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The Relationship Between Online Referral Marketing and Price Promotion: Evidence from a Large E-Commerce Platform

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ABSTRACT

We empirically examine the effectiveness of referral marketing and price promotion in generating sales in a large e-commerce platform. Our results show that although referral marketing increases sales, its effect is attenuated by price promotion. We argue that price promotion arouses quality concerns and undermines the credibility of online paid referrals in a weak-tie environment. This finding implies diminishing marginal returns for referral marketing and price promotion spending. We conduct a battery of validation tests to support our argument. Our research highlights the importance of scrutinizing the complementarity of marketing promotions in the unique context of the Internet. Depending on the persuasiveness of the brand and the promotional channel, promotional strategies may conflict in addressing consumers' quality concerns. Our findings suggest that marketing managers should use discretion in combining online referral marketing and price promotion. We advise sellers against using both marketing tactics if they lack a strong brand image.

Keywords

Referral marketing; Price promotion; Product uncertainty; Quality concern; E-commerce platform; Online marketing

Introduction

The massive connectivity of the Internet has greatly enabled e-commerce exchanges, giving rise to two emerging trends. First, businesses can leverage consumers' online social networks to expand their reach and clientele. In particular, they can better cultivate word-of-mouth (WOM) referrals, which have long been recognized to influence consumers' attitudes and purchase behaviors [7, 12, 21, 44]. Instead of passively waiting for new consumers to visit, firms can proactively use incentives and tracking technologies to motivate people to make referrals [24, 38]. We call this practice of incentivizing consumers to refer their peers to make purchases *referral marketing*.

Referral marketing is commonly deployed on e-commerce platforms. For example, Amazon operates an affiliate program that pays members up to 10% commissions if they successfully refer others to make purchases on its marketplace.[1] eBay operates a similar partner network that pays members commissions up to 70% of eBay's revenue share if they generate sales from their own networks.[2] These referral programs help sellers acquire new

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customers by exploiting participating members' personal networks or influences. Indeed, according to a recent survey, 51% of UK consumers trust recommendations from friends or partners more than brand advertising.[3]

However, online referrals differ from conventional WOM referrals in that the relationships between senders and recipients tend to be weaker. The ease of forming "connections" on the Internet enables weak ties, in which people do not know each other well and thus do not necessarily feel responsible or concerned for others' needs and well-being [26, 49, 51, 54]. This might dampen referrals' effectiveness when consumers face uncertainty in appraising a referred product's quality. Rewarding referrals adds further uncertainty for the recipients. The literature suggests that distinguishing rewarded referrals from organic referrals is crucial. In pursuing the reward, an opportunistic sender may abuse the referral program by recommending unsuitable products [3]. This could weaken the credibility and persuasive effect of referrals. The recipients may value the recommendations less because they suspect the referrals were motivated by a reward instead of product quality [3, 30, 45, 50, 51, 52, 54]. Weak ties and potential doubts regarding senders' motivations could undermine the effectiveness of referral marketing on the Internet, an empirical issue that we examine in this study.

The second emerging trend in e-commerce is the use of dynamic pricing and promotions. Internet retailing often features economies of scale, which lowers sellers' costs and hence provides more room to offer discounts to consumers. The literature suggests that product pricing is an important element in designing a referral program [e.g., 5, 24, 34]. An outstanding empirical question is whether price promotions, or discounts, influence the effectiveness of referral marketing in generating sales.

Answering this question is important because sellers must strategically allocate their budgets to the marketing mix. Theoretically, referral marketing and price promotions could affect sales differently. If a recipient considers a referral a genuine recommendation of a good-quality product [34], a price promotion might strengthen the referral's persuasiveness because the cost savings make the purchase even more attractive in the absence of quality concerns. This is perhaps the common wisdom that justifies combining referral marketing and price promotions.

However, consumers often face product uncertainty because of the temporal and spatial separation of sellers and buyers in online markets [13, 20]. Weak social ties and referral incentives may further weaken the referrals' ability to ease recipients' quality concerns. Ample experimental evidence shows that when consumers face significant product uncertainty, they may adopt a *price–quality heuristic*, using product price as a quality signal [46, 47]. This implies that price promotion could degenerate to a negative quality cue and arouse quality concerns amid Internet referral marketing [8, 11, 17, 37, 29]. Intuitively, when consumers are wary of receiving referrals from acquaintances, adding a discount may increase their suspicion. After all, why would a seller aggressively use multiple marketing tactics that erode its profit to persuade consumers if the product is good?

Accordingly, price promotion and referral marketing can either complement each other in persuading a consumer to buy a product or reinforce the quality concern when the consumer is skeptical about the quality of a product recommended by a weak tie. The net interaction effect between price promotion and referral marketing is an empirical question. We empirically study the effects on sales of referral marketing and its interaction with price promotions in the setting of Alibaba Group's Taobao (http://www.taobao.com), the world's

largest online trading and e-commerce platform. We construct a panel data set at the seller-month unit for all sellers of baby care products. We then assess how referral marketing and price promotions affect sales using a seller-level fixed-effects model and the generalized method of moments (GMM) estimator [1].

We find positive effects of referral marketing and price promotions on sales, but their interaction effect is negative, i.e., their contributions to sales are attenuated when they are deployed together. In light of the foregoing theoretical discussion, one explanation is that price promotions may elicit quality concerns regarding products referred by acquaintances on Taobao. Although referral marketing informs more consumers about a product, adding a price promotion may weaken the persuasive effect because of product uncertainty.

We provide empirical evidence that supports this explanation. First, we show that the negative interaction effect between referral marketing and price promotions is more salient for strollers, a relatively expensive durable item, than for diapers, a relatively inexpensive consumable product. As strollers are often used for at least a few years and cost considerably more, consumers are probably more concerned about a stroller's quality than about diapers' quality. A price promotion on top of a paid referral may aggravate such quality concerns.

Second, we find the negative interaction effect between referral marketing and price promotions is stronger for less reputed sellers than for more reputed sellers, meaning that reputation mitigates the attenuation of referral marketing by price promotions. Seller reputation is a notable factor in consumers' deliberation of product quality.

Last, as a falsification test, we examine the interaction effect between referral marketing and a quantity-based promotional strategy in which the discount is tied to the number of units purchased. Quantity-based discounts should arouse less quality concern because, by selling in bulk, the sellers can earn more surplus, which is a sound basis for them to transfer the savings to consumers. The signal such promotions carry should be different from that of dumping products at a cheap price via the discount strategy. Indeed, we find that quantity-based discounts do not attenuate the positive impact of referral marketing on sales.

Taken together, these results point to a converging conclusion: price promotions attenuate the effect of referral marketing on sales because they elicit more quality concerns from consumers when used together. Our back-of-the-envelope calculation indicates that an average seller would attract eight more transactions in a month by doubling its referral marketing expenditure from the conditional sample mean of CNY53 (about USD8)[4] and not offering a simultaneous discount. The increment would be only three transactions if the seller offered a discount. Our findings imply there are diminishing returns when referral marketing and price promotions are combined in the presence of quality concern, meaning Internet sellers should plan the marketing mix holistically. One plus one may equal less than two in Internet marketing.

Related Literature

Previous research has theoretically analyzed the optimal design of a referral program under various market conditions. Biyalogorsky et al. [5] compare the trade-offs between lowering product price and offering rewards to motivate customers to make referrals. They derive the optimal mix of product price and referral fee to obtain the most profitable referrals. The key factor they consider is how likely existing customers are to obtain a positive surplus from the purchases and thus be delighted to refer new

customers. Kornish and Li [34] study the optimal mix of product price and referral rewards. They regard referrals as not only spreading awareness but also providing a signal about a product's value to recipients. This signal is affected by the extent to which the sender cares about the recipient's satisfaction from the recommendation. Xiao et al. [57] characterize the conditions in which it is optimal for a firm to reward the sender only, reward the recipient only, or reward both in a referral program. Guo [24] investigates the optimal product price and referral reward under different linear and nonlinear demand schedules. Lobel et al. [38] analyze the optimal referral payment as a function of the number of successful referrals when a firm wants to use a referral program to maximize its benefits in terms of extracting immediate revenues or advertising to potential consumers.

These theoretical studies focus on the optimal mix of referral rewards and product price from the sellers' and referral senders' perspectives. The motivation is often to generate referrals or maximize the referral programs' profitability. This strand of the literature mostly assumes that referrals and pricing affect referral recipients' utilities independently. This assumption warrants empirical scrutiny, a task we undertake in this study.

In the empirical domain, various studies find positive effects of referral programs on consumer purchases. Schmitt et al. [50] and Van Den Bulte et al. [53] show that bank customers obtained via referral programs have higher contribution margins and lower churn rates than non-referred customers, possibly because of better matching and enriched relationships between the referred customers and the bank. Garnefeld et al. [18] find that customers participating in referral programs are more loyal because they have enhanced commitments to the firm. Hong et al. [26] assess how the fairness of splitting referral rewards and the social distance between senders and recipients affect the probability of sending and accepting referrals.

In these studies, the referral recipients often have strong ties with the senders by, for example, being family members or close friends. Our research expands the literature by investigating the effect of referral marketing in an e-commerce setting in which weak ties are prevalent between consumers.

Prior experimental research has investigated whether monetary rewards increase senders' referral likelihood and how tie and/or brand strength moderate the effectiveness of incentives in increasing referral likelihood [49, 55]. Jin and Huang [30] compare the effects of monetary versus in-kind rewards on referral generation and acceptance likelihood, and they examine how their differential effects are moderated by brand strength. Focusing on referral acceptance, Tuk et al. [52] show that the presence of a financial incentive may harm the perceived sincerity of referral senders and thus negatively affect acceptance of the referral. Sciandra [51] and Verlegh et al. [54] examine how referral rewards and tie strength jointly affect recipients' responses to a referral.

Our study empirically addresses how price promotions influence the effectiveness of referral marketing on the Internet, a question not well addressed in the literature. Answering this question is important because it can inform the design of referral programs and help sellers improve their marketing mix decisions in e-commerce.

Setting and Data

Background

Online marketplaces and platforms such as eBay, Taobao, Craigslist, and Etsy, which enable interaction and transactions between users through auctions, classified advertisements, forums, and product pages, have been among the fastest-growing domains in e-commerce.[5] One salient feature of these platforms is their low entry costs, which give rise to a tremendous scale of participants. This study focuses on Taobao.com, a large e-commerce platform with nearly 500 million registered users and an average of 60 million visitors per day.[6] Its gross merchandise volume in fiscal year 2018 was approximately CNY2.7 trillion (about USD402 billion).[7]

One feature that is particularly relevant to our research is that knockoffs or fake products are prominent on Taobao, including during our 2011–2013 sample period.[8] This is common knowledge among Taobao users, meaning that product quality concerns are pervasive on the platform.

Taobao runs a referral program via a separate network called Taobaoke, a channel within Taobao's integrated promotional platform Taobao Alliance, http://pub.alimama.com. Taobaoke is an intermediary platform connecting Taobao sellers with agents who are willing to recommend the sellers' products to other consumers. Sellers post their referral programs with details about the products and commission rates on the platform. Registered users can participate in the programs that they find attractive. They then promote and recommend the sellers' products to potential buyers. For example, they can embed the sellers' product links in their websites or blogs or mention the sellers' products in online discussion forums or social media.

Taobaoke uses technologies such as tracking URLs and cookies to trace the sources of purchases. Once a purchase is made, the corresponding referral sender is rewarded with the predetermined referral bonus. The platform settles all payments from sellers to referral senders and takes a fraction of each payment as a service fee. Figure 1 presents Taobaoke's description on the Taobao Alliance platform.[9]

Note that Taobaoke's referral program differs from traditional referral programs in two ways. First, participants need not be existing customers of the sellers. This differs from the studies in which referral programs mostly encourage existing customers to make referrals. Second, Taobaoke referral senders can use mass media, such as self-developed websites or

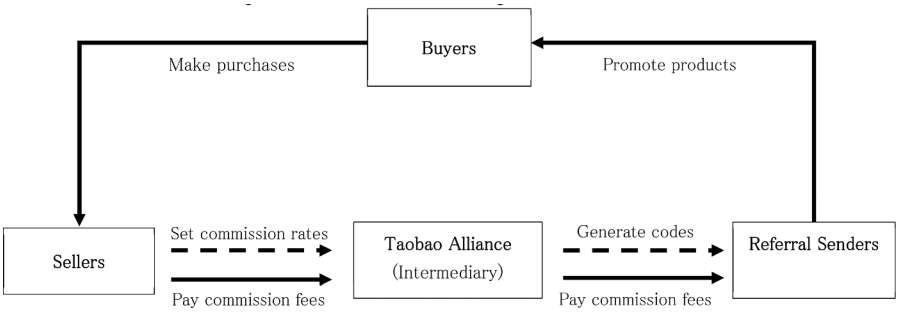


Figure 1. The Taobaoke Referral Program

blogs, or social media to promote products instead of being restricted to targeted one-to-one communications. The possibility of mass promotion makes Taobaoke somewhat similar to affiliate marketing [25].

Nevertheless, we consider Taobaoke a referral program because it mostly focuses on individuals, making interpersonal relationships salient. This is consistent with the studies on referral marketing or customer referral programs that focus on interpersonal influences and relationships between referral senders and recipients [see, e.g., 34, 49, 50, 53]. Furthermore, although referral marketing and affiliate marketing are closely related, the literature on affiliate marketing predominately treats affiliate programs as partnerships and contracts between sellers instead of interpersonal relationships between customers [see, e.g., 15, 16]. Such interpersonal relationships underscore the referral marketing examined in this study.

Data

We obtain a data set that includes all of the sellers in the baby care category from Taobao.com with a comprehensive list of seller attributes, which are all used in our subsequent analysis (more details about these attributes follow). Each seller may sell products in various subcategories, such as diaper, stroller, shampoo, bath liquid or soap, and baby wipes. A seller usually sells in several related subcategories. The data set spans November 20, 2011 to May 26, 2013, and contains information on the sellers' sales volumes (i.e., number of completed transactions), expenditures on referral programs via Taobaoke, and a dummy variable indicating whether they offered discounts monthly or on a four-week basis.[10] Note that we do not observe the actual discount levels in our data set.

Besides these key variables, the data set also includes a list of seller attributes on a monthly basis, including the average price of all items offered, expenditure on sponsored search advertising in the platform's search engine, and the platform-awarded score for overall quality and trustworthiness. Table 1 provides the detailed variable descriptions. The focal independent variables are seller expenditure on referral marketing (*Ref_mkgt*) and a dummy variable indicating whether a seller offered price promotions in terms of giving a certain percentage discount off the original transaction amount (*Pr_disc*).

We exclude sellers with less than three observation periods, i.e., 12 weeks, to focus on regular and serious sellers.[11] Our sample comprises 8,674 sellers with 114,242 observations. The panel is unbalanced because of sellers' entry and exit. At the seller-month unit, 33.9% and 14.9% of the sellers used referral marketing and price promotion, respectively, and 8.3% used both at the same time. There is substantial variation in the use of referral marketing and price promotion. Table 2 presents the summary statistics.[12]

Model-free Evidence

Figure 2 presents a scatter plot of logged sales, in terms of the number of completed transactions, against logged referral program spending. It shows a clear positive correlation between referral marketing spending and sales. To inspect the relation between discounts and sales, we compare the mean logged sales with and without discounts in Figure 3. Sales

Table 1. Variable Definitions

Variable	Definition and Measurement
Dependent Variable	
$Sales_{it}$	The number of transactions seller *i* attracts in period *t*
Independent Variables	
Ref_mkgt_{it}	Seller *i*'s expenditure on the referral program, Taobaoke, in period *t*
Pr_disc_{it}	Whether seller *i* offers discounts in period *t*
Avg_pr_{it}	The average price of all items seller *i* offers at the end of period *t*
$Search\_adv_{it}$	Seller *i*'s expenditure on search advertising on the platform's product search engine in period *t*
Qty_disc_{it}	Whether seller *i* offers quantity-based discounts, i.e., consumers enjoy discounts if the purchase exceeds a threshold quantity pre-specified by the seller in period *t*
$Flash\_deal_{it}$	Whether seller *i* participates in the platform's flash-deal promotion campaign in a dedicated channel, wherein a seller offers extremely deep discounts and the transaction price almost approaches zero
$Free\_shipping_{it}$	Whether seller *i* offers free shipping on orders exceeding a threshold amount in period *t*
$Fake\_comp_{it}$	Whether seller *i* promises compensation if fake products are detected at the end of period *t*
$Deliv\_ins_{it}$	Whether seller *i* provides insurance for product delivery at the end of period *t*
Sec_dep_{it}	Whether seller *i* makes a security deposit to the platform at the end of period *t*
$Free\_return_{it}$	Whether seller *i* grants free return on items within 7 days of purchase at the end of period *t*
$Spdy\_deliv_{it}$	Whether seller *i* offers speedy delivery at the end of period *t*
$Warranty_{it}$	Whether seller *i* offers a 30-day warranty at the end of period *t*
$Shop\_desg_{it}$	Whether seller *i* uses the add-on service from the platform to better design its shopping pages at the end of period *t*
Pay_on_deliv	Whether seller *i* allows consumers to pay at the time of product delivery at the end of period *t*
$Seller\_score_{it}$	seller *i*'s score, on a scale of 0 to 100, awarded by the platform at the end of period *t*
Rev_cnt_{it}	The number of reviews seller *i* received from buyers at the end of period *t* (Buyers can give either a positive or negative review of the product(s) they purchased.)
Pct_pos_rev	The percentage of positive reviews among all reviews seller *i* received from buyers at the end of period *t*
Pict_cnt	The number of pictures seller *i* used in its product description at the end of period *t*
Age	The number of days since seller *i* joined the platform until the end of period *t*

Table 2. Summary Statistics

Variable	N	Mean	Std Dev	Min	Max
ln(*Sales*)	114,242	4.760	2.125	0	12.773
ln(*Ref_mkgt*)	114,242	1.354	2.140	0	10.947
Pr_disc	114,242	0.149	0.356	0	1
ln(*Avg_pr*)	114,242	4.282	0.961	0	8.848
ln(*Search_adv*)	114,242	2.161	3.093	0	12.164
Qty_disc	114,242	0.031	0.174	0	1
Flash_deal	114,242	0.042	0.201	0	1
Free_shipping	114,242	0.055	0.227	0	1
Fake_comp	114,242	0.008	0.090	0	1
Deliv_ins	114,242	0.035	0.185	0	1
Sec_dep	114,242	0.904	0.294	0	1
Free_return	114,242	0.561	0.496	0	1
Spdy_deliv	114,242	0.001	0.025	0	1
Warranty	114,242	0.002	0.045	0	1
Shop_desg	114,242	0.864	0.343	0	1
Pay_on_deliv	114,242	0.044	0.206	0	1
ln(*Seller_score*)	114,242	4.319	0.086	3.850	4.465
ln(*Rev_cnt*)	114,242	7.509	2.270	0	15.941
Pct_pos_rev	114,242	0.982	0.112	0	1
ln(*Pict_cnt*)	114,242	1.128	1.238	0	5.303
ln(*Age*)	114,242	6.580	0.987	0	8.201

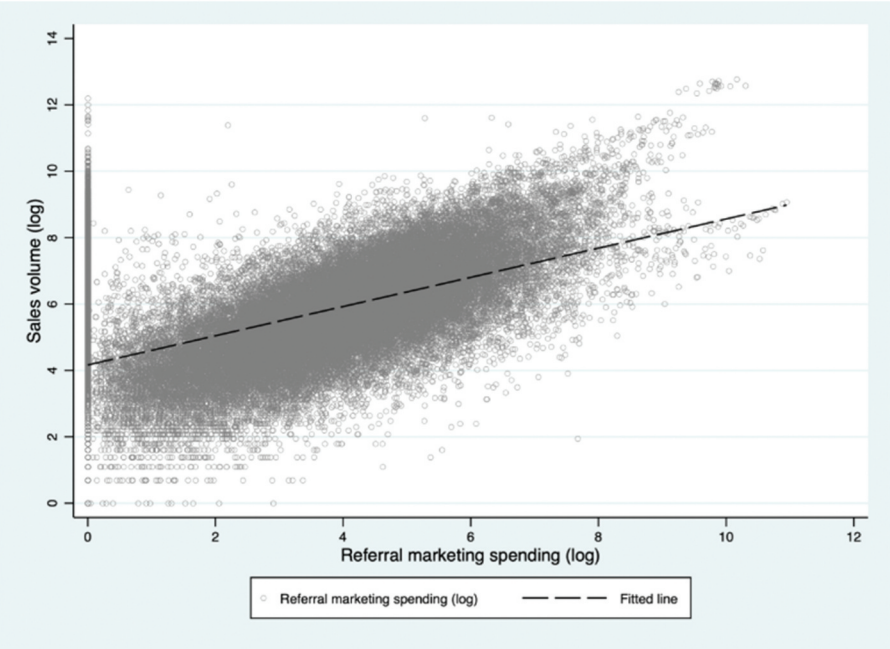


Figure 2. Sales and Referral Marketing

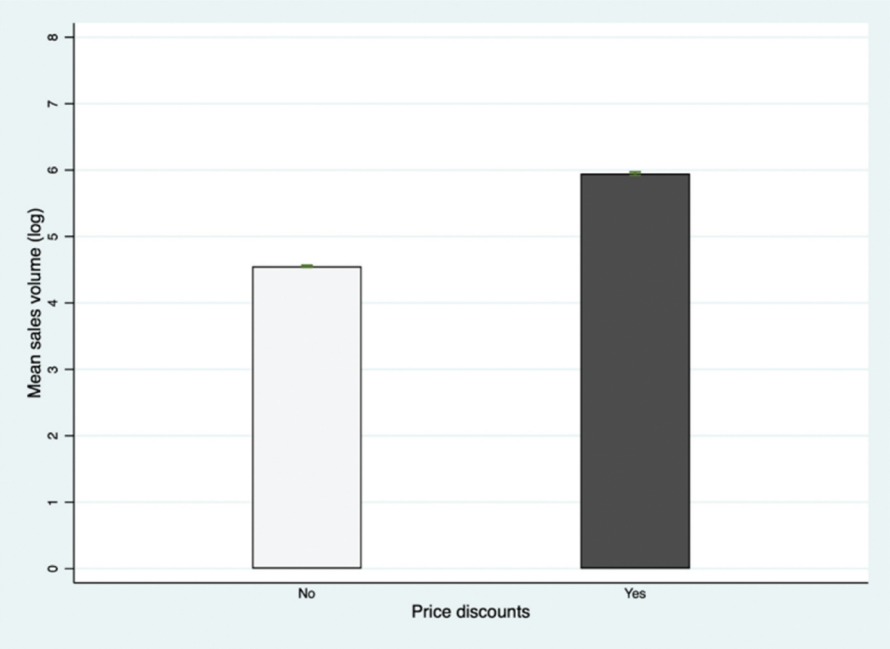


Figure 3. Sales with and without Discounts

are greater when discounts are offered, suggesting that price promotions and sales are positively correlated. A t-test confirms that the differences are statistically significant (t = 98.62, $p < 0.01$).

We next consider the interaction effect of referral marketing and price promotion on sales. Figure 4(a) presents two scatter plots similar to that in Figure 2: one shows observations when sellers offered discounts and the other when they did not. As shown in the fitted trends, the positive correlation between referral marketing and sales is smaller with discounts. Figure 4(b) shows the differences in sales due to discounts under different levels of referral marketing spending. Level 0 indicates the observations in which the sellers did not use referral marketing. The other four levels correspond to four quartiles of sellers in the truncated distribution of referral marketing spending (conditional on the spending being positive). The use of discounts produced the largest difference in sales when the sellers did not use referral marketing, i.e., when referral marketing spending was zero.

Taken together, the findings shown in Figure 4 point to a negative interaction effect between referral marketing and price promotion on sales, a surprising finding that has not been documented in the literature. We next turn to regression analysis and control for a wide range of seller attributes, other promotional activities, and unobserved influences.

Empirical Model and Results

We use a seller fixed-effects model in the following form:

$$y_{it} = \alpha y_{i,t-1} + \beta X_{it} + \delta_i + \tau_t + \varepsilon_{it}, (1)$$

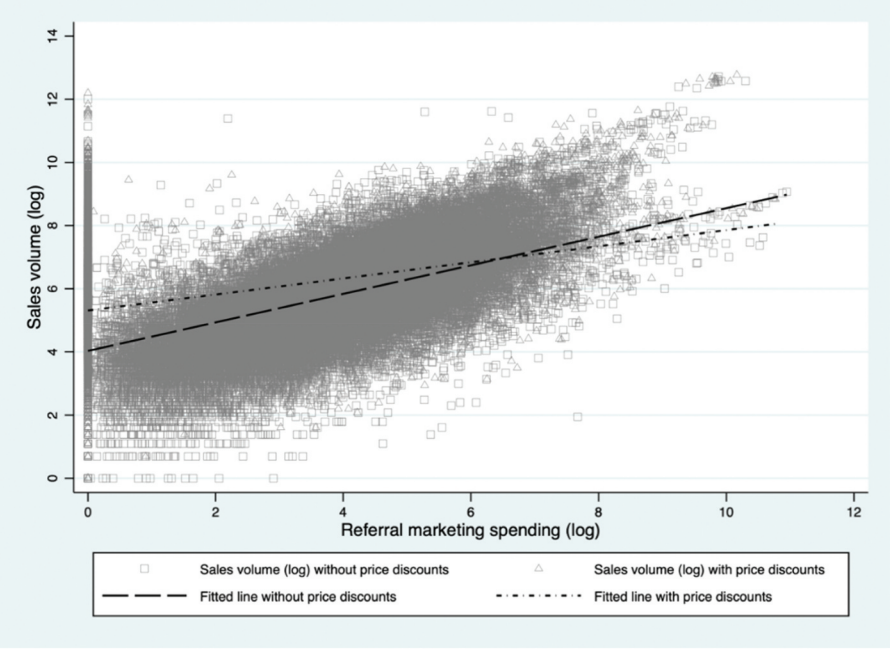
where y_{it} is seller i's logged sales in terms of the number of completed transactions in period t and X_{it} is a set of time-varying regressors as described in Table 1. Important to our research focus, X_{it} includes the interaction term between referral marketing and discount. δ_i captures seller fixed effects (FE), which help control for time-invariant seller heterogeneity. τ_t captures time FE, which help control for seasonality (e.g., sales usually soar during holiday seasons). ε_{it} captures idiosyncratic random errors. We specify all of the continuous variables in logarithm because the distributions of some of the variables are heavily skewed [56]. The inclusion of seller FE ensures that the focal interaction effect of interest is identified by within-seller temporal variations in the two promotional tactics.

We also include lagged sales as an additional regressor because Taobao displays the previous month's sales on each seller's web page. This information could induce observational learning, as prospective consumers may infer a seller's quality from previous sales [4, 9]. However, estimating FE models with a lagged dependent variable introduces bias. The lagged dependent variable is correlated with the FE, giving rise to dynamic panel bias [41]. We address this bias by applying the GMM estimation proposed by Arellano and Bond [1]. GMM estimation also addresses the endogeneity of referral marketing and discounts: the sellers might have deployed and adjusted their use of these promotions depending on expected sales.

Specifically, applying first differences to Equation (1) to eliminate the seller FE produces the following:

$$y_{it} - y_{i,t-1} = \alpha\left(y_{i,t-1} - y_{i,t-2}\right) + \beta\left(X_{it} - X_{i,t-1}\right) + \left(\tau_t - \tau_{t-1}\right) + \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right). (2)$$

(a)



(b)

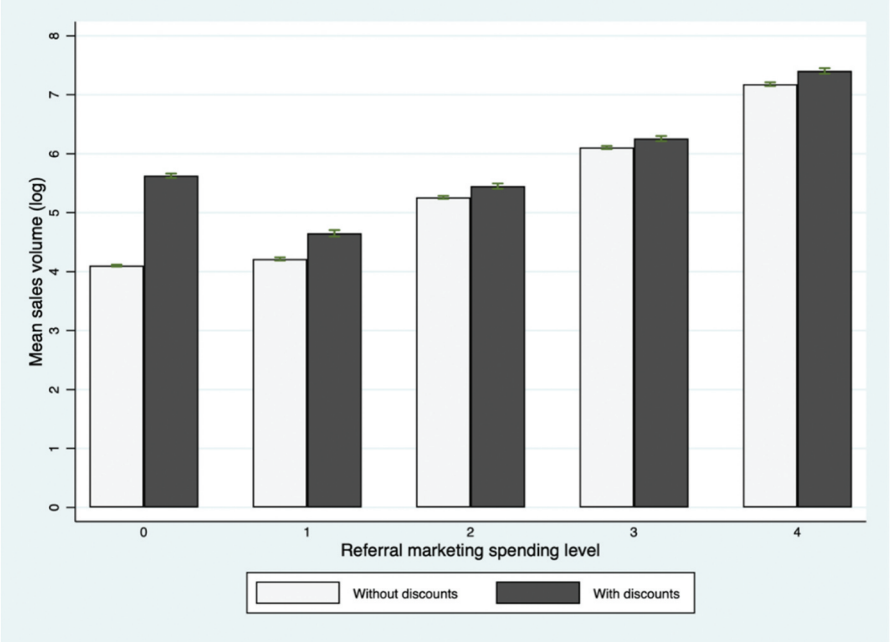


Figure 4. Joint Effect of Referral Marketing and Discounts on Sales

The identifying assumption for Arellano and Bond's [1] GMM estimation is that there is no serial correlation between the errors in Equation (2). As shown below, this assumption is satisfied in our context. The values of y_{it} lagged two periods or more can serve as instruments in the equations of first differences to obtain a consistent estimate of α. We also construct valid instruments for the other endogenous regressors in X_{it} in a similar fashion.

In the main GMM estimations, we treat the focal independent variables—referral marketing and discount—and the interaction terms involving either of them as endogenous. Furthermore, it is customary to consider price endogenous because it is subject to simultaneity bias. We thus treat the seller's average price as endogenous and instrument for it according to the GMM style.[13] For all of the reported estimates, we cluster the standard errors by sellers to account for any demand correlations for the same sellers over time.

The GMM estimation requires at least three observations per seller: two periods for the first-difference transformation in Equation (2) and at least one extra period for constructing the instruments. As we focus on sellers with at least three consecutive periods of observations, this requirement is satisfied.

Results

We start by estimating the seller FE model specified in Equation (1) using ordinary least squares regressions and omitting the interaction between referral marketing and discount. As reported in column (1) of Table 3, the estimates are largely consistent with our *a priori* expectation. Lagged sales are positively correlated with current-period sales, which is consistent with the presence of observational learning or other social influences [4, 9]. The average price of all items listed in a seller's shop is negatively correlated with sales. Consistent with prior findings [see, e.g.,14, 40], search advertising positively contributes to sales. Other promotional tactics such as flash deals and free shipping also increase sales. In general, consumers should have more confidence in sellers that provide security deposits to the platform, use the add-on service offered by the platform to better design the layout and configuration of their web pages, have a more favorable score from the platform, have more reviews (especially positive reviews) from previous buyers, use more pictures to display their items, and have longer tenure on the platform. Indeed, the variables corresponding to these features are significantly and positively correlated with sales.

An unexpected result is that offering "free" returns is negatively correlated with sales because a return is never free, as it requires significant time and cost. Consumers may perceive such an offer to be a tactic by low-quality sellers to entice purchases yet preempt bad reviews from dissatisfied buyers. None of the other attributes significantly affect sales.

Regarding the focal variables, the estimates indicate that referral marketing positively and significantly affects sales. Consistent with advertising theories, this may be driven by two effects: informative and persuasive [2, 35, 36].[14] First, the referral program increases sellers' exposure to a larger pool of consumers, some of whom might be converted to buyers because of decreased search costs (i.e., the informative effect). Second, participants in referral programs not only help increase awareness but also ease product uncertainty. Prospective consumers may view a recommendation as a positive signal about the value of the product (i.e., the persuasive effect) [34]. Nevertheless, as discussed, the persuasive

Table 3. Effects of Referral Marketing and Discounts on Sales

Variable	(1)	(2)	(3)	(4)
	FE	FE	GMM	GMM
Lag_sales	0.426***	0.426***	0.530***	0.527***
	(0.006)	(0.006)	(0.010)	(0.010)
Ref_mkgt	0.119***	0.126***	0.036***	0.073***
	(0.004)	(0.004)	(0.010)	(0.011)
Pr_disc	0.132***	0.156***	0.068***	0.108***
	(0.009)	(0.010)	(0.025)	(0.026)
*Ref_mkgt * Pr_disc*	–	-0.026***	–	-0.045***
		(0.003)		(0.009)
Avg_pr	-0.043***	-0.044***	-0.065	-0.098*
	(0.014)	(0.014)	(0.059)	(0.058)
Search_adv	0.074***	0.074***	0.075***	0.074***
	(0.002)	(0.002)	(0.003)	(0.003)
Qty_disc	0.037*	0.037*	0.039	0.040
	(0.020)	(0.020)	(0.026)	(0.026)
Flash_deal	0.235***	0.235***	0.253***	0.249***
	(0.018)	(0.018)	(0.024)	(0.024)
Free_shipping	0.093***	0.092***	0.088***	0.084***
	(0.020)	(0.020)	(0.029)	(0.029)
Fake_comp	-0.091	-0.103	0.103	0.085
	(0.141)	(0.139)	(0.143)	(0.138)
Deliv_ins	-0.002	-0.003	-0.047	-0.046
	(0.029)	(0.029)	(0.039)	(0.038)
Sec_dep	0.283***	0.281***	0.255***	0.251***
	(0.030)	(0.030)	(0.046)	(0.046)
Free_return	-0.131***	-0.131***	-0.084***	-0.087***
	(0.017)	(0.017)	(0.023)	(0.023)
Spdy_deliv	0.137	0.118	-0.454	-0.515
	(0.312)	(0.301)	(0.479)	(0.454)
Warranty	-0.172	-0.175	0.007	-0.026
	(0.201)	(0.199)	(0.149)	(0.143)
Shop_desg	0.347***	0.344***	0.229***	0.223***
	(0.014)	(0.014)	(0.018)	(0.018)
Pay_on_deliv	0.002	0.002	0.023	0.018
	(0.026)	(0.026)	(0.036)	(0.035)
Seller_score	4.624***	4.616***	4.996***	4.982***
	(0.072)	(0.072)	(0.085)	(0.084)
Rev_cnt	0.165***	0.165***	0.032	0.028
	(0.011)	(0.011)	(0.022)	(0.022)
Pct_pos_rev	0.245***	0.246***	1.317***	1.326***
	(0.064)	(0.064)	(0.112)	(0.112)
Pict_cnt	0.028***	0.029***	0.025***	0.024***
	(0.005)	(0.005)	(0.008)	(0.008)
Age	0.346***	0.351***	1.391***	1.396***
	(0.065)	(0.065)	(0.137)	(0.136)
Age_sq	0.234***	0.235***	0.502***	0.502***
	(0.017)	(0.017)	(0.032)	(0.032)
Constant	-19.032***	-18.985***	-20.860***	-20.596***
	(0.300)	(0.300)	(0.454)	(0.448)
Seller fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	105,568	105,568	96,894	96,894
Sellers	8,674	8,674	8,674	8,674
Arellano–Bond test for AR(2) in error differences (*p*-value)	–	–	0.94	0.92

Note. Robust standard errors clustered by seller are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

effect of referral marketing may be weak and fragile in our setting because of the use of financial incentives and the weak-tie relationships between the referral senders and recipients.

The effect of price promotion on sales is also positive and statistically significant. Discounting generally has the opposite effect. On one hand, it reduces consumers' costs and thus increases their utility of buying the products. On the other hand, because price may signal product quality, discounts might be viewed as a negative quality signal and thus discourage purchases [8, 11, 17, 29, 37]. The net effect of price promotion on sales is an empirical question. The positive effect of discounting here indicates that on average, Taobao consumers value the cost-saving aspect of discounting despite the potentially heightened quality concern.

Of particular importance to our research goal is the interaction effect between referral marketing and price promotion. We next add the interaction term of referral marketing and price promotion to Equation (1).[15] As reported in column (2) of Table 3, the interaction effect between referral marketing and price promotion on sales is negative and statistically significant (-0.026, $p < 0.01$). This finding is consistent with the trends shown in the model-free graphs.

As discussed, one potential concern regarding the estimates from the FE model is that the lagged dependent variable and our focal marketing variables might be correlated with contemporaneous errors (i.e., endogeneity). Columns (3) and (4) of Table 3 replicate the specifications of columns (1) and (2) of Table 3, respectively, using the GMM estimation. Most of the estimates are similar. Importantly, the GMM estimates consistently suggest that both referral marketing and price promotion positively affect sales, but their interaction effect is negative and statistically significant (-0.045, $p < 0.01$).

The GMM estimator may not give consistent estimates if the error terms are serially correlated. One common check is to conduct the Arellano–Bond test for second-order serial correlations [1]. The presence of significant second-order serial correlations in the first-differenced errors suggests that the identifying assumption of the GMM estimator is violated. The p-values from the Arellano–Bond test are reported in the last row of Table 3 for the GMM estimates. The second-order serial correlations are not statistically significant.[16]

According to the GMM estimates reported in column (3) of Table 3, a 1% increase in a seller's referral marketing expenditure leads to a 0.036% increase in sales. Offering discounts increases sales by $(e^{0.068} - 1) \times 100\% = 7\%$ compared with not offering discounts. In the focal interaction effect, the GMM estimates reported in column (4) of Table 3 indicate that when no discount is offered, a 1% increase in a seller's referral marketing expenditure leads to a 0.073% increase in sales volumes. However, when a discount is offered, a 1% increase in a seller's referral marketing expenditure leads to only a 0.028% increase in sales. The effect is considerably smaller when a discount is offered.

Using the sample mean for a back-of-the-envelope calculation, the estimates suggest that if an average seller doubles its referral marketing spending from the conditional sample mean of CNY53 and does not offer a discount, it can secure an average of $116 \times 7.3\% = 8$ more purchases in a month. If, however, it increases its referral marketing spending by the same amount and offers a discount, it can only secure an average of $116 \times 2.8\% = 3$ more purchases.[17]

To illustrate how the effect of discounting on sales depends on the intensity of referral marketing, we use one standard deviation below (above) the mean to represent the low (high) value of referral marketing expenditure and compare the average differences in sales with and without discounts as predicted by the preferred estimates in columns (3) and (4) of Table 3. When referral marketing spending is low, the effect of discounting on sales is positive and significant (0.204, $p < 0.01$), which implies that discounting increases sales by $(e^{0.204} - 1) \times 100\% = 22.6\%$. Using the sample mean for another back-of-the-envelope calculation, this implies that an average seller would attract $116 \times 22.6\% = 26$ additional transactions. When referral marketing spending is high, the effect of discounting on sales remains positive but is much smaller and becomes statistically insignificant (0.012, $p = 0.62$).

Note that combining referral marketing and a discount could still lead to higher sales than when either is used alone. As shown in Figure 4(b), for each level of referral marketing spending, offering a discount generates some additional sales. Moreover, when referral marketing spending is sufficiently high, offering a discount in addition yields more sales than when only a discount is offered. This negative interaction effect suggests that there are diminishing returns for referral marketing with price promotion. The return on investment is lower (although still positive) when the two promotions are used together.

Propensity Score Matching

One challenge in our empirical analysis is that referral marketing and price promotions are strategically selected by sellers striving to maximize their profits. Our estimates of their effects could be biased by self-selection: sellers with higher sales may tend to conduct marketing promotions. Although such self-selection could lead to the positive correlations between sales and referral marketing and price promotions, it is unclear how it contributes to discounting's attenuation of referral marketing's impact on sales.

Econometrically, the GMM estimator should address selection bias because it uses lagged variables as instruments. Another way to address such selection bias is to use propensity score matching (PSM) to identify a sample of "treated" and "control" sellers with similar propensities.

We must accommodate several peculiar features of our data to implement the PSM method. First, referral marketing expenditure is a continuous rather than categorical variable. Following Goh et al. [22], we create a dummy variable that indicates whether a seller used referral marketing in each period and use it in place of the original variable in the PSM.[18] Second, PSM is usually applied to cross-sectional data. We create a cross-sectional view of our data by averaging each seller's attributes over time. The referral marketing (price promotion) dummy variable equals one if a seller participated in referral marketing (price promotion) in at least one period.

As we have two treatment variables, referral marketing and price promotion, we perform PSM separately using each treatment variable and then conduct regression analysis on the two matched subsamples. We use one-to-one nearest neighbor matching without replacement and an appropriate caliper to balance all of the covariates between the treated and control groups. We construct 1,884 pairs of matched sellers according to the treatment dummy for referral marketing and 1,932 pairs of matched sellers according to the treatment

dummy for price promotion. We report the details of the PSM procedure in the Online Appendix. We repeat the estimations in Table 3 using the two matched samples to separately assess the robustness of the effects of referral marketing and price promotion, and their interaction, on sales.

Table 4 reports the estimation results for the sellers matched by the propensity to use referral marketing. The FE estimates remain similar to those for the full sample. Importantly, the interaction effect between referral marketing and discounting is statistically significant and negative (-0.021, $p < 0.05$). The GMM estimates differ slightly: discount still positively affects sales, but the effect is statistically insignificant. Meanwhile, the interaction effect between referral marketing and discounting remains negative and statistically significant at the 10% level (-0.036, $p < 0.10$).

Table 5 reports similar estimations for the sellers matched by the propensity to use price promotion. Both the FE and GMM estimates are similar to the estimates reported in Table 3 for the full sample. Importantly, the interaction effect between referral marketing and discounting is negative and statistically significant in both the FE (-0.021, $p < 0.01$) and GMM (-0.047, $p < 0.01$) estimations.

To summarize, the estimation results using the PSM samples are consistent with those reported in Table 3 in terms of the direction of the focal interaction effect between referral marketing and discounting. This lends more support to the idea that price promotion's attenuation of referral marketing's effect on sales is not driven by seller self-selection.

The Underlying Mechanism

We find a robust attenuation effect between referral marketing and price promotion even though their individual main effects on sales are positive. What causes such a negative interaction effect? One possibility is that exposure to multiple marketing promotions may trigger quality concerns. This is especially relevant as our research setting—Internet retailing on Taobao—entails substantial quality uncertainty.[19]

In the Taobao setting, referral marketing can happen between weak ties with financial incentives. Although such referral marketing might increase sales via informative advertising by enhancing consumer awareness of the promoted products, it may be less persuasive, as people might see the referral as extrinsically motivated. With the proliferation of persuasive communication platforms such as social media, microblogging, and instant messaging, it has become increasingly common for opportunistic users to abuse online referral programs by extensively and indiscriminately recommending products to earn more referral fees [3]. Such extrinsic motivation may cause referral recipients to doubt the credibility of referrals because the incentives might dilute their value as unambiguous positive recommendations of product quality [3, 30, 50, 51, 52, 54].

Moreover, the weak ties between referral senders and recipients, as is often the case in online referral programs, can put another dent in paid referrals' credibility. People connected by weak ties may not feel responsible for others' needs and well-being [49, 51, 51]. A referral from a weak tie may be less likely to dispel the potential product uncertainty or risks faced by the recipient. Also, people in weak-tie relationships generally prefer equitable exchanges. If referral senders get all of the monetary rewards

Table 4. Sample Matched by Use of Referring Marketing

	(1)	(2)	(3)	(4)
Variable	FE	FE	GMM	GMM
Lag_sales	0.403***	0.403***	0.508***	0.505***
	(0.009)	(0.009)	(0.016)	(0.015)
Ref_mkgt	0.140***	0.143***	0.091***	0.113***
	(0.008)	(0.008)	(0.022)	(0.021)
Pr_disc	0.168***	0.174***	0.033	0.054
	(0.018)	(0.019)	(0.047)	(0.047)
*Ref_mkgt * Pr_disc*	–	-0.021**	–	-0.036*
		(0.010)		(0.022)
Avg_pr	-0.018	-0.018	0.058	0.027
	(0.019)	(0.019)	(0.082)	(0.077)
Search_adv	0.077***	0.077***	0.075***	0.075***
	(0.004)	(0.004)	(0.006)	(0.005)
Qty_disc	0.029	0.029	-0.040	-0.040
	(0.050)	(0.050)	(0.063)	(0.063)
Flash_deal	0.272***	0.272***	0.238***	0.237***
	(0.032)	(0.032)	(0.044)	(0.044)
Free_shipping	0.060	0.060	0.093	0.098
	(0.047)	(0.046)	(0.072)	(0.071)
Fake_comp	0.703	0.700	0.832	0.800
	(0.529)	(0.526)	(0.539)	(0.514)
Deliv_ins	0.096*	0.095*	0.021	0.041
	(0.052)	(0.052)	(0.066)	(0.066)
Sec_dep	0.204***	0.204***	0.269***	0.266***
	(0.043)	(0.043)	(0.063)	(0.063)
Free_return	-0.121***	-0.121***	-0.126***	-0.125***
	(0.025)	(0.025)	(0.034)	(0.034)
Spdy_deliv	-1.349***	-1.348***	-1.703***	-1.701***
	(0.031)	(0.031)	(0.036)	(0.036)
Warranty	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Shop_desg	0.376***	0.376***	0.248***	0.246***
	(0.021)	(0.021)	(0.025)	(0.025)
Pay_on_deliv	0.039	0.039	0.103	0.097
	(0.074)	(0.075)	(0.094)	(0.094)
Seller_score	5.033***	5.032***	5.303***	5.290***
	(0.109)	(0.109)	(0.126)	(0.125)
Rev_cnt	0.212***	0.212***	0.075**	0.074**
	(0.018)	(0.018)	(0.031)	(0.031)
Pct_pos_rev	0.051	0.051	1.287***	1.289***
	(0.096)	(0.096)	(0.145)	(0.145)
Pict_cnt	0.032***	0.032***	0.025*	0.024*
	(0.009)	(0.009)	(0.014)	(0.014)
Age	0.401***	0.400***	1.492***	1.478***
	(0.101)	(0.101)	(0.203)	(0.201)
Age_sq	0.260***	0.259***	0.544***	0.540***
	(0.026)	(0.026)	(0.047)	(0.047)
Constant	-20.912***	-20.907***	-22.894***	-22.682***
	(0.450)	(0.450)	(0.641)	(0.629)
Seller fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	43,944	43,944	40,176	40,176
Sellers	3,768	3,768	3,768	3,768
Arellano–Bond test for AR(2) in error differences (*p*-value)	–	–	0.60	0.63

Notes: Robust standard errors clustered by seller are in parentheses. *Warranty* is omitted from the regressions because it does not vary in these subsamples. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 5. Sample Matched by Use of Price Promotion

	(1)	(2)	(3)	(4)
Variable	FE	FE	GMM	GMM
Lag sales	0.447***	0.446***	0.525***	0.520***
	(0.009)	(0.009)	(0.015)	(0.015)
Ref_mkgt	0.123***	0.127***	0.054***	0.079***
	(0.005)	(0.006)	(0.014)	(0.015)
Pr_disc	0.167***	0.171***	0.074**	0.078**
	(0.014)	(0.014)	(0.034)	(0.034)
*Ref_mkgt * Pr_disc*	–	-0.021***	–	-0.047***
		(0.006)		(0.013)
Avg_pr	-0.024	-0.024	-0.121	-0.123
	(0.022)	(0.022)	(0.092)	(0.086)
Search_adv	0.070***	0.070***	0.073***	0.072***
	(0.003)	(0.003)	(0.004)	(0.004)
Qty_disc	0.084**	0.085**	0.033	0.033
	(0.035)	(0.035)	(0.048)	(0.048)
Flash_deal	0.264***	0.263***	0.258***	0.254***
	(0.027)	(0.027)	(0.039)	(0.038)
Free_shipping	0.067**	0.066**	0.118**	0.116**
	(0.031)	(0.031)	(0.047)	(0.047)
Fake_comp	0.165	0.163	0.076	0.094
	(0.142)	(0.142)	(0.188)	(0.187)
Deliv_ins	0.011	0.010	-0.030	-0.031
	(0.036)	(0.035)	(0.045)	(0.044)
Sec_dep	0.323***	0.321***	0.391***	0.381***
	(0.048)	(0.048)	(0.079)	(0.078)
Free_return	-0.163***	-0.163***	-0.126***	-0.124***
	(0.022)	(0.022)	(0.032)	(0.032)
Spdy_deliv	-1.342***	-1.341***	-1.670***	-1.675***
	(0.027)	(0.027)	(0.039)	(0.035)
Warranty	[Omitted]	[Omitted]	[Omitted]	[Omitted]
Shop_desg	0.337***	0.335***	0.230***	0.224***
	(0.021)	(0.021)	(0.025)	(0.025)
Pay_on_deliv	-0.015	-0.014	0.018	0.017
	(0.037)	(0.037)	(0.055)	(0.055)
Seller_score	4.555***	4.548***	4.816***	4.792***
	(0.125)	(0.125)	(0.155)	(0.155)
Rev_cnt	0.138***	0.138***	0.001	0.000
	(0.017)	(0.017)	(0.034)	(0.034)
Pct_pos_rev	0.342***	0.341***	1.684***	1.690***
	(0.107)	(0.107)	(0.228)	(0.227)
Pict_cnt	0.036***	0.036***	0.032***	0.031***
	(0.007)	(0.007)	(0.012)	(0.012)
Age	0.514***	0.518***	1.591***	1.588***
	(0.094)	(0.094)	(0.207)	(0.205)
Age_sq	0.284***	0.285***	0.550***	0.549***
	(0.025)	(0.025)	(0.049)	(0.049)
Constant	-18.811***	-18.773***	-20.111***	-19.956***
	(0.512)	(0.512)	(0.776)	(0.757)
Seller fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	49,838	49,838	45,974	45,974
Sellers	3,864	3,864	3,864	3,864
Arellano–Bond test for AR(2) in error differences (*p*-value)	–	–	0.81	0.80

Notes: Robust standard errors clustered by seller are in parentheses. *Warranty* is omitted from the regressions because it does not vary in these subsamples. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

from recipients' purchases (which is the case in our setting), the recipients might be more suspicious of the referrals' credibility and thus less likely to follow the recommendations [49, 51, 51].

This argument points to a limitation of referral marketing in addressing quality uncertainty. Referrals can still expose the promoted products to more consumers, which may lead to an increase in total purchase volume. In other words, the informative advertising effect of referral marketing could lead to a net increase in sales, which plausibly explains its positive main effects in our estimation.

Why would price promotion matter in online referral marketing? Consumers seek quality cues from a wide variety of marketing mix variables, including price [33]. Ample experimental evidence shows that consumers tend to associate quality with price when objective quality information is unavailable and quality assessment is difficult, giving rise to the so-called price–quality heuristic [46, 47]. The information economics literature suggests that it is rational for consumers to associate a high price with high quality because only high-quality firms can afford to use a high price as a quality signal [33, 46]. Hence, a price discount could be a negative product quality cue and arouse quality concern [8, 11, 17, 29, 37].[20]

When a seller adds a price promotion to a paid referral (which tend to be rather impersonal and reward-driven on Taobao), consumers may wonder why the seller is promoting the product so desperately. The price promotion might create worries about product quality, leading consumers to perceive the referral as less credible and persuasive. Realistically, referral marketing, price promotions, and product quality are all costly. Consumers may infer that the seller incurs a substantial cost to run these promotions, meaning that it may compromise product quality to maintain a reasonable profit margin. Although discounting saves consumers money, its marginal impact when used with referral marketing could backfire. There may be diminishing returns for referral marketing paired with price promotions.

Supporting Evidence

To test the theoretical explanation that price reduction dampens the persuasive effect of WOM referrals, we compare the focal interaction effect for two types of products: diapers and strollers. Consumers should be more prudent and wary of quality concerns when buying big-ticket items or durable goods, such as strollers, than when purchasing cheaper and frequently repurchased non-durable goods, such as diapers, because the former involves more financial commitment and purchase deliberation [19, 31]. For cheaper and non-durable items, consumers can always switch to another product if the quality is unsatisfactory. Therefore, consumers are more likely to be attracted by discounts and less concerned about product quality when they buy diapers, as they can sample diapers with a discount to learn the true quality of the product. By this reasoning, price promotion is less likely to attenuate the effect of referral marketing on sales for diapers than strollers.[21]

We classify sellers based on their primary business subcategories. Sellers indicating diapers (strollers) as their primary business are considered diaper (stroller) sellers. We exclude 24 sellers whose primary businesses include both diapers and strollers. Altogether, we have 2,104 diaper sellers with 25,209 observations and 1,193 stroller sellers with 15,641 observations in our data set. Columns (1) and (2) of Table 6 show the results for the GMM estimations using observations from only diaper sellers and only stroller sellers, respectively. The focal interaction effect is small and statistically insignificant for diaper sellers

Table 6. Tests of the Quality Concern Explanation

Variable	(1) Diaper Sellers	(2) Stroller Sellers	(3) Non-reputed Sellers	(4) Reputed Sellers	(5) Falsification: Quantity Discount
Lag_sales	0.448***	0.564***	0.259***	0.478***	0.524***
	(0.020)	(0.020)	(0.017)	(0.031)	(0.010)
Ref_mkgt	0.094***	0.078***	0.192***	0.116***	0.080***
	(0.019)	(0.016)	(0.040)	(0.020)	(0.011)
Pr_disc	0.108**	0.082*	0.437***	-0.007	0.116***
	(0.049)	(0.049)	(0.113)	(0.052)	(0.026)
*Ref_mkgt * Pr_disc*	-0.013	-0.049***	-0.122**	-0.008	-0.047***
	(0.017)	(0.015)	(0.052)	(0.014)	(0.008)
*Ref_mkgt * Qty_disc*	–	–	–	–	0.005
					(0.016)
Avg_pr	0.060	-0.136	-0.076	0.040	-0.105*
	(0.085)	(0.098)	(0.064)	(0.153)	(0.056)
Search_adv	0.069***	0.067***	0.062***	0.058***	0.073***
	(0.006)	(0.005)	(0.015)	(0.006)	(0.003)
Qty_disc	0.020	0.121	-0.118	0.073	-0.039
	(0.067)	(0.081)	(0.154)	(0.061)	(0.052)
Flash_deal	0.267***	0.205***	0.343***	0.144**	0.247***
	(0.054)	(0.037)	(0.090)	(0.057)	(0.024)
Free_shipping	0.071	0.078	-0.029	0.078	0.098***
	(0.068)	(0.135)	(0.139)	(0.059)	(0.034)
Fake_comp	-0.323	-0.016	1.378***	-0.086	0.086
	(0.239)	(0.222)	(0.219)	(0.169)	(0.138)
Deliv_ins	-0.095	0.086	0.089	-0.201***	-0.043
	(0.065)	(0.079)	(0.213)	(0.075)	(0.038)
Sec_dep	0.395***	0.180	0.201***	0.328	0.253***
	(0.073)	(0.115)	(0.070)	(0.213)	(0.046)
Free_return	-0.132***	-0.077	-0.034	0.053	-0.090***
	(0.042)	(0.049)	(0.077)	(0.068)	(0.023)
Spdy_deliv	-1.192**	[Omitted]	[Omitted]	[Omitted]	-0.436
	(0.553)				(0.471)
Warranty	-0.168	-0.152	[Omitted]	[Omitted]	-0.010
	(0.188)	(0.324)			(0.141)
Shop_desg	0.177***	0.214***	0.228***	0.133***	0.222***
	(0.029)	(0.039)	(0.063)	(0.046)	(0.018)
Pay_on_deliv	-0.051	0.111	-0.254	0.004	0.019
	(0.092)	(0.091)	(0.395)	(0.075)	(0.035)
Seller_score	4.755***	4.957***	5.172***	0.669	4.979***
	(0.173)	(0.164)	(0.106)	(0.511)	(0.084)
Rev_cnt	0.108***	-0.045	0.368***	-0.216***	0.030
	(0.035)	(0.052)	(0.032)	(0.080)	(0.022)
Pct_pos_rev	1.553***	1.414***	0.315***	7.553	1.326***
	(0.186)	(0.259)	(0.112)	(20.907)	(0.112)
Pict_cnt	0.054***	0.005	0.056**	0.020	0.024***
	(0.013)	(0.022)	(0.023)	(0.015)	(0.008)
Age	1.042***	1.570***	0.064	0.253	1.372***
	(0.243)	(0.303)	(0.350)	(0.490)	(0.135)
Age_sq	0.414***	0.525***	0.220***	-0.048	0.496***
	(0.058)	(0.068)	(0.072)	(0.214)	(0.032)
Constant	-20.531***	-20.297***	-21.613***	-6.364	0.954***
	(0.785)	(0.918)	(0.585)	(21.189)	(0.294)
Seller fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	25,209	15,641	8,813	10,847	96,894
Sellers	2,104	1,193	1,190	710	8,674
Arellano–Bond test for AR(2) in error differences (*p*-value)	0.21	0.34	0.41	0.63	0.91

Notes: Robust standard errors clustered by seller are in parentheses. Some variables are omitted from the regression as there is no variation in the subsamples. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

(-0.013, $p > 0.10$), whereas it is much larger, negative, and statistically significant for stroller sellers (-0.049, $p < 0.01$). This is consistent with our theory that price promotion is less persuasive when used with referral marketing for a more expensive durable product.[22]

Our next test considers how the focal interaction effect varies with seller reputation. We identify two groups of sellers based on their contrasting reputations. We expect the negative interaction effect between referral marketing and price promotion is stronger for non-reputed sellers because consumers should have less quality concerns for reputed sellers.[23] We use *seller score* and *review count* to differentiate the sellers. *Seller score* is a dynamic score, on a scale of 0 to 100, assigned by the platform to indicate a seller's overall quality and trustworthiness. *Review count* is the number of customer reviews that a seller has accumulated. High-quality sellers should attract large sales volumes and more customer reviews. In general, consumers should have more confidence when they purchase products from a seller with a higher score and more customer reviews [10].

To separate the sellers by reputation, we first compute the average seller score and average review count for each seller over time. We then classify a seller as a reputed (non-reputed) seller if its average seller score and review count are in the top 25% (bottom 25%) among all sellers.[24] We have 1,190 non-reputed sellers with 8,813 observations and 719 reputed sellers with 10,847 observations. Columns (3) and (4) of Table 6 report the GMM estimations using observations from the non-reputed and reputed sellers, respectively. The focal interaction effect is small and statistically insignificant for reputed sellers (-0.008, $p > 0.10$) but much larger, negative, and statistically significant for non-reputed sellers (-0.122, $p < 0.05$). This further supports our theoretical analysis.[25]

We conclude our investigation with a falsification exercise. The quality concern explanation hinges on price promotions, which are indicative of product quality when consumers use the price–quality heuristic. If, however, a discount is not associated with the product itself but is extended for another reason, then we should not observe its attenuation of the referral marketing effect on sales if quality concern is the key explanation.

On this premise, we construct a falsification test in which we check the interaction effect between referral marketing and quantity-based discounts, i.e., a promotional strategy that deducts a certain amount from the transaction price when a purchase exceeds a specified threshold. Research on quantity-based discounts posits that product quality perception is unaffected by quantity discounts [see, e.g., 23, 27, 28]. Intuitively, consumers are less likely to view quantity- or threshold-based discounts as a negative quality cue because sellers have obvious incentives to increase their marginal revenues and profits by selling more units. With higher sales per transaction, sellers can better exploit economies of scale and have more room to transfer the savings to consumers. The signal sent by such discounts is different from the signal that a seller is simply dumping a product at a cut-throat price via the discount strategy.

Column (5) of Table 6 presents the GMM estimates of the specification including the interaction term between referral marketing and quantity-based discounts. Instead of attenuation, quantity-based discounts actually complement referral marketing in generating sales, although the effect is not statistically significant (0.005, $p > 0.10$). In contrast, the interaction effect between referral marketing and discounting continues to be statistically significant and negative (-0.047, $p < 0.01$).

Robustness Tests

Sellers incur expenses for referral marketing if and only if a purchase is made via the promotion. This means that the referral marketing variable is endogenous, as it is correlated with sales volume. We conduct two tests to alleviate this concern. The first test uses the one-period lagged referral marketing expenditure as the independent variable in the GMM estimation. The results are reported in column (1) of Table 7. The results are consistent, as the focal interaction effect remains negative and statistically significant (-0.026, $p < 0.01$).[26]

In the second test, similar to price promotion, we operationalize referral marketing using a dummy variable indicating whether a seller used referral marketing in each period. This conversion should remove most of the correlations between referral marketing and the number of transactions. Column (2) of Table 7 presents the GMM estimation results. The focal interaction effect between the two (dummy) marketing promotion variables remains large, negative, and marginally significant at the 10% level (-0.090, $p < 0.10$).

Next, because of low entry and exit costs on Taobao, some sellers may run their shops for a short period and then exit the market. If they deployed more diverse marketing promotions and had lower sales, the negative interaction effect might arise because of the prevalence of such sellers. As discussed, our use of GMM estimation and the PSM strategy should address such selection bias. To construct a more focused test, we repeat our estimation excluding sellers with fewer than 12 periods of observations. The results are reported in column (3) of Table 7. The focal interaction effect between referral marketing and discounts is consistent with those obtained using the full sample in column (4) of Table 3.

Thus far, we have only considered several key regressors as endogenous variables in the GMM estimations. It is possible that other covariates, such as expenditure on search advertising and number of reviews, are also endogenous. This could bias the coefficients of our focal variables. To account for this possibility, we re-estimate the model treating all regressors except seller age and its squared term and month FE as endogenous, using the corresponding lagged regressors as the instruments. The results are reported in column (4) of Table 7. The focal interaction effect remains close to the baseline estimate in column (4) of Table 3. This implies that our results are robust to the presence of other endogenous regressors.

The GMM estimator may perform poorly if the distant lagged variables are not well correlated with the focal endogenous variables but are used as instruments [48]. Following Roodman [48], we assess the sensitivity of our results to reductions in the number of instruments. We repeat the estimation of the GMM model using a maximum of two, three, four, five, and six lagged variables as the instruments. Column (5) of Table 7 reports the estimates with two lagged variables.[27] The results are consistent with those obtained using the full set of instruments.

Finally, we conduct another test using sales revenue measured by the total transaction amount instead of the number of transactions as the dependent variable. The estimation results, which are reported in column (6) of Table 7, remain robust.

Discussion and Conclusion

By conducting a series of statistical analyses using comprehensive panel data from the Taobao platform, we find that consumer referral programs can effectively increase sales in an online e-commerce platform. More importantly, we find that the effectiveness of a referral program in

Table 7. Robustness Checks

Variable	(1) Lag Referral Marketing Spending	(2) Referral Program Dummy	(3) Earnest Sellers	(4) More Controls Instrumented	(5) Less Lags as Instruments	(6) Sales Revenue
Lag_sales	0.448***	0.537***	0.572***	0.510***	0.461***	0.223***
	(0.006)	(0.010)	(0.010)	(0.009)	(0.015)	(0.008)
Ref_mkgt	0.018***	0.015	0.064***	0.093***	0.045**	0.182***
	(0.003)	(0.052)	(0.011)	(0.009)	(0.018)	(0.018)
Pr_disc	0.153***	0.106***	0.059**	0.136***	0.213***	0.265***
	(0.010)	(0.035)	(0.025)	(0.025)	(0.036)	(0.040)
*Ref_mkgt * Pr_disc*	-0.026***	-0.090*	-0.031***	-0.050***	-0.058***	-0.048***
	(0.003)	(0.047)	(0.008)	(0.008)	(0.014)	(0.014)
Avg_pr	-0.034**	-0.032	-0.105	-0.150***	-1.172***	-0.272**
	(0.014)	(0.060)	(0.065)	(0.049)	(0.175)	(0.109)
Search_adv	0.088***	0.078***	0.070***	0.069***	0.076***	0.068***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Qty_disc	0.044**	0.043	0.024	0.032	0.034	0.009
	(0.021)	(0.026)	(0.027)	(0.042)	(0.026)	(0.027)
Flash_deal	0.239***	0.254***	0.215***	0.217***	0.253***	0.241***
	(0.018)	(0.024)	(0.025)	(0.044)	(0.024)	(0.025)
Free_shipping	0.109***	0.095***	0.068**	-0.060	0.097***	0.063**
	(0.020)	(0.029)	(0.030)	(0.041)	(0.030)	(0.030)
Fake_comp	-0.058	0.078	0.147	0.207	0.017	0.041
	(0.144)	(0.146)	(0.102)	(0.271)	(0.125)	(0.117)
Deliv_ins	0.026	-0.042	-0.036	0.291***	-0.042	0.004
	(0.030)	(0.039)	(0.037)	(0.081)	(0.041)	(0.047)
Sec_dep	0.235***	0.246***	0.278***	0.608***	0.307***	0.254***
	(0.030)	(0.046)	(0.056)	(0.064)	(0.050)	(0.069)
Free_return	-0.102***	-0.080***	-0.098***	0.020	-0.094***	-0.551***
	(0.017)	(0.023)	(0.025)	(0.046)	(0.024)	(0.030)
Spdy_deliv	0.130	-0.513	0.012	0.829***	-0.473	0.196
	(0.299)	(0.473)	(0.077)	(0.267)	(0.459)	(0.779)
Warranty	-0.020	-0.043	0.020	0.209	-0.097	0.003
	(0.207)	(0.150)	(0.159)	(0.564)	(0.125)	(0.304)
Shop_desg	0.359***	0.229***	0.225***	0.240***	0.234***	0.301***
	(0.014)	(0.018)	(0.019)	(0.048)	(0.019)	(0.025)
Pay_on_deliv	0.010	0.028	0.005	-0.112*	0.027	0.048
	(0.026)	(0.036)	(0.037)	(0.060)	(0.035)	(0.041)
Seller_score	4.613***	4.994***	4.843***	3.499***	4.876***	15.998***
	(0.073)	(0.085)	(0.096)	(0.217)	(0.090)	(0.172)

(*Continued*)

Table 7. (Continued).

Rev_cnt	0.177***	0.037*	-0.024	-0.166***	0.159***	0.265***
	(0.011)	(0.022)	(0.024)	(0.019)	(0.028)	(0.023)
Pct_pos_rev	0.168***	1.299***	1.264***	-0.677***	1.006***	0.981***
	(0.064)	(0.113)	(0.139)	(0.211)	(0.117)	(0.148)
Pict_cnt	0.031***	0.030***	0.030***	0.008	0.047***	0.060***
	(0.005)	(0.008)	(0.008)	(0.008)	(0.009)	(0.013)
Age	0.353***	1.427***	1.441***	1.642***	1.201***	0.141
	(0.065)	(0.138)	(0.151)	(0.118)	(0.161)	(0.172)
Age_sq	0.239***	0.511***	0.511***	0.422***	0.476***	0.249***
	(0.017)	(0.032)	(0.039)	(0.029)	(0.036)	(0.041)
Constant	-19.189***	0.511*	1.042***	4.333***	5.079***	-63.880***
	(0.302)	(0.307)	(0.330)	(0.338)	(0.750)	(0.868)
Seller fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,894	96,894	81,077	96,894	96,894	96,894
Sellers	8,674	8,674	5,132	8,674	8,674	8,674
Arellano–Bond test for AR(2) in error differences (*p*-value)	0.94	0.90	0.83	0.40	0.14	0.69

Notes: Robust standard errors clustered by seller are in parentheses. In column (1), *Ref_mkgt* is operationalized using the one-period lagged value of referral marketing expenditure (instead of the current-period value), and in column (6), the dependent variable is sales revenue measured as total transaction amount (instead of sales volume). *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

generating sales is attenuated by price promotion, a somewhat surprising result not previously documented in the literature. Our back-of-the-envelope calculation indicates that an average seller would attract about eight more transactions in a month by doubling its referral marketing expenditure from the current conditional sample mean of CNY53 (about USD8) and not offering a discount at the same time. This increment would decrease to three if the seller offers a discount at the same time.

As another illustration, our estimates suggest that for sellers with high referral marketing spending, defined as one standard deviation above the sample average, price promotions have practically no effect on sales. In contrast, for sellers with low referral marketing spending, defined as one standard deviation below the sample average, price promotions significantly increase sales by approximately 23% (on average, 26 more transactions based on our back-of-the-envelope calculation), which is economically significant.

The results of various tests indicate that price promotions may arouse salient quality concerns in the context of paid referral marketing in weak-tie relationships on Taobao even though the promotions save consumers money. This implies that there may be diminishing returns from price promotions. The quality concern explanation draws particular attention to the purpose of the promotions. Do sellers offer referral marketing to increase their products' exposure to consumers (i.e., an informative purpose), to persuade consumers to buy the products through the referral senders' personal influence (i.e., a persuasive purpose), or both? Furthermore, do sellers use price promotions to simply entice a sale?

Answering these questions is fundamental to the success of marketing promotions. Referral marketing has a compelling informative advertising benefit because it increases the exposure of the promoted products. This informative advertising benefit probably explains why referral marketing has a consistently positive main effect on sales in almost all of the estimations. However, its persuasive effect is questionable when tie strength is weak and when the referral senders might have strong incentives to earn the referral commissions. Discounts probably further mitigate this persuasive effect because consumers may associate them with low product quality.

This means that sellers should combine referral marketing and price promotions only when their quality image is strong and they want to boost sales via expanding their customer base and offering savings for consumers. In practice, it is tempting for sellers to use both tactics without discretion. Yet we find that price promotions' attenuation of the referral marketing effect on sales is particularly strong among stroller sellers. Based on our findings, stroller sellers and other relatively less-known sellers of expensive and durable goods might not want to offer price promotions with referral marketing because the referrals may become non-credible. Worse still, the price promotions might arouse unintended and unnecessary quality concerns in consumers.

For platforms that offer referral marketing services, our research points to an important way to enhance the effectiveness of referral programs on the Internet: easing consumers' quality concerns amid weak ties and paid referrals. One way to do this is by establishing a league of quality or "certified" merchants that provide exogenous quality signals to consumers. Another way is to calibrate the referral commission rates to suppress users' incentives to massively refer products to even unknown recipients. Finally, a platform could provide novel value-added services to ease consumers' concerns regarding referred purchases. For example, it could liaise escrow services between sellers and referral senders and recipients or enable warranties and product return guarantees for expensive and durable

items. All of these measures may help ease consumers' concerns, as implied by our statistical tests supporting the quality concern explanation, particularly the tests concerning stroller vs. diaper sellers and reputed vs. non-reputed sellers.

Without these value-added services provided by the referral marketing platform, sellers' immediate job is to ascertain their promotional purposes and their own quality image. Our prescription is as follows: if sellers want to expand their customer base when they lack a quality brand image, they should engage in referral marketing but not price promotions. If they have a good brand image and want to boost sales by offering value savings to consumers, they should offer discounts. If they have a good brand image and want to both expand their clientele and boost sales by offering value savings to consumers, they should offer both referral marketing and price promotions. Regardless of which path they choose, addressing the incentives of referral senders seems to be an important task in Internet referral marketing programs.

Online sellers with poor or unknown quality images that offer discounts in a paid referral program may suffer from an unintended double whammy: the discount erodes the sellers' margins and hence their bottom line profits, while it might also turn prospective buyers away and inadvertently spread a poor quality image among a broader consumer base because of the expanded reach of the referral program. We advise sellers against using both promotional tactics if they are not sure of their brand image.

This study contributes to the literature mainly in two aspects. First, it adds to the literature on information asymmetry in online markets [20, 32, 42, 43] by showing that a single promotional tactic, such as referral marketing on the Internet, may have multiple and heterogeneous effects. More importantly, it highlights the importance of scrutinizing the potential composite effects of multiple marketing promotions in view of the contextual characteristics of the Internet.

Second, by advancing the argument that paying for weak-tie referrals could be the reason underlying the negative interaction between referral marketing and price promotions, we offer a novel theoretical perspective from which to examine the effectiveness of the increasingly popular Internet business strategies that leverage weak ties or pay for performance of intermediaries [3, 26]. Easing consumers' product quality concerns may be a critical antecedent of a successful promotion campaign. Depending on the underlying nature of persuasiveness, different promotion strategies may conflict in reducing consumers' quality concerns.

Finally, we discuss the limitations of this study and future research opportunities. First, because of data limitations, we could not generate conclusive evidence regarding the existence of a weak persuasive effect of paid referrals. Future research could directly observe or measure the persuasiveness of a referral, perhaps by scrutinizing consumer-level data at the recipient end.

Second, our data set only captures whether a seller offered price promotions but not the depth of the promotions. Lu et al. [39, 40] find that WOM volume and coupons have a substitution effect on sales. Interestingly, they also find that coupon availability is more important than coupon value in affecting consumer behavior. Consistent with their findings, we show that discounting as measured by a binary variable has a significant attenuation effect on referral marketing. It would be meaningful to examine whether this attenuation is generic across discount levels.

Third, the generalization of the focal negative interaction effect between referral marketing and price promotion needs to be critically examined in future research. Two considerations warrant special attention. The first is the type or nature of a product/service, which might be a contingent factor for the negative interaction effect. In our study, the products are largely

experience or credence goods for which quality uncertainty cannot be resolved before consumption. It would be interesting to examine the nature of the interaction effect for search goods, such as movies and airplane tickets, whose quality is less subject to manipulation and can be more easily ascertained before consumption.

The second future research opportunity related to generalization is whether the negative interaction effect between referral marketing and price promotion persists in other e-commerce platforms with salient product/seller quality heterogeneity and uncertainty. It would be interesting to investigate whether and how the interaction effect is dependent on platform characteristics such as eBay's buyer protection policy, which is used to resolve disputes between buyers and sellers when sellers fail to deliver products as promised, or the degree of platform openness in terms of the difficulty in becoming affiliated with the platform.

Last, as is evident from our empirical analysis and success stories such as Dropbox and Uber, online referral programs are a powerful marketing tool to attract new consumers. It is important that future research establish systematic guidance for such an effective promotional tactic on the Internet.

Notes

1. For more details about Amazon's referral program, see https://affiliate-program.amazon.com/ (accessed March 20, 2021).
2. For more details about eBay's referral program, see https://pages.ebay.com/seller-center/service-and-payments/ebay-affiliate-program.html (accessed March 20, 2021).
3. See https://www.thedrum.com/profile/mention-me/news/51-of-uk-consumers-trust-their-friends-or-partners-recommendations-more-than-any-other-brand-advertising (accessed March 20, 2021).
4. The conditional mean is the sample's mean referral marketing spending conditional on sellers making positive spending.
5. For some statistics about their growth, see http://www.statista.com/markets/413/topic/983/c2c-e-commerce/ (accessed March 20, 2021).
6. See http://www.taobao.com/about/ (accessed March 20, 2021).
7. See https://www.statista.com/statistics/959633/china-taobao-gross-merchandise-volume/ (accessed March 20, 2021).
8. See, for example, the *Wall Street Journal*. Knockoffs Thrive on Alibaba's Taobao: Critics Say Chinese E-Commerce Giant Needs to Do More About Counterfeit Goods, April 28, 2014, available at https://www.wsj.com/articles/knockoffs-thrive-on-alibabas-taobao-1398645388 (accessed March 20, 2021).
9. The diagram in Figure 1 is created by the authors based on the original description in Chinese.
10. We use "month" and "four weeks" interchangeably in this paper.
11. As we use GMM estimations, sellers with less than three periods of observations are excluded from the analysis anyway.
12. The table showing the correlations of the variables is presented in the Online Appendix.
13. In one robustness test, we assume additional endogeneity between some of the remaining regressors that could be strategically determined by the sellers.
14. Another oft-discussed advertising effect is signaling, whereby high-quality sellers may "burn money" on advertising up front to signal quality. As referral marketing expenditures are tied to performance and an upfront lump sum payment is not required, we expect that the signaling effect is weak in our setting.
15. We mean-center the continuous variables in the interaction term in all of the regressions.

16. However, the Hansen test of overidentifying restrictions indicates that the validity of the instruments is questionable in our setting. We thus caution readers about the consistency of the GMM estimators reported here. Nevertheless, given the similar results for the focal interaction effect from various specifications (including the FE estimations without the GMM instruments), we believe that the direction of the focal interaction effect is sound. We advise readers to interpret the estimated effect sizes with care.
17. The (unconditional) sample mean of sales volume, 116, is used in this and subsequent calculations.
18. Price promotion is already measured by a dummy variable in our data set. Hence, we can directly use it in the PSM procedure.
19. See, for example, the report referenced in Footnote 8.
20. Price promotion can have other salient impacts on consumer purchases. Here, we only highlight the perspective most relevant to our setting, its role as a quality cue. Interested readers are referred to Blattberg et al. [6] for a comprehensive review of the price promotion literature.
21. Note that this test assumes that people make more careful deliberations when buying durable and more expensive items than when buying nondurable frequently repurchased items under the influence of referral marketing when the exposure to the promoted items comes from possibly weak-tie referrals. It does not depend on the main effects of price promotion and referral marketing on sales across the two product categories.
22. In another regression, we pool the observations of diaper and stroller sellers and create a dummy variable, *Stroller*, for the stroller sellers. We investigate the three-way interaction effect involving referral marketing, discounts, and the stroller dummy variable. Consistent with the results reported in columns (1) and (2) of Table 6, the three-way interaction effect is statistically significant and negative. The detailed regression results are reported in the Online Appendix.
23. Here again, this test assumes people deliberate less when considering a referral to a reputed seller, so price promotion should carry a less important quality signal amid a referral. The test is largely orthogonal to the main effects of price promotion and referral marketing across the two types of sellers.
24. We use stringent criteria to ensure that the two groups of sellers are well differentiated by their reputations and quality images.
25. In another regression, we pool the observations of reputed and non-reputed sellers and create a dummy variable, *Reputed*, for the reputed sellers. We assess the three-way interaction effect involving referral marketing, discounts, and the *Reputed* dummy variable. Consistent with the results reported in columns (3) and (4) of Table 6, the three-way interaction effect is statistically significant and positive. The detailed regression results are reported in the Online Appendix.
26. Note that the number of observations remains the same because the lagged dependent variable is already (and always) included in the specification.
27. The estimates are qualitatively similar with other numbers of lagged variables.

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Appendix A. Detailed Results of Propensity Score Matching

As explained in the main text, we apply PSM to identify subsamples of control and treated sellers based on the cross-sectional data converted from the original panel data. First, we use a probit model to estimate the propensities of sellers in the sample to participate in referral marketing or offer price discounts. We use all of the available seller characteristics except for sales volume (see Table 1 in the main text) in the probit model. Moreover, we include all of the two-way interaction terms between seller characteristics to achieve a better balance of the covariates between the treated and control sellers after matching (Caliendo and Kopeinig 2008).

We use the one-to-one nearest neighbor without replacement matching method. In our setting, if no caliper (i.e., the maximum permitted difference between matched subjects) is set, the matched sample is quite imbalanced in the covariate distributions. Therefore, based on trial and error, we use 0.01 as the caliper for matching according to the treatment variable of whether a seller participated in referral marketing in at least one period and 0.001 as the caliper for matching according to the treatment variable of whether a seller offered price discounts in at least one period. These caliper values are the largest values that achieve the best balance in all of the covariate distributions. Altogether, we identify 1,884 pairs of matched sellers according to the treatment variable of participating in referral marketing and 1,932 pairs of matched sellers according to the treatment variable of offering price discounts.

Nearly all of the covariate distributions are balanced between the treated and control groups in the PS matched subsamples. Table A.1 shows the *T*-tests of the mean differences between the treated and control groups for all of the characteristics after and before PSM according to the treatment variable of participating in referral marketing. Table A.2 shows the same set of *T*-tests after PSM according to the treatment variable of offering price discounts. After PSM, the characteristics of the two groups do not differ significantly (the exceptions are *Flash_deal* in Table A.1 and *Free_shipping* in Table A.2).

Reference:
Caliendo, M. and Kopeinig, S. Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Survey*, 22, 1 (2008), 31–72.

Table A.1. T-test results for the matched and unmatched samples (I)

	Matched Sample				**Whole Sample**			
	Mean		*T*-test (Control – Treated)		Mean		*T*-test (Control – Treated)	
	Control	Treated	*t*	*Pr(|T| > |t|)*	Control	Treated	*t*	*Pr(|T| > |t|)*
Pr_disc	0.071	0.072	-0.396	0.654	0.049	0.217	-36.302	0.000
Avg_pr	4.221	4.218	0.272	0.393	4.161	4.288	-6.227	0.000
Qty_disc	0.116	0.011	0.134	0.447	0.023	0.048	-9.655	0.000
Flash_deal	0.033	0.027	3.899	0.000	0.033	0.060	-19.939	0.000
Free_shipping	0.021	0.022	-0.510	0.695	0.016	0.076	-17.732	0.000
Fake_comp	0.003	0.003	-0.066	0.947	0.003	0.008	-3.006	0.003
Deliv_ins	0.024	0.024	-0.089	0.930	0.015	0.053	-12.013	0.000
Sec_dep	0.930	0.924	0.998	0.318	0.760	0.964	-29.948	0.000
Free_return	0.466	0.458	0.595	0.552	0.302	0.681	-41.259	0.000
Spdy_deliv	0.055	0.055	-0.007	0.994	0.038	0.109	-15.770	0.000
Shop_desg	0.845	0.845	-0.097	0.923	0.811	0.892	-12.777	0.000
Pay_on_deliv	0.015	0.013	0.461	0.645	0.010	0.055	-14.113	0.000
Seller_score	4.312	4.310	1.144	0.253	4.282	4.330	-29.994	0.000
Rev_cnt	6.749	6.741	0.129	0.898	6.060	7.616	-33.788	0.000
Age	6.307	6.306	0.034	0.973	6.214	6.512	-12.597	0.000
Pict_cnt	0.929	0.926	0.114	0.909	0.773	1.181	-29.302	0.000

Appendix B. Additional Regression Results

Column (1) of Table A.3 reports the estimates for the pooled observations of diaper and stroller sellers. We create a dummy variable, *Stroller*, for the stroller sellers. We include the focal three-way interaction term, *Ref_mkgt* * *Pr_disc* * *Stroller*, and other lower-order interaction terms in the regression model (the dummy variable *Stroller* cannot be separately estimated because seller fixed effects are included). The focal three-way interaction effect, *Ref_mkgt* * *Pr_disc* * *Stroller*, is negative and significant (-0.065, $p < 0.01$), indicating that stroller sellers are significantly more susceptible to the negative interaction effect between referral marketing and price promotion.

Column (2) of Table A.3 reports the estimates for the pooled observations of reputed and non-reputed sellers. We created a dummy variable, *Reputed*, for reputed sellers. We include the focal three-way interaction term, *Ref_mkgt* * *Pr_disc* * *Reputed*, and other lower-order interaction terms in the regression model (the dummy variable *Reputed* cannot be separately estimated because seller fixed effects are included). The focal three-way interaction effect, *Ref_mkgt* * *Pr_disc* * *Reputed*, is positive and significant at the 10% level (-0.090, $p < 0.10$), indicating that reputed sellers are significantly less susceptible to the negative interaction effect between referral marketing and price promotion.

Table A.2. T-test results for the matched and unmatched samples (II)

	Matched Sample				Whole Sample			
	Mean		*T*-test (Control − Treated)		Mean		*T*-test (Control − Treated)	
	Control	Treated	*t*	*Pr(|T| > |t|)*	Control	Treated	*t*	*Pr(|T| > |t|)*
Ref_mkgt	1.304	1.243	1.134	0.257	0.676	2.002	-34.144	0.000
Avg_pr	4.285	4.263	0.726	0.468	4.181	4.323	-7.042	0.000
Search_adv	2.065	1.975	1.173	0.241	1.023	3.193	-39.386	0.000
Flash_deal	0.032	0.031	0.388	0.698	0.029	0.052	-7.886	0.000
Free_shipping	0.031	0.047	-2.494	0.013	0.013	0.110	-22.652	0.000
Fake_comp	0.004	0.005	-0.555	0.579	0.004	0.008	-2.457	0.014
Delivery_ins	0.043	0.040	0.538	0.590	0.025	0.058	-8.796	0.000
Sec_dep	0.964	0.961	0.699	0.485	0.825	0.973	-29.822	0.000
Free_return	0.614	0.612	0.138	0.890	0.427	0.694	-29.144	0.000
Spdy_deliv	0.088	0.083	0.718	0.473	0.058	0.117	-11.470	0.000
Shop_desg	0.906	0.896	1.502	0.133	0.823	0.916	-17.900	0.000
Pay_on_deliv	0.038	0.035	0.556	0.579	0.023	0.058	-9.125	0.000
Seller_score	4.329	4.327	1.689	0.091	4.297	4.332	-27.395	0.000
Rev_cnt	7.372	7.356	0.261	0.794	6.391	7.922	-34.707	0.000
Age	6.451	6.457	-0.214	0.831	6.264	6.591	-14.852	0.000
Pict_cnt	1.133	1.119	0.690	0.490	0.872	1.243	-27.289	0.000

Appendix C. Correlations of Variables

Table A.3. Additional Regression Results

	(1) GMM: Diaper vs. Stroller Sellers	(2) GMM: Reputed vs. Non-Reputed Sellers
Lag_sales	0.528***	0.368***
	(0.014)	(0.018)
Ref_mkgt	0.075***	0.199***
	(0.019)	(0.038)
Pr_disc	0.097**	0.330***
	(0.048)	(0.111)
*Ref_mkgt * Pr_disc*	-0.004	-0.122**
	(0.017)	(0.051)
*Ref_mkgt * Stroller*	0.048**	–
	(0.025)	
*Stroller * Pr_disc*	-0.037	–
	(0.069)	
*Ref_mkgt * Pr_disc * Stroller*	-0.065***	–
	(0.024)	
Avg_pr	-0.011	-0.000
	(0.067)	(0.060)
Search_adv	0.067***	0.058***
	(0.004)	(0.006)
Qty_disc	0.069	0.010
	(0.053)	(0.056)

(*Continued*)

Table A.3. (Continued).

Flash_deal	0.228***	0.214***
	(0.035)	(0.049)
Free_shipping	0.079	0.046
	(0.064)	(0.056)
Fake_comp	-0.055	0.068
	(0.167)	(0.280)
Deliv_ins	-0.000	-0.021
	(0.052)	(0.115)
Sec_dep	0.309***	0.196***
	(0.064)	(0.073)
Free_return	-0.109***	-0.044
	(0.032)	(0.060)
Spdy_deliv	-1.239**	[Omitted]
	(0.526)	
Warranty	-0.090	-0.215
	(0.180)	(0.314)
Shop_desg	0.186***	0.173***
	(0.024)	(0.041)
Pay_on_deliv	0.016	-0.003
	(0.067)	(0.071)
Seller_score	4.866***	5.055***
	(0.122)	(0.109)
Rev_cnt	-0.008	0.254***
	(0.030)	(0.033)
Pct_pos_rev	1.613***	0.655***
	(0.162)	(0.119)
Pict_cnt	0.014	0.042***
	(0.010)	(0.014)
Age	1.438***	0.456*
	(0.192)	(0.235)
Age_sq	0.496***	0.311***
	(0.045)	(0.052)
*Ref_mkgt * Reputed*	–	-0.045
		(0.043)
*Reputed * Pr_disc*	–	-0.238*
		(0.124)
*Ref_mkgt * Pr_disc * Reputed*	–	0.090*
		(0.053)
Constant	-20.534***	-21.626***
	(0.606)	(0.523)
Seller fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Observations	40,850	19,660
Sellers	3,297	1,900
Arellano–Bond test for AR(2) in error differences (*p*-value)	0.77	0.50

Note. Robust standard errors clustered by seller are in parentheses. Some variables are omitted from the regression, as there is no variation in the subsamples. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A.4. Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. ln(*Sales*)	1.00																				
2. ln(*Ref_mkgt*)	0.44	1.00																			
3. *Pr_disc*	0.23	0.22	1.00																		
4. ln(*Avg_pr*)	-0.12	0.07	0.07	1.00																	
5. ln(*Search_adv*)	0.45	0.55	0.27	0.12	1.00																
6. *Qty_disc*	0.11	0.14	0.13	-0.01	0.14	1.00															
7. *Flash_deal*	0.07	0.08	0.09	0.06	0.08	0.04	1.00														
8. *Free_shipping*	0.16	0.17	0.16	-0.06	0.17	0.43	0.03	1.00													
9. *Fake_comp*	0.09	0.06	0.03	-0.01	0.05	0.01	0.00	0.02	1.00												
10. *Deliv_ins*	0.02	0.10	0.06	0.03	0.09	0.05	0.03	0.04	-0.01	1.00											
11. *Sec_dep*	0.42	0.20	0.13	0.04	0.22	0.06	0.04	0.07	0.03	0.06	1.00										
12. *Free_return*	0.32	0.32	0.15	-0.06	0.32	0.09	0.05	0.12	0.04	0.11	0.37	1.00									
13. *Spdy_deliv*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	1.00								
14. *Warranty*	0.03	0.05	0.03	0.02	0.06	0.01	0.00	0.01	0.00	0.01	0.01	0.04	0.00	1.00							
15. *Shop_desg*	0.30	0.15	0.13	0.02	0.18	0.05	0.04	0.06	0.02	0.02	0.15	0.11	-0.01	0.01	1.00						
16. *Pay_on_deliv*	0.08	0.15	0.08	0.02	0.13	0.06	0.03	0.09	0.03	0.07	0.07	0.13	0.00	0.02	0.04	1.00					
17.ln(*Seller_score*)	0.51	0.21	0.10	0.04	0.22	0.05	0.05	0.06	0.02	0.05	0.48	0.41	0.00	0.01	0.14	0.06	1.00				
18. ln(*Rev_cnt*)	0.69	0.38	0.17	-0.07	0.39	0.07	0.04	0.11	0.11	0.01	0.42	0.32	0.02	0.03	0.03	0.08	0.39	1.00			
19. *Pct_pos_rev*	0.24	0.07	0.04	-0.01	0.08	0.02	0.02	0.03	0.01	0.01	0.23	0.10	0.00	0.01	-0.03	0.02	0.37	0.38	1.00		
20. ln(*Pict_cnt*)	0.09	0.12	0.12	0.06	0.14	0.04	0.04	0.05	0.00	0.03	0.10	0.09	-0.01	0.01	0.13	0.07	0.09	0.04	0.02	1.00	
21. ln(*Age*)	0.21	0.17	0.05	0.02	0.15	0.03	0.02	0.03	0.05	0.00	0.17	0.10	0.01	0.02	-0.11	0.06	0.20	0.61	0.29	-0.01	1.00