Xueming Luo, Michelle Andrews, Yiping Song, & Jaakko Aspara

Group-Buying Deal Popularity

Group-buying (GB) deals entail a two-phase decision process. First, consumers decide whether to buy a deal. Second, they decide when to redeem the deal, conditional on purchase. Guided by theories of social influence and observational learning, the authors develop a framework predicting that (1) deal popularity increases consumers' purchase likelihood and decreases redemption time, conditional on purchase, and (2) the social influence–related factors of referral intensity and group consumption amplify these effects. The authors test this framework and support it using a unique data set of 30,272 customers of a GB website with several million data points. Substantially, these findings reveal a two-phase perspective of GB, longevity effects of deal popularity, and the amplifying role of customer referrals (influencing others) in the effects of deal popularity (others' influence). In light of the criticism of GB industry practice, this study builds the case for GB websites and merchants to heed deal popularity information and the social influence–related contingencies.

Keywords: group-buying deals, deal popularity, social influence, observational learning, sales

Group-buying (GB) deals are discounted products and services that are posted on websites such as Groupon.com and LivingSocial.com. Figure 1 exemplifies a GB deal. Diverging from traditional coupons, GB deals comprise an integrated two-phase process of consumer behavior. First, consumers decide whether to purchase a deal. If they decide to buy, they must pay for the deal in advance of its consumption. Second, conditional on its purchase, consumers then decide when to redeem the deal before it expires. Because each consumer benefits from the deep discounts obtained by the whole group of buyers, the GB business model has attracted millions of customers and billions of dollars in venture capital (Hartung 2012; Kim, Lam, and Tsai 2012).

A notable phenomenon of GB is that consumers seem to be influenced by deal popularity at both the purchase and redemption phases. Deal popularity is the visually displayed information of the cumulative number of deals sold to other consumers. An indication of how other consumers evaluate a GB offer, deal popularity can signal deal worth and influence a focal consumer's purchase and redemption decisions (i.e., creating a "bandwagon" effect).

Against this backdrop, our conceptual framework proposes that in the first phase, deal popularity affects the likelihood that consumers decide to purchase. Conditional on purchase, deal popularity also affects the redemption time in the second phase. Furthermore, such effects of deal popularity are contingent on two social influence–related factors: referral intensity and group consumption. Our conceptualization is informed by the theory of observational learning (OL) and social influence (Bandura 1977). We test and support this framework with a unique data set of 30,272 customers of a GB website with more than four million data points at the customer-deal-day level.

Our study proffers several contributions. It is the first study across the marketing, economics, and information systems literature streams to advance a *two-phase* perspective regarding the effects of deal popularity on purchase and redemption. The field's understanding of consumer GB behavior may be constrained if either phase is neglected, because both purchase and redemption are key components of GB business models. We know of only one study (Li and Wu 2013) that explores the aggregated level of GB deal purchase (without consumer-level data). Extending Li and Wu's (2013) work, we focus on the disaggregated level (with consumer-level data). Using this extensive data set, we also identify how deal popularity and other factors (deal price, savings, and customer experience) may differentially affect purchases in relation to redemptions.

Furthermore, we extend research on OL and social influence. Prior studies have documented that popularity and social influence affect consumer behaviors (Zhang 2010; Zhang and Liu 2012). We advance Zhang's studies in three key ways: (1) Whereas Zhang examines the effect of OL on a single-phase decision such as microlending, we investigate how OL affects two interrelated, but asynchronous, decisions—purchase and subsequent actual consumption; (2) extending Zhang's research on the impact of herding, our findings support the longevity effect of deal popularity; and (3) whereas Zhang and Liu (2012) address differential effects with rational or irrational herding, we examine heterogeneous effects with social influence–related moderators.

Managerially, our work is timely in light of mounting criticism of the GB industry. Critics argue that few switch-

Xueming Luo is Charles Gilliland Distinguished Professor of Marketing (e-mail: luoxm@temple.edu), and Michelle Andrews is a doctoral student in Marketing (e-mail: michelle.andrews@temple.edu), Fox School of Business, Temple University. Yiping Song is Associate Professor of Marketing, Fudan University (e-mail: ypsong@fudan.edu.cn). Jaakko Aspara is Assistant Professor, Department of Marketing, Aalto University (e-mail: jaakko.aspara@aalto.fi). The authors gratefully acknowledge the anonymous company that provided the unique and comprehensive data set, the financial support of the NSFC grant (No. 71172036), and constructive comments from three anonymous *JM* reviewers. Peter Danaher served as area editor for this article.

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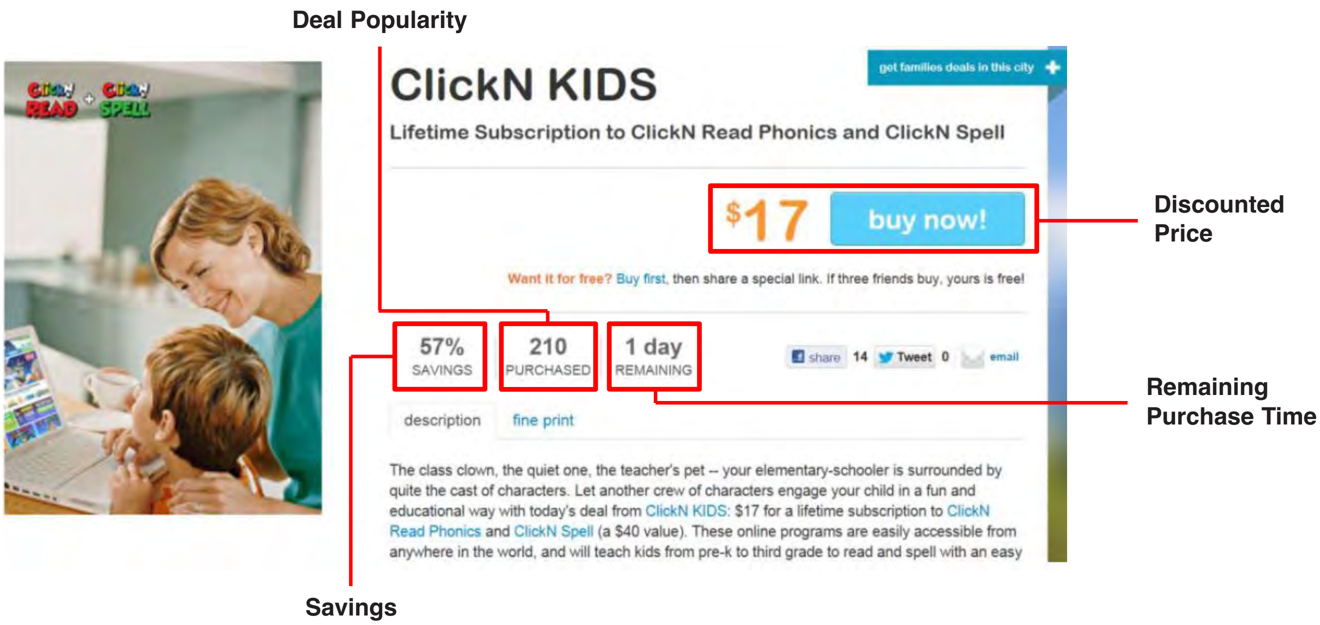
FIGURE 1
Example of a LivingSocial Deal



ing costs and low barriers to competitive imitation plague the GB industry (Mourdoukoutas 2012). We furnish actionable guidelines for marketers: they can leverage deal popularity to boost sales and attain faster redemption revenues from GB services. In addition, to gain competitive advantages and strengthen the effectiveness of deal popularity, GB merchants should encourage social interactions among consumers because social influence–related referral intensity and group consumption can amplify the effects of deal popularity on consumer purchase and redemption decisions. Next, we present the framework and hypothesis logic.

Framework and Hypotheses

As Figure 2 illustrates, our framework predicts that (1) deal popularity both increases consumers' purchase likelihood of GB deals and decreases redemption time conditional on purchase and (2) these effects are amplified by the social influence–related factors of group consumption and referral intensity. Table 1 defines the variables for each phase.

Our framework is grounded in the OL theory, which posits that people follow others' actions when they are able to observe them (Bandura 1977; Cai, Chen, and Fang 2009). In the GB setting, consumers may find it difficult to ascertain a deal's worth because deals are experience goods often promoted by new merchants (Wang, Zhao, and Li 2013). Yet through OL, consumers can update their imperfect information by observing deal popularity, or the cumulative number of deals sold to preceding peers (which GB websites typically display prominently in real time). The OL of this action-based deal popularity may boost consumer arousal and confidence regarding the deal (both of which affect purchase likelihood). In addition, OL may have longevity effects (which affect subsequent redemption) akin to long-term effects of social word of mouth (Berger and Schwartz 2011; Bone 1995; Luo 2009).

Effects of Deal Popularity on Consumer Purchase and Redemption

We posit that the higher the deal popularity (as embodied by the cumulative amount of GB deals purchased by other consumers), the higher the likelihood that the focal consumer will buy the deal. According to the OL theory, enabling a focal consumer to observe deal popularity can create an information cascade with signals of deal attractiveness and quality (Bandura 1977; Bikhchandani, Hirschleifer, and Welch 1998), which would reduce his or her uncertainty about a deal. That is, popular deals can reduce consumers' perceived risk of purchase. Indeed, qualitative research has indicated that uncertainty about deal quality is a key concern affecting consumers' GB behavior (Wang, Zhao, and Li 2013). In addition, the social influence literature stream (Cialdini 1984; Iyengar, Van den Bulte, and Valente 2011; McShane, Bradlow, and Berger 2012) implies that observing the collective actions of prior buyers enables the focal customer to infer deal worth. If deal worth is questionable, it is not likely that the GB deal would be as widely appealing to an increasing group of buyers (Zhang and Liu 2012). The more desirable and popular a deal seems to be, the more likely a consumer may purchase it. As such, we expect deal popularity to increase consumers' purchase likelihood.

> H_{1a}: Ceteris paribus, the higher (lower) the deal popularity, as embodied by the cumulative amount of GB deals purchased by other consumers, the higher (lower) the likelihood that the focal consumer will purchase the GB deal.

Moreover, the higher the deal popularity, the less time the focal consumer will take to redeem the GB deals. Deal popularity information signals deal worth, and the vivid dis-

FIGURE 2
GB Consumer Behavior

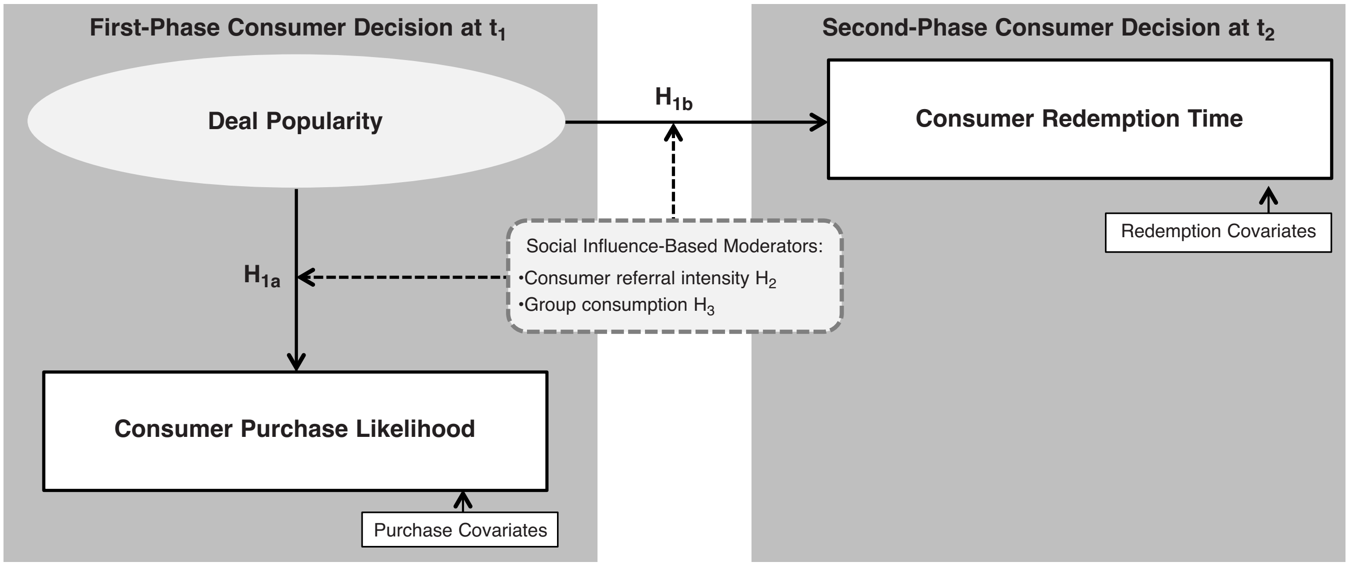


TABLE 1
Description of Independent Variables in the Purchase and Redemption Models

Variable	Operationalization	Purchase Phase Only	Redemption Phase Only	Both Phases
ODP	Deal popularity measured as the cumulative number of total purchases by other consumers			✓
CATE1	Restaurant GB deal			✓
CATE2	Massage and spa GB deal			✓
CATE3	Portrait photo GB deal			✓
CATE4	Entertainment GB deal (base = other categories)			✓
GC	Whether deal intended for group consumption			✓
PRICE	As the listed discounted price			✓
SAVE	As the percentage difference between discounted and original price			✓
DAY_R	Redemption duration in days			✓
DSALES	Average number of deals sold daily			✓
CS	Whether customer visits website independently or via referral			✓
NO_DEAL	Number of available deals at time of purchase	✓		
REST_T	Time left to purchase in days	✓		
SQ_REST_R	Square root of remaining purchase time	✓		
PPUR_P	Number of deals purchased before current purchase	✓		
PRED_P	Number of deals redeemed before current purchase	✓		
PREF_P	Number of referrals made before current purchase	✓		
CT_P	In days customer has been registered on the website before purchase	✓		
WEEKEND_P	Whether deal purchased on the weekend	✓		
DAY_P	Purchase duration in days	✓		
RATING	Measure of rating for merchant reputation	✓		
DP × PPUR_P	Interaction of deal popularity and prior purchase experience (before current purchase)	✓		
DP × PRED_P	Interaction of deal popularity and prior redemption experience (before current purchase)	✓		
PPUR_R	Number of deals purchased before current redemption		✓	
PRED_R	Number of deals redeemed before current redemption		✓	
CT_R	Days customer has been registered on the website before redemption		✓	
LAMBDA_R	Redemption-selection Mills lambda		✓	
WEEKEND_R	Whether deal was redeemed on the weekend		✓	
RED_L	Redemption remaining days before expiration		✓	
DL1	Redemption location close distance from city center		✓	
DL2	Redemption location medium distance from city center		✓	
DL3	Redemption location far distance from city center		✓	

play of such information can boost consumer arousal and increase consumer attention to the deal (Bone 1995; Ye, Cheng, and Fang 2012).[1] The increased arousal and attention to deal worth from deal popularity and OL may thus not only affect purchase likelihood but also carry over beyond the purchase phase and motivate customers to redeem the deal more quickly (Iyengar, Van den Bulte, and Valente 2011; Jing 2011; Liu 2006). If so, deal popularity should reduce the time consumers take to redeem the GB deals in the second phase, conditional on purchase in the first phase.

> H_{1b}: Conditional on purchase, the higher (lower) the deal popularity, the less (more) time a consumer will take to redeem the GB deals.

The Moderating Role of Customer Referral Intensity and Group Consumption

Because deal popularity embodies a form of social influence, our theoretical framework also considers two social influence–related moderators. Specifically, we identify customer referral intensity as a relevant moderating variable because people who recommend the GB experience to others can themselves be more susceptible to social influence and deal popularity. Moreover, we identify the deal's group consumption (group vs. individual use) as another moderator because, by definition, OL is more salient for group settings.

The moderating role of customer referral intensity. We define referral intensity as the number of other consumers that a customer successfully recommends to the GB website.[2] We expect referral intensity to amplify the effects of deal popularity on consumer purchase and redemption. This is because "people who influence others are themselves influenced by others in the same topic area" (Myers and Robertson 1974, p. 41; Sridhar and Srinivasan 2012). As influencers, customers who refer deals to others may themselves be influenced by others, so they may be more receptive to OL and deal popularity's effects. That is, the act of successfully referring deals to others can boost a focal consumer's own susceptibility to social influence and OL (Berger and Schwartz 2011; Iyengar, Van den Bulte, and Valente 2011). The more the focal consumer actively makes referrals and helps the GB website acquire new buyers, the more likely the focal consumer may trust the authenticity of deal popularity information, and the more likely he or she may use deal popularity and OL to infer deal worth and make the purchase and redemption decisions. If so, referral intensity should strengthen the effects of deal popularity on increasing consumer purchase likelihood and decreasing redemption time.[3]

> H_2: The effects of deal popularity on the purchase likelihood and redemption time are amplified by higher (vs. lower) customer referral intensity.

The moderating role of group consumption. Group consumption means the GB deals are designed for group use, such as dinner entrées for four people. In contrast, individual consumption denotes individual use, such as a massage for one person.

We expect group consumption to amplify the effects of deal popularity on consumer purchase and redemption. More specifically, group consumption deals are typically consumed in public with group interactions and thus endorse a greater "public appearance value" (McShane, Bradlow, and Berger 2012; Zhang 2010). Given this additional group-based public appearance value, it is more likely that consumers will use deal popularity information and OL to infer deal worth and make the purchase and redemption decisions. If so, group (vs. individual) consumption may strengthen the effects of deal popularity on increasing consumer purchase likelihood and decreasing redemption time.

> H_3: The effects of deal popularity on the purchase likelihood and redemption time are amplified by group (vs. individual) consumption.

Data and Model

Data

We collected our data from a GB company in China. This company (which has chosen to remain anonymous) provided a unique data set, which includes public information of the deals (e.g., deal popularity, group consumption, price, savings). In addition, the company provided private information of customer records (e.g., consumer purchase and redemption records, referral history). Prior studies have used GB deal purchase data but do not have proprietary consumption data of redemptions (Edelman, Jaffe, and Kominers 2012; Li and Wu 2013).

Our data set encompasses GB deal records from July 2010 to approximately the middle of May 2011 and contains 30,272 customers of the company. These customers made 56,738 deal purchases and 49,362 deal redemptions with an approximately 87% redemption rate. There are 56 GB deals across five product categories, mostly from service industries (i.e., restaurant, entertainment, massage and spa, portrait photo, and health and fitness). These five categories comprise more than 90% of GB deals offered.

Because the consumers' purchase, redemption, and referral intensity are time-varying by day, the total number of observations in our database equates to 4,484,650 at the customer-deal-day level. We selected a daily level of analysis for several reasons. First, the hourly level would generate more than 90 million data points and would be unwieldy, and the weekly level would be too coarse to reveal the time-varying pattern of GB. Second, the daily level more accurately reflects the nature of GB deals because new GB deals are typically released by day (each day at midnight) and not by hour or week. Third, consumers who subscribe to GB platforms such as Groupon or LivingSocial receive an e-mail promoting GB deals each day

[1]Using eye-tracking data, Ye, Cheng, and Fang (2012) find that consumers pay attention to this deal popularity information.

[2]A successful referral occurs when the referred customers (referees) have registered for and purchased a deal from the GB website. After the referees purchase a deal, the GB website rewards the focal consumer (referrer) for securing not merely prospects or leads but rather actual buying customers, because it is free advertising for the GB website.

[3]Prior studies have suggested the direct effects of referral and word of mouth (Liu 2006; Luo 2009; Van den Bulte 2010) and the interactive effect between word of mouth and OL on consumer purchase (Chen, Wang, and Xie 2011; Li and Wu 2013).

(rather than each hour or each week). Indeed, in our follow-up survey, many respondents confirmed that they search for GB deals daily because they are excited about deal savings and the new ability to conveniently shop for coupons online. For these reasons, we structured our data at the daily (rather than hourly or weekly) level.[4]

We Winsorized the data at the bottom 5% and top 95%. Table 2 provides the summary statistics. Appendix A provides an example of the GB deal studied, and Figure 1 exemplifies a typical U.S. deal. In addition, Figure 3 reports the consumer purchase distribution, and Figure 4 reports the consumer redemption distribution.[5]

The Model

This section presents the Tobit II model of purchase likelihood and redemption time with truncation.[6] We have a probit function for the buy/no-buy decision in the first phase and a lognormal function for the redemption time in the second phase, conditional on purchase (Bucklin and Sismeiro 2003; Van Diepen, Donkers, and Franses 2009). We model both purchase and redemption as functions of deal popularity after controlling for consumer- and deal-specific variables. Our model assumes the following: First, a prototypical consumer views GB deal features such as deal price, deal savings, popularity information, and other factors; considers his or her own prior experience; and then decides whether to buy it. Second, conditional on purchase, a consumer decides when to redeem the GB deal before the expiration date (Van Heerde, Gijsbrechts, and Pauwels 2008; Yli-Renko and Janakiraman 2008). A consumer will not purchase the deal and pay money if he or she has no intention of redeeming it. However, a deal may not be redeemed if the consumer procrastinates and passes the deal redemption expiration date. Thus, we specify a truncation at the expiration date for the Tobit II model in the GB setting.

Let P_{ijt} be a binary variable indicating whether consumer i purchases deal j at time t. Let P^*_{ijt} be the latent variable related to P_{ijt}. Furthermore, R_{ij} indicates the redemption time at which consumer i redeems the deal j conditional on the deal purchase (i.e., if $P^*_{ijt} > 0$). R^*_{ij} is the latent variable related to R_{ij}. Because GB deals can be redeemed as soon as the redemption window begins but must be used on or before the expiration date (τ), R^*_{ij} is truncated with $(0, \tau_j)$. Note that the modeled redemption time is conditional on the purchase decision ($R_{ij} = R^*_{ij}$ if $P^*_{ijt} > 0$) because only customers who purchased deals can decide when to redeem them. Our Tobit II model is

$$P_{ijt} = \begin{cases} 1 \text{ if } P^*_{ijt} > 0 \\ 0 \text{ if otherwise} \end{cases}, \text{and} \tag{1}$$

[4]In line with an anonymous reviewer's suggestion, we conducted additional analyses at the coupon level. Specifically, we assume that a prototypical consumer browsed the GB website, saw how popular a particular deal was, decided whether to purchase it, and later decided whether to redeem it. So, we drop the t and specify the model for each consumer by deal observation. The results from this additional analysis suggest that deal popularity consistently has a positive effect on purchase likelihood (.819, $p < .001$) and a negative effect on redemption time (–.046, $p < .01$), thus providing more evidence for our conclusion regarding the importance of deal popularity and OL.

[5]Figure 4 shows the comparable redemption pattern across the deals by dividing the redemption duration of every deal into ten periods of equal length for each deal.

[6]We acknowledge the area editor for suggesting this Tobit II model approach.

TABLE 2
Descriptives of Variables

	M	SD	Min	Max
Deal popularity (DP) in log	.046	.547	.000	8.661
Prior referral experience (before purchase) (PREF_P) in log	.088	.311	.000	6.850
Prior referral experience (before redemption) (PREF_R) in log	.079	.301	.000	6.850
Prior purchase experience (before purchase) (PPUR_P) in log	.831	.419	.000	4.407
Prior purchase experience (before redemption) (PPUR_R) in log	.916	.358	.000	4.331
Prior redemption experience (before purchase) (PRED_P) in log	.466	.497	.000	4.331
Prior redemption experience (before redemption (PRED_R) in log	.416	.585	.000	2.996
Group consumption (GC)	.389	.487	.000	1.000
Number of available deals (NO_DEAL)	2.331	1.396	1.000	6.000
Remaining purchase time (REST_T)	1.899	.459	.000	2.708
Customer source (self/referral) (CS)	.146	.353	.000	1.000
Customer tenure (before purchase) (CT_P) in log	3.785	1.004	.000	5.508
Restaurant dummy (CATE1)	.424	.494	.000	1.000
Massage and spa dummy (CATE2)	.217	.412	.000	1.000
Portrait photo dummy (CATE3)	.142	.349	.000	1.000
Entertainment dummy (CATE4)	.113	.317	.000	1.000
Average daily sales (DSALES) in log	4.929	.938	2.934	7.919
Discounted price (PRICE) in log	4.057	.896	1.792	6.604
Savings (SAVE) in log	5.182	1.118	3.178	7.286
Weekend purchase (WEEKEND_P)	.280	.449	.000	1.000
Rating (RATING)	3.639	.376	2.000	5.000
Customer tenure (before redemption) (CT_R) in log	3.655	1.093	.000	5.748
Weekend redemption dummy (WEEKEND_R)	.146	.353	.000	1.000
Redemption location dummy 1 (DL1)	.164	.370	.000	1.000
Redemption location dummy 2 (DL2)	.003	.054	.000	1.000
Redemption location dummy 3 (DL3)	.044	.204	.000	1.000

FIGURE 3
GB Deal Purchase Distribution (Whole Sample)

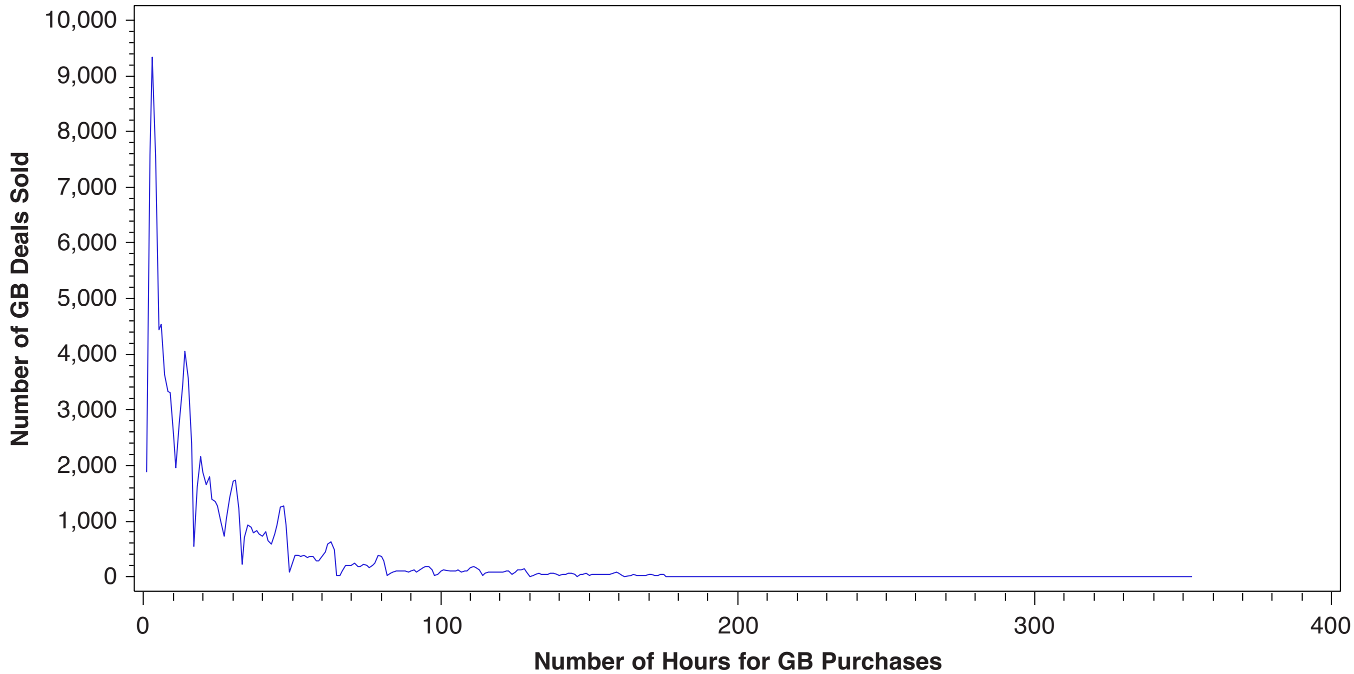
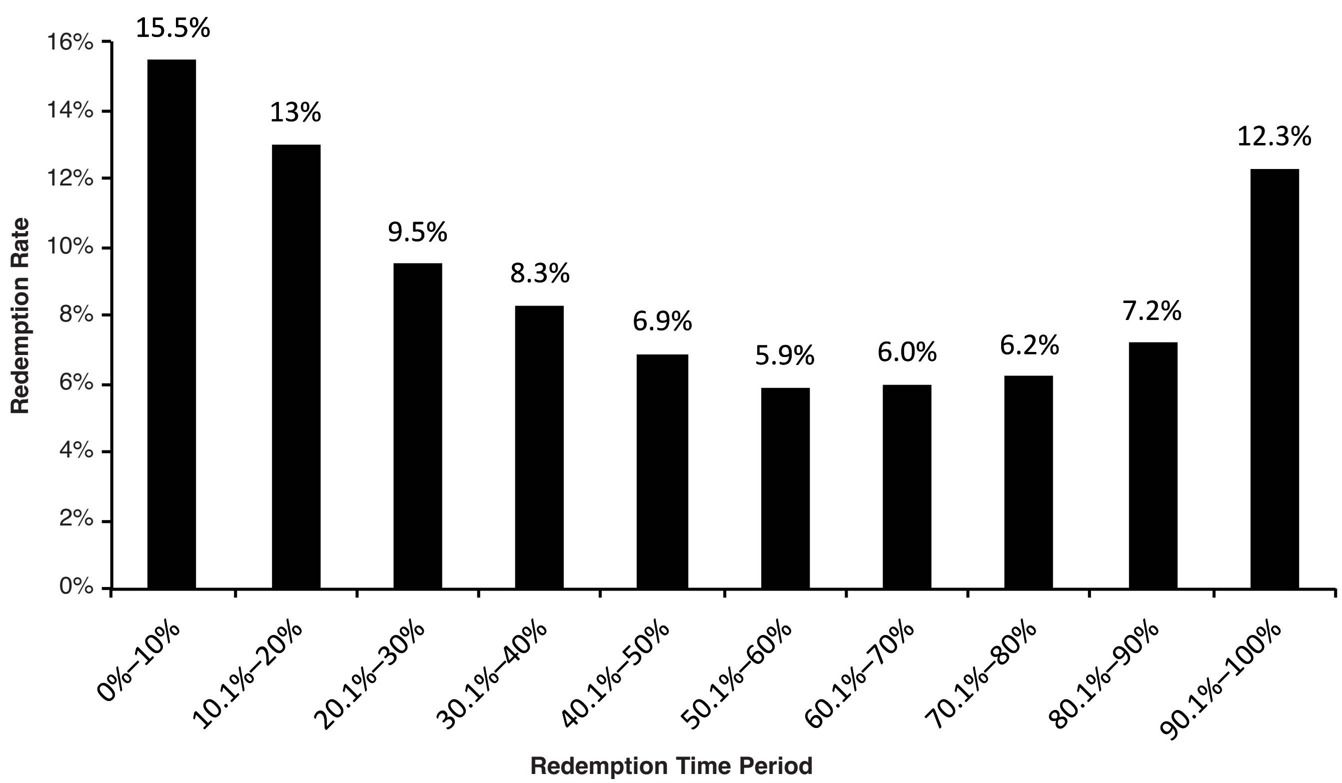


FIGURE 4
GB Deal Redemption Over Time



Notes: Because each deal has a different redemption window, the redemption time period is defined in relative terms (ten time periods, relative to the redemption window allotted).

$$\text{(2)} \qquad R_{ijt} = \begin{cases} R^*_{ij} \text{ if } P^*_{ijt} > 0 \text{ and } 0 < R^*_{ij} \le \tau_j \\ 0 \text{ if otherwise} \end{cases}, \text{ where}$$

$$\begin{aligned} \text{(3)} \quad P^*_{ijt} = {} & \delta_0 + \delta_1 DP_{ijt} + \delta_2 GC_j + \delta_3 PREF\_P_{it} + \delta_4 PPUR\_P_{it} \\ & + \delta_5 PRED\_P_{it} + \delta_6 CT\_P_{it} + \delta_7 DSALES_j + \delta_8 PRICE_j \\ & + \delta_9 SAVE_j + \delta_{10} CS_i + \delta_{11} WEEKEND\_P_t + \delta_{12} DAY\_P_j \\ & + \delta_{13} REST\_T_{jt} + \delta_{14} Sqr\_REST\_T_{jt} + \delta_{15} NO\_DEAL_t \\ & + \delta_{16} RATING_j + \delta_{17} DAY\_R_j + \delta_{18} CATE1_j + \delta_{19} CATE2_j \\ & + \delta_{20} CATE3_j + \delta_{21} CATE4_j + \Sigma\delta \text{Interactions} + \varepsilon_{ijt}, \text{ and} \end{aligned}$$

$$\begin{aligned} \text{(4)} \quad R^*_{ij} = {} & \psi_0 + \psi_1 DP_{ijt} + \psi_2 GC_j + \psi_3 PREF\_R_{it} + \psi_4 PPUR\_R_{it} \\ & + \psi_5 PRED\_R_{it} + \psi_6 CT\_R_{it} + \psi_7 DSALES_j + \psi_8 PRICE_j \\ & + \psi_9 SAVE_j + \psi_{10} CS_i + \psi_{11} WEEKEND\_R_t \\ & + \psi_{12} DAY\_R_t + \psi_{13} DL1_j + \psi_{14} DL2_j + \psi_{15} DL3_j \\ & + \psi_{16} RED\_L_{jt} + \psi_{17} CATE1_j + \psi_{18} CATE2_j \\ & + \psi_{19} CATE3_j + \psi_{20} CATE4_j + \Sigma\psi \text{Interactions} + \mu_{ij}, \end{aligned}$$

where ε_{ijt} and μ_{ij} represent model residuals.

In the P^*_{ijt} equation for the first purchase phase, we include the time-varying deal popularity (DP), time-unvarying deal heterogeneity variables (group consumption [GC], the discounted deal price [PRICE], the amount of savings [SAVE], and category dummies [CATE1, 2, 3, and 4]). We also include time-varying customer heterogeneity variables (the number of deals purchased [PPUR_P] and redeemed before the current purchase [PRED_P] and the number of referrals [PREF_P] made before the current purchase as well as customer tenure before the current purchase [CT_P]). Again, referral intensity is the number of other consumers that a customer successfully recommends to the GB website. A successful referral occurs when the referred customers (referees) have registered and purchased a deal from the GB website. In addition, we control for the remaining purchase time of deal j at time t ($REST\_T_{jt}$) and a quadratic term for its nonlinearity ($Sqr\_REST\_T_{jt}$) as well as the deal purchase duration (DAY_P) and deal redemption duration in days (DAY_R). Furthermore, we account for the effects of the number of available deals at time t (NO_DEAL_t), the merchant rating ($RATING_j$), the customer source (CS), average daily deal sales (DSALES) to capture unobserved factors affecting daily sales, and a weekend purchase dummy ($WEEKEND\_P_t$).

In the R^*_{ij} equation for the second redemption phase, we include deal popularity, the time-varying customer heterogeneity variables (the number of deals purchased [PPUR_R] and redeemed [PRED_R] before the current redemption, and the number of referrals [PREF_R] made before the current redemption), a weekend redemption dummy ($WEEKEND\_R_t$), and the time-unvarying deal heterogeneity variables (PRICE, SAVE, and category dummies of CATE1, 2, 3, and 4). In addition, we include customer tenure before the current redemption (CT_R), average daily deal sales (DSALES), and days remaining before redemption expiration (RED_L). To account for the possible bias that a subsample of consumers would never redeem the deals regardless of the expiration date, we include a redemption-selection Mills lambda (Lambda_R) as an additional covariate in the redemption time function. This lambda can help reduce biases that result from nonredemption in the estimated results beyond the truncation specification.[7] Finally, we control for redemption location with dummies ($DL1_j$, $DL2_j$, and $DL3_j$, indicating “between the inner and the middle rings,” “between the middle and outer rings,” and “outside of the outer ring,” respectively, with the base as the inner ring of the metropolitan city).

The covariates included in both the purchase likelihood function and the redemption time function of our Tobit II model are the discounted price, savings, average daily sales, group consumption, redemption duration, customer source, and deal categories. Although both the purchase and redemption functions include the covariates of prior purchase experience, prior redemption experience, and prior referral intensity, these variables are not identical, because they are time varying: customers may continue to make referrals after the purchase but before the redemption. Thus, the prior referral experience in the purchase function may be different from that in the redemption function. Similarly, consumer prior experience in purchase and redemption are time-varying, because in the interim, it is possible that consumers will buy another deal. Thus, the number of deals purchased before the current purchase may be different from the number of deals purchased before the current redemption. To test the moderating hypotheses, we also enter the interaction between deal popularity and the group consumption dummy and prior referral intensity in both functions.

Model Identification Strategy

To identify the models, we specify that the covariates used in the buy/no-buy probit model are not the same as those used for the redemption function. Specifically, the covariates used only in the purchase function are the number of available deals, the remaining purchase time, the squared term of the remaining purchase time, PPUR_P, PRED_P, PREF_P, customer tenure (before purchase), a weekend purchase dummy, deal purchase duration, and the merchant rating. In contrast, the covariates used only in the redemption function are PPUR_R, PRED_R, PREF_R, customer tenure (before redemption), a weekend redemption dummy,

[7]We include a Mills lambda because theoretically, our Tobit II model may be criticized because we skipped yes/no redemption. We model yes/no purchase and then redemption time without yes/no redemption. With this Mills lambda accounting for yes/no redemption, our Tobit II is free of this skipping bias. Thus, before estimating the Tobit II model, we ran a Heckman section model (redemption yes/no) to include the Mills lambda as an additional covariate in the redemption time function to account for the possible bias of skipping redemption yes/no in the Tobit II model. Still, empirically, we find that with or without this redemption-selection lambda, the results for the redemption time and purchase likelihood equations are qualitatively the same, consistently in support of our hypotheses. This is not surprising, because the majority (87%) of GB deals were indeed redeemed in our data.

a redemption-selection Mills lambda, the remaining redemption days, and three redemption location dummies. Importantly, the redemption location (the inner, middle, or outer ring of the city) captures the travel costs of effort and time required for the customer to redeem the deal, so it will more likely influence redemption decisions rather than purchase decisions. Thus, these redemption location covariates (and other covariates in the redemption phase but not the purchase phase) that we have controlled for enable us to identify the model with horizontal identification. This horizontal identification extends beyond the vertical identification (with deal worth).

Another identification strategy we use incorporates the time stamps in the matched data on the purchase and redemption records. Specifically, we are able to identify the actual time stamps for purchase and redemption for each customer of each deal because the GB website has the purchase records and merchants provide the redemption records (merchants report the redemption records to the GB website company to verify the authenticity of the prepaid deals and receive the revenue withheld by the company). The actual time stamp of purchase and redemption is recorded automatically though digital systems in real time on the Internet. These time-sequence records enable us to check deal popularity information *before* the purchase time, thus identifying the time-order effects of deal popularity on purchase likelihood. Moreover, we can identify the potential longevity effects of deal popularity information on redemption for two reasons. First, Ye, Cheng, and Fang (2012) use eye-tracking data to find that consumers indeed pay a great deal of attention to deal popularity information and engage in OL that often has longevity effects (Berger and Schwartz 2011). Second, in our data, conditional on purchase, consumers can print the voucher of their prepaid GB deal on which the deal popularity information is reported. Thus, consumers can access this information again when they are ready to redeem.[8]

Although we paid a great deal of attention to issues of model identification, this research may not perfectly identify causal impact, similar to other studies on GB and social influences (Li and Wu 2013; Sridhar and Srinivasan 2012; Zhang and Liu 2012). Unless researchers use randomized field experiments with corporate partners (Hinz et al. 2001; Lambrecht and Tucker 2013; Luo et al. 2014), it is difficult to identify causal effects in general.

Results

Results for Model Fitness

We estimated the Tobit II model with the SAS PROC QLIM procedure with truncation. In the Tobit II model, we entered the variables hierarchically. First, we entered only the control variables (Model 1: Akaike information criterion [AIC] = 186,520, and Bayesian information criterion [BIC] = 187,080). Then, we entered the main effects of deal popularity (Model 2: AIC = 42,176, and BIC = 42,762). Finally, we entered the interactions between deal popularity, prior referral intensity, group consumption, and purchase and redemption experience (Model 3: AIC = 40,295, and BIC = 40,985). We find that the incremental model fitness of likelihood ratio tests from Models 1 to 2 and from Models 2 to 3 are all statistically significant (p < .01). The predicted purchase of the Tobit II model matches well with the actual purchase, with a hit ratio of 99.57%. As Appendix B shows, the results confirm that the out-of-sample (25% of the data) root mean square error (RMSE) is smaller when we add deal popularity and its interactions to the model. This finding validates that OL meaningfully adds to the Tobit II model; that is, the addition of deal popularity and OL in the model improves prediction. The in-sample (75% of the data) AIC also improves when we add deal popularity and its interactions to the Tobit II model.

Results for the Effects of Deal Popularity on Purchase Likelihood and Redemption Time

Consistent with the prediction that deal popularity increases a focal customer's purchase probability in the first phase, our results in the probit function of Table 3 indicate a positive and significant effect (.705, p < .001). As such, this finding supports H_{1a}, suggesting that the higher (lower) the deal popularity, the more (less) likely the focal consumer will purchase the deal, holding everything else constant.

In addition, consistent with the prediction that deal popularity decreases customers' redemption time in the second phase, our results in the lognormal function of Table 3 indicate a negative and significant effect (–.040, p < .01). As such, this finding supports H_{1b}, suggesting that conditional on purchase, the higher (lower) the deal popularity, the more (less) quickly the focal consumer will subsequently redeem the deal before the deadline.

Results for the Moderating Role of Customer Referral Intensity and Group Consumption

H_2 predicts that referral intensity amplifies the effects of deal popularity on purchase likelihood and redemption time. The results in the probit function of Table 3 indicate that the coefficient of the interaction term of referral intensity × deal popularity is positive and significant (.249, p < .001), as we expected. In addition, consistent with the prediction that referral intensity will strengthen the negative effect of deal popularity on redemption time, the coefficient of referral intensity × deal popularity is negative and significant (–.065, p < .001). Thus, the positive effects of deal popularity on purchase likelihood and the negative effects of deal popularity on redemption time are indeed amplified by referral intensity, in support of H_2.

Similarly, H_3 predicts that group consumption amplifies the effects of deal popularity on purchase likelihood and redemption time. Consistent with the prediction that group consumption will strengthen the positive effect of deal popularity on purchase likelihood, the results in the probit function of Table 3 indicate that the coefficient of the interaction term of group consumption × deal popularity is positive and

[8]In line with an anonymous reviewer's suggestion, in a follow-up study with 200 interviews of GB consumers, we verified that 67% of consumers indeed paid attention to and remembered the deal popularity information when redeeming the GB deals.

TABLE 3
Estimation Results of Tobit II Model

	Purchase Likelihood Function		Redemption Time Function Conditional on Purchase	
Intercept	–.287	(.491)	.019	(.095)
Restaurant category (CATE1)	.291***	(.037)	.263***	(.031)
Massage and spa category (CATE2)	.119	(.082)	.332***	(.021)
Portrait photo category (CATE3)	.136	(.083)	.202***	(.022)
Entertainment category (CATE4)	.009	(.125)	.121	(.727)
Customer source (CS)	–.086	(.054)	–.007	(.011)
Average daily sales (DSALES)	.119***	(.030)	–.092***	(.007)
Discounted price (PRICE)	–.105**	(.031)	.019*	(.008)
Savings (SAVE)	.063†	(.034)	–.058***	(.008)
Redemption duration (DAY_R)	–.055	(.072)	.166***	(.016)
Group consumption (GC)	–.026	(.110)	–.075	(.046)
Number of available deals (NO_DEAL)	–.128***	(.023)		
Remaining purchase time (REST_T)	–.165	(.436)		
Square of remaining purchase time (Sqr_REST_T)	–.199	(.132)		
Prior purchase experience (before current purchase) (PPUR_P)	–.214***	(.049)		
Prior redemption experience (before current purchase) (PRED_P)	–.155*	(.078)		
Prior referral experience (before current purchase) (PREF_P)	.027*	(.013)		
Customer tenure (before current purchase) (CT_P)	–.250***	(.015)		
Weekend purchase dummy (WEEKEND_P)	.123*	(.050)		
Purchase duration (DAY_P)	–.085***	(.072)		
Rating (RATING)	.037	(.057)		
Deal popularity × prior purchase experience (before current purchase)	.591***	(.120)		
Deal popularity × prior redemption experience (before current purchase)	.060	(.062)		
Prior purchase experience (before current redemption) (PPUR_R)			–.769***	(.027)
Prior redemption experience (before current redemption) (PRED_R)			–.044**	(.016)
Prior referral experience (before current redemption) (PREF_R)			.116***	(.026)
Deal popularity × prior purchase experience (before current redemption)			.097***	(.014)
Deal popularity × prior redemption experience (before current redemption)			–.010***	(.003)
Customer tenure (before current redemption) (CT_R)			1.040***	(.004)
Lambda_R			.612	(1.038)
Redemption remaining days (RED_L)			–.045***	(.003)
Weekend redemption dummy (WEEKEND_R)			–.012	(.012)
Redemption location dummy 1 (DL1)			.061***	(.012)
Redemption location dummy 2 (DL2)			.127***	(.016)
Redemption location dummy 3 (DL3)			.224***	(.023)
Deal popularity (H_{1a}, H_{1b})	.705***	(.130)	–.040**	(.015)
Deal popularity × group consumption (H_3)	.407***	(.044)	–.016*	(.007)
Deal popularity × prior referral experience (before current purchase) (H_2)	.249***	(.068)		
Deal popularity × prior referral experience (before current redemption) (H_2)			–.065***	(.004)
Rho	.0784** (.0296)			
Log-likelihood	–20,094			
AIC	40,295			
BIC	40,985			

†$p < .1$.
*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: The sample size of the model estimation is 3,363,488 (75% of the whole sample). Among the estimation sample, 25,365 observations had purchased (Purchase = 1).

significant in the purchase phase (.407, $p < .001$). Moreover, consistent with the prediction that group consumption will strengthen the negative effect of deal popularity on redemption time, the coefficient of group consumption × deal popularity is also negative (–.016, $p < .05$). In summary, these findings indicate that the positive effects of deal popularity on purchase likelihood and the negative effects of deal popularity on redemption time are both amplified by group (vs. individual) consumption, thus lending support to H_3.

Results of Relative Effects of Deal Purchase Likelihood Versus Redemption Time

With regard to understanding the two-phase consumer decision process, the results in Table 3 provide several additional insights. First, the effect of deal popularity on purchase ($p < .001$) is at a lower statistical significance level than that on redemption ($p < .01$). In terms of theory development, this suggests that consumers are more attentive to, and more influenced by, the deal popularity information in the *immediate* purchase phase than the *distant* redemption phase (because the redemption phase is more distant from initial exposure to the deal popularity information). Appendix C presents a summary table.

Second, the results in Table 3 also suggest that deal savings increase purchase (.063, $p < .10$) and accelerate redemption (–.058, $p < .001$). Deal price decreases purchase likelihood (–.105, $p < .01$) but delays redemption (.019, $p < .05$). The results for deal purchase likelihood are intuitive because higher prices of a service typically decrease consumers' willingness to buy the service, whereas savings relative to the original price increase it. The results for deal redemption are more notable because they suggest that the deal price may not operate as a sunk cost factor that would accelerate the consumer's deal redemption (to reclaim the investment as soon as possible). Instead, the monetary savings of the deal do so. Thus, the theoretical implication is that deal savings rather than deal prices motivate consumers to redeem the GB deals more quickly, conditional on purchase.

Third, customers' prior deal buying and redeeming experiences decrease their likelihood of purchasing new GB deals (–.214, $p < .001$, and –.155, $p < .05$) but accelerate the redemption (–.769, $p < .001$, and –.044, $p < .01$). The former finding on purchase likelihood underlies the current criticism of the GB industry (a point we return to in our "Discussion" section). Yet prior buying experience also reinforces the positive effect of deal popularity on current deal purchase likelihood (.591, $p < .001$). This finding suggests that deal popularity is a particularly important factor in influencing experienced customers to buy new GB deals, implying that prior customers may particularly appreciate the "wisdom of crowds" in purchasing new GB deals online. Furthermore, the latter finding that customers with greater experience are *swifter* to buy and redeem new deals implies two types of learning among GB customers: (1) with experience, customers may become more skillful at purchasing deals that they like, which would manifest in faster deal redemption (vs. procrastination), and (2) experienced customers may learn that it pays off to redeem deals sooner rather than later because there might be service crowding near the redemption deadline (Inman and McAlister 1994), especially for popular deals. Consistent with these implications, Table 3 shows that prior redemption experience reinforces the accelerating influence of deal popularity on redemption time (–.010, $p < .001$), conditional on purchase.

Finally, referral intensity positively affects purchase likelihood and redemption time ($p < .05$), suggesting that referrals indeed may help secure more sales. Furthermore, group consumption and customer source do not directly affect either purchase or redemption. The location dummy variables are positive and significant regarding deal redemption time ($p < .001$), as we expected. This finding suggests that compared with the base location of the city center, the farther away the deal's redemption location, the more time it takes customers to redeem the deal, perhaps because of higher travel costs to redeem the GB deals purchased.

Discussion

Group-buying deal popularity can influence consumers' purchase likelihood and redemption time. Because most GB deals are offered by new, unbranded merchants, consumers may be uncertain about a deal's worth. Yet consumers may infer the quality and desirability of a deal by observing how many others have already purchased the deal. In this sense, the more popular a deal is, the more a focal consumer may be encouraged to partake of it. Our analyses of a unique data set of 30,272 customers confirm the influence of deal popularity as well as the moderating role of social influence factors of group consumption and referral intensity on consumer purchase and redemption decisions. These findings have several implications.

Implications for Theory

We extend the GB research by advancing a two-phase perspective. As Appendix D shows, we expand prior research (Kauffman and Wang 2001; Li and Wu 2013) by investigating both purchase and redemption with disaggregated consumer-level data for a deeper understanding of consumer behaviors of GB deals. Our investigation of both purchase and redemption phases may be critical for the future of the GB industry. As Groupon's drastic stock plunge fuels concerns about the sustainability of the business model, the survival of GB platform companies hinges on their ability both to stimulate more sales for merchants (through deal purchases) and to secure consumption value for customers (through deal redemptions). Amid investor doubts about GB's long-term viability, a more comprehensive understanding of consumer purchase and redemption behaviors may ameliorate these concerns (Edelman, Jaffe, and Kominers 2012; Gupta, Weaver, and Rood 2012). We find that deal popularity can stimulate sales purchases and accelerate redemption. This finding highlights the importance of deal popularity in alleviating such criticism of GB.

This research also advances the social influence and OL literature. Prior studies have shown that people seek out frequently downloaded songs, popular movies, and best-selling books (Elberse and Eliashberg 2003; Salganik, Dodds, and Watts 2006). We extend this notion of "success breeds success" by exploring the effects of deal popularity on interrelated decisions: purchase and actual consumption time, conditional on purchase. This extension is critical because of the increasing asynchrony of consumption decisions as more consumers buy online and plan in advance. We also show the longevity effect of deal popularity and OL, which may advance theories on social influence with a dynamic, temporal perspective. Prior research has suggested that others' actions have a powerful effect on individual behavior (Zhang 2010). Acknowledging this finding, we also add that neglecting the longevity effect would underestimate the power of OL and social influence. Furthermore, we show how consumers can influence and be influenced simultaneously. Prior research has demonstrated that the cars others drive can influence a consumer's car purchase (McShane, Bradlow, and Berger 2012). Our work adds that the social influence of deal popularity (others' influence) can be amplified when the focal consumer actively refers GB deals (influencing others) in the new online marketing platform of GB.

Our results also gauge the relative influence of deal popularity and other key factors on deal purchases versus redemptions, providing further theoretical development of GB's drivers. We find that deal popularity has a greater influence on deal purchase than on redemption, suggesting, inter alia, that the vivid deal popularity information may be more accessible and influential in the purchase stage than at the redemption stage. Regarding other key factors, we find that deal savings (rather than price) operate as a sunk cost in the redemption phase, motivating consumers to redeem the deals quickly. Finally, whereas prior buy and redemption experience decreases the likelihood of purchasing new deals, prior referral experience and deal popularity information provide a counterforce by increasing consumers' likelihood of purchasing new GB deals.

Our findings also extend the coupon literature stream. We respond to calls to identify additional mechanisms driving coupon redemption (Musalem, Bradlow, and Raju 2008; Venkatesan and Farris 2012) by revealing deal popularity and OL as relevant mechanisms. We also answer the call to identify contingencies of coupon redemption behaviors (Bawa, Srinivasan, and Srivastava 1997) by showing the moderating effects of group consumption and referral intensity. Prior research has discerned the need to "encourage immediate coupon use" (Shu and Gneezy 2010, p. 943) and reduce procrastination. We find that consumers influenced by deal popularity tend to redeem their deals more quickly, especially in the case of group consumption deals and for consumers who are active referrers. Furthermore, unlike traditional free coupons, GB deals are purchased in advance before actual consumption or redemption. We thus extend prior coupon models by developing an interrelated modeling system that incorporates a function for the purchase likelihood and another function for the redemption time with truncation, conditional on purchase.

Implications for Practice

Our findings are relevant for merchants and GB platform companies with both strategic and tactical implications. From a strategic perspective, some of our findings corroborate concerns regarding the overall GB business model by showing that customers with prior experience are less likely to purchase new deals. Indeed, the GB business model, which has thus far relied heavily on new customer acquisition (instead of repeat patronage), may have been effective during the nascence of the GB industry but may not be sustainable as the industry matures. To alleviate these pessimistic concerns, we proffer several specific recommendations. First, a vivid display of deal popularity in promoting the GB deals can stimulate consumers to purchase. Because consumers may find it difficult to ascertain GB deals' quality and worth from new merchants (Wang, Zhao, and Li 2013), deal popularity and OL may engender higher consumer confidence in the deal value. Second, comparing the main effects *alone*, deal popularity has a relatively stronger influence in increasing purchase likelihood than prior experience has in decreasing purchase likelihood (approximately three times stronger in effect size; see Table 3). Third, notably, although the main effect of prior GB buying experience is negative, its interaction effect with deal popularity is positive and significantly boosts consumer purchase likelihood ($p < .001$). This result suggests that managers may target returning customers with deal popularity information to counteract the negative direct effects of prior experience. Fourth, encouraging customers to make referrals to others will also stimulate new deal purchases from the referring customers. Thus, the GB online platform should make referrals easy and more rewarding (e.g., higher bonuses). This tactic would not only stimulate deal purchases and redemptions in general but would also encourage customers to purchase GB deals repeatedly to fight customer churn in particular.

From a tactical perspective, we provide additional suggestions beyond simply making deal popularity information visible for consumers on GB websites. For example, group consumption amplifies the effects of popularity information on purchase likelihood. Thus, to increase GB deal sales, merchants should not only display deal popularity but also offer more deals designed for group use and encourage social interactions among friends and family (Subramanian 2012). Furthermore, merchants and GB platform companies might consider encouraging consumers to refer deals to other potential consumers. They should incentivize consumers to make referrals because doing so creates word of mouth for the deals and can amplify the impact of deal popularity on purchase rates. In addition, to encourage consumers' swifter redemption, it may be effective to display popularity information. Understanding the direct and indirect effects of deal popularity on redemption time can better prepare managers for constraints such as capacity problems during the redemption period.

Finally, technological developments might change GB deal behaviors. When Groupon offered users a 50%-off Starbucks mobile gift card, the surge in respondents crashed the Groupon site. Although GB deals have struggled of late, such mobile offers are a testament to how the right deal coupled with mobile technology can drive results for both GB platform companies and merchants. Indeed, mobile app users can be high-value repeat customers rather than bargain shoppers (Tode 2013). Thus, marketers might consider leveraging these GB innovations to increase purchases. Group-buying deal companies are also considering advertising through search engines to reach potential customers beyond their inboxes, which would have required customers to sign up in advance (Campbell 2013). In addition, although GB as a marketing tool has passed the initial takeoff stage in the developed U.S. markets, its growth may still be significant in developing markets such as India, Brazil, and Russia. Thus, marketers should recognize that the GB industry practice is not limited to the U.S. market but rather has global potential.

Conclusion

In conclusion, we reveal that (1) deal popularity increases consumers' purchase likelihood of GB deals and decreases redemption time conditional on purchase and (2) these effects are amplified by the social influence–related factors of group consumption and referral intensity. We hope these findings spur more research on GB deals and two-staged consumer behaviors across purchases and redemptions.

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APPENDIX A
Example of GB Deal Studied

APPENDIX B
In-Sample and Out-of-Sample Statistics

	RMSE (Out-of-Sample, 25%)	AIC (In-Sample, 75%)
Tobit II model without deal popularity and interactions	.9211	186,520
Tobit II model with deal popularity and interactions	.5448	40,295

Notes: The RMSE measures the differences between values predicted by a model estimator and the values actually observed. Because we used RMSE with the out-of-sample statistics, it gauges the prediction errors. It aggregates the magnitudes of the errors in predictions into a single measure of predictive power, so we consider it a good measure of accuracy.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}},$$

where $\hat{y}_t$ is the predicted value, and y_t is the observed value out-of-sample. The AIC measures the relative quality of a statistical model when fitting a data set. It gauges the trade-off between the goodness-of-fit and the complexity of the statistical model. AIC = 2k – 2ln(L), where k = the number of model parameters, and L is the maximized value of the likelihood function for the estimated model.

APPENDIX C
Relative Influence of Deal Popularity and Other Drivers on Deal Purchase Versus Redemption

Key Factor	Result	Suggested Reasons/Mechanisms
Deal popularity	The effect of deal popularity is greater on deal purchase likelihood than on deal redemption timing.	Consumers are more attentive to, and more influenced by, deal popularity information in the more immediate purchase phase than the more distant redemption phase (i.e., redemption is more distant from initial exposure to the deal popularity information).
Deal price and savings	Deal price decreases deal purchase likelihood and deal savings increase it.	•With regard to deal purchases, the result confirms the intuition of price effects (higher prices decrease purchases, higher savings increase purchases).
	Deal price delays deal redemption and deal savings accelerate it.	•With regard to deal redemptions, deal savings (rather than deal price) act as a perceived sunk cost/investment factor for consumers in GB, motivating them to redeem the deal in which they have invested more quickly, conditional on purchase.
Prior experience	Prior experience of deal purchases and redemptions decrease deal purchase likelihood, but prior referral experience increases it.	•With regard to deal purchases, customers who have purchased deals in the past are less likely to buy in the future (i.e., many customers only buy once). Yet this negative tendency is counteracted by engaging customers in referrals and communicating deal popularity information.
	Prior experience of deal purchases reinforces the positive effect of deal popularity on new deal purchase likelihood.	•With regard to deal redemptions, two types of learning likely occur among GB customers: a. With experience, customers may become more skillful at purchasing deals that they like, which would manifest in their quicker redemption of deals purchased (instead of procrastinating or avoiding redemption). b. With experience, customers likely learn that it pays off to redeem deals sooner rather than later.
	Prior experience of deal purchases and redemptions accelerates deal redemptions.	

APPENDIX D
Overview of GB Research

Studies	Initial Purchase	Subsequent Redemption	OL/Social Influence	Group Consumption	Referral Intensity
Anand and Aron (2003)	Aggregated				
Edelman, Jaffe, and Kominers (2012)	Aggregated				
Kauffman and Wang (2001)	Aggregated		✓		
Kumar and Rajan (2012)	Aggregated			✓	
Subramanian (2012)	Aggregated		✓	✓	
Li and Wu (2013)	Aggregated		✓		✓
The present study	Disaggregated	✓	✓	✓	✓

Notes: Aggregated = at deal level; Disaggregated = at consumer level.