Social Influence, Competition, and Free Riding: Examining Seller Interactions Within an Online Social Network

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Abstract. Online social networks are increasingly being used to conduct commercial activities, and many online social networking platforms allow users to sell products to their online connections. Although extensive research has been conducted on the interactions among buyers within a social network, interactions among sellers have rarely been explored. Using seller data from a company that sells on a major online social networking platform in China, we empirically examine how a seller's effort and sales performance are affected by the effort and sales performance of other sellers she is connected to (i.e., her inviter and invitees) and the commissions she has received. We find evidence for social influence and competition effects in the "inviter-to-invitee" direction and sellers' free riding behavior driven by the commissions they receive from their invitees' sales. These results extend the social network literature that has largely focused on connected buyers (or users) to connected sellers and offer implications for social networking platforms to promote seller participation.

Keywords: social network, connected sellers, seller interaction, social influence, seller competition, free riding

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1. INTRODUCTION

The rapid development of social media has resulted in the increasing use of social networks to conduct commercial activities (Chen et al., 2016; Hong et al., 2017; Liang & Turban, 2011; Stephen & Toubia, 2010). According to eMarketer, sales from products sold through social networks are projected to reach $36.09 billion in 2021, up roughly 35% from 2020; the number of U.S. consumers buying through social networks will grow 12.9% to 90.4 million in 2021 from 80.1 million in 2020 (Lipsman, 2021). Many social networks allow their users to sell products to their online friends. For example, Facebook allows users to create listings in the Facebook Marketplace to sell products in their local communities and social circles. Similarly, Chinese social media giant WeChat also has a marketplace for users to sell products to their social connections.

This phenomenon of selling in online social networks has not drawn much attention from academic research. Prior literature has studied commercial activities in social networks, including peer recommendation (Crawford et al., 2018; Oestreicher-Singer & Sundararajan, 2012a), group shopping (Li, 2018; Wu et al., 2015), daily deals (Subramanian & Rao, 2016; Sun et al., 2021b), bicycle sharing (Lamberton & Rose, 2012), social sharing of promotional incentives (Sun et al., 2021a), consumer-to-consumer Facebook “buy and sell” groups (Chen et al., 2016), and the impact of Facebook likes on user decision-making on a linked e-commerce site (Bhattacharyya & Bose, 2020). However, most of these studies focus on customers (buyers) who make purchase or consumption decisions in social networks. In this paper, we focus specifically on the interactions among sellers within a social network.

To our best knowledge, only a few previous studies have attempted to examine sellers or providers in social networks, but their research settings are different from ours. Stephen and Toubia (2010) explored the economic impact of a social network among sellers, but the network ties are only hyperlinks among their shops, and the sellers do not have a personal relationship. Gu et al. (2010) studied social influence among a group of offline distributors who sell products from a well-known manufacturer, but the distributors are companies instead of individuals in an offline setting. Song et al. (2019) investigated reciprocal promotions among content providers on YouTube, but the products in their context are free virtual content, and the specific provider behavior examined is promotion behavior. The context studied in Cao et al. (2020), a WeChat-based commercial platform, is similar to ours. However, their paper only discussed the topological features of the platform and presented descriptive statistics on users' behavior without an econometric analysis.

This paper fills the research gap in the literature by examining interactions among sellers in online social networks, where sellers form a hierarchical structure as follows. A seller, Jeff, can invite another user, Jane, to become a seller, who can further invite her friend, Tim, to become a seller. (In this case, if we consider Jane as the "focal seller," Jeff is her "inviter," and Tim is her "invitee".) Sellers receive commissions from not only their own sales but also their direct invitees' sales. Using a unique dataset involving 1,684 sellers over 11 weeks, who sell on a major social networking platform (WeChat), we empirically explore the following research question: How do the inviter and invitee(s) affect the focal seller's selling activities in terms of effort in selling and sales performance?

We argue that the interactions among sellers can take three different forms: social influence, competition, and influence induced by correlated incentives. Social influence describes how the behavior of other people in a social environment changes the focal people's expected utility from that behavior and consequently the focal people's likelihood of taking that behavior (Aral, 2011). Much of the social influence literature has examined social influence among buyers or users. Social influence has been widely shown to increase buyers' intention to purchase a product (Bapna & Umyarov, 2015; de Matos et al., 2014; Jung et al., 2020; Ma et al., 2015; Risselada et al., 2014; Zhang et al., 2018) and to increase buyers' engagement and sustained use of the product after purchasing it (Aral & Walker, 2011; Wang et al., 2013). However, it is still unclear whether and how connected sellers affect each other's behavior because the set of factors affecting sellers' utility is different from factors affecting buyers' or users' utility. Buyers' or users' decisions are simply based on the utility they can receive by consuming or using a product, while sellers' utility is affected by their effort and the demand condition. Therefore, findings of social influence among connected buyers or users are not directly applicable to connected sellers.

Aral (2011) summarized several mechanisms of social influence, including raising awareness (Risselada et al., 2014), persuasion (Aral & Walker, 2011), and social learning (Hao et al., 2018; Wang et al., 2013). In our context, social learning is likely to be the primary mechanism of social influence among sellers. Specifically, following the cost-benefit analysis framework (Adler & Posner, 1999; Drèze & Stern, 1987), we posit that when a seller decides how much effort to exert in selling, she compares the expected benefit and the cost associated with the effort. Both the expected benefit and the cost increase with seller effort – more effort can generally increase sales and thus the commissions sellers can receive, but it also takes more time and energy. Sellers will choose an effort level such that the marginal benefit equals the marginal cost. From the sellers' perspective, there is no uncertainty about the cost, but the benefit is uncertain because demand and sales are uncertain. In an online social network, connected sellers can observe each other's behavior and learn about the market demand from each other. For example, when a seller observes that her inviter/invitees exert a large (small) amount of effort, the seller will infer that the inviter's/invitees' expectation of the demand or the marginal benefit from exerting effort in selling is high (low) since the marginal cost is certain. With this new piece of information, she will update her belief about the demand and the expected marginal benefit (Hao et al., 2018). A higher expected marginal benefit will lead to a higher effort level. Therefore, we expect that the inviter's and invitees' effort will have a positive effect on the focal seller's effort.

In addition to social influence, competition (Gorbenko & Malenko, 2011; Raghunathan & Sarkar, 2016; Tucker & Zhang, 2010; Wohlfarth et al., 2019) may also exist among sellers in a social network because there may be an overlap between the focal seller's connections (i.e., potential buyers) and the inviter's/invitees' connections in the social network (Hong et al., 2018). If a buyer has already purchased products from the focal seller's inviter or invitees, the buyer will not buy the same products from the focal seller. Therefore, we expect that the inviter's and invitees' sales performance will have a negative effect on the focal seller's sales performance.

How the inviter's and invitees' sales performance impacts the focal seller's effort could be much more complicated. On the one hand, continuing with the social influence argument, the inviter's and invitees' sales performance sends a direct signal on the demand and the expected sales. For example, when the inviter or the invitees achieve a high sales performance, the focal seller may learn that the demand for the products is high, and thus the expected marginal benefit from exerting effort in selling the products will also increase; with the known and certain marginal cost, the focal seller will exert more effort. Therefore, the inviter's and invitees' sales performance may have a positive impact on the focal seller's effort. On the other hand, anticipating the negative effect of the inviter's and invitees' sales performance on her sales performance, the focal seller's expected sales and expected marginal benefit from selling will decrease with the inviter's and invitees' sales performance. As a result, the focal seller's effort may be negatively impacted by the inviter's and invitees' sales performance. Taken together, the inviter's and invitees' sales performance can affect the focal seller's effort both positively (through social influence) and negatively (through competition). We argue that the negative competition effect is likely to be stronger than the positive social influence because the impact of competition is directly related to salient monetary returns. Hence, we expect that the inviter's and invitees' sales performance will have a negative (net) effect on the focal seller's effort.

Correlated incentives can also result in interdependence among sellers' decisions. In our context, sellers receive commissions from the sales of their direct invitees, which allows sellers to free ride on the effort and sales of invitees (Chung et al., 2021; Shin, 2007). It is reasonable to postulate that when a focal seller receives a higher commission amount from her invitees, her free-riding intention will increase. In addition, many sellers in online social networks are "part-time" sellers who sell products in their spare time. They face a tradeoff between spending time selling products in online social networks and engaging in many other and arguably more important work and leisure activities in their lives. Under such conditions, sellers may adopt the "income targeting" strategy (Camerer et al., 1997; Kőszegi & Rabin, 2006), i.e., set a target income and quit when the target is reached. Given an income target, the more commissions a seller has earned from her invitees' sales, the closer she is to the target. As a result, the seller's own effort in selling will decrease. Hence, we expect that commissions from invitees' sales will have a negative effect on the focal seller's effort.

Our empirical results confirm that in the social network under study, inviter effort increases the focal seller's effort, indicating social influence. Inviter sales performance decreases the focal seller's effort and sales performance, indicating competition. Invitee effort/sales performance has no significant effect on the focal seller, indicating that social influence and competition are one-directional and happen in the "top-down" manner. Furthermore, we find commissions from invitees' sales performance decrease the focal seller's effort, indicating free riding. Our research sheds new light on the social network literature because our empirical analyses present clear and consistent evidence regarding social influence, competition, and free riding among sellers in a prominent online social network. We extend the notion of social influence to connected sellers in online social networks, who face a different set of cost-and-benefit tradeoffs than connected buyers. To the best of our knowledge, we are the first to document the effects of social influence, competition, and correlated incentives among connected sellers in online social networks.

2. RESEARCH CONTEXT

In this paper, we study sellers' activities on WeChat[1], where users can enjoy free functions including text and voice messaging, broadcast messaging, voice calls, video calls, and

[1] The number of monthly active users on WeChat has reached 1.24 billion in the first quarter of 2021 (https://www.statista.com/statistics/255778/number-of-active-wechat-messenger-accounts/).

conference calls. Companies can also conduct commercial activities on WeChat. For example, a company can set up a virtual flagship store on the WeChat platform. The flagship store can sell directly to WeChat users connected to the store or invite WeChat users to become its sellers to sell products through their social connections on WeChat. Individual sellers can also invite their WeChat friends to become sellers. Thus, a seller hierarchical structure will be formed based on such invitations. Because we focus on sellers in this paper, for narrative convenience, we use the term "seller network" hereafter to refer to this hierarchical structure (although sellers are also regular social media users on WeChat).

WeChat users who accept the invitation, that is, register themselves as a seller, will receive an empty "shell" of a virtual shop, which is identical for all the sellers. Registered sellers (hereafter "sellers") can select products from the flagship store and add them to their virtual shops. In the data, we observe only sellers but not users who were invited but decided not to register. Our focus is to study sellers' effort in selling and their sales performance. Hereafter, we use "effort" to refer to sellers' effort in selling products and "performance" to refer to seller's sales performance.

Figure 1 provides a simplified illustration of the seller network that we observe in the data. All nodes in the network are users who have registered as a seller. First, the flagship store invites a few WeChat users to sell its products. The nodes on the first level, including A and E, are users who accept the store invitation and register themselves as sellers. Let us focus on the branch starting with A. A invites another set of users, and among them, B and F register as sellers. B then invites another set of users, and C is among those who are registered as sellers. Finally, D is among the users invited by C and accepts the invitation. In this illustrative example, D either does not invite anyone, or none of her invited users accepts the invitation. Sellers can send product messages and make advertisements on WeChat. When potential buyers (i.e., friends on WeChat[2]) see an advertisement sent by a seller, they can access the seller's shop through a hyperlink and browse the products the seller has listed in the shop. If a buyer makes a purchase, the flagship store delivers the products directly to the buyer. In essence, sellers are mainly responsible for selecting products to list in their shops, marketing, and attracting orders. Sellers are compensated in two ways: (1) commissions from their own sales and (2) commissions from the sales of the other sellers they invite directly (i.e., invitees). For example, B receives commissions from her (B's) own sales and her direct invitees' sales (e.g., C's sales). Sellers do not collect commissions from the sales of the invitees' invitees. For example, B cannot earn commissions from D's sales.

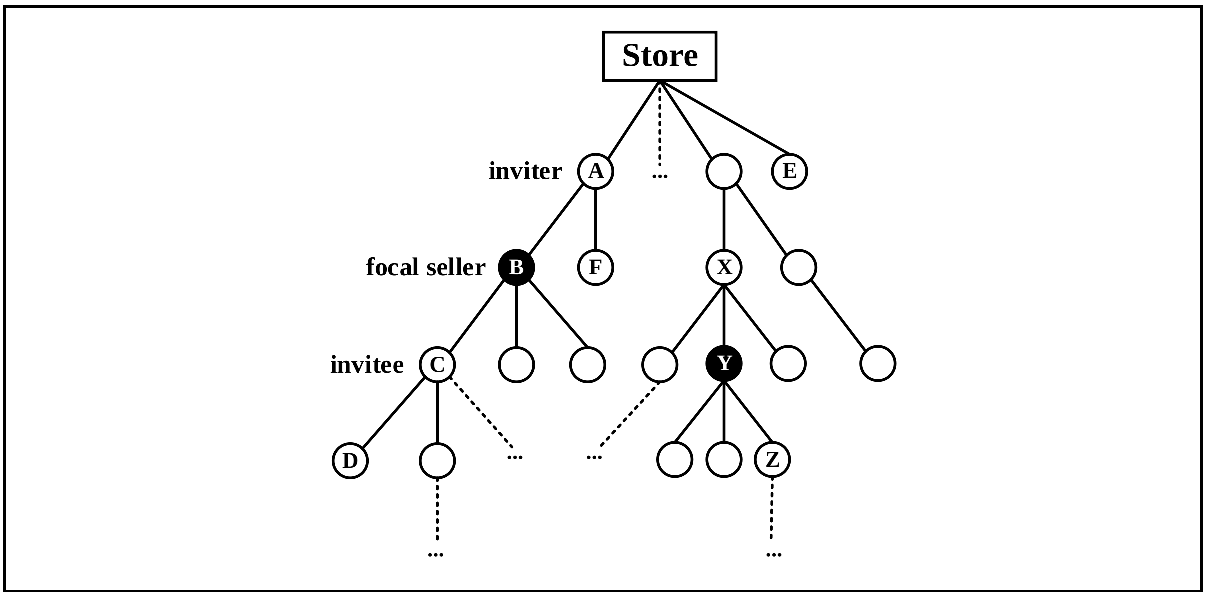

Figure 1. A Seller Network

As mentioned previously, one of the effects we are interested in examining is how the effort and performance of a seller's inviter and invitees affect her effort. Let us first clarify

[2] We do not observe sellers' social networks (i.e., friends) in our data.

the concepts of inviter and invitee. In Figure 1, if we consider B as the focal seller, she has an *inviter* (i.e., A) and a few *invitees* (e.g., C). If we consider C as the focal seller, then B is the inviter, and D is an invitee. It is worth noting that a seller may have many invitees but can have exactly one inviter (if she is not invited by the flagship store) because she can only accept one invitation to join the seller network. A seller may not have an inviter if she is invited directly by the flagship store (e.g., A or E), and a seller may not have any invitee if she does not invite anyone or no one accepts her invitation (e.g., D or E). The focal seller can observe her inviter's and invitees' effort by visiting their shops. Invitees' sales information is reported to the focal seller because it is used to compute commissions. Although the inviter's sales information is not reported to the focal seller, there are informal channels for the focal seller to learn about her inviter's performance. For example, because it is the inviter who introduced the focal seller to the possibility of selling products on WeChat and brought her to the seller network, the focal seller is likely to seek information (including sales information) and guidance from the inviter. The inviter also has an incentive to provide information and guidance to the focal seller to encourage her to sell more.[3] Therefore, we conjecture that the inviter's and invitees' effort and performance may affect the focal seller's effort decision. In contrast, it is difficult for the focal seller to see the effort and performance of other sellers to whom she is not directly connected, including those who share the same inviter as the focal seller (e.g., B and F); she may not even know the existence of those sellers.[4] Therefore, the

[3] The focal seller may receive partial information about her inviter's performance if her mutual friends with her inviter mention to her that they have purchased products from the inviter. However, this happens rarely, and even if it happens, the information obtained this way could be insufficient for the focal seller to infer her inviter's performance because the mutual friends who share purchase information with the focal seller usually would only account for a small fraction of the inviter's sales.

[4] We cannot completely rule out the possibility that the focal seller can get some information about the sales activities of other sellers who are not connected to her in the seller network. For example, non-connected sellers may interact with each other offline, or they can learn about each other's sales from their mutual friends on WeChat. But it is much more difficult for the focal seller to see the selling activities of sellers she is not directly connected to.

effort and performance of those sellers are unlikely to have an impact on the focal seller's behavior.

3. EMPIRICAL METHODOLOGY

3.1. Data and Variables

Our dataset is provided by a company that sells beauty and makeup products. This company is representative of companies selling on WeChat, and the dataset reflects the data any of those companies can observe. The dataset includes information on sellers, products, and sales transactions, covering 11 weeks from April 17, 2015, to July 7, 2015.[5] For privacy considerations, all sensitive features have been removed from the dataset.

3.1.1. Dependent Variables

Our goal is to study (1) how inviter/invitee effort and performance and commissions from invitees' sales affect the focal seller's effort decision, and (2) how inviter/invitee performance affects the focal seller's performance. Therefore, we consider two dependent variables (DVs). The first DV is a seller's effort in each period.[6] We use the number of products a seller inserts into her shop in each period (insertit) as a proxy for seller effort. The second DV is a seller's performance in each period. To measure sellers' performance, we use the number of sales transactions they have in each period (salesit). We define a period as a week.

3.1.2. Independent Variables

In Table 1, we summarize the definitions and notations of the independent variables used in our empirical analyses. Below, we explain the independent variables in the *effort* model and

[5] We focus on this period because, during this period, sellers need to manually add products into their shops, which will be used later to measure their effort in selling. After July 7, 2015, products are automatically added to sellers' shops, which affects our ability to measure sellers' effort.
[6] None of the sellers inserted all available products for sale (a total of 26 products) into their shops (i.e., reached the limit) at the end of the observation period.

those in the *performance* model.

In the *effort* model, we examine the effects of the inviter's and invitees' effort and performance and the focal seller's settled commissions in the *previous period* (*t-1*) on the focal seller's effort decision in the current period. When the focal seller makes the effort decision in period *t*, the inviter's and invitees' effort and performance in period *t-1* have been realized, and therefore, may affect the focal seller's effort decision. Specifically, we use the number of products the focal seller's inviter inserts in period *t-1* and the average number of product inserts across the focal seller's invitees in period *t-1* (denoted as $inviter\_insert_{i(t-1)}$ and $invitee\_insert_{i(t-1)}$, respectively) to measure inviter and invitee effort in period *t-1*, and the number of sales transactions the focal seller's inviter has in period *t-1* and the average number of sales transactions across the focal seller's invitees in period *t-1* (denoted as $inviter\_sales_{i(t-1)}$ and $invitee\_sales_{i(t-1)}$, respectively) to measure their respective period *t-1* performance. We also consider the variables regarding commissions sellers receive in the effort model: $CFS_{i(t-1)}$ denotes the commissions that seller *i* receives from her own sales that are settled in period *t-1*, and $CFI_{i(t-1)}$ denotes the commissions that seller *i* receives from her invitees' sales that are settled in period *t-1*.

Other variables that are considered in the effort model as control variables include the number of invitees the focal seller has up until period *t-1* (denoted as $invitee\_num_{i(t-1)}$), the focal seller's own performance in period *t-1* (denoted as $sales_{i(t-1)}$) and time since registration (reg_time_{it}). Week fixed effects are included to control for potential time trends. Seller fixed effects are included to control for unobserved time invariant seller heterogeneity. In models where seller fixed effects are not included, we also consider a set of time-invariant variables,[7] including the level at which the focal seller is in the seller network ($level_i$)[8] and a set of indicators, $wechat_i$, $alipay_i$, and qq_i, which capture whether the focal seller provides a WeChat, an Alipay, and a QQ account upon registration, respectively. Among those three tools, WeChat and Alipay are more widely used for online transactions and are more familiar to buyers. Users' WeChat and QQ accounts are often linked. We also include two groups of time-invariant dummies as controls: province and mobile phone operator. China has three major mobile phone operators: China Mobile, China Unicom, and China Telecom. Among them, China Mobile provides better services but is more expensive. Thus, sellers' choice of mobile phone operator may partly reflect their heterogeneity in socio-economic status and interests in and attitude towards selling products on WeChat.

In the *performance* model, the main independent variables include the focal seller's inviter's current-period effort and performance (denoted as $inviter\_insert_{it}$ and $inviter\_sales_{it}$) and her invitees' average effort and performance (denoted as $invitee\_insert_{it}$ and $invitee\_sales_{it}$). Note that these variables are measured in the *current* period because we are interested in testing whether there is competition between the focal seller and her inviter/invitees within the same period. The focal seller's own effort in the current period ($insert_{it}$) is also considered in this model because the focal seller's effort in a period is likely to have a direct impact on her performance in the period. Control variables in this model include $invitee\_num_{it}$ and reg_time_{it}. Similar to the effort model, the time-invariant control variables, including $level_i$, $wechat_i$, $alipay_i$, qq_i, and the province and mobile phone operator

[7] These time-invariant variables are absorbed into the seller fixed effects in models with seller fixed effects.
[8] Sellers who are directly invited by the flagship store have a level of 1, while those who are invited by other individual sellers have a level larger than 1. We can also interpret $level_i$ as seller i's topological distance to the flagship store.

dummies, are included in alternative specifications of the performance model without seller fixed effects.

Table 2 presents the descriptive statistics of the dependent and independent variables, omitting the province and mobile phone operator dummies. The correlations of the variables are presented in Table 3.

Table 1. Variable Summary

Variable name	Variable definition
$insert_{it}$	Number of products the focal seller i inserts in period t
$sales_{it}$	Number of sales transactions the focal seller i has in period t
$inviter\_inserts_{it}$	Number of products the inviter inserts in period t
$invitee\_inserts_{it}$	Average number of product-inserts over the invitees in period t
$inviter\_sales_{it}$	Number of sales transactions the inviter has in period t
$invitee\_sales_{it}$	Average number of sales transactions over the invitees in period t
CFS_{it}	Commissions the focal seller i earns from her own sales that are settled in period t
CFI_{it}	Commissions the focal seller i earns from her invitees' sales that are settled in period t
$level_i$	Level at which the focal seller i is in the seller network
$invitee\_num_{it}$	Number of sellers invited by the focal seller i up to period t
reg_time_{it}	Time (days) since the focal seller i registered as a seller in period t
$wechat_i$	1 if the focal seller i provided a WeChat account when signing up, and 0 otherwise
$alipay_i$	1 if the focal seller i provided an Alipay account when signing up, and 0 otherwise
qq_i	1 if the focal seller i provided a QQ account when signing up, and 0 otherwise

Table 2. Descriptive Statistics

Number	Variable	Mean	SD	Min	Max
1	$insert_{it}$	.043	.330	0	8
2	$sales_{it}$	.065	.400	0	10
3	$inviter\_inserts_{it}$	.181	.604	0	8
4	$invitee\_inserts_{it}$	.005	.081	0	4
5	$inviter\_sales_{it}$	.309	1.042	0	10
6	$invitee\_sales_{it}$	.009	.122	0	8
7	CFS_{it}[9]	.836	30.338	0	3315.800
8	CFI_{it}	.345	6.901	0	426.180
9	$level_i$	2.271	1.001	1	8
10	$invitee\_num_{it}$	.786	4.300	0	107
11	reg_time_{it}	33.994	22.383	.012	142.301
12	$wechat_i$	.358	.480	0	1
13	$alipay_i$	.045	.207	0	1
14	qq_i	.374	.484	0	1

[9] CFS_{it} (CFI_{it}) is not highly correlated with $sales_{it}$ ($invitee\_sales_{it}$) because it only counts *settled* commissions. There may be delays between sales transactions and the settlement of commissions.

Table 3. Correlation Matrix											
	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	$insert_{it}$	1									
2	$sales_{it}$	.441	1								
3	$inviter\_inserts_{it}$	.174	.158	1							
4	$invitee\_inserts_{it}$	.306	.324	.085	1						
5	$inviter\_sales_{it}$	.142	.183	.483	.029	1					
6	$invitee\_sales_{it}$	.205	.318	.060	.470	.043	1				
7	CFS_{it}	.047	.118	.007	.040	.015	.032	1			
8	CFI_{it}	.093	.209	.015	.170	-.002	.231	.055	1		
9	$level_{i}$	.005	.055	.076	.019	.107	.034	-.004	.004	1	
10	$invitee\_num_{it}$	.104	.150	-.014	.068	-.023	.077	.016	.140	-.120	1
11	reg_time_{it}	-.013	-.005	-.079	.013	-.096	.024	-.016	.011	.013	.073
12	$wechat_{i}$	.057	.055	-.019	.047	-.025	.045	.003	.041	-.001	.049
13	$alipay_{i}$	.168	.267	.034	.122	.086	.138	.088	.064	.017	.155
14	qq_{i}	.026	.029	-.030	.028	-.041	.020	.002	.028	.019	.032

	11	**12**	**13**	**14**
11	1			
12	.019	1		
13	.033	.137	1	
14	.021	.691	.127	1

3.2. Empirical Models and Strategies

3.2.1. Seller Effort

We first test how the inviter's and invitees' effort and performance affect the focal seller's effort in selling using the following regression:

$$insert_{it} = \alpha_i^1 + \delta_t^1 + \beta^1 X_{it}^1 + \gamma^1 Z_{it}^1 + \varepsilon_{it}^1 \quad (1)$$

In Equation (1), X_{it}^1 is a vector of main explanatory variables of interest (i.e., $inviter\_insert_{i(t-1)}$, $inviter\_sales_{i(t-1)}$, $invitee\_insert_{i(t-1)}$, $invitee\_sales_{i(t-1)}$, $CFS_{i(t-1)}$, and $CFI_{i(t-1)}$); Z_{it}^1 is a vector of time-varying control variables (i.e., reg_time_{it}, $invitee\_num_{i(t-1)}$, and $sales_{i(t-1)}$). α_i^1 is the seller fixed effect, δ_t^1 is the week fixed effect, and ε_{it}^1 is the idiosyncratic error term.

3.2.2. Seller Performance

Next, we test how a seller's performance is affected by her inviter's and invitees' effort and performance, as well as her own effort (Equation (2)). The DV in this regression is $sales_{it}$.

$$sales_{it} = \alpha_i^2 + \delta_t^2 + \beta^2 X_{it}^2 + \gamma^2 Z_{it}^2 + \varepsilon_{it}^2 \quad (2)$$

X_{it}^2 includes $inviter\_insert_{it}$, $inviter\_sales_{it}$, $invitee\_insert_{it}$, $invitee\_sales_{it}$, and $insert_{it}$, and Z_{it}^2 includes reg_time_{it} and $invitee\_num_{it}$. Again, α_i^2 is the seller fixed effect, δ_t^2 is the week fixed effect, and ε_{it}^2 is the idiosyncratic error term. Note that an important difference between Equation (1) and Equation (2) is that performance should be viewed as a market outcome resulting from sellers' decisions; therefore, unlike Equation (1) which intends to describe how decisions and outcomes in the *past* affect sellers' decisions in the *current* period, Equation (2) captures how sellers' decisions in the *current* period affect their *current* period outcomes. Also note that we only use sellers that have made an effort in selling (i.e., with product-inserts) to estimate this performance model (1,225 observations involving 195 sellers).

3.2.3. Endogeneity

A challenge in the estimation of the models described previously is that the effort and performance variables in $\boldsymbol{X_{it}}$ in both the effort and performance models are potentially endogenous. That is, if unobserved reasons that lead seller *i* to participate in selling or achieve a certain performance relate to the reasons why she is invited by her inviter or why she invites her invitee(s), then the inviter/invitee effort and performance variables will be correlated with $\boldsymbol{\varepsilon_{it}}$. Following de Matos et al. (2014), we use a strategy that combines the use of control variables and instrumental variables to address this endogeneity issue. Specifically, we control for heterogeneity across sellers and over time with seller fixed effects, week fixed effects, and a rich set of control variables mentioned in Section 3.1.2. These control variables capture some of the unobserved homophily and market-level week-specific effects, which can help reduce the potential for unobservables that drive both network formation and seller behavior/outcome. In addition, we explore the structure of the seller network to derive a set of instrumental variables for the inviter/invitee effort and performance variables. Let us use *j* to denote seller *i*'s inviter and *k* to denote seller *j*'s inviter. In other words, *k* invites *j*, and *j* invites *i*. We argue that *k*'s effort and performance are correlated with those of *j*,[10] but they do not directly affect the effort and performance of *i*. If *k*'s effort and performance ever affect *i*, it is through the effort and performance of *j* (de Matos et al., 2014; Oestreicher-Singer & Sundararajan, 2012b; Tucker, 2008). Therefore, we can use *k*'s effort and performance to instrument for *j*'s (inviter's) effort and performance when *i* is considered the focal seller. By the same logic, we can also use *i*'s effort and performance to instrument for *j*'s (invitees') effort and performance when *k* is considered the focal seller.

Another potential source of endogeneity is that sellers may strategically decide how many friends to invite to become sellers, and therefore, $invitee\_num_{it}$ may be endogenous. To alleviate this concern, we take advantage of a promotion event that started on June 9, 2015, where the flagship store offered a coupon for opening a new shop, or equivalently, registering as a seller, and the coupon expired at the end of June 12, 2015. Given that the number of invitees is a cumulative measure, this promotion event provides an exogenous shock to $invitee\_num_{it}$. During and after the promotion event, $invitee\_num_{it}$ will experience a positive

[10] The correlation between the effort of the inviter (invitees) and the effort of the inviter's inviter (invitees' invitees) is significant and positive with a p-value <0.01 (<0.01); the correlation between the performance of the inviter (invitees) and the performance of the inviter's inviter (invitees' invitees) is also significant and positive with a p-value <0.01 (<0.01).

jump because the event incentivizes sellers to invite more friends and encourages those being invited to register as a seller. Based on this reasoning, we construct a binary instrument for $invitee\_num_{it}$, which takes the value 0 for all weeks[11] prior to June 9, 2015, and 1 for all weeks after June 9, 2015 (including the week in which June 9, 2015, was in).

4. ESTIMATION RESULTS

In Table 4, we present the estimation results for Equation (1) with the instrumental variables (abbreviated as IV thereafter). The estimation results reveal a number of interesting effects. First, the coefficient of $inviter\_inserts_{i(t-1)}$ is positive and significant, suggesting that the inviter's effort has a positive effect on the focal seller's effort. As previously argued, a higher inviter effort signals the inviter's expectation about the returns, which positively influence the focal seller's effort decision. This process is a form of social influence (via social learning). Second, the coefficient of the inviter's performance ($inviter\_sales_{i(t-1)}$) is negative and significant. As mentioned in Section 1, the inviter's performance may affect the focal seller's effort both positively via social influence and negatively via competition. The negative coefficient of $inviter\_sales_{i(t-1)}$ provides evidence for competition between the focal seller and her inviter. We cannot conclude whether the positive social influence from the inviter's performance exists based on this result; but even if it exists, the negative competition effect dominates the positive social influence. Such a competition effect is possible because the focal seller and her inviter may share some mutual friends in the WeChat social network. When the inviter achieves more sales, the demand for the focal seller is reduced because her friends may have bought the products from the inviter. We provide further evidence for the

[11] Recall that in our model, a period is defined as a week.

competition effect later.

It turns out that invitees' effort and performance do not have a significant impact on the focal seller's effort level. This could be because, in the seller network, social influence occurs only in the "inviter-to-invitee" direction, not the other way around. Sellers typically "learn" from their inviter, which makes sense because the inviter started selling earlier than the focal seller and "brought" the focal seller into the system. It is also not surprising that the competition from the inviter is stronger because compared with the focal seller, the inviter has a longer presence and arguably a more "senior" status in the seller network and is more likely to cannibalize the focal seller's market.

The coefficient of $CFI_{i(t-1)}$ is negative and significant, which suggests that a higher commission the focal seller collects from her invitee(s) in the previous period discourages her from exerting effort and encourages her to free ride. Interestingly, the coefficient of $CFS_{i(t-1)}$ is also negative and significant, but smaller in size compared to the coefficient of $CFI_{i(t-1)}$, indicating that a higher commission from own sales in the last period also discourages the focal seller's effort in the current period. These negative effects are consistent with the "income targeting" behavior (Camerer et al., 1997), i.e., sellers may set a target level of earnings/returns from participating in selling, and after they find they have achieved or are on track to achieve the goal, they will reduce their effort.

In terms of control variables, we find that the focal seller's last-period performance, $sales_{i(t-1)}$, positively affects the focal seller's current-period effort, indicating potential experience-based learning. That is, a good past performance that sellers experienced on their own also increases the expected return from participating in selling, and therefore, encourages sellers to put in more effort. Note from Table 3 that although $CFS_{i(t-1)}$ depends on $sales_{i(t-1)}$, $sales_{i(t-1)}$ and $CFS_{i(t-1)}$ are not very highly correlated because $CFS_{i(t-1)}$ refers to the amount of the *settled* commissions, and there is often a lag between the time when a transaction occurs and the time when the seller receives the corresponding commission. The coefficient of $invitee\_num_{i(t-1)}$ is negative and significant, suggesting that sellers reduce their effort level when they have more invitees from whom they can collect commissions. This provides additional evidence for the "free-riding" behavior discussed above. Finally, it turns out that the effect of reg_time_{it} is positive, indicating an increasing level of effort over time.

Table 4. Inviter's and Invitees' Impacts on the Focal Seller's Effort

Variables	DV=$inserts_{it}$
$inviter\_inserts_{i(t-1)}$	.098* (.058)
$inviter\_sales_{i(t-1)}$	-.264*** (.089)
$invitee\_inserts_{i(t-1)}$	-.028 (.018)
$invitee\_sales_{i(t-1)}$	-.003 (.013)
$CFI_{i(t-1)}$	-.002** (.0007)
$CFS_{i(t-1)}$	-.0006*** (.0001)
$sales_{i(t-1)}$	.119*** (.031)
$invitee\_num_{i(t-1)}$	-.055*** (.007)
reg_time_{it}	.003*** (.0003)
Seller fixed effects	YES
Week fixed effects	YES
No. of observations	13,056
No. of sellers	1684

Note: ***p<0.01, **p<0.05, *p<0.1.

In Table 5, we present the IV results for Equation (2). First, the estimated coefficient of the inviter's performance ($inviter\_sales_{it}$) is negative and significant, providing direct evidence for competition between the focal seller and her inviter. That is, the inviter's sales can cannibalize the focal seller's sales. This result is consistent with the negative effect of inviter performance in the effort model discussed above – sellers know that they have to compete with their inviter for the market demand, and if their inviter has been selling well in the past, they will face more intense competition and a lower expected return, which discourages them from exerting effort. Not surprisingly, the focal seller's own effort in the current period ($inserts_{it}$) positively affects her performance in the current period. Put differently, the more effort one exerts, the higher performance one can achieve. Inviter effort in the current period ($inviter\_inserts_{it}$) does not seem to have a direct effect on the focal seller's performance. Similar to the effort model, neither invitee effort nor invitee performance has a significant effect on the focal seller's performance, indicating that the demand cannibalization effect is asymmetric – only from inviter to invitee but not the other way around. The effect of reg_time_{it} is not significant either, suggesting that conditional on the focal seller's effort and inviter/invitee effort and performance, the focal seller's performance does not increase or decrease as the focal seller's time since registration increases.

Table 5. Inviter's and Invitees' Impacts on the Focal Seller's Performance

Variables	DV=$sales_{it}$
$inviter\_inserts_{it}$	-.240 (.191)
$inviter\_sales_{it}$	-.316* (.168)
$invitee\_inserts_{it}$	-.043 (.059)
$invitee\_sales_{it}$	-.117 (.096)
$inserts_{it}$	.400*** (.067)
$invitee\_num_{it}$	-.055 (.063)
reg_time_{it}	-.0006 (.006)
Seller fixed effects	YES
Week fixed effects	YES
No. of observations	1,225
No. of sellers	195

Note: ***p<0.01, **p<0.05, *p<0.1.

5. ROBUSTNESS CHECKS

We conduct several checks to ensure that our results are robust to alternative measures and model specifications. Below, we discuss those robustness checks in sequence.

First, in the main effort model, we consider the effects of inviter/invitee last-period effort/performance and the focal seller's last-period commissions, and in the main performance model, we consider the effects of inviter/invitee current-period effort/performance. One may argue that the effect of social influence and/or free riding can go beyond consecutive periods, and there may be inter-temporal competition as well. To test those possibilities, we consider three alternative models, where we replace the last-period measures with the average weekly measures over the most recent two/three/four weeks. It is worth noticing that in the alternative effort models, "the most recent two periods" refer to periods *t-1* and *t-2*, whereas in the alternative performance models, "the most recent two periods" refer to periods *t* and *t-1*. This is consistent with the timing of the events reflected in the main effort and performance models. The "most recent three/four periods" are defined in a similar way.

The results for the alternative effort models (as shown in Table 6) suggest that social influence, or the effect of past inviter effort, remains positive in the models that consider the last two/three weeks' average, demonstrating the robustness of this result. However, the effect of past inviter effort becomes insignificant in the model that considers the last four weeks' average. A possible explanation is that it is difficult for sellers to keep track of their inviter's effort for too many weeks, and therefore, the effect of the more recent inviter effort is more significant. The same pattern is found in the effect of inviter recent performance on the focal seller's effort. Again, likely due to cognitive constraints, sellers may not remember what their inviter's performance was many periods back. The effect of the commissions from invitees' sales ($CFI_{i(t-1)}$) in those alternative models is consistent with that in the main model, which presents robust evidence for sellers' free-riding behavior. The effects of invitee effort and performance are consistently insignificant in all the models considered. The effects of the commissions from the focal seller's own performance ($CFS_{i(t-1)}$) and the focal seller's last-period performance ($sales_{i(t-1)}$) are less consistent in those alternative models, and in light of this, we caution making any conclusive statements about their effects.

The results for the alternative performance models (as shown in Table 7) are consistent with those for the main model – the effects of both the current-period and recent performances of the inviter on the focal seller's performance are negative, indicating significant immediate and intertemporal competition between the focal seller and her inviter. The signs and significance levels of all other coefficients are consistent throughout, except for a change in the significance level of the coefficient of $invitee\_num_{it}$ in one of the alternative models, confirming the robustness of the results for the performance model.

Table 6. Inviter's and Invitees' Impacts on the Focal Seller's Effort with Inviter and Invitee Effort and Performance Averaged over Recent Weeks

Variables	(1) Average over the most recent two weeks	(2) Average over the most recent three weeks	(3) Average over the most recent four weeks
$inviter\_inserts_{i(t-1)}$	.350** (.174)	.311* (.161)	-1.054 (.770)
$inviter\_sales_{i(t-1)}$	-.588* (.349)	-.206 (.155)	.854 (.557)
$invitee\_inserts_{i(t-1)}$	-.113 (.070)	-.040 (.029)	.138 (.098)
$invitee\_sales_{i(t-1)}$	-.007 (.020)	.005 (.015)	.043 (.039)
$CFI_{i(t-1)}$	-.003** (.001)	-.003*** (.001)	-.013** (.006)
$CFS_{i(t-1)}$	-.0001 (.0002)	-.0001 (.0001)	-.0002 (.0003)
$sales_{i(t-1)}$	.179* (.108)	.023 (.035)	-.116* (.069)
$invitee\_num_{i(t-1)}$	-.041*** (.010)	-.038*** (.008)	-.057*** (.025)

reg_time$_{it}$	.002 (.001)	-.0008* (.0005)	.003 (.002)
Seller fixed effects	YES	YES	YES
Week fixed effects	YES	YES	YES
No. of observations	13,056	13,056	13,056
No. of sellers	1684	1684	1684

Note: ***p<0.01, **p<0.05, *p<0.1. In Model (1)/(2)/(3), inviter and invitee effort/performance, commission variables, and the focal seller's previous sales are measured by the averages over the most recent two/three/four weeks (up to week t-1).

Table 7. Inviter's and Invitees' Impacts on the Focal Seller's Performance with Inviter and Invitee Effort and Performance Averaged over Recent Weeks

Variables	(1) Average over the most recent two weeks	(2) Average over the most recent three weeks	(3) Average over the most recent four weeks
inviter_inserts$_{it}$	-.078 (.128)	-.068 (.133)	-.033 (.123)
inviter_sales$_{it}$	-.278* (.157)	-.354* (.213)	-.273* (.142)
invitee_inserts$_{it}$	-.081 (.055)	-.065 (.067)	-.073 (.067)
invitee_sales$_{it}$	-.113 (.071)	-.202 (.154)	-.137 (.118)
inserts$_{it}$	.368*** (.073)	.464*** (.088)	.426*** (.086)
invitee_num$_{it}$	-.031 (.047)	-.006 (.043)	-.072* (.039)
reg_time$_{it}$	.002 (.004)	.002 (.004)	.003 (.004)
Seller fixed effects	YES	YES	YES
Week fixed effects	YES	YES	YES
No. of observations	1,225	1,225	1,225
No. of sellers	195	195	195

Note: ***p<0.01, **p<0.05, *p<0.1. In Model (1)/(2)/(3), inviter and invitee effort/performance are measured by the averages over the most recent two/three/four weeks (up to week t).

Second, we consider an alternative model where we use the cumulative number of inserts/sales and the cumulative commission amounts, instead of the last-period/current-period measures, as the main independent variables. Since all these cumulative measures are increasing over time by definition, we omit seller fixed effects in those models to allow cross-sectional comparisons. The results about the main independent variables from this robustness check (as shown in Model (1) of Table 8 and Table 9) are consistent with the main results, except that in the performance model, the effect of the cumulative inviter effort on the focal seller's performance becomes positive and significant. A plausible explanation for this positive effect is that in the longer run, the inviter's effort can spill over to the focal seller (Haviv et al., 2020). For example, the inviter's effort can make potential buyers become aware of or familiar with the products, and since the inviter and the focal seller may share common buyers, the inviter's cumulative effort can positively affect the focal seller's performance.

Table 8. Inviter's and Invitees' Impacts on the Focal Seller's Effort with Cumulative/Logged Measures and "No-invitee" Subsample

Variables	(1) Cumulative measures	(2) Logged measures	(3) "No-invitee" sellers only
$inviter\_inserts_{i(t-1)}$	.118*** (.028)	.094* (.054)	.150** (.063)
$inviter\_sales_{i(t-1)}$	-.092*** (.022)	-.112 (.069)	-.148** (.066)
$invitee\_inserts_{i(t-1)}$	-.018 (.028)	-.0005 (.009)	-
$invitee\_sales_{i(t-1)}$	.017 (.016)	.0008 (.008)	-
$CFI_{i(t-1)}$	-.0006*** (.0002)	-.006 (.013)	-
$CFS_{i(t-1)}$	.0003*** (.0001)	-.020*** (.005)	-.0001 (.0001)
$sales_{i(t-1)}$	.017** (.008)	.093*** (.029)	.016 (.032)
$invitee\_num_{i(t-1)}$	.0000 (.004)	-.141*** (.021)	-
$alipay_i$	.253*** (.029)	-	-
$wechat_i$	.065*** (.014)	-	-
qq_i	-.029** (.013)	-	-
reg_time_{it}	-.0009*** (.0002)	.0002 (.0002)	-.0004* (.0002)
$level_i$	.009* (.005)	-	-
Seller fixed effects	NO	YES	YES
Week fixed effects	YES	YES	YES
No. of observations	13,056	13,056	11,402
No. of sellers	1684	1684	1540

Note: ***p<0.01, **p<0.05, *p<0.1. In Model (1), inviter and invitee effort/performance, commission variables, and the focal seller's previous sales are cumulative measures. The estimation results for the province and mobile operator dummies are omitted. In Model (2), inviter and invitee effort/performance, commission variables, the number of invitees and the focal seller's previous sales are log transformed. In Model (3), the sellers with any invitee are excluded.

Table 9. Inviter's and Invitees' Impacts on the Focal Seller's Performance with Cumulative/Logged Measures and "No-invitee" Subsample

Variables	(1) Cumulative measures	(2) Logged measures	(3) "No-invitee" sellers only
$inviter\_inserts_{it}$	.405*** (.123)	-.292 (.184)	-.206 (.725)
$inviter\_sales_{it}$	-.101** (.048)	-.426* (.259)	-.467* (.250)

$invitee\_inserts_{it}$	-.014 (.053)	-.112 (.072)	-
$invitee\_sales_{it}$	-.017 (.035)	.022 (.088)	-
$inserts_{it}$	.329*** (.037)	.740*** (.195)	.274 (.187)
$invitee\_num_{it}$	.032*** (.009)	-.384 (.433)	-
$alipay_i$	.380*** (.083)	-	-
$wechat_i$	.076 (.082)	-	-
qq_i	.033 (.080)	-	-
reg_time_{it}	.003 (.002)	.014** (.006)	-.016** (.007)
$level_i$	.010 (.059)	-	-
Seller fixed effects	NO	YES	YES
Week fixed effects	YES	YES	YES
No. of observations	1,225	1,225	555
No. of sellers	195	195	116

Note: ***p<0.01, **p<0.05, *p<0.1. In Model (1), inviter and invitee effort/performance are cumulative measures. The estimation results for the province and mobile operator dummies are omitted. In Model (2), inviter and invitee effort/performance, the number of invitees, and the focal seller's effort are log transformed. In Model (3), the sellers with any invitee are excluded.

Third, we consider an alternative model where we log-transform the number of inserts/sales and the commission amounts, as well as the DVs, to account for the skewness of their respective distributions. The results from this robustness check (as shown in Model (2) of Table 8 and Table 9) are consistent with the main results, except for some differences in the coefficients' significance levels.

Finally, to further alleviate the endogeneity concern about $invitee\_num_{i(t-1)}$ and $invitee\_num_{it}$ (i.e., the focal seller might "strategically" choose to focus on earning commissions by inviting more invitees and not to sell products themselves), we estimate Equations (1) and (2) with data about sellers who have no invitees and exert all their effort in selling products themselves. Note that the sample size in this robustness check is significantly smaller than that in the main analysis, and therefore, the significance levels of the coefficients drop. The invitee related variables (including $CFI_{i(t-1)}$) are also removed from the models due to the absence of variation (zero throughout). The results from this robustness check (as shown in Model (3) of Table 8 and Table 9) again confirm the positive effect of inviter effort (i.e., social influence) and the negative effect of inviter performance (i.e., competition).

6. CONCLUSIONS

To our knowledge, this paper provides the first empirical analysis of how the effort and performance of connected sellers (i.e., the inviter and invitees) in an online social network affect the focal seller's effort and performance. We show that the inviter's effort has a positive effect on the focal seller's effort, while the inviter's performance has a negative effect on the focal seller's effort and performance, indicating both social influence and competition in the inviter-to-invitee direction. The coexistence of the positive social influence and negative competition effects suggests an interesting dichotomy – while inviter effort has a positive externality as it increases the focal seller's effort through social influence, it does not necessarily lead to a higher performance by the focal seller because the effect of the increased effort by the focal seller can be offset by competition from the inviter. Additionally, neither invitees' effort nor their performance has a significant effect on the focal seller's effort or performance. These results combined show that social influence and competition among sellers only happen in the "top-down" manner. We also find evidence for the free-riding behavior of sellers: when the focal seller has received more commissions from her invitees' sales, the focal seller will significantly reduce her effort. Our results call for a more complete theory and testing for the mechanisms of interactions among sellers on social media platforms in the IS literature.

The contributions of this research are threefold. First, we contribute to the nascent literature of commercial activities on online social media platforms. Prior studies have examined the purchase and consumption activities of connected buyers or users (e.g., Lamberton & Rose, 2012; Subramanian & Rao, 2016; Sun et al., 2021a; Wu et al., 2015). We extend this literature by studying sellers' effort in selling as well as their performance, which is very important for companies selling in online social networks. We find three forms of interactions among connected sellers in an online social network – social influence, competition, and free riding. We believe these forms of interactions are not unique to the platform we study – social influence and competition are likely to be present among connected sellers in other contexts, and in contexts where the commission structure exists but is different from the context we study, the direction of the effect of commissions may still be similar. Second, social influence among buyers or users has been explored extensively in prior literature (Aral & Walker, 2011; Bapna & Umyarov, 2015; de Matos et al., 2014; Ma et al., 2015; Wang et al., 2013), but social influence among sellers, especially in online social networks, has been an uncharted field. We find evidence for social influence among connected sellers, which can be explained by social learning and a cost-benefit analysis process that considers a different set of factors than those considered by buyers. Third, we focus on a seller network, which has a hierarchical structure. This type of seller network has been adopted extensively by many business giants, such as Amway and Avon. The method we use to explore the different roles of inviters and invitees in affecting the focal seller's behavior could be extended to other business settings in addition to online social networks.

Our work also makes a valuable practical contribution. Our findings highlight the role social influence plays in driving sellers to make an effort in selling. Therefore, to help companies selling products on online social networking platforms succeed, platforms could design creative communication channels or mechanisms to promote social influence among sellers, such as informing them of their connected sellers' recent commercial activities automatically. We provide evidence for competition among connected sellers, which calls for strategies to alleviate competition and promote coordination among sellers. We also find evidence for sellers' free-riding behavior, which has implications for the design of the seller compensation or payment structure (e.g., setting the optimal commission rate).

This study is subject to some limitations that can be explored in future studies. First, as mentioned previously, we do not observe the users who receive the invitation but decide not to register, and therefore, we cannot study users' decision to register as a seller. Hence, we focus on studying sellers' efforts and outcomes. However, with better data availability, it would be interesting to examine users' registration decisions. Second, we do not observe sellers' social network on WeChat and thus cannot study the potential social influence among sellers at the same level of the seller network or explicitly control for the demand variations among sellers due to different numbers of connections on WeChat. To alleviate the latter issue, we include seller fixed effects to account for potential unobserved confounding factors. Future studies can consider exploring the influence of other users in the social network besides that of the inviter/invitees in the seller network. Third, due to data limitations, we are unable to rule out some alternative explanations, such as demand shocks that affect sellers in higher positions in the seller network immediately and have a delayed effect on sellers in lower positions. With more detailed data, one could test more alternative mechanisms. Finally, we only observe sellers' actions of adding new products into their shops. Their effort in advertising and marketing is not observed. Future research can explore the effects of social influence on different types of seller effort if such data are available.

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