International Journal of Information Management 39 (2018) 38–48

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Do your social media lead you to make social deal purchases? Consumer-generated social referrals for sales via social commerce

Namil Kim, Wonjoon Kim*

School of Business and Technology Management, College of Business, 291, Daehak-ro, Yusoeng-gu, Daejeon 305-701, Republic of Korea

ARTICLE INFO

Keywords:
Facebook
Social commerce
Social influence
Social referrals
Twitter

ABSTRACT

The advent of social commerce has resulted in a new business model for e-commerce. Although studies on this business model have increased over time, they have paid less attention to its core business model: consumer-generated social influence on sales on a social commerce site. Therefore, in this paper, we examine the effect on sales of social sharing, such as Facebook "likes" and Twitter tweets, which generate social influence, using data from major social commerce companies. We find that consumer-generated social referrals regarding deals significantly boost sales in social commerce. When we examine deals involved in national sales, this finding holds only for Facebook but not for tweets. These findings have the implication for managers that not all social referrals are meaningful in increasing sales for their business.

1. Introduction

Social commerce, from deals on Groupon.com to buyable pins on Pinterest, has grown to a value of several billion dollars (Dholakia, 2011a) and continues to grow at a significant rate (Anderson, Sims, Price, & Brusa, 2011). For example, in 2012, Groupon.com reported annual revenue of approximately $2.3 billion[1] and tens of millions of registered users (Byers, Mitzenmacher, Potamias, & Zervas, 2011), serving more than 500 markets in over 48 countries. In 2015, Pinterest launched "buyable pins" to allow customers to shop on its social media platform. The rapid growth of social commerce has been driven by synergy between e-commerce and social media, which has enabled existing e-commerce business models to successfully utilize and adapt to the changes that resulted from the rise of social media.[2] To amplify the use of social media in e-commerce business models, social commerce firms such as Groupon.com employ a strategy of offering deep discounts as a decoy (Mason, 2013) and focus more on products or services from local merchants.

Using this attractive business model during the early period of social commerce, social commerce firms acted as online distributors of deals offering significant discounts, and they aggressively increased their business by seeking to operate in multiple locations (Liu & Sutanto, 2012). However, they have begun to depart from that initial business model, retaining the use of social influence but discarding the use of the tipping point[3] and focusing less on local merchants to introduce goods and services for sale nationwide.

Social commerce is a new phenomenon, prompting studies to examine it. On the empirical side, a recent study examines the effects of other customers on sales in social commerce, focusing on word-of-mouth (WOM) (Amblee & Bui, 2011; Ullah, Amblee, Kim, & Lee, 2016 ; Ullah, Zeb, & Kim, 2015). Other studies also consider social influence from online WOM (Okazaki, 2009) and suggest that it changes customers' attitudes about a product, which in turn affects sales. However, the focus of WOM is mostly online product reviews, which rarely spread through social networks. Furthermore, reading online reviews at the online store implies that an individual already has an intention to purchase a product. A recent report shows that the main traffic to content articles is driven via social referrals, rather than Google searches (DeMers, 2015), and some e-commerce firms receive high amount of referrals from social media (Shields, 2015; Yang, Kim, Amblee, & Jeong, 2012). So it is questionable whether this widely employed business model utilizing social referral actually plays a significant role in sales.

From a behavioral perspective, previous studies investigate the relationship between social media and social commerce based on users' trust and the intention to use social commerce. Specifically, they

* Corresponding author.
E-mail address: wonjoon.kim@kaist.edu (W. Kim).

[1] Retrieved from financial information available at http://investor.groupon.com/financials.cfm

[2] There is no single accepted definition of social commerce (Busalim, 2016). However, we follow the generally accepted definition of social commerce, which is social media mediated e-commerce (Busalim, 2016; Liang, Ho, Li, & Turban, 2011; Zhou, Zhang, & Zimmermann, 2013).

[3] Retrieved from financial information available at http://www.grouponworks.com/merchant-resources/FAQs/

https://doi.org/10.1016/j.ijinfomgt.2017.10.006
Received 17 January 2017; Received in revised form 19 September 2017; Accepted 21 October 2017
0268-4012/

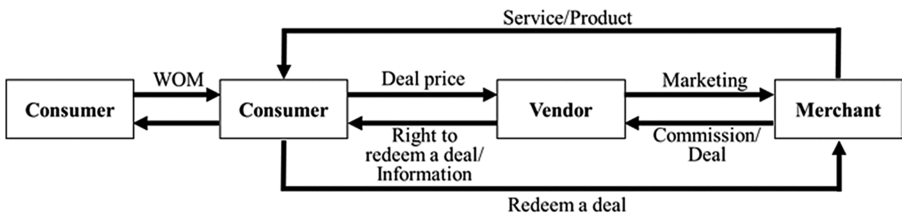

Fig. 1. Social Coupon Promotion Business Model.

consider the perspective of social support and social presence. Social support is based on reciprocity among social network users and the perception that how others care about a user affects the intention. Previous studies show that social support is positively associated with the intention to engage in social commerce (Hajli & Sims, 2015; Liang et al., 2011). In addition, studies from the social presence perspective propose that the presence of a vendor on social media increases the trust of sellers, which in turn changes the purchase intention in that social commerce (Lu, Fan, & Zhou, 2016). To put it differently, this behavioral research does not examine the direct relationship between social media and sales in social commerce; rather, they focus on perceptions about interpersonal communications and relationships among users in social networks. Social referrals generated on social networking sites (SNS), such as Facebook likes and Twitter tweets have not been a primary focus in previous studies. Furthermore, they also do not pay attention to sales patterns in different sales types, such as those for products from local versus national merchants.

Therefore, concerns have arisen as to whether the pattern of growth seen up to now will be sustainable in the long run (De la Merced, 2011; Raice, 2011). Namely, the role and the effect of the key parameter of the business model—consumer referrals over social networks—have not been closely examined or confirmed with regard to sales performance over time and how this business model works beyond local merchants. Unlike the tipping point, the utilization of consumer-generated referrals on SNS is a major factor not only in social commerce but also in other industries. For example, many e-commerce companies, such as Amazon.com and eBay.com, utilize similar consumer-generated social referrals in their business operations.

For this reason, in this study we examine the effect of social referrals on deal sales in social commerce. Because social commerce is an early adopter of the use of consumer-generated social influence to share product information, social commerce firms are suitable for examining the effect of social referrals on sales. In order to investigate the relationship between a change in sales and consumer sharing of deals through social networks, we analyze data from deal-level observations and their shared number of Facebook likes and Twitter tweets. Using the data, we found that consumer-generated social referrals, such as through Facebook likes and Twitter tweets, increase sales in social commerce, and we explain this mechanism from the perspective of social influence. There might be a concern over possible endogeneity issues. To address these issues, we adopt the instrument-free method (Park & Gupta, 2012), which suggests a way to obtain consistent parameters for endogenous regressors without any instrument variables by modeling correlation between the error term and endogenous regressors via copulas. Even after endogeneity is accounted for, the effect of Facebook likes and Twitter tweets on deal sales is statistically significant. Therefore, we contribute to an understanding of issues regarding social commerce, with a focus on analyzing the effect of social influence on sales performance.

The following sections outline the nature of social commerce and the methodology we adopt in this study in order to obtain and analyze data on them. First, we begin by briefly explaining a traditional form of typical social commerce transactions and review previous research on this industry. Second, we develop hypotheses regarding social influence on sales on a social commerce platform. Third, we present our empirical analysis of consumers' social referrals on sales on a social commerce platform. Afterward, we discuss our findings and provide the implications of our results. Finally, we conclude the paper, discuss the limitations of the study, and offer suggestions for future research to address these limitations.

2. Overview of social commerce

This paper deals with a traditional form of social commerce, meaning a form of e-commerce that uses social networks to influence sales (Liang et al., 2011; Zhou et al., 2013), or Groupon-like social commerce. Because social commerce borrows business models from e-commerce, three important entities are retained: customers, merchants, and vendors. Fig. 1 shows the relationship among these entities. Vendors, such as Groupon.com, are platform providers whose main role is to connect bargain-seeking customers with merchants offering goods and services. Merchants feature their own goods, either tangible or intangible, together with discounted prices, in exchange for an advertising effect or price discrimination effect (Edelman, Jaffe, & Kominers, 2016).

Each offer from a merchant at the early stage of social commerce is called a "deal" or a "coupon." Although the term "deal" is used more frequently in this business, we use "deal" and "coupon" interchangeably in this study. Information regarding the deal is delivered to customers via various channels in both traditional media and social media, such as e-mail, vendors' websites, and SNS. After the vendor distributes the deal, consumers spread word-of-mouth (WOM) about it over their networks.

This kind of business model is initially differentiated from the traditional e-commerce and coupon-based discount model in three ways: the types of products, the duration of discount periods, and the use of social media. First, e-commerce is traditionally based on the sale of tangible goods from national, or even international, merchants. However, social commerce sites such as Groupon.com, at least at the initial stage of their business, target local businesses, including restaurants and service providers, such as dry cleaners and auto repair shops. This offers local businesses an opportunity to advertise and reach a larger audience than they could using traditional marketing.[4] As they gain popularity beyond the local level or at the national level, they extend the market to non-local business, such as physical goods sold nationwide.

To differentiate itself from traditional price discount promotions, this business model adopts an up-front payment system. Traditionally, coupon-based discounts allow consumers to pay less when they purchase a good or service. However, the social commerce business model sells the *right* to consume a good or service, which assures local merchants of the expected sale from the promotion. This kind of right is similar to purchasing an open-ended airline ticket. The open-ended airline ticket lacks a specific return date; rather, it gives a customer the right to use the ticket within a time period. Similarly, social coupons also give customers a time limit within which to avail themselves of the right to have the services rendered. This implies that the sale of the service occurs at the time of the purchase, not when it is rendered. For this reason, we consider the sale of the social coupon the real sale of the service.

[4] http://www.tuck.dartmouth.edu/newsroom/articles/the-pros-and-cons-of-groupon/.

Although these different types of products and time availability of the discount are distinct characteristics of social commerce sites, they are not the key characteristic—that which causes the business to be called *social* commerce. The use of SNS to generate WOM among consumers is what distinguishes social commerce from traditional e-commerce.

Thus, a core component of social commerce is that it takes advantage of social influence among online consumers. Because a deal is made attractive by the offer of a deep discount, consumers are encouraged to tell their friends about it. The deals are featured for a short period—from as little as a day or two to a week—so there is not enough time for consumers to meet with many of their friends and share information about the deal in person. Thus social commerce relies on SNS, where consumers can spread information about the deal to their friends, and the system helps merchants to promote their business using the power of social networks.

3. Literature review and hypothesis

3.1. Previous studies on social commerce

Although the social commerce industry has only a short history, the number of studies on social commerce has increased tremendously recently. Because it is an emerging research area (Lin, Li, & Wang, 2017), many studies focus on the effectiveness of the business. For example, some attempt to explore and clarify the meaning and domain of daily deals by using a framework derived from social commerce theory (Liang & Turban, 2011; Yadav, De Valck, Hennig-Thurau, Hoffman, & Spann, 2013), by examining the factors that affect sales quantity (Byers et al., 2011; Dholakia, 2011b), by seeking consumers' reactions to deals or WOM (Byers, Mitzenmacher, & Zervas, 2012; Dholakia, 2011b; Kimes & Dholakia, 2011; Liu, Li, & Hu, 2013; Parsons, Ballantine, Ali, & Grey, 2014; Zheng, Zhu, & Lin, 2013), or by assessing the profitability of its business model (Edelman et al., 2016). If we extend the business beyond the daily deals to general social commerce, we find other interesting studies that examine consumers' impulse purchasing behavior (Xiang, Zheng, Lee, & Zhao, 2016), information-sharing behavior (Liu, Cheung, & Lee, 2016), or purchase intention (Hajli, 2015; Hu, Huang, Zhong, Davison, & Zhao, 2016). Studies that focus on firm performance are still lacking (Busalim, 2016); in particular, the studies to date have not adequately addressed the effect of consumer-generated social sharing on deal sales or social commerce per se.

Understanding the role of social influence in social commerce is important. It is widely assumed that social networking and media based on electronic communication will change e-commerce markets (Alt & Klein, 2011). The question here is whether the key business model in social commerce is effective in promoting sales or whether its success is due to traditional marketing promotion methods. At present, the sustainability of social commerce has not yet been confirmed from a social influence perspective, and, therefore, it is important to examine the following question: Do consumer-generated social factors matter in sales on a social commerce platform? To address this question, in the present study we focus on the effect of social influence on social coupon sales.

3.2. Social influence on social commerce

Previous studies on social commerce research focus on the changes in consumer behavior due to connected others in social networks or social media. Some of the studies show that social network users' perception of how other users care about them, or social support, is positively related to the intention to use social commerce (Hajli & Sims, 2015; Liang et al., 2011). Those studies are based on users' perceptions and reciprocity among social network users, but lack a consideration of whether social referrals such as Facebook's likes and Twitter's tweets exposed to their friends or followers will create any form of mutual communications or support for others. Other research shows that social presence increases customers' trust in the sellers in social commerce (Lu et al., 2016). They consider the presence of Facebook's likes and Twitter's tweets when they examine its relationship with customers' trust in sellers, not with customers' purchase intention directly. In other words, although the relationship between the spread of social referrals and actual sales in social commerce has more direct and important implications for the management of social commerce, it has not been explored in studies to date.

Another stream of research examines how others change one's behavior or attitude from different perspectives, apart from social support or trust. Some argue that consumer behavior changes because of social referrals or WOM effects (Okazaki, 2009; Turban, Strauss, & Lai, 2015). Amblee and Bui (2011), in particular, show that a change in sales occurs as online customer reviews signal a (brand) reputation. However, in their study, customers are exposed to reviews only when they visit an online store, which implies that they already have an intention to buy a product or a service. In addition, customers do not know who wrote the reviews and do not have any social contact with them. In other words, although social referrals through social platforms such as Facebook and Twitter are becoming more important in general in social commerce, the relationship between consumer-shared social posts and sales in social commerce has not been well examined.

Increasingly, consumer-shared social referrals have become one way of spreading information. On SNS, the consumer-shared social referrals spread information about a product or a service to one's social friends or groups. In this case, when an unexpected deep discount for a product or a service occurs that exceeds someone's expectation of the product or the service, the positive and voluntary spreading of that information is more likely to occur than it would for altruistic motives (Sundaram, Mitra, & Webster, 1998). Furthermore, the motivation for sharing the information online is the pursuit of social interaction with other consumers (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004).

We consider consumer-shared social referrals the medium of social influence. Here, social influence occurs when individual's attitudes and actions are affected by their peers and occurs through three processes (Kelman, 1958): compliance, identification, and internalization. Compliance is the process of earning rewards and avoiding punishment. People conform with others' beliefs publicly without agreeing with or believing in them privately that those beliefs are correct. Identification occurs when a person adopts the opinion of others to maintain a desired relationship. Celebrity endorsement is one example of identification, if a consumer's purchasing behavior changes because of celebrity effects. Internalization occurs when people adopt the opinion of peers based on congruencies or similarities between their values and those of other group members.

If a social referral causes one's social friends to purchase a product or a service, then we can say that social influence occurs. Among these three processes of social influence, we believe that identification and internalization in particular capture the relationship between social referrals and social commerce deal sales. In the case of identification, this could imply that, when a person who is admired or attractive refers a deal to others, they might find the deal more attractive. This is similar to the effects of celebrity-endorsed advertising (Basil, 1996). Argo, Dahl, and Morales (2008) show that the purchase intention can be affected even by physical contact with the product by that attractive other in an offline retail setting, which is referred as physical social contagion. This means that even mere exposure to the socially shared posts of that admired person that one is following could increase one's purchase likelihood, so identification occurs. In this case, (active) mutual communications with those who post social posts and their followers may not exist.

In the case of internalization, consumers could purchase a deal by accepting the referrals of peers who share similarities in their value of the social community. In general, friends in a social network have similar preferences and interests (Hogg, 2010; McPherson, Smith-Lovin,

& Cook, 2001; Wasserman & Faust, 1994). This kind of social network shows small-world properties or high closure. Individuals in a network with more closure or in a cohesive network build social capital, such as mutual trust, with one another (Coleman, 1988). For this reason, information in the network is more similar, reliable, and trustworthy (Coleman, 1988; Coleman & Coleman, 1994). Therefore, accepting the shared information of a socially similar group can comprise internalization. This implies that the exposure to the socially shared referrals from their online friends who share similar values increase one's likelihood of purchasing the product or service that is shared. In sum, when a consumer is exposed to a deal through a social network, the product that the consumer can purchase is highly likely to be something that a friend is interested in buying, so internalization or identification occur. Therefore, we hypothesize as follows.

H1. *Consumer-shared social posts on social networks increase deal sales on social commerce platforms.*

We examine the early stage of social commerce. As mentioned before, the social commerce we examine mostly focuses on local merchants, but the deal types can be extended to nationally sold deals. The local merchants usually have only one store or a few stores, which implies that the deal can be redeemed in only one place or a few places, while the deal from national merchants can be used at multiple stores across regions. Because they operate in more than one region, they tend to be more popular and have greater economic scale. Therefore, because their targeting goes beyond a local region, a national deal is expected to achieve more sales than local deals. However, this does not imply that the nationally sold deal positively increases the relationship between consumer-shared social posts via social networks and deal sales on a social commerce platform.

We believe that nationally sold deals decrease the relationship between consumer-shared social posts via social networks and deal sales on social commerce platform. The internet, including social networking, is sometimes used to communicate with offline friends from local community, and offline relationships are reflected to some degree in one's virtual social life (Facer, Sutherland, Furlong, & Furlong, 2001; Gross, Juvonen, & Gable, 2002; McMillan & Morrison, 2006). This implies that information beyond the local community may contain less common value among one's online friends and attract their awareness less. Therefore, when the shared information is exposed to socially or physically distant users, the information can be less suitable for the online communities or a user. In addition, the fact that the information or social referrals will receive less awareness beyond the local community is the second reason. This lower awareness and lower frequency of a deal leads consumers to have less interest in and purchase intention toward a deal (Tellis, 1988; Vakratsas & Ambler, 1999). In other words, consumer-shared social referrals regarding a non-local deal have less influence other consumers with respect to adoption of those referrals.

One may argue that social referrals containing non-local information can be more important than those containing local information. However, many previous studies in social impact theory show that social influence decreases with distance in a space, including a physical space, as the immediacy is one of the main drivers of the social impact (Latané, 1996; Latané, Liu, Nowak, Bonevento, & Zheng, 1995). Thus, social influence through internalization or identification is weaker in non-local deals, which implies that the relationship between consumer-shared social posts and deal sales on social commerce platforms decreases in nationally sold deals. Therefore, we hypothesize as follows.

H2. *The relationship between consumer-shared social posts on social networks and deal sales on social commerce platforms is weaker in nationally sold deals than regionally sold deals.*

4. Data and empirical models

4.1. Data

To test and confirm the effect of consumer-generated social posts, we considered the following aspects in choosing a vendor in the social coupon industry. First, our ideal vendor should consistently operate in multiple locations, that is, multiple cities, and have a nationally recognized reputation. This implies that a vendor has been in the market for a substantial time and is trustworthy. Second, the vendor should offer a link or a widget button for well-regarded SNS, such as Facebook and Twitter. This helps a consumer to share a deal through SNS and allows researchers to track how many times the link has been shared or the widget button has been clicked. Third, the vendor should have a website from which the history of previous deals can be collected. This criterion, however, restricts the collection of data from US-based social commerce sites. Sites such as Groupon.com do not allow searches for deals that they had previously sold but are now expired. Therefore, we were forced to choose market leaders that offer social commerce sites in Korea (Cho, 2011; Kim, 2011), namely, Ticket Monster, Coupang, We Make Price, and Groupon Korea. Our chosen company satisfies all three of these criteria.

Unlike Groupon.com and LivingSocial.com in the United States, most Korean social commerce vendors do not provide an application programming interface (API) with which to efficiently and accurately gather data. To deal with this, we used Python to crawl the sites for all searchable previous deals. However, the rapid growth in the industry pushes vendors to continually innovate and modify their websites to keep up with current trends and sometimes display some key features of their deals in images rather than in text. This frequent modification and contextual harnessing of recognition make it difficult for researchers to collect data from the sites in this way.

To verify the legitimacy of the information on deals obtained via web crawling, we also collected information from one of searchable social commerce metasites, which indexes the deals of vendors. The metasite does not feature its own deals; rather, it provides links to coupons from other vendors and the key features of a deal, such as the deal price, discount rate, and sales quantity. With these numbers, we were able to confirm that our collected data were appropriate.

To measure social referrals, we observed social activities on Facebook and Twitter. The APIs of both Facebook and Twitter provide the number of Facebook likes and Twitter tweets, respectively. The social commerce service we analyzed offers widget buttons for both Facebook likes and Twitter tweets. Specifically, each deal's page has widget buttons to help consumers share a deal or deal's page with his or her social network. After a consumer clicks on either of these buttons, a link containing information about a deal is posted on the consumer's Facebook Timeline or Twitter account, that is, his/her personal page. Subsequently, a consumer's friends on the SNS can see this posting. Therefore, we are able to track consumer social deal-referring activity using these sites.

Each deal in the dataset contains the following information: date of the featured deal, volume of ordered deals (regardless of whether a transaction followed), discounted price, actual price (face value) of the deal, sales duration of the deal, regions where the deal can be redeemed, and the number of Facebook likes and Twitter tweets. For the data period, we focused on the early stage of social commerce. At the early stage, even the leading firms were not fully established and recognized nationally. This gives us an advantage as it minimizes the vender-level loyalty or brand effects. The promotional effects from social influence might be biased or less effective if an individual is a loyal customer of a specific vender or he or she mostly receives information directly through its own marketing channels or website shortcuts. As they distinguished themselves as social commerce vendors, promoting social deals through social networks was vital in the initial period. Therefore, we obtained a total of 15,028 searchable deals, archived on a social commerce site from the end of November 2010 to the end of February 2012. The data cover almost all deals that site has featured. Furthermore, Facebook and Twitter activities are also collected on the same date as corresponding deals.[5]

In analyzing these deal data, we first removed those with missing or incorrect contents. We further eliminated event-like coupons or sales of socially taboo products that may have caused biased customer selection and social influence—for instance, those that offered a coupon at a zero price or were adult-oriented products.

Within our dataset, two of the key variables—the maximum sales volume available and the number of the same coupon that can be purchased at once—were available only after September 12, 2011. In addition, we excluded certain data after considering the following aspects. First, we excluded durable goods and travel products. This is because durable goods and travel products are not locally bounded. If deals are not locally bounded, we might have a problem similar to that with nationwide deals. This may affect the discussion of the importance of social influence because the consumers and sales location of a deal are different. Second, we dropped the data prior to September 12, 2011, because there was no information about maximum sales volume and the maximum purchase amount at once. If the deal reaches the maximum sales volume, there is a censoring of sales, which may create some bias in our analysis. Furthermore, if it is possible to make several purchases at a time, the sales of the deal may be boosted. Therefore, considering possible effects of these variables can increase the robustness of our analysis.

This data management process resulted in 3679 deals that were considered suitable for our study. The correlation matrix and descriptive statistics of the data are shown in Table 1, and histograms of social referral variables are shown in Fig. 2.

4.2. Method

This study aims to examine changes in deal sales resulting from social networking activities among consumers. We capture the effect of Facebook likes and Twitter tweets on deal sales in Eq. (1). Therefore, for each deal, i, we formulate four empirical models as follows:

$$log(Q_i) = \beta_0 + \beta_{fb}\cdot log(\#\ FB_i) + \beta_{tw}\cdot log(\#\ tweet_i) + \beta_{nat}\cdot nation + \beta_{fb\_nat}\cdot log(\#\ FB_i)\cdot nation + \beta_{tw\_nat}\cdot log(\#\ tweet_i)\cdot nation + \beta_{DV}\cdot DealVars_i + \beta_D\cdot Dummies_i + \epsilon_i \quad (1)$$

where Q_i is the value of the quantity sold, $\#\ FB_i$ is the number of Facebook likes, and $\#\ tweet_i$ is the number of Twitter tweets for each coupon i.[6]

Several considerations need to be controlled for in order to correctly describe the relationship between sales and the shared numbers in a deal via social networks; deal-specific characteristics, time trends, and locations are also required. $DealVars_i$ denotes deal-specific features, such as sales price, discount rate, the squared value of the discount rate, the sales period of the deal, and how many of the same coupon can be purchased at once. $Dummies_i$ are used to cover where and when a deal is registered, such as the province, the day of the week, and the week. Details of the variables used in the study are shown in Table 2.

However, the nature of social commerce does not allow us to observe how many deals are sold in the ideal case. One extreme case is that the maximum stock of coupons is a priori set. This implies that sales are bounded after the maximum available capacity is reached. The results of Eq. (1) are discussed in the next section, along with the endogeneity problems with respect to social influence.

5. Results

The results of estimation values of Eq. (1) are shown in Table 3, where the coefficients for log($\#\ FB_i$) and log($\#\ tweet_i$) capture the effects of social influence on deal sales. Column (A) in Table 3 shows the results without including social influence variables. Columns (B) and (D) do not contain the conditional role of nationally sold deals, while Columns (C) and (E) contain it. Columns (D) and (E) are designed to account endogeneity issues, which are discussed later.

As both independent and dependent variables are log-transformed, we can analyze the coefficients in terms of elasticity, which can be understood as the percentage change in deal sales with respect to a 1 percent increase in related social posts. Therefore, having observed positive and statistically significant coefficients, we can say that a 1 percent increase in the number of Facebook likes and Twitter tweets about a deal leads, on average, to 0.32 percent and 0.13 percent increases in deal sales in Column (B), respectively (H1 is supported).

When we examine the conditional role of nationally sold deals, the results are somewhat interesting. The conditional role differs by SNS platform. The conditional role in the relationship between Facebook and social commerce deal sales (denoted as log($\#\ FB_i$) x nation) does not seem to exist without having statistical significance, while the conditional role in that of Twitter (denoted as log($\#\ tweet_i$) x nation) shows a negative and statistically significant role (H2 is partly supported). The test statistic shows that the coefficient of Twitter tweets on sales is the same as the coefficient of the conditioning role; the null hypothesis that these two coefficients are the same is not rejected (p-value = 0.51). So, we can infer that the relationship between Twitter tweets and social commerce sales disappears when it comes to nationally sold deals. We discuss this finding in Discussions and Implications.

We also checked whether the effect of social influence on deal sales is subject to endogeneity. For example, uncaptured factors, such as the popularity of a merchant, may be correlated with consumers' deal-posting behavior. To handle this kind of endogeneity, we adopted the instrument-free method proposed in Park and Gupta (2012). What that study suggests is a way to obtain consistent parameters for endogenous regressors without any instrument variables by modeling correlation between the error term and endogenous regressors via copulas.

Specifically, this approach assumes that the joint distribution of the endogenous variable and the structural error can be achieved using a copula, which forms a relationship between multivariate joint distribution and the univariate marginal distribution. By assuming that the structural error is normally distributed and the distribution of endogenous variables is informative enough and not normally distributed,[7] the proposed copula model can properly capture the correlation structure between the endogenous variables and the error, which implies that we can obtain a consistent estimate. Because of its advantage in circumventing endogeneity problems without finding valid instrument variables, this method (Tran & Tsionas, 2015) has been widely used among empirical researchers in the field of business and economics (Blauw & Franses, 2016; Burmester, Becker, van Heerde, & Clement, 2015; Datta, Ailawadi, & van Heerde, 2017; Datta, Foubert, & van Heerde, 2015; Lenz, Wetzel, & Hammerschmidt, 2017).

This idea provides an easy way to implement this method to obtain a consistent estimate: adding additional regressors, which are the inverse normal of the marginal distribution of the endogenous variables (Park & Gupta, 2012, pp. 572–573). Here, the endogenous variables are

[5] A question can be raised concerning the collected date for social referral measures — the accumulation of social activities extending beyond the sales duration. However, assuming that the contributions of consumers to social media are mostly to increase their image-related utility, i.e., prestige- and stature-seeking behavior, by attracting new followers (Toubia & Stephen, 2013), there is less incentive to broadcast outdated deals via social networks, because this is not a good strategy for content providers to use to attract their friends and followers.

[6] When we take the logarithm, we add 1 to each value and then take its log value.

[7] In this study, the structural errors are ϵ_i in Eq. (1), which is assumed to be normally distributed. Normality of the structural error is not required for this method. For the distributional assumption, the method will work properly when the distribution of endogenous variables is different from the distribution of the structural error.

Table 1
Correlation Matrix and Descriptive Statistics.

	Variables	Mean	Std. Dev.	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Quantity sold (Q)	514.33	1,151.92	1	29,291	1								
(2)	# FB likes	4.21	10.46	0	205	0.303	1							
(3)	# tweet	6.58	23.87	0	394	0.168	0.180	1						
(4)	Price (in KRW)	34,226.28	92,317.42	300	1,790,000	−0.105	0.026	0.003	1					
(5)	Discount rate	0.52	0.14	0.1	0.99	−0.064	−0.038	−0.048	−0.123	1				
(6)	Duration (number of days of sales)	7.09	3.78	1	21	0.026	−0.052	−0.104	−0.066	0.106	1			
(7)	Maximum available deals to sell (MAX)*	1,292.59	2,497.67	6	70,000	0.601	0.231	0.191	−0.093	0.026	−0.051	1		
(8)	Is nationwide	0.12	0.33	0	1	−0.022	0.033	0.150	0.422	−0.037	−0.139	0.096	1	
(9)	Is maximum available capacity reached	0.01	0.09	0	1	0.011	−0.002	0.003	−0.004	−0.028	0.014	−0.024	−0.003	1

Note: Exchange rate as of July 2011 was KRW 1066 = USD 1. KRW = Korean won.

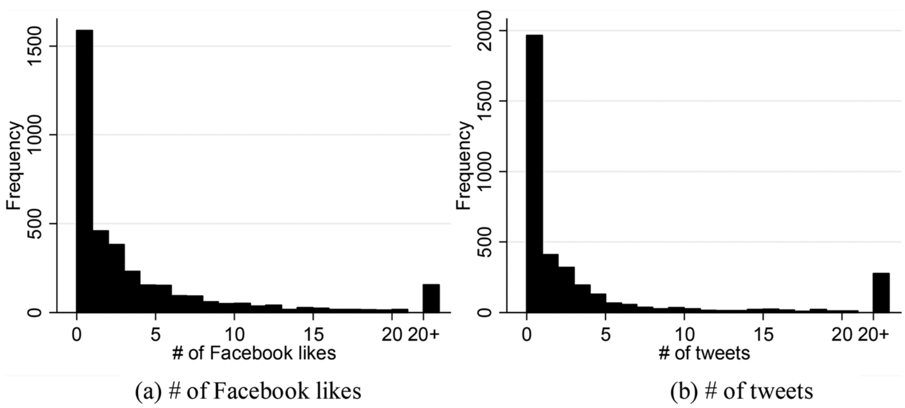

Fig. 2. Histograms of Social Posts of Coupons.

Table 2
List of Variables Used.

Variable	Description
log(Q_i)	The log of quantity sold for each deal
log(# FB_i)	The log of the number of Facebook likes
log(# $tweet_i$)	The log of the number of tweets
nation	Dummy variable for indicating whether a deal is sold nationwide
DealVars	
log($price_i$)	The log of the coupon price for a deal
Rate	The discount rate of the price
Ratesq	The squared value of the discount rate
log($duration_i$)	The log of how many days a deal is registered
log(ONCE)	The maximum amount of social coupon, which a customer can purchase per coupon
ismax	Dummy variable for indicating whether the maximum available capacity is reached
Dummies	
Location	Dummy variables for where a deal is featured (categorized as provinces in South Korea)
Day of week	Dummy variables for the day of week
Week	Dummy variables for the week when a deal is registered

log(# FB_i) and log(# $tweet_i$) in Eq. (1). A brief method for constructing additional regressors is as follows.

$$log(\#\ FB_i)^{E} = \Phi^{-1}(H(log(\#\ FB_i)))\ and$$

$$log(\#tweets_i)^{E} = \Phi^{-1}(H(log(\#\ tweet_i)))$$

where $H(.)$ is the empirical cumulative distribution function, and $\Phi^{-1}(.)$ is an inverse normal cumulative distribution function. To identify estimates, endogenous regressors should not be normally distributed (Datta et al., 2015; Park & Gupta, 2012). We test the normality of these variables with a Shapiro-Wilk test by following (Datta et al., 2015), and the test shows non-normality, with test statistics (W) of 0.9861 and 0.9429 for log(# FB_i) and log(# $tweet_i$), respectively, which are both significant and have a p-value of less than 0.0001. This implies that adding log(# FB_i) ^{E} and log(# $tweet_i$) ^{E} to Eq. (1) is a way to obtain consistent estimators for log(# FB_i) and log(# $tweet_i$). This new equation can be expressed as Eq. (1A).

$$log(Q_i) = \beta_0 + \beta_{fb}{\cdot}log(\#\ FB_i) + \beta_{tw}{\cdot}log(\#\ tweet_i) + \beta_{nat}{\cdot}nation + \beta_{fb\_nat}{\cdot}log(\#\ FB_i){\cdot}nation + \beta_{tw\_nat}{\cdot}log(\#\ tweet_i){\cdot}nation + \beta_{fbE}{\cdot}log(\#\ FB_i)^{E} + \beta_{twE}{\cdot}log(\#\ tweet_i)^{E} + \beta_{DV}{\cdot}DealVars_i + \beta_D{\cdot}Dummies_i + \epsilon_i^{E} \quad (1A)$$

The results of adding these two additional regressors are shown in Columns (D) and (E) in Table 3, which shows the estimates of Eq. (1A). From the data, endogeneity does not seem to be a problem unless there is a substantial change in the magnitude and the statistical significance of log(# FB_i) and log(# $tweet_i$). After considering endogeneity issues, the statistical signifiance of Twitter tweets becomes relatively weaker, although it is still (at least marginally) statitically significant, while the effect of Facebook likes on deal sales remains important. We also check whether our findings are robust under different settings or specifications. For this, we estimated Eq. (1A) separately for Facebook likes and Twitter tweets. Although the results are not shown here, they do not change substantially. (See the Appendix A for the separate estimations.) We further considered the case that the variables of a consumer's deal-sharing activities should be regarded as discrete variables. Even under this assumption, the results presented here do not substantially change (see the Appendix B for the results). Although the results become weaker after endogeneity is accounted for, they are still statistically significant at least at the 10 percent level. From these results, we can infer that our findings are robust under different settings, but the results of Twitter tweets are slightly subject to endogeneity issues.

6. Discussions and implications

6.1. Theoretical discussions and implications

We found that consumer-shared social referrals via social networks indeed increase sales on the social commerce platform, and their relationships vary according to whether the deals are local or national.

Table 3
Estimation Results of Relationship between Social influence and Deal Sales.

Dependent Variable Independent Variables	(A) log(Q)	(B) log(Q) Coeff. (Std. Err.)	(C) log(Q) Coeff. (Std. Err.)	(D) log(Q) Coeff. (Std. Err.)	(E) log(Q) Coeff. (Std. Err.)
log(# FB_i)		0.323***	0.319***	0.422***	0.414***
		(0.0185)	(0.0200)	(0.0449)	(0.0456)
log(# $FB_i)^E$				−0.114*	−0.109*
				(0.0468)	(0.0466)
log(# $tweet_i$)		0.133***	0.189***	0.108**	0.173***
		(0.0214)	(0.0237)	(0.0337)	(0.0358)
log(# $tweet_i)^E$				0.0371	0.0226
				(0.0373)	(0.0372)
log(# FB_i) x nation			−0.00261		−0.00581
			(0.0521)		(0.0521)
log(# $tweet_i$) x nation			−0.213***		−0.209***
			(0.0390)		(0.0391)
nation		0.941**	1.311***	0.918**	1.288***
		(0.286)	(0.296)	(0.286)	(0.296)
DealVars					
log($price_i$)	−0.686***	−0.682***	−0.692***	−0.682***	−0.692***
	(0.0199)	(0.0190)	(0.0190)	(0.0190)	(0.0190)
$rate_i$	−1.530	−1.128	−1.158	−1.090	−1.111
	(0.788)	(0.751)	(0.749)	(0.751)	(0.749)
$ratesq_i$	0.826	0.628	0.660	0.602	0.627
	(0.705)	(0.672)	(0.670)	(0.672)	(0.670)
log($duration_i$)	0.880***	0.758***	0.758***	0.759***	0.758***
	(0.0585)	(0.0565)	(0.0563)	(0.0565)	(0.0563)
log($ONCE_i$)	0.0984***	0.0879***	0.0869***	0.0889***	0.0878***
	(0.0233)	(0.0222)	(0.0222)	(0.0222)	(0.0222)
ismax	0.340	0.242	0.229	0.223	0.212
	(0.228)	(0.217)	(0.217)	(0.217)	(0.217)
Dummies					
location	Included	Included	Included	Included	Included
day of week	Included	Included	Included	Included	Included
week	Included	Included	Included	Included	Included
Constant	9.603***	9.292***	9.236***	9.213***	9.148***
	(0.579)	(0.555)	(0.554)	(0.558)	(0.557)
N	3679	3679	3679	3679	3679
R^2	0.3977	0.4536	0.4581	0.4546	0.4589

Notes: * significant at the 0.1 level, ** significant at the 0.05 level, and *** significant at the 0.01 level. Standard errors of models (D) and (E) are calculated with a bootstrap procedure with 1000 repetitions.

We conceptualize why the relationship between social referrals and deal sales could be regarded as social influence. We show that it happens through internalization and identification. To empirically show that, we employed the two most popular social networks: Facebook and Twitter. However, as we discussed above, they do not have similar effects on social commerce deal sales.

As for our findings on the conditional role, why is Twitter not associated with social influence on nationally sold deal sales? This finding probably results from the dissimilar nature of Facebook and Twitter. Although they share some common themes in terms of social networking behavior, their inherently different online-friendship structure might lead to different effects on sales. Facebook asks users whether they really know their friends in person, while, in Twitter, users can follow anyone or any topic. In addition, people tend to use Twitter to hide their identity and to remain anonymous on the internet (Huberman, Romero, & Wu, 2008; Hughes, Rowe, Batey, & Lee, 2012; Panek, Nardis, & Konrath, 2013). This implies that friends on Facebook are more likely to be sources of credible information, and to be locally bounded with the initiating consumers than are Twitter users. Furthermore, they are also to know one another offline. Because they have less similar groups of online friends, group users on Twitter tend to have fewer common opinions or values and less shared information. Furthermore, this kind of one-way following relationship and anonymity on Twitter makes interpersonal communication among Twitter users less frequent and leads to less social support. Because of the lack of similarity or local support, consumers on Twitter are not able to confirm the shared idea of their desired person. This implies that less social influence from their peers is likely to occur, making social posts less influential on Twitter. This is because social support is positively related to the intention to use social commerce (Hajli & Sims, 2015; Liang et al., 2011).

6.2. Practical implications

Although our findings are based on deal sales on a specific social commerce platform, the findings are easily applied to other e-commerce platforms, as our definition of social commerce uses social influence among consumers on e-commerce platforms. For this reason, this study has some important implications for e-commerce in general. First, this study shows the importance of consumer-generated and shared social influence. The findings imply that online commerce platforms should embed buttons so that users can share products or service information via social networks. Moreover, such buttons should be noticeable and accessible. Doing so will make it easy for consumers to share the information from that site to their online friends who are potential customers.

In the same vein, providing incentives for sharing information via social networking is an easily implemented strategy. Currently most e-commerce does not provide consumers with any incentive for social sharing of the site's information. In other words, social commerce is currently based on the natural degree of social sharing among consumers in their business. Many vendors use social networking, but they do not give consumers any monetary incentives for generating social influence, or they do not have enough activities to encourage consumers to refer a deal to their network. Business's engagement in online WOM communication on social media increases the consumers' engagement in online WOM communication (Zhang, Jansen, & Chowdhury, 2011). Overall deal sales via social commerce can grow further if vendors provide consumers with incentives for social sharing of deals, such as offering a reward for sharing on SNS or if vendors engage in more online WOM communication. Offering different types of incentives for social sharing and more engagement in online WOM communication may stimulate more voluntary deal sharing and eventually increase the overall size of the deals in social commerce.

However, based on our findings on the conditional role of nationally sold deals, merchants should keep in mind that social influence is not always an effective strategy. If one wants to increase one's sales via social influence, one should carefully examine the similarity among target users in social networking. If they do not share congruencies or similarities, social influence through internalization might not be achieved.

7. Conclusions

Along with the surge of social networking platforms, social commerce, such as Groupon.com, has been growing rapidly by taking advantage of the influence of social networks in their business. This paper aims to contribute to an understanding of issues regarding social commerce, with a focus on analyzing the effect of social influence on deal sales from the perspective of social influence. Based on data on major social commerce service companies that offer a link or a widget button to well-regarded SNS such as Facebook and Twitter, we examine whether the amount of shared information through social networking significantly and positively increases sales. In doing so, we use the instrument-free method proposed in Park and Gupta (2012) to overcome the endogeneity problems in our estimation of the model. This method models correlation between the error term and endogenous variables via copulas and enables us to obtain consistent parameters for endogenous variables.

Our empirical analyses using deal sales data yield an important result: consumer-generated social influence, such as from Facebook likes and Twitter tweets, boosts sales. Even after endogeneity is accounted for, the effect of Facebook likes and Twitter tweets is statistically significant with respect to deal sales. Therefore, our results confirm that customers' voluntary sharing of deal information via social networks constitutes an important business model in social commerce or online commercial site in general. We also discuss that although consumer-generated social influence matters for sales performance, the channels of information sharing might also matter. We also provide some implications of our findings that can help increase sales on online commercial sites.

Despite the meaningful findings and insights in this study, our research has some limitations that create a need for further study. First, the coverage of social networking is not complete—that is, we have not considered all SNS in South Korea. During our period of analysis, Cyworld was also a popular SNS in South Korea, but it has now been surpassed in popularity by Facebook and Twitter. Despite its popularity, we were unable to include this data in our sample as the vender does not have a widget for sharing its deals to Cyworld, and it does not provide an API to gather posts shared through this service. Furthermore, social networking is not bounded by a specific platform. Although (SMS-type) text messaging is no longer widely used in developed countries, during the early 2010 s it was a popular way to communicate with social peers. Our results could have been richer if we had been able to include Cyworld and text messaging information in our sample.

Second, the models developed in this study do not perfectly reflect market dynamics. The social commerce service industry is an emerging as well as a burgeoning market, and thus market conditions are still volatile and rapidly changing. Corporate giants in the information technology industry, including Google, Facebook, and Yahoo!, are also entering the market with their own platforms and business models. We attempted to reduce the possible impacts of these limitations by controlling for weekly trends in the empirical models.

Third, other factors affecting daily deal sales and different social factors are not fully included in this study. We examined only one specific vendor, which does not control for brand awareness, consumer targeting, and other factors affecting different consumers' purchasing behaviors. This could be a concern if the results exhibit biases because of the observations of the specific vendor. To deal with this issue, researchers can gather data on various vendors with more identified characteristics for social commerce. Furthermore, social factors, such as the number of friends on social networks and the frequency of a consumer's interaction with these online friends, are not also considered because of limitations on data collection. These limitations may cause omitted variable biases, introducing an endogeneity issue. Although it is not perfect, we tried to deal with it via the instrument-free method proposed. Future researchers could add more control variables to achieve more robust results.

Fourth, our findings come from an emerging industry. The fundamental nature of the industry may change as time goes on. For example, if social influence has an advertising effect on a deal of which consumers are unaware, that social effect will diminish as more and more people become aware of a vendor and that vendor engages in more advertising. In order to determine the long-term sustainability of the business model, researchers could examine a longer period by focusing on social influence dynamics.

Finally, as social commerce is still emerging, especially in the e-commerce sector, many topics still need to be studied, such as the optimization of social influence and the impact of the local fame of a merchant on the effectiveness of social networking promotions. The sustainability of social commerce businesses, service quality and customer satisfaction, repurchasing rates and determinants, and a deeper understanding of consumer behavior regarding social influence are all valid topics for future investigation.

Acknowledgment

This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2015-S1A3A-2046742).

Appendix A. Separate Estimation of Social Influence

Here we estimate Eq. (A1) separately for Facebook likes and Twitter tweets. Columns (A) and (B) in Table A1 are estimations that include Facebook's effects for Eq. (A1), and Columns (C) and (D) are for those of Twitter.

Appendix B. Discrete Facebook and Twitter Posts.

Here we assume that Facebook likes and Twitter tweets are discrete rather than continuous. The discrete variables version of Eq. (1) is Eq. (A1), and they are as follows.

$$log(Q_i) = \beta_0 + \beta_{fb}\cdot(\#\ FB_i) + \beta_{tw}\cdot(\#\ tweet_i) + \beta_{nat}\cdot nation + \beta_{fb\_nat}\cdot(\#\ FB_i)\cdot nation. + \beta_{tw\_nat}\cdot(\#\ tweet_i)\cdot nation + \boldsymbol{\beta}_{DV}\cdot DealVars_i + \boldsymbol{\beta}_D\cdot Dummies_i + \epsilon_i{}^E.$$

Table A1
Estimation Results of Relationship between Social Influence and Deal Sales.

Dependent Variable	(A) log(Q)	(B) log(Q)	(C) log(Q)	(D) log(Q)
Independent Variables		Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
log(# FB_i)	0.429***	0.436***		
	(0.0451)	(0.0459)		
log(# $FB_i)^E$	−0.107*	−0.107*		
	(0.0469)	(0.0469)		
log(# $tweet_i$)			0.105**	0.180***
			(0.0351)	(0.0371)
log(# $tweet_i)^E$			0.0954*	0.0782*
			(0.0385)	(0.0384)
log(# FB_i) x nation		−0.0413		
		(0.0522)		
log(# $tweet_i$) x nation				−0.238***
				(0.0403)
nation	0.773**	0.812**	1.285***	1.694***
	(0.287)	(0.291)	(0.297)	(0.304)
DealVars				
log($price_i$)	−0.684***	−0.684***	−0.683***	−0.694***
	(0.0191)	(0.0191)	(0.0197)	(0.0197)
$rate_i$	−1.148	−1.124	−1.470	−1.490
	(0.755)	(0.756)	(0.782)	(0.778)
$ratesq_i$	0.641	0.623	0.795	0.822
	(0.675)	(0.676)	(0.699)	(0.696)
log($duration_i$)	0.809***	0.808***	0.811***	0.810***
	(0.0562)	(0.0562)	(0.0587)	(0.0584)
log($ONCE_i$)	0.0938***	0.0940***	0.0919***	0.0906***
	(0.0223)	(0.0223)	(0.0231)	(0.0230)
ismax	0.255	0.252	0.292	0.278
	(0.218)	(0.218)	(0.226)	(0.225)
Dummies				
location	Included	Included	Included	Included
day of week	Included	Included	Included	Included
week	Included	Included	Included	Included
Constant	9.563***	9.537***	9.208***	9.134***
	(0.556)	(0.557)	(0.579)	(0.576)
N	3679	3679	3679	3679
R^2	0.4485	0.4486	0.4086	0.4143

Notes: * significant at the 0.1 level, ** significant at the 0.05 level, and *** significant at the 0.01 level. Standard errors are calculated with a bootstrap procedure with 1000 repetitions.

(A1)

The results of estimation values of Eq. (A1) are shown in Columns (A) and (B) in Table A2.

One possible way to implement the method of Park and Gupta (2012) to obtain a consistent estimate is to include additional regressors. Here, the endogenous variables are Facebook likes (# FB_i) and Twitter tweets (# $tweet_i$), which are discrete variables. A brief method for constructing additional regressors for discrete variables is as follows. Let $U_{fb,i}$ and $U_{tw,i}$ be latent variables for a social coupon, i, for # FB_i and # $tweet_i$, respectively, and be uniformly distributed [0,1]. Then we can relate $U_{fb,i}$ and $U_{tw,i}$ with the endogenous regressors, # FB_i and # $tweet_i$, respectively, as follows.

$$H_{fb}(\# FB_i - 1) < U_{fb,i} H_{fb}(\# FB_i) \; H_{tw}(\# tweet_i - 1) < U_{tw,\ i} < H_{tw}(\# tweet_i).$$

where $H_{social}(.)$ is the step function to mimic the marginal distribution function of each social network's posts. This function can be calculated from the data we have. As we assume that the structural errors for them are normally distributed, the inverse normal of $U_{fb,i}$ and $U_{tw,i}$ can capture the correlation of the endogenous regressor and the error, respectively, for Facebook likes and Twitter tweets. According to the copula model, this implies that by adding # $FB_i{}^E = \Phi^1(U_{fb,i})$ and # $tweet_i{}^E = \Phi^1(U_{tw,i})$ in Eq. (A1) with the discrete assumption, where $\Phi^{-1}(.)$ is the inverse normal function, the estimates of # FB_i and # $tweet_i$ are no longer subject to an endogeneity problem. By adding these terms to Eq. (A1) with the discrete assumption, we can obtain the equation below.

$$log(Q_i) = \beta_0 + \beta_{fb}\cdot(\# \ FB_i) + \beta_{tw}\cdot(\# \ tweet_i) + \beta_{nat}\cdot nation + \beta_{fb\_nat}\cdot(\# \ FB_i)\cdot nation. + \beta_{tw\_nat}\cdot(\# \ tweet_i)\cdot nation + \beta_{fbE}\cdot(\# \ FB_i)^{E} + \beta_{twE}\cdot(\# \ tweet_i)^{E.} + \boldsymbol{\beta}_{DV}\cdot DealVars_i + \boldsymbol{\beta}_D\cdot Dummies_i + \epsilon_i{}^E \ . \tag{A2}$$

The results of estimation values of Eq. (A2) is shown in Columns (C) and (D) in Table A2.

Table A2
Estimation Results of Relationship between Social Influence and Deal Sales with Discrete Assumptions for Facebook Likes and Twitter Tweets.

Dependent Variable	(A) log(Q)	(B) log(Q)	(C) log(Q)	(D) log(Q)
Independent Variables		Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
# FB_i	0.0299***	0.0297***	0.0157***	0.0146***
	(0.00185)	(0.00209)	(0.00250)	(0.00274)
# FB_i^E			0.128***	0.130***
			(0.0156)	(0.0156)
# $tweet_i$	0.00277***	0.00468***	0.00166*	0.00380***
	(0.000863)	(0.00114)	(0.000967)	(0.00125)
# $tweet_i^E$			0.0514***	0.0466***
			(0.0150)	(0.0151)
# FB_i x nation		−0.00258		0.000840
		(0.00465)		(0.00461)
# $tweet_i$ x nation		−0.00433***		−0.00444***
		(0.00164)		(0.00164)
nation	0.938***	1.048***	0.953***	1.040***
	(0.288)	(0.290)	(0.287)	(0.289)
DealVars				
log($price_i$)	−0.683***	−0.688***	−0.683***	−0.688***
	(0.0191)	(0.0192)	(0.0189)	(0.0190)
$rate_i$	−0.808	−0.784	−0.858	−0.856
	(0.759)	(0.759)	(0.751)	(0.751)
$ratesq_i$	0.322	0.302	0.395	0.391
	(0.679)	(0.678)	(0.672)	(0.671)
log($duration_i$)	0.831***	0.831***	0.776***	0.778***
	(0.0566)	(0.0566)	(0.0564)	(0.0564)
log($ONCE_i$)	0.0918***	0.0912***	0.0877***	0.0874***
	(0.0224)	(0.0224)	(0.0222)	(0.0222)
ismax	0.283	0.276	0.242	0.237
	(0.219)	(0.219)	(0.217)	(0.217)
Dummies				
location	Included	Included	Included	Included
day of week	Included	Included	Included	Included
week	Included	Included	Included	Included
Constant	9.449***	9.430***	9.463***	9.470***
	(0.557)	(0.557)	(0.554)	(0.554)
N	3679	3679	3679	3679
R^2	0.4435	0.4446	0.4557	0.4568

Notes: * significant at the 0.1 level, ** significant at the 0.05 level, and *** significant at the 0.01 level. Standard errors are calculated with a bootstrap procedure with 1000 repetitions.

References

Alt, R., & Klein, S. (2011). Twenty years of electronic markets research-looking backwards towards the future. *Electronic Markets, 21*(1), 41–51.

Amblee, N., & Bui, T. (2011). Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International Journal of Electronic Commerce, 16*(2), 91–114.

Anderson, M., Sims, J., Price, J., & Brusa, J. (2011). *Turning Like to Buy social media emerges as a commerce channel.* Booz & Company Inc.

Argo, J. J., Dahl, D. W., & Morales, A. C. (2008). Positive consumer contagion: Responses to attractive others in a retail context. *Journal of Marketing Research, 45*(6), 690–701.

Basil, M. D. (1996). Identification as a mediator of celebrity effects. *Journal of Broadcasting & Electronic Media, 40*(4), 478–495.

Blauw, S., & Franses, P. H. (2016). Off the hook: Measuring the impact of mobile telephone use on economic development of households in Uganda using copulas. *The Journal of Development Studies, 52*(3), 315–330.

Burmester, A. B., Becker, J. U., van Heerde, H. J., & Clement, M. (2015). The impact of pre-and post-launch publicity and advertising on new product sales. *International Journal of Research in Marketing, 32*(4), 408–417.

Busalim, A. H. (2016). Understanding social commerce: A systematic literature review and directions for further research. *International Journal of Information Management, 36*(6), 1075–1088.

Byers, J. W., Mitzenmacher, M., Potamias, M., & Zervas, G. (2011). *A month in the life of groupon.* arXiv:1105.0903v1 [cs.SI]. Retrieved from http://arxiv.org/abs/1105.0903.

Byers, J. W., Mitzenmacher, M., & Zervas, G. (2012). Daily deals: Prediction, social diffusion, and reputational ramifications. *Paper presented at the Proceedings of the fifth ACM international conference on Web search and data mining*.

Cho, J.-h. (2011). *Ticket Monster sale signals shift in industry.* The Korea Herald. 11 August 2011 Retrieved from http://nwww.koreaherald.com/view.php?ud=20110811000636.

Coleman, J. S., & Coleman, J. S. (1994). *Foundations of social theory.* Harvard university press.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, S95–S120.

Datta, H., Foubert, B., & van Heerde, H. J. (2015). The challenge of retaining customers acquired with free trials. *Journal of Marketing Research, 52*(2), 217–234.

Datta, H., Ailawadi, K. L., & van Heerde, H. J. (2017). How well does consumer-based brand equity align with sales-based brand equity and marketing mix response? *Journal of Marketing, 81*(3), 1–20.

De la Merced, M. J. (2011). *Is Groupon's Business Model Sustainable?* The New York Times. June 8, 2011, Retrieved from http://dealbook.nytimes.com/2011/06/08/is-groupons-business-model-sustainable/.

DeMers, J. (2015). *Social Media Now Drives 31% Of All Referral Traffic.* Forbes. 3 Feburary 2015, Retrieved from www.forbes.com/sites/jaysondemers/2015/02/03/social-media-now-drives-31-of-all-referral-traffic.

Dholakia, U. M. (2011a). *How businesses fare with daily deals: A multi-site analysis of groupon, livingsocial, opentable, travelzoo, and BuyWithMe promotions.* Rice University – Jesse H. Jones Graduate School of Business.

Dholakia, U. M. (2011b). *What makes groupon promotions profitable for businesses?* Rice University – Jesse H. Jones Graduate School of Business.

Edelman, B., Jaffe, S., & Kominers, S. (2016). To Groupon or not to Groupon: The profitability of deep discounts. *Marketing Letters, 27*(1), 39–53.

Facer, K., Sutherland, R., Furlong, R., & Furlong, J. (2001). What's the point of using computers? The development of young people's computer expertise in the home. *New Media & Society, 3*(2), 199–219.

Gross, E. F., Juvonen, J., & Gable, S. L. (2002). Internet use and well-being in adolescence. *Journal of Social Issues, 58*(1), 75–90.

Hajli, N., & Sims, J. (2015). Social commerce: The transfer of power from sellers to buyers. *Technological Forecasting and Social Change, 94*, 350–358.

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. *International Journal of Information Management, 35*(2), 183–191.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing, 18*(1), 38–52.

Hogg, T. (2010). Inferring preference correlations from social networks. *Electronic*

Commerce Research and Applications, 9(1), 29–37.
Hu, X., Huang, Q., Zhong, X., Davison, R. M., & Zhao, D. (2016). The influence of peer characteristics and technical features of a social shopping website on a consumer's purchase intention. *International Journal of Information Management, 36*(6, Part B), 1218–1230.
Huberman, B., Romero, D. M., & Wu, F. (2008). Social networks that matter: Twitter under the microscope. *First Monday, 14*(1) 10.5210/fm.v14i1.2317.
Hughes, D. J., Rowe, M., Batey, M., & Lee, A. (2012). A tale of two sites: Twitter vs. Facebook and the personality predictors of social media usage. *Computers in Human Behavior, 28*(2), 561–569.
Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Journal of Conflict Resolution, 2*(1), 51–60.
Kim, L. (2011). *Top 3 social commerce websites dominate Korean online shopping scene.* CNN Travel. 5 July 2011 Retrieved from http://travel.cnn.com/seoul/shop/social-commerce-sites-869074.
Kimes, S. E., & Dholakia, U. M. (2011). *Customer response to restaurant daily deals.* Retrieved from http://ssrn.com/paper=1925932.
Latané, B., Liu, J. H., Nowak, A., Bonevento, M., & Zheng, L. (1995). Distance matters: Physical space and social impact. *Personality and Social Psychology Bulletin, 21*(8), 795–805.
Latané, B. (1996). Dynamic social impact: The creation of culture by communication. *Journal of Communication, 46*(4), 13–25.
Lenz, I., Wetzel, H. A., & Hammerschmidt, M. (2017). Can doing good lead to doing poorly? Firm value implications of CSR in the face of CSI. *Journal of the Academy of Marketing Science,* 1–21.
Liang, T.-P., & Turban, E. (2011). Introduction to the special issue social commerce: A research framework for social commerce. *International Journal of Electronic Commerce, 16*(2), 5–14.
Liang, T.-P., Ho, Y.-T., Li, Y.-W., & Turban, E. (2011). What drives social commerce: The role of social support and relationship quality. *International Journal of Electronic Commerce, 16*(2), 69–90.
Lin, X., Li, Y., & Wang, X. (2017). Social commerce research: Definition, research themes and the trends. *International Journal of Information Management, 37*(3), 190–201.
Liu, Y., & Sutanto, J. (2012). Buyers' purchasing time and herd behavior on deal-of-the-day group-buying websites. *Electronic Markets, 22*(2), 83–93.
Liu, Y., Li, H. X., & Hu, F. (2013). Website attributes in urging online impulse purchase: An empirical investigation on consumer perceptions. *Decision Support Systems, 55*(3), 829–837.
Liu, L., Cheung, C. M. K., & Lee, M. K. O. (2016). An empirical investigation of information sharing behavior on social commerce sites. *International Journal of Information Management, 36*(5), 686–699.
Lu, B., Fan, W., & Zhou, M. (2016). Social presence, trust, and social commerce purchase intention: An empirical research. *Computers in Human Behavior, 56*, 225–237.
Mason, A. (2013). U.S. Patent No. US8355948 B2. U.S. Patent and Trademark Office.
McMillan, S. J., & Morrison, M. (2006). Coming of age with the internet A qualitative exploration of how the internet has become an integral part of young people's lives. *New Media & Society, 8*(1), 73–95.
McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*, 415–444.
Okazaki, S. (2009). Social influence model and electronic word of mouth: PC versus mobile internet. *International Journal of Advertising, 28*(3), 439–472.
Panek, E. T., Nardis, Y., & Konrath, S. (2013). Mirror or Megaphone? How relationships between narcissism and social networking site use differ on Facebook and Twitter. *Computers in Human Behavior, 29*(5), 2004–2012.
Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science, 31*(4), 567–586.
Parsons, A. G., Ballantine, P. W., Ali, A., & Grey, H. (2014). Deal is on! Why people buy from daily deal websites. *Journal of Retailing and Consumer Services, 21*(1), 37–42.
Raice, S. (2011). IPO? Groupon plans in flux. *Wall Street Journal*. 17 September 2011, Retrieved from http://online.wsj.com/article/SB10001424053111904537404576554812230222934.html.
Shields, M. (2015). These E-commerce companies are seeing lots of referral traffic from pinterest. *The Wall Street Journal*. 25 November, 2015, Retrieved from https://www.wsj.com/articles/these-e-commerce-companies-are-seeing-lots-of-referral-traffic-from-pinterest-1448449201.
Sundaram, D. S., Mitra, K., & Webster, C. (1998). Word-of-mouth communications: A motivational analysis. *Advances in Consumer Research, 25*, 527–531.
Tellis, G. J. (1988). Advertising exposure, loyalty, and brand purchase: A two-stage model of choice. *Journal of Marketing Research, 25*(2), 134–144.
Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. image-related utility in social media: Why do people contribute content to twitter? *Marketing Science, 32*(3), 368–392.
Tran, K. C., & Tsionas, E. G. (2015). Endogeneity in stochastic frontier models: Copula approach without external instruments. *Economics Letters, 133*, 85–88.
Turban, E., Strauss, J., & Lai, L. (2015). *Social commerce: Marketing technology and management.* Springer.
Ullah, R., Amblee, N., Kim, W., & Lee, H. (2016). From valence to emotions: Exploring the distribution of emotions in online product reviews. *Decision Support Systems, 81*, 41–53.
Ullah, R., Zeb, A., & Kim, W. (2015). The impact of emotions on the helpfulness of movie reviews. *Journal of Applied Research and Technology, 13*(3), 359–363.
Vakratsas, D., & Ambler, T. (1999). How advertising works: What do we really know? *Journal of Marketing, 63*(1), 26–43.
Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications.* Cambridge; New York: Cambridge University Press.
Xiang, L., Zheng, X., Lee, M. K., & Zhao, D. (2016). Exploring consumers' impulse buying behavior on social commerce platform: The role of parasocial interaction. *International Journal of Information Management, 36*(3), 333–347.
Yadav, M. S., De Valck, K., Hennig-Thurau, T., Hoffman, D. L., & Spann, M. (2013). Social commerce: A contingency framework for assessing marketing potential. *Journal of Interactive Marketing, 27*(4), 311–323.
Yang, J., Kim, W., Amblee, N., & Jeong, J. (2012). The heterogeneous effect of WOM on product sales: why the effect of WOM valence is mixed? *European Journal of Marketing, 46*(11/12), 1523–1538.
Zhang, M., Jansen, B. J., & Chowdhury, A. (2011). Business engagement on Twitter: A path analysis. *Electronic Markets, 21*(3), 161–175.
Zheng, X., Zhu, S., & Lin, Z. (2013). Capturing the essence of word-of-mouth for social commerce: Assessing the quality of online e-commerce reviews by a semi-supervised approach. *Decision Support Systems, 56*, 211–222.
Zhou, L., Zhang, P., & Zimmermann, H.-D. (2013). Social commerce research: An integrated view. *Electronic Commerce Research and Applications, 12*(2), 61–68.