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Social Promotion: A Creative Promotional Framework on Consumers' Social Network Value

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Red packets have symbolized happiness and good luck in Asian culture for centuries. An emerging number of online merchants in Asia are adopting *social red packets* as a promotion strategy. Social red packets not only digitalize traditional coupons to be readily transferred within consumer social networks but also can reallocate the promotional rewards based on consumers' social network value rather than their personal value to the firm. In this study, we conceptualize social red packets as an implementation of the *social promotion* framework, where consumers with higher social network value receive better promotional rewards. Leveraging a unique dataset from an online retailing platform, our vector autoregression (VAR) analysis reveals that: (1) under the social red packet design, consumers with higher social network value (who are connected to more new consumers or frequent consumers) will enjoy better promotional rewards; and (2) in order to receive better promotion rewards, consumers under the social red packet design are encouraged to voluntarily enhance their social network value (e.g., by recruiting more new customers or cultivating more frequent consumers). Moreover, we identify several critical characteristics of focal consumers and their social networks that can moderate the effectiveness of social red packets. Our findings provide important managerial insights for online retailing platforms on how to design effective social promotion strategies.

Key words: social promotion; social red packet; social commerce; platform design
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1. Introduction

Red packets have symbolized happiness and good luck in East Asian and Southeast Asian societies for hundreds of years. A red packet, which comes in a rectangular red envelope, usually contains a monetary gift and is often given during holidays or special occasions such as birthdays or weddings to bestow happiness and blessings on the recipients. Recently, online retailing platforms have adapted and modernized this ancient tradition by introducing the *social red packet*. Specifically, this new form of red packet contains digital coupons that can be shared through consumers' social networks.

A growing number of retailing platforms are adopting social red packets as a promotion strategy. *WeChat Read*, an online book-reading platform by *WeChat*, encourages readers to share red packets with friends and rewards readers if their shared red packets are redeemed by friends.[1] Both *Meituan* and *Eleme*, two leading food delivery platforms in China, send red packets of coupons to consumers and encourage them to share with friends in their social network.[2] Ucar (a Chinese counterpart of Uber) offers passengers multiple red packets after each ride that are sharable within

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social networks. Friends can get these social red packets on a first-come-first-served basis.[3]

Social red packets in these examples can be shared and transferred within social networks, which cannot be easily achieved with traditional physical coupons in non-social settings. It is noteworthy that a key feature of social red packets is the voluntary reallocation of promotional rewards, from being based on consumers' personal value (commonly defined as potential customer lifetime value to the firm), to being based on consumers' social network value (defined in this study as the number of high personal value consumers in the social network). Interestingly, in the social red packet setting, consumers who have low personal value and thus are not traditionally targeted by the firm are now able to acquire attractive promotional rewards if they have high social network value.

Inspired by the examples above and many others, we conceptualize *social promotion* as a promotion customization framework under which consumers with higher social network value receive better promotional rewards. Social promotion extends promotion on consumers' personal value to their social network value. Consumers' personal value has been well recognized in traditional promotion targeting. Firms tend to actively provide rewards to high personal value customers to influence their future purchases (Kumar and Shah 2004). Online retailers typically focus on two types of high-value customers: new customers and frequent customers (Ovchinnikov et al. 2014). New customers with the potential of bringing in large customer lifetime value (CLV) are typically rewarded with introductory deals (Van Ackere and Reyniers 1995). Frequent customers who have shown evidence of large CLV are offered various loyalty rewards (Zhang and Breugelmans 2012). In social promotion campaigns, firms target consumers' social network value, which is characterized as the number of high personal value friends in a focal consumer's social network. A consumer who is well connected to more high-value friends is considered to have higher social network value.

To test the effectiveness of social promotion, we conduct an empirical study at a leading online food delivery platform in China. This retailing platform implements social promotion in the form of social red packets. By design, the platform assigns red packets to consumers based on their personal value and allows these red packets to circulate within consumer social networks voluntarily. Under the social red packet strategy, the platform still assigns better promotional rewards to consumers with higher personal value, but the shareable feature of red packets targets consumers with higher social network value. We operationalize "social network value" as the number of new consumers or frequent consumers in a focal consumer's social network, consistent with the platform's goals to promote new purchases and repeat purchases.

Leveraging a unique dataset that integrates both promotional rewards (in the form of red packets) and consumer social networks between October 2016 and September 2017, our empirical study aims to answer the following research questions: (1) Does the social promotion strategy benefit consumers? If so, which segments of consumers can benefit most? (2) Does social promotion motivate consumers to enhance the commercial value of their social networks? (3) What characteristics of focal consumers and their social networks moderate the above effects in social promotion campaigns? The answers to these research questions are not only theoretically interesting but also critical for platform managers to design effective social promotion strategies.

Our empirical study shows that social promotions can benefit both consumers and the platform. The VAR analysis reveals that under social red packet promotions, consumers with higher social network value enjoy larger promotional rewards due to the socially shareable design. Social promotion can benefit the platform as well: Larger promotional rewards motivate consumers to increase the value of their social networks by voluntarily recruiting new consumers or cultivating frequent consumers, which in turn helps the retailing platform reach its promotional goals.

Several characteristics of focal consumers can moderate the effects of social red packets. First, the positive relationship between social network value and promotional rewards is stronger if the focal consumers are more price sensitive (e.g., consumers with low vs. high income), or if the consumers are more socially active (e.g., consumers in more socially active media industries vs. in more solo-oriented high-tech industries). Second, we explore the moderating role of age group (older consumers vs. younger consumers). Interestingly, an increase in social red packet rewards can better motivate older consumers to cultivate *frequent* buyers in their social networks, but can better stimulate younger consumers to acquire *new* buyers. Third, the consumer behavior of variety seeking also shows interesting moderating effects. Among variety-seeking consumers, the positive relationship is stronger between social red packets and the consumer's social network value in acquiring new buyers, but is weaker between social red packets and the social network value in developing frequent buyers.

The characteristics of focal consumers' social networks also matter. The positive relationship is strong in a social network that is heterogeneous in personal value; specifically, the social network contains higher personal value friends. Furthermore, localization of consumer social networks (i.e., residential proximity of connected consumers) can strengthen the effects of social network value on social red packets. However, it asymmetrically influences the two feedback effects of social red packets on social network value: When localization of a consumer's social network is higher, social red packets are more effective in developing *frequent* consumers in the social network but less effective in recruiting *new* consumers into the social network.

This study provides important conceptual and practical implications. Conceptually, we propose social promotion as a new framework of promotion customization. To the best of our knowledge, our study is the first attempt to explore customized promotion strategies based on consumers' social network value. Like price discrimination, in which sellers manipulate prices based on consumers' willingness to pay, promotion customization aims to manipulate promotional rewards based on consumers' value to the sellers. Social promotion aims to customize promotional rewards based on a consumer's social network value. Practically, our research offers novel insights into the emerging social commerce literature by identifying a segment of price sensitive but socially active consumers. Such consumers are considered to have low personal value among traditional promotion strategies targeting CLV, but they possess high value to the firm due to their social network connections. By identifying this promising segment, we offer new insights on how to improve effectiveness of social promotion by targeting consumers with specific characteristics.

The rest of the paper is organized as follows. In the next section, we review related literature and discuss our contributions. In Sections 3 and 4, we introduce the study context and empirical settings, respectively. Section 5 presents empirical results. The paper concludes with a discussion on managerial implications and possible avenues for future research.

2. Literature Review

Our study has points of contact with three relevant streams of literature: (1) customer rewards, (2) the relationship between firm promotion and consumers' social value, and (3) sellers' management of consumer social interactions. However, it also deviates from the existing literature in some essential aspects.

First, this study contributes to the broad literature of customer rewards. A fundamental assumption of this literature is that the assignment of promotional rewards is based on consumers' personal value (e.g., Kumar and Shah 2004; Ovchinnikov et al. 2014). In sharp contrast, our study extends the assignment of promotional rewards from personal value to social network value. In this way, we expect that consumers with higher social network value can enjoy better promotional rewards. In our research setting, our study is motivated by exploring whether a focal consumer with a larger number of high-value peers can receive more attractive red packets through social networking, that is, the effect of social network value on social red packets.

In particular, social red packets are relevant to referral rewards (e.g., Garnefeld et al. 2013; Ryu and Feick 2007; Van den Bulte et al. 2018): Both are promotional rewards for referring peer purchases. However, these two promotional rewards differ in the following aspects: (1) In social red packets, referrals are not limited to new customers. Consumers may cultivate existing consumers to purchase more frequently. (2) Consumers consider social red packets as being from peer consumers rather than from the firm. (3) Social red packets target a promising segment of referrers: consumers who are price sensitive but socially active. Also, social red packets differ from social coupons (also known as shareable coupons, and social deals), another popular type of promotional rewards containing a social element (e.g., Luo et al. 2014; Subramanian and Rao 2016). Social coupons use promotional discounts to increase awareness or encourage observational learning and thus are indiscriminate (Kumar and Rajan 2012). In comparison, a social red packet is a customized promotion strategy in which a consumer's promotional rewards match that consumer's social network value in a dynamic manner.

Second, our paper is closely related to the literature that examines promotion strategies targeting consumers' social value. One stream of research focuses on identifying consumers with high social value, for example, influential users in a social network (Trusov et al. 2010), innovative adopters of new products (Van den Bulte and Joshi 2007), and opinion leaders who contribute high "network value" (Iyengar et al. 2011). However, these studies offer no further insights about how firms should design marketing strategies to benefit from the targeted segment. Studies by Bakshy et al. (2012) and Tucker (2016) are more relevant in examining social advertising that utilizes consumer relationships in social networks containing similarly responsive consumers. To the best of our knowledge, the current study is among the first to explore a new dimension of firm promotion (i.e., firm-initiated rewards to promote future purchases) and examines how consumers' social network value can be integrated into the assignment of promotional rewards. Our research confirms that the new promotion framework can benefit firms by increasing commercial value of consumer social networks. As a novel implementation of this promotion framework, the policy of social red packets motivates consumers to proactively increase their social network value by recruiting new consumers and developing frequent consumers, which are exactly the two promotional goals of the retailing platform.

Third, our research adds to the broad literature on the effectiveness of consumer social interactions. This growing literature is motivated by ample evidence that consumer social interactions are more effective in promoting sales than firm marketing (e.g., Trusov et al. 2009; Villanueva et al. 2008). In particular, one stream of research shows that the effects of consumer social interactions are highly dependent on consumer characteristics (Park et al. 2018; Zhu and Zhang 2010). Our study aims to explore characteristics of focal consumers and their social networks that maximize the effectiveness of consumer social interactions in social promotion campaigns.

Although consumer social interaction is desired for its high credibility, firms cannot manipulate this consumer-generated variable directly. This is particularly important given the fact that consumer social interactions often generate unfavorable effects on firms. Yan (2018) explores the negative side of social networks by finding that a mismatch between needed and received social support from peers can negatively influence weight-loss outcomes. Consumer social interaction, if not properly managed, may generate negative word of mouth (WOM). Negative WOM is known to inflict tremendous damage on both cash flow and stock return (Luo 2009). Even if firms are proactively managing consumer social interaction, the effectiveness of social interaction is not certain. A low-level firm interference may not generate the desired positive valence, while a deep interference may cause social interaction to lose its credibility. Tucker (2016) points out that social advertising may backfire if the firm's intention to utilize consumer relationships in a social network is revealed. In our study, the creative combination of firm promotion and consumer social networks can enhance social interactions to achieve firms' promotional goals and increase accuracy of promotional targeting among consumer social networks.

3. Study Context

Although researchers have realized the importance of consumer connections, few studies have focused on consumers' social network value. This can be mainly attributed to the following facts: (1) Prior to the emergence of social networking platforms, it was extremely difficult to observe consumer interactions. Correspondingly, a consumer's social network value is hard to assess and differentiate (e.g., Katona et al. 2011; Trusov et al. 2009). (2) The use of social networking data to target individual consumers may be restricted due to concerns of consumer privacy (Tucker 2014). (3) It is difficult to collect and match datasets that include both marketing information (e.g., sales and promotions) and consumer social interactions. Clearly, a proper setting containing both the retailer's marketing data and consumer social interactions becomes the key to examining promotional customization on consumers' social network value. Fortunately, we have access to a dataset combining the data on platform-assigned promotional rewards and consumer social networking, allowing us to investigate this critical research issue.

3.1. Online Platforms for Food Delivery

Our research context is an online food ordering and delivery platform.[4] Several unique features make this context appealing to our study: (1) The food delivery market has grown tremendously in recent years. In China, revenue has surged from 125.03 billion RMB in 2015 to 241.38 billion in 2018 and is expected to reach 324.96 billion in 2020 (iiMedia Research 2019). As a result, potential findings of our study would contribute valuable managerial implications for this thriving market. (2) A food delivery platform is a typical intermediary between merchants and consumers. Findings in this context can be generalized to other intermediary markets. (3) The intermediary market of food delivery is structured as a dominant platform with small merchants. This power asymmetry enables the retailing platform to dictate full cooperation from merchants when a platform-wide policy (e.g., social red packet) is carried out. (4) The food delivery business covers consumers who vary significantly in demographics and social network structures, which can provide us rich variables and data for additional analyses and robustness checks.

Our empirical study is set in a leading food ordering and delivery platform in Asia, which fits our research purpose with three distinct merits. First, this food delivery platform (*the platform* hereafter) is one of the leading platforms in the world in terms of market share, scale of merchants covered, and number of daily orders. As a major player in the market, its practices are consistent with those of other leading platforms, which ensures our results can be generalized. Second, to test the social aspect of red packet promotion, our empirical study requires integrated data on firm promotion and social network structure. The platform formally builds an interface with *WeChat* (akin to *WhatsApp* in the United States), the most popular mobile app for social networking and mobile payment in China. Thus, the platform can provide complete data in support of our research objectives. To participate in social red packet promotions, consumers must authorize the platform to access their social networking data through *WeChat*, so the platform owns authorized data on social network structure.

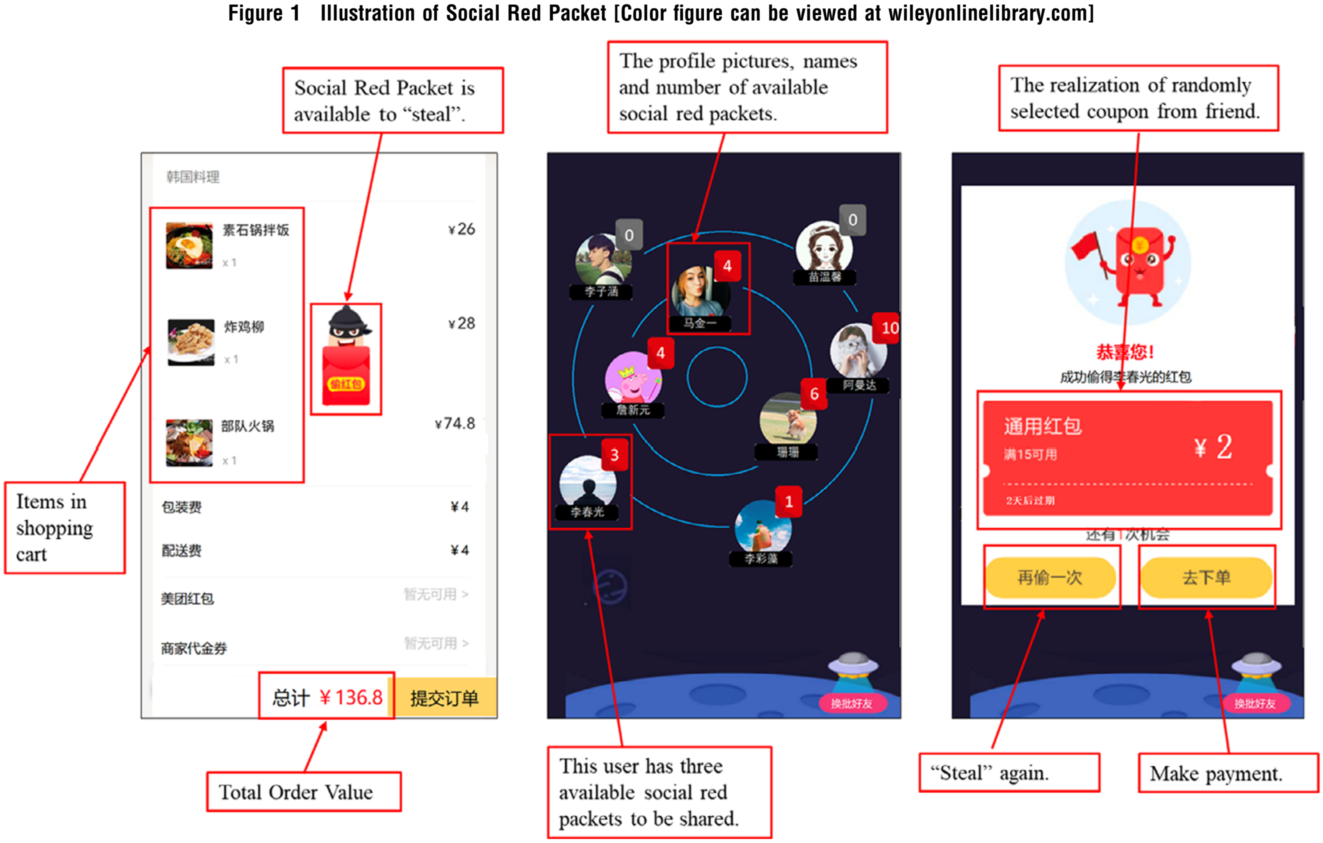
3.2. Social Red Packet

To begin with, the rules of non-social red packets are straightforward: The platform assigns promotional rewards in the form of digital coupons to consumers based on their personal value and these rewards cannot be shared or redeemed by other users. Accordingly, higher-value consumers are rewarded with better red packets. In particular, the platform rewards two types of high-value consumers: new consumers and frequent consumers. For new consumers, red packets are introductory discounts to encourage new purchases. For frequent consumers, red packets are deep discounts to encourage repeat purchases. The rule of assigning promotion rewards is exogenous; that is, the platform consistently assigns red packets based on personal value of consumers, regardless of whether social red packets are implemented or not. In addition, the platform's assignment rule is public knowledge. Thus, consumers can easily identify who may have good red packets available.

Compared to non-social red packets, the only difference in social red packets is that the platform allows red packets assigned on consumers' personal value to transfer within consumers' social networks. We illustrate the transferability of the social red packet in Figure 1. Specifically, upon placing an order, a focal consumer can "steal" (i.e., request) an unused red packet from a friend. A red packet obtained from peers in social networks rather than from the platform directly is defined as a social red packet. The focal consumer can choose any friend in her social network to steal from. After the steal, the focal consumer is randomly assigned with a red packet from those available from that friend. The friend who owns the red packet cannot prevent the "stealing" but can keep the most desired one from being taken away. Each focal consumer can request social red packets twice a day. Each red packet can be redeemed only once by either the original owner or the consumer who steals it. Each social red packet expires in 2 days.

It is important to note that, under the social red packet design, the platform still assigns red packets to consumers based on their personal value, that is, consumers of higher personal value to the platform (new consumers and frequent consumers) are assigned better red packets. This assignment rule of red packets by the platform is consistent before vs. after the adoption of social red packets. The policy of social red packets merely allows red packets assigned by the platform to be transferred within consumer social networks. In other words, the only source of red packets

Figure 1 Illustration of Social Red Packet [Color figure can be viewed at wileyonlinelibrary.com]



Note: The option of social red packet appears after a consumer adds items into the shopping cart. The texts in the callout boxes are translation. The users in the example are created artificially for the purpose of illustration.

is the platform. For social red packets, consumers who are not satisfied with the red packets assigned based on their personal value may choose to obtain others' red packets through social networking. The latter helps the platform to relocate better promotional rewards to consumers with higher social network value.

We argue that the social red packet design leads to the following two patterns: (1) Consumers with higher social network value eventually receive better red packets, and (2) better social red packets will motivate consumers to increase social network value. The former, if verified, presents the effectiveness of social promotion in circulating promotional rewards, the benefit of social promotion to consumers. The latter, if captured, shows the effectiveness of social promotion in enhancing the commercial value of consumer social networks, the benefit of social promotion to the firm.

The proposed patterns of social red packets are supported by the theory of social capital (Adler and Kwon 2002; Bolander et al. 2015, Seibert et al. 2001). Social capital mainly refers to peoples' resources in social networks (Coleman 1990; Nahapiet and Ghoshal 1998). On one hand, consumers in higher-value social networks own more social resources, which can be converted into economic benefit (Adler and Kwon 2002; Van den Bulte et al. 2018), that is, better promotion rewards in our research setting. On the other hand, consumers under the economic incentive of promotion rewards may actively convert social resources into the commercial value of their social networks, after considering the perceived benefits and costs of the exchange (Ryu and Feick 2007).

As a specific implementation of social promotion, social red packets have two unique features. First, the platform in our setting aims to promote both new purchases and repeat purchases. Thus, the platform considers a social network to have higher value if it contains a larger number of new consumers or frequent consumers. Second, in social red packet promotions, the retailing platform is a mediator of consumer social interactions, rather than a participant. Social red packets create an environment for social networking of promotional rewards. Promotional rewards that match consumers' social network value are relocated through consumer social interactions rather than the platform's direct interference. In this way, the platform effectively manages social interactions while maintaining credibility by not interfering directly.

4. Empirical Setting

4.1. Variables

Our empirical study examines the relationship between social network value and social red packets. Data frequency is set at the daily level for two reasons. First, consumers demonstrate a high frequency of ordering food delivery, often daily. Second, the policy of social red packets is implemented at the daily level. Next, we introduce the variables of interest as well as control variables.

4.1.1. New consumer size. Under the policy of social red packet, a focal consumer's connection with new consumers is an important dimension of the consumer's social network value. Our study uses new consumer size ncs_t, the number of new consumers in a focal consumer's social network at day t, to represent this aspect of social network value. In our setting, new consumers are platform users who signed up less than a week before. This specification is consistent with the rule that the platform offers attractive red packets as introductory rewards to new users only during their first week.

New consumer size in a focal consumer's social network dynamically updates at the daily level over the study period of 1 year. In other words, for each focal consumer each day, we track the number of new consumers in each focal consumer's social network based on the specification above. In a dynamic manner, a new consumer will lose this status after 7 days of registration. Thus, in order to maintain a large number of new consumers as friends, a focal consumer must proactively recruit potential consumers into the social network. This is possible in our empirical setting: The online food delivery platform is in the growth stage during the policy of social red packets. Plenty of new consumers join the platform every day.

4.1.2. Frequent consumer size. Similarly, for social red packets, having frequent buyers as social resources is another important dimension of social network value. Our study uses frequent consumer size fcs_t, the number of frequent consumers in a focal consumer's social network at day t, to measure this part of social network value. We specify that a frequent consumer orders at a daily frequency of three or more times on average over the past week. This specification is consistent with the fact that the platform rewards large red packets to existing consumers only when they reach that purchasing frequency.

It is worth noting that the dynamics of new consumers and frequent consumers in a social network are common in our empirical setting. Food delivery platforms are in rapid growth. New users sign in every day and existing users order repeatedly. Meanwhile, competitors emerge, and switching between different platforms is quite common. Before consumers develop strong loyalty toward the focal platform, their purchasing frequency may fluctuate over time. Ordering food delivery is also affected by other channels of food consumption (e.g., cooking or dining out) dynamically. In sum, in our research setting, social network value of a consumer (i.e., number of new buyers and frequent buyers in the consumer's social network) may change dynamically, and the consumer has plenty of opportunities to influence it dynamically.

4.1.3. Social red packets. As another critical variable in our study, social red packets srp_t measure the average discount percentage in the red packets that a focal consumer obtains from the social network at day t. Please note that social red packets are those from a focal consumer's social network. The red packets assigned directly by the platform are not counted.

Several variables are used as control variables: (1) We use a time trend variable t to control for omitted, dynamic changes in consumer characteristics as well as the food delivery market. (2) We use a dummy variable sea_t to indicate a high demand day due to seasonality. For a food delivery business, national holidays and weekends are high demand periods. Using time trend and seasonality as controls is supported by prior studies (Joshi and Hanssens 2010; Steenkamp et al. 2005; Trusov et al. 2009). (3) The demand for food delivery may be positively influenced by bad weather (e.g., rainy; unusually hot, or cold temperature). We use a dummy variable $rain_t$ to indicate a rainy day and a dummy $temp_t$ to indicate a hot or cold day. According to our specifications, a day t is hot (cold) if its temperature is two standard deviations above (below) the average temperature of that day historically.

4.2. The VAR Model

We use vector auto-regression (VAR) models to examine how the variation in social network value over time can be explained by the variation in social red packets, and vice versa. These variables are endogenous in the sense that they are explained by their own past and the history of other endogenous variables (Dekimpe and Hanssens 1999). A VAR model fits particularly well with our research purposes. To begin with, VAR captures Granger causality of multiple variables' lagged behaviors in a full dynamic model. Granger causality is used in a time series setting to examine how a change of one variable in the past can cause the change of another variable in the future (Granger 1969). This temporal causality is the best proxy for causality between variables in time series when manipulating causality in controlled experiments is not possible (Trusov et al. 2009). Second, VAR is capable of examining the two patterns of social red packets in one model. Specifically, VAR can measure the direct impact of social network value on social red packets. At the same time, it can evaluate the feedback impact of social red packets on social network value, accounting for the potential issue of reverse causality. Third, VAR can measure how the interactions between endogenous variables (i.e., social red packets and social network value) evolve. In other words, VAR models can capture both short-term and long-term impacts, which represent the efficiency of reassigning promotional rewards among social networks as well as the efficiency of focal consumers' efforts to increase social network value.

We focus on VAR instead of a panel simultaneous model for several reasons: First, VAR only needs the weak assumption that the relationship between social network value and social red packets is consistent cross-time, which is reasonable according to the social red packet policy. A panel simultaneous model requires a stronger assumption that the relationship is both cross sectional (focal consumers) and cross-time, which is not guaranteed. Second, the critical variables of interest are endogenous to each other, that is, they can be explained by their own past and the past of other endogenous variables. A panel simultaneous model of these variables will be subject to serious problems including endogeneity and reserve causality. Third, the VAR model is robust to the omitted variable problem, while in a panel simultaneous model, omitted variables due to unobserved heterogeneity are an importance source of estimation bias.

Correspondingly, our empirical study specifies a three-variable VAR model for each focal consumer in the sample:

$$\begin{pmatrix} ncs_t \\ fcs_t \\ srp_t \end{pmatrix} = \begin{pmatrix} \zeta_{10} \\ \zeta_{20} \\ \zeta_{30} \end{pmatrix} + \sum_{j=1}^{J} \begin{pmatrix} \zeta_{11}^j & \zeta_{12}^j & \zeta_{13}^j \\ \zeta_{21}^j & \zeta_{22}^j & \zeta_{23}^j \\ \zeta_{31}^j & \zeta_{32}^j & \zeta_{33}^j \end{pmatrix} \begin{pmatrix} ncs_{t-j} \\ fcs_{t-j} \\ srp_{t-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}, \tag{1}$$

where ncs_t is the size of new consumers in a focal consumer's social network at time t, fcs_t is the size of frequent consumers in the social network at time t, srp_t is the average discount of social red packets at time t. ζ_{10}, ζ_{20}, ζ_{30} are estimates of intercepts. $\varepsilon_{1,t}$, $\varepsilon_{2,t}$, $\varepsilon_{3,t}$ are white-noise residuals that correspond to the three endogenous variables. These residuals follow the distribution of $N(0,\Sigma)$, where Σ is the variance–covariance matrix of the residuals. For the system of equations, the order J is determined by minimizing the Schwartz's Bayesian information criterion (*SBIC*). For ease of exposition, the control variables introduced before are not presented in the model.

The estimates capture four types of effects. First, ζ_{31} and ζ_{32} are the direct effects of new consumer size and frequent consumer size on social red packet discount, respectively. Second, ζ_{13} and ζ_{23} are the feedback effects of social red packet discount on new consumer size and frequent consumer size, respectively. Third, ζ_{11}, ζ_{22}, and ζ_{33} are the carryover effects of the endogenous variables. Fourth, ζ_{12} and ζ_{21} are the cross effects between new consumer size and frequent consumer size. The variance–covariance matrix of white-noise residuals models the contemporaneous effects.

In the main analysis, we randomly select 200 active users of social red packets at the daily frequency during the period of October 1, 2016–September 30, 2017. The focal consumers were from Wuhan, a commercial center in central China. Each consumer is a unit of analysis in the VAR model. The sample corresponds to 200 VAR models, each having 365 data points at the daily level over the observation period of 1 year.

Our empirical study uses a consumer (instead of a firm) as the unit of analysis and examines the dynamic relationship between consumers' social network value and their social red packets. Among VAR studies, our size of 200 sample units is relatively large. Joshi and Hanssens (2010) use 9 units to run the VAR analysis. Luo (2009) also considers 9 units. Pauwels et al. (2004) focus on 41 units. Some studies (Trusov et al. 2009; Villanueva et al. 2008) even choose one unit for analysis.

The collected sample can represent the population of users of the retailing platform: (1) The orders from the sample cover all major categories including meals, snacks, fruits, desserts, and drinks. (2) 89% of orders are meals, consistent with the fact that ordering for meals contributes most revenue of the platform. (3) The sample shows a typical distribution of 12% (88%) as new (existing) consumers, which is consistent with the platform's overall distribution. (4) Among existing consumers, 31% (69%) are frequent (infrequent). Again, these numbers are consistent with the platform's statistics. (5) The sample covers consumers who are heterogeneous in both demographics and the structure of social networks. These characteristics are potential moderators to further investigate the impacts of social red packets.

Table 1 presents definitions of variables and summary statistics of the sample. New consumer size (ncs_t) has a sample average of 3.12 and a standard deviation of 2.33, indicating that a focal consumer's social network has about three new consumers on average and a sufficient variation in new consumer acquisition. Frequent consumer size (fcs_t) has a sample average of 9.75 and a standard deviation of 3.26, indicating that a consumer's network maintains nearly 10 frequent consumers and a relatively small variation in frequent consumer development. Next, social red packets (srp_t) show an average discount of 8.67% and a standard deviation of 5.18%. All these time-variant variables are used in our VAR analysis.

Next, Table 2 reports summary statistics of time-invariant characteristics to give an impression of the randomly selected focal consumers. These characteristics have two parts. The first part covers three critical demographics: gender, age, and household size. The second part contains three purchasing-relevant characteristics: Tenure represents a consumer's loyalty toward the food delivery platform, purchasing frequency is the number of orders at the daily level over the last month before the study period, and order value is the average purchasing amount per order (in RMB) over the last month before the study period.

For the first part of consumer demographics, 58.0% focal consumers are female. An average consumer is 33.7 years old and has a household size of 2.5 family members. For the second part of purchasing behaviors, an average consumer has a tenure of 2.3 years, purchases at the frequency of 2.2 times daily, and pays the order value of 25.9 RMB per order on average.

Table 1 Definition of Variables and Summary Statistics

Variables	Terms	Definition	Data Source	Mean	SD
Variables of interest					
New consumer size	ncs	Number of new consumers in a focal consumer's social network	Platform/*WeChat*	3.12	2.33
Frequent consumer size	fcs	Number of frequent consumers in a focal consumer's social network	Platform/*WeChat*	9.75	3.26
Social red packets	srp	Average red packets (discount in percentage) obtained by a focal consumer from the social network	Platform/*WeChat*	8.67	5.18
Controls					
Time trend	t	A variable of deterministic time trend			
Seasonality	sea	A dummy variable indicating whether day t is a high seasonality day	Calendar	0.31	0.46
Rainy	rain	A dummy indicating whether day t is a rainy day	Weather channel	0.18	0.39
Bad temperature	temp	A dummy indicating whether day t has bad (hot or cold) temperature	Weather channel	0.17	0.38

Table 2 Characteristics of Randomly Selected Focal Consumers

Variables	Definition	Mean	SD
Demographics			
Female	Dummy variable whether focal consumer is female	0.58	0.50
Age	Average age of focal consumers	33.7	11.8
Household size	Number of family members in a focal consumer's household	2.5	1.1
Purchase characteristics			
Tenure	Average tenure of consumers with the food delivery platform (in year)	2.3	1.2
Purchasing frequency	Average purchasing frequency at daily level over the last month before the study period	2.2	0.9
Order value	Average order value per order (in RMB) over the last month before the study period	25.9	11.2

5. Results

Our empirical analysis starts with the unit root tests to determine whether the endogenous variables are evolving or stationary. Following existing studies (e.g., Fang et al. 2015; Luo 2009; Villanueva et al. 2008), we use both the augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–-Shin (KPSS) test. The ADF statistics generate values from −4.19 to −5.83, all significant at the level of 5%. Thus, we can reject the null hypothesis of a unit root. The KPSS statistics range from 0.15 to 0.23, all insignificant at 5%. Thus, we cannot reject the null hypothesis of stationarity. Both tests indicate that the three endogenous variables are stationary. Thus, we specify them in levels. Referring to prior VAR studies (e.g., Fang et al. 2015; Trusov et al. 2009), we conduct a Granger causality test to check whether the history of a variable X can explain a variable Y beyond Y's own history. The test indicates the need for a full dynamic VAR model. The optimal number of lags is 2 according to SBIC. The 200 estimated VAR models (one for each focal consumer) show good model fit (the R^2 in levels ranges from 0.79 to 0.96, and the F-statistic ranges from 8.37 to 17.69).

5.1. Main Analysis

To test the interactions between a focal consumer's social network value and social red packets, we calculate relevant Impulse Response Functions (IRFs) based on VAR estimates. These IRFs capture incremental effects of a one-standard-deviation shock of one variable on the other in the short term and the long term. IRFs can capture temporal causal effects between the different endogenous variables in VAR models (Steenkamp et al. 2005). Table 3 reports the two types of impacts of interest averaged over the sample of 200 consumers.

5.1.1. Impacts of Social Network Value on Social Red Packets. First, we verify whether social red packets generate the defining pattern of social promotion, that is, consumers with higher social network value can enjoy better promotional rewards. Since the platform appreciates two dimensions of social network value, we expect two relevant impacts as follows: (1) A larger number of new consumers in a focal consumer's social network results in better social red packets (i.e., larger promotional discounts) of that consumer, and (2) a larger number of frequent consumers in a consumer's social network results in better social red packets for that consumer.

The IRF results based on VAR estimates verify these two conjectures. Table 3 shows that a larger new consumer size significantly increases social red packet discounts in both short term ($b = 2.521$, $p < 0.05$) and long term ($b = 4.095$, $p < 0.05$). The long-term impacts last for 3 days. These results can be interpreted as follows: An increase in new consumer size corresponds to acquiring new consumers into a focal consumer's social network. During their first week, new consumers are offered introductory red packets. The unused red packets can be transferred to other consumers as social red packets. Among these

Table 3 Estimated Relationship between Social Network Value and Social Red Packets

	Estimated Impacts in IRFs Averaged over 200 Focal Consumers		Percentage of Positive Impacts among 200 Focal Consumers	
Section A: Impacts of Social Network Value on Social Red Packets				
Social network value	Short term	Long term	Short term	Long term
New consumer size	2.521**	4.095**	81%	90%
Frequent consumer size	1.639**	3.317**	75%	83%
Section B: Impacts of Social Red Packets on Social Network Value				
Social network value	Short term	Long term	Short term	Long term
New consumer size	0.011**	0.026**	67%	78%
Frequent consumer size	0.038**	0.065**	76%	89%

**$p < 0.05$;
*$p < 0.10$.

social red packets, the most attractive ones immediately trigger purchases. Less attractive ones take a longer time to circulate among the social network and trigger purchases by the recipients. As shown in Table 3, this positive impact exists among the majority of sample consumers in both the short term (81%) and long term (90%).

Next, frequent consumer size also shows positive impacts in the short term ($b = 1.639$, $p < 0.05$) as well as the long term ($b = 3.317$, $p < 0.05$), lasting 6 days. The impacts of frequent consumer size are weaker than those of new consumer size, likely for two reasons: (1) Many attractive red packets for rewarding frequent consumers are redeemed by the original owners and thus are not available as social red packets, and (2) peers in a consumer network may exhibit similar purchasing behavior. The spare red packets from the original owners may not be favored by the focal consumer, at least not immediately.

The above results show that consumers with enhanced social network value benefit from larger social red packet discounts. We further examine how consumers with different personal value to the platform benefit differently from this policy of social promotion. New consumers and frequent consumers have higher personal value, while existing infrequent consumers are less valuable. Accordingly, we randomly selected another three groups of consumers with different personal value, that is, 200 new consumers, 200 frequent consumers, and 200 existing infrequent consumers, subject to the treatment of social red packet value. Each treatment group is specified on October 1, 2016, when the platform started to implement social red packets. The treatment period lasted until September 30, 2017. Since these three groups are examined during the period when social red packets were adopted, we label them as the treatment groups. Correspondingly, we identify three control groups from September 1, 2015 to August 31, 2016 before the implementation of social red packets. We label them as the control groups. In the control groups, red packets cannot be shared among consumer social networks, so consumers cannot request or receive a social red packet from a member of their social network.

We compare how consumers with different personal value benefit differently from promotional rewards before vs. after the policy of social red packet. As shown in Table 4, before the platform adopts social red packets, consumers with higher personal value receive better red packets: The average red packet discounts for new consumers and frequent consumers are 12% and 9%, respectively, significantly higher than 2% for existing infrequent consumers (at the level of 0.05). However, after a social red packet policy is implemented, the average red packet discounts are 11%, 10%, and 8% for new consumers, frequent consumers, and existing infrequent consumers, respectively, showing no significant differences at 0.10.

These results reveal that existing infrequent consumers benefit most from social red packets. Social red packets offer consumers with low personal value another chance to receive desired red packets if they have high social network value. Such consumers, due to their low willingness-to-pay, may not purchase without desirable red packets from their social networks.

Our results also imply that social red packets neither benefit nor cause a loss to consumers with higher personal value (i.e., new consumers and frequent consumers). High-value consumers cannot obtain better red packets from the social channel. Instead, they mainly use personal red packets assigned by the platform based on their personal value.

5.1.2. Impacts of Social Red Packets on Social Network Value. We argue that impacts between social network value and social red packets are mutual. Feedback impacts exist because consumers who desire better social red packets have a strong incentive to increase the value of their social networks. In our research setting, consumers can make efforts to enhance social network value facilitated by the platform. The platform regularly sends two types of purchase links: the referral link for new purchases, and the merchant offering (a link to recommend purchase of certain products) that can be forwarded to peers. Accordingly, the focal consumers may recruit new consumers by sending referral links. They may

Table 4 Promotional Rewards for Consumers with Different Personal Value (before and after social red packet)

	New Consumers (1)	Frequent Consumers (2)	Existing Infrequent Consumers (3)	(1)–(3)	(2)–(3)
Before social red packet	12%	9%	2%	10%**	7%**
After social red packet	11%	10%	8%	3%	2%
After–before	–1%	1%	6%**	–7%*	–5%*

**$p < 0.05$;
*$p < 0.10$.

also develop frequent consumers by recommending merchant offerings.

The VAR results verify the feedback impacts. First, an increase in social red packet discount leads to a larger number of frequent consumers in the social network. We capture an immediate effect ($b = 0.038$, $p < 0.05$) as well as a long-term effect ($b = 0.065$, $p < 0.05$), lasting for 4 days. As demonstrated in Table 3, these feedback impacts commonly exist among the sample consumers. In line with our expectation, better social red packets will motivate consumers to increase social network value by encouraging frequent purchases. Since consumers know the preferences of their friends, such recommendations can more efficiently lead to purchases.

Second, better social red packets also encourage consumers to increase social network value by recruiting new consumers. The empirical results show that an increase in social red packet discount increases the size of new consumers immediately ($b = 0.011$, $p < 0.05$) and enduringly ($b = 0.026$, $p < 0.05$), lasting for 9 days.

Overall, social red packets can motivate a focal consumer to acquire new consumers as well as cultivate frequent consumers in the social network. These results are consistent with prior studies (Iyengar et al. 2015; Toker-Yildiz et al. 2017) showing that consumer social interactions can influence new purchases as well as repeat purchases. Our results show that it is more difficult for a consumer to refer new purchases than elicit frequent purchases, in terms of both effectiveness and efficiency. In other words, the impact of social red packets on new consumer size is smaller and takes a longer time.

5.2. Moderators

5.2.1. Characteristic of Focal Consumers. Several key characteristics of the focal consumers and their social networks may moderate the impacts of social red packets. First, social activity level of a focal consumer is a relevant moderator. On one hand, socially active consumers have good social resources, which can be converted into attractive social red packets. On the other hand, active social interactions can help focal consumers effectively encourage purchases by friends, which in turn increases commercial value of their social networks.

We use occupation to identify this personal characteristic of focal consumers. We argue that occupation is a good proxy of consumers' social activity level, for two reasons: (1) The socialization level of a consumer's occupation determines the consumer's chance to find new friends as well as the consumer's effort to maintain old friends, and (2) the pattern of socialization at work may readily spill over to daily life. In the empirical analysis, we choose consumers in the media industry vs. high-tech firms to represent occupations requiring high vs. low capability of social interactions, respectively. While people in high-tech jobs usually work in an isolated environment, people in the media industry tend to socialize more actively with others.

We take two steps to construct the segment of media industry consumers. In the first step, we use delivery address to identify a consumer's affiliation or employer, which should be a media-related firm. In the second step, under a strict data privacy framework, we manually check each selected consumer's location to exclude consumers who do not fit our research profile (e.g., a technician in a media firm). Specifically, after knowing a consumer's affiliation, we identify media people as those who demonstrate a high level of mobility, since media employees travel frequently. In the empirical study, we choose focal consumers with more than three delivery addresses every week at non-local cities. Following a similar procedure, we construct the segment of high-tech consumers. High-tech people usually have a fixed local workplace and a low degree of mobility. Accordingly, we select consumers with two or less local delivery addresses (one business address and one residential address). Each segment (media or high tech) has 200 randomly selected focal consumers that fit our research profile. The relevant impacts for these two segments are presented in Table 5.

As shown in Table 5, in the socially oriented segment, the impacts of social network value (either new consumer size or frequent consumer size) on social red packets are larger. Consumers in this segment may find better promotional rewards by more actively interacting with new consumers or frequent consumers in their social networks. Again, in this segment, the impacts of social red packets on both aspects of social network value are larger. Consumers who are more socially active may have stronger ties with existing friends, so their persuasion of repeat purchases is more convincing. These consumers may also have a better chance to meet new friends and encourage them to make new purchases.

Second, price sensitivity is another critical characteristic of the focal consumer (e.g., Cui et al. 2019; Yao and Zhang 2012). As indicated before, lower-value consumers who have stronger price sensitivity but better social resources benefit more from social red packets and have a stronger incentive to increase commercial value of their social networks. Consequently, we expect the impacts of social red packets can be largely influenced by price sensitivity of the focal consumers.

We use income as the proxy of price sensitivity. High-income consumers are generally considered to be less price sensitive. We construct two random samples of 200 high- vs. low-income consumers,

Table 5 Characteristics of Focal Consumers as Moderators

		Impacts of social network value on social red packets		Impacts of social red packets on social network value	
Social Activity		Short term	Long term	Short term	Long term
High (media)	New consumer size	3.164**	4.917**	0.017**	0.032**
	Frequent consumer size	2.035**	3.846**	0.050**	0.087**
Low (high tech)	New consumer size	1.973**	3.261**	0.008*	0.020*
	Frequent consumer size	1.252**	2.638**	0.031**	0.049**
Strong (low income)	New consumer size	3.428**	5.296**	0.019**	0.037**
	Frequent consumer size	2.217**	3.958**	0.046**	0.083**
Weak (high income)	New consumer size	1.806**	3.021**	0.006*	0.011*
	Frequent consumer size	1.073*	2.319*	0.024*	0.045**
Age groups					
Older	New consumer size	2.409**	3.870**	0.008*	0.019*
	Frequent consumer size	1.787**	3.015**	0.055**	0.084**
Younger	New consumer size	2.371**	3.758**	0.019**	0.039**
	Frequent consumer size	1.933**	3.129**	0.028**	0.053**
Variety seeking					
Variety	New consumer size	3.047**	4.712**	0.015**	0.034**
	Frequent consumer size	1.256**	2.539**	0.031**	0.055**
Inertial	New consumer size	2.168**	3.275**	0.009*	0.021*
	Frequent consumer size	2.179**	3.903**	0.052**	0.078**

**$p < 0.05$;
*$p < 0.10$.

respectively. We use residence address data to identify these two segments. For example, living in a high-end apartment is a good proxy for a resident's high income, regardless of whether the resident owns or rents the apartment. In our specification, a consumer has high (low) income if the price of residence is two standard deviations above (below) the city average during the sample period. The results in Table 5 show that the positive relationship between social network value and social red packets is weaker for high-income consumers. On one hand, high-income consumers have less incentive to seize red packets through social networking, resulting in weaker impacts of social network value on social red packets. On the other hand, high-income consumers are less motivated to increase the value of their social networks, leading to weaker feedback impacts.

Next, our study explores how the relationship between social network value and social red packets differs among focal consumers in different age groups. People in different age groups may present different behavior due to their different social network structure. In general, older people may have a more stable network of friends while younger people may be able to expand their social network more easily. Accordingly, we construct two age groups, each containing 200 randomly selected focal consumers. The consumers have an average age of 51 and 23 in the older and younger groups, respectively.

As expected, an increase of social network value has a similar impact on the two group's social red packets, and larger social red packet discounts also motivate both age groups to enhance social network value. But interestingly, an increase in social red packet value can better motivate older people to cultivate frequent purchases, and better stimulate younger people to attract new buyers into their social networks. This result is consistent with our previous intuition: older people tend to socialize with existing friends and encourage their frequent purchases, while younger people are more likely to meet new friends and introduce them as new users.

Furthermore, we explore the moderating effect of consumer variety-seeking behavior. We construct two random samples of 200 variety-seeking vs. inertial buyers, respectively. We specify that variety-seeking consumers patronize three or more categories every week, while inertial consumers concentrate on one particular category (mostly meals). To reduce the possibility of endogeneity, this classification is based on 1-year purchasing history right before the study period. Consistently, we observe that the variety-seeking behavior maintained during the study period.

The estimation results in Table 5 show that for variety-seeking consumers, the positive relationship is stronger between social red packets and the focal consumers' social network value in acquiring new consumers, but is weaker between social red packets and the social network value in developing frequent consumers. On one hand, variety-seeking consumers are more interested in finding new friends (new consumers), but may interact less with existing friends (existing consumers). On the other hand, better red packets from new consumers will encourage variety-seeking consumers to find more new friends to join the platform.

5.2.2 Characteristic of Focal Consumers' Social Networks. We also explore two characteristics of focal consumers' social networks: (1) value asymmetry within a social network and (2) localization. First, we argue that *heterogeneity in personal value among a social network* (i.e., the social network contains higher personal value friends) is important to initiate a social red packet promotion. This initial condition will push low-value consumers to socialize with high-value friends in order to receive attractive social red packets. After redeeming these red packets, low-value consumers increase their purchasing frequency, which in turn increases their personal value. This is consistent with Garnefeld et al. (2013) that customer referral increases loyalty of the referring customers. This process iterates until such heterogeneity becomes minimal or demand of the social network eventually saturates.

We select four cases to investigate this issue. First, we identify a heterogeneous case: The focal consumer is an existing infrequent consumer, but her social network consists of nearly 1/3 new consumers and approximately 1/3 frequent consumers on October 1, 2016, the beginning of our study period. As a result, 2/3 of her friends have higher personal value (i.e., new consumers or frequent consumers). Next, we identify three homogeneous cases. The first is a homogeneous case of new consumers: The focal consumer is new and her social network mainly consists of new consumers on October 1, 2016. In the other two cases, homogeneity is based on purchasing frequency. We identify a homogeneous case of frequent consumers and a homogeneous case of infrequent consumers. In all three homogeneous cases, the focal consumers *barely* have higher-value friends at the beginning.

In Table 6, we report VAR results for each case. Consistent with our expectation, the impact of new consumer size on social red packets is largest in the heterogeneous case ($b(\text{hetero})_{short} = 2.976$, $p < 0.05$; $b(\text{hetero})_{long} = 4.633$, $p < 0.05$), and is smallest in the homogenous case of new consumers ($b(\text{homo\_new})_{short} = 0.891$, $p > 0.10$; $b(\text{homo\_new})_{long} = 1.537$, $p > 0.10$). This is because new consumers can personally own introductory red packets and thus are less likely to get better promotional rewards through social networking. It is also possible that a lack of experience leads to a lack of motivation or inability to seek out social promotional rewards. Therefore, the policy of social red packet is hard to initiate. For the same reasons, the impact of frequent consumer size on social red packets is largest in the heterogeneous case ($b(\text{hetero})_{short} = 2.038$, $p < 0.05$; $b(\text{hetero})_{long} = 3.614$, $p < 0.05$), and is still smallest in homogenous case of new consumers ($b(\text{homo\_new})_{short} = 0.675$, $p > 0.10$; $b(\text{homo\_new})_{long} = 1.049$, $p > 0.10$).

We obtain similar results for the feedback impacts: The effectiveness of social red packets in enhancing consumers' social network value (through acquiring new consumers or developing frequent consumers) is strongest in the case of heterogeneous consumers, and is weakest in the case of homogenous new consumers. We argue that new consumers who own attractive introductory red packets are least motivated to enhance the value of their social networks. Together, these results suggest that a significant existence of higher-value friends in a focal consumer's social network is critical for social red packet promotions to succeed.

Second, we explore localization of a focal consumer's social network. Social red packets allow consumers in different cities to share red packets. We are curious about how geographic proximity among a

Table 6 Characteristics of Focal Consumers' Social Networks as Moderators

		Impacts of social network value on social red packets		Impacts of social red packets on social network value	
Heterogeneity in Personal Value		**Short term**	**Long term**	**Short term**	**Long term**
Homogeneous (new)	New consumer size	0.891	1.537	0.002	0.007
	Frequent consumer size	0.675	1.049	0.011	0.019
Homogeneous (frequent)	New consumer size	1.173	1.902	0.003	0.009
	Purchasing frequency	0.792	1.187	0.014	0.025
Homogeneous (old infrequent)	New consumer size	1.215	2.079	0.005	0.012
	Frequent consumer size	0.884	1.351	0.019*	0.029*
Heterogeneous	New consumer size	2.976**	4.633**	0.016**	0.030**
	Frequent consumer size	2.038**	3.614**	0.042**	0.071**
Localization level					
High	New consumer size	3.218**	5.246**	0.007*	0.018*
	Frequent consumer size	2.653**	4.189**	0.048**	0.077**
Low	New consumer size	1.836**	2.987**	0.014**	0.033**
	Frequent consumer size	1.471**	2.625**	0.027**	0.059**

$^{**}p < 0.05$;
$^{*}p < 0.10$.

consumer's social network plays a moderating role. Although we select focal consumers from the city of Wuhan, the corresponding social networks may cover consumers in other cities as well. We collect two samples of 200 consumers with high vs. low localized social networks, respectively. For the high localization sample, more than 80% of consumers reside in Wuhan during the study period. For the low localization sample, less than 50% of consumers are located in Wuhan. Since local people tend to have local friends, we set asymmetrical thresholds for high vs. low localization (i.e., 80% vs. 50%).[5]

As shown in Table 6, in the high localization sample, the impacts of social network value (new consumer size and frequent consumer size) on social red packets are greater. This is because WOM between local consumers may lead to active purchases from the same local merchants, but this effect is diminished if the connected consumers are in different cities.

It is interesting that the impact of social red packets on new consumer size is weaker in the sample of high localization. This is because (1) local consumers tend to have local resources of friends and thus find few new non-local friends, and (2) a local consumer network may become mature, making it hard for the focal consumer to recruit locals as new consumers. The impact on frequent consumer size, however, is still greater in the high localization sample. Local consumers know local merchants and local friends better, making their recommendations for frequent purchases more convincing.

5.3. Robustness Check

The VAR models in our empirical analysis can address several major concerns of estimation biases including endogeneity, simultaneity, and omitted variables. After excluding these potential biases, the remaining major threat is homophily.[6] In this section, we check if our findings are robust to potential homophily in two aspects. First, we address homophily among social networks of the sample consumers to verify if our findings remain the same when the social networks of focal consumers do not overlap. In the main analysis, the 200 focal consumers' social networks are either interconnected or intra-connected. The interconnected networks contain consumers who are connected with other networks. In contrast, the intra-connected networks are closed from social connections with other networks. A sample that covers both inter- and intra-connected consumers, as used in the main analysis, can better represent reality. However, the interconnected social networks may cause homophily, leading to a biased estimate.

To check robustness to potential homophily in this aspect, we construct a subsample of intra-connected only social networks using a random node sampling adapted from Wagner et al. (2017): We randomly pick a seed consumer among the original sample and identify that consumer's social network. Then, we randomly pick another consumer and check whether the consumer's network overlaps with the first consumer's. If yes, we drop that consumer and choose another consumer randomly. Otherwise, we include this consumer in the subsample. This process iterates until we cannot add any consumers who contribute to non-overlapping social networks. The constructed subsample contains 87 focal consumers. As shown in Table 7, the VAR estimation using the homophily-free subsample continues to support our main findings.

Table 7 Robustness Check for Homophily

	Estimated Impacts in IRFs Averaged over 200 Focal Consumers		Percentage of Positive Impacts among 200 Focal Consumers	
Social network value	short term	long term	short term	long term
(a) Homophily among Social Networks of the Sample Consumers				
Section A: Impacts of Social Network Value on Social Red Packets				
New consumer size	2.687**	4.379**	85%	92%
Frequent consumer size	1.893**	3.648**	78%	84%
Section B: Impacts of Social Red Packets on Social Network Value				
New consumer size	0.009*	0.023*	64%	76%
Frequent consumer size	0.035**	0.061**	75%	85%
(b) Homophily Among Social Networks of All Members in a Consumer Network				
Section A: Impacts of Social Network Value on Social Red Packets				
New consumer size	3.178**	4.837**	89%	95%
Frequent consumer size	2.015**	3.982**	81%	88%
Section B: Impacts of Social Red Packets on Social Network Value				
New consumer size	0.008*	0.020*	61%	75%
Frequent consumer size	0.031**	0.058**	73%	82%

**$p < 0.05$;
*$p < 0.10$.

Second, in the main analysis, for each focal consumer, her social network and those of her peers could be interconnected. This issue of homophily is pointed out by Nejad et al. (2015) as adjacent consumers in a social network have similarities (i.e., common friends in our study). In reality, this homophily cannot be removed but can be reduced if the focal consumers are deliberately selected at the beginning of sample period. We screen focal consumers in the original sample as follows: (1) For each focal consumer, we identify all peers in her social network. (2) We identify all social networks of these peers. (3) The focal consumers least subject to homophily are selected. Specifically, a focal consumer is qualified if overlap (i.e., number of common friends) among the social networks (of the focal consumer and her peers) is two standard deviations below sample average. The VAR estimation using the subsample of restricted homophily still supports our findings.

Next, in the main analysis, the results from the 200 VAR models are aggregated for interpretation. In this section, we use the aggregate version of VAR. Specifically, we aggregate the variable data of 200 focal consumers to conduct a firm-level analysis.[7] The optimal number of lags is still 2, determined by SBIC. We test whether our results are robust to the aggregate VAR model. The estimation results in Table 8 indicate that our main findings about the mutual impacts between social network value and social red packets hold consistently.

Furthermore, according to the theory of social capital, a person's social network value conceptually represents the amount of social resources available to that person. In our setting, the number of red packets available to steal from high-value friends (i.e., the social resources) can accurately represent a focal consumer's social network value. In the main analysis, we use network size of high-value friends (new buyers and frequent buyers) to measure social network value. This network size measurement by counting head is managerially relevant in customer referral. By using this measurement, we implicitly assume that a consumer with a larger network size of new buyers or frequent buyers has a larger number of red packets to steal from. In this section, we relax this assumption. Specifically, we replace new consumer size and frequent consumer size with the actual number of red packets available to steal from the two segments of high-value friends. Table 9 shows that our main findings still hold.

Lastly, in the main analysis, we randomly choose 200 focal consumers as the units of analysis. In addition, we also randomly select two larger samples of 400 and 800 focal consumers, respectively. The results show that our findings are robust to different choices of sample size.[8]

Table 8 Robustness Check for the Aggregate Version of VAR Models

	Impacts of social network value on social red packets		Impacts of social red packets on social network value	
Social network value	Short term	Long term	Short term	Long term
New consumer size	2.478**	3.875**	0.012**	0.028**
Frequent consumer size	1.670**	3.409**	0.035**	0.061**

**$p < 0.05$;
*$p < 0.10$.

Table 9 Robustness Check for Alternative Measurement of Social Network Value (number of red packets available from high-value friends)

	Impacts of social network value on social red packets		Impacts of social red packets on social network value	
Social network value	Short term	Long term	Short term	Long term
New consumers	0.239**	0.387**	0.125**	0.291**
Frequent consumers	0.027**	0.061**	2.263**	3.785**

**$p < 0.05$;
*$p < 0.10$.

6. Discussion

This study proposes a conceptual framework of social promotion, a new type of promotion strategy that allocates better promotional rewards to consumers with higher social network value. We empirically examine social red packet policies that are prevailing in Asian markets as a specific implementation of social promotion. Our empirical results show that social promotion can lead to a causal cycle where consumers who are connected to more high-value friends (e.g., new consumers and frequent consumers) are offered better promotional rewards, and better promotional rewards will in turn encourage consumers to increase their social network value by recruiting more new consumers and cultivating more frequent consumers. Our findings provide important guidance to platforms on how to design social promotion campaigns.

6.1. Managerial Implications

Our research reveals important managerial insights to online merchants and platform managers. First, by proposing the social promotion framework, we identify a segment of high-value consumers who could be neglected by traditional promotion strategies. In current marketing practice, if a consumer has low willingness to pay, she will be considered as having low personal value to the firm. However, we argue that such consumers could possess high value in the social dimension. Under the social red packet design, this segment of consumers will be active in recruiting new consumers or cultivating frequent consumers, which will bring economic value to the retailing platform.

Second, we lay out details on how social promotion campaigns are carried out by introducing a concrete implementation of social red packets. The major findings of our study are the mutual impacts between consumers' social network value and their social red packets. Basically, the direct impacts of social network value on social red packets explain how consumers with higher social network value can benefit from the firm's adoption of social red packets, that is, better promotional rewards from the social network. The feedback impacts of social red packets on social network value explain how firms can benefit from this novel promotion strategy, that is, consumers who aim to pursue better promotional rewards from the social channel will actively socialize to increase social network value. To achieve this purpose, consumers will recruit new buyers for the platform or encourage frequent purchases by existing buyers, which are exactly the two promotional goals of the platform.

More specifically, the platform could be better off after adopting social red packets since this new promotion policy would lead to an increase in social network value. When new consumer size in the focal consumer's social network increases, the platform achieves the promotion goal of new customer acquisition. When frequent consumer size increases, the platform achieves the goal of existing customer retention. Creatively, under a social red packet promotion, the platform's promotional goals are achieved through consumer social interactions. In this way, promotional goals of the platform become the tasks of those consumers who desire social red packets, for example, a segment of consumers who are price sensitive but socially active. Under the incentive of social red packets, this segment will actively fulfill the promotional goals for the platform through social networking. It is well known that consumer social interactions have shown greater effectiveness than firm marketing. Thus, we expect the industry can move forward to employ social red packet promotions to (partially) replace their traditional promotions.

Next, our study also identifies several moderators that determine the effectiveness of social red packets. There are two types of moderators. The first type pertains to characteristics of focal consumers including price sensitivity, social activity, age groups, and variety-seeking behavior. Our results suggest that to maximize the impacts of social red packets, firms should target consumers with specific characteristics. The second type is relevant to characteristics of focal consumers' social networks, which include heterogeneity in personal value and the localization level. Again, firms that aim to benefit most from social red packets must consider consumers whose social networks possess desirable characteristics.

All the moderating effects are consistent with the fundamental mechanism of social red packets. For example, price-sensitive consumers have stronger intention to seek red packets from social networks. Socially active consumers have better chances to meet new friends and persuade them into new purchases. Moreover, all the moderators contribute managerial insights for targeting focal consumers as well as their social networks in order to effectively achieve the firm's promotion goals (acquire new consumers and develop frequent consumers in our empirical setting).

Lastly, we discuss the issue of generalizability. The red packet culture is rooted in Asia and we have not seen popularity of the same practice in Western enterprises such as Netflix and Amazon. This is exactly the contribution of our paper: to explain the mechanism of a novel promotion strategy that is emerging in a limited geographic area for the moment, and to predict the effect that may also apply in a more generalized setting.

We argue that the underlying mechanism of a social red packet strategy is social promotion. Under the conceptual framework of social promotion, the core design of social red packets is that consumers with higher social network value (in terms of a larger number of high-value friends) will enjoy better promotional rewards (in the form of red packets). As long as the framework of social promotion is adopted (not necessarily in the format of a red packet), we consider the practice of social red packets as generalizable.

We have seen widespread adaptation of social promotion in Asia, but not in many in other regions. The implementation of a social promotion strategy requires the integration of online merchant platforms and consumer social network information. As a market dominator, WeChat is the de facto social network account for almost everyone in the market and can be integrated into online merchant platforms. In this way, consumers can use their WeChat accounts to log into many platforms and simplify the payment process using WeChat Pay. The good news for marketers is that they can now combine the sales data from the online merchants and the social network data from WeChat, which is the empirical setting of this study. As for the Western market, we believe that the implementation of social promotion will have great potential if merchants can integrate with a leading social media platform, for example, Twitter, WhatsApp, etc.

6.2. Future Research

Our research on social promotion provides several promising directions for future research. First, our research setting focuses on perishable goods with relatively high purchase frequency. How can a platform design a social red packet for non-perishable goods or services, for example, electronics, travel, or entertainment? This direction of future research applies to online merchants such as Amazon, Adorama, Netflix, Airbnb, etc., which do not yet have the social interface to gain access to consumers' social network information.

Next, the current study uses the number of new consumers and frequent consumers in a focal consumer's social network to represent the platform's performance under the policy of social red packets. That measurement is a good proxy of platform performance since the platform's goal is to encourage new purchases and frequent purchases. However, this measurement cannot directly reflect how social red packets influences sales revenue for the firm. Future research, upon data availability, may conduct an economic impact analysis to offer supplementary insight about how social red packets and consumer social networks would impact firm revenue.

Furthermore, future research may test other designs of social red packets in a more controlled environment such as a field experiment. For example, in the current empirical setting, the option of a social red packet arises when a consumer places an order. The platform may change the sequence of the social red packet stealing process by allowing a consumer to steal a red packet before she adds items into a shopping cart. In this way, consumers know their discounts before shopping. Thus, social red packets are expected to have a larger impact: If consumers can expect red packets in advance, they may make unplanned purchases.

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Notes

[1]http://www.woshipm.com/operate/1634727.html (In Chinese, accessed on May 26, 2020).

[2]http://www.woshipm.com/operate/793088.html (In Chinese, accessed on May 26, 2020).

[3]https://www.weibo.com/5445804653/Gu7QOufYY (In Chinese, accessed on May 26, 2020).

[4]The identity of the platform is confidential due to a non-disclosure agreement.

[5]We test other combinations of high vs. low thresholds (90%-60% vs. 60%-30%). The results still hold.

[6]Homophily refers to the phenomenon that people who are similar in certain attributes tend to form social ties (Nejad et al. 2015). Consumers with close ties tend to have similar decision patterns. Aral et al. (2009) claim that "A key challenge in identifying true contagions in such data is to distinguish peer-to-peer influence, in which a node influences or causes outcomes in its neighbors, from homophily, in which dyadic similarities between nodes create correlated outcome patterns among neighbors that merely mimic viral contagions without direct causal influence."

[7]We thank an anonymous reviewer for this suggestion.

[8]Due to page limit, the results are available upon request to the corresponding author.

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