IS ANYONE LISTENING? MODELING THE IMPACT OF WORD-OF-MOUTH AT THE INDIVIDUAL LEVEL

Andrew T. Stephen and Donald R. Lehmann*

Andrew T. Stephen
Doctoral Candidate in Marketing
Columbia University, Graduate School of Business
3022 Broadway, 311 Uris, New York, NY 10027
Email AStephen05@gsb.columbia.edu
Tel. (646) 709-4675, Fax. (212) 854-7647

Donald R. Lehmann
George E. Warren Professor of Business
Columbia University, Graduate School of Business
3022 Broadway, 507 Uris, New York, NY 10027
Email drl2@columbia.edu
Tel. (212) 854-3465, Fax. (212) 854-7647

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ABSTRACT

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 to others). This paper instead focuses on the reception process at the individual level (i.e., "listening" to information from others), 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.

Keywords: word-of-mouth, attitudes, social interactions, multivariate analysis

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 paper 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 paper 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 paper is organized as follows. In section 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 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 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 we conclude with a discussion of our findings, their implications, and directions for future research

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.[1]

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

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[1] 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.

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 the important role of confidence in consumer decision-making and behavior featured in the Howard and Sheth (1969) model of buyer behavior.

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 paper 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.

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).[2] 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.

3. STUDY 1: WORD-OF-MOUTH RECEPTION

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.

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[2] 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).

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.

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.[3] 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 "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) × 2 (consistency) between-subjects factorial. Nested within each of these conditions was a 2 (tie strength) × 2 (connectivity) × 2 (taste) × 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.

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 1). All the differences except for connectivity were significant at the .05 level.

[INSERT TABLES 1 & 2 ABOUT HERE]

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[3] 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.

Table 2 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%; $p < .05$).

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 establishes 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. We now consider how these factors impact attitudes.

4. STUDY 2: THE IMPACT OF WORD-OF-MOUTH ON ATTITUDES

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."[4] 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 brands, they were in-stock and apparently suitable for their purposes. Each product was described on four 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 on price. No other product information was provided.

4.1.1 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 computer data; Consumer

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[4] The acquaintance was described to them as someone who they know but not very well.

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.

4.1.2 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 student population and found that the manipulation operated as intended.[5]

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

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[5] 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 1.77 (s.d. = .99), consistent with the desired effect of this manipulation.

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.[6]

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 (and who was not a salesperson).

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[6] 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 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 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.

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.

4.1.3 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.

Attitude updating (the main, multivariate dependent variable) was computed accounting for the limitations of the interval measurement scales (see Appendix A). 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 interval 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 changes in measures could be spurious and just due to participant (response) error.[7]

4.2 Analysis Method

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[7] 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.

We did not use a simple regression model for four reasons. First, the dependent variables (changes in disposition and certainty), were represented as the proportions of the respective scales that were moved along after WOM exposure (i.e., values lied between 0 and 1; see Appendix A). We handled this by using conditional beta distributions on dependent variables.

Second, we have two correlated dependent variables (changes in disposition and certainty; $r = .23$, $p < .001$) that should be modeled jointly. We used a bivariate model, estimated endogenous effects (i.e., disposition 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.[8]

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 (e.g., generalized logit) or discriminant analysis where the class probability (relative to a baseline class, e.g., the no impact class) is

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[8] 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).

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.[9]

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 A and B. This model allows us to estimate, simultaneously, the effects of the four experimental factors (all 0/1 dummy variables) on the WOM impact class probabilities and 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).

4.3 Results

4.3.1 Preliminary Analysis. Descriptive statistics are reported in Table 3. 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 =

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[9] 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.

.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.

[INSERT TABLE 3 ABOUT HERE]

Almost half (46%) the participants updated *both* attitude components after being exposed to the message (class 4; see Table 3). 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, 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).

4.3.2 Model Fit. We estimated the BZIB regression model using maximum likelihood (see Appendix B 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 4. The full model is clearly better than these restricted models, and allowing for heteroskedasticity appears to be helpful here.

[INSERT TABLE 4 ABOUT HERE]

4.3.3 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 5. To illustrate these effects, we report the estimated empirical distributions of impact classes at each level of the four factors in Table 6 for main effects and Table 7 for selected interactions (computed at the means of the other factors).

[INSERT TABLES 5, 6 & 7 ABOUT HERE]

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 ($.28 + .54 = .82$ for negative versus $.09 + .50 = .59$ for positive), positive messages were on average more likely to lead to changes in certainty ($.22 + .50 = .72$ for positive versus $.06 + .54 = .60$ for negative).

Table 6 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 7. 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 (section 5).

4.3.4 Amount of Word-of-Mouth Impact. There is strong evidence of endogenous effects between the two attitude components (see Table 8). 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. [10] 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.

[INSERT TABLE 8 ABOUT HERE]

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 (ps < .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

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[10] 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 them in the model.

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.[11]

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

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[11] 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.

.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.

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).

4.3.5 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, $p = .01$).[12] 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 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 key finding here, though, is that WOM that

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[12] 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.

only impacts a recipient by changing their certainty (with 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. DISCUSSION

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 considered 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 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 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 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 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, altering their 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 higher for stranger novices than for stranger experts).[13] These results highlight the importance of strangers as viable—and potentially influential—transmitters of WOM.

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[13] 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.

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. 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. The influence of strangers, of course, is not new to marketing. For example, strangers in advertisements can influence how consumers think and behave. "Normal" people in advertisements, for instance, are thought to be influential (this "normality" is sometimes emphasized; e.g., 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 C 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 the impact of strangers, even novices, hinges on whether the information they give makes recipients more certain (e.g., it reduces doubt, making it helpful and even comforting). When it does, strangers are perceived as more credible. 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.

5.2 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 B), BZIB is estimable with maximum likelihood procedures and can be implemented in standard software.[14]

An additional methodological (and practical) 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 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

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[14] For example, we implemented the BZIB model in SAS 9 with a customized likelihood and nonlinear optimization routine. We encourage researchers to consider using either univariate or multivariate Beta regressions when they have data that lie between 0 and 1 (or can be transformed to this interval).

the impact of WOM activity. 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 "no impact." 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).

5.3 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 result 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.

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TABLE 1

AVERAGE PROBABILITIES OF RECEPTION: STUDY 1

Transmitter and Relationship Characteristics				Percentage of Subjects Receiving ("Listen")
Tie Strength	**Transmitter Experience**	**Transmitter Taste**	**Transmitter Connectivity**	
Strong	Direct	Good	High	99.2
Strong	Direct	Good	Low	93.7
Strong	Direct	Poor	High	36.2
Strong	Direct	Poor	Low	34.9
Strong	Indirect	Good	High	68.5
Strong	Indirect	Good	Low	59.8
Strong	Indirect	Poor	High	21.3
Strong	Indirect	Poor	Low	13.4
Weak	Direct	Good	High	78.0
Weak	Direct	Good	Low	74.8
Weak	Direct	Poor	High	22.8
Weak	Direct	Poor	Low	13.4
Weak	Indirect	Good	High	56.7
Weak	Indirect	Good	Low	41.7
Weak	Indirect	Poor	High	12.6
Weak	Indirect	Poor	Low	8.7

TABLE 2

DRIVERS OF RECEPTION: STUDY 1

Effects	Standardized Coefficient (Standard Error)	
Main Fixed Effects:		
Overall intercept	-.13	(.12)
Tie strength	**27.65****	**(3.76)**
Transmitter experience	**35.95****	**(3.78)**
Transmitter taste	**71.58****	**(5.33)**
Connectivity	**12.12****	**(2.57)**
Valence of message[a]	.21	(.23)
Consensus/mixed opinions[a]	.39	(.22)
Two- and Three-Way Interaction Fixed Effects:		
Tie strength × Transmitter experience	**11.41****	**(2.44)**
Tie strength × Transmitter taste	**7.35****	**(2.75)**
Tie strength × Connectivity	-1.12	(2.08)
Transmitter experience × Transmitter taste	**14.36****	**(3.05)**
Transmitter experience × Connectivity	-1.60	(2.11)
Transmitter taste × Connectivity	.76	(2.52)
Tie strength × Transmitter experience × Transmitter taste	**7.14***	**(2.62)**
Tie strength × Transmitter experience × Connectivity	1.49	(2.21)
Tie strength × Transmitter taste × Connectivity	3.18	(2.34)
Transmitter experience × Transmitter taste × Connectivity	1.41	(2.10)
Random Effects Variance Components:		
Var(Intercept) (between-individual variance)	**.96****	**(.24)**
Var(ε_{0i}) (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).

TABLE 3
DESCRIPTIVE STATISTICS: STUDY 2

	Brand X (focal product)	Brand Y (other product)
Updating of Disposition toward Brand ($y_{1i,2}$)		
Mean (standard deviation) on (0,1) scale	.19 (.18)	.10 (.13)
Percent of cases at 0	32.6%	54.4%
Maximum on (0,1) scale	.83	.67
Updating of Certainty in Disposition toward Brand ($y_{2i,2}$)		
Mean (standard deviation) on (0,1) scale	.19 (.21)	.10 (.13)
Percent of cases at 0	39.1%	48.9%
Maximum on (0,1) scale	.83	.83
Distribution of Word-of-Mouth Reception Classes		
Class 1, no reception: $y_{1i,2} = 0$, $y_{2i,2} = 0$	17.7%	30.1%
Class 2, only disposition changes: $0 < y_{1i,2} < 1$, $y_{2i,2} = 0$	21.4%	18.8%
Class 3, only certainty changes: $y_{1i,2} = 0$, $0 < y_{2i,2} < 1$	14.9%	24.3%
Class 4, both change: $0 < y_{1i,2}$, $y_{2i,2} < 1$	46.0%	26.8%

TABLE 4
MODEL COMPARISONS: STUDY 2

Model	Impact Type Effects[a]	Amount of Impact Effects[a]	Variance in Amount of Reception Effects[a]	Number of Parameters Estimated	-2 Log-Likelihood[b]	AIC BIC[c]
Null	Intercepts	Intercepts	Intercepts	7	428.7	442.7 468.1
Heteroskedastic (Full model)[d]	Intercepts Main effects Two-way interactions	Intercepts Main effects Two-way interactions Endogenous effects Other product effects	Intercepts Endogenous effects	85	-40.5	129.5 437.2
Homoscedastic	Intercepts Main effects Two-way interactions	Intercepts Main effects Two-way interactions Endogenous effects Other product effects	Intercepts	83	218.1	384.1 684.6

Sample size: $N = 276$ for all models.

[a] 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).

[b] The maximized log-likelihood is used; smaller -2 Log-Likelihood indicates better model fit.

[c] AIC is the Akaike Information Criterion and BIC is the Bayesian Information Criterion; smaller AIC and BIC indicate better model fit.

[d] This is the model reported in the paper and upon which the findings are based.

TABLE 5
PARAMETER ESTIMATES FOR PROBABILITIES OF CLASS OF IMPACT: STUDY 2[a]

Effect[b]	Class 2 Disposition Change		Class 3 Certainty Change		Class 4 Disposition, Certainty Changes	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Intercepts: case k vs. case 1	1.43	.97	.98	1.05	**2.03****	**.91**
Main and two-way interaction effects: case k vs. case 1						
Strong tie transmitter (vs. stranger)	-.68	1.13	-.98	1.26	-1.62	1.05
Weak tie transmitter (vs. stranger)	-1.18	1.07	-1.87	1.23	**-1.73***	**1.01**
Expert transmitter (vs. novice)	-.93	1.04	**-2.45****	**1.25**	-.82	.95
Positive message (vs. negative)	.15	1.12	.27	1.24	-.08	1.02
Impassioned message (vs. matter-of-fact)	-1.36	1.04	-1.55	1.16	-1.04	.94
Strong tie × Expert	.60	1.22	1.83	1.32	**2.26****	**1.05**
Strong tie × Positive message	-1.63	1.24	-.07	1.36	.75	1.00
Strong tie × Impassioned tone	.91	1.16	-.56	1.30	1.15	1.02
Weak tie × Expert	**1.98***	**1.13**	**3.02****	**1.24**	**2.48****	**1.05**
Weak tie × Positive message	-.85	1.07	-.95	1.24	-.52	.97
Weak tie × Impassioned tone	.61	1.09	1.43	1.17	1.30	1.00
Expert × Positive message	**-2.17****	**.97**	.46	1.08	-1.24	.83
Expert × Impassioned tone	**1.81***	**.96**	1.32	1.06	1.02	.85
Positive message × Impassioned tone	1.23	.88	1.63	1.04	.13	.76

[a] 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.
[b] The baseline class is class 1.
* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE 6
ESTIMATED MAIN EFFECTS ON PROBABILITIES OF CLASS OF IMPACT: STUDY 2

Effect		Class 1 No Reception p_1	Class 2 Disposition Change p_2	Class 3 Certainty Change p_3	Class 4 Disposition, Certainty Changes p_4
Empirical Distribution		.18	.21	.15	.46
Main effects[a,b]					
Tie strength:	Strong tie friend	.15	.11	.09	.65
	Weak tie acquaintance	.17	.16	.12	.55
	No tie stranger	.15	.27	.15	.43
Transmitter credibility:	Expert	.10	.11	.11	.68
	Novice	.24	.24	.12	.40
Message valence:	Positive	.19	.09	.22	.50
	Negative	.12	.28	.06	.54
Message tone:	Emotional/impassioned	.12	.20	.11	.58
	Matter-of-fact	.22	.14	.14	.50

[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 7
ESTIMATED INTERACTION EFFECTS ON PROBABILITIES OF CLASS OF IMPACT: STUDY 2

Effect		Class 1 No Reception p_1	Class 2 Disposition Change p_2	Class 3 Certainty Change p_3	Class 4 Disposition, Certainty Changes p_4
Empirical Distribution		.18	.21	.15	.46
Transmitter credibility × 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 × 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 × 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.

TABLE 8
PARAMETER ESTIMATES FOR AMOUNT OF IMPACT

Effects		Disposition Change		Certainty Change	
		Estimate	Std. error	Estimate	Std. error
Intercept		**-.85***	.16	**-1.57***	.20
Endogenous effects:	Disposition change	-----	-----	**3.87***	.84
	Certainty change	**2.92***	.83	-----	-----
Other product effects:	Disposition change	**1.36***	.34	-.18	.37
	Certainty change	.34	.35	**2.12***	.25
Main and two-way interaction effects: case *k* vs. case 1					
Strong tie transmitter (vs. stranger)		**-.37***	.21	.08	.22
Weak tie transmitter (vs. stranger)		**-.61***	.19	-.31	.23
Expert transmitter (vs. novice)		-.19	.18	-.33	.22
Positive message (vs. negative)		**-.70***	.20	**.40***	.22
Impassioned message (vs. matter-of-fact)		.25	.19	-.19	.20
Strong tie × Expert		**.93***	.22	.28	.23
Strong tie × Positive message		**.40***	.23	**-.39***	.24
Strong tie × Impassioned tone		**-.56****	.22	-.05	.22
Weak tie × Expert		**.62***	.20	**.43****	.22
Weak tie × Positive message		**.56***	.21	-.16	.23
Weak tie × Impassioned tone		.00	.20	.34	.22
Expert × Positive message		.05	.19	.01	.18
Expert × Impassioned tone		-.18	.17	.04	.18
Positive message × Impassioned tone		-.02	.19	**.31***	.18

$* p < .10, ** p < .05, *** p < .01$

ONLINE APPENDIX A: MODELING WORD-OF-MOUTH IMPACT

A.1 Basic Approach

Let $\mathbf{a}_{it} = [a_{1i,t}, a_{2i,t}]'$ represent the dispositional and certainty components of the attitude that person i has toward a given brand or product at time t, and $\mathbf{y}_{i,t} = [y_{1i,t}, y_{2i,t}]' = [|a_{1i,t} - a_{1i,t-1}|, |a_{2i,t} - a_{2i,t-1}|]'$ 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 $\mathbf{y}_{i,t}$) 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.[15] 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.

A.2 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 for attitude disposition $a_{1i,t} \in [s_{min}, s_{max}]$ and one for attitude certainty $a_{2i,t} \in [s_{min}, s_{max}]$.[16] The following transformation and preparation steps are required:

1. Compute the raw absolute difference between priors and posteriors:

   $$\mathbf{y}_{i,t}^{raw} = [|\, a_{1i,t} - a_{1i,t-1}\,|,|\, a_{2i,t} - a_{2i,t-1}\,|]', \text{ and } y_{1i,t}^{raw}, y_{2i,t}^{raw} \in [0, \, s_{max} - s_{min}];$$

2. Transform each element of $\mathbf{y}_{i,t}^{raw}$ to the unit interval: $\mathbf{y}_{i,t} = \mathbf{y}_{i,t}^{raw} /(s_{max} - s_{min})$. This gives

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

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

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[15] 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%.
[16] The min and max here are the scale minimums and maximums.

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., $a_{1i,t-1}$ and $a_{2i,t-1}$) 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.[17]

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 $0 + \varepsilon$ and 1 values to $1 - \varepsilon$ (where ε is a very small number). Although reasonable when either 0 or 1 values (or both) are not 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 $y_{1i,t} = 1$ or $y_{2i,t} = 1$. 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.

A.3 Statistical Model

In Appendix B 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,

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[17] 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.

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 B. Consider the

following four distinct classes:

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

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.[18] 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 (ω) and dispersion (τ) 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: α-, β-, and γ-effects. The α-effects are the effects of transmitter and message characteristics on

---

[18] For response variable g_i (for $i = 1, \ldots, N$), $g_i \sim Beta(\omega,\tau)$, the Beta density is $f(g_i \mid \omega,\tau) = \dfrac{\Gamma(\omega+\tau)}{\Gamma(\omega)\Gamma(\tau)} g_i^{\omega-1}(1-g_i)^{\tau-1}$,

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 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 β-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 γ-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 B).

ONLINE APPENDIX B: BETA REGRESSION DETAILS

B.1 Univariate Beta Regression Model

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

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

$L = \sum_{i=1}^{N} \ln L(\omega, \tau \mid g_i)$ is maximized in the usual fashion to obtain maximum likelihood estimates of

the parameters. Note that $E(g) = \omega/(\omega + \tau)$ and $Var(g) = \dfrac{\omega\tau}{(\omega + \tau)^2(\omega + \tau + 1)}$. 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 $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})/[1 + \exp(\mathbf{x}_i\boldsymbol{\beta})]$, and the precision parameter usually has a

logarithmic link $\phi_i = \exp(-\mathbf{w}_i \boldsymbol{\gamma})$.[19] Here $\mathbf{X}$ is an $N \times M_1$ matrix of covariates (including a column of

ones) that can affect $E(g)$ with $\boldsymbol{\beta}$ an M_1-vector of the corresponding coefficients, and $\mathbf{W}$ is an $N \times M_2$

matrix of covariates (including a column of ones) that can affect $Var(g)$ with $\boldsymbol{\gamma}$ an M_2-vector of the

corresponding coefficients (these effects 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 $\mathbf{X} = \mathbf{W}$.

B.2 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:

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

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

---

[19] The negative sign is simply so that positive γ coefficients mean that the dispersion is *increasing*.

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 $\tau = \tau_1 + \tau_2$):

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

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 $\Pr(c_{i,t} = k) = p_{ki,t} = \exp(\mathbf{z}_{ik}\boldsymbol{\alpha}_k) / \sum_{j=1}^{4} \exp(\mathbf{z}_{ij}\boldsymbol{\alpha}_j)$, with $\mathbf{Z}$ an $N \times M_3$ matrix of

covariates (including a column of ones) that can affect the mixture probability for the given case, with

$\boldsymbol{\alpha}_k$ 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 $\mathbf{X}$, $\mathbf{W}$, and $\mathbf{Z}$ can overlap.

The likelihood function is a standard mixture model likelihood, and is as follows:

$$
L_{i,t} = \begin{cases}
p_{1i,t} \times & 1 & \text{for } c_{i,t} = 1 \quad (\text{"Class 1"}) \\[2em]
+ p_{2i,t} \times & \left[\dfrac{\Gamma(\omega_1 + \tau_1)}{\Gamma(\omega_1)\Gamma(\tau_1)} y_{1i,t}^{\,\omega_1-1}(1-y_{1i,t})^{\tau_1-1} \right] & \text{for } c_{i,t} = 2 \quad (\text{"Class 2"}) \\[2em]
+ p_{3i,t} \times & \left[\dfrac{\Gamma(\omega_2 + \tau_2)}{\Gamma(\omega_2)\Gamma(\tau_2)} y_{2i,t}^{\,\omega_2-1}(1-y_{2i,t})^{\tau_2-1} \right] & \text{for } c_{i,t} = 3 \quad (\text{"Class 3"}) \\[3em]
+ p_{4i,t} \times & \left[\begin{array}{c} \dfrac{\Gamma(\omega_1 + \omega_2 + \tau)}{\Gamma(\omega_1)\Gamma(\omega_2)\Gamma(\tau)} \\[1em] \times \dfrac{y_{1i,t}^{\,\omega_1-1} y_{2i,t}^{\,\omega_2-1}(1-y_{1i,t})^{\omega_2+\tau-1}(1-y_{2i,t})^{\omega_1+\tau-1}}{(1-y_{1i,t}y_{2i,t})^{\omega_1+\omega_2+\tau}} \end{array} \right] & \text{for } c_{i,t} = 4 \quad (\text{"Class 4"})
\end{cases}
$$

The complete data log-likelihood is $LL_{C,t} = \sum_{i=1}^{N} \ln L_{i,t}$.

ONLINE APPENDIX C: ADDITIONAL STUDY ON THE IMPACT OF STRANGERS

C.1 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 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 non-significant, $p = .96$).

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).

C.2 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. When the information being transmitted makes recipients feel more certain, this lifts perceived credibility.