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Stated Choice Analysis of Conditional Purchase and Information Cue Effects in Online Group Purchase

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Abstract

Group-purchase institutions, a type of Internet shopping website, allows consumers to aggregate their demands for a product to gain discounts in purchase price. Modeling consumers' bidding behavior in this institution using the economic perspective of constraint, expectation, and preference interactions, we study two group-purchase mechanisms (i.e., conditional purchase and information cue) on a buyer's purchase choice across competing group-purchase alternatives. Using a conditional purchase mechanism, a buyer is not obliged to commit to the purchase if the best price is not met (i.e., the final offered price is greater than the best available lowest price). Through the information cue, a buyer could obtain information on the current number of orders collected. We analyzed a set of laboratory experimental data based on a group-purchase institution using the stated choice method. We find that a buyer is more likely to buy through group-purchase when a conditional purchase mechanism is provided. However, providing more information does not necessarily alleviate buyer uncertainty and inertia. The presence of information cue does induce them to choose a riskier but cheaper group-purchase option. In such cases, the choice elasticity of a risky group-purchase option is more sensitive to the information cue than to the conditional purchase mechanism.

***Keywords**: Group Purchase, Stated Choice Analysis, Conditional Purchase, Information Provision.*

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1. Introduction

Group-purchase institutions (GPI), specialized Internet-enabled shopping institutions, enable consumers to aggregate their demands for identical products to obtain attractive deals in the form of highly discounted prices (Geoffrion & Krishnan, 2003). In recent years, business analysts have increasingly expressed concern about the group-purchase industry's low-entry barriers and intensifying rivalry to compete for buyers (Bosker, 2011). At their core, GPI work on the basis that they need to attract people with sufficient aggregated commitment to a purchase (i.e., to buy products in sufficient volumes to obtain a discounted price) (Azfar, 2001). However, buyers may not come to a common action such as committing to a specific product purchase for everyone's collective benefit of getting a lower price (Sandler, 1992). Thus, other than examining GPI sellers' profitability (Grewal et al., 2011), an important way to examine GPI, which prior studies have largely ignored, is via implementing mechanisms or marketing-mix policies that can influence the viability of such GPI websites (Kumar & Rajan, 2012).

Various commercial GPI implementations exist, but two types are prominent. The first type allows online consumers to aggregate their similar product purchases through either a fixed price with quantity threshold (i.e., minimum number of orders before a group-buying deal is established); in contrast, the second type uses a staggered pricing scheme (i.e., the transaction price decreases as the number of orders increases). While championed and popularized by Groupon, the first type is a simplified version of group-purchase. The second type is a more sophisticated yet flexible version of group buying in which a buyer is first assured of a price ceiling (i.e., the maximum price payable for a product) and subsequently enjoys a lower price should the higher order-quantity threshold be met[1] (Anand & Aron, 2003; Chen, Chen, Kaufman, & Song, 2009a; Chen, Kauffman, Liu, & Song, 2009b; Kauffman & Wang, 2001). In this research, our focus is on the second type of group buying.

In a typical group-buying setting, buyers thinking about whether other buyers have similar purchase inclinations can trigger uncertainty in their mind, which can lead the buyers to not commit to a purchase or to choose an option that is of lower price uncertainty[2] (Anderson, 2003; Dhar & Nowlis, 1999). As such, we need a good understanding of the interactions among GPI buyers and their behavioral decisions in the face of uncertainty. As a result, we ask:

> **RQ:** *What are the kinds of mechanism that GPI can implement that can encourage prospective buyers, who may be uncertain over whether the lowest purchase price can be attained, to place orders?*

To answer this question, following Manski (2000), we conceptualize that there are constraint, expectation, and preference interactions among buyers in GPI. Moreover, we propose that, to address such interactions, GPI needs to afford two mechanisms; namely, 1) information cues to facilitate observational learning among buyers, and 2) conditional purchases to alleviate potential negative economic outcomes should the best available price in GPI not materialize. The information cue mechanism, which comes from the information provision paradigm (Charness & Villeval, 2009; Sandler, 1992), displays information on the latest number of orders collected during the decision time. This increased transparency could allow buyers to assess the probability of the best price being met. The conditional purchase mechanism, on the other hand, allows buyers the opportunity to forfeit a purchase without incurring any monetary penalty (Bendor & Mookherjee, 1987; Giebels, De Dreu, & Van de Vliert, 2000) and, thus, serves as an "exit" option (Bendor & Mookherjee, 1987; Giebels et al., 2000).

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[1] For instance, a typical group-buying retail situation of this latter form could entail two purchase options for an identical camera. Option A lists $450 as the base price (i.e., price ceiling) and accepts $400 (i.e., best price) if a low order-quantity threshold of three or more orders is received. Option B has $450 as the base price and $350 if a high order-quantity threshold of at least 6 orders is received. This example illustrates a more general pricing mechanism with two prices as compared to the former group-buying form exemplified by Groupon where a product deal is only available at one price when the number of committed buyers crosses a predetermined minimum threshold.

[2] Possibly symptomatic of this problem, an update in the industry by Forrester Research estimates that only about 30 out of the 140 million (less than 22%) of Groupon subscribers have ever purchased through Groupon (Bosker, 2011).

This study, by empirically validating the influence of conditional purchase and information cue on buyers' GPI decision to order, adds to the literature in at least two ways. First, we introduce the economics perspective of constraint, expectation, and preference interactions among buyers to the GPI literature (Manski, 2000). We conducted experimental research and econometric modeling of such interactions in GPI by allowing individuals in GPI to observe others' behavior through the information cue feature and then make decisions. Furthermore, we allowed purchase commitments in GPI to be reversible (i.e., not honor the order should the best price be not met). Second, we consider both information cue and conditional purchase features to be valuable because many prior information systems (IS) studies have predominantly focused on the information provision mechanism and its impact on user interactions. Prior work on information provision advocates that making information available reduces the asymmetry among individuals and, thus, should lead to improved overall welfare (Ba & Pavlou, 2002). Our results indicate that it is only when the potential of suffering from non-cooperative outcomes in GPI emerges, through conditional cue, will the information cue mechanism in GPI be able to achieve what it is supposed to resolve.

2. Theoretical Foundations

We can view multiple buyers' involvement in achieving a specific economic objective (i.e., whether to purchase from a GPI) as a form of economically driven social interaction (Manski, 2000). Such interactions in the context of GPI refer to interaction activities such as initiating a purchase or responding to others' actions when making purchase decisions (Suh, Couchman, & Park, 2003). Manski (2000), in studying the economic paradigm of social interaction, highlights the importance of considering the social interactions among a sampled population of economic interest (e.g., consumers) in a given setting. We can also view buyers in GPI as engaging in a process of economically driven interaction but such that it involves multiple buyers whose purchase outcomes depend on the cooperative, aggregated decisions of two or more buyers (Chen et al., 2009a).

As Section 1 notes, Manski (2000) conceptualizes social interaction in economic settings along three channels: constraints, expectations, and preferences. We assume economic agents to be decision makers who are endowed with preferences (written as formal expressions in utility functions), form expectations (proxied through subjective probability distributions), and maximize their utility subject to specific constraints. In the GPI context, we elaborate below how constraint, expectation, and preference interactions among buyers in GPI are relevant to our discussion.

First, in the GPI market, there are typically constraints in both the demand and supply of the products transacted. The decisions of the consumers and the GPI firm in response to the demand and supply of products transacted collectively determine the price of products sold as a result of the order-quantity constraints in the GPI. In the case of positive constraint interactions (i.e., the more that some buyers choose a product on GPI, the more available it is to all), the product's sufficient demand meets the order-quantity threshold, which leads to a lower price level for all buyers. In contrast, for negative constraint interactions, the product's insufficient demand results in it costing the default (higher) price for all interested buyers.

Second, a buyer evaluating a decision will form expectations about what outcomes will result from their choosing different actions. A buyer establishing expectations may also seek to draw lessons from observing others' actions and these actions' associated outcomes. For example, a potential buyer in GPI may form expectations such as "Am I getting a really good cheap price for this item since many people are also buying this?", or "Is there a problem with poor quality of this item since no one is buying it through the GPI?". As such, observational learning generates expectation interactions in market institutions such as GPI.

Third, preference interactions occur when a buyer's preference for a product depends on others' actions, a concept that is central to non-cooperative game theory (Manski, 2000). Thus, a buyer's preference ordering on the alternative options in their choice set depends on other consumers' actions. Such preference interactions could occur in GPI when a potential buyer is contemplating the purchase of a product that exhibits product network effects or individuals' self-presentation effects (Leary & Kowalski, 1990).

To understand GPI's information cue and conditional purchase features better, we anchored on the prior GPI literature even though most studies do not explicitly consider these two mechanisms (see Table 1). Indeed, prior works have examined GPI mainly from two perspectives (see Table 1): revenue generation for sellers and the GPI itself (Anand & Aron, 2003; Chen, Chen, & Song, 2007; Chen et al., 2009a; Jing & Vie, 2011; Kumar & Rajan, 2012) and buyers' bidding response to price and order quantity (Chen et al., 2009b; Kauffman & Wang, 2001; Li, Chawla, Rajan, & Sycara, 2004). These previous studies are mostly analytical in nature except Kauffman and Wang (2001).

Table 1. Prior Key Studies on GPI

Authors and year	Key research question(s)	Key variables	Consideration of GPI mechanism?
Analytical			
Anand & Aron (2003)	What is the optimal group-purchase schedule if a firm decides to participate in a purchase and how does the performance differ from that of the posted offer institution?	Price, number of orders, and seller's revenue	No: the focus is on justifying the value of GPI against the benchmarking posted offer institution.
Chen et al. (2007, 2009a)	Can GPI generate more profit than the fixed pricing mechanism? Under what situations does the GPI perform better?	Price, revenue and profit	No: the focus is on comparing the GPI and fixed pricing institution.
Chen et al. (2009b)	What are the optimal buyers' bidding strategies?	Price, valuation, bid	No: the focus is on bidding strategy.
Jing & Xie (2011)	When and how a seller can gain from group buying compared with individual selling strategies and referral reward programs?	Information/knowledge gap between expert and novice consumers, interpersonal information sharing, product valuation, firm profit	Not explicitly, though information sharing is considered.
Kumar & Rajan (2012)	Are social coupons profitable for businesses? Can businesses influence social coupon profitability? How can businesses recover the shortfall in profits from the coupon launch? How long will it take for businesses to recover the shortfall in profits from the coupon launch?	Firm profitability, coupon discount rate, percentage of existing customers using coupons, number of new customers and percentage retained, business types	No: the focus is on firm profitability.

Table 1. Prior Key Studies on GPI (cont.)

Authors and year	Key research question(s)	Key variables	Consideration of GPI mechanism?
Empirical			
Kauffman & Wang (2001)	How does the price threshold affect buyer behavior? How does the number of existing orders influence the number of new orders?	Number of orders and price	No: the focus is relating price to orders. The analysis is based on secondary data from Mobshop.com.
Li et al. (2004)	What types of GPI mechanism could promote coalition stability and incentive compatibility (efficiency) of an economy with incomplete information?	Private valuation information (reservation price), number of buyers, efficiency	No: the focus is on buyer coalition formation. The analysis is through simulation.
Our research	**What are the kinds of mechanism that can be put in place in GPI which can encourage prospective buyers, who may be uncertain over whether the lowest purchase price can be attained, to place orders?**	**Conditional purchase and information cue**	**Yes: we explicitly consider two GPI mechanisms to induce purchases. The data is based on an experiment that followed the principles of experimental economics.**

2.1. Conditional Purchase

Since GPI outcome is contingent on buyers' constraint interactions and aggregated purchase decisions, buyers will face decision uncertainty when evaluating their own purchase in a GPI. Pavlou, Liang, & Xue (2007) define buyer's decision uncertainty as the extent to which the buyer is unable to fully ascertain the consequence or outcome of making a purchase. Payne and Bettman (1992) explain decision uncertainty in more detail in terms of guessing the consequences of the actions or decisions made now and guessing the subsequent actions or decisions arising from these consequences. A buyer may face uncertainty due to the product (e.g., a product under consideration might be of low quality) (Dimoka, Hong, & Pavlou, 2012), the price (e.g., whether the price of a product is reasonable) (Mehta, Rajiv, & Srinivasan, 2003), and even the seller (e.g., if the seller might delay product delivery) (Pavlou et al., 2007). In the case of GPI, a buyer's decision uncertainty may stem from the unconfirmed purchase decisions of other buyers who might be interested in a product but are not yet committed to the purchase (i.e., uncertainty due to negative constraint interactions). As Azfar (2001) notes, the need for a cohort of people with sufficient aggregated commitment on a decision (e.g., choosing the same GPI purchase option) could be a challenge because each individual's propensity to coalesce on a common action may not coincide with those of the rest of the cohort (Sandler, 1992). For an individual, the expectation of whether others will take a similar action could trigger uncertainty and lead the buyer to not commit to a purchase or to choose an option with lower uncertainty (Anderson, 2003; Dhar & Nowlis, 1999). Providing features that afford sufficient incentives to motivate buyers to commit to purchase decisions early could somewhat address the issue of GPI buyers not committing to eventual GPI purchases. To this end, a way to alleviate negative constraint interactions and, thus, the decision uncertainty in GPI purchases is to implement a conditional purchase feature in GPI, which essentially sets a ceiling as to how high a buyer would be expected to pay for a product.

2.2. Information Cue

Prior research has traditionally advocated the importance of facilitating information sharing to resolve the issue of information asymmetry (Healy & Palepu, 2001). Information asymmetry refers to a state in which an economic agent has imperfect information about an item to be transacted or the transacting party (Shapiro, 1982). To examine the support for information sharing, prior experimental studies on auctions have indicated that sequential (versus simultaneous) bidding (i.e., one buyer makes a bidding decision after seeing another doing so) could facilitate the signaling of the buyers' preferences (Klemperer, 1999). Sequential bidding in auctions typically leads to an advantage for the sellers since there tend to be more aggressive biddings as a result of the increase in the extent to which preferences are revealed (Hausch, 1986). This long-held notion of reducing information asymmetry in markets through increasing support of information sharing (i.e., display number of bids received) is, however, questionable because, for example, in relation to GPI, Kauffman and Wang (2001) observed the herding effect, price drop effect, and cycle-ending effect[3] in research based on secondary data collected from a GPI website. This research highlights that buyers in GPI may delay making purchase decisions until the final price can be clearly determined (i.e., when sufficient buyers have committed to the purchase). We contend that the effect of information cue in GPI could be determined by the GPI buyers' expectation and/or preference interactions, which we validate in this research.

3. Hypothesis Development

We consider two GPI mechanisms; namely, (1) the conditional purchase mechanism, which allows a decision maker to reduce the outcome dependency; and (2) the information cue mechanism, which allows a decision maker to influence others to purchase (thus reducing information asymmetry in GPI). We argue that the former mechanism alleviates the extent and consequences of decisional uncertainty arising from the economic outcome of the GPI purchase and that the latter mechanism addresses information asymmetry in GPI such that it can potentially increase (or decrease) the propensity among buyers to purchase through GPI depending on the nature of social interactions (i.e., in the form of constraint, expectation or preference interactions) among buyers in GPI.

3.1. Conditional Purchase

Compared to a non-GPI website such as Amazon.com in which buyers can only buy products based on fixed offered prices, GPI provides buyers with opportunities to obtain substantially discounted prices from the offered prices based on aggregated demand. Indeed, this is the benefit of positive constraint interaction in GPI such that the more that buyers choose a product on GPI, the cheaper it is to all. However, when a buyer's decision outcome is dictated by the aggregated actions of other buyers as in GPI, the buyer is likely to expend considerable effort on understanding the situation and to develop expectations about other buyers' probable behaviors (Arriaga & Rusbult, 1998). The GPI mechanism of conditional purchase addresses this issue by offering the opportunity for buyers to benefit from positive constraint interactions in a GPI and yet mitigate the potential loss due to negative constraint interactions. Specifically, the conditional purchase mechanism shares the same underlying principle of conditional cooperation (Bendor & Mookherjee, 1987) and the opportunity to terminate a bargaining session in negotiation research (Giebels et al., 2000).

In the GPI setting where conditional purchase is not provided, a buyer would need to honor the purchase at the final offered price regardless of whether this price is equal to the best available lowest price or not. When a buyer is not provided with the conditional purchase option, the individual is aware that any decision will result in an irreversible consequence (i.e., honoring the purchase even at a high price). This situation could lead to a cognitive tension that could prompt buyers to choose the "safer" option—not to purchase a product in GPI, which is in accordance with inaction inertia theory in the decision uncertainty literature (Dhar, 1997).

However, in the presence of the conditional purchase mechanism, a buyer only honors or commits to a purchase should the final offered price equate to the best available lowest price offered with a sufficient number of buyers crossing the order-quantity constraint and, thus, reaps the benefit of a positive constraint interaction in GPI. The GPI mechanism of conditional purchase could reduce the impact of detrimental consequences associated with negative constraint interactions in GPI (i.e., an insufficient number of buyers committed to a GPI), leading to a lack of supply of the good to be procured at the desired price in GPI. Thus, we hypothesize:

[3] The cycle-ending effect refers to the phenomena of more orders being received towards the end of a product sale period.

H1a: *Providing the conditional purchase in a GPI will elicit a buyer's higher propensity for purchasing through the GPI compared to not providing it.*

Prior research indicates that offering buyers with the flexibility to "quit" (e.g., not honoring the purchase should the final offered price be higher than the best available lowest price in the case of GPI's conditional purchase mechanism) can reduce worries and concerns with respect to the plausible consequences of a decision (Giebels et al., 2000). When a buyer has the ability to quit without suffering from a negative consequence (Giebels et al., 2000), one might be more willing to choose the riskier competing purchase option (Jonas, Graupmann, & Frey, 2006). This case refers to an option that may expose a buyer to a chance of greater loss or gain compared to another less-risky choice. To illustrate, a buyer may be given two mutually exclusive competing options; namely, (1) a high quantity threshold constraint but a low best price, and (2) a low quantity threshold constraint but a high best price[4]. The former is a riskier choice because it requires more buyers to select the option before the low best price (that endows the buyer with a high consumer surplus) is reached (i.e., the minimum satisfying condition to achieve positive constraint interactions has been raised or made more difficult to achieve). Nevertheless, we conjecture that a buyer presented with the conditional purchase mechanism in GPI will have a higher tendency to choose the first option, which is riskier, because a conditional purchase mechanism enables the individual not to honor the transaction if the best possible price is not reached (i.e., mitigating the potential risk or loss from a negative constraint interaction in GPI). Hence, we hypothesize:

H1b: *When a buyer has decided to purchase through GPI, providing the conditional purchase will elicit the individual's higher propensity to choose a riskier option when presented with competing alternatives (i.e., favoring an option with a high quantity threshold requirement but a low best price rather than one with a low quantity threshold but a high best price).*

3.2. Information Cue

We operationalize information cue as numeric information about the number of buyers who have committed to a purchase in the GPI, which is similar to the way in which auction experiments are conducted (Klemperer, 1999).

In the absence of an information cue, the buyers have no source of reference to determine other buyers' response (i.e., whether and how many buyers have committed to a purchase in the GPI). Thus, providing information cues addresses the problem of information asymmetry (Charness & Villeval, 2009; Payne & Bettman, 1992). Decision uncertainty arising from information asymmetry can be addressed through various forms of IT-enabled features such as providing informative displays (Mahoney, Roush, & Bandy, 2003). This focus on addressing information asymmetry also echoes Kelley et al. (2003), who suggest that information availability about buyers' actions could influence one's or others' expectations or preferences in making purchase commitments.

Information cues (e.g., cues that disclose the number of orders received) could facilitate cooperative behavior by reducing the uncertainty associated with GPI purchase decisions (Azfar, 2001; Kelley et al., 2003). Thus, a buyer could use information cues to learn about the actions of other potential buyers and follow the decisions of these individuals. Indeed, humans have a tendency to conform and make decisions by inferring from others based on information that is available (Bikhchandani, Hirshleifer, & Welch, 1992). Further, in the absence of information, people may behave in diverse manners that can result in, for example, market volatility (Lee, 1998). In a similar vein, in a GPI context, given the overarching retail or pricing concept of price discounts with high volumes in a group purchase, there is a strong likelihood of positive expectations interaction as a result of providing information cues in the market (i.e., a buyer inferring positive information (e.g., price is attractively low relative to prevailing price outside of GPI) from the observed actions or outcomes of other buyers who have committed to GPI purchases). Consequently, this would induce a buyer to have a higher

[4] A relevant analogy for this choice situation would be akin to choosing to buy an identical product from either Groupon (i.e., dominant leader with the biggest customer base) or LivingSocial (i.e., a smaller rival in the market).

propensity to also purchase from the GPI. This is even so in the case of positive preferences interactions among buyers in a GPI (i.e., the utility[5] of an individual consumer's purchase increases with the number of other buyers buying the same product in GPI, which could heighten the propensity to purchase in a GPI). For these reasons, we hypothesize:

> **H2a:** *Providing an information cue in a GPI will elicit a buyer's higher propensity for purchasing through the GPI compared to not providing it.*

Further, we need to know whether the presence of information cues enable buyers to choose a riskier competing option that offers a lower price but has a high quantity threshold requirement. We posit that providing information cues may induce buyers toward choosing the riskier choice (as in H2b) because, assuming that an information cue is available in the GPI, the number of orders placed could have a positive impact on the newly placed orders. This position follows Anand and Aron (2003) and Kauffman and Wang (2001) and theories such as the information cascading theory (Bikhchandani, Hirshleifer, & Welch, 1992). Based on the positive expectation and/or preference interactions argument, offering potentially committed buyers the opportunity to observe the behaviors of others could reinforce the positive interactions, such that this could increase the propensity to choose the riskier option in a GPI. Such an argument is also in line with the decision uncertainty literature which documents that the provision of information cues could mitigate the information asymmetry amongst buyers and sellers alike (Shapiro, 1982). Therefore, hypothesize:

> **H2b:** *When a buyer has decided to purchase through a GPI, providing an information cue will elicit the individual's higher propensity to choose a risker option when presented with competing alternatives.*

Further, it is an open question about why buyers would not take on a proactive role in influencing others to purchase by submitting orders early. According to the principle of inaction inertia, people may choose to wait or delay committing to a purchase even when waiting may be detrimental to them (Anderson, 2003). If a buyer delays in making a commitment to a group-buying purchase and should the sale period terminate, it is plausible that the buyer may need to purchase the same item at a listed price that is likely to be higher than if the buyer purchased it through the GPI. However, if buyers have already committed to the purchase, then we posit that others would prefer the riskier option with a high-quantity threshold requirement but a low best price because it yields the maximum buyer surplus or welfare. This result arises because the presence of information cues can transmit signals of purchase commitment to the yet-to-commit onlookers and, thus, reinforce the effects of all the constraint, expectation, and preference interactions in a GPI. Therefore, other buyers' propensity to choose a specific purchase option in GPI could increase in the presence of information cues (Ariely & Levav, 2000). Specifically, when other buyers' actions are visible through information cues, a buyer could also use such information cues to induce similar actions from other buyers. As such, we hypothesize:

> **H2c:** *When a buyer has decided to purchase through a GPI, by providing an information cue, the individual's propensity to choose a specific competing option will increase with the number of buyers choosing the same option.*

4. Research Method

We employed a controlled laboratory experimentation method with a 2×2 between-subjects full factorial design to investigate the effects of an information cue and the conditional purchase on buyers' decision making outcomes in the GPI. Each treatment comprised two experiment sessions, with 10 participants being recruited for each session. In each session, the participants assigned the role of buyers had to decide whether to purchase through a GPI and, if they decide to do so, the specific option to select. In the presence of an information cue, buyers gained access to information

[5] Utility is the perceived ability or value of a good to satisfy the needs or wants of an economic agent.

indicating the latest number of purchase orders received in the group-purchase exercise[6]. In the presence of the conditional purchase, buyers could only honor the purchase when the final offered price equated to the best available lowest price given by the quantity threshold requirement.

Figure 1(a) illustrates the GPI mechanisms we studied. The figure also depicts the experimental system for the treatment containing both information cue and conditional purchase conditions. Figure 1(a) presents two options: shop A and shop B, with two corresponding purchase options of radio button inputs (i.e., “buy at best price only” and “buy at final closing price”). If the conditional purchase was absent, then the purchase option of “buy at best price only” would be unavailable and the default radio button selection would be “buy at closing price” (i.e., but at the final offered price). In this case, a buyer would need to commit to purchase the product regardless of the final offered price (labeled as “final closing price” in the system). However, if the conditional purchase (i.e., the purchase option of “buy at best price only”) was available and the buyer chose it, then the buyer would only need to honor the purchase when the final offered price was equal to the best price (i.e., the best available lowest price). For other buyers who did not choose or who did not have the “buy at best price only” option, they would need to pay for the final offered price. If the information cue was present (red boxed information in Figure 1(a)), it presented information about the number of bids received (i.e., “X potential buyer(s) have bid for this item and X out of Y will “buy at best price only” as Figure 1(a) depicts). Thus, a buyer could use this information to make the eventual purchase decision. Figure 1(b) depicts the screen that was displayed at the end of a trading period. As Figure 1(b) shows, for this particular buyer, he had previously bid for shop B and indicated that he would buy at the final offered price regardless of whether the final offered price reached the best available lowest price.

We measure the dependent variables as the actual choice decisions of purchase (i.e., first, whether to order or not, and, second, which purchase option to choose in the GPI). The first purchase option, the low risk one, was to purchase from shop A, which had a low number-of-orders threshold to reach the best price. The second option, the high risk one, was to purchase from shop B, which had a high number-of-orders threshold to reach the best price. The best price for shop A was higher than that for shop B. Should a buyer have chosen to purchase and the minimum threshold was yet to be met, the buyer would have to purchase the product, known as a “unit”, at the retail price (i.e., the highest price) in the absence of the conditional purchase mechanism (see Figure 1 for sample screenshots of the experimental system).

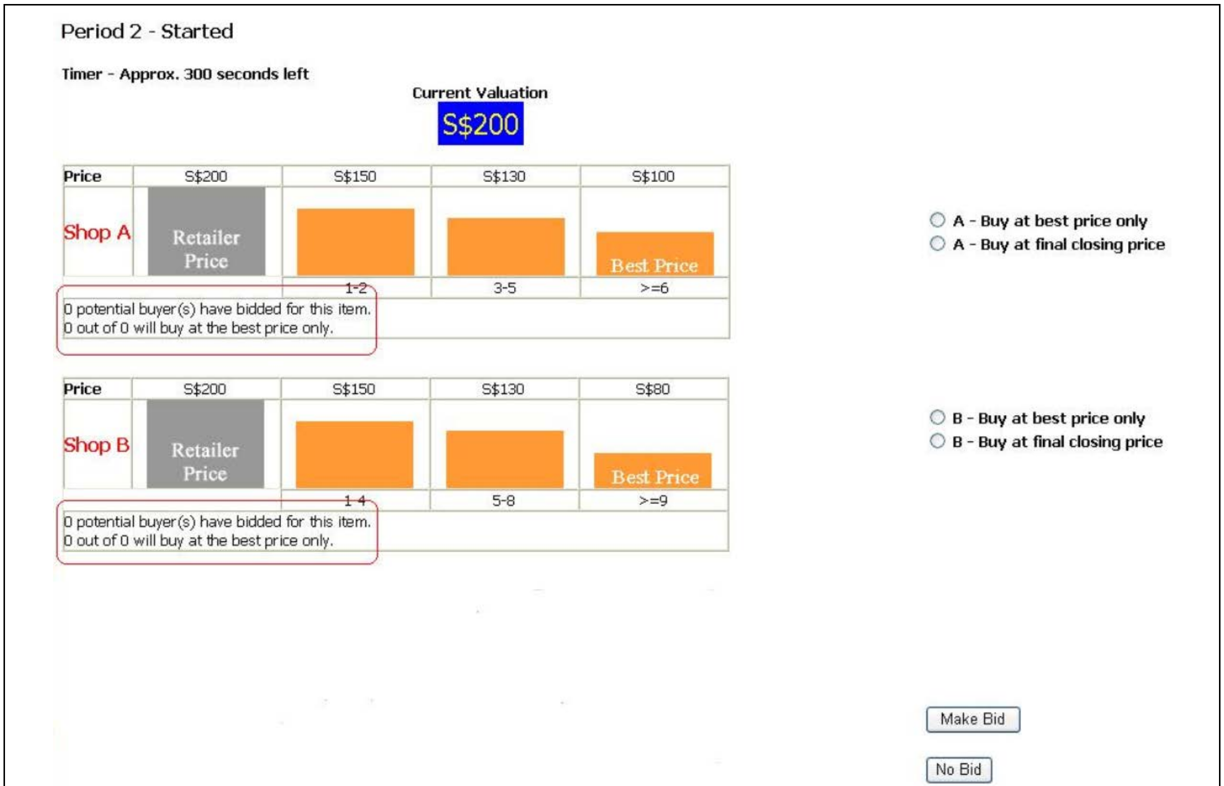
We performed all experiments in a public university. We recruited 80 graduate students from across the university, 40 of whom were male and had no previous experience of laboratory experiments, in a repeated buying and selling game on a computer platform. The participants were primarily business major students. We controlled for individual characteristics, such as age and computer proficiency (measured by the years of computer experience), by randomly assigning participants to different treatments. We also performed control checks. Our results indicated no significant differences in age ($F=1.689$, $p>0.1$) and computer proficiency ($F=1.109$, $p>0.1$) across the treatments. Thus, control over participant characteristics through randomization appeared to be successful.

In each session, we provided participants with detailed instructions on paper and via online forms. The same experiment administrator conducted each set of experiment sessions by following a standard set of guidelines and instructions. Before the start of each session, the participants underwent a trial-trading period and completed a test designed to check their understanding of the trading rules and incentive structures. Each experiment session entailed one trial period and 19 actual trading periods in which multiple measurements of dependent variables were made for each participant. Each actual trading period lasted for a maximum of two minutes. Participants were presented with a realistic market scenario in which they were to purchase a generic commodity product identified as a “unit” with no name or brand. They were primed to come across online GPIs selling an identical product. Each participant had to make a purchase decision during the given time

[6] In the self-developed experimental system simulating the GPI, the experimental participants had access to updated information on the purchase orders when the information cue is present. This information was automatically refreshed by the system on the terminal of each participant.

period. Once the decision was made, the participant was not allowed to amend the decision. No order of decision making among the participants was enforced; they were free to make a purchase decision any time within each period.

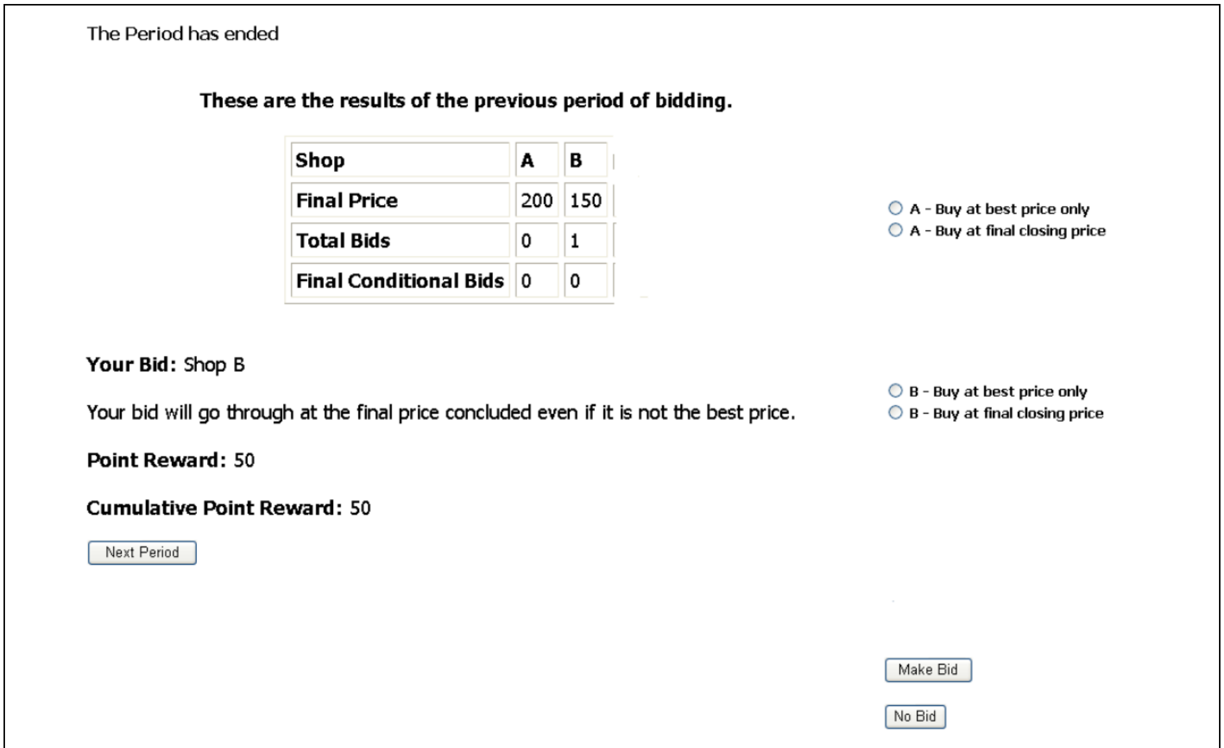
To ensure experimental realism, we told the participants that the experiment focused on individual purchase decision making and they would be paid in cash for their participation. Specifically, we told the participants that they would be paid a fixed participation incentive (approximately USD$5) and a variable performance-based incentive (up to an additional USD$10, on average, depending on the performance). We told them that an initial amount of USD$5 was credited into their individual accounts at the start. The money would be given as cash if the amount remained the same until the end of the experiment. Participants earned (lost) money by buying below (above) their valuation price for the product7. We explicitly informed them that higher payments were possible based on performance but were not guaranteed. Each participant was paid an average of USD$15 for about an hour's work.



(a)

Figure 1. Experimental System Screen Shot (Treatment for Presence of Conditional Purchase and Information Cue)

[7] The valuation price across different trading periods did change during the experiment and was predetermined according to a normal distribution, with distribution supports of the lowest best price and the retail price marked up by 10 percent. To reduce the possibility of collusion, we added a different (random) parameter-disguising scalar to the derivations of the valuation prices and the shops' prices, such that the trading units were not readily comparable across experiment sessions. Indeed, the price valuation changes in this normal distribution across trading periods and across treatments. We alleviated the possibility of systematic bias resulting from sequencing the valuation prices through randomization. We also included valuation as a controlled variable in the analyses. Such an approach is in accordance with the market institutional principle in experimental economics (Davis & Holt, 1993) and prior studies such as that by Brewer, Huang, Nelson, and Plott (2002).



(b)

Figure 1. Experimental System Screen Shot (Treatment for Presence of Conditional Purchase and Information Cue) (cont.)

5. Stated Choice Model Specification

Stated choice methods are typically used with a formal structure to investigate the responsiveness of potential and actual participants in markets for products and services, explain individual and aggregate choice behavior in such markets, and predict behavioral responses to changing opportunities (McFadden, 1979, 1981). As such, we conceptualize decision making in a GPI as a two-stage model; that is, a buyer decides (1) whether to purchase and, (2) if purchasing, which purchase option. This two-stage model is in accordance with the prior theoretical modeling of consumer decisional behavior (Bucklin, Gupta, & Siddarth, 1998). Table 2 summarizes some prior works that adopt the two-stage model. In particular, Chintagunta (1992) suggests that considering the two-stage decision making process and applying the subsequent nested logit (NL) model can account for the heterogeneity in intrinsic preferences and intrinsic purchase propensities across individuals; conversely, disregarding the process may result in the model estimations generating biased coefficients of the independent variables. Several papers on a similar setting of online auctions also consider two-stage nested models, such as Bapna, Goes, Gupta, and Karuga (2008).

Table 2. Examples of Auction Bidding Research using the Two-stage Analysis Model

Authors (year)	Domain	Two-stage decision model applied
Bidding		
Ahmad (1990)	Construction contract bidding problem	Propose a two-stage bidding model of bidding problem. First stage is concerned with bid/no-bid decision. Second stage deals with the bidding options with explicit parameters such as type of project and location.
Fleten & Kristoffersen (2007)	Hydropower bidding problem	A two-stage stochastic programming model is proposed. The first stage involves the bidding process and the second stage focuses on the production aspects.
Skitmore (1989)	Contract bidding problem	Proposes a two-stage model of contract bidding with two sequential decisions: (1) whether to bid or not, and (2) the bid level to win the contract.
Wang, Xu, & Li (2009)	Engineering project bidding problem	Proposes a two-stage model of project selection where the first stage is concerned with "bid/no-bid decision" and the second stage with "which project to bid".

Consistent with the econometric methodology in stated choice methods, we adopt the choice modeling approach in specifying our empirical model to test our research hypotheses (Louviere, Hensher, & Swait, 2000). Our empirical model specification is based on the NL model (Louviere et al., 2000; McFadden, 1979, 1981). Consistent with an NL framework, we assume that a buyer makes a purchase decision following a two-stage process. First, a buyer decides whether to bid (i.e., to acquire through a group-purchase website) or not to bid. If a buyer decides to bid, then the buyer chooses among one of the competing group-purchase options available. Figure 2 depicts the structural view of the behavioral decision tree. In the NL framework, choosing between shop A and shop B forms one nest, and the decision to bid or not to bid forms the other. Shop A (subscripted as $j = 1$ in Equation (1)) represents a less-risky choice with the number of order thresholds demanded being comparatively lower than that of shop B (subscripted as $j = 2$ in Equation (1)). However, the tradeoff between choosing either of the two shops is that the best price that can be yielded by shop A is higher than that of shop B.

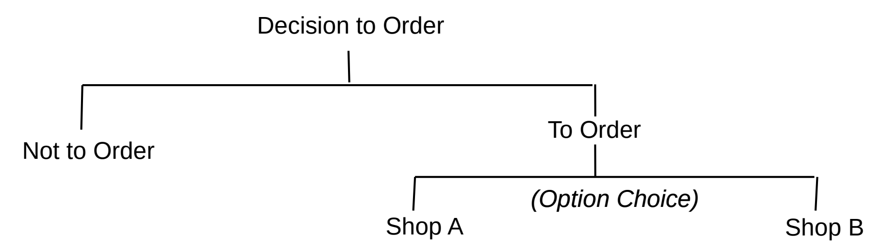


Figure 2. Decisional Choice (Nested Logit)

We use the multinomial logit (MNL) model as a benchmark comparison to the aforementioned proposed NL model. The MNL model is essentially a specific case of the NL model, such that individuals are assumed to make choice decisions in one stage or a single nest (without a multiple stage or nest structure). For example, in our group-purchase context, we assume that individuals evaluate their choice decisions of choosing one alternative among the three options of (1) not to order, (2) order from shop A, and (3) order from Shop B. An individual simultaneously evaluates all three options and chooses the alternative that gives the highest utility.

Although the MNL model is an empirically tractable and robust model for probabilistic choice, it is attached with the assumption of independence-from-irrelevant alternatives[8] (IIA). Consequently, we choose the NL model as our final empirical model specification to evaluate our research hypotheses because the NL model has an intuitive staged decisional-processing interpretation based on different hierarchical decisional nests in which choice alternatives sharing close similarities are grouped together. Such decision nest structures of the NL model alleviate the problems associated with the IIA property of the MNL model. In our empirical estimation, we also formally test for the presence of the IIA property associated with the MNL model to justify our specification of the NL model in the GPI context. In Section 5.1, we elaborate the details of the NL model specification as applied to a group-buying scenario.

5.1. Shop Choice

We can specify an individual's choice of shop when buying through a GPI by a random utility model (RUM) (McFadden, 1973). RUM assumes that a decision maker selects one option (i.e., shop in a GPI context) from among the competing options in a choice set. We start by specifying that, if buyer *i* decides to bid, then the buyer chooses among the *j* shops available in the choice set. The utility for buyer *i* to choose to bid at shop *j* can be expressed as:

$$\begin{aligned} U_{ij}(\text{buyer } i \text{ chooses shop } j \mid \text{bid}) &= V_{ij} + \varepsilon_{ij} \\ &= \alpha_j + X_{ij}\beta + \varepsilon_{ij} \text{ , for } i = 1 \text{ to } N \text{ and } j = 1 \text{ to } 2 \end{aligned} \quad (1)$$

V_{ij} is assumed to be the deterministic part of the utility, and ε_{ij} is the random unobserved component assumed to be identically and independently distributed with an extreme value distribution (i.e., the Gumbel distribution). X_{ij} denotes the row vector of individual and option alternative-specific characteristics, and α_j and β are the estimated utility parameters for alternative-specific constants and choice attributes, respectively. If we observe that buyer *i* chooses shop 1 rather than shop 2, then we can infer that $U_{i1} > U_{i2}$. In this light, the probability that buyer *i* chooses shop *j*, conditional on deciding to purchase using a GPI in the first stage, can be represented using a logit specification as follows:

$$\begin{aligned} P_{ij}(\text{buyer } i \text{ chooses shop } j \mid \text{bid}) &= \frac{\exp[\mu V_{ij}]}{\sum_{k=1}^{K} \exp[\mu V_{ik}]} \\ &= \frac{\exp[\mu(\alpha_j + X_{ij}\beta)]}{\sum_{k=1}^{K} \exp[\mu(\alpha_k + X_{ik}\beta)]} \text{ , for } i = 1 \text{ to } N \text{ and } j,k = 1 \text{ to } 2 \end{aligned} \quad (2)$$

where μ is the scale parameter for the lower level shop-choice nest of the NL model.

Intuitively, Equation 2 suggests that the larger the utility of shop *j* as a proportion of total utility from all seller options, the larger the probability of selecting shop *j*. Estimating the NL model generates a column vector of parameters β that indicates the effect of individual and shop-specific characteristics *X* on the probability that a buyer, having already decided to bid through a GPI, would choose shop *j*. From Equation 2, we can observe that any variable that does not vary across choices (i.e., shop) will drop out from the choice probability Equation 2. Hence, variables such as a buyer's product valuation, risk propensity, previous returns from acquiring products through a GPI, and trading experience are excluded from the lower level seller-choice decision nest during model estimation. These buyer-specific variables will appear in the upper level decision-to-bid nest, which we discuss in Section 5.2.

[8] The MNL model builds on an assumption that the probabilities of choosing any two options (e.g., shop A and shop B) would be independent of the presence or attributes of a third option (i.e., the IIA).

5.2. Decision to Bid

The upper level decision-to-bid nest requires a decision to be made on whether to acquire the product via group-purchase websites; that is, to bid or not to bid. This specification employs the binary logit framework. We assume that an individual's utility for bidding through a GPI is:

$$
\begin{aligned}
U_i(\text{buyer } i \text{ chooses to bid}) &= V_i + \xi_i \\
&= Z_i\gamma + \frac{1}{\mu} I_i + \xi_i \text{ , for } i = 1 \text{ to } N
\end{aligned} \qquad (3)
$$

where V_i is the deterministic part of the utility, and ξ_i is the extreme value distributed random error term. Z_i denotes the row vector of individual buyer-specific characteristics and $I_i = \log \sum_{j=1}^{J} \exp\left[\mu(\alpha_j + X_{ij}\beta)\right]$, for $j = 1$ to 2 is the inclusive value index. γ and μ are the respective estimated vector and scalar of utility parameters for the NL model. Denoting the decision not to bid as the null choice with zero utility, the probability of deciding to bid is:

$$
\begin{aligned}
P_i(\text{buyer } i \text{ chooses to bid}) &= \frac{\exp\left[\delta V_i\right]}{1 + \exp\left[\delta V_i\right]} \\
&= \frac{\exp\left[\delta(Z_i\gamma + \frac{1}{\mu} I_i)\right]}{1 + \exp\left[\delta(Z_i\gamma + \frac{1}{\mu} I_i)\right]} \text{ , for } i = 1 \text{ to } N
\end{aligned} \qquad (4)
$$

where δ is the scale parameter for the upper level decision-to-bid nest of the NL model.

The inclusive value I_i denotes the utility associated with having both shops available in the decision-to-bid choice set. If the coefficient of the inclusive value, $\frac{1}{\mu}$, is not statistically different from 1.0, then the decision to bid is independent of the utility value of the shops in the shop choice set. In this regard, a sufficient reason to warrant the nesting of the two decisions is lacking (i.e., the decision to bid and the selection decision of the shop to purchase from). Hence, the coefficient $\frac{1}{\mu}$ provides a test of determining whether the nesting of the two decisions in the NL model—the decision to bid and the choice of seller to purchase from—is appropriate. If the hierarchical nesting structure in the NL model is rejected, then an MNL model that assumes individuals to evaluate their choice decisions in one stage without a hierarchical structure would be more appropriate.

5.3. Unconditional Probability of Shop Choice

To estimate the utility parameters for shop choice and the decision to bid nests jointly, the NL model computes the unconditional probability that buyer *i* will choose shop *j* as shown in Equation 5. For the purpose of model parameters identification, we normalize the upper level scale parameter $\delta = 1$ but estimate the lower level scale parameter μ (i.e., the inclusive value parameter $\frac{1}{\mu}$) freely. Thus, this condition conforms to the specification of the random utility maximization NL model (RUMNL) rather than the non-normalized NL model (NNNL), which does not satisfy the utility maximization assumption (Louviere et al. 2000).

$$P_{ij}(\text{buyer } i \text{ chooses shop } j)$$
$$= P_{ij}(\text{buyer } i \text{ chooses shop } j \mid \text{bid}) \times P_i(\text{buyer } i \text{ chooses to bid}) \quad (5)$$
$$= \left(\frac{\exp\left[\mu(\alpha_j + X_{ij}\beta)\right]}{\sum_{k=1}^{K} \exp\left[\mu(\alpha_k + X_{ik}\beta)\right]} \right) \left(\frac{\exp\left[\delta(Z_i\gamma + \frac{1}{\mu} I_i)\right]}{1 + \exp\left[\delta(Z_i\gamma + \frac{1}{\mu} I_i)\right]} \right), \text{ for } i = 1 \text{ to } N \text{ and } j,k = 1 \text{ to } 2$$

For the purpose of model parameters identification, we normalize the upper level scale parameter $\delta = 1$ but estimate the lower level scale parameter μ (i.e., the inclusive value parameter $\frac{1}{\mu}$) freely. Thus, this condition conforms to the specification of the random utility maximization NL model (RUMNL) rather than the non-normalized NL model (NNNL), which does not satisfy the utility maximization assumption (Heiss 2002; Louviere et al. 2000).

6. Data Analysis and Findings

We tracked the dependent variable measures of decision-to-order and shop choices throughout the trading periods. Table 3 lists the frequency counts and relative row-level percentages of decisional choices made by experiment participants in each treatment condition. Manipulated and independent variable measures of conditional purchase, information cues, number of buyers in each period choosing a specific option, buyer's valuation, risk aversion, and earnings from trade in group purchase are recorded and included as covariates in the empirical validation of the proposed RUMNL model. Table 4 provides the descriptive statistics for these variables across 1,520 observed periods. Generally, most participants were risk-averse because the mean of the risk aversion measure[9] is at 5.71 along a seven-point Likert scale.

Table 3. Frequency Statistics of Choices Made by Treatment Conditions

Conditional purchase	Information cue	Decision not to order	Choice for shop A (less risky)	Choice for shop B (more risky)
Absence	Absence	50 (13.16%)	309 (81.32%)	21 (5.52%)
	Presence	194 (51.10%)	160 (42.10%)	26 (6.80%)
Presence	Absence	57 (15.00%)	300 (78.95%)	23 (6.05%)
	Presence	48 (12.63%)	262 (68.95%)	70 (18.42%)
Conditional purchase				
Absence		244 (32.11%)	469 (61.71%)	47 (6.18%)
Presence		105 (13.82%)	562 (73.95%)	93 (12.23%)
Information cue				
Absence		107 (14.10%)	609 (80.10%)	44 (5.80%)
Presence		242 (31.84%)	422 (55.53%)	96 (12.63%)

Note: Decision not to order, choice for shop A, and choice for shop B are binary in nature.

[9] Risk aversion is a perceptual measure that reflects the degree to which a buyer is willing to choose a risky option. The question item was: "I am very concerned with a potential financial loss from making a poor choice".

Table 4. Descriptive Statistics of Manipulated and Independent Variables				
Variable	**Mean**	**Std. dev.**	**Min**	**Max**
Conditional purchase	0.50	0.50	0	1
Information cue	0.50	0.50	0	1
Number of buyers choosing not to order	2.30	3.00	0	10
Number of buyers choosing shop A	6.78	3.80	0	10
Number of buyers choosing shop B	0.92	1.99	0	10
Valuation	165.37	35.01	130	200
Risk aversion	5.71	1.27	1	7
Current period earning	47.08	43.78	-70	120
Previous period earning	44.64	44.15	-70	120
Previous period choice (shop A)	0.67	0.47	0	1
Previous period choice (shop B)	0.09	0.29	0	1

6.1. MNL Model Results (for the Decision to Order)

We examined the effects of the manipulated variables (i.e., conditional purchase and information cues) on the decisional choice to not to order, buy from Shop A, or buy from Shop B by estimating a RUMNL model using maximum likelihood estimation methods. For benchmark comparison, we also estimated an MNL model based on only the upper level decision to order or not to order from the GPI. We included the manipulated variables of conditional purchase and information cues (interacted with the bid dummy) as predictor variables. We also included control variables of the current valuation, risk aversion attitude, earnings and option choices of the previous period, and time period dummies as covariates. Table 5 shows the model estimation results for our MNL model.

Table 5. Multinomial Logit Model of Decision to Order (0: Not to Order; 1: Order)			
Variable	**Coef.**	**Std. err.**	**z**
Independent variables			
Bid dummy	-1.67	0.66	-2.52
Conditional purchase * Bid dummy	0.64	0.17	3.68
Information cue * Bid dummy	-0.73	0.17	-4.23
Control variables [* bid dummy]			
Valuation	0.02	0.00	8.23
Risk aversion	-0.19	0.08	-2.38
Previous period earning	0.01	0.00	3.85
Previous period choice (shop A)	2.37	0.23	10.41
Previous period choice (shop B)	1.39	0.27	5.11
Period dummies (for period 3 to 20)	Estimated but not shown		
Auxiliary statistics			
Model log-likelihood	-514.20		
Model LR: chi-square (df)	348.51 (25)		

The benchmark MNL model was statistically significant in terms of the model likelihood ratio test. The MNL model estimation results suggest that a buyer is more likely to order from a GPI in the presence of the conditional purchase mechanism. However, a buyer is significantly less inclined to order if provided with information cues[10]. Hence, H1a and H2a(ii) were supported but H2a(i) was not. A buyer was significantly more inclined to order if the valuation and previous period's earnings were higher and if the risk aversion measure was lower.

6.2. NL Model Results (for Option choice)

For the overall choice model of the decision-to-order and the choice-of-option-to-order, we set up and estimated a RUMNL model in Equation 5. We included the manipulated variables of conditional purchase and information cue as the predictor variables in the lower-level option-choice decision nest. We interacted the manipulated variables with the shop A and shop B dummies because variations in the independent variable values across the available option choices are needed in the RUMNL model setup. For the upper-level decision-to-bid nest, we used the same control variables in the benchmark MNL model estimated in Table 5.

For the NL specifications, we tested two model specifications: RUMNL models 1 and 2. RUMNL model 1 included the variables computed by the interaction of the information cue dummy, the option dummies, and the number of buyers choosing each option in a period. RUMNL model 2 nested model 1 but added the variables computed by the interaction of the conditional purchase dummy, the option dummies, and the number of buyers choosing each option in a period. Table 6 shows the model estimation results for RUMNL models 1 and 2.

Table 6. Nested Logit Model of Decision to Order and Option Choice

	RUMNL model 1			RUMNL model 2		
Variable	**Coef.**	**Std. err.**	**z**	**Coef.**	**Std. err.**	**z**
Independent variables (in nest for option choice)						
Shop A	-3.70	1.00	-3.71	-6.01	1.05	-5.72
Shop B	-7.47	1.21	-6.20	-10.62	1.74	-6.11
Conditional purchase * shop A	-0.22	0.36	-0.62	-7.63	1.26	-6.04
Conditional purchase * shop B	-0.59	0.54	-1.10	-2.23	0.96	-2.33
Information cue * shop A	-5.68	0.72	-7.93	-5.11	0.85	-5.98
Information cue * shop B	-1.51	0.65	-2.33	-1.11	0.82	-1.36
Number of buyers choosing shop A * information cue * shop A	0.80	0.09	8.76	0.62	0.08	7.29
Number of buyers choosing shop B * Information cue * shop B	0.85	0.12	6.99	0.70	0.18	3.88
Number of buyers choosing shop A * conditional purchase * shop A	--	--	--	1.17	0.14	8.12
Number of buyers choosing shop B * conditional purchase * shop B	--	--	--	0.51	0.15	3.42
Control variables [* bid dummy] (in nest for bid/no bid decision)						
Valuation	0.03	0.00	6.69	0.05	0.01	8.53
Risk aversion	-0.06	0.10	-0.60	-0.21	0.14	-1.47
Previous period earning	0.00	0.00	0.91	0.00	0.00	0.57
Previous period choice (shop A)	2.45	0.39	6.28	3.10	0.51	6.12
Previous period choice (shop B)	1.30	0.50	2.61	1.57	0.62	2.53
Period dummies (for period 3 to 20)	Estimated but not shown			Estimated but not shown		
Inclusive value (dissimilarity) parameters						
No bid	1.00	--	--	1.00	--	--
Bid	1.50	0.24	6.35	1.75	0.39	4.46
Auxiliary statistics						
Model log-likelihood	-611.40			-439.77		
Model LR: chi-square (df)	553.67 (31)			531.10 (33)		
LR test for IIA assumption: chi-square (df)	6.82 (1)			15.06 (1)		

[10] The significance level is based on the z-score values. We interpret the z-score values using a 95 percent confidence level. This means that, when z-score values fall within -1.96 and +1.96, then the p-values would be more than 0.05.

Our proposed RUMNL Models 1 and 2 estimated using the aforementioned independent and control variables were significant in terms of the model likelihood ratio tests. Furthermore, the likelihood ratio test of homoscedasticity in the logit random error terms across decision nests in both RUMNL models indicated that homoscedasticity (i.e., the IIA assumption) was rejected (see Table 6, last row, χ^2=6.82 and χ^2=15.06, respectively). Thus, our use of the RUMNL model (rather than the MNL model) for modeling the overall decisional choice was justified. However, RUMNL model 2 provided a better model fit than RUMNL model 1 because the model log-likelihood for RUMNL model 2 was significantly higher. Estimated model coefficients (that were statistically significant) were similar in signs and magnitudes across both specifications. We next discuss all model estimation results and implications for only RUMNL model 2.

In Table 6, the RUMNL model 2 estimation results indicate that a buyer was more likely to choose shop B (the high-risk option) rather than shop A if the conditional purchase option was provided (see coefficients of -2.23 vs. -7.63, respectively). Similarly, a buyer was more likely to choose shop B rather than shop A if the information cue mechanism was provided (see coefficients of -1.11 vs. -5.11, respectively). Therefore, H1b and H2b were both supported. RUMNL model 2 results reveal, as we hypothesized, that, in the presence of an information cue, a buyer was more likely to choose a specific option if more buyers chose the same option. Therefore, H2c was supported. This effect was more pronounced for shop B than shop A (comparing coefficients of 0.70 vs. 0.62, respectively). Based on the results of a post-hoc analysis in RUMNL model 2, we found that, in the presence of a conditional purchase, a buyer was also more likely to choose a specific option if more buyers chose the same option. In terms of the control variables, buyer valuations have a positive influence on the decisions to bid or use GPI. Specifically, buyers with higher valuations tended to choose to order. Significant evidence of inertia or state dependence in the buyers' choices for shop B across the periods in the experiments apparently existed.

6.3. Robustness Check Using Multinomial Logit Model

To ascertain the robustness of our analysis findings from the RUMNL model 2, we additionally estimated a MNL model based on the assumption of a one-stage decision process of simultaneously evaluating the decision to order and the shop A or shop B option. We essentially included the same set of model variables as those used in the estimation of the RUMNL model 2 (i.e., the manipulated variables of conditional purchase and information cues (interacted with the dummy variables of shop A and shop B options), the current valuation, risk aversion attitude, earnings and shop choices of the previous period, and time period dummies).

Table 7 shows the model estimation results for our MNL model used for robustness check. We obtained identical results relative to those from the RUMNL model 2 in Table 6 in terms of the relative magnitudes of model coefficients related to variables associated with shop A and shop B. As such, the results of the hypotheses tests remained consistent across the model estimation results from both RUMNL and MNL. Nevertheless, as we state earlier, since the RUMNL model does not suffer from the IIA problem, we derive implications of our model application using the RUMNL results.

Table 7. Multinomial Logit Model of Decision to Order and Option Choice			
Variable	**Coef.**	**Std. err.**	**z**
Independent variables			
Shop A	-5.62	1.00	-5.63
Shop B	-5.64	1.20	-4.70
Conditional purchase * shop A	-6.03	0.60	-10.09
Conditional purchase * shop B	-2.44	0.62	-3.92
Information cue * shop A	-3.93	0.43	-9.10
Information cue * shop B	-1.81	0.50	-3.62
Number of buyers choosing shop A * information cue * shop A	0.46	0.06	7.39
Number of buyers choosing shop B * information cue * shop B	0.61	0.17	3.57
Number of buyers choosing shop A * conditional purchase * shop A	0.97	0.09	10.41
Number of buyers choosing shop B * conditional purchase * shop B	0.45	0.16	2.70
Control variables [* option A dummy]			
Valuation	0.04	0.00	8.40
Risk aversion	-0.07	0.12	-0.58
Previous period earning	0.00	0.00	0.85
Previous period choice (shop A)	3.16	0.34	9.37
Previous period choice (shop B)	1.63	0.42	3.93
Period dummies (for period 3 to 20)	Estimated but not shown		
Control variables [* option B dummy]			
Valuation	0.05	0.01	8.78
Risk aversion	-0.42	0.14	-3.10
Previous period earning	0.00	0.00	0.84
Previous period choice (shop A)	1.84	0.44	4.17
Previous period choice (shop B)	0.95	0.47	2.01
Period dummies (for period 3 to 20)	Estimated but not shown		
Auxiliary statistics			
Model log-likelihood	-430.22		
Model LR: chi-square (df)	393.89 (54)		

6.4. Model Application: Choice Elasticities

Using the aforementioned estimated model coefficients for RUMNL model 2, we computed the NL choice elasticities for both the competing shop option choices and the GPI order choices using the sample enumeration method (Louviere et al., 2000). Table 8 shows the probability-weighted aggregate point elasticities. Figures 3 and 4 illustrate the corresponding distributions of the elasticities of choice probabilities.

Table 8 shows that the availability of a conditional purchase option will, all else being equal, lead to a 0.889 percent and 0.126 percent increase in the overall probability of choosing the high-risk shop B and low-risk shop A, respectively. However, the availability of an information cue mechanism will, all else being equal, lead to a 1.451 percent increase and a 0.036 percent decrease in the probability of choosing shop B and shop A, respectively. Thus, this premise suggests that whether one chooses a high-risk option (shop B) is more sensitive to the availability of an information cue than to the presence of a conditional purchase option. However, this relationship is reversed for the choice of a low-risk option (shop A) in that such a choice is more sensitive to the presence of a conditional purchase than an information cue.

Figure 3 shows that the distributions of both the conditional purchase and the information cue elasticities of choice probabilities for shop B were unimodal (modes near 0) and had wider ranges compared to those of shop A that are bimodal (modes at 0 and -1). This result implies that, although a majority of the elasticities of choice probabilities for shop B were concentrated around 0, a significant "long tail" of the high-magnitude elasticities still existed. Correspondingly, for shop A, the bimodal distributions of the choice probability elasticities reveal that two majority groups of elasticities centered around -1 and 0, which indicates two different majority consumer segments in the studied experimental GPI market.

Table 8. Elasticities of Choice Probabilities from Nested Logit Model

Nest 2: shop A | shop B	**Shop A**	**Shop B**
Conditional purchase	0.126	0.889
Information cue	-0.036	1.451
Number of buyers choosing same option * information cue	0.013	0.080
Number of buyers choosing same option * conditional purchase	0.011	0.115
Nest 1: order-no | order-yes	**Order: no**	**Order: yes**
Valuation	1.832	0.546
Risk aversion	-0.303	-0.090
Previous period earning	0.013	0.004

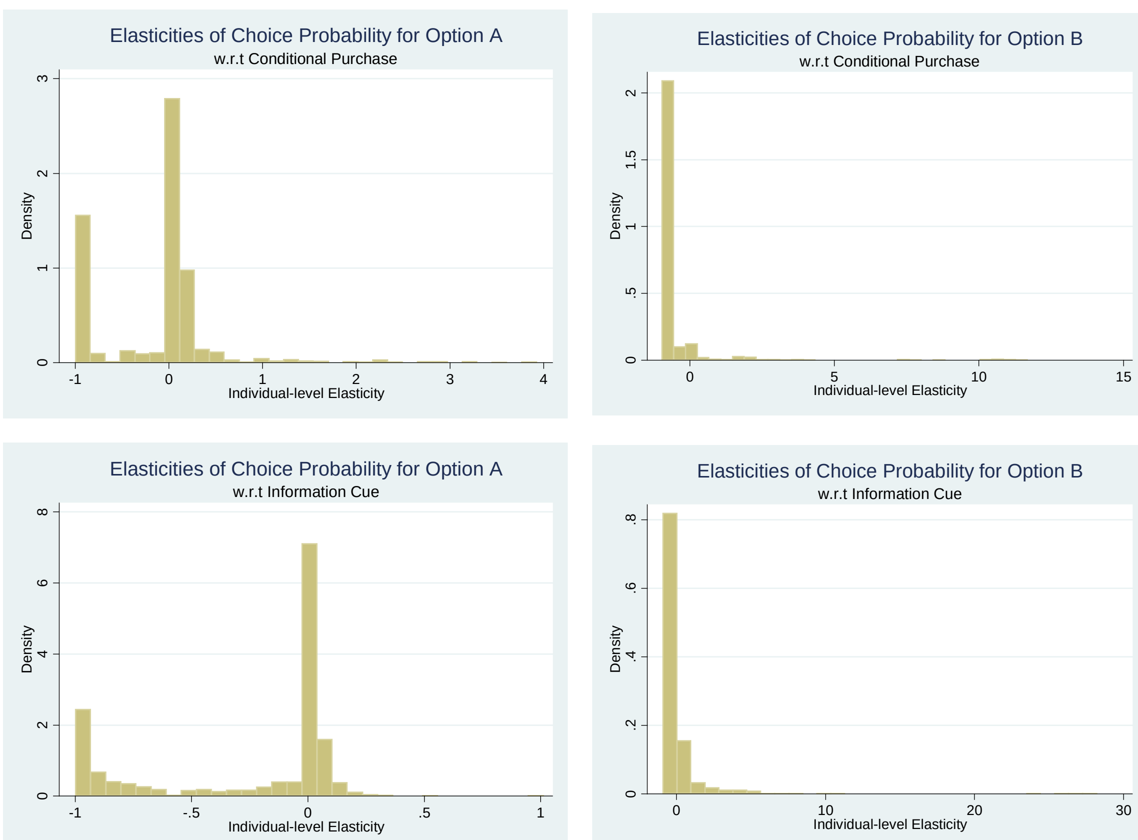


Figure 3. Distribution of Choice Probabilities with respect to Conditional Purchase and Information Cue

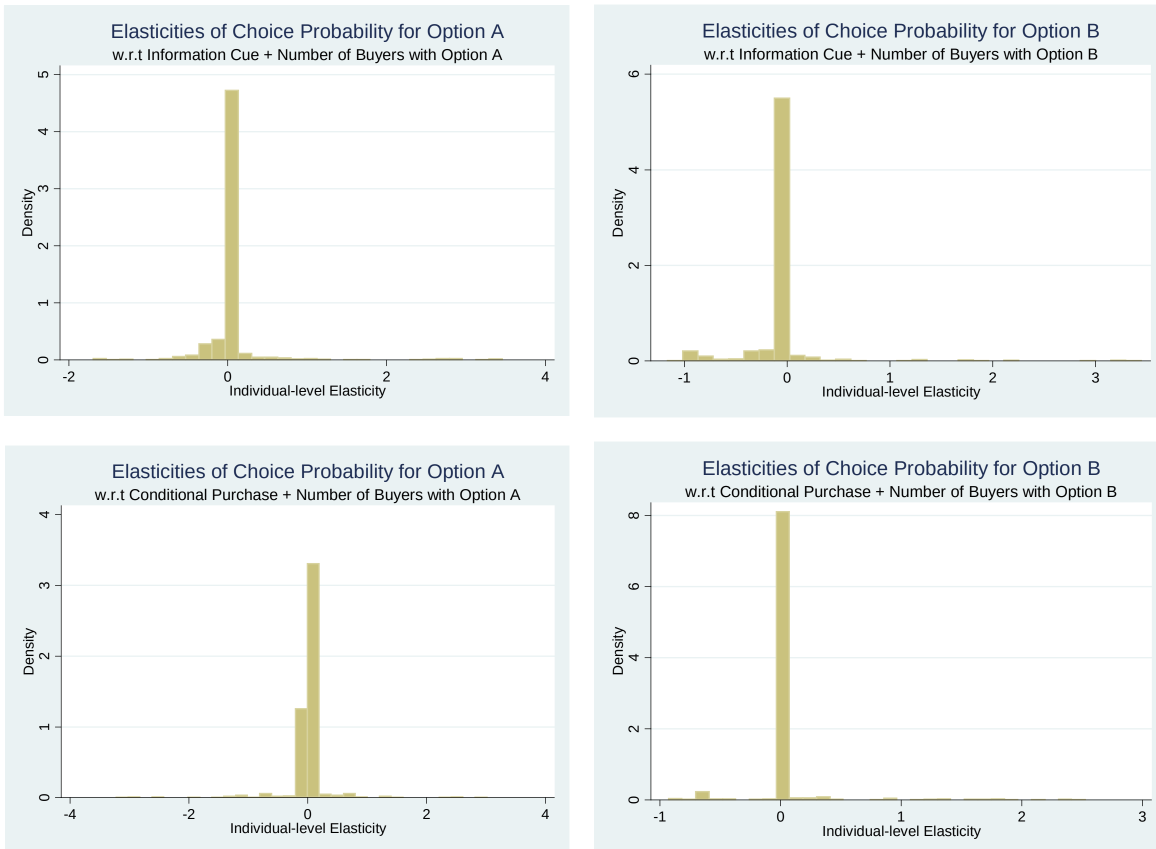


Figure 4. Distribution of Choice Probabilities with respect to Number of Buyers Choosing the Same Option

From Table 8, a 1 percent increase in the number of buyers choosing the same option in the presence of an information cue (but with all else being equal) will lead to a 0.080 percent and 0.013 percent increase in the overall probability of choosing shop B and shop A, respectively. Moreover, a 1 percent increase in the number of buyers choosing the same option in the presence of a conditional purchase (but with all else being equal) will lead to a 0.115 percent and 0.011 percent increase in the overall probability of choosing shop B and shop A, respectively. Figure 4 shows that the distributions of these elasticities of choice probabilities for both shop A and shop B are unimodal and have both positive and negative supports.

7. Discussion

In this paper, we examine GPI via manipulating conditional purchase and information cue. The results indicate that a buyer is more likely to purchase through GPI when a conditional purchase is provided. These results provide further empirical justification for our conjecture that the conditional purchase could reduce the impact of detrimental consequences associated with negative constraint interactions in GPI. This observation is also in accordance with the decision-avoidance literature, which contends that reducing an action's negative consequences induces a lesser likelihood to select inaction inertia (Dhar, 1997; Dhar & Nowlis, 1999), which is a primary concern of GPI. Furthermore, by providing conditional purchase, buyers are encouraged to choose riskier options to a certain extent. Using the illustrative example of Groupon and based on our choice elasticities analysis, a 10 percent increase in the average daily number of 73 customers who purchased Groupon deals across approximately 400 markets to date (i.e., an incremental increase of approximately seven customers) would result in an 11.5 percent increase in the probability of the next prospective customer participating in the GPI of Groupon[11].

In contrast to the conditional purchase findings, our results on providing the information cue suggest that participants exhibit higher levels of risk aversion when confronted with the choice between inaction inertia (i.e., the decisions not to order) and action (i.e., the decisions to order), arguably due to negative expectation and/or preference interactions in GPI. However, in the event that a choice is to be made between a riskier and a less-risky option, the presence of the information cue (coupled with positive expectation and/or preference interactions) could lead to a higher propensity for the riskier choice. We observe that a buyer is more likely to choose a specific option if the buyer is able to see numerous buyers choosing the same option. Again, illustrating with the real-world example of Groupon (which provides real-time information cue of the current number of customers who have purchased in the GPI), our choice elasticities analysis implies that an incremental increase of approximately seven customers could result in an 8 percent increase in the probability of a potential customer participating in Groupon.

These results suggest, at best, that information cues works only to the effect of leading buyers to make similar purchase decisions when a particular number of others have already made the choice. At worst, information cues may cause inaction inertia from a buyer when they display no commitment from the rest of the buyers. Hence, information cues may be a double-edged sword in GPI depending on the specific nature of expectation and/or preference interactions. Thus, we add to the theory that providing information cues may be insufficient in motivating buyers to abandon inaction inertia (Anderson 2003). However, once the inaction inertia has been bridged, our choice elasticities analysis indicates that the choice of the riskier but more rewarding alternative in the GPI is more sensitive to the information cue mechanism than to the conditional purchase option in the GPI.

7.1. Limitations

This study has several limitations. First, our set of experiments restricts the market to a small number of buyers. Despite the small number of players in each experiment session, we were able to project significant differences in the decisions. Our experiment involving 10 buyers is analogous to the situation where only a handful of buyers contemplate the purchase of similar items in a period of time.

Second, although we used a laboratory experimental setting with strict controls, there may still be concerns on the realism of the study because the experiment participants were all postgraduate university students, albeit with working experience. Given that our laboratory markets were real markets in that the principles of economics apply there as elsewhere and that the participants earned real profits in the context of realistic market trading rules (Smith, 1982), we believe that we have somewhat mitigated these concerns.

Third, there might be other mechanisms at play in GPI. To this end, there are two fundamental types of GPI; namely, the daily-deal variant model and the dynamic discount pricing mechanism. In this research, we focus on the latter. Thus, future research could also examine the former type.

Fourth, in our experiment, we considered the minimum quantity threshold difference between the different shop options in our experimental GPI market. We determined this value through manipulation checks conducted through several rounds of pilot tests carried out before the main experiment sessions. However, it is plausible that successfully manipulating low-risk and high-risk options in GPI hinges on a perceptible difference (in the minds of consumers) in the minimum quantity threshold requirement across different purchase options of GPI. Future research could explore this issue on the relationship between the extent of risk in GPI options and minimum quantity threshold differences.

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[11] We acknowledge that our results may not apply to the GPI case of Groupon, which is a simplified version of our studied GPI. Thus, due to the lack of other published examples, we use Groupon's published statistics. As of January 2011, Groupon lists the total number of GPI deals transacted as 22 million on its website (http://www.groupon.com/pages/press-kit). In existence since November 2008 for about 25 months, Groupon seems to be averaging approximately 73 customers a market daily who purchased Groupon deals across its 400 different markets.

Fifth, we did not examine the increasing or decreasing rate of the number of buyers when we evaluated the effect of conditional purchase and information cue. Thus, future research could explore decision making behaviors when the number of buyers changes.

Sixth, information cues may not be only applicable to GPI context and its application can be witnessed in other domains. However, conditional purchase is a more distinct feature of GPIs' dynamic pricing mechanism. Through selecting one general feature (i.e., information cue) and one more distinct feature (i.e., conditional purchase) from GPI, we are able to formulate more generalizable insights from our findings while retaining a degree of relevance to GPI. Despite so, we acknowledge that GPIs' existence and features are also strongly affected by prior market institution features such as information provision in auction markets.

7.2. Implications for Research and Practice

With this study, we provide five key theoretical implications. First, this study is among the first attempts to assess two GPI mechanisms that could potentially influence buyer purchase behavior across competing GPI options. Prior studies on GPIs (as Table 1 reviews) have focused on examining the revenue generation for sellers and the GPI itself (e.g., Anand & Aron, 2003; Chen et al., 2007, 2009a) and on buyers' bidding response to price and order quantity manipulations (e.g., Chen et al., 2009b; Kauffman & Wang, 2001). They do not examine the important issue of how a GPI can be designed to attract people with sufficient aggregated commitment to a purchase. The empirical evidence suggests that providing conditional purchases and information cues can have different impacts on different decisions that GPI buyers make (Rusbult & van Lange, 2003). Thus, our work complements prior GPI research by showing that providing GPIs would fail to attract buyers to order unless appropriate mechanisms are available.

Second, we conducted this study in part to answer Manski's (2000) call to analyze social interactions in an economics paradigm. Specifically, in reviewing the intersection between economics and sociology, Manski (2000, p. 117) writes that "the broadening of economic theory has coincided with new empirical research by economists on social interactions. Unfortunately, the empirical literature has not shown much progress". He supports this view with two reasons: 1) the "dearth of clear thinking in the empirical literature" and 2) "the inherent difficulty of drawing inferences from the data". In line with his perspective, we believe empirical modeling of constraint, expectation, and preference interactions with a clear, standard setup that affords clear conceptualization of the interaction process (e.g., GPI and our focal manipulations) could be a way to understand interactions in a market setting. The results from this study allow us to observe the nature and outcome of expectations and preferences interactions in a cooperative gaming mode.

Third, much current understanding about cooperative game is built based on individuals' committing to purchase simultaneously. In this situation, decision making is independent from others' decisions and individuals' purchase commitments are non-reversible. Demanding individuals to make decisions simultaneously creates a fundamental concern that the observations made from the social interactions among the consumers result from their aggregated individual preferences rather than "interaction" per se. This research examines constraint, expectation, and preference interactions by letting the consumers observe others' behavior and make decisions (i.e., decision to buy). By using conditional purchases and information cues, we examined a setting that does not explicitly demand the individuals to define the decisions simultaneously at the beginning of each trading period. Furthermore, we allowed the commitments to be reversible (i.e., individuals did not have to honor the purchase should the best price not be met). Thus, our findings add an additional dimension of empirical understanding to the cooperative game literature.

Fourth, our considering both information cues and conditional purchases features extends prior IS work that has mostly focused on information-provision mechanisms and their impact on user-interaction. Prior work on information provision has advocated that making information available reduces the asymmetry among individuals (Charness & Villeval, 2009; Sandler, 1992) and, thus, should lead to improved overall welfare (Healy & Palepu, 2001). Our results indicate that providing information in a GPI can also lead to a bystander, observatory behavior that causes individuals to withhold or delay decisions. It is only when the potential of suffering from non-cooperative outcomes in GPI emerges will the information cue mechanism in GPI be able to achieve what it is supposed to resolve.

Fifth, we contribute to the extant literature on decision under uncertainty by examining the implementation of conditional purchase. Prior studies have highlighted that buyers have a tendency to exhibit loss aversion (Kim & Kankanhalli, 2009) and inaction inertia (Tykocinski & Pittman, 1998) due to the inability to estimate the likelihood that a decision that results in negative consequences will occur. We explicitly consider a mechanism, in the form of conditional purchase, that could alleviate such a concern. The condition purchase mechanism allows buyers to “quit” should they better realize negative consequences (e.g., when the final offered price is higher than the possible available lowest price).

Our research also has four important practical implications. First, our research suggests the need to have adequate GPI mechanisms in place to induce buyers to purchase. As GPI and similar electronic market variations become more sophisticated in terms of aggregating buyer demands, our proposed GPI mechanisms could be mutually beneficial to both buyers in terms of lower prices and to shops in terms of liquidating stocks in large quantities, particularly in situations characterized by high acquisition costs and where buyer outcomes are interdependent.

Second, there is an escalating concern over GPIs’ long-term existence due to the intensifying rivalry to compete for buyers (Azfar, 2001; Bosker, 2011). Our results reveal that buyers could gather or remain as onlookers when they are aware of others’ actions (i.e., through information cues). This calls for attention to how and what kind of information retailers and GPI operators can provide to enhance the probability of buyers gathering together to commit to purchasing products on a GPI.

Third, the effects of conditional purchases and information cues on judgment and choice are not limited to GPIs but could influence buyers in a large number of activities, such as signing up for group tour packages. Practitioners should be aware that any purchase decision made carries a risk, and sufficient information and/or incentives must be available to motivate a buyer to purchase. Hence, they could consider providing the option of conditional purchases, aside from other popular marketing tools such as money-back guarantee, to alleviate such an uncertainty and, thereby, induce deviation from inaction inertia. Likewise, GPI competitors promoting riskier options to buyers could contemplate reducing the risk or uncertainty entailed in the options by providing information about the decisions that other buyers make. For example, in this age of the popular social media usage, one could integrate GPI information cues with Facebook’s “like” or “recommend” mechanisms in social graphs to accentuate the impact of social recommendations for GPI purchases among a circle of like-minded buyers who are friends in a social network. The study of such explicit “social” information cues in the GPI context could potentially be the subject of immense interest in future GPI research.

Fourth, our setting on the GBI, which considers conditional purchase and information cue, could be extended to situations where online retailers are pricing their new products through discovering and approximating the consumers’ willingness to pay. Such an approach could, in a more general outlook, allow dynamic pricing to truly occur in the digital world where the bulk of the current pricing scheme remains as a posted offer (i.e., buy at the listed price). From another point of view, promoting indirect bargaining of prices through the staggered pricing mechanism, which we focus on in this research, could also be beneficial to consumers at large.

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