>.35</td>
</tr>
</tbody>
</table>

**Main and two-way interaction effects:** case k vs. case 1

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong tie transmitter (vs. stranger)</td>
<td>-.37*</td>
<td>.21</td>
</tr>
<tr>
<td>Weak tie transmitter (vs. stranger)</td>
<td>-.61***</td>
<td>.19</td>
</tr>
<tr>
<td>Expert transmitter (vs. novice)</td>
<td>-.19</td>
<td>.18</td>
</tr>
<tr>
<td>Positive message (vs. negative)</td>
<td>-.70***</td>
<td>.20</td>
</tr>
<tr>
<td>Impassioned message (vs. matter-of-fact)</td>
<td>.25</td>
<td>.19</td>
</tr>
<tr>
<td>Strong tie × Expert</td>
<td>.93***</td>
<td>.22</td>
</tr>
<tr>
<td>Strong tie × Positive message</td>
<td>.40*</td>
<td>.23</td>
</tr>
<tr>
<td>Strong tie × Impassioned tone</td>
<td>-.56**</td>
<td>.22</td>
</tr>
<tr>
<td>Weak tie × Expert</td>
<td>.62***</td>
<td>.20</td>
</tr>
<tr>
<td>Weak tie × Positive message</td>
<td>.56***</td>
<td>.21</td>
</tr>
<tr>
<td>Weak tie × Impassioned tone</td>
<td>.00</td>
<td>.20</td>
</tr>
<tr>
<td>Expert × Positive message</td>
<td>.05</td>
<td>.19</td>
</tr>
<tr>
<td>Expert × Impassioned tone</td>
<td>-.18</td>
<td>.17</td>
</tr>
</tbody>
</table>

* *p < .10, ** p < .05, *** p < .01*
Updating of attitudes toward the focal product (X) was also related to changes in attitudes toward the other, unmentioned product (Y). Specifically, there were positive effects of brand X disposition and certainty changes on brand Y disposition and certainty changes ($p < .01$), and vice versa. These spill-over effects, where WOM about brand X has an impact on brand Y despite brand Y not being mentioned in the message, may be because the two products were otherwise identical (in their specified attributes). In this case participants might have treated the lack of WOM about brand Y as “missing information” which they then filled in based on the information about X. While not of theoretical interest to us, we controlled for these effects (i.e., interdependence between the brands) by including changes in attitude toward Y as a predictor of changes in attitudes toward brand X and vice versa.

Regarding the focal brand X, we find that negative messages are more influential than positive messages in terms of changing targets’ dispositions toward focal products. Unlike in the first study, where message valence did not affect choice of recipient (i.e., listening/reception decisions), it does affect how a message that is listened to affects the recipient’s attitudes. This is consistent with recent studies demonstrating that negative WOM can be more impactful in the context of online reviews of books and subsequent book sales rankings (Chevalier and Mayzlin 2006), and that negative publicity can have a stronger effect on awareness of cultural items and products (Berger, Sorensen, and Rasmussen 2008). It is also generally consistent with findings in psychology that people are more affected by negative information than positive information, such as the “bad is stronger than good” effect (Baumeister, Bratslavsky, Finkenauer, and Vohs 2001).
Nonetheless, this remains a debatable issue as East, Hammond, and Lomax’s (2008) analysis of multiple studies finds the asymmetric effect to be a function of floor and ceiling effects. Interestingly, however, the effect of valence on certainty change is positive. Positive, not negative, messages have a greater impact on the certainty of a target’s disposition toward a product. Thus, it may be that differences in the directions of valence effects in past research can be accounted for by considering whether the WOM mostly affected disposition or certainty.\(^{51}\)

The effects of message valence, however, are moderated by other factors. Negative messages only have a stronger impact on disposition when they come from friends (mean disposition change: positive .36 vs. negative .42) or strangers (mean disposition change: positive .31 vs. negative .47), but not when they come from acquaintances (mean disposition change: positive .36 vs. negative .39). In addition, positive messages only have a greater impact on certainty when they come from acquaintances (mean certainty change: positive .42 vs. negative .32) or strangers (mean certainty change: positive .44 vs. negative .31), but not friends (mean disposition change: positive .39 vs. negative .35). Overall, strangers transmitting negative WOM can have a large influence on dispositions, and strangers transmitting positive WOM can have a large influence on certainty, often larger than the impact of WOM from known transmitters.

\(^{51}\) This is particularly true for work on aggregate-level impacts of WOM on, for instance, product sales. When a positive valence effect is found this suggests that certainty of the majority of people in the underlying population is what is affected. Conversely, when a negative valence effect is found the majority of people likely have disposition affected. Also, in cases where no valence effects are found in the aggregate-level research it may be that there are two latent classes of people in the population of relatively equal size, one who experience disposition changes and another who experience certainty changes.
These individual-level results help us understand aggregate-level results and infer some underlying characteristics of WOM. At the aggregate level, this pattern of results suggests that if a strong negative effect of WOM on, for example, sales, is detected, then the WOM likely operates by affecting peoples' dispositions. On the other hand, if a strong positive aggregate effect of WOM is found, then the WOM often predominately influences certainty.

Tie strength also plays an additional role in disposition (but not certainty) change at different levels of transmitter credibility. The mean disposition changes in response to messages from friends, acquaintances and strangers were .47, .42 and .36 when the transmitter was an expert, and .31, .34 and .42 when the transmitter was a novice. As before, novice strangers have quite a strong impact, certainly larger than expert strangers. Generally, the amount of disposition change increases with increasing tie strength when the transmitter is an expert, but decreases with increasing tie strength when the transmitter is a novice. This is a particularly interesting result because a novice stranger (mean disposition change = .42) is on average as influential as an expert weak tie acquaintance (mean disposition change = .42), and only slightly less influential than an expert strong tie friend (mean disposition change = .47).

Finally, another set of effects relate to the tone of the message. For disposition change, whether a message is delivered in a more or less emotional/impassioned tone only matters if it is coming from a friend: matter-of-fact messages from friends are more impactful on disposition (mean disposition change = .44) than more emotional/impassioned messages from friends (mean disposition change = .34). For
certainty change, the reverse occurs: emotional/impassioned messages from acquaintances have a greater impact on certainty than matter-of-fact messages (mean certainty change: emotional .41 vs. matter-of-fact .33). Overall, emotional/impassioned messages enhance the effect of positive valence on certainty (positive, mean certainty change: emotional .44 vs. matter-of-fact .37).

**Word-of-Mouth Impact and Intentions.** We measured pre- and post-WOM purchase intent (1 = "definitely buy X to 7 = "definitely buy Y), and predicted the proportion change on the scale using a univariate zero-inflated Beta regression with purchase intent change as the dependent variable and changes in disposition and certainty for both the focal brand and the other brand as regressors. Controlling for other-brand spillover effects (which were not significant here), changes in both disposition and certainty positively influenced changes in purchase intent, with the effect of disposition change (.96, \( p < .001 \)) slightly stronger than the effect of certainty change (.61, \( p = .01 \)).\(^{52}\) A mediation analysis found the effects of transmitter, message and relationship characteristics on changes in purchase intent are completed mediated by changes in the two attitude components.

A comparison of mean changes in purchase intent across the four impact classes was significant \( F(2,272) = 10.76, p < .001 \). The highest mean change in purchase intent was for class 4 (disposition and certainty change; mean = .23), then class 2 (disposition change only; mean = .18), then class 3 (certainty change only; mean = .14), and finally

---

\(^{52}\) This result is not surprising given the generally well accepted relationship between attitudes and behaviors. Although an ancillary result, the attitude—intention relationship found here underscores the importance of the effects of WOM on consumers’ attitudes.
class 1 (no change; mean = .09). Apparently disposition and certainty changes have additive impacts: going from class 1 to classes 2 and 3 gives differences of .09 and .05 respectively, while their sum, .14, is equal to the difference between classes 1 and 4. The important finding here, though, is that WOM that only impacts a recipient by changing their certainty (holding disposition constant; i.e., class 3) can result in changes in purchase intentions. This reinforces the importance of considering certainty as well as disposition as relevant attitude components.

5.5 General Discussion

5.5.1 Substantive Findings

We examined drivers of WOM reception as a binary “listen” versus “not listen” choice and as an attitude updating process with two studies. In particular, we consider whether and—critically—to what extent WOM influences a person’s disposition and certainty in their disposition toward a brand or product. Overall, our findings indeed paint a picture of WOM reception and impact as being complex and multiply-determined. Other than the obvious result that transmitters who are objectively more credible sources because they possess product or category expertise have more impact, few simple or stylized results can be extracted. Rather, different types of transmitters and different types of messages all have some impact on recipients’ attitudes and purchase intentions and—under the right conditions or with the right combinations of these characteristics—WOM of almost any type and from almost any transmitter can be impactful.
The first study examined whether individuals were willing to listen to (i.e., receive) different types of WOM information from different types of individuals. Listening—or reception—decisions are a necessary first step for WOM impact. While transmitter characteristics affect the probability that WOM from them is listened to, message characteristics do not. In terms of binary reception decisions, the main determinant of whether a transmitter is or is not listened to was how good their taste or judgment (as a measure of “expertise” and credibility) was for the given product category (in this study, movies). Direct experience was a weaker driver. This is not surprising and is consistent with source credibility being important in determining how persuasive or influential a message is (Katz and Lazarsfeld 1955). What is interesting, however, is that deficiencies in this transmitter characteristic seem to be able to be compensated for by other factors (tie strength and experience). In other words, other factors related to the transmitter’s experience and the relationship between the transmitter and the recipient also matter. Although interesting, however, these results say nothing about impact.

The second study examined how individual transmitter and message characteristics affected both changes in disposition toward a brand (“mean”) and the certainty with which that disposition was held (“variance” or “uncertainty”). Some WOM (and information more generally) might not change consumers’ dispositions towards brands or products, but still result in them updating the certainty with which existing dispositions are held, and, accordingly, their behavioral (purchase) intentions. Our empirical results support this; a nontrivial proportion of participants in our second study updated certainty but not disposition, and even more updated both. Moreover, the main
drivers of disposition change were somewhat different from the main drivers of certainty change. Also importantly, the drivers of listening/reception are not the same as drivers of impact.

In particular, transmitter credibility (expert versus novice) and tie strength between the transmitter and recipient largely jointly determine the likelihood of there being any impact at all. The likelihood of WOM having some impact on a target is high when the transmitter is known (strong or weak tie) and an expert and less likely when the transmitter is known and a novice. This reverses when the transmitter is a stranger, however (i.e., the likelihood of some type of impact is high for stranger novices than for stranger experts). These results highlight the importance of strangers as viable—and potentially influential—transmitters of WOM.

Our second study also showed that transmitter and message characteristics can have different impacts on the amount of change in disposition versus certainty. For example, negative WOM is best at changing consumers' evaluations of products (disposition), but positive WOM is best at changing how certain consumers are about these evaluations. Further, while friends may be more likely to be listened to (Study 1), once a person decides to listen it appears to matter less who the transmitter is in terms of tie strength. This underscores the importance of considering strangers, which is relevant given that online WOM often comes from anonymous and thus unknown transmitters.

53 Recall that our manipulation of transmitter credibility was whether the transmitter's education background was indicative of them having expert knowledge about the product category, and thus was a relatively objective signal of their credibility.
Another interesting finding was that WOM impact increases with tie strength when the transmitter is an expert but decreases with tie strength for novice transmitters.

A particularly interesting set of results in Study 2 are those involving the impact of WOM from strangers. Strangers can influence how consumers think and behave, for instance through advertising. “Normal” people in advertisements, for example, are thought to be influential (this is sometimes emphasized, such as in advertisements for the homeopathic cold prevention powder “Airborne” that is advertised as being “created by a school teacher”). But why does WOM from strangers sometimes change recipients’ attitudes? We ran an additional experimental study (N = 272, from an online panel; see Appendix IV for full details). The purpose of this study was to shed light on these results. Instead of examining the impact of credibility on attitude change (as in Study 2), we looked at how attitude change impacted the perceived credibility of transmitters. The results suggest that impact of strangers, even novices, hinges on whether the information they give makes recipients more certain (e.g., it reduces doubt and is thus helpful and perhaps even comforting). When it does, strangers end up being perceived as more credible sources. We leave further examination of the phenomenon of the influence of strangers for further research, although the findings here indeed suggest that there is much more to learn about strangers and why, under specific circumstances, they can be very impactful transmitters.
5.5.2 Methodological Contributions

We used a combination of experimental methods and statistical modeling to arrive at our conclusions. There are two important aspects of our approach. First, we examined WOM impact in terms of individual attitudes. Extant research that has examined WOM impact in terms of “harder” marketing outcomes, such as the relationship between WOM and sales, is typically at the aggregate level and has not assessed the important mediating role of consumers’ attitudes in this process. Second, the statistical model in Study 2—bivariate zero-inflated beta regression—is relatively new to the marketing literature and is well suited to the type of data generated by our second experiment. More straightforward regression models (e.g., OLS or non-mixture models) that do not account for a mixture of response classes did not fit the data as well as our BZIB model. Therefore accounting for classes of WOM impact—and their determinants—is important. Also, despite its relatively complex likelihood function (see Appendix III), BZIB is estimable with maximum likelihood procedures and can be implemented in standard software.54

An additional methodological implication of this work is related to how firms measure and track customer responses to WOM. Currently, it is common to look at aggregate measures of the amount of “buzz” for a given product or brand (e.g., by looking at the number of times a product is mentioned on blogs and online discussion

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54 For example, we implemented the BZIB model in SAS 9 with a customized likelihood and nonlinear optimization routine. Code is available upon request from the authors. We encourage researchers to consider using either univariate or multivariate Beta regressions when they have data that lie on the unit interval.
forums within a given timeframe). This focuses on transmission—not reception—and, given our findings on the impact of WOM on reception, attitudes, and subsequent behaviors, seems inadequate to use to capture the impact of WOM activity. Instead, an attitude-based perspective on the reception side is more appropriate. As we mentioned earlier, if certainty changes cannot be observed it is possible that zero changes in dispositions could be erroneously interpreted as WOM having no impact. Of course in the absence of certainty data, a latent class-type model could be used to allow for the possibility that zero changes in dispositions may mean either no change (class 1) or no change in disposition but a change in certainty (class 3). A simple, practical solution that does not require additional statistical machinery is to simply measure certainty (which is a low-cost solution: one more question on, say, a customer survey).

5.5.3 Limitations and Future Research

A number of limitations and directions for future research exist. First, we used experimental data on hypothetical conversations about a hypothetical product in a single category. An obvious extension would be to examine real conversations (e.g., online), again at the individual level, possibly across categories. While such data are not easy to collect, if available they could lead to more insights into individual-level WOM impact.

Second, it would be interesting to examine other types of WOM impacts. We focused on attitude-based WOM impact as well as intentions but other impacts are worth exploring, specifically actual purchase behaviors and WOM retransmission. With regards to WOM retransmission, we have some evidence suggesting a link between attitude
changes and retransmission intentions. At the end of Study 2 we asked participants to indicate their likelihood of retransmitting WOM in-person to friends, acquaintances and strangers, and their likelihood of retransmitting WOM by posting a message to an online forum or blog (on a 1 = “very unlikely” to 7 = “very likely” scale). When regressed on disposition and certainty changes (and controlling for other-brand spill-over effects; i.e., same as for the analysis of changes in purchase intent in Study 2), we found that retransmission to friends or acquaintances is positively affected by both disposition and certainty changes ($ps < .05$), but not retransmission to strangers or retransmission in an online environment (in effect also to strangers). Additional research is needed on this, though this suggests paradoxically that while people may be willing to listen to—and let their attitudes be changed by—strangers, they may be less inclined to transmit WOM to them.

Finally, we treated the experimental factors as exogenous, whereas it is possible that they might influence each other and might themselves be influenced by WOM activity (e.g., WOM between two people today might lead to the strengthening of their social tie in the future). Including the dynamic effects of WOM on social relationships and peoples’ perceptions of others is an interesting area for future research. We encourage future research on these and related topics to better understand, at the individual level, the nature of WOM reception and the impacts that product-related WOM can have.
6 References


Appendices

I  Bayesian Estimation Procedure in Essay 1

Priors

- \( Ability_i \sim N(-1, \eta^2) \).
- Diffuse on \( \beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, a_0, a_1, \gamma_0 \) and \( \gamma_1 \).
- \( \sigma^2 \sim \text{InverseGamma} \left( \frac{r_0}{2}, \frac{s_0}{2} \right) \), where \( r_0 = s_0 = 1 \).
- \( \eta^2 \sim \text{InverseGamma} \left( \frac{r_0}{2}, \frac{s_0}{2} \right) \), where \( r_0 = s_0 = 1 \).
- \( \Lambda \sim \text{InverseWishart} (n_0, n_0 \Delta_0) \), where \( n_0 = p + q + 3 \), and \( \Delta_0 = I \), with \( p \) the number of network-related variables (7) and \( q \) the number of assortment-related variables (3).

Markov Chain Monte Carlo Simulation Steps

Step 1

\[
L(Ability_i | Performance_i, Performance^*, \beta, \delta, \xi, \sigma^2, a_0, a_1, \gamma_0, \gamma_1) \sim \text{Normal}(m_i, V_i),
\]

where

\[
m_i = V_i \left( \frac{Performance^* - \beta_0 - \beta_1 \text{Age}_i - \sum_{j=1}^N \beta_{k,j} \delta_{j,k} - \sum_{j=1}^N \beta_{k,j} \xi_{j,k} - \sum_{j=1}^N \beta_{k,j} \delta_{j,k} - \sum_{j=1}^N \beta_{k,j} \xi_{j,k}}{\beta_i^2 \frac{\sigma^2}{\eta^2}} \right) \\
+ [a_1, \gamma_1] \Lambda^{-1} [(\text{Network}_i - \gamma_0)^T (\text{Assortment}_i - a_0)] + \frac{1}{\eta^2}
\]

\[
V_i = \left( \frac{\beta_i^2}{\sigma^2} + [a_1, \gamma_1] \Lambda^{-1} [a_1, \gamma_1] + \frac{1}{\eta^2} \right)^{-1}
\]
Step 2

\[ L(\text{Performance}_i^* \mid \text{Performance}_i, \text{Ability}_i, \beta, \delta_i, \xi_i, \sigma^2, \alpha_0, \alpha_1, \gamma_0, \gamma_1) \sim \]

\[ \text{TruncatedNormal}(\beta_0 + \beta_i \text{Ability}_i + \beta_j \delta_i + \beta_k \xi_i, \sigma^2) \]

if Performance\(_i < 0\). Otherwise Performance\(_i^* = \) Performance\(_i\).

Step 3

\[ L(\eta^2 \mid \text{Performance}_i, \text{Performance}_i^*, \text{Ability}_i, \beta, \delta_i, \xi_i, \sigma^2, \alpha_0, \alpha_1, \gamma_0, \gamma_1) \sim \]

\[ \text{InverseGamma} \left( \frac{r_0 + \sum_{i=1}^N (\text{Ability}_i + 1)^2}{2}, \frac{s_0 + N}{2} \right) \]

Step 4

\[ L(\sigma^2 \mid \text{Performance}_i, \text{Performance}_i^*, \text{Ability}_i, \beta, \delta_i, \xi_i, \eta, \alpha_0, \alpha_1, \gamma_0, \gamma_1) \sim \]

\[ \text{InverseGamma} \left( \frac{r_0 + \sum_{i=1}^N (\text{Performance}_i^* - (\beta_0 + \beta_i \text{Ability}_i + \beta_j \delta_i + \beta_k \xi_i + \beta_p \delta_i^2 + \beta_o \delta_i \xi_i))^2}{2}, \frac{s_0 + N}{2} \right) \]

Step 5

\[ L(\Lambda \mid \text{Performance}_i, \text{Performance}_i^*, \text{Ability}_i, \beta, \delta_i, \xi_i, \sigma^2, \alpha_0, \alpha_1, \gamma_0, \gamma_1) \sim \]

\[ \text{InverseWishart}(n_0 + N, n_0 \Lambda_0 + \sum_{i=1}^N [\delta_i^*, \xi_i^*][\delta_i, \xi_i]) \]

Step 6

\[ L([[\beta_0; \beta_1; \beta_2; \beta_3; \beta_4; \beta_5]; \beta_6]] \mid \text{Performance}_i, \text{Performance}_i^*, \text{Ability}_i, \delta_i, \xi_i, \sigma^2, \alpha_0, \alpha_1, \gamma_0, \gamma_1) \sim \]

\[ \text{Normal}\left((X'X)^{-1} \text{X}^* y^*, \sigma^2 (X'X)^{-1}\right) \]

where \(X_i = [1, \text{Ability}_i, \text{Age}_i, \delta_i, \xi_i, \delta_i^2, \delta_i \xi_i]\)

Step 7

For all j:

\[ L([\gamma_{ij}^0; \gamma_{ij}^1] \mid \text{Performance}_i, \text{Performance}_i^*, \text{Ability}_i, \beta, \delta_i, \xi_i, \sigma^2, \alpha_0, \alpha_1, \gamma_0((i \neq j), \gamma_1((i \neq j)) \sim \]

\[ \text{Normal}\left((X'X)^{-1} \text{X}'W_j, \Lambda_{ij, j}/(X'X)^{-1}\right) \]

where \(X_i = [1, \text{Ability}_i]\) and \(W_j = \text{[Network}_{i,j}\), and similarly for all k:
\[
L([\alpha_{0,k}; \alpha_{1,k}] \mid \text{Performance}_i, \text{Performance}_i^*; \text{Ability}_i, \beta, \delta, \zeta, \sigma^2, \alpha_{0,(l\times k)}, \alpha_{1,(l\times k)}, \gamma_0, \gamma_1) \sim \text{Normal}
\]
\[
(X'X)^{-1} X' W, \Lambda_{J+k,J+k} \text{ or } (X'X)^{-1}
\]

Note that we did not update \([\gamma_{0,j}; \gamma_{1,j}]\) and \([\alpha_{0,j}; \alpha_{1,j}]\) for all \(j\)'s and \(k\)'s simultaneously for tractability reasons.
II Modeling Word-of-Mouth Impact in Essay 4

Basic Approach

Let \( a_{it} = [a_{1it}, a_{2it}] \) represent the dispositional and certainty components of the attitude that person \( i \) has toward a given brand or product at time \( t \), and \( y_{jt} = [y_{1jt}, y_{2jt}] \) = \([|a_{1it} - a_{1i,t-1}|, |a_{2it} - a_{2i,t-1}|]\) the change in these attitude components from period \( t - 1 \) to period \( t \). Assume that attitudes are measured on interval scales at two points in time in a standard pre-post experiment design (e.g., attitudes toward product quality are measured on a scale at two points in time; “1 = very low quality” to “7 = very high quality”). While this type of scale is commonly used in practice (by both researchers and practitioners), it does present certain problems. First, it is not obvious what an appropriate change measure (i.e., for \( y_{jt} \)) should be (e.g., raw differences versus proportional changes), since the choice of scale width (i.e., the number of points on the scale) can have an effect and the scale is inherently interval- rather than ratio-scaled. Second, ceiling and floor effects may be present. We take these potential problems into account in the modeling approach used.

The response variable (absolute change in disposition, absolute change in certainty) is censored below at zero (no change) and above at \( b \) where \( b \) is the difference between the lowest and highest possible ratings (e.g., 7 – 1 = 6). Because ordinary least-squares (OLS) will be a biased estimator, one alternative is to use a Tobit regression with censoring above and below, assuming that the response variables come from a doubly-truncated normal distribution. This, however, may not be a good assumption in this case since the response variable (i.e., the absolute change in disposition or in certainty) has a
finite, fixed range. Therefore it is preferable to use a distribution that naturally is bounded (unlike the normal distribution).

The approach that we adopt is Beta regression (Cook, Kieschnick, and McCullough 2008; Cragg 1971; Ferrari and Cribari-Neto 2004; Kieschnick and McCullough 2003; Paolina 2001; Smithson and Verkuilen 2006). Beta regression assumes that the response variable is conditionally Beta distributed and is defined on the (0,1) unit interval (note that the values of 0 and 1 are thus impossible, which is a problem addressed below). This makes it ideal for modeling proportions, which we have if proportional attitude changes are used.\(^{55}\) Although not used extensively in marketing, Beta regression is used in finance (e.g., Cook et al. 2008), statistics (e.g., Ferrari and Cribari-Neto 2004; Kieschnick and McCullough 2003), political science (e.g., Paolina 2001), and psychology (e.g., Smithson and Verkuilen 2006). In fact, Smithson and Verkuilen (2006) demonstrated that Beta regressions provide superior fits over alternative models such as doubly-censored Tobit regressions for psychological response variables that are either proportions or rates.

\textit{Data Preparation}

To be suitable for Beta regression, data needs to be transformed to the unit interval. Suppose that for each person at each time period \(t (1, 2)\) there is one observation

\(^{55}\) Proportions as they are referred to here are not percentage changes. Rather, proportions here refer to the proportion of the scale width that is covered by each attitude-change response variable. E.g., moving along a seven-point scale from a position of 1 to a position of 7 covers the entire width of the scale, thus the proportion change measure equals 1. The percentage change for the same movement is 700\%. 
for attitude disposition $a_{1,t} \in [s_{\text{min}}, s_{\text{max}}]$ and one for attitude certainty $a_{2,t} \in [s_{\text{min}}, s_{\text{max}}]$. The following transformation and preparation steps are required:

1. Compute the raw absolute difference between priors and posteriors:
   
   $y_{1,t} = |a_{1,t} - a_{1,t-1}|, \quad y_{2,t} = |a_{2,t} - a_{2,t-1}|', \quad \text{and} \quad y_{1,t}^{\text{raw}}, y_{2,t}^{\text{raw}} \in [0, s_{\text{max}} - s_{\text{min}}]$;

2. Transform each element of $y_{1,t}^{\text{raw}}$ to the unit interval: $y_{1,t} = y_{1,t}^{\text{raw}} / (s_{\text{max}} - s_{\text{min}})$.

   This gives $y_{1,t}, y_{2,t} \in [0,1]$; and

3. Create an indicator variable for WOM reception case: let $c_{i,t} = k$ for case $k$ defined in section 2 ($k = 1, \ldots, 4$).

The result of step 2, the response vector used in the bivariate Beta regression described below in section 3.3, is not the percentage changes in the attitude components but rather the change in terms of the proportion of the scale that the component moved. Note that the starting positions (i.e., $a_{1,t-1}$ and $a_{2,t-1}$) can also be entered into the model as covariates to control for the possibility that the size of the change is dependent on the initial scale position.

The response vector in step 2 can take on values of 0 or 1 (as well as in between), which is incompatible with the assumed Beta distribution. Some authors (e.g., Smithson and Verkuilen 2006) simply convert 0 values to $0 + \epsilon$ and 1 values to $1 - \epsilon$ (where $\epsilon$ is a very small number). Although reasonable when either 0 or 1 values (or both) are not

56 The min and max here are the scale minimums and maximums.
57 This makes the model a first-order autoregressive model (dynamic regression) with additional exogenous covariates. When we tried this specification in the modeling reported in section 5, in all cases the lagged dependent variable ("starting position" or "prior") effects were not significant and the fit of the model was worsened so these lagged effects were removed.
meaningful, in our case the value of 0 is meaningful because it indicates no updating.

Fortunately, in the data described in section 4 there are no instances of $y_{1,t} = 1$ or $y_{2,t} = 1$.

We therefore employ a multivariate model that (1) assumes a Beta distribution on the response variables, and (2) explicitly accommodates all four WOM reception cases, including explicitly modeling zero change.

**Statistical Model**

In Appendix III we describe the bivariate zero-inflated beta (BZIB) regression. This is a generalized linear model and assumes that response variables are beta-distributed conditional on covariates. Beta distributions can be fully characterized with location (mean-like) and dispersion (variance-like) parameters. The parameters are functions of covariates (allowing the dispersion parameter to vary as a function of covariates allows for heteroskedasticity). The zeros and the different reception cases are explicitly handled by having a mixture of Betas for the different cases. Thus, the models described in the appendix are Beta distribution versions of the family of zero-inflated finite mixture models that often used to handle the “mass at zero” or “spike at zero” problem in count data, such as zero-inflated Poisson (ZIP) and zero-inflated negative Binomial (ZINB) models (cf. Greene 2003; Lambert 1992).

We provide an overview of the model here, leaving the details to Appendix III. Consider the following four distinct classes:
(y_{1,t}, y_{2,t}) \sim \left\{ \begin{array}{l}
(0,0) \quad \text{w.p. } p_1 \quad ("\text{Class 1}\") \\
(Beta(\omega_1, \tau_1), 0) \quad \text{w.p. } p_2 \quad ("\text{Class 2}\") \\
(0, Beta(\omega_2, \tau_2)) \quad \text{w.p. } p_3 \quad ("\text{Class 3}\") \\
(Beta(\omega_1, \tau_1), Beta(\omega_2, \tau_2)) \quad \text{w.p. } p_4 \quad ("\text{Class 4}\")
\end{array} \right.

Where \( \sum_{k=1}^{4} p_k = 1 \), location parameter \( \omega_l = \mu_l \phi_l \) and dispersion parameter \( \tau_l = \phi_l (1 - \mu_l) \) for \( l = 1, 2 \).\(^{58}\) In class 1 both attitude change responses are zero. In class 2 the change in disposition is a Beta random variable, but the change in certainty is zero. Class 3 is the opposite of class 2: the change in certainty is Beta, and the change in disposition is zero. Class 4 assumes that both responses change and come from a bivariate Beta distribution.

The location (\( \omega \)) and dispersion (\( \tau \)) parameters are modeled in typical GLM fashion as functions of covariates through link functions. The covariates (columns of data matrix \( X \) for location, and columns of data matrix \( W \) for dispersion) are the transmitter and message characteristics, as well as other control variables. Since the four different reception/impact classes are assumed to occur probabilistically, our BZIB model allows for the mixture probabilities to vary as a function of some covariates (the columns of data matrix \( Z \)) through an appropriate link function. More details and the link functions are outlined in Appendix B, along with the likelihood function for the full model.

Three types of effects, each with a different meaning and implication, are estimable in this model: \( \alpha \), \( \beta \), and \( \gamma \)-effects. The \( \alpha \)-effects are the effects of transmitter

---

\(^{58}\) For response variable \( g_i \) (for \( i = 1, \ldots, N \)), \( g_i \sim Beta(\omega, \tau) \), the Beta density is

\[
f(g_i | \omega, \tau) = \frac{\Gamma(\omega + \tau)}{\Gamma(\omega) \Gamma(\tau)} g_i^{\omega - 1} (1 - g_i)^{\tau - 1}, \quad \text{with} \quad g_i \in (0,1), \Gamma(.) \text{ is the gamma function, } \omega > 0 \text{ is the location parameter, and } \tau > 0 \text{ is the dispersion parameter.}
\]
and message characteristics on the class of WOM reception/impact response that the
target has (i.e., how these characteristics influence the probability of occurrence of class 1
vs. class 2 vs. class 3 vs. class 4). The $\beta$-effects are the effects of transmitter and message
characteristics on the size of the disposition and/or certainty changes (i.e., extent of
impact). The $\gamma$-effects are the effects of transmitter and message characteristics on the
dispersion (variance) of the changes in attitude disposition and certainty (i.e.,
heteroskedasticity effects). Allowing for heteroskedasticity is done primarily for
statistical purposes, and we show that this improves the fit of the model. All the effects
are estimated simultaneously using a maximum likelihood procedure (see Appendix III).
III Beta Regression Model in Essay 4

Univariate Beta Regression Model

We first develop the basic concepts of the bivariate zero-inflated Beta (BZIB) model. For $g_i$ (for $i = 1, \ldots, N$), $g_i \sim \text{Beta}(\omega, \tau)$, the beta density is

$$f(g_i | \omega, \tau) = \frac{\Gamma(\omega + \tau)}{\Gamma(\omega) \Gamma(\tau)} g_i^{\omega-1} (1 - g_i)^{\tau-1},$$

with $g_i \in (0,1)$, $\Gamma(.)$ is the gamma function, $\omega > 0$ is the location parameter, and $\tau > 0$ is the dispersion parameter. The individual-level log-likelihood is

$$\ln L(\omega, \tau | g_i) = \ln \Gamma(\omega + \tau) - \ln \Gamma(\omega) - \ln \Gamma(\tau) + (\omega - 1) \ln g_i + (\tau - 1) \ln (1 - g_i),$$

and $L = \sum_{i=1}^N \ln L(\omega, \tau | g_i)$ is maximized in the usual fashion to obtain maximum likelihood estimates of the parameters. Note that $E(g) = \omega/(\omega + \tau)$ and

$$\text{Var}(g) = \frac{\omega \tau}{(\omega + \tau)^2 (\omega + \tau + 1)}.$$ These parameters are usually reparameterized for the GLM as follows: let location be $\mu = \omega/(\omega + \tau)$ and precision be $\phi = \omega + \tau$ (see Smithson and Verkuilen 2006 for details). In a GLM framework the location parameter usually has a logit link $\mu_i = \exp(x_i \beta) /[1 + \exp(x_i \beta)]$, and the precision parameter usually has a logarithmic link $\phi_i = \exp(-w_i \gamma)$.\textsuperscript{59} Here $X$ is an $N \times M_1$ matrix of covariates (including a column of ones) that can affect $E(g)$ with $\beta$ an $M_1$-vector of the corresponding coefficients, and $W$ is an $N \times M_2$ matrix of covariates (including a column of ones) that can affect $\text{Var}(g)$ with $\gamma$ an $M_2$-vector of the corresponding coefficients (these effects

\textsuperscript{59} The negative sign is simply so that positive $\gamma$ coefficients mean that the dispersion is increasing.
capture heteroskedasticity). Note that the sets of covariates in the columns of \( \mathbf{X} \) and \( \mathbf{W} \) need not be mutually exclusive; indeed, it is possible for \( \mathbf{X} = \mathbf{W} \).

**Bivariate Zero-Inflated Beta Regression Model**

This is a relatively straightforward extension of the univariate Beta regression, except for the inclusion of the bivariate Beta distribution and the mixture. Although not previously developed in the marketing literature, the BZIB model that we develop here is similar to a multivariate version of the zero-inflated Poisson regression model (e.g., Li, Lu, Park, Kim, Brinkley, and Peterson 1999).

For completeness, consider the following four latent classes that are introduced in the paper:

\[
(\gamma_{1,t}, \gamma_{2,t}) \sim \begin{cases} 
(0,0) & \text{w.p. } p_1 \text{ ("Class 1") } \\
(Beta(\omega_1, \tau_1), 0) & \text{w.p. } p_2 \text{ ("Class 2") } \\
(0, Beta(\omega_2, \tau_2)) & \text{w.p. } p_3 \text{ ("Class 3") } \\
(Beta(\omega_1, \tau_1), Beta(\omega_2, \tau_2)) & \text{w.p. } p_4 \text{ ("Class 4") } 
\end{cases}
\]

Where \( \sum_{k=1}^{4} p_k = 1 \), \( \omega_l = \mu_l \phi_l \) and \( \tau_l = \phi_l(1 - \mu_l) \) for \( l = 1, 2 \). Recall that: (1) in class 1 both attitude change responses are *not* Beta random variables (they are zeros); (2) in class 2 the change in disposition is a Beta random variable, but the change in certainty is a zero; (3) class 3 is the opposite of case 2: the change in certainty is Beta, and the change in disposition is a zero; and (4) class 4 assumes that both responses come from a bivariate Beta distribution.

The bivariate Beta in class 4 is required to allow for the possibility that the two response variables are related. Unfortunately, a bivariate Beta distribution complicated
matters, since the bivariate Beta distribution is not a straightforward distribution (unlike, for example, a bivariate normal distribution or even a bivariate Poisson distribution). Several specifications of the bivariate Beta's density function are presented in the literature (e.g., Macomber and Myers 1983; Olkin and Liu 2003). We adopt Olkin and Lin’s (2003) specification for the bivariate Beta density (where $\tau = \tau_1 + \tau_2$):

$$f(y_{1,t}, y_{2,t} \mid \omega_1, \omega_2, \tau) = \frac{\Gamma(\omega_1 + \omega_2 + \tau)}{\Gamma(\omega_1)\Gamma(\omega_2)\Gamma(\tau)} \frac{\omega_1^{\alpha_1} y_{1,t}^{\alpha_1 - 1} y_{2,t}^{\alpha_2 - 1} (1 - y_{1,t})^{\alpha_2 + \tau - 1} (1 - y_{2,t})^{\alpha_1 + \tau - 1}}{(1 - y_{1,t} y_{2,t})^{\alpha_1 + \alpha_2 + \tau}}$$

Consistent with the GLM link functions for the univariate Beta regression above, the location parameters have a logit link and the precision/dispersion parameters have a logarithmic link. Since these are the same as in the univariate case we do not repeat them here.

An additional link function is required here for the mixture probabilities (i.e., the $p_k$'s). Since there are four possible classes of WOM reception, the mixture probabilities come from a multinomial distribution, and can be modeled as a multinomial choice. We use a logit submodel for the link function (and the probabilities are proper; i.e., they lie on the unit interval). This submodel takes a familiar form: let

$$\Pr(c_{i,t} = k) = p_{k,i,t} = \frac{\exp(z_{ik} \alpha_k)}{\sum_{j=1}^{4} \exp(z_{ij} \alpha_j)}$$

with $Z$ an $N \times M_3$ matrix of covariates (including a column of ones) that can affect the mixture probability for the given case, with $\alpha_k$ an $M_3$-vector of the corresponding coefficients for reception type $k$. As is common practice when estimating multinomial choice models, one case is selected as the baseline case with zero “utility.” Case 1 (no reception) is set as the baseline case. Columns in $X$, $W$, and $Z$ can overlap.
The likelihood function is a standard mixture model likelihood, and is as follows:

\[
L_{i,t} = \begin{cases} 
  p_{1i,t} \times & 1 & \text{for } c_{i,t} = 1 \quad \text{("Class 1")}, \\
  + p_{2i,t} \times & \frac{\Gamma(\omega_1 + \tau_1)}{\Gamma(\omega_1)\Gamma(\tau_1)} y_{1i,t}^{\omega_1-1} (1-y_{1i,t})^{\tau_1-1} & \text{for } c_{i,t} = 2 \quad \text{("Class 2")}, \\
  + p_{3i,t} \times & \frac{\Gamma(\omega_2 + \tau_2)}{\Gamma(\omega_2)\Gamma(\tau_2)} y_{2i,t}^{\omega_2-1} (1-y_{2i,t})^{\tau_2-1} & \text{for } c_{i,t} = 3 \quad \text{("Class 3")}, \\
  + p_{4i,t} \times & \frac{\Gamma(\omega_1 + \omega_2 + \tau)}{\Gamma(\omega_1)\Gamma(\omega_2)\Gamma(\tau)} y_{1i,t}^{\omega_1-1} y_{2i,t}^{\omega_2-1} (1-y_{1i,t})^{\omega_2 + r - 1} (1-y_{2i,t})^{\omega_1 + r - 1} (1-y_{1i,t}y_{2i,t})^{\omega_1 + \omega_2 + r} & \text{for } c_{i,t} = 4 \quad \text{("Class 4")}.
\end{cases}
\]

The complete data log-likelihood is then \( LL_{C,t} = \sum_{i=1}^{N} \ln L_{i,t} \). This is maximized to obtain parameter estimates.
IV Study on the Impact of Strangers in Essay 4

Procedure and Design

In this study we more deeply examine the relationship between the nature of the transmitter—recipient relationship. In particular we focus on how credible and trustworthy recipients perceive transmitters to be.

Two hundred seventy-two members of a large online panel participated in this study for a nominal cash payment. The participants were 55% female and 45% male, and from a relatively wide spread of ages (33% 18-25, 34% 26-35, 30% 36-45, and the remainder over 45). Participants were given information about a real new movie (“Duplicity”) that was released in the United States approximately six weeks after the time of the study (this lead time was chosen to get in before the movie’s advertising and publicity campaigns began). We gave participants a brief synopsis, cast list, genre, and the movie’s MPAA rating. Only people who reported not having heard about this movie and not knowing much about this movie were allowed to participate so that strong priors were unlikely (this resulted in us dropping 36 participants, leaving a sample size of 236).

As in the two previous studies, we asked participants to imagine themselves in a scenario where they were talking to a person and received WOM about this movie. Instead of giving them a message, we simply told participants from whom this WOM came (a friend, acquaintance or stranger; same as Study 2), and how this WOM changed their disposition toward the movie (expectation of how good it will be) and the certainty they had in this expectation. This resulted in a 3 (disposition: increase, decrease, same) × 3 (certainty: increase, decrease, same) × 3 (tie strength: friend, acquaintance, stranger)
between-subjects design. Participants were randomly assigned to one of the 27 conditions. Before exposing them to the WOM but after reading the movie description, participants rated their expectation of how good the movie would be (disposition) on a seven-point scale (1 = “It will be terrible” to 7 = “It will be excellent”) and how certain they were about this expectation (on a 0-100% scale). Neither of these measures significantly differed across experimental conditions (mean disposition = 4.85, mean certainty = 74.06; in a mixed ANOVA with the prior measures as repeated measures and the experimental condition as a between-subjects factor, the condition effect was clearly non-significant, $F(26, 209) < 1, p = .96$).

To measure transmitter credibility, after exposure to the manipulation we had participants rate the credibility of their transmitter on five five-point Likert scales (1 = “strongly disagree” to 5 = “strongly agree”). Example items included “I trust what [friends/acquaintances/strangers] think about movies,” and “I think [friends/acquaintances/strangers] are credible sources of information about movies.” These five items loaded on to a single factor (67% variance explained) and were reliable (alpha = .87). We took the average of these five items to create a single perceived credibility measure (ranging from 1 to 5). Finally, at the end of the study we also measured participant involvement (e.g., using scales like “I took this task seriously” and “I could easily imagine myself in this situation”). We found evidence of reasonable involvement (mean = 4.06 on a five point scale of increasing involvement; s.d. = .53).
Results

The perceived transmitter credibility measure was subjected to an analysis of variance including the main and two- and three-way interaction effects of the three experimental factors. Only the main effect of relationship \( (F(2, 208) = 25.56, p < .001) \) and the two-way interaction between relationship and change in certainty \( (F(2, 208) = 3.28, p = .013) \) were significant.

The stronger the transmitter—recipient relationship, the more credible the transmitter is perceived to be as a source of information about movies (mean friends = 3.80, mean acquaintances = 3.57, mean strangers = 3.02), and known transmitters are perceived as more credible than strangers (contrast \( F(1, 208) = 44.26, p < .001 \)). This main effect, however, is qualified by the interaction with change in certainty. When WOM comes from a stranger and does not change a recipient’s certainty, the mean perceived transmitter credibility is 2.86. It is only slightly (but not significantly) higher when WOM makes a recipient less certain (mean = 2.91; contrast \( F(1, 208) < 1, p = .97 \)). However, when WOM makes a recipient feel more certain, the transmitter’s perceived credibility significantly increases (mean = 3.22; contrast between certainty increase and pooled certainty decrease and no change \( F(1, 208) = 3.99, p < .05 \)).

Apparently people like having their opinions confirmed and therefore perceive as more credible those who do so. Put simply, when WOM from strangers is helpful in the sense that it makes a recipient more certain, that stranger will be perceived as more credible. As we know from both previous studies, information from more credible transmitters is substantially more likely to lead to WOM reception and WOM impact on
attitudes. This helps explain why, in Study 2, novice strangers—objectively less credible transmitters—were likely to have an impact on recipients' attitudes. Basically, when the information being transmitted makes recipients feel more certain, this can lift perceived transmitter credibility.