Thumbs Up, Sales Up? The Contingent Effect of Facebook Likes on Sales Performance in Social Commerce

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ABSTRACT: In this study we investigate whether social reference systems, such as Facebook “likes” (FBLs), promote sales in social commerce, wherein adverse selection and quality uncertainty often severely damage consumer trust and impede efforts to achieve sustainable growth. We also examine the extent to which product characteristics (product uncertainty and product franchising) and deal characteristics (tipping points,

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Journal of Management Information Systems / 2015, Vol. 32, No. 4, pp. 109–143.

ISSN 0742–1222 (print) / ISSN 1557–928X (online)
DOI: 10.1080/07421222.2015.1138372

discount rates, and deal durations) moderate the social selling stimulated by FBLs. On the basis of 1,327 samples collected from a major social commerce platform provider, we identify several interesting empirical regularities regarding the relationship between FBLs and social commerce sales. The findings suggest that FBLs drive traffic and increase sales. Information technology artifacts and social technologies, such as FBLs, can endow a consumer's shopping experience with a socialization component and induce social selling in collective buying platforms. Nevertheless, significant variations occur across products and deals. For example, consumers who purchase experience goods more frequently depend on FBLs than do those who buy search goods. FBLs exert a far greater influence on the sales of goods from independent stores than those from franchise chains. Social commerce consumers are unaffected by heavy discount rates as they make purchase decisions, but they extensively rely on FBLs, particularly when purchasing products that have low tipping points. Our results suggest that social commerce can be a powerful marketplace when the economic utility that is driven by price incentives is further strengthened and protected by the social utility that originates from trust and sharing.

Key words and phrases: deal characteristics, Facebook likes, information asymmetry, online sales, product characteristics, social commerce, social network sites, social utility.

Social commerce platforms have given birth to new business trends that are rapidly attaining commercial prominence. Although the debate over the operational definition of social commerce continues unabated, the emerging paradigm that uses social media for commerce has expanded at a phenomenal rate and has shifted the competitive dynamics of several retail sectors. A case that reflects such expansion and shift is Groupon, a leading social commerce provider, whose business continues to thrive despite its sluggish international expansion and recent encounter of management problems. For the fourth quarter of 2014, it posted revenues of US$2.1 billion, which points to a 31 percent increase from the revenues earned in the same quarter in 2013.[1]

Despite the rapid expansion of social commerce, however, the upheaval in the value propositions and risk profiles of market sectors remains controversial. Customer complaints abound as to dubious deals, extraneous costs, information deficiencies, inflated savings, and low-quality products and services [17]. Most of the products and services offered by social commerce sites are associated with experience attributes [59]; this association increases the vulnerability of these goods to market frictions that emanate from information asymmetry [7]. According to a recent report by Song [73], many social commerce consumers experience friction specific to social commerce; these conflicts include discrimination or unfair treatment, service failures due to retailers' overselling, and refund complications. In addition, social commerce vendors exclusively sell local products and services, thus exacerbating information asymmetry given the increased difficulty and perplexity that are experienced by consumers in locating genuinely objective and accurate peer reviews. Finally, these sites restrict the ability of consumers to take advantage of deals by limiting the duration of an offer to a single day. This time pressure prevents consumers from exercising the presence of mind necessary to carefully weigh options; instead, it causes them to make impulsive purchases as they race against the clock [36].

In the face of these diverse market imperfections, which are less relevant to regular e-commerce, consumers that patronize collective buying venues have discovered ways to reduce risks and costs. One of the most prevalent measures adopted by social commerce consumers in coping with asymmetric information is leveraging peer-driven Facebook "Likes" (FBLs) that are enabled by social media platforms. FBL is one of the most trusted and reliable social reference systems (SRSs) that represents the aggregated opinions of consumers [78];[2] this credibility stems from the fact that product recommendations are solicited only from people with whom a Facebook user maintains camaraderie and kinship. A Nielsen survey on more than 28,000 users across the world indicates that 92 percent of consumers trust recommendations from friends and family.[3] Compared with regular online reviews that are often extolled as being characterized by "blind" rating systems, FBL recommendations are made by people who care enough to reveal their identities; consumers who are confronted with information asymmetry and quality uncertainty therefore perceive FBLs as highly valuable [35]. An extensive body of literature (e.g., [22, 40, 51, 65]) demonstrates that anonymity reduces individuals' self-imposed behavioral constraints and enables them to conduct themselves in a manner otherwise discouraged by transparency.

Unlike anonymity-based online review systems, FBLs systematically encourage transparency because they require sign-in and public identification before using FBL features. In addition, FBLs promote social engagement and monitor the quality of recommendations by levying social risks; product recommendations can inadvertently harm the reputation of the recommenders [28]. The combination of transparency and social risk can mitigate the threat of adverse selection in online commercial settings. FBL voters using their SNS accounts are less likely to be characterized as online "flamers" or "trolls" given that their use of those accounts naturally discloses personal identity [1]. Consequently, comments or opinions crafted through transparent FBLs are of higher quality [61].

Although research interest has increasingly focused on the effectiveness of FBLs in e-commerce in general and in social commerce in particular, few studies have thus far been devoted to consumers' adoption of FBLs in response to the heightened transactional uncertainty in online marketplaces. The literature on online reviews and ratings is extensive, but no coherent discourse has emerged regarding the effects of online ratings and reviews on sales performance. Empirical results are mixed, equivocal, and inconclusive; these deficiencies point to the need to exercise meticulousness in evaluating the economic impact of peer-driven online reviews and ratings. With the exception of Forman et al. [30], the majority of previous studies [11, 18, 19, 25, 27, 58, 80] have focused on "blind" reviews, in which a rater's identity is unknown to the public. Furthermore, few studies have examined how the contextual factors (e.g., sale durations, minimum buyer thresholds, and discount rates) that influence consumer behaviors moderate the relationship between identity-revealing FBLs and sales performance.

To redress this oversight, this study aims to investigate the following questions: Do FBLs increase social commerce sales? If so, what factors moderate the relationship between FBLs and sales growth? More specifically, we look into how product characteristics (e.g., product uncertainty and product franchising) and deal characteristics (e.g., tipping points, discount rates, and deal durations) temper consumers' willingness to embrace social reference mechanisms when purchasing goods over social commerce platforms. Specific research issues along this line of inquiry include the following: Are consumers who use social commerce more likely to depend on FBLs when they purchase products characterized by high uncertainty (e.g., experience goods) as opposed to products with low uncertainty (e.g., search goods)? To what degree does product franchising moderate the impact of FBLs on sales performance? Do tipping points—the minimum quantity thresholds set by social commerce platforms—significantly influence how consumers perceive quality uncertainty and their subsequent reliance on FBLs? Finally, we examine how the discount rates and deal durations offered by social commerce companies affect FBL use.

To systematically delve into these issues, we reinforce our work with adverse selection and quality uncertainty frameworks and conceptualize consumers' reliance on FBLs as a rational act of reducing uncertainty and information asymmetry. To gain empirical insights into the effects of FBLs, we collected the individual transaction data by using our independently developed software agent, which regularly pores through major social commerce providers (e.g., Groupon) and crawls through transactional data, such as the sale of daily deals across 51 cities in the United States and Canada. The goals of this study are to enhance our understanding of social commerce's viability as a legitimate business model and to shed light on the measures required to develop the full potential of social commerce through social feedback systems.

Theoretical Background

Social Commerce

Liang and Turban [48] define social commerce as a form of e-commerce that occurs by virtue of social media, conceptualizing it broadly as the combination of social and commercial interactions. Olbrich and Holsing [60] analyzed clickstream data detailing 2.73 million visiting sessions to determine how social shopping features, such as tags, ratings, lists, and styles, influence purchasing propensities. Tags and high review ratings are positively associated with increases in the likelihood of purchase. Pelaez et al. [64] investigated the dynamics of the relationships between group size, communication capacity, and buyer performance on group-buying social commerce platforms. Liang et al. [47] discovered that social support and website quality play significant roles in governing a user's intention to patronize social commerce platforms and subsequently continue subscribing to the sites.

Quality Uncertainty and Feedback Systems

Using principal–agent theory, Pavlou et al. [63] identified various sources of perceived uncertainty in consumers' purchase decisions, including information asymmetry, vendor's opportunism, privacy concerns, and security issues. Animesh et al. [7] suggest that low-quality retailers can manipulate their rankings on the results pages of sponsored search engines by exploiting information asymmetry. Dimoka et al. [26] recently endeavored to conceptually distinguish product uncertainty from seller uncertainty, investigating both the antecedents and consequences of product uncertainty in the online used car market. Erdem and Keane [29] revealed that under product uncertainty, consumers choose brands on the basis of their past usage experience and advertising exposure to maximize the expected present value of utility through "forward-looking."

When uncertainty plagued the capability of e-commerce to fully evolve into a legitimate market [53], feedback systems emerged as redeeming mechanisms for enhancing consumers' purchase confidence [8]. One research stream has zeroed in on the effects of rating systems on various performance outcomes, including consumers' perceptions of rating utility [58], rating credibility [39], purchase decision [80], sales growth [20], and product sales volumes [18, 19, 27, 61]. Another stream has examined the design and functional aspects of feedback systems and their differential effects on consumer behavior. For example, Forman et al. [30] found that online community members react more positively to product reviews wherein reviewers' identities are disclosed than to reviews provided by anonymous contributors.[4] This result suggests that the disclosure of a reviewer's identity builds consumer trust and therefore presents positive sales implications. Li and Hitt [46] demonstrated that consumers are inclined to take product price into account when writing product reviews.

Scholarship has also recently leaned toward determining how uncertainty affects a number of factors related to consumers' information-processing behaviors. Luo et al. [50] revealed that high product uncertainty negatively affects customer satisfaction but that these undesirable outcomes can be successfully managed by providing retailer-specific quality signals, such as a retailer's service quality and a well-designed website. Using signaling theory as a frame of reference, Wells et al. [79] illustrated that in the face of insufficient product information, many consumers turn to website quality as a signal of product quality. Finally, Mudambi and Schuff [58] revealed that in the case of experience goods, reviews with extreme ratings are less helpful than those with moderate ranking.

Effectiveness of Peer Reviews and Ratings

Despite growing interest in e-commerce issues, research pertaining to the effects of reviews and ratings on sales has been fragmented and ambiguous. Benlian et al. [11] disclosed that the recommendations of providers more strongly amplify perceived value and ease of use than do consumer reviews. However, consumer reviews prevail over provider recommendations in terms of trustworthiness and perceived affective quality. Chen et al. [18] found that consumer reviews are not significantly related to sales; by contrast, recommendations and the number of consumer reviews exhibit a significant association with sales. In the context of the film industry, Duan et al. [27] determined that viewer ratings exerted no significant effect on box office revenues after accounting for endogeneity. Analyzing the sales of digital books on Amazon.com, Amblee and Bui [5] demonstrated that peer reviews and ratings are inaccurate predictors of sales, but that the number of reviews can serve as accurate estimators. Finally, Hu et al. [37] discovered that an average rating does not necessarily represent a product's true quality.

As opposed to the absence of effects in the studies discussed above, a positive association between ratings and reviews and sales have been reported elsewhere [19, 80]. Using Amazon.com's customer review data, Chevalier and Mayzlin [19] identified positive empirical regularities between customer reviews and book sales. Dellarocas et al. [25] identified an intriguing U-shaped pattern of the relationship between moviegoers' propensity to publish reviews and box office revenues, suggesting that users are more likely to write reviews for either niche products or hit products than for "average" products that fall between the two categories. In a similar vein, Zhu and Zhang [80] uncovered the differential effects of consumer reviews on sales when product and consumer characteristics are factored into assessment equations. With the elaboration likelihood model as a basis, Ma et al. [52] found that numerous reviewers and review characteristics produce significant systematic biases, which make the interpretation of the relationship between online reviews and business profitability (e.g., sales) somewhat difficult and unreliable. To address this self-selection issue, the authors identified the key sources of such biases and examined the dynamics between previous and subsequent reviews after controlling for the biases.

An assessment of the literature in the fields of information systems and marketing reveals an increasing preoccupation with the effects of anonymous peer reviews and ratings on business performance and user perception. Notwithstanding this intensified focus, however, a significant research gap remains. The extant literature has predominantly centered on anonymity-based reviews and ratings in a variety of e-commerce contexts, and little is known about how social network-based recommendations, which require identity disclosure and entail social risks, influence consumers' purchase behaviors. Furthermore, the literature is silent regarding the manner by which contextual factors specific to online commerce environments moderate the dynamics of the relationship between FBLs and sales performance. The current work aspires to fill these voids.

Hypotheses Development

Impact of FBLs on Sales in Social Commerce

FBLs offer one fundamental and distinctive advantage over other alternative feedback systems; they collect the opinions of a user's friends, family, and other acquaintances rather than those of an unknown group of people. People in social exchange relationships are expected to place their faith in this rating system because the product referral votes are tendered by individuals whose judgments could actually matter to them. As evidenced in the study conducted by Timian et al. [76], aggregated FBL counts are significantly associated with user satisfaction.

The presence of these social elements separates FBLs from anonymous online reference systems. FBL users can frequently maintain social engagement and share their preferences and interests with their Facebook friends. In contrast, most anonymity-based online review systems do not generally offer that type of social function. In anonymous systems, an individual's identity is unknown and product reviews are not directly sent to social networks, and, therefore, no significant social engagement and sharing can take place. By enabling people to share their preferences and interests, social engagement preserves social exchanges [4]. In this respect, FBLs may serve as a conduit that facilitates interpersonal interaction and keeps people connected.

However, sharing preferences and interests can also entail a social risk that can result in inadvertent effects on a person's reputation. Social risk can be defined as "the potential loss of esteem, respect, and/or friendship by other individuals" [44, p. 198]. Product preferences that are unveiled through FBLs are usually posted to the walls of numerous Facebook friends, and some of them may be highly motivated to purchase the recommended offering. If a Facebook friend is dissatisfied with the product, however, the reputation of the person who recommended it may be inadvertently damaged. Schlenker and Leary [71] postulated that a high level of social risk is involved when providing a recommendation to a social network in which one's reputation is established and maintained. Eisingerich et al. [28] demonstrated that many consumers are unwilling to provide a product recommendation to their online social network friends because of the potential negative effects on their reputation.

Unlike regular review systems in which a reviewer's identity is mostly unknown and the aforementioned social risk is kept to a minimum, FBL users are required to log in to exhibit their preferences; thus, their identity can be easily discovered. In addition, FBL recommendations are disseminated to numerous friends and are posted on their Facebook wall for extensive periods. As a result of these structures and mechanisms, users are more careful about offering product recommendations to people in their social networks because doing so could result in damaging their reputation [28]. Since FBLs enable social engagement and monitor the quality of recommendations by levying inherent social risks, FBLs can be reliable and positively influence the sale of products and services in social commerce, which has severely suffered from many forms of market friction. Therefore, we posit the following hypothesis:

> *Hypothesis 1: FBLs positively affect the sale of products and services in social commerce.*

Moderating Effects of Product and Deal Characteristics

On the basis of the theoretical tenets associated with adverse selection and quality uncertainty, we identified two categories of moderating factors that are specifically germane to social commerce (Figure 1).

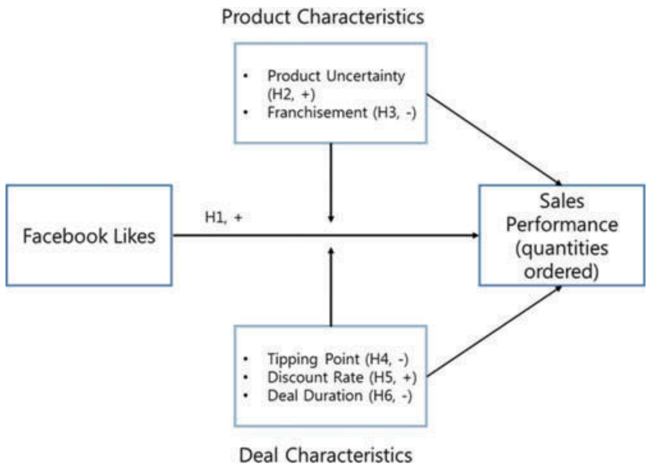

Figure 1. The Research Model

One category reflects deal characteristics and the other represents product characteristics. Adverse selection occurs owing to information asymmetry between parties transacting under market mechanisms, thus potentially leading to transactional instability and market failure [3]. The adverse selection arising from the exchange of asymmetric information between seller and buyer is the primary source of market friction in social commerce today. This evaluation is manifested by complaints about the lack of information regarding product quality and conditions disclosed to them prior to purchase. The two categories of moderating factors shown in Figure 1 determine the degree of perceived uncertainty and information asymmetry about transactions, thereby influencing the relationship between FBLs and sales in social commerce. When all other factors are held constant, the higher the level of uncertainty about transactions, the greater the effects of FBLs on purchases. This section provides details about how each factor moderates the dynamics of the relationship between FBLs and social commerce transactions.

Product Characteristics

Product Uncertainty

Despite the appeal of seemingly low search costs, the Internet-facilitated electronic market is far from perfect, and this creates an assortment of new market frictions that are unheard of in strictly physical markets [9, 16]. Among the many types of imperfections that impair e-commerce, information asymmetry that emanates from a buyer's inability to ascertain the quality of physical products before purchase constitutes one of the most precarious challenges that retard the long-term prospects of online markets. Dimoka et al. define product uncertainty as "the buyer's difficulty in evaluating the product (description uncertainty) and predicting how it will perform in the future (performance uncertainty)" [26, p. 397]. A large proportion of the products and services offered in social commerce are vulnerable to both description and performance uncertainty. The copious "special deals" announced are highly uncertain and subject to complex adverse risks because the commercial platforms from which these commodities are plied neither sufficiently describe the offers in question nor accurately evaluate their true quality. Without any point of reference, consumers who have no experience with goods characterized by high uncertainty are likely to suffer from asymmetric information problems when sellers are unwilling to disclose the true quality of such products.

Numerous research frameworks and empirical findings (e.g., [42, 59]) have shown that the quality of some products and services is inherently difficult to assess prior to purchase. A widely accepted search/experience classification paradigm [59] suggests that with all factors equal, experience goods whose attributes are difficult to evaluate prior to consumption tend to vary in quality more highly than do search goods whose characteristics are relatively easier to assess before purchase. Nelson [58] claims that the utility variation resulting from quality differences often outweighs the utility variation attendant from price dispersion—an argument that emphasizes the role of quality information in governing consumer behavior and market dynamics.

A consumer's reliance on product reviews varies depending on product characteristics. Zhu and Zhang [80] demonstrated that the impact of online reviews on product sales is more pronounced for lesser-known products than for popular products. Reinstein and Snyder [67] indicated that positive reviews have a significant influence on demand of experience goods, such as dramas and movies. Similarly, Chevalier and Mayzlin [19] found that a review of books (experience goods) is positively associated with sales. These studies collectively suggest that consumers generally turn to online reviews in the presence of ambiguity and uncertainty; experience goods are more difficult to objectively substantiate than search goods. Consistent with these observations, we expect product uncertainty to positively moderate the relationship between the reliance on FBLs and sales performance in social commerce. A concomitant hypothesis, therefore, is:

> *Hypothesis 2: The effect of FBLs on sales is more pronounced for products characterized by high uncertainty than for those characterized by low uncertainty.*

Product Franchising

Certain products or services that are peddled through social commerce sites can be purchased at several physical store locations of a franchise, whereas other goods are available only at a single, independent store. In this arena, some unique characteristics set franchises apart from the rest. A large number of restaurants that are involved in social commerce (e.g., family restaurants) operate in multiple geographical locations, thus allowing consumers to redeem restaurant vouchers at any of the franchisee stores. A chain can leverage inherent and substantial economic benefits, including fast resource mobilization, to standardize the quality of its products and services [66]. The institutional structure of a franchise enables a franchisor to exercise almost complete control over the behaviors and resources of a franchisee; some of the factors that can be regulated are products sold, product price, hours of operation, inventory, personnel, and accounting and auditing [70]. By way of illustration, because of stringent control and close coordination, chain affiliation reduces uncertainty about restaurant quality, which, in turn, may diminish the potentially unfavorable effect of a consumer concern. Luca [49] found that online reviews, such as Yelp ratings, exert a far greater influence on the sales of independent stores than on those of chains. The author affirms that such rating systems shift consumer demand not only between independent stores, but also between chains and independent stores.

Consumers who patronize franchise stores whose reputations are strengthened by trademark generally possess a thorough understanding of the price and quality of the products sold by franchise establishments. When acquiring a franchise, a franchisee is also purchasing the trademark, which legally empowers a franchisor to standardize quality across chain stores [70]. Considering minimal quality uncertainty about the products and services offered by franchise chains, consumers may downplay the importance of FBL evaluations. Against this backdrop, FBLs are systematically less beneficial to franchise products than to independent products. By contrast, users are more likely to accept FBLs intended to evaluate the products available in one specific location than FBLs that aggregate the evaluations of franchise products. Accordingly, we posit the following:

> *Hypothesis 3: The effect of FBLs on sales is more pronounced for products offered through a single, independent store than those available through a franchise.*

Deal Characteristics

Tipping Points

Social commerce vendors have initiated a salient group-buying feature that involves quantity thresholds. For example, Groupon sets minimum quantity thresholds called *tipping points* for offerings that can be redeemed only when preset thresholds are reached; any offerings that fail to satisfy the tipping point requirement are automatically revoked upon time expiration. Sellers are granted the privilege to process transactions at their discretion. Social commerce platforms have imposed this compulsory rule in the anticipation that it will naturally encourage interested consumers to act as sales people and promote deals through their social networks. When successful, this strategy reduces marketing expenses and leverages the power of viral marketing and mass exposure facilitated by social media.

A tipping point prespecified for each offering may pose important effects on consumers' uncertainty sentiments and use of FBLs. Offerings are voided upon failure to satisfy the minimum quantity requirement; thus, retailers prudently establish tipping points in such a way that not only avoids the cancellation of a deal and the incurrence of opportunity costs but also maximizes profits. A tipping point often serves as a measure or signal of product quality, reflecting a retailer's confidence in its sales prospects. As a general pattern, products offered with high tipping points usually attract many consumers because the sellers are a priori cognizant of the high demand and popularity of the products in question. These vendors then establish thresholds accordingly. Kauffman et al. [41] revealed that consumers who participate in Internet-based group-buying auctions perceive less psychological uncertainty in a given auction when the number of other consumers willing to bid on the underlying auction increases. The research findings amassed in the psychology literature demonstrate that individuals tend to exhibit more risk-taking behaviors in groups than when acting alone—a phenomenon commonly known as the risky shift [75, 77]. A case in point is the fact that adults who shop in groups are more confident about their purchase-related actions and buy more products than those who shop alone [72]. This self-assuredness derives from infallibility that consumers feel against the risk of adverse selection in situations wherein many other people attempt to buy the same product at the same price.[5]

Altogether, these findings suggest that offerings preset to high tipping points in social commerce naturally attract numerous buyers and subsequently reduce interested consumers' perceptions of the uncertainty associated with a purchase decision. In the eyes of social commerce consumers, high tipping points produce many purchase "pals," albeit in virtual form. These pals not only co-enjoy likely benefits but also share the same unlikely adverse selection risk (i.e., risk is interpreted to be distributed across consumers). When considering purchasing offerings set to high tipping points, therefore, consumers depend to a lesser extent on FBLs because of the low uncertainty and information asymmetry perceived in such offerings. Conversely, consumers perceive that offerings with low tipping points are likely to draw a relatively small number of purchase pals; this recognition increases the uncertainty that they see in the offerings. To mitigate uncertainty, then, consumers interested in purchasing products with low tipping points are likely to rely heavily on FBLs. The hypothesis drawn from this tendency is as follows:

Hypothesis 4: The effect of FBLs on sales is more pronounced for products with low tipping points than for those with high tipping points.

Discount Rates

Price discounts have been regarded as one of the most common and effective promotional tactics for generating sales. All the same, these prevalent monetary incentives are also thought to merely create the illusion of enhanced value, thus granting sellers outwardly legitimate leeway within which to deceive consumers [56]. As a result, many consumers are skeptical of advertised discounts and often disregard price discounts [14]. Sensible consumers may feel that discounts "come with strings attached." Therefore, perceived price discounts, which consumers calculate on the basis of their internal reference prices [45], are far smaller than that declared in advertised discounts. Blair and Landon [14] assert that consumers who are sensitive to such promotional incentives tend to discount advertised reference prices (i.e., comparison prices cited as evidence of monetary savings) by up to 25 percent.

A consumer's predisposition toward depreciating price discounts increases vis-à-vis the magnitude of advertised savings [13, 32]. High levels of price reduction are often construed as signaling either the inferior quality of the product on sale or the excessive inflation of reference prices (i.e., list price or manufacturer's suggested retail price) [56]. Furthermore, a consumer's perception of price discounts can be influenced by diverse contextual cues, such as brand name, store image, and brand familiarity. Gupta and Cooper [32] empirically validated that consumers harbor a natural tendency to undervalue price discounts and that their inclination for downplaying price reduction offers increases when advertised savings are excessively high and brand names are less known. Madan and Suri [76] found that consumers who are offered a 45 percent discount attribute a significantly higher quality to an alternative product of the same price, but with no discount indicated.

The amount of price discounts is likely to influence the relationship between the consumer's reliance on an SRS and sales volume in social commerce. A consumer's perception of uncertainty and adverse selection increases according to the amount of the price reduction [13]. This pattern holds particularly true in social commerce, where the misrepresentation of product quality and sellers' opportunistic behavior have cast serious doubts on the new commercial platform's long-term survival.

The excessive price markdowns that are omnipresent in online commerce may reduce the attractiveness of a product and herald its inferior quality or a seller's opportunism (e.g., inflated reference price) [68]. Consumers shopping through social commerce may detect that extraordinary price reductions come with costs; they may perceive an advertised offer as inauthentic and that a seller is spuriously eliciting demand by manipulating reference prices. Such deceitful manipulations are liable to proliferate in social commerce because most products are associated with experience attributes. For this reason, consumers turn to FBLs to validate the credibility of substantially discounted products and services. Conversely, in response to small discount rates, consumers neither suspect the trustworthiness of a product or service nor feel the need to seek "social validation" through FBLs. This reaction leads to the limited use of such references as bases for purchase decisions. We, therefore, propose the following:

> *Hypothesis 5: The effect of FBLs on sales is more pronounced for products offered with a large discount rate than for commodities that come with a small discount rate.*

Deal Duration

Major social commerce sites initially opted to keep deal duration to a maximum of one day, but they later eliminated such conservative time constraints in an effort to draw in more potential buyers and sales profits. Interestingly, the reduced time pressure and increased choice manageability that are enabled by the extension of deal durations may present important ramifications for consumer decision making and rational purchase behaviors. During a consumer's decision-making process, the amount of available time foreseeably affects the actual quality and execution of a decision because the capacity to collect and process information is an increasing function of time granted [12]. Bronner [15] revealed that the demand for additional information radically decreases under time pressure. Such dynamics accounts for consumers' tendency to make impulse or unplanned purchases under time pressure [38]. With all else equal, then, consumers' willingness and desire to obtain additional information about a product increases proportionately with time availability.

Given that consumers can capitalize on additional time, those who consider purchasing a product offered under an extended deal duration are anticipated to be less dependent on FBLs than customers who wish to buy a product that is available for only a day. Information integration theory [6] maintains that people are apt to assign different weights to information to maximize the total value of information. In this respect, as consumers gather more information with additional time availability, they may accordingly rely less on the existing information source (e.g., FBL) because every piece of information obtained diminishes the significance ascribed to existing facts. This decrease holds, unless the value of the newly added information is nonzero. In a similar vein, if a deal period is extended, the penchant for seeking additional information increases, which in turn, decreases the importance of an FBL. In keeping with these observations, we put forward the following:

> *Hypothesis 6: The effect of FBLs on sales is more distinct for products offered under short deal durations than for those available for an extended period.*

Methods

Data Description

To provide empirical insights into the hypotheses related to the effectiveness of SRS, we collected data from Groupon, a leading social commerce enterprise that offers daily discounted deals on numerous commodities and service goods. Launched in November 2008, this global leader in the group-buying businesses is highly localized to serve more than 42 million users in 500 cities and local areas across 48 countries worldwide [33]. As reflected in its name Groupon, which is a mashup of "group coupon," the company seeks to harness the power of social networks and benefit from collective group purchase invigorated by heavily discounted deals.

An automated proprietary software agent was developed to crawl through the Groupon website (www.groupon.com) and collect the data necessary for validating the hypotheses. The variables for which the data was collected include the specific identify of each daily deal, quantities ordered, advertised discount rates, tipping points, and other pertinent parameters that appeared on the deal pages across 51 cities in the United States and Canada from November 2 to December 9, 2010. At Groupon.com, daily deals in each city normally begin at 12:00 midnightand end at the same time the next day. When time expires, new deals are announced immediately on the same page and another 24-hour time frame becomes effective until the offering is terminated. To capture the sales volume (i.e., quantities ordered) of deals available in numerous cities, the software agent sifted through the deal pages around 12:00 a.m. every day during the data collection period while taking the time difference into consideration.

Using the automated crawler, we collected 1,363 deal samples. If the data included only one-day deals, the total number of observations should be 1,938 (51 cities*38 days). However, the data also contained two-day and three-day deals in which a single deal lasted more than a day. Therefore, deals with extended durations have reduced the total number of samples. When two-day and three-day deals are taken into account, our sample size becomes 1,734, which results in 204 missing samples (= 1,938 – 1,734). Furthermore, 29 samples were omitted because one city (Fort Myers) joined Groupon after we began our data collection. It is important to note that some of the access attempts to the Groupon pages using the automated agent were delayed or even denied by the company's servers, which resulted in 175 missing samples. The 175 uncollected samples are spread across various cities, not concentrated in specific cities. We carried out a statistical test to validate the randomness of the uncollected samples. The average number of missing samples per city was 3.5 and the standard deviation was 2.05. The results of the normality test indicate that our findings are not subject to a systematic bias since the pattern of missing samples is equally distributed across all states [21]. Therefore, the uncollected samples do not significantly influence the results. Finally, 36 deals that failed to reach the predetermined tipping points were excluded from our sample, which leaves 1,327 deals. Table 1 provides the descriptions for the variables included in the econometric models.

Table 1. Variable Description

Variable	Description
QUANT_ORDER	The amount of quantity ordered for each deal
PRICE	Price of each deal that customer actually pays
FBL	The accumulated counts of Facebook Likes for each deal
TIPPING	The preset minimum quantity threshold for a deal to be activated
DISCOUNT	The discount rate of each deal
PERIOD	The number of days for which a deal lasts
FRANCHISE	A dichotomous variable indicating deals selling vouchers of a franchise store. The value is coded as 1 when the merchant is a franchise and 0 otherwise
UNCERTAINTY	A dichotomous variable indicating deals having experience characteristics rather than search characteristics. Experience goods are coded as 1 and search goods as 0
YELP_SCORE	The average Yelp score for each deal
YELP_COUNT	The number of Yelp reviews for each deal
YELP_STD	The standard deviation of Yelp reviews for each deal

Figure 2. Facebook Like on Groupon Page

As displayed in Figure 2, a number of attributes representing deal characteristics appear on the deal page. In the left column of the figure, "535 bought" indicates the specific quantities ordered (purchased). This information was captured by the variable, QUANT_ORDER. The deal's discounted price (PRICE) appears on the same column with the discount rate shown in percentage (DISCOUNT). A small rectangular box on the left bottom of the figure represents the accumulated counts of Facebook Likes (FBL), which indicate how many people recommended the particular products or services. The tipping point (TIPPING) refers to a minimum quantity threshold only above which a deal on the table can be redeemed. For example, the preset tipping point for the product in Figure 2 was 15. As indicated in the note ("Tipped at 6:36 a.m. with 15 bought"), the minimum quantity condition for this particular offering was met and therefore this deal was redeemed. Although infrequent, deals are often voided as they fail to reach the threshold. When such unwanted incidents occur, consumers who signed up for the deals get their money back. PERIOD specifies the number of days for which the deal is available, and FRANCHISE indicates whether the deal is associated with a franchise store or not.

To measure the degree of product uncertainty, we followed previous studies (e.g., [7]) where product categories were used to determine whether products were search or experience goods. In so doing, we first classified 1,327 deals into 21 product categories. We then adopted the search/experience framework [59] to divide product categories into two groups, experience goods and search goods, which have different degrees of product uncertainty.[6] Experience goods are known to have higher uncertainty than search goods [7].

Although this widely accepted measurement scheme captures the extent of uncertainty for diverse product categories, we employed an additional objective measure to further ensure the reliability of our coding results. We collected information on product review from Yelp.com. To measure product uncertainty, we calculated the standard deviation of

Table 2. Summary Statistics

Variable	N	Mean	Std. dev.	Min	Max
lnQUANT_ORDER	1,327	5.46	1.39	1.95	9.77
lnPRICE	1,327	3.10	0.75	1.39	5.30
lnFBL	1,327	2.41	1.48	0	7.60
UNCERTAINTY	1,327	0.72	0.45	0	1
lnTIPPING	1,327	3.31	0.89	0.69	6.91
DISCOUNT	1,327	0.56	0.10	0.37	0.96
PERIOD	1,327	1.28	0.67	1	3
FRANCHISE	1,327	0.11	0.32	0	1
YELP_STD	507	0.22	0.22	0	1.41
YELP_SCORE	507	3.84	0.84	1	5
lnYELP_COUNT	507	1.93	1.12	0.69	6.01

user rating of the store at which the deal was offered (YELP_STD). The standard deviation captures the extent to which the evaluation of a particular product or service varies across individuals. A large variation in the evaluation implies that the product contains various quality dimensions, which lead to a wide range of preferences. Therefore, a degree of variation could represent a degree of uncertainty [26]. In addition, we also included the average review score (YELP_SCORE) and the number of reviews (YELP_COUNT) to control for the differences in quality and popularity across deals. It should be noted that the Yelp reviews do not exist for all of the deals that appeared in each group. When the Yelp rates were incorporated in our model, the sample size decreased to 507. For this reason, we employed the Yelp scores as a complement to the search/experience good classification.

Table 2 shows the summary statistics of the variables included in the econometric analysis. Due to the positive skewness, we took the natural logarithm on these variables. Table 3 presents a pairwise correlation test among the variables, showing the absence of multicollinearity.

Empirical Model Specifications

To investigate the effect of FBL on sales performance (QUANT_ORDER), an econometric model was developed (Equation 1).

$$\begin{aligned}\ln\ QUANT\_ORDER_i = {} & \beta_0 + \beta_1 \ln PRICE_i + \beta_2 \ln FBL_i + \beta_3 UNCERTAINTY_i \\ & + \beta_4 FRANCHISE_i + \beta_5\ \ln\ TIPPING_i + \beta_6 DISCOUNT_i\,. \\ & + \beta_7 PERIOD_i + \varepsilon_i\end{aligned} \tag{1}$$

The dependent variable, the amount of quantity ordered for each deal (lnQUANT_ORDER), was log-transformed using a natural logarithm in order to stabilize the variance and adhere to the normality requirement. As the amount of quantity ordered is largely influenced by the price level, the baseline model includes the variables that represent the price level of each deal (lnPRICE) and the magnitude

Table 3. Pairwise Correlation (N = 1,327)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
lnQUANT_ORDER	1.00										
lnPRICE	–0.12	1.00									
lnFBL	0.57	–0.03	1.00								
UNCERTAINTY	0.17	0.05	0.11	1.00							
lnTIPPING	0.68	0.04	0.41	0.10	1.00						
DISCOUNT	–0.04	0.25	–0.03	–0.02	–0.06	1.00					
PERIOD	–0.15	0.22	–0.09	0.04	–0.18	0.04	1.00				
FRANCHISE	0.25	0.02	0.15	0.09	0.19	0.12	–0.09	1.00			
YELP_STD*	–0.01	–0.01	–0.01	0.09	0.03	–0.05	0.09	–0.03	1.00		
YELP_SCORE*	–0.14	0.06	–0.11	–0.02	–0.09	–0.06	0.04	–0.12	–0.24	1.00	
lnYELP_COUNT*	0.45	–0.09	0.29	0.17	0.44	–0.17	–0.04	0.05	0.10	–0.12	1.00

*Number of observations (N) for the Yelp-related variables is 507.

of discount rates (DISCOUNT). The variable that represents product uncertainty (UNCERTAINTY) is also considered in the baseline model. The tipping point (lnTIPPING) was included in the model because it sets the minimum quantity threshold that is required in order for each deal to be redeemed. Given that this variable may reflect a retailer's sales confidence and also stimulate collective buying actions, it is presumed to have a significant bearing on sales performance. The demand of a deal is also influenced by how many days a deal is available (PERIOD) because it extends the exposure time to potential customers. Finally, the fact that a deal is offered by a franchise store can also change the demand as such vouchers are redeemable in multiple franchise stores that participated to the offering.

In addition to the baseline model designed to give a general understanding of the relationship between the amount of quantity ordered and pertinent predictors, we formulated a full model (Equation 2) that includes both the main components and interaction terms in order to examine the moderating effect of product and deal characteristics on the association between SRS (lnFBL) and sales (lnQUANT_ORDER). The simultaneous relationship between SRS (lnFBL) and sales (lnQUANT_ORDER) will be discussed in more detail in the next section where the endogeneity issue is addressed.

$$\begin{aligned} \ln QUANT\_ORDER_i &= \beta_0 + \beta_1 \ln PRICE_i + \beta_2 \ln FBL_i + \beta_3 UNCERTAINTY_i \\ &\quad + \beta_4 FRANCHISE_i + \beta_5 \ln TIPPING_i + \beta_6 DISCOUNT_i \\ &\quad + \beta_7 PERIOD_i + \beta_8 \ln FBL_i * EXPERIENCE_i \\ &\quad + \beta_9 \ln FBL_i * FRANCHISE_i + \beta_{10} \ln FBL_i * \ln TIPPING_i \\ &\quad + \beta_{11} \ln FBL_i * DISCOUNT_i + \beta_{12} \ln FBL_i * PERIOD_i + \varepsilon_i \\ \ln FBL_i &= \gamma_0 + \gamma_1 \ln QUANT\_ORDER_i + \gamma_2 \ln FBUSER_i \\ &\quad + \gamma_3 \ln PRICE_i + \varepsilon_i. \end{aligned} \tag{2}$$

As noted earlier, some of the deals do not have the Yelp-related variables, and thus we had to deal separately with product uncertainty (YELP_STD) in the reduced sample. Equation (3) is designed to involve this variable as well as other situational effects considered in Equation (2).

$$\begin{aligned} \ln QUANT\_ORDER_i &= \beta_0 + \beta_1 \ln PRICE_i + \beta_2 \ln FBL_i + \beta_3 UNCERTAINTY_i \\ &\quad + \beta_4 FRANCHISE_i + \beta_5 \ln TIPPING_i + \beta_6 DISCOUNT_i \\ &\quad + \beta_7 PERIOD_i + \beta_8 YELP\_SCORE_i + \beta_9 \ln YELP\_COUNT_i \\ &\quad + \beta_{10} YELP\_STD_i + \beta_{11} \ln FBL_i * EXPERIENCE_i \\ &\quad + \beta_{12} \ln FBL_i * FRANCHISE_i + \beta_{13} \ln FBL_i * \ln TIPPING_i \\ &\quad + \beta_{14} \ln FBL_i * DISCOUNT_i + \beta_{15} \ln FBL_i * PERIOD_i \\ &\quad + \beta_{16} \ln FBL * YELP\_STD_i + \varepsilon_i \\ \ln FBL_i &= \gamma_0 + \gamma_1 \ln QUANT\_ORDER_i + \gamma_2 \ln FBUSER_i \\ &\quad + \gamma_3 \ln PRICE_i + \varepsilon_i. \end{aligned} \tag{3}$$

Both the interaction between UNCERTAINTY and FBL, and between YELP_STD and FBL test H2, which states that the effect of an SRS is more pronounced when products are high in uncertainty than when they are low in uncertainty. Likewise, four interaction components (lnFBL * lnTIPPING), (lnFBL * DISCOUNT), (lnFBL * PERIOD), and (lnFBL * FRANCHISE) are included to test H3, H4, H5, and H6, respectively. To minimize multicollinearity among the interaction terms and their component terms, the interaction terms are mean-centered, as suggested by Aiken and West [2].

Endogeneity Validation: Three-stage Least Squares and Propensity Score Matching

Since the data collected for this study are cross-sectional in nature, a reverse causality or simultaneity between the amount of quantity ordered (lnQUANT_ORDER) and FBL (lnFBL) can potentially exist and create endogeneity problems that may lead to biased ordinary least squares (OLS) estimations. More specifically, although we assume that FBL induces the amount of quantity ordered, in certain situations a reverse causality can occur, albeit rarely, in which the amount of quantity ordered drives the FBL. Furthermore, although unlikely, these two parameters can form reciprocal relationships, simultaneously influencing each other. These problems may occur because, in addition to displaying information for FBL counts, the deal pages also show information about the actual quantities ordered for specific deals. We expect that the tally on FBLs signals the quality or the value of the products in question, prompting users that are connected via social networks to purchase the recommended products. However, the amount of the quantity ordered that was exhibited on the deal page can signal a product's popularity and quality. Users who perceive the quantity ordered as a signal of the product's quality may be inclined to recommend it to other users in their social circles by clicking on the "like" button.

To address this potential endogeneity problem, we employed an econometric approach that makes use of the system of equations and runs the three-stage least squares (3SLS) regression in line with the literature [43]. Combining the 2SLS method with multivariate regressions (i.e., seemingly unrelated regression (SUR) estimation), the 3SLS approach estimates the full system where endogenous variables in an equation are used as explanatory variables in other equations [31, p. 692]. More specifically, the 3SLS mechanism is intended to generalize the 2SLS method by considering the correlations between equations in the same manner that SUR generalizes OLS. When the error terms of the equations are correlated, 3SLS can achieve asymptotic efficiency by restructuring the variance-covariance matrix and applying feasible generalized least square (FGLS). In addition, we used propensity score matching methods (PSM) [24, 69] to further validate the endogeneity issues. For reliable and efficient estimates of parameters, 3SLS is widely adopted when dealing with endogeneity and contemporaneous cross-equation correlation between error terms. On the basis of the 3SLS approach, we designed the FBL model as specified in Equation (2). In the first stage, the full system, the equations are separately estimated with all the exogenous variables included in the system. The parameters of these equations are then simultaneously estimated in the second stage using the covariance matrix derived in the first stage.

In keeping with a general principle, in this model we included a new exogenous variable (lnFBUSER) that represents the number of Facebook users in a city where a deal is offered. The quantitative data for this variable were obtained through a Facebook page (http://www.facebook.com/advertising) that allows advertisers to get a sense of how many potential users are in a targeted area. This newly added instrument variable is correlated with FBL because it may reflect the intensity of Facebook use in each city. However, at the same time this variable should be excluded in the QUANT_ORDER in Equation (2) because the number of Facebook users is unrelated to the sales volume of a particular deal offered through Groupon, given that the demographics of Groupon users are distinct from the demographics of Facebook users.[7] In addition, to validate the strength of our instrument variables, we performed the weak instrument tests suggested by Stock and Yogo [74]. We first calculated the first-stage F-statistic and then compared this value with a threshold in order to determine whether the value is sufficiently large to reject the null hypothesis. The F-statistic from our model was 50.37 ($R^2 = 0.21$), which is significantly higher than the threshold, 10. From the results, FBUSER can be considered not a weak instrument for the FBL variable. Additional variables are included to control for the possible effects of price levels and product categories.

Results

Table 4 shows the results obtained from the 3SLS approach. In Table 4, column (1) exhibits the 3SLS regression analysis for the base model, column (2) for the integrated model including all of the moderators (Equation [2]), and column (3) for the reduced samples, including product uncertainty (Equation [3]). Column (4) exhibits the results for the integrated model (Equation [2]) with the assumption that the main and interaction terms are both endogenous. In the economics literature (e.g., [10]), it is widely accepted to instrument interactions of endogenous variables with interactions with instruments. Instead of using the interaction terms that may have endogeneity problems (i.e., lnFBL × DISCOUNT), we reestimate the model by including the instrument interaction terms (i.e., lnFBUSER × DISCOUNT). The results in column (4) are very similar to those reported in column (2) with one exception on deal periods. In accordance with the literature, we interpret the results on the basis of those shown in column (2). The highest variance inflation factor (VIF) (lnFBL*PERIOD) among all the interaction variables was 7.31, which is less than 10, the threshold for detecting a multicollinearity issue [34]. As shown in all columns, the coefficient for lnFBL is positive and significant at the 99 percent confidence level. Therefore, H1, which states that FBLs positively influence sales volume, is supported by the data ($p < 0.01$).

Table 4. The Contingent Effects of SRS

		(1) Base model		(2) Exogenous interactions		(3) Subsample		(4) Endogenous interactions	
Dependent variable	Independent variable								
lnQUANT_ORDER	lnPRICE	–0.191***	(–3.62)	–0.156***	(–2.88)	–0.155	(–1.43)	–0.279***	(–7.49)
	lnFBL	1.106***	(7.89)	3.133***	(8.06)	4.292***	(4.55)	1.227***	(11.26)
	UNCERTAINTY	–0.136**	(–2.37)	–1.501***	(–5.00)	–3.017***	(–3.24)	–0.566***	(–4.42)
	lnTIPPING	0.302***	(3.12)	0.618***	(8.08)	1.436***	(4.77)	1.093***	(9.68)
	DISCOUNT	0.168	(1.45)	1.237*	(1.94)	–0.400	(–0.20)	–0.660	(–0.95)
	PERIOD	0.031*	(1.73)	2.783***	(6.17)	5.716***	(3.84)	–0.062	(–0.45)
	FRANCHISE	0.176***	(2.65)	1.890***	(5.64)	2.113***	(3.03)	1.120***	(4.91)
	lnFBL*UNCERTAINTY			0.586***	(5.19)	0.989***	(3.14)	0.168***	(3.44)
	lnFBL*lnTIPPING			–0.223***	(–6.05)	–0.431***	(–3.86)	–0.219***	(–9.26)
	lnFBL*DISCOUNT			–0.435*	(–1.93)	0.033	(0.06)	0.353	(1.23)
	lnFBL*PERIOD			–1.311***	(–6.20)	–2.283***	(–3.90)	0.054	(0.83)
	lnFBL*FRANCHISE			–0.661***	(–5.49)	–0.656***	(–3.01)	–0.263***	(–3.27)
	YELP_STD					–1.419*	(–1.93)		
	YELP_SCORE					0.113	(1.26)		
	lnYELP_COUNT					–0.059	(–0.72)		
	lnFBL*YELP_STD					0.530**	(2.08)		
	Constant	3.373***	(8.04)	–1.173	(–1.28)	–4.750*	(–1.90)	3.435***	(11.04)
lnFBL	lnQUANT_ORDER	0.551***	(9.57)	1.186***	(21.06)	1.424***	(11.23)	0.221***	(6.70)
	lnPRICE	0.036	(0.70)	0.291***	(5.16)	0.509***	(4.49)	0.016	(0.54)
	lnFBUSER	0.148**	(2.23)	–0.458***	(–6.65)	–0.720***	(–5.30)	0.203***	(5.35)
	Constant	–2.608***	(–4.55)	0.871	(1.38)	2.080**	(2.00)	–1.439***	(–4.33)

(continues)

Table 4. Continued

Dependent variable	Independent variable	(1) Base model	(2) Exogenous interactions	(3) Subsample	(4) Endogenous interactions	
lnFBL*UNCERTAINTY	lnFBUSER*UNCERTAINTY				0.178***	(55.26)
	Constant				–0.033	(–1.36)
lnFBL*lnTIPPING	lnFBUSER*lnTIPPING				0.211***	(66.83)
	Constant				0.427***	(10.93)
lnFBL*DISCOUNT	lnFBUSER*DISCOUNT				0.191***	(63.64)
	Constant				–0.005	(–1.39)
lnFBL*PERIOD	lnFBUSER*PERIOD				0.167***	(42.00)
	Constant				0.271***	(3.19)
lnFBL*FRANCHISE	lnFBUSER*FRANCHISE				0.224***	(71.34)
	Constant				0.006	(0.41)
Observations		1,327	1,327	507	1,327	
System weighted R^2		0.2983	0.3204	0.1817	0.4790	

Notes: t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H2 was validated using two variables, UNCERTAINTY and YELP_STD. According to the full sample analysis (column [2] in Table 4), the interaction between FBL and UNCERTAINTY exhibits a positive coefficient as expected and this relationship is statistically significant ($p < 0.01$). This suggests that the impact of FBLs on sales is greater for experience goods than for search goods, hinting that consumers are more inclined to rely on FBLs when faced with higher product uncertainty. Due to the moderate number of reviews ($N = 507$), we separately analyzed Equation (3), which contains YELP_STD in the reduced sample (column [3] in Table 4). The original parameter for product uncertainty, UNCERTAINTY, is also included with the new variable. Consistent with the results shown in column (2), the coefficient between UNCERTAINTY and FBL is positive and significant ($p < 0.01$). The interaction of YELP_STD also shows a positive and significant relationship ($p < 0.05$). This result is also in conformity with H2, which states that a user's reliance on FBLs is more pronounced when the products or services for sale through social commerce are high in perceived uncertainty than when such products or services are low in perceived uncertainty.

The coefficients of other variables are consistent with the previous results. In addition, column (3) represents the impact of the Yelp reviews on the demand of Groupon deals. YELP_SCORE is positively related to the quantity sold, but this relationship is statistically insignificant ($p > 0.1$). The result suggests that consumers are not fully reliant on Yelp review scores when they purchase goods through social commerce. lnYELP_COUNT also shows the insignificant coefficient ($p > 0.1$), which indicates that the number of reviews written for the store is not significantly associated with its demand. Finally, the negative coefficient of YELP_STD, the variable intended to measure product uncertainty, suggests that people are reluctant to purchase the deals involving high levels of product uncertainty. This relationship, however, is also found to be insignificant ($p > 0.05$).

The interaction with FRANCHISE is found to have significantly negative effects on the efficacy of FBLs ($p < 0.01$), indicating that the impact of FBLs on sales is more pronounced for independent stores than for chain stores. Therefore, H3 is supported. The interaction between lnTIPPING and lnFBL had a significantly negative association with lnQUANT_ORDER and, hence, H4 is also supported ($p < 0.01$). As predicted, deals preset to high tipping points in social commerce entice a large number of buyers, which subsequently lowers the participating consumers' perceived uncertainty of the product and their reliance on FBLs. Conversely, consumers' dependency on FBLs increases when they opt to purchase products that have low prespecified tipping points.

The interaction between DISCOUNT and lnFBL was found to be negative, rather than positive. However, the interaction is not statistically significant ($p > 0.05$), rejecting H5. Price-sensitive consumers are naturally attracted by products with deep discounts. However, our data provide no concrete support for this conventional understanding. One speculation is that while bargain hunters are prompted by high utility accruing from deep discounts, less price-conscious consumers may sense that deep discounts come with costs. The presence of this ambivalence may explain the mixed moderating effect of discount rates on the relationship between FBLs and sales. Finally,

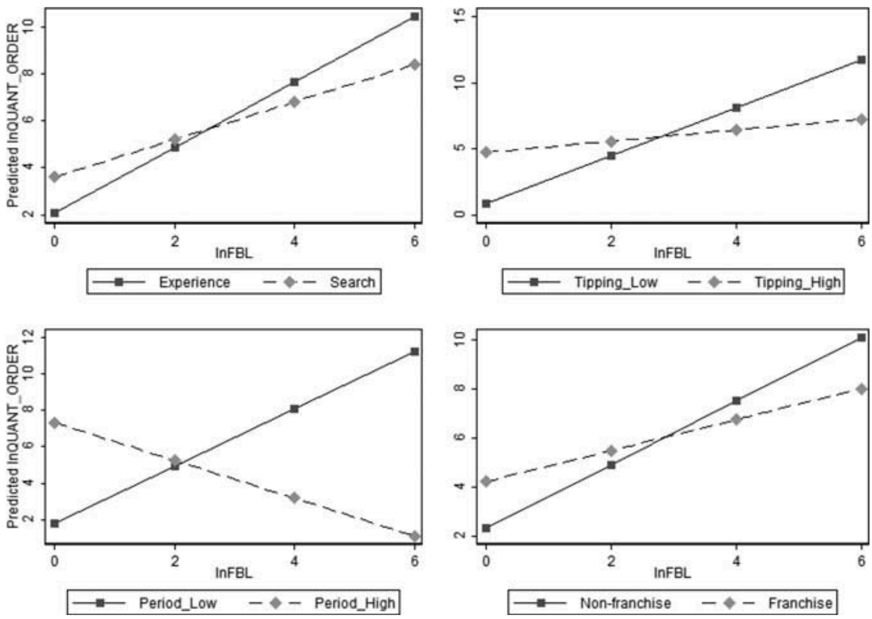

Figure 3. The Interaction Effects for the Relationship Between FBL and Sales

deal period (PERIOD) was found to negatively moderate the relationship between FBL and QUANT_ORDER ($p < 0.01$), which supports H6. Consumers become less dependent on FBLs when they have additional time available before making a purchase decision. When consumers are given extra time to contemplate a purchase decision, they tend to seek additional information about the product. The additional search and information-gathering opportunity subsequently reduces the value of FBLs. Figure 3 is a schematic representation of the four supported interaction effects.

The findings for other explanatory variables are consistent with what we expected. The coefficient of lnPRICE is significantly negative ($p < 0.01$), indicating that consumers tend to buy less when the price of the deal increases. Interestingly, a higher discount rate (DISCOUNT) does not stimulate the demand ($p > 0.05$). Social commerce consumers seem unaffected by high discount rates when making purchase decisions, probably due to the low reputation and credibility of sellers who exercise such aggressive pricing promotions in social markets [8]. The quantity ordered (lnQUANT_ORDER) is positively associated with the tipping points ($p < 0.01$). Finally, the quantity ordered (lnQUANT_ORDER) was found to decrease as product uncertainty (UNCERTAINTY) becomes larger ($p < 0.01$).

Robustness Check

For most online merchants, including social commerce retailers, sales that occur during the holiday periods account for a significant portion of their annual revenues and growth. Since our data set includes one of the major holidays in the United States (Thanksgiving), it is necessary to investigate whether our findings can be generalized to regular periods. To investigate the holiday effect, we carried out the same 3SLS analyses using the data that exclude all the transactions occurring two weeks prior to the Thanksgiving holiday. Similar tests were performed with the data that were removed one week prior to the holiday. As expected, the average volume of transactions during the holiday period (314,896 deals sold between November 15 and November 28) was higher than those during the regular period (251,004 deals sold between November 2 and November 14). However, the results based on the subsample that excludes holiday transactions were consistent with those based on the full sample.[8] Furthermore, the results based on the data that include only the transactions during the holiday periods exhibit similar empirical patterns. Consequently, we found no evidence of the holiday effect.

Propensity Score Matching (PSM) Results

One potential caveat with the econometric approaches that were leveraged earlier is that such mechanisms cannot fully convey whether or not the deal characteristics influence consumers' likelihood of clicking FBLs. We used PSM methods [69] to determine whether such self-selection biases remained in our data. In so doing, we divided all the deals into two categories; the treatment group includes deals with FBLs and the control group contains deals without FBLs. Of the 1,327 deals, 222 are identified as having no FBLs. Then, following the procedures recommended by Rosenbaum and Rubin [69], we matched the treated and untreated groups on the basis of observed characteristics, that is, the closeness of their propensity scores predicted by deal characteristics (lnTIPPING, DISCOUNT, PERIOD) and the other explanatory variables included in the original model (lnPRICE and lnFBUSER). The results suggest that, even after controlling for the observed heterogeneity inherent in the deal characteristics, the TREATED variable (i.e., nonzero FBLs) still exerts a positive effect on sales (column [2] in Table 5). The results remain unchanged when a more rigorous matching standard is adopted (column [3] in Table 5). Consequently, it can be said that the results are robust against the potential self-selection biases.

A Test of Exclusion Restriction

An econometric method proposed by Stock and Yogo [74] suggests that our instrument variables are valid given that they exhibit strong correlations with endogenous regressors. Further appraising the instruments' strength necessitates an exclusion restriction test to determine whether the chosen instrument is uncorrelated with any other covariates of the dependent variable. Conley et al. [23] formulate a systematic method by which to evaluate violations of the exclusion restriction. The proposed mechanisms estimate confidence intervals with a "plausibly exogenous exclusion restriction." In brief, Conley et al.'s method relaxes the instrument variable

Table 5. Propensity Score Matching

	(1) Selection model		(2) NN matching		(3) NN matching w/ caliper 0.01	
	TREATED		lnQUANT_ORDER		lnQUANT_ORDER	
lnPRICE	–0.101*	(–1.69)	–0.216***	(–7.08)	–0.213***	(–6.94)
lnTIPPING	–0.033	(–0.52)	0.996***	(40.65)	0.995***	(40.36)
DISCOUNT	–0.404	(–0.92)	0.207	(0.88)	0.190	(0.80)
PERIOD	–0.017	(–0.27)	0.047	(1.36)	0.048	(1.40)
lnFBUSER	0.278***	(4.65)				
UNCERTAINTY			–0.304***	(–6.39)	–0.307***	(–6.44)
FRANCHISE			0.809***	(11.51)	0.810***	(11.51)
TREATED			0.233***	(5.45)	0.232***	(5.40)
Constant	–1.888***	(–2.81)	2.459***	(14.31)	2.463***	(14.16)

Notes: t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. NN: nearest neighbor.

assumption such that a parameter (γ) for a matrix of instruments is presumed to be near zero (see [23] for more details). We use the approach recommended by Conley et al. to determine whether the effects of FBL on sales remain robust under the aforementioned special condition. We employ a local-to-zero approximation, which "models uncertainty about γ as being the same order of magnitude as sampling uncertainty" [23, p. 264]. With this approximation, the correlation between our instrument (lnFBUSER) and the error terms in the sales equation is drawn from the modeled distribution. Figure 4 depicts the estimated confidence intervals of lnFBL along with various levels of correlation, or delta, a modified version of γ that allows asymmetric confidence intervals. The results suggest that even with a

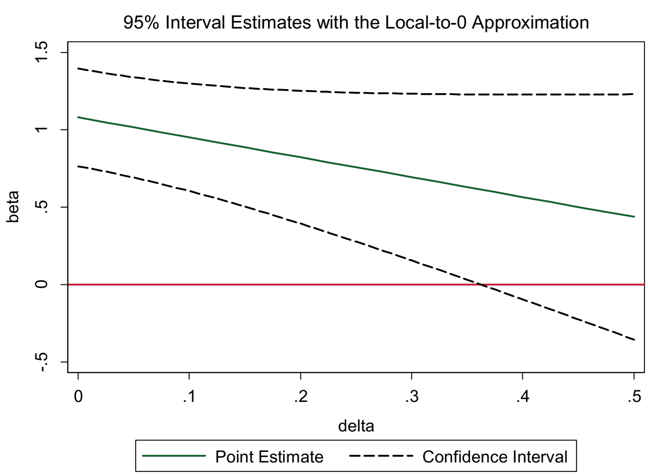

Figure 4. Ninety-Five Percent Interval Estimates Along with Nonzero Correlation Between IV and Error Term

positive delta value, the estimated coefficient remains far from zero, thus supporting the validity of our findings. Up to a value of 0.37, which is considered sufficiently large, FBLs positively affect sales at the 5 percent significance level.

Implications

Implications for Research

Over the past several years, researchers have increasingly turned their attention to examining the effectiveness of online reviews in promoting sales. However, thus far, these scholarly inquiries have yielded contradictory results (e.g., [5, 18, 27, 37, 80]). Despite the many positive functions of online review systems, their trustworthiness and authenticity are often called into question due to their susceptibility to deliberate manipulation and systematic biases [37]. A surge of recent anecdotes affirms that unethical sellers either plant or pay strangers to post glowing positive reviews of their products. Moreover, these fraudulent sellers seek to sabotage their competitors by posting unfavorable ratings of their rivals' offerings. The proclivity for such unethical behavior is the monotonically decreasing function of a product's true quality. Our assessment may advance the discernment of the contradictory findings reported in the literature. The anonymity afforded by the web entices many unscrupulous retailers to exploit the Internet's popularity as a source of information; these vendors often have a vested interest in fabricating reviews and misusing these channels for "promotional chat" [55]. In contrast, FBLs solicit evaluations only from people whom other users know and whose perspectives they care about, thereby structurally discouraging the manipulation of ratings.[9]

This study makes theoretical contributions to the growing body of literature on online review bias [25, 46, 52]. On the basis of adverse selection and quality uncertainty frameworks, this paper assessed market frictions in social commerce and conceptualized consumers' reliance on FBLs as a rational act for reducing uncertainty and information asymmetry in friction-prone platforms. In addition, drawing from social engagement and social risk frameworks, the paper offers theoretical explanations about users' motivation to provide credible product recommendations through FBLs. Moreover, we identified the key contextual factors that moderate the relationship between FBLs and sales in the context of social commerce. This theoretical approach offers information systems scholars an enhanced understanding of the circumstances under which IT artifacts and social technologies, such as FBLs, successfully socialize a consumer's shopping experience and induce social selling in these collective buying platforms. Our frameworks also provide theoretical insights into how the economic value of social utility changes in response to variations in the product and deal characteristics, which have a profound effect on adverse selection and quality uncertainty in e-commerce environments.

The findings of this study suggest that, in social commerce, the effect of FBLs on sales performance is rather complex. Significant variations were found from product to product and deal to deal. This suggests that a consumer's reliance on an FBL is significantly influenced by product characteristics (e.g., product uncertainty and product franchising) and deal characteristics (tipping points, price discounts, and deal duration) that either moderate or buffer the risk of adverse selection and quality uncertainty. Consequently, scholarly works along this line of inquiry should identify additional idiosyncratic contextual factors that represent a source of systematic bias across products, consumers, and deals; moreover, they should explore how these factors work together to influence the business profitability of online review systems.

Despite the fact that social commerce is pervasive in online business domains, little research has been conducted in this channel, which basically aims to unite two fundamental components of human nature—shopping and social interaction. From a research point of view, social commerce can be construed as a business platform where economic utility "meets" social utility. Consumers who shop through this channel typically are motivated by great deals and monetary savings (economic utility). At the same time, by virtue of the collective validation and shared recommendations (social utility) from people in their social networks, consumers endeavor to minimize any potential loss that may stem from adverse selection and quality uncertainty. In essence, social commerce consumers can enhance their welfare to the extent that social utility complements and strengthens economic utility. Furthermore, the social utility created by FBLs can trigger economic actions by easing market frictions. Thus, research that investigates the effects of FBLs on sales performance should take into account the connection and potential synergy between economic utility and social utility.

Implications for Social Commerce Platform Providers

Amid growing complaints, social commerce platform providers, such as Groupon and Living Social, are striving to find ways to diminish market imperfections. Due to their quick responses, the backlash appears to have subsided, at least temporarily, as revenues are back on the rise. From our study, we learned that FBLs, even without detailed commentary texts or testimonials, are instrumental in promoting sales in the social commerce space. Compared to regular online reviews and ratings that are produced by anonymous strangers, social evaluation schemes have a natural advantage because they preserve the genuineness of the reviews via soliciting feedback only from trusted people who care about the welfare of others in their social networks. Although it may be premature to predict the success of social commerce with any certainty, our findings suggest that SRSs have the potential to expand the horizons of social commerce and become the cornerstone of a social economy that leverages the strength of social network platforms.

Despite the significant economic value of FBLs, many social commerce platform providers have not leveraged social reference schemes to their full capacity. Many critics complain that social commerce is not social at all because these platforms do not intensely promote social exchanges among active users. Given that the success of social commerce will eventually be determined by how seamlessly it is integrated into social platforms, providers of social commerce should maximize the use of social features and functions. For example, social commerce platform providers should encourage users to sign in through Facebook or other social networking service (SNS) accounts at log-in pages to be "ready" to use social functions and engage in social interaction. Furthermore, social commerce providers should display FBLs at the center of their deal pages, not in the peripheral corner area, which requires users to scroll down the page in order to spot them. In addition, it may be a wise idea to exhibit the tally of FBLs for an array of products that are exhibited in the recommendation area when users are viewing the product of interest. To provide more accurate and complete information about FBLs, social commerce should allow users to keep track of the growth trajectory of FBLs for a given product. Rather than merely exhibiting the static total votes, more dynamic and detailed data about FBLs (e.g., how rapidly do FBL counts increase over time?) can provide consumers with information about the preference of their peers.

Our findings suggest that discount rates are not significantly associated with sales. It appears that high discounts alone do not seduce social commerce users into making purchases. This result is consistent with the findings from previous studies (e.g., [49]), which demonstrate that too much discount often signals either the poor quality of the product on sale or the excessive inflation of reference prices (i.e., list price or manufacturer's suggested retail price). Interestingly, however, most social commerce platform providers currently concentrate exclusively on price promotions by highlighting the difference between two prices (original and discounted) to advertise the economic "savings." Finally, to maintain a semblance of trust from their patrons and encourage their social exchange, social commerce providers should, at the outset, prevent dishonest sellers from entering their platforms. Rooting out the origin of the fraud requires social commerce providers to have appropriate administrative maneuvers in place. Additional prescreening and relentless monitoring are also warranted to systematically prevent self-interested sellers from manipulating the social utility. All in all, social commerce vendors should not just focus on low prices; instead, they should fully integrate social elements into their sites, including SRSs, to enrich the user experience and encourage social exchanges.

Implications for Retailers and Social Selling

According to the findings of our study, consumers tend to seek out shared recommendations and highly value their friends' opinions when purchasing products through social commerce. This suggests that retailers operating in the social commerce space should focus on the social validation of their products and proactively find ways to promote favorable evaluations of their offerings. For example, to entice more "thumbs-up" votes, retailers might consider, based on past transaction performances, adjusting discount rates and tipping points in a dynamic way that steers more favorite votes to their products. Furthermore, to enhance the foundations of social selling, retailers must improve their social presence, make long-term investments in social technologies, and build customer loyalty over the long term through social media.

The findings of the present study also provide retailers with specific practical insights into how deal characteristics can influence social selling mediated by FBLs. Consumers purchasing experience goods, whose valuation can be determined only upon consumption, are more dependent on FBLs than those buying search goods. In addition, FBLs have been found to exert a far greater influence on the sales of goods from independent stores than those from franchise chains. Taken together, social commerce consumers tend to consult heavily with FBLs when they purchase products with high uncertainty and information asymmetry. Retailers that sell experience goods or operate independently without franchises should consider implementing more aggressive FBL strategies, such as free trials or money-back guarantees, which significantly reduce the buyer's risk and increase the tally of FBLs.

In addition, sellers that seduce consumers with aggressive discount incentives must be mindful that most buyers do not trade quality for discounts, even in the social market that was formed and operated under the rubric of price incentives. Finally, tipping points have been construed as a key attribute of social commerce that encourages consumers to promote products naturally through their social networks. Our empirical analysis reveals that consumers rely extensively on FBLs, particularly when purchasing products that have low tipping points. As the risky-shift framework suggests, people naturally feel more secure about avoiding the risk of adverse selection and seller opportunism when many other people are buying the same product at the same price. Therefore, sellers are advised to more closely monitor social selling through FBLs when their offerings have low tipping points.

Limitations and Future Research

This study has several limitations that need to be addressed in future research. The data collected and analyzed were obtained from one major social commerce platform provider, Groupon. Although this company accurately represents the current social commerce market, having data from only one source precludes the ability to generalize the findings. Thus, we make no attempt to generalize our findings to other social commerce channels. Future studies in this area should enhance the generalizability of their findings by diversifying the data collection sources. Furthermore, such studies should compare and contrast the findings across different social commerce platforms to determine whether or not platform-specific attributes (e.g., company size and experience, deal policies and rules, and the characteristics of the participating retailers) influence the dynamics of the social transaction and consumers' perceptions of quality uncertainty.

Another caveat is also related to the deficiencies in our data. Our econometric analysis represents aggregated rather than individual preferences and motives. Although the large volume of transactional data investigated sufficiently reflects the norm of consumer behaviors and motives at the holistic level, the study would have been more robust if individual-level analyses had been conducted. For example, users might click on FBLs due to their familiarity with a local merchant rather than their satisfaction with their purchases. A survey should be conducted among social commerce consumers to capture individual motives for using the social commerce platform and SRS. In addition, our data cannot verify whether users who clicked on FBLs indeed purchased the product. Moreover, many consumers who bought the deal may not click on FBLs. Consequently, the FBL data we used in this study may represent a subset of the customers who purchased the product. Future studies can address these deficiencies by undertaking a more qualitative approach that enhances the understanding of the behavioral and attitudinal aspects of social commerce consumers.

Conclusion

Online consumers are often impacted by opportunistic sellers who seek to exploit adverse selection that is caused by disparities in access to product information. Online peer references in the form of commentary testimonials or numerical scores have been rapidly institutionalized to attenuate such market risks and enhance online transactions. This study aimed to examine whether or not social reference systems such as FBLs influence sales in social commerce in which quality uncertainty and adverse selection have become prominent and often discourage consumers from actively engaging in daily transactions. Furthermore, we investigated the extent to which product characteristics and deal characteristics moderate the relationship between FBLs and sales performance.

Based on 1,327 samples collected from a U.S.-based major social commerce platform provider, we found that social sharing (e.g., an FBL "thumbs-up") can be transformed into a sale. However, the transformation from a share into a sale was moderated by manifold contextual factors, such as product uncertainty, product franchising, tipping points, discount rates, and deal duration. These contextual factors have important ramifications for the observed market frictions (e.g., adverse selection and quality uncertainty) that have plagued social commerce. Due to their presence, there are reasons to be worried about the future prospects of social commerce. However, there are also signs of hope that this marketplace can become trustworthy, due largely to FBLs and other social technologies. Despite some negative sentiments, social commerce has the potential to become an entrenched part of the retail ecosystem, offering an ideal marketplace where economic utility driven by price incentives is furthered strengthened and protected by social utility that originates from trust and sharing.

Notes

1. http://investor.groupon.com/eventdetail.cfm?eventid=155603.
2. Other SRSs include the "Tweet button" (Twitter), "Google+ button," and "Pin it button" (Pinterest).
3. See http://www.nielsen.com/us/en/newswire/2012/consumer-trust-in-online-social-and-mobile-advertising-grows.html.

4. Our work differs from Forman et al. [30] in several ways. Forman et al. also examined the effects of identity-revealing on review performance. The present study focused exclusively on SRSs that are facilitated through social networks. In addition, we paid close attention to how such SRSs interact with contextual factors. Moreover, we used real sales data, whereas Forman et al. adopted sales ranks, which are less accurate to gauge review performance. Finally, while Forman et al. concentrated on e-book markets where information asymmetry does not pose a significant threat to the transaction, our work focused exclusively on social e-commerce markets in which consumers are confronted with high degrees of information asymmetry and quality uncertainty.

5. Some consumers may prefer deals with small tipping points because this enables them to avoid the risk of falling to purchase a product. In this study, we assessed tipping points from the perspective of quality signaling and collective actions because these are strongly related to the role of FBLs.

6. The specific coding scheme about search/experience classification is available upon request.

7. Some industry reports indicate that substantial portions of Facebook users are older than forty, and 68 percent of Groupon users are under thirty-four (http://www.groupon.com/pages/9). Age is not the only dimension where differences between these two groups can be seen; income and education levels also separate the two groups. See http://pewinternet.org/Reports/2013/Social-media-users.aspx.

8. The specific statistical results that pertain to the holiday effect are available on request.

9. Facebook declared that only 1 percent of Likes on a page will be removed following the implementation of their automated fraud detection system, which prevents merchants from providing perks for Likes on their sites [68].

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