How Interest Shapes Word-of-Mouth Over Different Channels

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Contribution statement:

There has been a great deal of recent interest in word-of-mouth, but while it has been shown to boost diffusion and sales, less is known about its causes, or what leads people to talk about certain products or brands rather than others. Further, consumers share word-of-mouth through different conversation channels (e.g., online vs. face-to-face), but do these channels shape what types of products and brands get discussed, and if so, how? This research addresses this question, providing insight into how the channel people share word-of-mouth through impacts what gets discussed.
Consumers share word-of-mouth face-to-face, online, and through various other channels. But do these channels affect what people talk about, and if so, how? Analysis of over 21,000 conversations, as well as a laboratory experiment, demonstrate that conversation channel continuity norms shape what gets discussed. In discontinuous conversation channels (e.g., online posts or text), pauses between conversational turns are expected, so people have time to select and craft what they say. Consequently, more interesting products should be talked about more than boring ones. In channels where conversations are expected to occur more continuously (e.g., face-to-face or on the phone), however, there is less time to selectively pick what one talks about. Consequently, how interesting products are to talk about should have less of an impact on whether they get discussed. These findings shed light on what drives word-of-mouth and how companies can design effective word-of-mouth campaigns.
Word-of-mouth is frequent and important. Consumers talk about restaurants they like, post reviews of movies they hate, and share information about the best child safety seats. Social transmission also has a significant impact on what people buy and how they behave (Godes et al. 2005; Godes and Mayzlin 2004; 2009; Iyengar, Van den Bulte, and Valente 2011; Leskovec, Adamic, and Huberman 2007). Consequently, organizations have come to realize that generating word-of-mouth is an important part of marketing strategy.

But while its consequences are clearly valuable, much less is known about word-of-mouth’s causes, or what leads people to talk about certain products or brands rather than others. Further, the little work in this area has mostly ignored whether the conversation channel shapes what people talk about. Word-of-mouth can be shared in different ways. People have face-to-face conversations, post on blogs, send texts, or write online reviews. Do these different channels shape what types of products and brands people talk about, and if so, how?

Consider the brands that get talked about most over different channels. Virtue.com does an annual ranking of which brands are talked about most online and The KellerFay Group provides a similar index for offline word-of-mouth. Comparing the top 10 brands on each list, however, shows little overlap. Verizon is 2nd in offline word-of-mouth, for example, but ranks 85th in online conversations.

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While these differences might reflect different methodologies used by the two firms, or differences in people who talk more over one channel versus another, might they also say something deeper about the psychology behind word-of-mouth?

This paper distinguishes between different types of conversation channels (i.e., continuous and discontinuous) and uses this notion to shed light on one way in which the channel itself shapes word-of-mouth. In particular, we examine how conversation channel continuity moderates the relationship between how interesting a product or brand is to talk about and how much word-of-mouth it receives. We do this in two ways. First, we analyze two unique datasets of thousands of everyday conversations across different channels to provide evidence for our theoretical perspective in the field. Second, building on these results, we conduct a controlled laboratory experiment where we manipulate conversation continuity to directly examine its effects. The results underscore the causal impact of channel continuity on word-of-mouth. Taken together, the results deepen understanding about what drives word-of-mouth and provide insight into how to design more effective word-of-mouth marketing campaigns.

THEORETICAL BACKGROUND

Most research on word-of-mouth has focused on how it affects diffusion and sales. Consumers are more likely to buy DVDs their friends recommend (Leskovec et al. 2007) and doctors are more likely prescribe new prescription drugs that other doctors they know prescribed previously (Iyengar et al. 2011). Similarly, word-of-mouth and online reviews have been shown to boost new customer acquisitions (Schmitt, Skiera, and Van den Bulte 2011; Trusov, Bucklin,
and Pauwels 2009) and increase sales in various product categories (Chevalier and Mayzlin 2006; Godes and Mayzlin 2009). Certain types of word-of-mouth (i.e., explaining language) have even been shown to impact evaluations of consumption experiences (Moore 2012).

But while research has focused on the consequences of word-of-mouth, there has been much less attention paid to its causes (Cheema and Kaikati 2010; Goldenberg, Libai and Muller 2001), or how different communication channels (e.g., face-to-face vs. online vs. phone) shape what people talk about or share. Most papers rely on data from only one channel, such as online reviews (Chevalier and Mayzlin 2006), newsgroups (Godes and Mayzlin 2004), email forwards (Berger and Milkman 2012), email referrals (Leskovec et al. 2007; Trusov et al. 2009) or face-to-face communication (Berger and Schwartz 2011; Cheema and Kaikati 2010; Godes and Mayzlin 2009). But when only one channel is examined, it is difficult to say much about how the channel itself impacts behavior. Indeed, researchers have noted that there may be fundamental differences between online and offline social interactions (Godes et al. 2005), yet little research has addressed this point.

This issue is particularly important given that groups that want to increase word-of-mouth must decide which channel(s) they want to target. They choose whether to try and create a viral video, encourage online referrals, stage a flash mob, or generate some other event, promotion, or campaign to increase mentions of the brand. But these approaches are designed to encourage word-of-mouth through different channels. Consequently, to understand how to make them effective, we need to understand the nature of the channels themselves and whether they have different impacts on what gets shared.
CONVERSATION CONTINUITY

We distinguish between continuous and discontinuous conversations and use this notion to shed light on how conversation channels shape conversation.

People communicate information when they talk, but as with many types of consumption behaviors (Levy 1959), they also communicate things about themselves (Tannen 2005; Wojnicki and Godes 2010). If someone quotes Shakespeare and Thoreau, people may assume they are well-read. If someone always talks about restaurants that just opened, people may infer that they are a foodie. Along these lines, Wojnicki and Godes (2010) show that consumer propensities to talk about satisfying and dissatisfying experiences depend in part on their desire to communicate domain expertise.

But people not only communicate through what they talk about, they also communicate through how they talk. Tannen (2005) notes that stylistic elements of conversation, such as rate of speech, speed of turn taking, and avoidance of pauses between conversational turns, all communicate things about the speaker. Failures to live up to expectations on these different dimensions can lead others to make negative attributions about a person (Loewenstein, Morris, Chakravarti, Thompson, and Kopelman 2005). Transitions from one party speaking to the other, for example, usually occur with no long gap or silence in between. Consequently, people who take long to respond may be seen negatively (Clark 1996; Sacks, Schegloff, and Jefferson 1974; Tannen 2000).

Expectations about conversation style, however, vary based on the conversation channel (e.g., face-to-face vs. email). Different types of conversations come with different norms (Grice 1975; Levinson 1983). Think about the last time you had lunch with a friend or shared a cab
with an acquaintance. Most face-to-face settings as well as phone conversations involve continuous discussion (Sacks et al. 1974). There is an expectation that ongoing conversation will occur, and it is awkward to sit in silence. Both parties try to keep the conversation flowing, filling the conversational space, and discussion is relatively continuous with few breaks in between. Long pauses are somewhat uncomfortable and may lead people to infer that someone is not a good conversationalist.

Contrast that, however, with the types of conversations that often occur in online discussion forums, like blogs or Facebook, that are mostly discontinuous in nature. One person writes a post or comment, but there is no expectation that someone else will respond right away. In fact, even if a person does decide to respond, it may occur hours or even days later. This is not only true of broadcast conversations (i.e., one-to-many like a blog post) but even in narrowcast or dyadic online conversations where only two people are involved. When someone posts on someone else’s Facebook wall, or sends them an email or text, they do not usually expect an immediate response, and even an “immediate” response is seen as one that occurs minutes later, rather than right away. Further, because the expectation is that conversation is asynchronous, people have time to deliberate and think through what they say. Text and email are similar. Overall, discontinuous conversations generally involve no expectation of immediate response, and pauses in the conversation are not seen to signal anything about the conversation partner.

Thus in an attribution sense, how strongly conversation partners will make inferences about the person they are talking to depends on the salience of a situational attribution. If Jason takes a while to respond, does it say something about him or just the medium over which we are conversing? If the conversation is over a channel that is expected to be discontinuous (e.g.,
email), people will be more likely to attribute a delayed response to the channel (e.g., he must not have received the note or had a chance to respond) and infer little about the person. If the conversation is over a channel that is expected to be continuous (e.g., face-to-face), however, people will be more likely to attribute a delayed response to something about the person.

THE CURRENT RESEARCH

We suggest that these differences in conversation continuity will impact the types of things that get discussed.¹ In particular, we suggest that whether or not a product, topic, or brand is interesting to talk about will have a greater impact on whether it gets mentioned in certain channels (e.g., online) rather than others (e.g., offline), and that this is driven by differences in the conversation continuity of the channels.

We focus on product interest for two reasons. First, it is one of the most, if not the most, frequently discussed potential drivers of word-of-mouth. Practitioners often argue that products need to be interesting (i.e., novel or surprising in some way) to be talked about (Dye 2000; Hughes 2005; Knox 2010; Rosen 2008). In his popular book on word-of-mouth marketing, for example, Sernovitz (2006) argues that the most important way to generate word-of-mouth is to “be interesting” and that “nobody talks about boring companies, boring products, or boring ads,” (p. 6). Thus we test whether this common wisdom holds, and whether it holds equally, in different word-of-mouth channels (e.g., online and offline).

Second, prior work has found conflicting relationships between interest and WOM. While theory suggests that more interesting products should be talked about more than less

¹ Researchers have also described this difference in terms of synchronous vs. asynchronous communication (Poole, Shannon, and DeSanctis 1992), but we prefer to talk about conversation continuity (see Saks et al. 1974) because it more concretely reflects the pauses that do, or do not happen between conversational turns.
interesting ones (Dichter 1966), and some empirical work supports this notion (Berger and Milkman 2012), other work shows that more interesting products do not get more word-of-mouth (Berger and Schwartz 2011).

We suggest that this seeming discrepancy in prior findings is at least partially due to differences in the expected conversation continuity of the different word-of-mouth channels examined. When conversations are expected to be discontinuous, people have time to select and craft what they say. They have more opportunity to think of a clever or interesting response and can wait to respond until they have something worthwhile to talk about. One author’s friend, for example, notes that he is much more suave over text than in person because he can take the time to craft the perfect response. Consequently, in discontinuous channels people should be more likely to post or share something if they think it will be interesting. Indeed, prior work shows that more interesting *New York Times* articles are shared more frequently online, and are more likely to make the *Times* most emailed list (Berger and Milkman 2012).

When conversations are expected to be continuous, however, as in most face-to-face interactions, there is less time to selectively pick what one talks about. As noted previously, it is awkward to have dinner with a friend in silence, or ride in a cab with a colleague without conversing, so rather than waiting to think of the most interesting thing to say, people will talk about whatever is top-of-mind to keep the conversation flowing. It is not that people do not have enough interesting things to talk about; rather, they do not have the time to select the most interesting thing. They just talk about whatever is accessible. Almost anything is better than dead silence and few things will be deemed too boring to talk about. Consequently, interesting things may not be talked about any more than boring ones. Consistent with this notion, prior
work on face-to-face word-of-mouth shows that compared to less interesting brands, more interesting brands do not get more word-of-mouth (Berger and Schwartz 2011).

Overall then, we suggest that in discontinuous conversation channels, such as online posts or text messaging, more interesting products or brands (e.g., iPads or Hollywood movies) should be more likely to be discussed than their less interesting counterparts (e.g., toasters and Walmart). In more continuous channels, however, such as face-to-face conversation, interest should have less of an impact on word-of-mouth. Interesting products or brands may not even be talked about any more frequently than less interesting ones.

Carefully studying these issues is hampered, however, by data availability. One could imagine comparing the relationship between the amount of interest a brand evokes and the amount of word-of-mouth it receives over different channels, but aggregate data introduces selection issues. Any differences in the results could be attributed to different people that tend to talk online versus offline, for example, rather than the channel itself.

We address this problem in three ways. First, in preliminary analyses we use aggregate word-of-mouth data from people who have conversations both online and offline (pilot study). Second, we use a unique, individual-level dataset covering word-of-mouth over various channels (study 1). It contains over 35,000 brand and product mentions from a nationally representative sample of approximately 6,000 people who recorded all of the word-of-mouth they engaged in, as well as the channel they used (e.g., face-to-face, online posts, or text) over a one-day period. By controlling for variation at the individual and product levels, we examine the impact of different conversation channels on word-of-mouth.

Third, we directly test the causal impact of conversation continuity through an experiment (study 2). We keep the conversation channel itself the same but manipulate whether
people expect to pause (or not) before and between conversational turns. We then examine how this affects the relationship between how interesting a topic is and whether it is discussed.

PILOT STUDY: INTEREST AND WORD-OF-MOUTH ACROSS DIFFERENT CHANNELS

In a preliminary analysis, we examined aggregate data on word-of-mouth, both from online posts and from face-to-face conversations.

Data were provided by the Keller Fay Group, a marketing research firm that specializes in word-of-mouth marketing. Throughout the year, the company surveys thousands of people about their daily conversations. Rather than just collecting a convenience sample, or people who use a specific social network, they use a large, nationally representative sample of Americans to avoid potential sampling biases. Each participant is asked to keep a diary that records what products and brands they talked about over a 24-hour period. Respondents also report the channel over which that conversation occurred, such as whether it was face-to-face or in an online post (i.e., over a blog, on twitter, or a social networking site, all lumped into one category that the company does not break out).

In our first study, we examined aggregate data on how often approximately 1,200 products and brands were talked about. The list includes everything from large brands like Coca-Cola, Verizon, and Walmart, to smaller brands like Jack’s Links, Monopoly, and Toll House. The data was collected from 5,960 people in 2009 who had at least one online post and
one face-to-face conversation. By focusing on people who have conversations of both types, we reduce the possibility that any relationships observed between channel type and interest are driven by different types of people having conversations on one channel or the other. We more fully cast doubt on that concern in the next study by using individual-level data.

Two coders rated each product or brand based on how interesting it would be to talk about (1 = not at all, 7 = a great deal; adapted from Berger and Schwartz 2011; Heath, Bell, and Sternberg 2001). Their ratings were reasonably highly correlated (r = .68) and averaged to form an interest score for each brand. We then examined the correlation between how interesting a product or brand is to talk about and how much word-of-mouth that product or brand received face-to-face as well as online.

Results

Consistent with prior work (Keller and Libai 2009), face-to-face word-of-mouth was more frequent than online word-of-mouth (figure 1).

More importantly, as predicted, the relationship between interest and word-of-mouth differed by channel. There was a positive and significant relationship between interest and online posts (r = .08, p < .01): in online conversations, more interesting products were mentioned more frequently than their less interesting counterparts. In contrast, there was no relationship between interest and face-to-face word-of-mouth (r < .01, p > .70): in face-to-face conversations, more interesting products were not mentioned more frequently than their less interesting counterparts. These correlations are significantly different from one another (t = 8.54, p < .001).

2 Mentions of different brands are weighted based on the age and demographics of the respondent to reflect the population as a whole. Information about whether the product or brand was talked about positively or negatively was not provided.
It is worth noting that these results are not driven by lots of small brands never being mentioned online. The difference between online posts and face-to-face word-of-mouth actually becomes even sharper when dropping brands that are mentioned infrequently. Looking only at the 500 most frequently discussed brands, for example, shows a stronger relationship between interest and online posts ($r = .10, p < .05$) and an even weaker relationship between interest and face-to-face word-of-mouth ($r = .003, p = .95$). Results are also robust to only looking at the smallest brands as well.

Results are also the same if we take the log of the number of mentions to avoid any concerns about outliers driving the results. There is an even stronger relationship between interest and online posts ($r = .13, p < .001$) and an even weaker relationship between interest and face-to-face word-of-mouth ($r < .01, p > .86$). Further, if we regress the log of WOM on channel, interest, and their interaction we find a significant interaction ($\beta = -0.09, p < .005$). This indicates that the relationship between interest and word-of-mouth is significantly weaker for face-to-face word-of-mouth.
STUDY 1: INDIVIDUAL-LEVEL DATA

Study 1 differs from the pilot study in two main ways. First, we use individual-level data to provide better controls. One could argue that people who tend to talk more online also tend to mention more interesting brands or care more about how they look to others. Younger people may also talk more online. But by controlling for individual-differences in the propensity to talk over different channels we can rule out the possibility that any effects attributed to channel are really driven by different types of people talking more over one channel than another.

Second, we provide a broader test of our underlying theoretical proposition by examining a broader set of conversation channels. We suggested that the relationship between interest and word-of-mouth differs for online posts and face-to-face conversations due to the nature of conversations in these two types of channels; face-to-face conversations tend to be continuous, while online conversations tend to be more discontinuous. But these are not the only channels over which word-of-mouth can travel. People also talk over text, for example, or the phone. Both of these channels are technically offline (people are on their phones, not on the internet), but our conceptualization suggests they should have a different impact on the types of things discussed. While phone is a more continuous mode of communication, text is more discontinuous (Loewenstein et al. 2005; Poole et al. 1992). Consequently, if our theoretical proposition is correct, the relationship between interest and word-of-mouth over these channels should differ. Email is also more discontinuous, so it should show patterns similar to text and online posts. We start by looking at face-to-face conversations and online posts and then move to a broader analysis of word-of-mouth over continuous and discontinuous channels.
Data

Study 1 uses a different dataset, cataloging individual-level data on over 21,000 conversations from Keller Fay collected in 2010. For each individual, the data includes what products or brands that person talked about during the day they were surveyed, as well as what channel they talked about it over. In addition to containing face-to-face and online word-of-mouth, the data also includes other communication channels such as telephone (which is continuous) and text and email (which are discontinuous). The dataset is not restricted to people who had both a face-to-face and online conversation, so while some people had both types of conversations, others had conversations of only one type or of other types entirely. Each person only talked about a given product or brand once, and mentioned 11.78 brands on average. The data also includes many more small brands that were only mentioned once andcatalogues 6,500 products and brands.

Coders again rated each product based on how interesting it would be to talk about and we examined the relationship between these ratings and how often different products or brands were talked about over different conversation channels.³

Results

Aggregate Analysis. First, we perform the same aggregate level analysis as in the pilot study. We examine how interesting a product or brand is to talk about and how frequently people mentioned that product or brand in face-to-face conversations as well as online.

³ Given the huge number of brands in this study, not every coder rated every brand, but for brands rated by multiple coders the reliability was quite high (r = .74).
Results are similar to those found in the pilot study. There is a positive and significant relationship between interest and online word-of-mouth ($r = .04, p < .005$); compared to less interesting products, more interesting products were again mentioned more frequently online. In a face-to-face context, however, more interesting products were not mentioned more frequently than less interesting ones ($r = .002, p > .87$). As in the pilot study, these correlations are significantly different from one another ($t = 6.82, p < .001$). These results show that the findings of the pilot study are not somehow limited to people who have conversations both face-to-face and online.

*Individual-Level Analysis – Number of Conversations.* Next, we incorporate the individual-level data. This analysis closely mirrors the aggregate analyses done previously and allows us to examine how the relationship between interest and word-of-mouth changes for different channels. It also allows us to cast doubt on the possibility that any effects attributed to channel are really driven by certain types of people both having more conversations and tending to talk more over certain channels.

As each individual mentions a brand only once, we cannot estimate an individual-level model with the number of mentions of a specific brand as the dependent variable. Thus, we investigate how many conversations people have at different interest levels and how that varies by conversation channel. To do so, we use a Poisson model and accommodate the count nature of the data. Let Online be an indicator variable that takes a value of 1 for conversations that are online and 0 otherwise. Let $Y_{ijk}$ be the number of conversations that individual $i$ has with interest level $j$ ($j=1,\ldots,6$) in channel $k$ ($k = 0$ for face-to-face and $k=1$ for Online). Then, we specify the following model:

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4 Face-to-face word-of-mouth was again more frequent than online word-of-mouth.
5 We specified a conversation to have an interest level of 1, 2… 6 if the coders gave it an average rating between 1 and 2, 2 and 3… .6 and 7, respectively.
\[ P(Y_{ijk} = y) = \frac{\hat{\lambda}_{ijk}^y e^{-\hat{\lambda}_{ijk}}}{y!}, \]

\[ \log(\lambda_{ijk}) = \alpha_i + \beta_1 j + \beta_2 (k) + \beta_3 (j \times k). \]

Here, the parameter \( \alpha_i \) is an individual-specific fixed effect, which captures any variation across people in the total number of conversations.\(^6\) The parameters \( \beta_1, \beta_2 \) and \( \beta_3 \) capture the impact of interest, channel and its interaction on the expected number of conversations. The face-to-face channel (\( k = 0 \)) serves as the baseline channel for conversations.

As predicted, results indicate a positive and significant interaction (Online * Interest = 0.15, \( p < .01 \)); how interesting products or brands are to talk about has a larger impact on whether they are talked about in online conversations as compared to face-to-face conversations.

Results are similar when we look at all types of continuous and discontinuous conversations. As noted earlier, phone conversations are continuous (no long breaks in between partners’ responses) and text and email are more discontinuous (time elapses between one person talking and the other). We create two groups of channels, continuous (f2f and phone) and discontinuous (online, text, and email) and replicate the above fixed effect analysis. The baseline channel for these results is continuous communication. As predicted, there is a positive and significant interaction (Discontinuous * Interest = 0.09, \( p < .01 \)), indicating that interest has a larger impact on discontinuous conversations than on continuous conversations.

Results also remain the same when we drop online and face-to-face conversations from this analysis and only consider text (discontinuous), email (discontinuous) and phone (continuous) conversations. There is a positive and significant interaction (Discontinuous *

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\(^6\) Note that a Poisson model, unlike other count models, does not suffer from the incidental parameters problem (Lancaster 2000).
Interest = 0.08, \( p < .01 \) indicating that interest has a larger impact on discontinuous conversations than on continuous conversations.

**Individual-Level Analysis – Conversation-by-Conversation.** We also conduct a second individual-level analysis that examines each conversation separately. This allows us to rule out the possibility that the results are merely driven by people who tend to talk about more or less interesting brands also tending to talk over certain channels.

To address this issue, we perform a regression of the interest level of each conversation on a channel (Online or face-to-face) after controlling for an individual-level fixed effect. Let \( IR_{ijk} \) be the interest rating for a conversation \( j \) that individual \( i \) has in channel \( k \) (\( k = 0 \) for face-to-face and \( k=1 \) for Online). We specify the following parsimonious model:

\[
IR_{ijk} = \alpha_i + \beta (k),
\]

where the parameter \( \alpha_i \) is an individual-specific fixed effect and \( \beta \) captures the effect of online channel as compared to face-to-face on the interest level of conversations.

Results indicate that even controlling for individuals, the average interest level of brands that are talked about is higher in online conversations than face-to-face conversations (\( \beta_{\text{Online}} = 0.35, p < .001 \)).

Results are similar when we look at continuous and discontinuous conversation channels more broadly. We again create two groups of channels, continuous (f2f and phone) and discontinuous (online, text, and email) and perform the same fixed effect analysis above. The regression shows that the average interest level of brands that are talked about is higher in discontinuous than continuous conversations (\( \beta_{\text{Discontinuous}} = 0.22, p < .001 \)).

\[7\] Results of this, and the rest of the analyses, are similar when interest ratings from a broader set of coders are used. Having the same coders rate most of the product and brand creates continuity, but one could argue that their particular viewpoints might be biased in some way. Consequently, we also used mechanical Turk to collect ratings of how interesting each product or brand would be to talk about from a much larger sample of coders from across...
Finally, to ensure that the results of our continuous/discontinuous analysis are not driven solely by online and face-to-face conversations, we also replicate the fixed effect analysis but only consider text, email (grouped together as discontinuous) and phone conversations (continuous). The results remain the same: the average interest level of brands that are talked about is higher in discontinuous than continuous conversations ($\beta_{\text{Discontinuous}} = 0.29$, $p < .001$).

Discussion

Results of the pilot study and study 1 support our underlying conceptualization. First, the channel over which communication occurred moderated whether more interesting products were talked about more than less interesting ones. Interest has a much larger impact on online conversations than offline conversations. Similarly, interest has a larger impact on text or email rather than phone conversations. These effects persisted even while using individual-level data, casting doubt on the possibility that they are due to the type of people who tend to talk more online or offline.

Second, the results suggest that the continuity of the conversation channels drove these effects. Not only was the relationship between interest and word-of-mouth different in online and offline channels, but results were the same for other types of continuous (phone) and discontinuous (text and email) conversation channels. Thus rather than being driven by whether the conversation is online or offline per se, the set of results is better explained by whether the conversation channel is continuous or discontinuous.

the United States ($N = 400$, mean age = 34). To reduce fatigue, each coder was only asked to rate a random sample of 240 products and brands, so each product was rated by approximately 9 coders. While it was not possible to train these coders as carefully as our main ones, it is worth noting that even using these alternate ratings, the results of the various analyses remained the same. This consistency further supports the validity of the findings.
Our results also cast doubt on a number of alternate explanations. First, while online and face-to-face conversations differ on a number of dimensions besides just conversation continuity, the fact that the results are similar for other types of continuous and discontinuous channels rule out some alternative interpretations for the results. One could argue, for example, that interest has a larger impact on online conversations because people can more easily engage or disengage depending on whether they are interested in the topic. The presence of a conversation partner looms larger when they are physically there, so learned norms about civility may make it harder to exit boring face-to-face conversations (while people can more easily do so online). The physical presence of a conversation partner, however, cannot explain the difference between phone and text conversations. One’s partner is not present in either type of conversation, yet they differ on how much interest shapes what gets discussed.

Second, while one could argue that the conversation data may be biased in some way, it is hard for such biases (were they to exist) to explain our pattern of results. Despite using a diary to keep track of their conversations, one could imagine that respondents underreported the number of conversations they actually have on a daily basis, for example, or even underreport online conversations in particular for some reason (e.g., due to a bias in memory or failure to make accurate use of the diary). One could also imagine that people underreport the number of times they talk about small brands, or are more likely to remember or encode interesting conversations than boring ones (i.e., because they fail to stick out in memory). But while such issues would result in a smaller than accurate number of daily conversations, an overestimation in the relative frequency of offline conversations, or an overestimation of the number of interesting conversations, such main-effect explanations cannot explain our interactive pattern of
results. Why the relationship *between* product interest and word-of-mouth would differ for different channels.

Third, while one could argue that our measure of how interesting a product is to talk about is somehow noisy or biased, it has repeatedly been shown to be valid in prior work (Berger and Schwartz 2011; Berger and Milkman 2012). In addition, it is hard for this issue to explain our pattern of results. Even if the measure was noisy, or biased, that alone cannot explain why it predicts the amount of word-of-mouth over one channel but not the other. The noise or bias would have to somehow be correlated with mentions online, but not offline, which seems unlikely. Further, our results remain the same when interest ratings from a different set of coders is used (see footnote 5), showing that the findings are not restricted to the set of raters used. Finally, the pilot study shows that our results persist (and in fact, get stronger) using a smaller set of 500 brands that are mentioned both online and off, casting doubt on the possibility that our results are somehow driven by different products or brands being talked about online and offline.

Fourth, the data also cast doubt on the possibility that the results are driven solely by audience differences. Status or self-enhancement concerns shape word-of-mouth (Wojnicki and Godes 2010) and appearing boring or interesting may be more likely to affect one’s status among strangers or weak ties (because they do not know someone as well). Consequently, one could argue that another reason people are more likely to talk about interesting things online is that online word-of-mouth is more likely to be in a public forum or with strangers, so people care more about saying interesting things to impress others. But while this explanation may certainly help explain product reviews or posting on blogs, it has trouble explaining our full pattern of results. Most texting occurs with close friends, for example, not strangers, yet we found that more interesting brands are still talked about more frequently over text (a pattern that mimics
other discontinuous channels more broadly). Thus, while audience differences may certainly
explain some of the variation between, for example, blog posting and face-to-face word-of-
mouth, it cannot fully explain our results.

That said, to more directly rule out these alternatives, and provide even stronger evidence
for the causal impact on conversation continuity on word-of-mouth, we conducted an
experiment. We kept everything else the same (e.g., audience, conversation channel, and type of
respondent) and simply manipulated whether people had a continuous or discontinuous
conversation.

STUDY 2: EXPERIMENTAL EVIDENCE

The results of the first two studies provide evidence for our theory in the field, but to
provide more direct evidence of the effects of conversation continuity, we turn to the laboratory.
Manipulating the channel over which people have a conversation (e.g., face-to-face vs. online)
would allow us to see how channel impacts word-of-mouth, but the results would say less about
the underlying process behind those effects. Consequently, we keep the channel itself constant
but manipulated conversation continuity to directly examine how our proposed mechanism
impacts the relationship between interest and what people talk about.

All participants sat face-to-face, but we manipulated whether they expected a pause
before and between conversational turns (discontinuous conversation) or not (continuous
conversation). We then measured how that affected the relationship between interest and
whether a given topic was discussed. Consistent with the prior two studies, we predict that more
interesting topics will be more likely to be discussed in discontinuous conversations, but that
interest will have less of an effect (or none at all) on what gets mentioned when the conversation is continuous.

This experimental approach is particularly useful because it allows us to test the mechanism we believe underlies the effects observed in the field. Conversation channels differ on a number of dimensions, but by keeping channel constant, and simply manipulating conversation continuity, we isolate the impact of continuity in a situation when these other factors are silent. People who care more about seeming interesting may talk more online than offline, people may encode or remember interesting conversations that occur over one channel versus another, and some brands may be inherently more likely to be talked about online rather than face-to-face. Similarly, it may be easier to leave a boring conversation when your conversation partner is not physically there. But by having everyone have a face-to-face conversation, and just manipulating the length of time people expect before and between conversational turns, we can isolate the causal impact of conversation continuity on what gets discussed.

Importantly, we also collect data on the consideration set of topics for each individual. This allows us to disentangle preferential transmission from mere base rates when examining whether topics of different interest levels were discussed (see Godes et al. 2005 for a related discussion regarding word-of-mouth positivity). If we only knew what people mentioned, but not what they could have talked about, then it would be unclear whether any count-type results at the individual level are the result of what people prefer to share or just the distribution of available options. In study 1, for example, there were many low interest brands but few high interest ones. Thus, a given individual might talk about boring brands more frequently than interesting ones just based on the base-rate of what they could choose from (i.e., there are more
boring brands). Individual-level consideration set data was not available for that study, but by collecting such data in this study we can more fully examine whether more interesting brands are talked about more frequently than less interesting ones both in continuous and discontinuous conversation.

Method

One hundred and ninety five undergraduates engaged in a conversation task. They were paired with another participant and asked to have a five minute face-to-face conversation about classes at their university.

The only difference between conditions was the conversation style participants were asked to adopt (i.e., whether pauses between and before conversation turns was expected). In the continuous condition, participants were told that research on conversation styles has shown that some people tend to pause less during conversations than others, and they were asked to adopt this style of conversation. They were told that they should speak at a regular pace when talking, but that they should start speaking right away at the beginning of the conversation and try not to pause before responding to what the other person said.

In the discontinuous condition, participants were told that research on conversation styles has shown that some people tend to pause more during conversations than others, and they were asked to adopt this style of conversation. They were told that they should speak at a regular pace when talking, but that they should wait 20 seconds at the beginning of the conversation and try to wait at least 5 seconds before responding to what the other person said. Pilot data show the manipulation had its intended effect. Participants reported more time to think about what to say
(1 = no time at all, 7 = a great deal of time) in the discontinuous condition ($M_{\text{Discontinuous}} = 3.96$ vs. $M_{\text{Continuous}} = 2.61$; $F(1, 40) = 5.69, p < .03$).

After finishing the conversation, participants were asked to write down all the classes they had taken this year as well as any additional classes they had talked about during the conversation. They were also asked whether or not they had talked about each of the classes they listed during the experiment (these responses were confirmed by a research assistant who listened to a recording of the conversations).

We then took the full set of courses listed, randomized their order, and gave them to a set of outside raters (undergraduates from the same university as the students in the experiment) who coded how interesting they thought most students would find them to talk about (1 = not at all, 7 = a great deal).

Results

**Preliminary Analysis.** As should be expected based on random assignment, there was little difference in the consideration set of the courses listed by participants in the two conditions. There was no difference in either the number of courses listed ($M_{\text{Continuous}} = 7.72$ vs. $M_{\text{Discontinuous}} = 7.35, p > .35$) or interest level as rated by the coders ($M_{\text{Continuous}} = 2.83$ vs. $M_{\text{Discontinuous}} = 2.96, p > .25$).

**Main Analysis.** We use a logistic regression to model the likelihood that a class is mentioned. We use the respondent condition, the interest level of a class, and the interaction between the condition and the interest level for a class as independent variables. To address
unobserved heterogeneity among respondents, we perform an individual-level fixed effect analysis.

As predicted, the analysis reveals a significant condition x interest interaction (estimate = 0.30, \( p < .05 \)), such that the effect of interest on mentioning a topic depends on whether the conversation was continuous or discontinuous (Table 1). For discontinuous conversations, the interest level of the course impacted whether it was mentioned (estimate = 0.43, \( p < .001 \)). More interesting courses were more likely to be discussed. For continuous conversations, however, the interest level of the course did not affect whether it was mentioned (estimate = 0.12, \( p = .11 \)), indicating that more interesting courses were just as likely to be mentioned as less interesting ones.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest level</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
</tr>
<tr>
<td>Discontinuous * Interest level</td>
<td>0.30*</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
</tr>
</tbody>
</table>

* \( p < 0.05 \) There is no simple effect of discontinuous condition as using fixed effects accounts for all effects that are invariant for all observations from a participant (e.g., condition, age, gender, number of classes that a participant has taken).

Figure 2 plots the probability of mentioning a class as a function of its interest level (we use the average of the estimated individual-level intercept across respondents in the two conditions). It shows that how interesting a class would be to talk about has a much higher impact on the probability of it being mentioned in the discontinuous condition as compared to the continuous condition.
Ancillary Analysis. Further analysis also cast doubt on an alternative explanation based on conversation time. While our results are supportive, one could argue that they are driven by the nature of the discontinuous condition. Because they had to pause briefly before talking and responding, people in the discontinuous condition may have had less time to talk and thus talked about fewer courses. Consequently, if interest determined the order in which people talked about courses (talking about the most interesting course first, the second most interesting second, and so on), then people in the discontinuous condition may not have mentioned less interesting courses simply because they did not have the time to talk about them (while people in the continuous condition did).

But this is not the case. While people in the continuous condition did discuss slightly more courses ($p < .05$), interest did not determine the order in which courses were discussed. In the continuous condition, for example, people talked about two courses on average, but the average interest rank of these courses (among all the courses they could have talked about) was 4.24. This indicates that rather than starting by talking about the first most interesting course,
and then moving to their second most interesting one (which would have resulted in an average
rank of around 1.5), interest was not the main factor in determining which courses were
discussed, and there were many interesting courses that could have been mentioned but were not.
Similarly, the average interest rank of mentioned courses in the discontinuous condition was
3.66. Thus, people in the continuous condition did not merely talk about more boring courses
because they mentioned more courses and had no interesting courses left to talk about.

Discussion

By experimentally manipulating conversation continuity, and measuring what people
talked about, study 2 provides direct casual evidence for our theoretical perspective.
Conversation continuity moderated whether interesting things were talked about more frequently
than less interesting ones. When people had more time to think about what to say (i.e.,
discontinuous conversation), they were more likely to talk about interesting classes than less
interesting ones. But when this time was reduced (i.e., continuous conversation), interesting
classes were no more likely to be discussed than their less interesting counterparts.

The study also casts doubt on the possibility that our results are somehow driven by
different base rates of interesting versus boring topics available online versus offline. In this
case, people had similar sets of things they could talk about, but what they ended up talking
about depended on conversation continuity. Further, as noted earlier, having the consideration
set of options allows us to better disentangle preferential transmission from mere base rates. The
results show that even taking into account the full set of options people could talk about, more
interesting things were only more likely to be talked about than less interesting ones when the conversation was discontinuous.

The results also bolster our perspective by showing that even when the audience and method of communication are the same, and people are randomly assigned to different types of conversations, the relationship between interest and word-of-mouth disappears when conversations are more continuous in nature. This shows that while audience differences, ability to walk away from boring conversations, self-selection of people into channels, and self-selection of topics into channels may all also impact how different conversation channels shape word-of-mouth, these factors alone cannot fully explain the results observed here.

That said, to further examine the role of conversation continuity across different channels we ran another study where we independently manipulated both conversation continuity and conversation channel. The design was similar to study 2. Participants had a brief conversation about classes and we manipulated whether the conversation was continuous or discontinuous. In addition, we also manipulated whether participants had this conversation face-to-face (as in study 2) or over instant messenger. We then performed the same analyses where we looked at how conversation continuity, conversation channel, and their interaction, shaped the relationship between interest and whether a course was discussed. There was no effect of channel itself, but there was an effect of conversation continuity. Again, people were more likely to talk about interesting things than boring ones if they were having a discontinuous (rather than continuous) conversation. This provides further evidence that it is conversation continuity, rather than the channel itself, that is driving these effects.
GENERAL DISCUSSION

Given its ability to boost diffusion and sales, word-of-mouth has become an integral part of marketing strategy. But while it has clear beneficial consequences, much less is known about its causes, or why people talk about certain things rather than others. Further, by focusing on only one channel at a time, existing research has mostly ignored how word-of-mouth may differ depending on the channel over which conversation takes place.

Three studies address this issue. First, they show that conversation channels impact what gets discussed. While more interesting products or brands get talked about more frequently online, they do not get any more face-to-face word-of-mouth (pilot study and study 1). Similarly, while more interesting products or brands get talked about more frequently over text or email, they do not get any more word-of-mouth over the phone (study 1).

Second, our results show that this is at least partially driven by differences in conversation continuity across different channels. While face-to-face and phone conversations are usually more continuous in nature, online conversations as well as emails and texts are more discontinuous, with pauses expected between responses. This relatively simple difference has an important impact on word-of-mouth (study 2). When pauses between and before conversational turns are expected (i.e., discontinuous conversation), more interesting topics and brands are more likely to be discussed than less interesting ones. In contrast, when pauses between and before conversational turns is not expected (i.e., continuous conversation), this difference disappears.

By showing these results in large datasets of over 21,000 conversations, as well as a tightly controlled laboratory experiment, we both illustrate the causal mechanism behind these effects while also demonstrating their generalizability to actual word-of-mouth in the field.
Taken together, the studies deepen understanding about what drives word-of-mouth and provide insight into how to design more effective word-of-mouth marketing campaigns.

Directions for Future Research

The findings suggest several directions for further research. It would be interesting to consider how other drivers of word-of-mouth might vary across different conversation channels. Our results suggest that interest may matter less in continuous conversations because people have less time to formulate a reply (See also Loewenstein et al. 2005). In online conversations, or even over text messaging, people have time to think of a clever response or think about the most interesting thing that they can write before responding. But this is not the case in more continuous conversations. Long pauses are awkward in face-to-face conversations, so rather than searching for the most interesting thing to say, people may just mention whatever happens to come to mind. This suggests that any factor which requires deliberation should have more of an effect in discontinuous, compared to continuous conversation. More practically useful things, for example, might be mentioned more online, but not more in face-to-face conversation. Similarly, emotion may have a larger impact on continuous conversations because there is no break for them to dissipate.

As noted earlier, self-enhancement might also play more of a role in certain conversation channels due to the audience people tend to be talking to. People are more likely to be communicating with strangers or weak ties when they blog, for example, as opposed to when they send a text. Consequently, they may be more likely to talk about things that make them look good. Similarly, while some research has examined consumer embarrassment (Dahl, Gorn,
and Weinberg 1998; Dahl, Manchanda, and Argo 2001), there has been less attention to when and why people share embarrassing experiences or embarrassing preferences (e.g., guilty pleasures) with others. Consumers might be less likely to share embarrassing things to weak ties, or broadcast them to larger social groups.

More broadly, more attention should be paid to how conversation channels shape both communication and influence. Most recent research on word-of-mouth has used online data, presumably because it is more available and easier to collect. But given that over 75% of WOM actually occurs face-to-face (Keller and Libai 2009) more attention to offline word-of-mouth seems warranted. Further, there may also be important differences even within the various online channels. Though they were all grouped together in our data, Facebook is not the same as Twitter which is not the same as blogs. The way conversation channels are designed has important implications for the conversations that evolve over them and—our results imply— the brands and products that get discussed.

We found that interest matters more in discontinuous conversations, but there may be some types of continuous conversations where interest plays a role. In cases where people are motivated to look smart, clever, or funny, for example, interest may play a greater role in shaping what people discuss. Thus when people are on a date, or talking with a prospective employer, interesting things may get brought up more than boring ones, even if the conversation is face-to-face.

Finally, future work might examine the temporal order of topic and channel selection. In most conversations it seems like the channel comes first. People are sitting next to a friend at lunch or chatting with a colleague online and then decide what to talk about. But in some cases the opposite may occur. In a negotiation, for example, one party might purposefully decide to
have the conversation online so that they have more time to carefully craft their response. Similarly, a salesperson might prefer a face-to-face interaction because it is harder for the customer to say no. In these cases of purposeful interaction, the topic may come first and then the channel. More research into the relative frequency of these types of interactions, and how they shape word-of-mouth, seems warranted.

Marketing Implications

These results also have a number of important marketing implications. First, they underscore the important role of channel selection when designing word-of-mouth marketing campaigns. Word-of-mouth marketing companies like BzzAgent help accelerate word-of-mouth for their clients to drive sales, but they can do it through various channels. Originally they focused on sending consumers coupons or rebates to encourage them to have face-to-face conversations with their friends, but more recently they have also started online initiatives, encouraging bloggers and others to post company-relevant content on the web.

Given a company or organization with a particular product, which word-of-mouth channels should they pursue? Take a consumer packaged goods company that just introduced a new type of toothpaste. This company could try to generate online word-of-mouth, offline word-of-mouth, or both. How should they decide? Part of the decision certainly depends on how effective those different types of word-of-mouth are for generating sales. Online word-of-mouth may be more useful in driving people to a website as opposed to an offline store because all they have to do is click. Online and offline information may also be differentially useful for different types of purchases (Cheema and Papatla 2010). That said, the relative value also depends on
how easily the company can get people talking over those different types of channels. Because toothpaste is probably not the most interesting or exciting product to discuss, our results suggest that it may be easier for the company to generate offline (as opposed to online) discussion.

Second, the findings shed light on product dimensions marketers should emphasize depending on the word-of-mouth channel they are trying to use. Practitioners often believe that products need to be interesting to be talked about, but our results suggest they are only right for certain word-of-mouth channels. If the goal is to get more discussion online, our results suggest that framing the product in an interesting or surprising way should help. Ads or online content that surprises people, violates expectations, or evokes interest in some other manner should be more likely to be shared. Blendtec’s “Will It Blend” infomercials, for example, have generated over 150 million views on YouTube. But while the product itself (a blender) is certainly not the most exciting, by framing it in a novel way (i.e., showing how it can be used to chop up everything from golf balls to an iPhone), the campaign has been highly shared.

If the goal is to get more offline word-of-mouth, however, then other factors may be more important than evoking interest. In a face-to-face context, making the product accessible in consumer minds, or publicly visible, may be more important (Berger and Schwartz 2011). Indeed, while it is probably not the most exciting topic, data on mostly face-to-face word of mouth finds that food and dining is the most frequently discussed product category, even more than media and entertainment or technology (Keller and Libai 2009). Thus for offline word-of-mouth, considering how to trigger people to think about the product or brand may be a helpful approach to generating discussion.

In conclusion, while a great deal of work has focused on the impact of word-of-mouth on consumer behavior, there is much more to learn about what drives conversation in the first place.
By examining how the relationship between product characteristics and word-of-mouth varies across different channels, greater insight into the behavioral process behind word-of-mouth can be obtained.
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