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The Squeaky Wheel Gets the Grease—An Empirical Analysis of Customer Voice and Firm Intervention on Twitter

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Firms are increasingly engaging with customers on social media. Despite this heightened interest, guidance for effective engagement is lacking. In this study, we investigate customers' compliments and complaints and firms' service interventions on social media. We develop a dynamic choice model that explicitly accounts for the evolutions of both customers' voicing decisions and their relationships with the firm. Voices are driven by both the customers' underlying relationships and other factors such as redress seeking. We estimate the model using a unique data set of customer voices and service interventions on Twitter. We find that redress seeking is a major driver of customer complaints, and although service intervention improves relationships, it also encourages more complaints later. Because of this dual effect, firms are likely to underestimate the returns on service intervention if measured using only voices. Furthermore, we find an "error-correction" effect in certain situations, where customers compliment or complain when others voice the opposite opinions. Finally, we characterize the distinct voicing tendencies in different relationship states, and show that uncovering the underlying relationship states enables effective targeting. We are among the first to analyze individual customer level voice dynamics and to evaluate the effects of service intervention on social media.

Keywords: service intervention; social media; microblogging; word of mouth; customer relationship; hidden Markov model; choice model
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1. Introduction

The proliferation of Internet social media has created significant excitement among marketers. Of particular interest are sentiment analysis and complaint management. A recent industry report shows that more than two-thirds of firms are already using social media, with marketing and service being the top two functions (CRM Magazine 2012).[1] Recognizing the openness of social media platforms and the vastness of their information content, firms come to these websites to gauge customer perceptions. Increasingly, firms are also moving from passive listening to active service intervention. Companies such as Dell, Verizon, and Comcast all have storefronts on popular platforms such as Twitter, some with dedicated service personnel who reach out to address customer complaints. With these interventions, firms seek to stem negative sentiments and improve customer relationships. Such interest in service intervention has spawned a subindustry that supplies the relevant tools: tracking services for automatically extracting relevant customer messages, text-mining services for classifying messages into compliments or complaints, and aggregation algorithms for summarizing overall sentiments. Sentiment indexes are supplied by both large service providers, such as IBM and Thomson Reuters, and smaller specialized marketing firms, such as sentimentmetrics.com and monitter.com.

The literature has long established the importance of maintaining good relationships with customers (e.g., Zeithaml et al. 1993, Rust and Chung 2006, Netzer et al. 2008). Grounded in the theory of exit and voice (Hirschman 1970), numerous studies show that

[1] http://www.destinationcrm.com/articles/Columns/Departments/The-Tipping-Point/Using-Social-Media-for-Customer-Service-81584.aspx (accessed November 2, 2012).

Table 1 Positioning and Contributions of This Paper in Internet WOM Literature

Topic	Underlying drivers	Brand/product level dynamics	Individual consumer level dynamics
Creation of Internet WOM	Anderson (1998), Hennig-Thurau et al. (2004), Schlosser (2005), Dellarocas and Narayan (2006), Ying et al. (2006), Berger and Schwartz (2011), Albuquerque et al. (2012), Berger and Milkman (2012), Yang et al. (2012), Chen and Kirmani (2015), Lovett et al. (2013), Toubia and Stephen (2013), etc.	Li and Hitt (2008), Wu and Huberman (2008), Moe and Trusov (2011), Godes and Silva (2012), Moe and Schweidel (2012), Schweidel and Moe (2014)	
Online sentiment analysis		Schweidel and Moe (2014)	This Paper
Online complaint management			
Effect of Internet WOM	Godes and Mayzlin (2004), Chevalier and Mayzlin (2006), Liu (2006), Duan et al. (2008), Godes and Mayzlin (2009), Trusov et al. (2009), Chintagunta et al. (2010), Sonnier et al. (2011), Stephen and Galak (2012), Tirunillai and Tellis (2012), etc.		

effectively addressing customer complaints is crucial for good customer relationships (Fornell and Wernerfelt 1987, Blodgett et al. 1993, Blodgett and Anderson 2000, Knox and van Oest 2014). However, existing complaint management research does not address the unique aspects of social media. Despite powerful tools at their disposal, firms have only a limited understanding of the dynamics of customer sentiment and the effect of managing complaints on social media. Many questions remain open. What drives customers to compliment or complain on social media websites? Do customers' voices reflect their underlying relationships with the firm, or are they also driven by other factors, and if so, how should the underlying relationships be assessed? Do service interventions on social media improve customer sentiment, or do other factors complicate matters? With limited resources, how should a firm target its service interventions? These questions are crucial for effective sentiment management on social media.

Compliments and complaints are specific types of Internet word of mouth (WOM). Internet WOM has substantial implications for sales and other marketing outcomes (Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Duan et al. 2008, Godes and Mayzlin 2009, Trusov et al. 2009, Chintagunta et al. 2010, Stephen and Galak 2012, Tirunillai and Tellis 2012, Kumar et al. 2013, Gopinath et al. 2014, Tirunillai and Tellis 2014). Meanwhile, numerous studies show that WOM is motivated by many underlying factors, such as self-enhancement, emotions, social considerations, images, economic incentives, etc. (Anderson 1998, Hennig-Thurau et al. 2004, Schlosser 2005, Albuquerque et al. 2012, Lovett et al. 2013, Toubia and Stephen 2013), and is also affected by external factors, such as product characteristics, quality, and content type (Dellarocas and Narayan 2006, Berger and Schwartz 2011, Berger and Milkman 2012, Lovett et al. 2013). One implication of this stream of literature is that WOM reflects but may not accurately represent customers' underlying opinions. Although the literature is rapidly growing, few studies have investigated the dynamics of online sentiment (with the exception of Schweidel and Moe 2014), and to the best of our knowledge, none has investigated firms' service intervention. Furthermore, existing studies on WOM creation either do not address the dynamics of WOM, or investigate the dynamics only at the product level (Li and Hitt 2008, Wu and Huberman 2008, Godes and Silva 2012, Moe and Schweidel 2012).[2] These studies often use product review data that are *product centric*, with low social interactivity among reviewers (Schweidel and Moe 2014). In contrast, popular social media platforms such as Facebook and Twitter are *user centric*, with much higher levels of social interaction. To accurately gauge sentiment and evaluate the effect of service intervention, we need to understand how a customer's relationship and voice evolve in these social environments and in response to the firm's actions. In other words, we need a dynamic analysis at the individual customer level that explicitly accounts for the underlying relationship. This heightened need and the gap in the literature motivate our study (Table 1).

In this study, we investigate how customers' *compliments* and *complaints* on a microblogging site are driven by their relationships with the firm and by social factors at the site, and how the firm's service intervention affects customers' voices and relationships. Recognizing that many factors other than underlying opinions also affect voices, we develop a dynamic model to explicitly account for both voicing decisions and underlying relationships. We model

[2] Although certain studies account for individual customer level heterogeneity (Berger and Schwartz 2011, Godes and Silva 2012, Moe and Schweidel 2012), they do not allow for repeated interactions between a customer and a firm.

three key drivers of voicing decisions. First, customers may compliment or complain to satisfy their intrinsic needs. Second, they may do so to serve a social function, e.g., to share their opinions with others. Finally, they may complain to seek redress, hoping to get the issues resolved. Meanwhile, we model a customer's *underlying relationship* with the firm and its dynamic evolution using a hidden-Markov model (Netzer et al. 2008, Li et al. 2011). The relationship is reflected in the customer's intrinsic tendency to compliment and complain, and it also moderates the effects of social and service factors. The firm's service intervention affects both voices and relationships.

We use a unique panel data set obtained from a Fortune 500 company. The data set contains the history of individual customers' complaints, compliments, and general chatter on Twitter, over an 11-month period. It also contains information on the firm's service interventions. We identify several underlying relationship states with distinct voicing tendencies and other behavioral traits. More importantly, we find two opposite effects of service intervention: on one hand, it does improve the firm's relationship with the customer. On the other hand, we find that *redress seeking* is a major driver of complaints and that service intervention *encourages even more complaints* in the future. A major implication of this "squeaky wheel gets the grease" effect is that sentiment will be underestimated if we look at only customer voices. Firms, thus, need to uncover the underlying relationship to accurately evaluate the effect of service intervention. Furthermore, we find that messages from friends on the website (defined as other users on the website whom the focal customer follows) affect both relationships and voicing decisions. Although positive voices from friends improve a customer's relationship with the firm, their effect on the customer's voice is nuanced. A significant error-correction or differentiation effect exists in certain situations and a tendency to conform exists in others. Finally, we show that uncovering the underlying relationship enables effective targeting of service interventions.

We contribute to the literature in the following ways. First, we are among the first to explicitly model the dynamics of complaint and compliment decisions at the individual customer level. Second, we are the first to empirically investigate firms' service interventions on social media and to show the nuanced effects of these interventions. Third, we separate the observed voice from the underlying relationship, which allows us to analyze how customers' voices are driven by the underlying relationship but are also influenced by social and service factors on microblogging websites. For industry managers, our study offers a framework to uncover underlying customer relationships, and to discover ways to target customers more effectively. All of these contributions advance our understanding of customer engagement on social media, a topic with rapidly growing importance.[3]

2. Industry Background and Data

Our data are obtained from a Fortune 500 telecommunications firm that provides telecommunications, Internet, and wireless services, and that wishes to remain anonymous. With the growth of social media, customers increasingly post their comments about the firm's products and services online. The firm recognizes the importance of proactive customer engagement on social media. It uses a third-party tracking service to automatically extract relevant customer messages from popular social media websites, such as Twitter, Facebook, and CNET. Approximately 75% of the messages come from Twitter, which our study focuses on.[4] Twitter is one of the most popular microblogging sites on the Internet. Created in 2006, it had more than 200 million active monthly users in 2014. Users send messages that do not exceed 140 characters in length, called "tweets." Users can also subscribe to other users' tweets, known as "following" a user. These "following" links form a directed social network (in contrast to other popular sites, such as Facebook or LinkedIn, which have undirected networks) through which messages may propagate. The website has attracted great attention from industry and academia alike (see, e.g., Jansen et al. 2009, Smith et al. 2012, Toubia and Stephen 2013). Twitter has been shown to host more brand-central content than Facebook or YouTube (Smith et al. 2012). Among brand-related tweets, a great majority are neutral in sentiment, and in almost half, the brand is not the primary focus (Jansen et al. 2009). Sentiment on Twitter can vary widely across brands and can be quite negative (Smith et al. 2012). Furthermore, user activities at the site are shown to be motivated by image-based utility more than by intrinsic utility (Toubia and Stephen 2013). Given Twitter's

[3] Another paper that investigated sentiment analysis is Schweidel and Moe (2014). Their approach controls for content, venue/audience, and self-selection of customers to venues. They derive a brand sentiment metric that correlates well with an offline brand tracking survey. Both their study and our study use latent constructs to capture customer sentiment, although our study differs from theirs in a few notable aspects. First, we focus on customers' sentiment and voices at the individual customer level. Second, we explicitly incorporate social influence on the website. Finally, and most important, we investigate the effect of the firm's service intervention on customer relationship and customer voice. We do note that by accounting for multiple venues, Schweidel and Moe (2014) provide a broader view of social media than our study.

[4] Other than Twitter, the only website with a significant share is Facebook, accounting for 8.9% of messages. No other individual website accounts for more than 1% of the messages. We do not have social network data from Facebook.

Table 2 Sample Messages in the Data Set

Compliments
I love ⟨*the name of the firm's service*⟩ its the best
The Droid on ⟨*the firm's name*⟩ is an excellent deterrent to being approached by ⟨*a competitor's name*⟩ kiosk reps
But if you do want to switch consider ⟨*the firm's name*⟩, ⟨*the firm's Twitter ID*⟩ is extremely responsive :D
⟨*the name of the firm's service*⟩ is KICK A$$ GOOD! Even Iron Man good! ;)
Tweeting from ⟨*the name of the firm's service*⟩ TV. Love it!
⟨*the firm's name*⟩ leads carriers in customer satisfaction, ⟨*a URL*⟩
Complaints
Your ⟨*a channel delivered through the firm's service*⟩ feed is failing miserably! FIX IT PLEASE!! Missing the game
Can you find out why ⟨*a channel delivered through the firm's service*⟩ fails every Caps game (it's a ⟨*a channel delivered through the firm's service*⟩ not a ⟨*the name of the firm's service*⟩ Issue, but still…)
I can't get into ⟨*the firm's name*⟩.com/⟨*the name of the firm's service*⟩. It tells me to sign up, I already have ⟨*the name of the firm's service*⟩. ⟨*the firm's name*⟩ site is a mess.
⟨*the firm's name*⟩, are you telling me that you can't get someone to go to the next room at your office until Thursday?
⟨*the firm's name*⟩, I need to talk to techs at the #Morgantown office. Your CSRs refuse to do that. Unacceptable.
If my modem had failed, I could just dash off to Best Buy for a replacement, but ⟨*the firm's name*⟩ can't even tell me that.
Neutral messages
⟨*the firm's name*⟩ opens up ⟨*the name of the firm's product*⟩ pre-orders ⟨*a URL*⟩
where can i find free ⟨*the name of the firm's product*⟩??
Breaking newS:: Jim Furyk Tops Brian Davis in Playoff ⟨*the name of the firm's service*⟩ ⟨*a URL*⟩
Today yankees vs. texas in the bronx and the game at 1:05 P.M. and is only on ⟨*the name of the firm's service*⟩ 76 on io is 70
⟨*two phone products*⟩ appear in ⟨*the firm's name*⟩ database?: What's this? Two devices apparently of…
⟨*The firm's name*⟩ narrows 4G launch window down to ⟨*a date*⟩

unique position in social media, research related to this microblogging site is rapidly growing.

The tracking service uses a text-mining algorithm to classify each extracted message as negative, positive, or neutral. A positive message is typically a *compliment* of the firm's product or service, such as "⟨*firm's service name*⟩ *was successfully installed, now my home internet is blazingly fast*." A negative message is typically a *complaint*, such as "*the customer service rep keeps passing the buck to the telesales rep and vice versa*."[5] Table 2 lists examples of the messages contained in our data set. The majority of the messages are classified as *neutral* (consistent with the findings of Jansen et al. 2009). A team of service agents at the telecom company focuses on customer engagement on social media. When a complaint is routed to the company by the tracking service, an agent tries to respond. The response may also be posted on the corresponding website. Each instance of intervention is recorded internally as a *case*. Our data set contains the information on these cases, including whether a complaint was responded to, the name of the agent who responded, and, in certain cases, the message content. About half of the customer complaints on the website were responded to (i.e., received service intervention). Given the fast pace of social media, complaints were usually responded to on the same day they were posted, often sooner.

2.1. Summary Statistics

The data set contains all of the messages relevant to the firm posted by customers on Twitter from February 2010 to December 2010. For each message, we observe the date it was posted, the account name of the customer, the message content, and the sentiment classification. Also contained in the data set are the firm's service intervention records. We further augmented the data set by downloading the social network structure from Twitter. We refer to those whom these customers follow on Twitter as their *friends*, and those who follow these customers as their *followers*. We downloaded the list of friends of a randomly selected subset of customers. This network information allows us to infer the messages each particular customer's friends sent, to which the customer is potentially exposed.[6]

[5] Automatic sentiment classification is common in the industry, given the high volume of data involved. Its use is also increasing in academic research (e.g., Sonnier et al. 2011 and Tirunillai and Tellis 2012). According to the firm that provided the data, they also added a manual step—if the agent at the firm did not believe a message was classified correctly, the agent would manually correct it. We further verified the classification using a publically available tool: sentiment140 (http://help.sentiment140.com/api). Classification using this tool matches those given by the firm for 84.7% of positive messages and 89.6% of negative messages, indicating a high degree of consistency.

[6] We used stratified random sampling. Specifically, 50% of customers in the sample are randomly selected from those who have voiced five or more times in our data set, whereas the other 50% are from those who have voiced fewer than five times. For the latter group, an equal proportion is selected from those who voiced one, two, three, or four times. We performed disproportional instead of proportional stratified sampling, both because the portion of consumers who voiced only one or two times is too high (93% combined), and because literature that focuses on individual level dynamics tends to focus on "heavy users," who provide more longitudinal information for analysis (e.g., Erdem and Keane 1996).

Table 3 Summary Statistics by Customer

	Mean	SD	Min	Max
Number of compliments	2.47	3.51	0	27
Number of complaints	3.05	2.68	0	20
Number of neutral messages	30.21	26.41	0	234
Number of interventions	1.42	1.57	0	14
Number of compliments sent by friends	31.07	44.2	0	417
Number of complaints sent by friends	37.39	55.72	0	561
Message ratio[a]	0.465	0.165	0	1
Number of followers	3,156.58	50,894.46	0	1,355,922
Number of friends	1,030.94	1,422.49	0	5,000
Total customers	714			
Number of days	310			

[a]Message ratio is the ratio of compliments sent by friends (i.e., message ratio = compliments sent by friends/(compliments sent by friends + complaints sent by friends)).

The sample data set used for our estimation contains the three types of messages of 714 customers over 310 days, and the messages each customer's friends sent on each day.[7] The summary statistics are reported in Table 3. On average, customers posted slightly more complaints than compliments (3.05 versus 2.47), as did their friends (37.39 versus 31.07). Note that this is markedly different from online product reviews, where ratings are typically positive (Chevalier and Mayzlin 2006). The ratio of compliments over the sum of compliments and complaints is 0.465. The average number of followers and friends per customer are 3,157 and 1,031, respectively. As is typical in social network data, both numbers are positively skewed. About half of the complaints received service intervention. According to the firm, slight preference was given to customers with more followers. In the data set, those with an above-average number of followers had 52% of their complaints responded to. In contrast, the response ratio for those with a below-average number of followers was 45%.

Table 4 reports the variables' pairwise correlations. The number of compliments is slightly positively correlated with that of complaints. The number is also positively correlated with the numbers of friends' compliments and complaints. This is preliminary evidence that customers' voices are related to friends' messages. The number of complaints voiced by a customer is not correlated with friends' messages, however. This suggests either that complaints are less subject to network influence or that such influence is more nuanced. Complaints and interventions are positively correlated, as the former triggers the latter. Interestingly, the number of compliments is also slightly positively correlated with interventions, indicating that service intervention possibly leads to more positive customer voices. In summary, these statistics suggest that customers' voicing behavior on social media is closely related to that of friends and to firms' service interventions, which calls for a more detailed investigation of their interactions.

[7] The data set provided by the firm contains more customers. However, downloading the network data from Twitter for all of them would take a prohibitively long time. Thus, our estimation data set contains only a subset of these customers. Our original stratified sample yielded 1,000 customers. Because of technical issues, we could extract the network links for only 714 of them.

3. Model

3.1. Theoretical Foundation

We first discuss the theoretical foundation of our model. The key to our study is to recognize customers' voices and underlying relationships as two distinct constructs. We explicitly model the dynamic evolutions of both. Our modeling of the customer's voicing decisions is grounded in the WOM creation literature, and our modeling of the customer's underlying relationship with the firm draws from the customer relationship management (CRM) literature. The conceptual diagram of our model is shown in Figure 1.

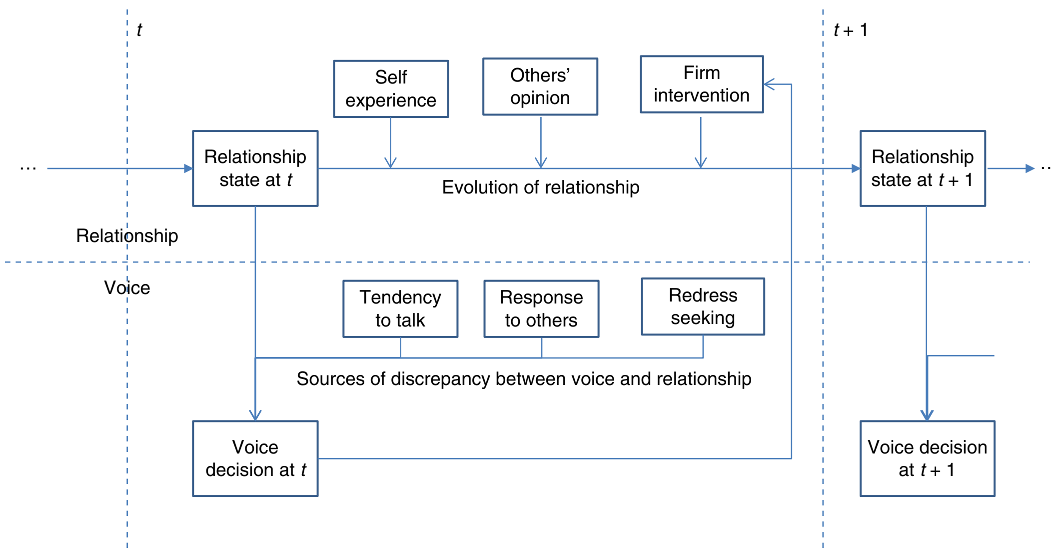
Relationship. Building and maintaining good relationships with customers leads to stronger loyalty, more purchases, and higher customer lifetime value (e.g., Zeithaml et al. 1993, Rust and Chung 2006). Firms' eagerness to manage sentiment on social media is also driven by their quest for good customer relationships. Conceptually, customers form their perceptions of (and relationships with) the firm based on their past direct and indirect experiences. These relationships are often characterized using discrete states that evolve over time (Dwyer et al. 1987, Fournier 1998, Aaker et al. 2004, Luo and Kumar 2013). State transitions may be triggered by interactions between firms and customers (Netzer et al. 2008, Li et al. 2011). The complaint management literature shows that firms' service interventions also shape customers' relationships (Blodgett et al. 1993, 1995). Furthermore, social media websites are unique in that they provide easy access to others' opinions, which also may affect customers' relationships with firms.

Accordingly, in our model, customers form their perceptions about the firm based on three sources of information: their own experience of the firm's products and services, the firm's responses to their complaints, and their exposure to the opinions expressed by others. First, relationships may change over time, depending on the customers' own experiences. This appears random in the eyes of the researcher, as such experience is typically not observed. Second, after learning friends' opinions about the firm, they may

Table 4 **Correlation Matrix of Observed Variables**

	Compliments	Complaints	Neutral messages	Interventions	Friends' compliments	Friends' complaints	Message ratio	ln(Followers + 1)
Compliments								
Complaints	0.168							
Neutral messages	0.409	−0.005						
Interventions	0.132	0.653	−0.025					
Friends' compliments	0.155	0.040	0.075	0.065				
Friends' complaints	0.185	−0.008	0.118	0.047	0.953			
Message ratio	−0.079	0.160	−0.104	0.038	0.030	−0.108		
ln(Followers + 1)	0.009	0.044	−0.018	0.072	0.279	0.236	−0.031	
ln(Friends + 1)	−0.006	0.058	−0.039	0.063	0.544	0.506	0.006	0.389

Figure 1 **(Color online) Conceptual Framework**



change their own perceptions of the firm. For example, hearing compliments may make a customer perceive more favorably of the firm. Finally, service interventions may also change customers' perceptions. For instance, if a firm intervenes every time a complaint is made, customers may improve their perceptions and develop more favorable opinions of the firm.

Compliments and Complaints on Social Media. Our model accounts for three factors—intrinsic, social, and service—that drive customer voices. First, customers may compliment a firm or complain about it on social media to satisfy their intrinsic psychological needs (Anderson 1998). Emotional desires, concerns for others, self-enhancement, and the like all motivate customers to voice their opinions (Feick and Price 1987, Hennig-Thurau et al. 2004, Toubia and Stephen 2013). Our first utility component, the *intrinsic utility*, accounts for these factors. This intrinsic utility will reflect and be driven by customers' underlying relationships with the firm. The intrinsic utility also varies from person to person (Berger and Schwartz 2011, Moe and Schweidel 2012, Toubia and Stephen 2013). For example, some customers may simply be more talkative than others, and some customers may have a stronger tendency than others to voice negative opinions (Goffman 1959, Richins 1984).

Second, as social media exposes customers to others' voices, one customer's voice may depend on what others have said (Schlosser 2005, Wu and Huberman 2008, Godes and Silva 2012, Moe and Schweidel 2012). Customers may be more likely to voice their opinions if those opinions differ markedly from what others have said. In this case, they are "correcting" others' mistakes or differentiating from others (Wu and Huberman 2008, Moe and Schweidel 2012). Alternatively, customers may be more likely to voice opinions similar to what others have said. In this case, they are "conforming" to their social environment (Moe and Schweidel 2012). Our second utility component, *social utility*, captures such effects. Terminologies vary across studies on WOM creation. Both the intrinsic and social utilities in our model can be mapped to multiple factors in the existing literature.[8] The *key distinction* between intrinsic and social utility is that the former depends on only the customers' own characteristics, and the latter depends on others' voices.

Furthermore, we include a third component, *service utility*, to account for customers' intentions to seek redress. Literature shows that customers often complain in order to receive services from firms (Day and Landon Jr 1976). Similarly, customers may simply complain on social media in order to reach out to the firm, hoping to get their issues resolved. This service utility is expected to depend on whether the firm addressed the customer's previous complaints. For example, if a firm consistently addressed a customer's past complaints on social media, the customer may develop higher expectations and become more willing to complain in the future.

Relationship and Voices. Customers' relationships with a firm and their voices on social media are two related but distinct constructs. The underlying relationship affects voices in several ways. The intrinsic utility is primarily determined by and reflects the underlying relationship. To illustrate, customers who have good relationships with the firm will have higher intrinsic utility to compliment than to complain. The relationship can also moderate social and service utility. Customers who do not have good relationships with the firm, for instance, might not expect that the firm will address their complaints. In this case, the service utility would be low. In another example, customers who do not have good relationships with the firm may be likely to "correct" others' compliments. Accordingly, in our model the intrinsic utility reflects the customer's underlying relationship with the firm, which also moderates the other two utility components.

Effect of Service Intervention. Modeling both relationships and voicing decisions, we can analyze the potentially opposing effects of a firm's service interventions. On one hand, by addressing customers' complaints, service interventions should improve the customers' relationships with the firm (Hirschman 1970, Fornell and Wernerfelt 1987, Blodgett et al. 1995). On the other hand, a higher perceived likelihood of success has been shown to encourage complaints (Day and Landon Jr 1976). By raising customers' expectations, a firm's service interventions may very well encourage customers to complain more in the future. Service intervention, thus, may have a positive effect on the underlying customer relationships but a negative direct effect on the customers' voices. Because relationship underlies voices, service intervention also affects voices indirectly through the relationship. The net effect of service intervention on voices, therefore, is not obvious ex ante.

In summary, our model builds on the WOM and CRM literature, and recognizes customers' underlying relationships with the firm and their voices as two distinct constructs. The dynamic evolutions of both of these constructs are explicitly accounted for in our model. We further account for the effects of the social media environment and the firm's service interventions, which may lead to a difference between relationship and voice. Sentiment management would be straightforward if customer voices strictly reflected the underlying relationship. However, the intrinsic, social, and service factors that also drive voices may have distorting effects. For example, pressure to conform might inhibit an angry customer's complaint. The desire to seek redress, as another example, may induce a reasonably happy customer to complain more. By explicitly modeling relationship and voice, we can probe beneath surface level observations to better understand the underlying relationship and the nuanced effects of a firm's service interventions.

3.2. Voicing Decision and Utility

Formally, there are I customers of a firm. Time is discrete and indexed by t, $t = 1, 2, \ldots, T$. Customers are connected on the microblogging site Twitter. As stated in §2, we call the customers who follow a focal customer the customer's followers, and those whom the customer follows the customer's friends. In each time period, a customer decides whether to voice a positive, neutral, or negative message, or not to say anything about the firm. The decision of customer i at time t is denoted as

$$D_{it} = \begin{cases} 3 & \text{voices a } \textit{positive} \text{ message} \\ 2 & \text{voices a } \textit{neutral} \text{ message} \\ 1 & \text{voices a } \textit{negative} \text{ message} \\ 0 & \textit{does not} \text{ voice a message} \end{cases} \quad (1)$$

We use a latent utility approach: At time t, customer i's utilities of voicing a positive message (i.e., a

[8] Toubia and Stephen (2013), for example, compare intrinsic and image-based utility. Hennig-Thurau et al. (2004) provide a typology of four factors: social interaction, economic incentive, altruism, and self-enhancement. Given our observational data, we would not know, for example, whether a complaint is generated because of a desire to self-enhance or because of a concern for others, because in both cases the customer may complain when others have not. Our data allow us to separate only the utility that depends on the social environment from the utility that does not.

compliment), a neutral message, a negative message (i.e., a complaint), or saying nothing, are

$$U_{it} = \begin{cases} U_{i3t} = \bar{U}_{i3t} + \varepsilon_{i3t} = \alpha_i + \beta_{i3}(S_{it}) + \gamma_{i3}(S_{it}) N_{it}^S \\ \qquad\qquad + \varepsilon_{i3t} \qquad D_{it} = 3 \\ U_{i2t} = \bar{U}_{i2t} + \varepsilon_{i2t} = \alpha_i + \varepsilon_{i2t} \quad D_{it} = 2 \\ U_{i1t} = \bar{U}_{i1t} + \varepsilon_{i1t} = \alpha_i + \beta_{i1}(S_{it}) + \gamma_{i1}(S_{it}) N_{it}^S \\ \qquad + \nu_i(S_{it}) I_{it} + \varepsilon_{i1t} \qquad D_{it} = 1 \\ U_{i0t} = 0 + \varepsilon_{i0t} \qquad\qquad D_{it} = 0. \end{cases} \tag{2}$$

In Equation (2), the first two terms are the *intrinsic* components. The baseline term, α_i, enters the utility of all three voice types. It captures the intrinsic "talkativeness"—the desire to make the customer's voice heard. The terms $\beta_{i3}(S_{it})$ and $\beta_{i1}(S_{it})$ account for the intrinsic desires to compliment and complain (relative to voicing a neutral message). They depend on the customer's underlying relationship with the firm at the time, denoted as S_{it}. A customer who holds the firm in high regard, for instance, would be more apt to compliment the firm (i.e., $\beta_{i3}(S_{it})$ would have a higher value) than would another customer. We discuss the modeling and evolution of S_{it} in §3.3.

The terms $\gamma_{i3}(S_{it})N_{it}^S$ and $\gamma_{i1}(S_{it})N_{it}^S$ in Equation (2) represent the *social* utility of complimenting and complaining, respectively. The variable N_{it}^S denotes the *network sentiment*, which represents the sentiment contained in the messages the customer hears from friends on the website. Higher N_{it}^S indicates a more positive sentiment. We discuss the construction of this variable in §3.4. The coefficients $\gamma_{i3}(S_{it})$ and $\gamma_{i1}(S_{it})$ measure how network sentiment affects the customer's voice. A positive coefficient $\gamma_{i3}(S_{it})$ means that the customer is more likely to compliment the firm when the network sentiment is more positive. In other words, the customer tends to conform to what others say. If the coefficient is negative, then the customer tends to "correct" others' mistakes, or to differentiate from others' opinions. Similarly, a positive $\gamma_{i1}(S_{it})$ means that the customer is more likely to complain when the network sentiment is more positive, i.e., the customer tends to differentiate. Network sentiments do not necessarily affect compliments and complaints to the same extent. Having the two parameters allows for asymmetric effects. For example, $\gamma_{i3}(S_{it}) < 0$ and $\gamma_{i1}(S_{it}) = 0$ mean that hearing more positive messages makes a customer less likely to compliment but does not change the propensity to complain. This differs from the case where it also makes the customer more likely to complain, i.e., $\gamma_{i1}(S_{it}) > 0$, even though in both cases the customer demonstrates the error-correction tendency.

The fourth term of the utility of complaining, $\nu_i(S_{it})I_{it}$, is the *service* component. Customers may complain to get their issues resolved. This component represents the expected utility from the firm's service intervention. This expected utility should depend on how often the firm has helped the customer in the past. The variable I_{it} is the percentage of the customer's past complaints to which the firm responded

$$I_{it} = \frac{\sum_{\tau=1}^{t-1} I\{\tilde{I}_{i\tau} = 1\}}{\sum_{\tau=1}^{t-1} I\{D_{i\tau} = 1\}}. \tag{2a}$$

In Equation (2a), $\tilde{I}_{i\tau}$ denotes the firm's intervention decision: $\tilde{I}_{i\tau} = 1$ if the firm provided service in response to the complaint of customer i at time t and $\tilde{I}_{i\tau} = 0$ otherwise. To the customer, this variable reflects the likelihood, based on past experience, of the firm addressing the complaints. A positive coefficient $\nu_i(S_{it})$ indicates that the more a customer's complaints were addressed in the past, the more the customer expects to be helped, and the more prone to complain the customer becomes.

Finally, the mean utility of not saying anything is normalized to zero. We assume that the error terms in Equation (2) follow i.i.d. extreme value distribution, leading to the logit choice probability

$$\begin{cases} \Pr(D_{it} = 3) = \exp(\bar{U}_{i3t}) \Big/ \Big(\sum_{d=1}^{3} \exp(\bar{U}_{idt}) + 1\Big) \\ \Pr(D_{it} = 2) = \exp(\bar{U}_{i2t}) \Big/ \Big(\sum_{d=1}^{3} \exp(\bar{U}_{idt}) + 1\Big) \\ \Pr(D_{it} = 1) = \exp(\bar{U}_{i1t}) \Big/ \Big(\sum_{d=1}^{3} \exp(\bar{U}_{idt}) + 1\Big) \\ \Pr(D_{it} = 0) = 1 \Big/ \Big(\sum_{d=1}^{3} \exp(\bar{U}_{idt}) + 1\Big). \end{cases} \tag{3}$$

We note that existing studies have used two-stage models, incidence and evaluation, to characterize WOM decisions (e.g., Ying et al. 2006, Moe and Schweidel 2012). A two-stage model can capture empirical regularities such as the U-shaped response function of product reviews. However, since our model is state dependent, it is flexible enough to admit such patterns. Furthermore, the intrinsic talkativeness parameter, α_i, can be considered as representing the "incidence" aspect of WOM, i.e., how much a customer is generally prone to sending a message on Twitter. Because our focus is on customer complaints and compliments, we use the more parsimonious multinomial model instead of a two-stage model. These two models are expected to yield similar findings.

3.3. Relationship States

We model a customer's underlying relationship with the firm using a first-order discrete-time discrete-state hidden-Markov model (HMM) (e.g., Montgomery et al. 2004, Du and Kamakura 2006, Moon et al. 2007, Netzer et al. 2008, Li et al. 2013). The state of customer i at time t is denoted as S_{it}, $S_{it} \in \{1, \ldots, K\}$, where K is the total number of states. An HMM is invariant to permutation of states. For identification, we order the states based on sentiment. The intrinsic desire to complain is reflected by the coefficient $\beta_{i1}(S_{it})$ in Equation (2). Thus, we order states from 1 to K, where the value of $\beta_{i1}(S_{it})$ decreases with the state, with state 1 being the most negative. We account for the evolution of relationship states using a customer- and time-specific state transition matrix, denoted as

$$A_{it} = \begin{bmatrix} a_{it,1,1} & \cdots & a_{it,1,K} \\ \cdots & \cdots & \cdots \\ a_{it,K,1} & \cdots & a_{it,K,K} \end{bmatrix}. \tag{4}$$

In Equation (4), $a_{it,s,s'}$ is the probability that customer i transitions from state s at time t to state s' at time $t+1$. Since states are ordered from the most negative to the most positive, we model the state transition using an ordered-logit model (Netzer et al. 2008). To do so, we specify a set of threshold values as boundaries between states and a link function that incorporate other factors that may influence state transition. We denote these threshold values as $\delta_{i,ss'}$, where $s \in \{1,\ldots,K\}$ and $s' \in \{1,\ldots,K-1\}$, and denote the dependent variable for the link function as y_{it}. The state transition probabilities in Equation (4) can then be written as

$$\begin{cases} a_{it,s,1} = \dfrac{\exp(\delta_{i,s1} - y_{it})}{1+\exp(\delta_{i,s1} - y_{it})} \\ a_{it,s,s'} = \dfrac{\exp(\delta_{i,ss'} - y_{it})}{1+\exp(\delta_{i,ss'} - y_{it})} - \dfrac{\exp(\delta_{i,ss'-1} - y_{it})}{1+\exp(\delta_{i,ss-1'} - y_{it})}, \\ \qquad\qquad s' \in \{2,\ldots,K-1\} \\ a_{it,s,NS} = 1 - \dfrac{\exp(\delta_{i,s,K-1} - y_{it})}{1+\exp(\delta_{i,s,K-1} - y_{it})}. \end{cases} \tag{5}$$

Three factors drive the evolution of relationship states: the customer's own experience, the firm's history of service intervention, and the network sentiment. These factors are incorporated in the link function of the ordered-logit model

$$y_{it} = \phi_{i0} + \phi_{i1}(S_{it})M_{it} + \phi_{i2}(S_{it})I_{it} + \xi_t. \tag{6}$$

In Equation (6), ϕ_{i0} represents the individual customer-specific tendency to transition among relationship states. Customers may differ in their general experiences with a firm's product (e.g., quality will vary across different units of the same product) and, therefore, exhibit different state transition tendencies. Such factors are not observed by researchers, and are captured as unobserved heterogeneity using ϕ_{i0}. The variable M_{it} is the ratio of all positive messages in the past. The variable I_{it} is the ratio of past firm interventions, as defined in Equation (2a). The coefficients $\phi_{i1}(S_{it})$ and $\phi_{i2}(S_{it})$ are the coefficients on how friends' messages and the firm's service interventions affect a customer's state transition. The coefficients are state specific, as a factor may have different effects in different states. The term ξ_t in Equation (6) is a time-specific fixed effect that captures potential common shocks. A major interruption in service, for instance, may make everyone more likely to move to a more negative state. Finally, we denote the probability that a customer starts from state s as a_s^0.

3.4. Network Sentiment

Our construction of the network sentiment variable N_{it}^S closely follows standard industry practice and draws on recent literature on online social networks. Sentiment monitoring on social media typically relies on a voice sentiment index, defined as a percentage of negative or positive messages. We denote the total number of compliments and complaints voiced by customer i's friends at t as $\tilde{m}_{it} = \{\tilde{m}_{i,t}^P, \tilde{m}_{i,t}^N\}$; then, a straightforward construction of the network sentiment variable would be the proportion of positive messages at time $t-1$

$$\tilde{N}_{it}^S = \tilde{m}_{i,t-1}^P / (\tilde{m}_{i,t-1}^P + \tilde{m}_{i,t-1}^N). \tag{7}$$

However, on a fast-paced microblogging site, users receive many messages every day and may be selective in reading the messages. A customer may read certain friends' messages whereas routinely ignoring others. Furthermore, although users may follow many friends, not all of these friends will equally influence the focal user (Trusov et al. 2010).[9] To account for these potential differences in influence, we adopt the methodology of Trusov et al. (2010). We denote the friends of customer i (i.e., whom customer i follows) as $i1, i2, \ldots, iG_i$, where G_i is the number of friends whom customer i follows. We allow friends to have different levels of influence on a focal customer, and define the influence-adjusted compliments and complaints actually received by the customer as follows:

$$\begin{cases} m_{it}^P = \sum_{j=1}^{G_i} \lambda_{ij} I\{D_{ij,t} = 3\} \\ m_{it}^N = \sum_{j=1}^{G_i} \lambda_{ij} I\{D_{ij,t} = 1\}. \end{cases} \tag{8}$$

In Equation (8), $I\{\cdot\}$ is the indicator function, and λ_{ij} represents friend j's influence on customer i. The variables m_{it}^P and m_{it}^N are, thus, the weighted sum of compliments and complaints received by customer i, weighted by each friend's influence level. Analogous to Equation (8), the network sentiment index is then

$$N_{it}^S = m_{i,t-1}^P / (m_{i,t-1}^P + m_{i,t-1}^N). \tag{9}$$

[9] We thank an anonymous reviewer for this helpful suggestion.

We assume each dyad-specific λ_{ij} is an independent Bernoulli random variable, where value 1 indicates that the friend is influential and 0 not

$$\lambda_{ij} \sim \text{Bernoulli}(p_i). \tag{10}$$

In Equation (10), p_i is the probability that a friend is influential on customer i.

3.5. Heterogeneity

On social media websites in general and microblogging sites in particular, the number of followers a customer has influences WOM behavior (Toubia and Stephen 2013). For example, a customer with more followers may be more vocal. Furthermore, individuals also differ in their intrinsic voice tendencies, their responses to their social environments, and their expectations of the firm's service interventions. We adopt a hierarchical Bayesian framework to incorporate both observed and unobserved heterogeneity in the utility function. Each individual-specific parameter in the voicing utility function, generically denoted as θ_i, is modeled as

$$\theta_i = \theta_{i0} + \theta_1 F_i. \tag{11a}$$

In Equation (11a), θ_i denotes each parameter in the voicing utility function (α_i, $\beta_{i1}(S_{it})$, $\beta_{i3}(S_{it})$, $\gamma_{i1}(S_{it})$, $\gamma_{i3}(S_{it})$, and $\nu_i(S_{it})$). The term θ_{i0} is an individual-specific intercept term. $F_i = \ln(\tilde{F}_i + 1)$ is the log-transformed number of followers of the customer ($\tilde{F}_i$ is the number of followers), and θ_1 captures the difference across customers according to the number of followers. A positive θ_1 indicates that the parameter value is higher for those with more followers. To account for unobserved heterogeneity, we assume that the individual-specific intercepts are drawn from population level normal distributions

$$\theta_{i0} \sim N(\bar{\theta}_0, \sigma^2_{\theta_0}). \tag{11b}$$

Similarly, we account for unobserved heterogeneity across customers on state transition. Each individual-specific parameter in the state transition equations, denoted as ρ_i, is modeled as drawn from a population-level distribution

$$\rho_i \sim N(\bar{\rho}, \sigma^2_{\rho}). \tag{11c}$$

In Equation (11c), ρ_i denotes each parameter in the state transition equations ($\delta_{i,ss'}$, ϕ_{i0}, $\phi_{i1}(S_{it})$, and $\phi_{i2}(S_{it})$). Note that only unobserved heterogeneity—not the observed heterogeneity on the number of followers—is admitted to state transition parameters. This is because the number of followers is a characteristic specific to the microblogging website. It is expected to affect voices on the website, but it is not clear whether the theoretical foundation exists for it to affect the underlying relationship.

3.6. Endogeneity, Identification, and Estimation

As pointed out by Manchanda et al. (2004), response modeling should account for the possibility of nonrandom marketing mix variables. We capture two potential sources of such nonrandomness. First, it is possible that service intervention decisions are made based on characteristics of the customers who voiced complaints. Second, service intervention decisions may depend on time-specific factors. When there is a service outage, for instance, both customer complaints and the firm's intervention efforts may intensify. Following Manchanda et al. (2004), we model the intervention decision of the firm using a logistic regression over the customer's response parameters and time-specific effects

$$P(\tilde{I}_{it} = 1 \mid D_{it} = 1) = \exp(\omega_{it})/(1 + \exp(\omega_{it})), \tag{12a}$$

where

$$\omega_{it} = \Theta_i' \vec{\kappa} + \kappa_{\xi} \xi_t. \tag{12b}$$

In Equation (12b), Θ_i is the vector of all individual-specific parameters (θ_{i0} in Equation (11a), ρ_i in Equation (11c), and F_i) and a constant term, and $\vec{\kappa}$ is the coefficient vector for the intervention decision function. The term ξ_t is the time-specific fixed effect that accounts for common shocks, as shown in Equation (6), and κ_{ξ} is the corresponding parameter.

For identification, we normalize the population mean of ϕ_{i0} in Equation (6) to 0.[10] We estimate the model using the Markov Chain Monte Carlo (MCMC) approach. More details of identification and estimation can be found in the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0912).

4. Empirical Result

4.1. Model Comparison

We first compare the model fit statistics of our proposed model with those of several alternative and benchmark models. The results are reported in Table 5. We use log-marginal density for model selection (Newton and Raftery 1994, Chib 1995). We also calculate the overall hit rate, the hit rate when customers voiced messages, and the hit rate when customers complained or complimented, both in sample and out of sample. We use the first 230 days of data for estimation, and the remaining 80 days as the holdout sample.

Model 1 is our proposed model. We estimated four alternative specifications, from two to five states. The three-state version outperforms the others on log-marginal density, the out-of-sample log likelihood,

[10] An equal change of ϕ_{i0} and all $\delta_{i,ss'}$ will yield the same state transition probabilities, hence the normalization.

Table 5 Model Comparison

	In sample				Out of sample			
Model	LMD	HR (%)	HRV (%)	HRCC (%)	LL	HR (%)	HRV (%)	HRCC (%)
Model 1–2 state	−61,182.2	80.35	15.09	4.98	−21,434.1	80.60	14.15	1.71
Model 1–3 state	−60,186.5	80.54	15.57	6.78	−21,367.3	80.65	14.17	1.75
Model 1–4 state	−60,586.6	80.32	15.03	6.40	−21,433.1	80.55	13.91	1.73
Model 1–5 state	−60,372.0	80.35	15.18	7.08	−21,443.9	80.71	13.98	1.66
Model 2	−62,977.5	80.54	14.37	2.42	−21,454.2	80.58	14.23	1.61
Model 3	−61,377.9	80.33	14.90	6.01	−21,420.5	80.66	14.04	1.63
Model 4	−60,353.9	80.49	15.42	5.14	−21,352.4	80.79	14.02	1.59
Model 5	−61,574.5	80.27	15.03	5.04	−21,365.6	80.59	14.14	1.59
Model 6	−63,325.5	79.77	14.42	1.97	−21,455.4	80.56	13.16	1.43
Model 7	−63,254.9	80.05	14.46	1.95	−21,453.8	80.60	13.24	1.39
Model 8	−63,273.4	79.99	14.44	1.75	−21,440.7	80.54	13.16	1.32

Note. LMD, Log marginal density; LL, log likelihood; HR, hit rate; HRV, hit rate for messages; HRCC, hit rate for compliments/complaints messages.

and the hit rate for compliments and complaints. The overall hit rate and the hit rate for voices are similar across specifications. Considering these, we proceed with the three-state version of our proposed model.

Model 2 is the "one-state" version of our model, which does not contain multiple underlying relationship states. It underperforms the proposed model (and also the two-state version) on log-marginal density and on the hit rate for compliments and complaints. This confirms the importance of modeling the underlying relationship states and the transition dynamics. Models 3–5 are variations of the proposed model. They are estimated with three states to enable direct comparison with the proposed model. Model 3 makes state transitions conditional on the current period network messages and service intervention instead of the cumulative ones. It underperforms the proposed model. This suggests that state transition is more gradual and cumulative than instantaneous. Model 4 excludes the service component from the voicing utility function, and model 5 excludes both social and service components. The proposed model outperforms model 4 on log-marginal density and the hit rate for compliments and complaints. Model 4 also outperforms model 5. These suggest that both social and service utilities are critical components that should be included. Models 6–8 are standard hierarchical multinomial logit models that serve as outside benchmarks. Model 6 has only the intercept term and linear term on the number of followers. Model 7 is an extension from model 6. It includes both the number of complaints and the number of compliments heard by the customers in the utility functions. Model 8 is a variant of model 7, using the percentage of positive messages in the utility function. The proposed model outperforms all of these benchmark models.[11]

4.2. Parameter Estimates

Voice Utility. We report the population mean estimates of the voicing utility parameters in Table 6. The intercept of the intrinsic utility to voice a message of any type is −2.532. This corresponds to one message about every 13 days, consistent with the data. The intrinsic utilities of complimenting and complaining (β_3 and β_1 in Equation (2)) show that customers are more likely to voice neutral messages than to voice either compliments or complaints—most parameters are negative and statistically significant, with the utility to complain at the low state as the only exception.[12] Customers' intrinsic likelihood to complain is almost 155 times the likelihood to compliment in the low state (0.284 versus −4.760 for the two coefficients). In contrast, customers in the higher state are 61 times more likely to compliment than to complain (−0.651 versus −4.766). In the middle state, the intrinsic tendencies to compliment and to complain are similar. Considering these findings, we refer to the three states more intuitively as the negative, neutral, and positive states.[13] Customers have a higher desire to complain in the negative state than to compliment

[11] All of the models have a similar overall hit rate and the hit rate for voices. This is due to the nature of the data: in a given period, a customer is most likely not to say anything. When a customer does voice a message, it is more likely a neutral one than a compliment or complaint. Because our model focuses on compliments and complaints, it is reasonable that these two hit rates do not vary much across models. In contrast, the hit rates for compliments and complaints do differ significantly.

[12] We consider a coefficient "statistically significant" if the 95% credible interval does not include zero, and two coefficients as statistically different if their 95% credible intervals do not overlap. This is consistent throughout the paper.

[13] Note that although the states are ordered according to their intrinsic tendency to complain relative to voicing a neutral message, this alone does not mean that the three states are necessarily negative, neutral, and positive. For example, if in all three states the intrinsic tendency to complain is higher than it is to compliment, then all should be referred to as negative states of different levels. We refer to the three states as negative, neutral, and positive because doing so is consistent with the relative tendencies to complain and compliment for each state.

Table 6 Parameter Estimate—Voicing Utility

Voicing utility—Intercept			
Intrinsic utility	Relationship states		
Voice	−2.532 (*)		
	Negative	Neutral	Positive
Complaint (relative to neutral)	0.284 (*)	−3.344 (*)	−4.766 (*)
Compliment (relative to neutral)	−4.760 (*)	−3.223 (*)	−0.651 (*)
Effect of network sentiment			
Complaint	0.419 (*)	−0.073	0.474 (*)
Compliment	−0.106 (*)	−0.088	0.426 (*)
Effect of intervention	0.291	0.945 (*)	1.293 (*)

*The 95% credible interval does not include zero.

in the positive state. This suggests that the negative state is more intense than the positive one, possibly because customers are prone to sending emotional messages when they have negative relationships with the firm.

Looking at the social utility, we see that voicing decision is affected by friends' messages in certain situations. Customers in the negative state are more likely to complain and less likely to compliment when they hear more positive messages from friends. (The coefficient for complaint is positive and for compliment is negative, both statistically significant.) This demonstrates a differentiating, or error-correcting, behavior in the negative state. In contrast, customers in the positive state demonstrate a mix of conforming and differentiating tendencies. They are more likely to compliment when others do, and also more likely to complain when hearing more compliments. (The coefficients for both complaint and compliment are positive and statistically significant.) No systematic conforming or differentiating tendency is evident for customers in the neutral state. (Neither coefficient is statistically different from zero.) However, such tendencies may still exist at the individual customer level, as the variance estimates reported in Table 7 show wide dispersions of these coefficients across customers.

The estimates of service utility coefficients also confirm that redress seeking is a key driver of complaints. (The coefficients, also in Table 6, are positive for all three states, 0.291, 0.945, and 1.293, and statistically significant for the latter two.) Other things equal, a customer's past experience of receiving help from the firm will encourage the customer to complain again. This suggests that customers will become more confident of getting the firm's help if it has responded to their past complaints. This effect is more salient for the positive and neutral states, suggesting that customers in those states have higher expectations of the firm.

Table 7 Parameter Estimate—Voicing Utility Heterogeneity

Observed heterogeneity—Ln(No. of *Followers* + 1)			
Intrinsic utility	Relationship states		
Voice	0.129 (*)		
	Negative	Neutral	Positive
Complaint	0.051	0.071 (*)	−0.058
Compliment	0.414 (*)	0.000	0.017
Effect of network sentiment			
Complaint	0.151	−0.121	0.309
Compliment	0.923	−0.047	0.239
Effect of intervention	0.211	−0.311	1.344 (*)
Unobserved heterogeneity—Population variance			
Intrinsic utility	Relationship states		
Voice	1.052		
	Negative	Neutral	Positive
Complaint	1.169	0.131	0.107
Compliment	0.139	0.158	0.670
Effect of network sentiment			
Complaint	0.366	0.301	0.328
Compliment	0.287	0.344	0.384
Effect of intervention	13.841	6.343	0.570

*The 95% credible interval does not include zero (variance parameters are positive and are not marked).

We note a few additional results from estimates of heterogeneity parameters, reported in Table 7. First, as expected, customers with more followers are more vocal on the website. (The coefficient is 0.129 and statistically significant.) Next, in the negative state, customers with more followers are more likely to compliment. (The coefficient for compliment is positive and statistically significant.) A potential explanation is that in the negative state, those with more followers are comparatively more "measured" in their voices, whereas those with fewer followers are more "extreme." Note that this is on a relative basis only, as the tendency to compliment is low in general for the negative state. Third, in the positive state, customers with more followers are more apt to respond to past interventions. (The coefficient is 1.344 and statistically significant.) Finally, the unobserved heterogeneity parameter estimates show wide dispersions across customers of their voicing tendencies, particularly on their expectation of receiving service interventions. (The variance of the service utility coefficient is high for the negative and neutral state.)

State Transition. Table 8 reports state transition parameter estimates. From the negative, neutral, or positive state, the unconditional probability of the customer remaining in the same state in the next time period is 35.53%, 94.05%, or 65.83%, respectively (first region of Table 8). This suggests that the neutral and

Table 8 Parameter Estimate—Relationship State

Relationship state and transition probability			
From/To state	Negative	Neutral	Positive
	Unconditional transition probability		
Negative (%)	35.53	63.91	0.56
Neutral (%)	3.25	94.05	2.70
Positive (%)	0.78	33.39	65.83
	Initial state probability		
Probability (%)	9.21	73.36	17.42
	Conditional transition parameter		
Network sentiment	1.261 (*)	1.091 (*)	−0.13
Firm intervention	1.044 (*)	0.587 (*)	0.422 (*)

*The 95% credible interval does not include zero.

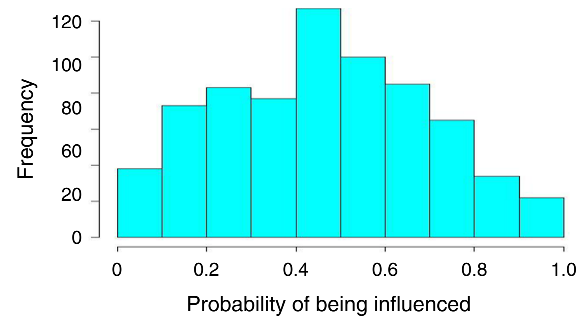
positive states are relatively "sticky." The neutral state is more sticky than the positive state, whereas the negative state is more transient. That both the positive and negative states are more transient than the neutral state suggests a natural "reversion to the mean" over time. Furthermore, customers in the negative or positive state are more likely to switch to the neutral state than to the opposite one, suggesting that the relationship is more likely to evolve gradually than to change drastically.

When the firm addresses a customer's complaints more actively, the customer is more likely to transition to a more positive relationship state. (The coefficients for firm's service intervention, reported in the third region of Table 8, are positive and statistically significant for all three states.) The mean estimates suggest that, from the negative state, an intervention could increase the instantaneous probabilities of moving to the neutral and positive states in the next period to 82.19% and 1.57%. From the neutral state, an intervention could increase the probability of moving to the positive state to 4.75%. The cumulative effect of intervention over time is even larger, which we discuss in §4.5. Meanwhile, when customers in the negative or neutral state hear more positive messages from others, they are also more prone to form more positive perceptions of the firm. (The coefficients for network sentiment are positive and statistically significant for these two states.) In summary, the state-transition parameter estimates show that customers' underlying relationships evolve over time naturally and gradually, that the firm's relationships with customers can indeed be improved through service interventions, and that friends' opinions also help shape customers' perceptions of the firm.[14]

Service Intervention. For the effect of service intervention, an interesting contrast can be made between voicing utility and the underlying relationship. Although active service interventions would improve

[14] We also estimated the same model using data aggregated at the weekly level. The results remain qualitatively the same.

Figure 2 (Color online) Histogram of Probabilities of Being Influenced by Friends



the firm's relationships with customers, they also raise the customers' expectations of being helped. This makes them more likely to complain in the future. The firm needs to be cognizant of this dual role, as it can lead to systematic differences between observed voices and the underlying relationships. Similarly, although positive network opinions help customers form positive perceptions of the firm, these opinions can also trigger complaints due to a differentiation effect in certain situations.

In summary, the parameter estimates reveal markedly different behavioral tendencies in different underlying relationship states. Customers in the negative state likely hold negative views about the firm and are prone to complain. They become even more so when others praise the firm, eager to "correct" other people's compliments. Customers in the neutral state likely hold neutral views about the firm and do not exhibit a tendency to either compliment or complain about the firm. Redress seeking seems to be an important motivating factor for these customers to complain. Customers in the positive state are likely to compliment the firm, reflecting positive relationships, and are likely to reinforce the compliments voiced by their friends. Redress seeking is also a key motivating factor for customers in this state to complain. Within each relationship state, the behavior further varies across customers. Both friends' messages and the firm's service interventions can induce customers to transition among these relationship states. Recognizing this diverse and state-dependent nature of voicing behaviors and understanding the intricacies of service intervention as well as friends' messages are crucial for successfully engaging customers on social media.

4.3. Network Influences

As discussed in §3, we estimate the probabilities of customers being influenced by their friends. The histogram of the posterior means of this influence parameter is plotted in Figure 2. The average probability across all customers is 0.469. This indicates that on average customers are influenced by slightly

Table 9 Regression—Influence Probability and Followers

	Regression 1	Regression 2
Dependent variable	logit(prob. to be influenced)	logit(prob. to influence)
Independent variable	ln(no. of friends + 1)	ln(no. of followers + 1)
Slope coefficient	−0.077 (***)	0.447 (***)
R^2	0.016	0.008

Note. Significance codes: "***", 0.001; "**", 0.01; "*", 0.05; "·", 0.1.

less than half of those they follow. The histogram is slightly right skewed, with most customers having a probability of lower than 0.8.[15] From the posterior of dyad-specific λ_{ij}s, we also compute the probability of each customer being influential on others in the sample. We then perform post-hoc analysis by running two regressions. In the first, the dependent variable is the probability of a customer being influenced by those the customer follows, logit transformed. The independent variable is the number of friends of the customer, log transformed. The result, reported in Table 9, shows that as customers follow more people, the probability of them being influenced by each individual friend is lower. (The coefficient is negative and statistically significant at the 0.001 level.) This is intuitive, as when a person follows more friends, the amount of time that can be spent on each friend's tweet is smaller. This lowers the probability of being influenced. In the second regression, the dependent variable is the probability of a customer being influential on the customer's followers, logit transformed. The independent variable is the number of followers the customer has, log transformed. The result shows that a customer with more followers is more likely to be influential, again a reasonable result. (The coefficient is positive and statistically significant at the 0.001 level.)

4.4. Voice and Relationship

A key aspect of our study is to separate the underlying relationships from the observed voices. We now compare and contrast these two constructs. To begin, Table 10 shows the empirical distribution of complaints and compliments over the underlying relationship states. States are recovered using the filtering approach for HMM (Montgomery et al. 2004, Netzer et al. 2008). We first note that voice and relationship are generally consistent: 70% of all complaints

[15] In Trusov et al. (2010) the reported average probability of being influenced is 0.22. The estimate here is higher, possibly because of the difference in context. Trusov et al. (2010) use log-in activities as indirect measures of usage, and the extent to which friends observe such activities is unclear. In contrast, Twitter users explicitly choose whom they follow, and their friends' tweets will be pushed to them. It is not, therefore, surprising to get a higher estimate of influence in the context of Twitter. An in-depth analysis of drivers of influence on Twitter is left for future study.

Table 10 Complaints and Compliments by Relationship State

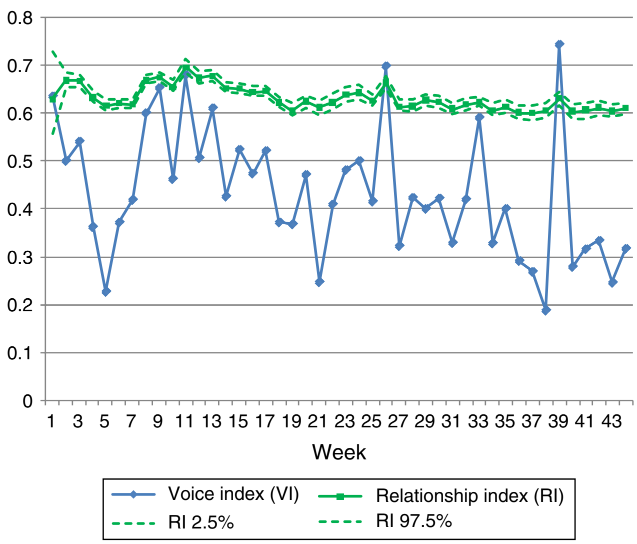
	Relationship state (%)		
	Negative	Neutral	Positive
Complaint	70.00	26.46	3.54
Compliment	0.75	25.03	74.22

were made by customers in the negative state, and 74% of compliments were made in the positive state. Furthermore, 26% of complaints and 25% of compliments were made by customers in the neutral state. Although the intrinsic desire to compliment or complain is low in the neutral state, customers spend the most time in this state, with social factors and redress-seeking effects also playing a role.[16] Interestingly, 3.5% of complaints were also voiced by customers in the positive state, considerably higher than the 0.75% of compliments in the negative state. This difference is driven by redress seeking customers who have positive perceptions of the firm but who may still complain. They expect the firm to address their issues, and they may even complain precisely because they hold the firm in high regard, possibly because the firm has been responsive before.

To further compare voice and relationship over time, we compute two sentiment indexes, one using the observed voices and the other using relationship states. We term the former the "voice sentiment index" and the latter the "relationship index." Consistent with industry practice, the former is calculated by dividing the number of compliments by the total number of compliments and complaints. Accordingly, the latter is calculated by dividing the number of occurrences of positive relationship state by the total occurrences of positive and negative states. We compute both indexes at the *weekly* level to smooth out daily fluctuations. The two indices are plotted in Figure 3 (for the relationship index, both posterior mean and 2.5% and 97.5% credible interval are plotted), from which we make three observations. First, the two indexes generally track each other over time, confirming that the latent relationship is a key driver of customer voices. Second and more important, the voice sentiment index is on average lower than the relationship index. This suggests that directly using voices may underestimate customer sentiment. The discrepancy is likely driven by redress seeking, which disproportionately encourages complaints. Another reason behind this discrepancy is that negative customers are more motivated to complain than positive ones are to compliment. This mean difference

[16] Although the population level intercept estimates do not show the effect of social utility for the neutral state, at the individual customer level it does exist, as the population variances reported in Table 8 show a wide dispersion of the related coefficients across customers.

Figure 3 (Color online) Voice Sentiment Index and Relationship Index from the Data



between the observed voice and the underlying relationship is a key takeaway for managers, one that cannot be revealed without explicitly modeling the relationship. Third, the relationship index is much less volatile than the voice index, likely because customer voices are relatively sparse and depend on the social media environment. Industry managers often track negative voices in real time and are concerned with controlling damage to a firm's reputation. However, such concern may be misplaced or an overreaction. The relationship index shows a stable and gradual evolution of sentiment. Even the voice index, despite volatility, remains stable over time. This is likely due to the self-stabilizing effect in this environment, as customers often differentiate or correct others' voices. By capturing the underlying trend in a more persistent fashion, the relationship index is a good alternative to the voice index that managers typically rely on. Its lower volatility also makes it an easier-to-use tool.

4.5. Effectiveness of Firm's Service Intervention

Does service intervention on social media improve a firm's image? To what extent is the improvement reflected in customer voices? How should the firm manage interventions effectively? To answer these important but largely open questions, we investigate the effect of a firm's service intervention on voice and relationship over time. We do so through simulation. For each individual complaint in the data set, we simulate two paths, with the firm intervening in the first but not in the second. We then simulate forward for two weeks for both scenarios. We perform the simulation using individual MCMC draws, and compute both the mean and credible intervals for the relevant measures.

The result of the simulation is plotted in Figure 4, where we show the mean improvement in voice and relationship indexes through intervention, as well as the 2.5% and 97.5% posterior quantiles. Three things are notable. First, service intervention has a significant positive effect on both the voice sentiment and the relationship. The intervention improves the voice sentiment index by 0.048 after two weeks (95% credible interval is −0.001 to 0.088), and the relationship index by 0.170 after two weeks (0.145 to 0.192). Second, the effect of intervention persists over time. The first few periods show increasing improvements on both voice and relationship indexes. The effect erodes to a certain extent after that, as the improvement diminishes over time. However, the improvement does not regress to zero. This shows that interventions have a longer-term impact, as customers remember the firm's past responsiveness. Finally, and most important, the result again shows that using only observed voices will underestimate the effect of intervention. The improvement of the relationship index is much higher than that of the voicing sentiment index. This difference is also significant. (The two credible intervals do not overlap.)

The difference between the improvements in the voice and relationship indices can be attributed to the redress-seeking effect. To see this, we perform two additional simulations to measure the partial effects of intervention. In the first, we allow service intervention to affect relationship, but ignore the redress-seeking effect (by fixing the service utility component to the value before the service intervention). In the second, we admit the redress-seeking effect but ignore the effect on relationship (by fixing the service intervention term in the state transition equation). The changes to the voice index of these two simulations, along with the overall improvement in the voice index as discussed earlier, are shown

Figure 4 (Color online) The Effect of Firm Intervention

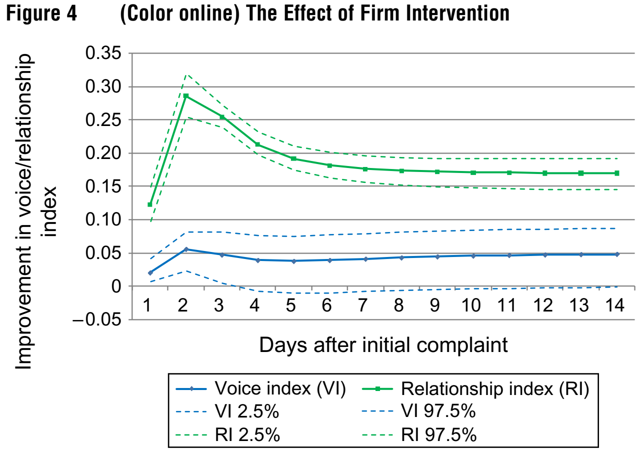
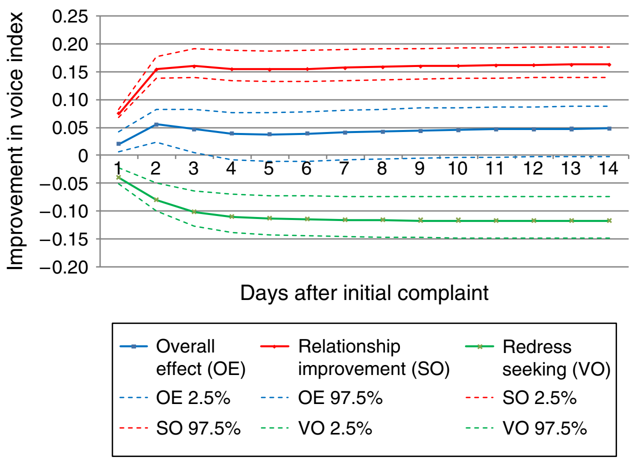


Figure 5 (Color online) Decomposing the Effect of Intervention on Voice Index



in Figure 5. If we consider only the effect of service intervention through improvement in relationship, the improvement stabilizes at 0.163 (0.139 to 0.194), very close to the improvement in the relationship index. However, if we consider only the redress-seeking effect of service intervention, then the voice index *reduces* by 0.117 (−0.148 to −0.074), as the customer subsequently complains more. Therefore, the redress-seeking effect offsets a significant portion of the would-be improvements in customer voices through improved relationship (almost two-thirds on average). This clearly illustrates the two opposing effects that service intervention has on customer voices. And it underscores the importance of understanding the nuances of customer voices and underlying relationships.

Recovering the underlying relationship state also provides an opportunity for targeting. To further investigate, we look at the effect of intervention conditional on the customer's relationship state at the time of complaint. Specifically, we break down complaint instances into five quintiles based on the posterior on relationship state, from negative to positive. The improvements in voice and relationship indices for the five quintiles are reported in Table 11. Although service intervention improves voice and relationship indices significantly for all quintiles, the improvement is higher for customers in the middle quintiles (third and fourth quintiles). Targeting the third or fourth quintile results in about 50% higher improvement than targeting the first quintile. Customers in the third or fourth quintiles are mildly negative. Firms, thus, should focus on the customers "on the margin" between negative and neutral states.[17] We also contrast this relationship state-based targeting with a common industry practice of targeting customers with more followers. We break down customers into quintiles based on the numbers of followers, and calculate the improvement in voice and relationship indices for each quintile. The results are also reported in Table 11. The difference across quintiles by numbers of followers is also quite significant for the voice index, largely driven by the observed heterogeneity of the service utility. However, the difference on the relationship index is muted, with all five quintiles getting similar improvements. Hence the underlying relationship can be used as an effective targeting criterion, supplementing the popular criterion of number of followers.

In summary, the managerial implications are threefold. First, service intervention improves both customers' voiced opinions and their relationships with the firm. Although service intervention is a double-edged sword in that it also encourages complaints, its indirect effect on voices through improved relationship states is stronger, and the net effect on customer voices is positive. Second, because of the dual effects of intervention, measuring only the voice will underestimate the return on service intervention. Third, recovering the underlying relationship enables effective targeting of service interventions.

5. Conclusion and Future Research

The ease of complaining on social media platforms empowers customers to speak up. With the expectation of firm participation on such platforms, customers' use of social media as a channel for complaints is rapidly increasing. It is equally easy to compliment as to complain on social media. Happy customers who appreciate the firm readily do so. Successfully engaging customers online through social media is quickly becoming an imperative for business practitioners. Although anecdotes abound, a clear understanding of customers' voicing behavior on social media and of the effect of firms' participation in this process is still lacking. Our study fills this gap by explicitly modeling the dynamics of customers' voices and their underlying relationships with firms on social media. We also investigate the effects of service intervention in this framework.

We show the importance of probing beneath the surface of compliments and complaints to uncover the underlying drivers of customer behavior. We find that customers' voices crucially depend on their underlying relationships with the firm. Customers who

[17] At the time of complaint, customers are much more likely to be in the negative state than in the positive one. The third and fourth quintiles are the "mildly negative" customers (posteriors show slightly higher chance of being in the negative state than in neutral), whereas the first and second quintile are the more negative customers (posteriors show a much higher chance of being in the negative state).

Table 11 ROI of Intervention by Relationship and Follower Quintiles

Target by	Measure	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile
Relationship	Voice index	0.042	0.050	0.053	0.052	0.043
		(0.012)	(0.017)	(0.022)	(0.027)	(0.028)
	Relationship index	0.144	0.171	0.189	0.195	0.145
		(0.010)	(0.013)	(0.016)	(0.017)	(0.016)
Number of followers	Voice index	0.026	0.059	0.056	0.058	0.044
		(0.043)	(0.016)	(0.014)	(0.020)	(0.039)
	Relationship index	0.168	0.170	0.163	0.182	0.166
		(0.014)	(0.014)	(0.014)	(0.015)	(0.016)

Notes. Average improvement in voice and relationship index through intervention after 14 days. Numbers in parentheses are standard errors.

have negative, neutral, or positive relationships with the firm have different inclinations to complain and to compliment. We further confirm that social factors and service intervention also affect customer voices. These factors create a discrepancy between the observed voices and the underlying relationships. This is especially true for redress-seeking motivation, which creates a negative bias in observed voices. We also provide a rich characterization of customers in different relationship states. For example, although redress seeking in general drives complaints, this effect is not evident for customers in the negative relationship state. As another example, customers in negative relationship states demonstrate a strong tendency to correct friends' messages. These detailed understandings are enabled by our focus at the individual customer level on the dynamics of both voices and relationships.

These findings have significant implications for sentiment and complaint management on social media. Industry managers tend to focus on positive or negative voices at the surface level. However, we show that customer voices are affected and biased by many other factors. It is, therefore, vital to uncover the underlying relationships of customers. Managers tend to fear the potential viral effect of complaints, but we show that such concern may be misplaced. We show that the sentiment indexes are generally stable and the social media environment is, to a certain extent, self-stabilizing. Managers tend to target their service interventions based on the numbers of followers a customer has. However, we show that targeting based on the customer's underlying relationship could be more effective. More important, managers should understand that service intervention has opposing effects. When the firm responds to a complaint, it also raises the customer's expectations. Responding to complaints thus encourages even more complaints. On the positive side, service intervention does help improve the customer's underlying relationship with the firm. The improved relationship also leads to more positive voices, and the positive effect outweighs the negative. It is important for practitioners to understand such nuances of service interventions in order to accurately evaluate their impact.

Several limitations of our study call for further research. First, the most direct and credible signal of customer sentiment is retention and purchase. However, as in many studies of social media, we do not have such data, nor do we have an offline tracking survey for external validation as done by Schweidel and Moe (2014). Such data can potentially provide a stronger validation of our findings and tie them directly to marketing outcomes. Second, we do not have customer demographic information other than the number of followers. It will be interesting to give a richer characterization of how voicing decisions differ across customer profiles. Similarly, it will be interesting to investigate how influence differs across friend profiles. Third, our data are for a single microblogging site. Although our model is grounded in general WOM theories, it is possible that certain results are specific to the site. Our model can be adapted with minor adjustments to other types of venues. It will also be interesting to see to what extent the various factors play a role on other platforms. Fourth, we focus on the dynamics at the individual customer level and take into account customer connections on social media only by including the direct effect of messages. Network structures of social media can be complex and multilayered, a fact that calls for more focused studies. Finally, firms may also benefit from proactively engaging with customers on social media, rather than just reacting to complaints. As customers respond favorably to service intervention, they may very well respond to other firm efforts, such as thanking customers for their compliments. This is an interesting topic for future study as firms expand their online activities.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0912.

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