When and How to Leverage E-commerce Cart Targeting: The Relative and Moderated Effects of Scarcity and Price Incentives with a Two-Stage Field Experiment and Causal Forest Optimization

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Abstract. The rise of online shopping cart–tracking technologies enables new opportunities for e-commerce cart targeting (ECT). However, practitioners might target shoppers who have short-listed products in their digital carts without fully considering how ECT designs interact with consumer mindsets in online shopping stages. This paper develops a conceptual model of ECT that addresses the question of when (with versus without carts) and how to target (scarcity versus price promotion). Our ECT model is grounded in the consumer goal stage theory of deliberative or implemental mindsets and supported by a two-stage field experiment involving more than 22,000 mobile users. The results indicate that ECT has a substantial impact on consumer purchases, inducing a 29.9% higher purchase rate than e-commerce targeting without carts. Moreover, this incremental impact is moderated: the ECT design with a price incentive amplifies the impact, but the same price incentive leads to ineffective e-commerce targeting without carts. By contrast, a scarcity message attenuates the impact but significantly boosts purchase responses to targeting without carts. Interestingly, the costless scarcity nudge is approximately 2.3 times more effective than the costly price incentive in the early shopping stage without carts, whereas a price incentive is 11.4 times more effective than the scarcity message in the late stage with carts. We also leverage a causal forest algorithm that can learn purchase response heterogeneity to develop a practical scheme of optimizing ECT. Our model and findings empower managers to prudently target consumer shopping interests embedded in digital carts to capitalize on new opportunities in e-commerce.

Introduction

The evolution of e-commerce has been shaped by various digital technologies (Tam and Ho 2005, Ghose 2009, Xu et al. 2012, Leong et al. 2016, Venkatesh et al. 2017). Previously, e-commerce leveraged web-page designs, banner ads, and online search ads to target covert shopping interests with sales potentials (Sherman and Deighton 2001, Chatterjee et al. 2003, Manchanda et al. 2006, Yao and Mela 2011, Ding et al. 2015).

Online shopping cart–tracking technologies offer a new targeting opportunity for e-commerce. Essentially, e-commerce cart targeting (ECT) refers to a business practice that leverages digital cart-tracking technology to target the overt interests of shoppers who have short-listed products but paused during the checkout process (Garcia 2018). Practitioners who can close these sales can thereby reclaim revenue lost

from cart abandonments[1] (Close and Kukar-Kinney 2010, Egeln and Joseph 2012, Garcia 2018). Indeed, ECT is unique to e-commerce because tracking physical carts when people browse in-store is difficult offline. However, shoppers leave digital trace data when browsing, searching, and carting online.

Industry practices of ECT have widely used price incentives and scarcity messages. For example, Pinterest.com sends pop-up deals and incentives to recover carts, whereas Zulily.com adds a countdown clock to signal urgency for shoppers to check out.[2] Comparing and contrasting these two common ECT designs are essential because each has its own pros and cons. First, price discounts (e.g., a percentage off) are widely adopted in e-commerce and mobile promotions (Luo et al. 2014, Fang et al. 2015, Andrews et al. 2016, Leong et al. 2016, Dube et al.

2017, Venkatesh et al. 2017). However, price incentives have some drawbacks: they are costly and can signal low quality (Jedidi et al. 1999, Kopalle et al. 1999). An alternative approach is to use a nonmonetary incentive whereby companies provide scarcity messages highlighting a limited supply (e.g., only two rooms left). The scarcity message is costless and can act as an "attention grabber" and nudge consumers to act immediately because of the fear of missing out and a sense of urgency to buy (e.g., Stock and Balachander 2005 and Balachander et al. 2009). A downside of scarcity messages is that they may be less powerful than price incentives in boosting customer purchases.

However, practitioners might simply target users without fully considering how ECT designs *interact* with the covert and overt consumer interests in the online shopping stages. That can be counterproductive for e-commerce because tension and negative interactions might exist between ECT designs and shopping stages with deliberative or implemental consumer mindsets. Without considering shopping goal stages in the path to purchase, a flood of discounts in e-commerce can waste marketing budget (Aydinli et al. 2014). For example, Vip.com provides discounts for every online display, and such discounts may be perceived as a signal of low quality and lead to boomerangs. Conversely, mindless usage of scarcity throughout the shopping journey cannot always create urgency for purchase (Chandon et al. 2000). Thus, the effectiveness of ECT with price incentives and scarcity may vary significantly in different shopping goal stages.

Against this backdrop, our objective is to address the question of when (with versus without carts) and how (scarcity versus price promotion) to target consumers for higher purchase rates in e-commerce. Grounded in the theory of consumer shopping goal stages (Lee and Ariely 2006), a conceptual model of ECT was, therefore, developed. In the early stage, consumers are less certain of shopping goals (which products to purchase at what prices). Monetary incentives with price discounts to encourage purchase of a product may signal low quality to consumers. By contrast, scarcity messages may serve as a cue that the product is popular because it is high quality. Thus, scarcity messages may perform better for consumers in the early stage without items in shopping carts. However, in the late stage, consumers are much clearer about their shopping targets (again, which products to purchase at what prices). Scarcity messages add little extra value or utility to consumers, but price discounts reduce the cost to purchase and, hence, increase the consumer surplus in e-commerce. As such, price discounts perform better than scarcity nudges in the late stage.

Data from a large-scale field experiment on more than 22,000 mobile users suggest that ECT has a substantial impact on consumer purchase responses, inducing a 29.9% higher purchase rate than e-commerce targeting without carts. Also, this impact is moderated by ECT designs: a price incentive amplifies the impact but leads to ineffective e-commerce targeting without digital carts. By contrast, a scarcity message attenuates the impact but significantly boosts purchase responses to targeting without carts. The results also reveal some interesting relative effects: the costless scarcity nudge is approximately 2.3 times more effective than the costly price incentive in the early shopping stage without carts, whereas the ECT design with a price incentive is 11.4 times more effective than a scarcity message in the late stage with digital carts.

Our paper makes the following contributions to the theory of e-commerce. (1) Previous studies have focused on web-page designs (e.g., Mandel and Johnson 2002 and Ansari and Mela 2003) and online banner/ search ads (e.g., Rutz and Trusov 2011 and Sahni 2015). We extend the literature by considering how to leverage ECT to recover shopping cart abandonments for e-commerce platforms. This is crucial because the average e-commerce cart abandonment rate can be as high as 69.89% with more than US$4.6 trillion of product items unpurchased.[3] Academic research has sought to examine cart targeting because this practice has been implemented in e-commerce, and data on ECT are becoming available. We are among the first to assess the value of ECT, a crucial but under-researched new source of revenue for e-commerce platforms, such as Amazon. Clearly, platform managers are interested in valuing users with both covert and overt product interests. One new insight here is that, although website design and banner/ search ads remain vital in attracting users who have covert shopping interests in the early stage of the customer conversion funnel, e-commerce platforms may achieve greater profits by focusing on overt shopping interests and targeting late-stage users with digital carts. (2) In e-commerce, merchants must go beyond the main effects to match different promotions with different online shopping stages. We extend e-commerce targeting theory by revealing the *moderated* effects of ECT design. Firms practicing ECT might fail to advance their digital businesses if they blindly target customers without considering online shopping stages because price incentives intended to motivate purchase responses may actually repel potential customers (Subramani and Walden 2001, Moe and Fader 2004, VanderMeer et al. 2012). E-commerce platforms may also misestimate the value of ECT. For example, the effect of ECT design with scarcity messaging would be significantly underestimated if it were examined only in the late shopping goal stage with carts. Conversely, the effect of price incentives would be overestimated if the focus were solely on digital carts rather than both the early and late stages on the path-to-purchase consumer journey. (3) We also offer new

insights into the *relative* effects of the costless scarcity message and costly price incentive for e-commerce targeting. A nonmonetary promotion with scarcity is relatively more effective than a monetary promotion in the early stage, thus protecting firms' financial budgets while achieving superior returns on investment. Alternatively, e-commerce platforms may get more bang for the buck: price incentives are relatively more effective than scarcity messages in the late stage for ECT. Thus, it is important for e-commerce platforms to employ the right promotional designs for consumers in the right online shopping stages and to avoid unproductive targeting (price incentives in the early stage or scarcity in the late stage). In this sense, our paper deepens the understanding of which marketing tools are effective at different consumer shopping goal stages in e-commerce.

We also contribute to broad theories on consumer behavior in several aspects. (1) To the best of our knowledge, our findings are among the first to test the theory of consumer shopping goal stages with large-scale randomized field experiment data as previous articles are based on laboratory data (Lee and Ariely 2006, Chan et al. 2010, Haans 2011, Song et al. 2017). We link the theory of consumer shopping goal stages to a new context of digital cart-tracking technology in e-commerce. In accordance with the shopping goal stage theory, empty carts embody the initial stage of shopping with few concrete shopping goals as opposed to the late stage with more concrete goals. By using the cart-tracking technique to gauge shopping goal stages, we can more thoroughly understand consumer behavior nuances in terms of attention versus value orientation, deliberative versus implemental mindset, and short-listed products of interest versus commitment to buying online. (2) The literature on consumer behavior recognizes two key factors influencing consumer decision-making processes: the focus of attention among consumers visiting an internet-based store (Novak and Hoffman 1997, Koufaris 2002, Jung et al. 2009) and the perceived value of buying a product (Richins and Dawson 1992, Swait and Sweeney 2000). In contrast to studies focusing on either factor, our study examines both holistically: the focus of attention is critical for empty carts in the early stage, and the value proposition is vital for cart checkout in the later decision-making stage. We identify appropriate situations to leverage the attention focus (e.g., implement a scarcity message for consumers without creating carts) and enjoy the returns of perceived value (e.g., deploy discounts for consumers with carts). (3) We also extend the theory of consumer behavior in the context of scarcity. Previous studies (Balachander et al. 2009, Zhu and Ratner 2015) have primarily addressed scarcity through
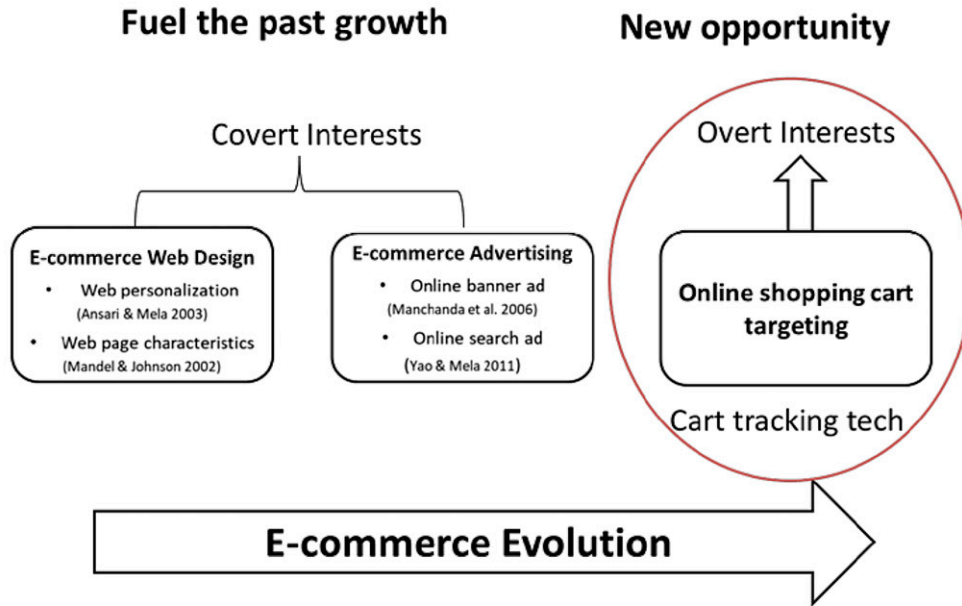
observational data and laboratory studies. We have validated existing theories by discerning causal evidence for scarcity on the basis of a field experiment. We also extend the theory of scarcity by suggesting that e-commerce platforms should adopt a scarcity message-based ECT design in the early stage rather than in the late stage. Our paper reveals that scarcity messaging is still effective when customers have yet to create carts. However, when customers have entered the late shopping goal stage with digital carts, the same scarcity nudge is ineffective with insignificant incremental purchases relative to a regular reminder. These findings enrich the scarcity literature by identifying a situation in which scarcity is not as powerful as might be expected. Furthermore, our relative results enrich the scarcity literature by suggesting that a scarcity message, as a means of grabbing consumer attention, is even more effective than monetary promotion in the early stage for e-commerce. (4) Finally, we extend the consumer behavior theory on price promotions by examining how price incentives may interact with online shopping stages. We demonstrate that, although consumers may not be fully committed to buying the short-listed product in digital carts, price incentives as purchase triggers can effectively encourage them to commit to checking out in the "last mile." Also, we enrich the literature by finding that a price incentive can be ineffective in the early stage of an online shopping journey, that is, good intentions with bad outcomes. Thus, practitioners should prudently leverage ECT with the relative and moderated effects of scarcity and price incentives to exploit new business opportunities in e-commerce.

Background and Conceptual Model
E-commerce Background
Figure 1 depicts a simple representation of the evolution of e-commerce. In its early days, e-commerce leveraged web-page designs and online banner/search ads to induce the conversion of covert consumer shopping interests with sales potential (i.e., consumers browsing certain web pages and clicking certain ads are likely to be interested in buying). Specifically, the early e-commerce literature examined the characteristics of website pages (e.g., Mandel and Johnson 2002, Song and Zahedi 2005, and Parboteeah et al. 2009) and web personalization and customization (Ansari and Mela 2003, Tam and Ho 2005). Later studies have investigated the use of online banner ads (e.g., Chatterjee et al. 2003, Drèze and Hussherr 2003, and Manchanda et al. 2006) and search ads (e.g., Rutz and Trusov 2011, Sahni 2015, and Du et al. 2017). Currently, the rise of online shopping cart–tracking technologies enables e-commerce retailers to target overt shopping interests with direct sales implications.[4]

Figure 1. (Color online) Representation of the Evolution of E-commerce
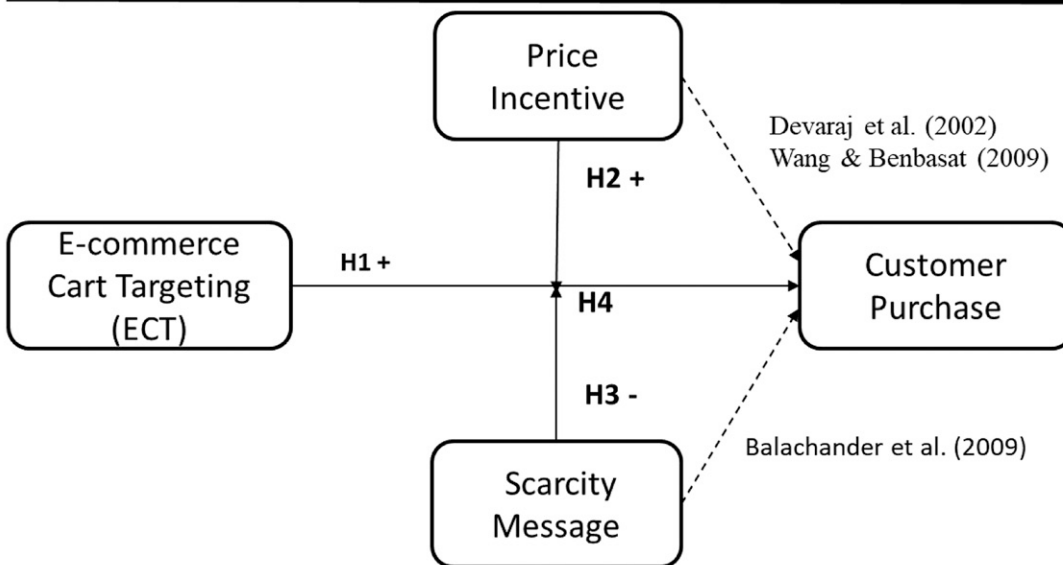

Our Conceptual Model of ECT

Figure 2 presents our proposed model, which conceptualizes the direct effects of ECT on consumer purchases as well as the moderated and relative effects of various designs of ECT: scarcity message and price incentive, incremental to a simple reminder message. Essentially, our model holds that the presence or absence of digital carts gauges online shopping goal stages: consumers with (without) digital carts tend to have relatively more (fewer) concrete shopping goals with overt (covert) shopping interests in the late (early) shopping stage. This is plausible

Figure 2. Conceptual Model

Notes. We do not hypothesize the dotted lines, which relate to the direct effects of scarcity messages and price incentives on customer purchases, because these are relationships that have been studied previously. The effects of price incentive and scarcity message are incremental to a simple reminder message.

because digital carts gauge consumers' shopping interests explicitly: otherwise, consumers would not add products to digital carts, which is in line with the two-stage shopping goal stage theory (Lee and Ariely 2006).[5]

Consumer Shopping Goal Stages Theory. Lee and Ariely (2006) theorized a two-stage framework of shopping goals. This framework combines the increasing concreteness of shopping goal stages with the sensitivity of these goals to external factors in the consumer purchase journey. In the early shopping stage, consumers have a *deliberative* mindset and are generally uncertain about what they want to buy and how much they want to spend. During this stage, they are exploring and collecting information on product attributes for consideration. They are open minded and susceptible to contextual and external factors that may help solidify their preferences and construct their shopping goals. In the late shopping stage, consumers have an *implemental* mindset. They have largely constructed concrete shopping goals and adhere to their goals by taking actions to attain them. In the customer purchase journey, when a customer transitions from the early abstract stage to the later concrete stage, that customer is ready to make a purchase decision.

The two-stage framework is consistent with a boarder literature suggesting that consumers pursue various goals in the shopping processes, including fundamental information collection, store browsing, bargain hunting, and final product purchasing (see a summary of prior studies in Online Appendix A). Indeed, Chan et al. (2010) proposed two phases of the shopping process: a predecisional phase when customers have yet to arrive at a decision (e.g., information search and alternative evaluation) and a postdecisional phase when customers have decided on the product to purchase (e.g., check out and postpurchase evaluation). Other studies on consumer shopping goals have focused on goal orientations. For example, Bridges and Florsheim (2008) found that a utilitarian goal orientation had positive effects on purchase intent, but a hedonic goal orientation had insignificant effects. Büttner et al. (2015) noted the existence of an experiential or task-focused shopping orientation. The former is a tendency to seek pleasure in shopping, whereas the latter is a desire to shop efficiently. They found that, although task-focused shoppers perceive monetary promotions as more attractive than nonmonetary promotions, experiential shoppers feel the two types of promotions are equally attractive. The consumer construal level theory holds that consumers tend to define abstract goals in superordinate terms in the early shopping stage and then have concrete goals as the

target activity approaches the late stage (Trope and Liberman 2003).

In addition, some studies have investigated the interactive effects of shopping goal stages and advertising content. Chan et al. (2010) noted that, when customers are in the predecisional phase, ads with implicit intent tend to be more effective than they are in the postdecisional phase. Song et al. (2017) found that, in the initial stage when customers are far from making purchase decisions, weak-tie recommendations with low deal scarcity are more effective. By contrast, in the late stage, strong-tie recommendations with high deal scarcity receive higher user evaluations. However, the findings of both Song et al. (2017) and Chan et al. (2010) were based on subjective scenarios to simulate online shopping stages in the laboratory as presented in Online Appendix A. Our research contributes to this stream of literature by (1) leveraging large-scale field experiments and the objective status of an online shopping cart to differentiate the early goal stage without carts from the late stage with carts, (2) applying the two-stage goal theory in a new setting of digital carts in e-commerce, (3) examining the interplay between shopping goal stages and two ECT designs, and (4) explicating how the two shopping goal stages may flip the relative effects of scarcity nudge and price incentives.

Scarcity Literature. Scarcity, namely the limited supply in quantity, is a fundamental and ubiquitous concept in economic theory. Numerous studies have argued that scarcity increases consumers' desire for the focal product (e.g., Stock and Balachander 2005 and Zhu and Ratner 2015). Online Appendix B summarizes research on scarcity. Previous research in consumer psychology suggests that scarcity creates a sense of urgency and fear of missing out. It may influence consumer decision making because of a constrained mindset or a perceived competitive threat. In a landmark study, Folkes et al. (1993) found that resource scarcity rather than abundance encouraged consumers to focus on consumption constraints (i.e., diminished supply of the product). Mehta and Zhu (2015) also argued that scarcity promotions would activate a cognitive orientation toward consumption constraints, which would heighten customer attention to the scarce product. Zhu and Ratner (2015) noted that scarcity broadens the discrepancy between the most- and less-preferred items, increasing choice share for the most-preferred option. Echoing this, Stock and Balachander (2005) proposed a signaling explanation of scarcity strategies, whereby the difficulty to obtain could signal the credible quality of the product to uninformed consumers. Balachander et al. (2009) demonstrated that the scarcity of a car at the time of introduction was

associated with higher consumer preference for the car. Alternatively, the exposure to scarcity can induce a competitive orientation whereby consumers perceive scarcity as signifying the potential competitive threat of other people who may also prefer the scarce resource. For instance, Kristofferson et al. (2016) found that scarcity promotions could incite consumers to engage in aggressively competitive actions, such as shooting, hitting, and kicking. Because of the competitive orientation, scarcity could guide consumers' decision making toward advancing their own welfare, thus leading to more selfish behavior and less charity donation (Roux et al. 2015). Advancing prior scarcity literature with subjective self-reported observational data or laboratory studies, we use field experiments with objective purchase data. Although Balachander et al. (2009) tested the main effect of scarcity, they did not randomize scarcity to be free from endogeneity bias. Also, extending prior research on the direct effects, we revealed more nuanced moderated and relative effects of scarcity, that is, identifying specific boundary conditions (with or without digital carts) and reference points for the scarcity effects (relative to price incentives and a regular reminder).

Price Incentive Literature. Price incentives are generally promotional discounts and coupons that can enhance value and create an economic incentive for purchasing (Devaraj et al. 2002, Wang and Benbasat 2009). Online Appendix C summarizes exemplar academic research that has highlighted the mixed effects of price promotions. Some studies have suggested that price incentives have a positive short-term effect on brand sales (Blattberg and Neslin 1990, Rossi et al. 1996, Alba et al. 1999). For example, Alba et al. (1999) noted that price promotion effectively creates an economic incentive toward making a purchase. In a similar vein, Rossi et al. (1996) presented the economic value of customizing promotional offers in the form of a simple price reduction for products. However, because low prices signal low quality, Kalwani et al. (1990) found a negative long-term effect of price promotions on brand choice. Echoing this, Jedidi et al. (1999) argued that discounts can hurt brand equity, thus reducing regular-price purchases. Similarly, Mela et al. (1998) and McCall et al. (2009) argued that consumers might learn to wait for deals, which may further decrease baseline sales. Kopalle et al. (1999) added that price promotions have negative effects on future organic sales because of dynamics in price sensitivity and expectations. Also, consumers may expect more price incentives to be given as reciprocal rewards for their loyalty to the brand and company (Reczek et al. 2014). Furthermore, Lal and Rao (1997) suggested that merely setting low prices is not a viable strategy for obtaining high profits. Aydinli et al. (2014) argued that the prospect of paying a lower price for a product can discourage deliberation and, thus, lower consumers' motivation to exert a mental effort when making brand choices. Extending prior research, our study identifies situations in which the price incentive is more or less effective. That is, we advance the literature by considering how online shopping cart status may regulate the effects of price incentives and by accounting for the magnitude of such effects relative to a costless scarcity message. The next section develops the hypotheses.

Hypotheses Development

Here we hypothesize the main effects of ECT, moderated effects of ECT designs with scarcity message and price incentives and the relative effects of a price incentive vis-à-vis scarcity message. Table 1 summarizes the logic underpinning the hypotheses.[6]

Main Effects of ECT. Lee and Ariely's (2006) two-stage shopping goal stage theory implies that when consumers with empty carts are still browsing, searching, and comparing distinctive choices, they are uncertain about their shopping goals. This means that they have a deliberative mindset and tend to focus their attention on short-listing products. By contrast, consumers with products in their shopping carts have relatively concrete shopping goals regarding what they want to buy. Thus, they have an implemental mindset and are committed to buying with a value orientation. Similarly, prior research on information systems (Tam and Ho 2005, Ho et al. 2011) has argued that it is important to adapt web recommendations to various phases of the consumer decision process, ranging from early phases, such as recognition, search, and evaluation, to later phases, such as choice and outcome. Echoing this, Fang et al. (2015) hold that consumer responses to mobile promotions may vary across various stages: problem recognition, information search, evaluation of product options, purchase decision, and postpurchase support. This line of research suggests that when consumers have short-listed specific products with concrete shopping goals in their carts, e-commerce targeting is likely to make them aware of the desired products in their carts and to incite them to make a purchase. Thus, ECT with carts should have a significant incremental effect on boosting consumer purchase responses relative to e-commerce targeting without digital carts.[7]

Hypothesis 1. *Ceteris paribus, compared with e-commerce targeting without digital carts, e-commerce targeting with digital carts has a positive impact on consumer purchases.*

Moderated Effects of ECT Design with a Price Incentive.
We expect that the ECT design with a price incentive is more effective in the late (versus early) shopping

Table 1. Hypotheses, Related Contributions, and Implications

Hypothesis	Theory support in brief	Contribution to e-commerce theory	Contribution to theory on consumer behavior	Managerial implications
1	Consumers with empty shopping carts browse products with deliberative mindsets and fewer concrete goals, thus being uncertain in their purchase. By contrast, consumers with digital carts are more certain about what they want to buy and have implemental mindsets and more concrete shopping goals.	Although previous e-commerce studies have focused on how web-page designs and online banner/search ads affect clickthroughs and sales, we extend the literature toward leveraging ECT to recover shopping carts for e-commerce platforms.	We link the theory of consumer shopping goal stage mindsets to digital cart tracking technology. By using a cart-tracking technique to gauge shopping goal stages, we can more thoroughly understand attention orientation versus value orientation, deliberative mindsets versus implemental mindsets, and short-list interested products versus commitment to buy.	E-commerce platforms may find focusing on overt shopping interests more rewarding and target users by using digital carts, whereas website design and banner/search ads are still a critical element in attracting users who have covert shopping interests at the early stage of the customer conversion funnel.
2	In the early stage, price incentive is viewed as an ineffective low-quality signal. By contrast, in the late stage, price incentive is viewed as an effective value enhancer, leading to more purchases.	Blindly targeting customers without considering online shopping goal stages means that monetary promotions may boomerang for e-commerce firms.	We extend the consumer behavior theory on price promotions by examining how price incentives may interact with online shopping stages.	The effect of an ECT design with a price incentive would be overestimated if solely focused on digital carts rather than both early and later goal stages in the path-to-purchase customer journey.
3	A scarcity message is an attention grabber for consumers who immediately act for fear of missing out; however, it offers no economic value and, thus, is ineffective at persuading customers to check out with the products in their digital carts.	A nonmonetary promotion with scarcity is relatively more effective than a monetary promotion in the early online shopping goal stage, thus lowering firms' financial budget while achieving superior performance.	We advance the scarcity literature by proving the interactive effect of scarcity and ECT on sales demand using real-world experiment data, the relative effects of scarcity versus price incentives.	The effect of an ECT design with scarcity messaging would be significantly underestimated if its effect were examined only in the late shopping goal stage with carts.
4	Scarcity, as a creator of urgency, is more effective than price discounts, which are an inferior quality signal in the early shopping stage. By contrast, scarcity as a nonmonetary incentive tactic should be less instrumental than price discounts, which offer a cost reduction to persuade consumers to check out the short-listed products in carts.	We offer new insights into the relative effects of the costless scarcity message and the costly price incentive for e-commerce targeting.	We identify appropriate situations to leverage the benefits of attention focus, for example, implement scarcity messaging for consumers without creating digital carts, and to enjoy the returns of economic value, for example, deploy discounts for consumers with digital carts.	E-commerce firms should use the right ECT promotional designs for consumers in the right online shopping goal stages and avoid incorrect targeting (price incentives in the early stage or scarcity in the late stage) for ECT.

stage. After consumers have short-listed products in carts with concrete shopping goals (Tam and Ho 2005, Lee and Ariely 2006), a fall in price, as an effective "value enhancer" for ECT, can encourage consumers to pay for products in the carts immediately. This is because the discounted price can lower the economic cost to consumers and enable them to buy what they want with less money (Alba et al. 1999). Price discounts increase the likelihood that a low-budget consumer can afford to purchase the product. Low-budget shoppers may give up desirable products despite demonstrated interests (e.g., by loading a shopping cart).

However, the availability of discounts enables shoppers whose financial budgets cannot accommodate the product of interest at the regular price to purchase it at the discounted price. Furthermore, shoppers with sufficient budgets can also enjoy cost reductions from price discounts (Blattberg et al. 1995). Indeed, cost issues are the most cited reason for abandoning carts; 74% of respondents do not complete a purchase because the final price is too expensive or a better deal is available elsewhere (eMarketer 2018). Previous studies have also documented the short-term positive effect of price incentives on purchase responses

(Blattberg and Neslin 1990, Rossi et al. 1996, Alba et al. 1999). Thus, an ECT design with a price incentive may eliminate the price barrier for purchasing (Lal and Rao 1997, Mela et al. 1998).

However, in an early shopping stage with empty carts, consumers are still browsing or comparing products in a deliberative mindset. In this situation, the same price discounts may signal lower quality products (Blattberg and Neslin 1990, Rossi et al. 1996, Jedidi et al. 1999, Cao et al. 2018). Unlike off-line shopping when consumers can touch, experience, and try the product in physical stores, online shopping prevents customers from evaluating the quality of the product prior to purchase (Dimoka et al. 2012). So consumers face a high degree of uncertainty regarding product quality: they might worry about the potential adverse selection (Ghose 2009) or moral hazard with which the product quality may be reduced after the item has been paid for (Pavlou et al. 2007). Such worries can be salient when consumers are in a deliberative mindset and carefully compare several competing products. In the early stage with abstract shopping goals (Tam and Ho 2005, Lee and Ariely 2006), consumers are highly sensitive to quality cues, especially those signaling possible low quality and, hence, may avoid products with price discounts. Thus, the signaled low quality resulting from price discounts in an early shopping stage can lead to ineffective e-commerce targeting.

In summary, consumers with digital carts are most likely to consider price incentives a value enhancer leading to more purchases relative to a regular reminder message. By contrast, when consumers are searching and comparing products without carts, they interpret price incentives as an ineffective low-quality signal. Therefore, we hypothesize the following:

Hypothesis 2. *Relative to a regular reminder message, a price incentive amplifies the effect of e-commerce targeting with digital cart, but leads to ineffective e-commerce targeting without carts.*

Moderated Effects of ECT Design with a Scarcity Message. By contrast, an ECT design with a scarcity message exerts different effects. In an early stage (Tam and Ho 2005, Lee and Ariely 2006), when consumers are searching for and collecting product information, exposure to scarcity promotions, such as the supply access constraint, can serve as an effective attention grabber and guide consumers' cognitive orientation to buy (Roux et al. 2015, Zhu and Ratner 2015). As the scarcity message creates a sense of urgency and fear of missing out the product, the consumer is likely to act promptly (Folkes et al. 1993, Shah et al. 2012, Mehta and Zhu 2015). Indeed, scarcity creates a feeling that the product

seems out of reach (Brehm 1972, Miyazaki et al. 2009), which can magnify the attractiveness and value of the product and heighten consumer motivation to possess it. Applying a similar line of reasoning, numerous studies have proven that scarcity increases customers' desire or preference for the focal product (Roux et al. 2015) and that limited-quantity promotions increase product sales (Stock and Balachander 2005, Kristofferson et al. 2016).

However, in the late shopping stage when a consumer has already decided on the focal product and added it to the shopping cart, a scarcity message might motivate the consumer to check out the product before the inventory is gone (Stock and Balachander 2005, Mehta and Zhu 2015). In this case, customers are sensitive to information that can help them attain their shopping goal and purchase products short-listed in the carts. Nevertheless, as a nonmonetary incentive, scarcity is of no economic value in attaining the goal of checkout. Although a scarcity message can trigger urgency and anxiety (Shah et al. 2012), this subjective urgency offers no economic value in reducing the objective financial budgets or monetary costs during checkout. In this sense, a scarcity message is relatively unappealing for customers with (versus without) carts to make a purchase.

The upshot is that, relative to a regular reminder, a scarcity message is a more effective attention grabber when targeting consumers without carts. By contrast, when carts are created with short-listed products, a scarcity message is ineffective for purchase conversion. Thus, we hypothesize the following:

Hypothesis 3. *Relative to a regular reminder message, a scarcity message boosts purchase responses to e-commerce targeting without digital carts but leads to ineffective e-commerce targeting with digital carts.*

Relative Effect of a Price Incentive Vis-à-vis Scarcity Message. Recall that shoppers in an early stage with empty carts most likely have a deliberative mindset and may not have concrete shopping goals (Tam and Ho 2005, Lee and Ariely 2006). If a consumer is exposed to a scarcity message that creates urgency and fear of missing out, the consumer is likely to act promptly. However, as discussed earlier, if the consumer is exposed to price discounts in the early shopping stage, the price discounts may signal inferior quality (Blattberg and Neslin 1990, Jedidi et al. 1999) and, thus, are ineffective in stimulating purchases. Together, this discussion suggests that the scarcity message as a consumer attention grabber is relatively more effective than a price incentive in the early shopping stage without digital carts.

However, if the consumer has created a shopping cart for the short-listed product but has not checked out in the late stage, most likely that consumer has an implemental mindset with a concrete shopping goal but is not fully committed to buying the short list. The consumer might be price sensitive and somewhat indifferent to buying or not buying. If the price drops substantially as a result of incentives, the consumer is more likely to pay immediately for the product in the cart (Mela et al. 1998, Close and Kukar-Kinney 2010, Egeln and Joseph 2012). In contrast, if the consumer receives a scarcity message concerning the product but without price discounts, the consumer may not give an immediate purchase response. That is, scarcity messages as a nonmonetary incentive tactic are less instrumental than price discounts in persuading consumers to check out. As such, a price incentive is relatively more effective than a scarcity message in the late stage for ECT. This leads to the following hypothesis:

Hypothesis 4. *A scarcity message is relatively more effective than a price incentive for e-commerce targeting without carts, whereas a price incentive is relatively more effective than a scarcity message for e-commerce targeting with digital carts.*

Data and Field Experiments
Company Background
To test the hypotheses, we conducted a randomized field experiment. A leading online maternal and baby products retailer in Asia (akin to Babies 'R' Us in the United States), hereinafter referred to as "the company," cooperated with us to conduct the field experiment. The company sells myriad maternal and infant supplies, including diapers, formula, gear, toys, baby clothes, and household items. The consumers are mainly young moms and dads with children younger than four years.

The collaborating retailer primarily uses mobile promotions (via short message service [SMS]) as its key method of promotion to impel its members to visit its website and make purchases (Luo et al. 2014, Li et al. 2017). For e-retailers, SMS is a vital technology for soliciting visits and purchases from consumers (Fong et al. 2015, Xu et al. 2017). Indeed, SMS is the second most effective tool in encouraging customers to make purchases in North America.[8] Furthermore, because regulations are less strict in Asia, SMS may surpass email as the most effective promotional method in our setting. Our corporate partner confirmed that SMS promotions have the highest consumer reach rates and fastest response rates (about 90% of SMSs are read within three minutes). However, people may not see the SMS or ignore it when they receive a message. This is why a randomized experimental design was required:

even if such a risk were to exist, it would be the same across all treatment groups of ECT designs. Consequently, our findings are free from such a risk and other confounding factors (as randomized field experiments are the gold standard for identifying causal effects).

Two-Stage Dynamic Field Experiment Design
Before we introduce the details of our experimental design, we highlight that the objective of this study is to understand when (with or without digital carts) and how (with price incentives or scarcity messages) to target consumers for higher e-commerce purchase conversions. The company can randomly assign price incentives or scarcity messages to its users to generate exogenous variations of ECT designs. Then, from the company data bank, we can directly observe cart status, which can be used to test the effects of ECT and the interactions between ECT and incentive/scarcity. This simple research design does not, however, account for what drives cart creation. The rationale for this simple design is as follows.[9] Users in different shopping stages are assumed to have different mindsets and goals (see Lee and Ariely 2006). Consumers with carts differ from those who have not started carts. There are always selection effects of cart status; for example, users who have placed items in their carts are likely to have a greater need to buy baby products at that point in time or have a greater preference toward the company's line of products compared with those who have not started carts. In other words, no company can force customers to create carts because cart creation is naturally self-selected and decided by consumers (who pay for the carted products) in the field. Given that our research goal is to enable managers to understand how to *market* to each of these consumer mindsets more effectively rather than explain why consumers create digital carts, this simple design is valid and practical. One can simply observe cart status and test the effects of ECT and the interactions between ECT and incentive/scarcity on purchases. Thus, some parts of our identification strategy and data analyses straightforwardly depend on simple observations of cart status along with the manipulated variations of incentive/scarcity without accounting for the reasons for cart creation.
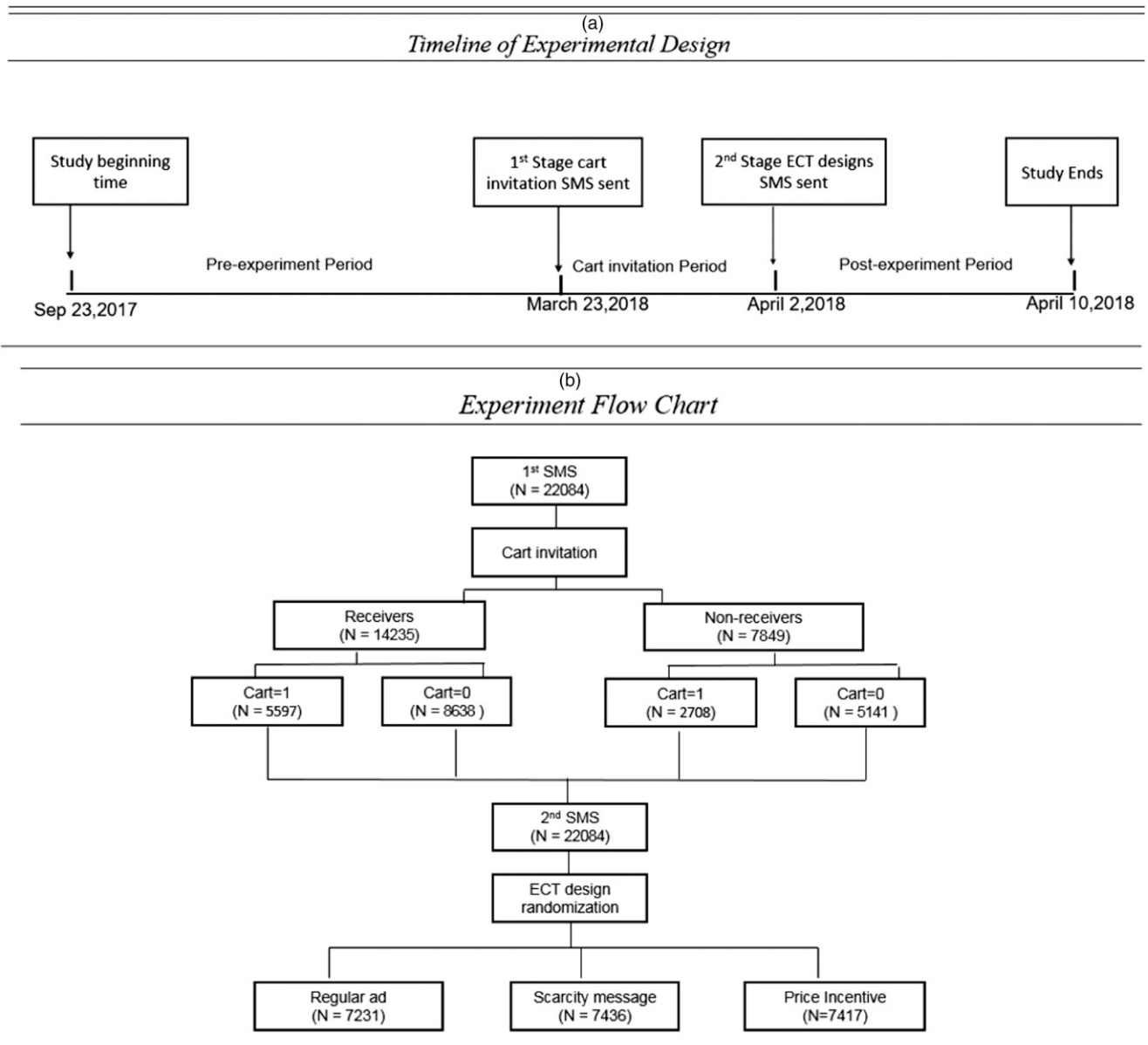
However, in addition to this simple method, our experiment design allows for an identification strategy that can directly account for the reasons for cart creation. Surveys (Close and Kukar-Kinney 2010, Egeln and Joseph 2012) have suggested that cart creation may arise from various alternative mechanisms, such as solicited carts by the company, the organic shopping processes of customers, various marketing promotion channels, seasonality, market competition, and other variables not observed in the data. In this study, we are concerned with the carts solicited by the company;

we isolate this from other mechanisms by employing a two-stage dynamic experimental design akin to that employed by Mochon et al. (2017). Specifically, Mochon et al. (2017) note that because Facebook page "likes" are self-selected (consumers decide to like or not), a two-stage experimental design was required. In the first stage of a like invitation, the company solicited likes by inviting its customers to like the brand (the treatment group received the invitation; the control group did not). In the second stage, they tested the effects of company-solicited likes on consumer behavior across groups over time. However, in the second stage, Mochon et al. (2017) did not use randomization as they tested the different effects of company-solicited likes over two time periods

(boosted and organic mechanisms). Because our corporate partner both solicits carts *and* randomizes ECT designs, we extended Mochon et al. (2017) by developing a two-stage dynamic experiment design (see Figure 3).

As Figure 3 illustrates, the experiment was conducted from March to April 2018. The first-stage SMS invitation was conducted on March 23, 2018, with 22,084 participants. The second-stage SMS randomization of ECT designs was conducted 10 days later on April 2, 2018. In the first stage of cart invitation, the company solicited carts by inviting its customers to add products to the cart (the treatment group received the invitation, whereas the control group did not). This step ensured that company-solicited carts were

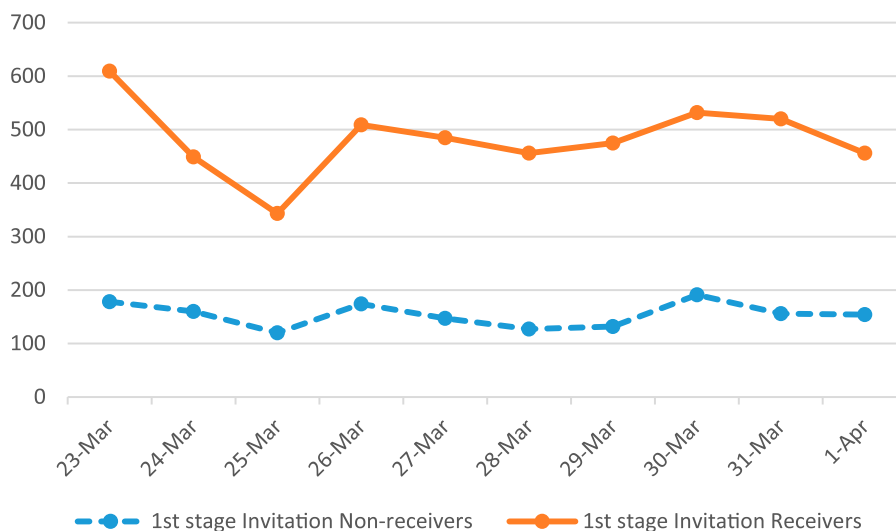**Figure 3.** Two-Stage Dynamic Experiment Design

not confounded by other reasons, such as the organic shopping processes of customers, various marketing promotion channels, seasonality, and market competition, all of which would be identical for both the control and treatment groups and, thus, canceled out. In the second stage of ECT design randomization, the company randomly assigned all customers to three ECT designs (price incentive, scarcity, and regular reminder message). The reason for including the control group of first-stage users who did not receive the initial SMS invitation in the second stage was to have a counterfactual baseline because some of these nonreceivers created carts over time for reasons other than company solicitation. The difference between receivers and nonreceivers rules out alternative reasons for cart creation. Thus, our two-stage dynamic experiment design comprising two randomizations with the same participants generated not only company-solicited carts (after accounting for alternative reasons for cart creation) but also exogenous variations in scarcity and incentive promotions, thereby offering an unconfounded explanation for cart creation and allowing for a more scientific quantification of the hypothesized effects of ECT.

First-Stage Invitation. The first-stage invitation message reads "Shop online for our special deals and promotions [company] and add products in your online shopping cart," and 14,235 participants out of a pool of 22,084 received the first message (first-stage treatment group). The remaining 7,849 participants (first-stage control group) did not receive any message. The first-stage invitation indeed generated significantly more carts for receivers than nonreceivers. Figure 4 plots daily cart creation behavior from March 23 to April 1. It proves that, over the 10-day period, the invitation receivers consistently generated

more carts. With respect to proportion, the invitation receivers also created more carts (5,597/14,235 = 39.31%) than nonreceivers (2,708/4,849 = 34.5%). These results suggest that our first-stage company solicitation indeed created more digital carts for receivers than would have been created by random chance.[10]

Second-Stage Randomization of ECT Designs. In the second stage, all customers, both first-stage solicitation receivers and nonreceivers, were again randomized and assigned to the second-stage conditions of the ECT designs. There were three designs: price incentive, scarcity message, and regular ad. The regular ad is a simple reminder message, and the SMS read "Shop online for our special deals and promotions [retailer company]." Additionally, the scarcity SMS read "Shop online for our special deals and promotions. Our products will be gone quickly. We have only limited inventory and supply. Hurry up! [retailer company]." Our manipulation of the scarcity message is grounded in the consumer behavior literature (Roux et al. 2015, Zhu and Ratner 2015, Kristofferson et al. 2016). Specifically, scarcity is primed with both quantity-based urgency (only limited inventory and supply) and time-based urgency (gone quickly and hurry up). In terms of face validity, in local markets, young parents understand the urgency of a message announcing a limited time window for buying. As an additional manipulation check for this priming, we conducted a pilot test involving 58 regular customers of this e-retailer; this confirmed that the two-dimensional priming of scarcity indeed triggers strong scarcity feelings and urgent need to make a purchase. Although relatively active users may suspect that the maternal and baby products are soon restocked, our randomization should have accounted for this difference as

Figure 4. (Color online) Digital Cart Creation Behavior After the First-Stage Invitation

supported by the randomization check. Moreover, the price incentive SMS read "Shop online for our special deals and promotions. You have a discount of RMB 20 toward your purchase [retailer company]." According to our data, the average order amounted to about RMB 220, and the price incentive in the experiment was a 10%–11% discount, a typical amount used by the e-retailer to incentivize its consumers. The SMS text length of the price incentive and the scarcity is similar in the local language, and thus, the receipt of different amounts of information regarding incentive/scarcity messages was not a major concern.

Data and Results

The descriptive statistics and randomization check results are reported in Table 2. The retailer provided data on the demographics of its loyal members, such as the age of babies, residence area, and consumer tenure as well as purchase history and shopping cart data. Our corporate partner assured us that there was no contamination from other marketing channel promotions in our results because they deliberately refrained from sending any other promotions to the sampled consumers during the period of the experiment. For our field experiment, as long as the user composition of each group was similar in the randomization check, we could measure the sales effects of ECT and attribute the effects causally to the treatment differences (incentive, scarcity, and regular ad).

Our randomization check verified that the ratio of receivers and nonreceivers as well as for the ratio of cart creation were equal across three ECT designs: price incentive, scarcity message, and regular ad (see Table 2). We found that all the ANOVA *F*-test results regarding the ratio of receivers and nonreceivers,

the ratio of cart creation, cart product numbers, cart add timing, purchase rate after the first-stage cart invitation by SMS, and background variables were not significant (smallest $p > 0.379$). Thus, these results prove that randomization in this study was successful.

We measured consumers' purchase response in terms of whether the focal consumer made a purchase from April 2 to April 10, 2018 (see Online Appendix D for a distribution of purchased product categories). The retailer runs promotional campaigns frequently. Based on its experience, the maximum time for a promotion campaign to be effective is one week; after that, the effect dissipates sharply (short-term effectiveness measure).[11]

Model-Free Results

Figure 5(a) presents the main effects of three ECT designs (scarcity, price incentive, and regular ad baseline). As expected, the results prove that both scarcity and price incentive are more effective than the regular ad baseline in engendering purchase responses.

Figure 5(b) illustrates the moderated effects, namely the purchase response rate for each treatment when the shopping cart is empty and when it is not. The results show that, when a shopping cart is empty, a scarcity message has a much stronger effect than the other two promotions in engendering purchase responses. However, when a shopping cart is not empty, the ECT design with a price incentive performs much better than the other two promotions.
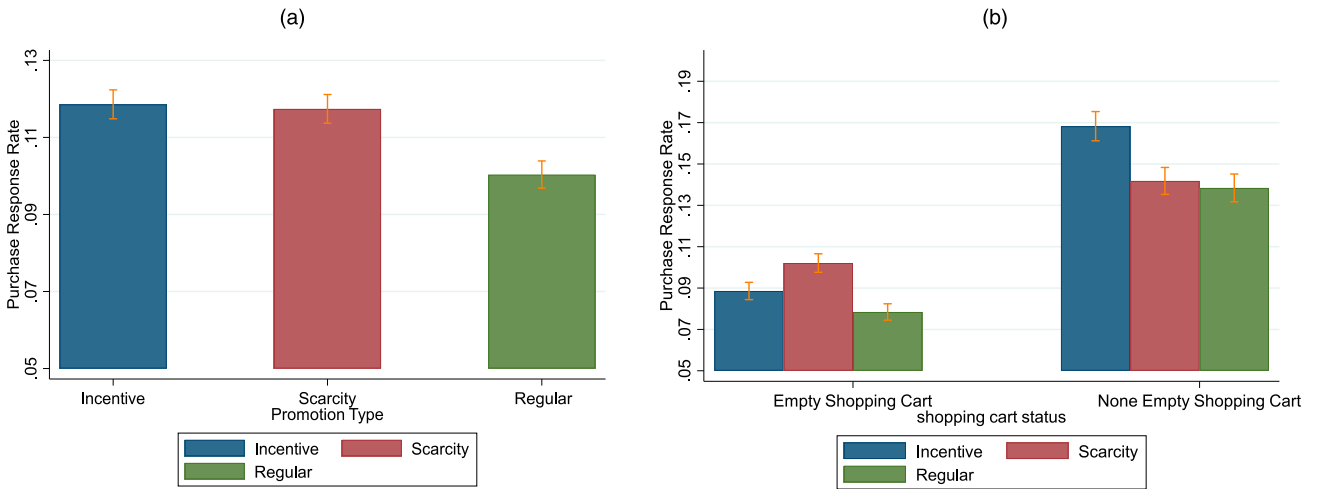
Models and Hypotheses Test Results

We then modeled consumers' purchase behavior using the field experiment data. As mentioned previously,

Table 2. Descriptive and Randomization Check Results

Variable name	Definition	Mean of incentive group	Mean of scarcity group	Mean of regular ad group	*F*-test	*P*-value
ln(*Baby*)	The age of the youngest baby (in months) of the consumer	3.654	3.690	3.494	0.220	0.803
ln(*Tenure*)	The consumer's tenure with the company since becoming a member (by day)	6.503	6.635	6.238	0.730	0.482
ln(*Amount*)	Purchase amount during the last six months, RMB	6.519	6.611	6.555	0.970	0.379
Area	Location indicator = 1 if living in Jiangsu Province; 0 otherwise	0.323	0.335	0.359	0.130	0.866
Cart1invit	Whether received first-stage cart invitation SMS	0.642	0.647	0.645	0.157	0.856
firstPurchase	Purchase or not within seven days after the first-stage cart invitation SMS	0.179	0.190	0.168	0.771	0.462
Cart	Empty cart = 0 for early shopping goal stage and deliberative mindset, otherwise = 1 for late shopping goal stage and implemental mindset	0.376	0.385	0.365	0.838	0.658
Cartpnumber	The product number in the cart	3.049	3.090	3.066	0.918	0.419
Cartweekend	Whether the product is added during the weekend	0.205	0.212	0.210	0.712	0.487
Number of observations		7,417	7,436	7,231	N/A	N/A

Figure 5. (Color online) Purchase Response Across Promotions (A) with Different ECT Designs and (B) by Digital Cart

(a)

(b)

our model has two main specifications: a simple probit model and a two-stage probit model.

Simple Probit Model Results. First, we simply observed cart status and did not account for reasons for cart creation, such as solicited carts by the company, the organic shopping processes of customers, various marketing promotion channels, seasonality, market competition, and other variables not observed in the data. Thus, we estimated a straightforward simple probit model for the purchase behavior of consumer i:

$$Prob(Buy_i) = \beta_0 + \beta_1 Scarcity_i + \beta_2 Incentive_i$$
$$+ \beta_3 Cart_i + \beta_4 Scarcity_i * Cart_i$$
$$+ \beta_5 Incentive_i * Cart + \delta X_i + \mu_i. \quad (1)$$

In this model, *Buy* denotes whether the focal consumer made a purchase (= 1) after the experiment. Digital cart status is denoted by *Cart*; one means there are products in the cart, and zero denotes an empty cart prior to the second-stage randomization of ECT designs. *Scarcity* and *Incentive* are the dummy variables for ECT design treatments, and the *Regular* ad is the comparison baseline. We also controlled for the effects of covariates, such as demographic variables and historical purchase behaviors as well as product category fixed effects denoted by the vector X_i in the equation. The cart timing effect was also controlled for by including a weekend dummy of cart creation behavior in the vector X_i.

Because of missing values in the demographic variables, our effective sample size was 20,495 out of the original 22,084 consumers. In Table 3, columns (1) and (2) report the simple probit model estimation results. As shown, the results suggest that the coefficient of *Cart* is positive and significant ($p < 0.01$). Thus, compared with e-commerce targeting without digital carts, ECT has a significant positive incremental

effect on consumer purchase responses, supporting Hypothesis 1. The economic magnitude of the effects is nontrivial: targeting carts results in a 29.9% increase in purchase response probability.

Although not hypothesized, both *Scarcity* and *Incentive* have a significant direct effect on purchase responses ($p < 0.01$). These findings support previous research regarding the effects of price incentive (Mela et al. 1998) and scarcity (Balachander et al. 2009) with causal evidence free from endogeneity bias. Furthermore, a price incentive results in a 14.1% increase relative to the regular ad, and scarcity has a smaller effect with a 11.5% increase relative to the regular ad, on average.

In Table 3, column (2) also exhibits the results for testing moderated effect hypotheses. Hypotheses 2 and 3 would be supported if the coefficient of *Scarcity×Cart* were negative and significant and the coefficient of *Incentive×Cart* were positive and significant. The results suggest that both conditions are satisfied because the coefficient of *Scarcity×Cart* is indeed negative ($p < 0.05$) and that of *Incentive×Cart* is positive ($p < 0.05$). We then tested whether scarcity and price incentive have significantly different effects. The result of the Wald test confirms that chi-square statistics are 12.20 ($p = 0.0005$) for the contrast test between coefficients of *Incentive×Cart* and *Scarcity×Cart*.

Figure 6 illustrates the magnitudes of the effects *incremental* to the regular ad baseline. These incremental purchase rates are the differences after subtracting the purchase rate of regular ads. First, we explored the *within*-ECT design effect. This clearly indicates that scarcity has a much stronger incremental effect without carts (0.023) than with carts (0.0025), and price incentive has a much stronger incremental effect with carts (0.0285) than without carts (0.0101). These results support the moderated effects. Thus, a price incentive

amplifies the incremental effect of ECT (magnifies the average effect of ECT to a large incremental effect of 0.0285, $p < 0.01$) but insignificantly affects the purchase response for e-commerce targeting without carts (a small incremental effect of 0.0101, which is not significantly different from zero, $p > 0.30$), thus supporting Hypothesis 2. By contrast, the ECT design with a scarcity message has an insignificant incremental effect (reduces the average significant effect of ECT toward a small incremental effect of 0.0025, which is not significantly different from zero, $p > 0.60$) but significantly improves purchase responses for targeting with empty carts (a large positive incremental effect of 0.023, $p < 0.01$), thus supporting Hypothesis 3. We then considered the *between*-ECT design effects and compared the relative effects of scarcity and incentive incremental to the regular ad. We found that scarcity was 2.3 times ($= 0.023/0.0101, p < 0.05$) more effective than incentive in the case of without carts, and incentive was 11.4 times ($= 0.0285/0.0025, p < 0.01$) more effective than scarcity in the case of with digital carts. Thus, the scarcity nudge works better than a price incentive in the early shopping stage without carts, whereas a price incentive is more effective in the late stage with carts created, supporting Hypothesis 4.

Two-Stage Probit Model Results. This model specification directly accounts for the reasons for cart creation. We used a two-stage Probit model to fit the two-stage dynamic experimental data. This isolates the effects of company-solicited carts so that they are unconfounded by alternative explanations, such as the organic shopping processes of customers, various marketing promotion channels, seasonality, market competition, and other variables not observed in the data. Thus, we estimated a two-stage probit model for the purchase behavior of consumer i as follows:

$$\text{Prob}(Buy_i) = \beta_0 + \beta_1 Scarcity_i + \beta_2 Incentive_i \\ + \beta_3 Cart_i + \beta_4 Scarcity_i * Cart_i \\ + \beta_5 Incentive_i * Cart + \delta X_i + \mu_i \quad (2)$$

$$Cart_i = \gamma_1 Cart1invit_i + \omega X_i + \theta_i, \quad (3)$$

where the first-stage model in Equation (3) has the variable *Cart* as a function of the manipulated variable of $Cart1invit_i$, which denotes whether consumer i received or did not receive the randomized first-stage SMS cart invitation. The first-stage $Cart1invit_i$ affected consumers' shopping cart status ($Cart_i$) but did not affect the dependent variable *Buy* because the second-stage SMS was randomized: all ECT designs had a similar likelihood of receiving the cart invitation (see Table 3).

We used maximum likelihood to estimate the two-stage models. Columns (3) and (4) in Table 3 report the two-stage instrumented probit estimation results,

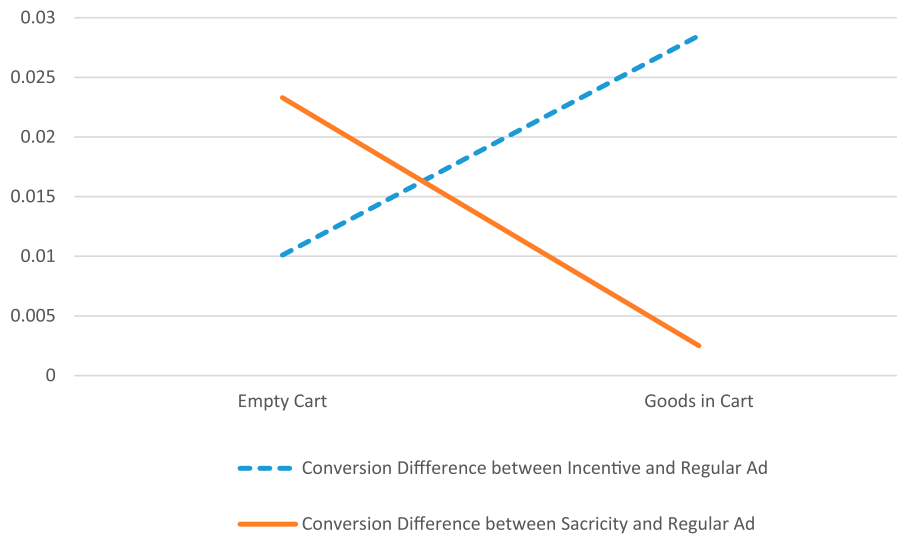**Table 3.** Model Results with Purchase Probability

	Simple probit model		Two-stage IVprobit model	
	(1)	(2)	(3)	(4)
Second-stage results				
Scarcity	0.115***	0.166***	0.111***	0.159***
	(0.032)	(0.041)	(0.032)	(0.041)
Incentive	0.141***	0.100**	0.139***	0.093**
	(0.031)	(0.041)	(0.031)	(0.041)
Cart	0.299***	0.355***	0.688***	0.694***
	(0.049)	(0.060)	(0.139)	(0.139)
Scarcity×Cart		−0.118**		−0.110**
		(0.060)		(0.060)
Incentive×Cart		0.112**		0.097*
		(0.051)		(0.05)
area	0.008	0.008	0.008	0.008
	(0.026)	(0.026)	(0.026)	(0.026)
ln(*babym*)	−0.051**	−0.051**	−0.049**	−0.049**
	(0.024)	(0.024)	(0.024)	(0.024)
ln(*amount*)	0.165***	0.165***	0.161***	0.161***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(*tenure*)	−0.045	−0.044	−0.042	−0.041
	(0.029)	(0.029)	(0.029)	(0.029)
ln(*cartpnum*)	0.011***	0.011*	0.007	0.007
	(0.004)	(0.006)	(0.004)	(0.006)
cartweekend	0.022	0.026	−0.008	−0.006
	(0.040)	(0.040)	(0.041)	(0.041)
_cons	−1.809***	−1.824***	−1.845***	−1.846***
	(0.164)	(0.164)	(0.164)	(0.164)
First-stage results				
Cart1invit			0.015***	0.015***
			(0.003)	(0.003)
area			0.004	0.004
			(0.003)	(0.003)
ln(*babym*)			−0.002	−0.002
			(0.003)	(0.003)
ln(*amount*)			0.002***	0.002***
			(0.000)	(0.000)
ln(*tenure*)			−0.003	−0.003
			(0.003)	(0.003)
ln(*cartpnum*)			0.092***	0.090***
			(0.001)	(0.001)
cartweekend			0.040***	0.041***
			(0.004)	(0.004)
_cons1			0.638***	0.634***
			(0.023)	(0.023)
N	20,495	20,495	20,495	20,495

Notes. Definitions of variables are presented in Table 2. Standard errors in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

explicitly treating cart status as endogenous. As presented in Table 3 (panel for the first-stage results), the data supported the premise that the first-stage company solicitation had a statistically significant and positive effect on the carting outcome ($p < 0.01$). Thus, the first stage cart invitation by the company was effective at generating digital carts.[12]

Figure 6. (Color online) Interactions and Relative Effects

As listed in Table 3 (panel for the second-stage results), the results consistently suggest that the coefficient of *Cart* is positive and significant ($p < 0.01$). Thus, compared with e-commerce targeting without digital carts, ECT has a significant positive incremental effect on consumer purchase responses, again supporting Hypothesis 1.

Table 3, column (4) presents the results for testing the moderated effect hypotheses. Again, the coefficient of *Incentive×Cart* is positive and significant ($p < 0.1$), thus supporting Hypothesis 2: a price incentive, thus, amplifies the incremental effect of ECT but reduces purchase responses to e-commerce targeting without digital carts.

The coefficient of *Scarcity×Cart* is also negative and significant ($p < 0.05$), supporting Hypothesis 3: a scarcity message, thus, attenuates the incremental effect of ECT but boosts purchase responses to e-commerce targeting without digital carts.

Finally, the results support that a scarcity message works better than a price incentive in the early shopping stage without carts ($p < 0.05$), whereas a price incentive is more effective in the late stage when carts are created ($p < 0.1$), thus supporting Hypothesis 4.

Robustness Checks with Alternative Dependent Variables

In our main models, we used purchase probability as the dependent variable. However, aside from purchase probability in Equations (1) and (2), our data can also gauge the effects with purchase quantity (the number of products purchased) and purchase amount (the total amount of spending). We therefore ran a Poisson model for purchase *quantity* and an ordinary least squares model for purchase *amount*. Given that the purchase quantity includes numerous zeros, we used the instrumented zero-inflated Poisson model. These additional models serve as a robustness check for alternative measures of purchase responses. The model specifications are as follows:

$$\log\left(E\left(PurchaseQuantity|Poisson\right)\right)$$
$$= \beta_0 + \beta_1 Scarcity_i + \beta_2 Incentive_i + \beta_3 Cart_i$$
$$+ \beta_4 Scarcity_i * Cart_i + \beta_5 Incentive_i * Cart_i + \delta X_i + \mu_i; \quad (4)$$

$$\log\left(E\left(PurchaseQuantity|Zero\,Inflated\,Poisson\right)\right)$$
$$= \beta_0 + \beta_1 Scarcity_i + \beta_2 Incentive_i + \beta_3 Cart_i$$
$$+ \beta_4 Scarcity_i * Cart_i + \beta_5 Incentive_i * Cart_i + \delta X_i + \mu_i; \quad (5)$$

$$\log\left(E\left(PurchaseAmount|OLS\right)\right)$$
$$= \beta_0 + \beta_1 Scarcity_i + \beta_2 Incentive_i + \beta_3 Cart_i$$
$$+ \beta_4 Scarcity_i * Cart_i + \beta_5 Incentive_i * Cart_i + \delta X_i + \mu_i. \quad (6)$$

The results in Table 4 support that the *Cart* has a positive and significant direct effect on purchase quantity and amount ($p < 0.05$). Thus, these results provide more evidence in support of Hypothesis 1. In a manner consistent with previous results, the coefficient of *Scarcity×Cart* is negative and significant across three models ($p < 0.1$), whereas that of *Incentive×Cart* is positive and significant ($p < 0.05$). These results therefore provide additional evidence in support of Hypotheses 2–4 with alternative dependent variables of purchase product quantity and amount.

Table 4. Estimation Results with Purchase Quantity and Amount

	Purchase count as DV, Poisson model		Purchase count as DV, zero-inflated Poisson model		Purchase amount as DV, OLS model	
Second-stage results						
Scarcity	0.215***	0.204***	0.095**	0.023	0.221***	0.286***
	(0.033)	(0.045)	(0.038)	(0.039)	(0.053)	(0.065)
Incentive	0.231***	0.110**	0.082**	0.111***	0.229***	0.153**
	(0.033)	(0.046)	(0.037)	(0.037)	(0.051)	(0.064)
Cart	0.347***	0.114**	0.311**	0.359**	0.920***	0.652***
	(0.043)	(0.057)	(0.144)	(0.143)	(0.102)	(0.126)
Scarcity×Cart		−0.128*		−0.171*		−0.268**
		(0.065)		(0.093)		(0.105)
Incentive×Cart		0.225***		0.156**		0.198**
		(0.062)		(0.064)		(0.101)
_cons	−3.601***	−3.612***	−1.271***	−1.343***	−3.753***	−3.749***
	(0.174)	(0.174)	(0.224)	(0.222)	(0.269)	(0.270)
First-stage results						
Cart1invit			0.172***	0.176***		
			(0.053)	(0.056)		
_cons1			2.056***	1.673***		
			(0.047)	(0.057)		
Control variables	Included	Included	Included	Included	Included	Included
N	20,495	20,495	20,495	20,495	20,495	20,495

Notes. Definitions of variables are presented in Table 2. The coefficients of first-stage control variables are not reported. Standard errors in parentheses. DV, dependent variable; OLS, ordinary least squares.
    *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Robustness Checks with Alternative Variables of Carts

Estimation with Number of Products in Cart. In our main models, we used the dummy variable of cart (empty or not). However, if not empty, the shopping cart may include multiple products after the first-stage randomization. Thus, as a robustness check, we also test the number of products in the cart (*Cartnum*). Results in Table 5 support that *Cartnum* has a positive and significant direct effect on purchase response rate ($p < 0.05$). In a manner consistent with previous results, the coefficient of *Scarcity×Cartnum* is negative and significant across all models ($p < 0.05$), whereas that of *Incentive×Cartnum* is positive and significant ($p < 0.05$). Thus, the findings are similar to our main results, providing more empirical evidence for all hypotheses.

Estimation with Recent Carts. We then conducted another robustness check with more recent carts. The main results focused on carts generated during the 10 days after the first-stage SMS invitation, whereas, in this instance, we focused only on carts generated during the seven days (*Cartoneweekago*) after the first-stage SMS invitation. If the results were robust, this would provide strong evidence because more recent carts mean consumers are more likely to still have a late shopping stage implemental mindset (relative to old carts generated one to six months ago). Results in

Table 6 affirm that the *Cartoneweekago* has a positive and significant direct effect on purchase quantity and amount ($p < 0.01$). Consistent with previous results, the coefficient of *Scarcity×Cartoneweekago* is negative and significant across all models ($p < 0.1$), whereas that of *Incentive×Cartoneweekago* is positive and significant ($p < 0.1$), thus providing additional empirical evidence for all four hypotheses.

Estimation with Newly Created Carts. We conducted another robustness check with the new carts only attributed to the first-stage SMS invitation. A total of 5,035 carts in the invitation receiver group and 2,994 carts in the nonreceiver group existed *before* our first-stage invitation. Thus, we can analyze the data without these preexisting carts; in other words, we can remove old carts that may have been created for other reasons. Such deletion provides a sample of new carts purely resulting from the first-stage company solicitation (this is similar to Mochon et al. 2017 who discarded the sample with likes *before* company solicitation). Results in Table 7 support that the *Newcart* has a positive and significant direct effect on purchase quantity and amount ($p < 0.01$). Consistent with previous results, the coefficient of *Scarcity×Newcart* is negative and significant across all models ($p < 0.1$) and that of *Incentive×Newcart* is positive and significant ($p < 0.05$), thus providing further empirical evidence for all four hypotheses.

Table 5. Estimation Results with Number of Products in Cart

	Simple probit model		Two-stage IVprobit model	
	(1)	(2)	(3)	(4)
Second-stage results				
Scarcity	0.115***	0.162***	0.074	−0.028
	(0.032)	(0.038)	(0.045)	(0.086)
Incentive	0.143***	0.066*	0.105**	0.201***
	(0.031)	(0.034)	(0.045)	(0.038)
ln(*cartnum*)	0.041***	0.006	0.370**	0.396**
	(0.006)	(0.005)	(0.182)	(0.187)
Scarcity×lncartnum		−0.006**		−0.028**
		(0.002)		(0.013)
Incentive×lncartnum		0.012**		0.015**
		(0.006)		(0.006)
_cons2	−1.582***	−1.922***	0.835	0.965
	(0.167)	(0.168)	(1.525)	(1.509)
First-stage results				
Cart1invit			0.110***	0.109***
			(0.027)	(0.025)
_cons1			−6.915***	−6.782***
			(0.174)	(0.160)
Control variables	Included	Included	Included	Included
N	20,495	20,495	20,495	20,495

Notes. Definitions of variables are presented in Table 2. The coefficients of first-stage control variables are not reported. Standard errors in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Estimation with Pure First-Stage Invitation Receiver Carts. We conducted a robustness check with a subsample of carts generated purely by the first-stage SMS invitation receiver group (*Receivercart*), thus excluding the nonreceiver group. A disadvantage of this test is that there is no counterfactual baseline (the nonreceiver group) to rule out other reasons for cart creation after the invitation. By excluding the non-receiver group, we also have no first-stage model to estimate. Table 8 reports the results and proves that the *Receivercart* has a positive and significant direct effect on purchase quantity and amount ($p < 0.01$). In a manner consistent with previous results, the coefficient of *Scarcity×Receivercart* is negative and significant across three models ($p < 0.05$), and that of *Incentive×Receivercart* is positive and significant ($p < 0.05$). The findings are similar to our main results, providing further empirical evidence for all hypotheses.

Additional Modeling Results with Web Login and Page View
Beyond purchase responses, the retailer also provided us with data on website logins and web-page views. The effects of ECT on purchase behavior may exist largely because ECT treatments affect consumers' intentions to revisit and engage more

actively with the e-retailers' website. Table 9 reports the estimation results using login frequency and number of page views as the dependent variables. The findings confirm that the significant effect ECT has on purchase behavior can be explained by the fact that ECT treatments affect the number of web-page revisits and page views in the conversion funnel (Ansari and Mela 2003, Tam and Ho 2005).

Optimizing ECT Using a Causal Forest Algorithm
Because individuals are different in terms of their demographics and purchase history (Farahat and Bailey 2012, Lambrecht and Tucker 2013), their purchase responses to ECT are different. Thus, in industry, e-retailers are highly interested in heterogeneous responses to targeting and how to further optimize ECT with scarcity and a price incentive across different individual characteristics. To inform managers about optimal targeting, we follow advances in state-of-the-art machine learning by using a causal random forest with honest tree algorithm (Wager and Athey 2018). This algorithm can simulate the treatment effects for every combination of individual demographics and purchase history and, thus, provide e-retailers with an optimal targeting scheme for ECT. The intuition of causal forest is straightforward but appealing: researchers can decompose global average treatment effects within a population into various subpopulation local treatment effects by learning and splitting the data without making any assumptions about the possible linear, nonlinear, or interactive model specifications of individual demographic and purchase history variables. In contrast, by adding interactions, traditional regression models must assume linear or nonlinear functions (e.g., linear, squared, or cubic terms of each variable in the interaction terms and two-way, three-way, or higher-order interactions). Because infinite numbers of such functions exist, there is no guarantee that such assumptions are correct.

Mathematically, we denote (X_i, Y_i) as independent samples that build a classification and regression tree and W_i as the treatment variable of scarcity or price incentive. Based on the random forest algorithm, we recursively split the feature space of samples until we have a set of leaves L, each of which contains only a few training samples. Then, given a test point x, we evaluate the prediction $\hat{\delta}(x)$ by identifying the leaf $L(x)$ containing x and setting

$$\hat{\delta}(x) = \frac{1}{|\{i : X_i \in L(x)\}|} \sum_{\{i : X_i \in L(x)\}} Y_i. \qquad (7)$$

In the context of a causal forest, the tree leaves are small enough for the (Y_i, W_i) pairs to correspond to the indices i for $i \in L(x)$ in a randomized experiment.

Table 6. Estimation Results with Recent Carts

	Simple probit model		Two-stage IVprobit model	
	(1)	(2)	(3)	(4)
Second-stage results				
Scarcity	0.114***	0.165***	0.110***	0.156***
	(0.032)	(0.041)	(0.032)	(0.041)
Incentive	0.140***	0.099**	0.137***	0.091**
	(0.031)	(0.041)	(0.031)	(0.041)
Cartoneweekago	0.359***	0.412***	0.815***	1.117***
	(0.053)	(0.065)	(0.168)	(0.248)
Scarcity×Cartoneweekago		−0.116*		−0.112*
		(0.060)		(0.060)
Incentive×Cartoneweekago		0.107*		0.183***
		(0.061)		(0.066)
_cons2	−1.813***	−1.824***	−1.850***	−1.896***
	(0.164)	(0.164)	(0.164)	(0.165)
First-stage results				
Cart1invit			0.009***	0.007***
			(0.003)	(0.002)
_cons1			0.548***	0.423***
			(0.021)	(0.018)
Control variables	Included	Included	Included	Included
N	20,495	20,495	20,495	20,495

Notes. Definitions of variables are presented in Table 2. The coefficients of first-stage control variables are not reported. Standard errors in parentheses.
  *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

We then estimate the treatment effect for any $X_i \in L(x)$ as

$$\hat{\gamma}(x) = \frac{1}{|\{i : W_i = 1, X_i \in L\}|} \sum_{\{i:W_i=1, X_i \in L\}} Y_i$$
$$- \frac{1}{|\{i : W_i = 0, X_i \in L\}|} \sum_{\{i:W_i=0, X_i \in L\}} Y_i. \quad (8)$$

Once the causal forest generates an ensemble of such trees, each of which casts a vote with an estimate $\hat{\gamma}_b(x)$, the forest aggregates their predictions by averaging these votes:

$$\hat{\gamma}(x) = B^{-1} \sum_{b=1}^{B} \hat{\gamma}_b(x).$$

To ensure clear interpretation and managerial relevance of the results for optimizing ECT, we only split the trees with two demographic and purchase history variables, namely customer tenure and purchase amount in the last six months (practitioners can easily use these variables). We then simulated the relative heterogeneous treatment effect (RHTE) between scarcity and price incentive as if one were the randomized treatment condition and the other were the control. We focused on simulating the RHTE of scarcity over incentive for targeting with empty carts (best relative case for scarcity) as illustrated in Figure 7, and the RHTE of incentive over scarcity for targeting with goods in carts (best relative case for price incentive) as depicted in Figure 8.

The results of Figure 7 suggest that scarcity has a higher overall treatment effect (0.013, 100% of the customers) than a price incentive with empty carts as expected. However, substantial heterogeneity exists across consumer segments. For example, if the purchase amount in the last six months is large (more than 1,732 RMB), the relative effect of scarcity is three times greater than that of price incentive (0.057, 21% of the consumers in our data). Thus, scarcity messaging is more effective for high-spending customers: high spenders are more sensitive to a shortage of product stock (Balachander et al. 2009). However, the right side of this leaf illustrates a worse outcome for targeting high-spending consumers with a very long tenure (more than 1,107 days) with which the relative effect of scarcity is negative (−0.017, 5% of the sample). This makes sense because such high-spending consumers may have long and extensive experience with the company's product lines and, thus, not only doubt the legitimacy of the scarcity message but also expect price incentives because of their large past spending (Reczek et al. 2014). Interestingly, after splitting the data further into smaller leaves, the RHTE of scarcity over incentive for consumers whose tenure is between 347 and 491 days is the highest and most optimal (0.28, 3% of the data). This suggests that, although, on average, scarcity has a higher overall treatment effect than a price incentive in the case of the early stage with empty carts, high-spending

Table 7. Estimation Results with Newly Created Carts

	Simple probit model		Two-stage IVprobit model	
	(1)	(2)	(3)	(4)
Second-stage results				
Scarcity	0.118***	0.165***	0.113***	0.139***
	(0.032)	(0.042)	(0.032)	(0.042)
Incentive	0.142***	0.098**	0.140***	0.073*
	(0.031)	(0.042)	(0.031)	(0.042)
Newcart	0.173***	0.153***	1.236***	0.970***
	(0.041)	(0.046)	(0.248)	(0.264)
Scarcity×Newcart		−0.104*		−0.120*
		(0.061)		(0.065)
Incentive×Newcart		0.179**		0.153**
		(0.084)		(0.062)
_cons2	−1.628***	−1.639***	−0.726***	−0.979***
	(0.203)	(0.204)	(0.266)	(0.274)
First-stage results				
Cart1invit			0.003**	0.004***
			(0.001)	(0.001)
_cons1			0.507***	0.492***
			(0.008)	(0.008)
Control variables	Included	Included	Included	Included
N	12,466	12,466	12,466	12,466

Notes. Definitions of variables are presented in Table 2. The coefficients of first-stage control variables are not reported. Standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

consumers with a middle-range tenure (too long tenure) are the optimal (worst) segment to be targeted with scarcity messaging rather than a price incentive in e-commerce.

Moreover, Figure 8 indicates that a price incentive has a higher overall treatment effect (0.029) than a scarcity message when targeting customers with carts as expected. We found that, when a consumer's tenure is greater than 139 days, a price incentive is more effective (0.038, 86% of the customers). Also, when a consumer's tenure is greater than 139 days but less than 817 days, the effect can be even higher (0.056, 62% of consumers). However, when consumers are relatively new to this retailer—with a short tenure—the prior purchase amount becomes a crucial segmenting variable. For example, for a consumer with a relatively short tenure of less than 139 days, if the purchase amount in the last six months is large (more than 4,154 RMB), the relative effect of incentive over scarcity is even stronger (0.2, 3% of the consumers in our data). Thus, consumers with longer or short tenure but higher previous purchase amount are optimal targeting segments for the ECT design with price incentives rather than a scarcity message if they generated digital carts.

Overall, the machine learning causal forest results are practical and pertinent for managers to understand the substantial heterogeneity in customer responses to ECT.

E-commerce managers can further optimize ECT designs with price incentives or a scarcity message by targeting consumer segments with large positive RHTE effects and by avoiding those with negative RHTE effects as shown in the bottom layer of the tree representation in Figures 7 and 8.

Discussion and Implications

The present study develops and supports a conceptual model of ECT with respect to when (with versus without carts) and how (scarcity versus price promotions) to boost consumer purchase conversion in e-commerce. Data from randomized field experiments involving more than 22,000 mobile users yielded the following notable findings:

• ECT has a significant incremental impact on purchase responses, inducing 29.9% greater purchase conversion on average than e-commerce targeting without carts.

• This incremental impact is moderated: the ECT design with a price incentive amplifies the impact, whereas such an incentive is ineffective in generating purchases for e-commerce targeting without carts.

Table 8. Estimation Results with Pure Invitation Receivers' Carts

Variables	Purchase (1)	Probability (2)
Scarcity	0.151***	0.202***
	(0.041)	(0.049)
Incentive	0.146***	0.118**
	(0.039)	(0.048)
Receivercart	0.271***	0.350***
	(0.058)	(0.070)
Scarcity×Receivercart		−0.127**
		(0.062)
Incentive×Receivercart		0.110**
		(0.052)
area	−0.004	−0.003
	(0.033)	(0.033)
ln(*babym*)	−0.036	−0.036
	(0.028)	(0.028)
ln(*amount*)	0.163***	0.163***
	(0.007)	(0.006)
ln(*tenure*)	−0.075**	−0.074**
	(0.037)	(0.037)
ln(*cartpnum*)	0.058**	0.058**
	(0.020)	(0.023)
cartweekend	0.020	−0.000
	(0.049)	(0.050)
_cons	−1.658***	−1.751***
	(0.208)	(0.208)
N	13,464	13,464

Notes. Definitions of variables are presented in Table 2. Standard errors in parentheses.
**$p < 0.05$; ***$p < 0.01$.

Table 9. Estimation Results for Browsing Process Behavioral Variables

DV	Web login frequency	Web login frequency	Page views	Page views
	OLS	OLS	OLS	OLS
Scarcity	0.444***	0.479***	0.567***	0.589***
	(0.058)	(0.068)	(0.074)	(0.092)
Incentive	0.321***	0.255***	0.413***	0.313***
	(0.056)	(0.066)	(0.072)	(0.090)
Cart	3.466***	3.229***	4.473***	4.199***
	(0.112)	(0.138)	(0.145)	(0.179)
Scarcity×Cart		−0.149**		−0.129*
		(0.068)		(0.70)
Incentive×Cart		0.167*		0.258**
		(0.095)		(0.125)
_cons	−4.688***	−5.272***	−4.151***	−1.637***
	(0.296)	(0.294)	(0.383)	(0.498)
Control variables	Included	Included	Included	Included
N	20,495	20,495	20,495	20,495
Adjusted R^2	0.178	0.194	0.178	0.191

Notes. Definitions of variables are presented in Table 2. Standard errors in parentheses.

   *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

• By contrast, the ECT design with a scarcity message attenuates the incremental impact, but significantly improves purchase responses for targeting without carts.

• A scarcity nudge is about 2.3 times more effective than price incentive in the early shopping stage without carts, whereas a price incentive is 11.4 times more effective than a scarcity message in the late stage with digital carts.

• We integrated field experiments with a machine learning causal forest algorithm to learn purchase response heterogeneity and demonstrate a practical scheme for optimizing ECT.

Theoretical Implications

These findings contribute to the literature in various ways. Overall, we have advanced the e-commerce literature regarding the emerging opportunity of ECT. Previous research on e-commerce has largely focused on web-page design (e.g., Mandel and Johnson 2002 and Ansari and Mela 2003) and online banner/search ads (e.g., Rutz and Trusov 2011 and Sahni 2015). Our study explored novel opportunities in e-commerce by targeting overt shopping interests with ECT. Our findings also provide fresh theoretical insights into understanding consumer mindsets at each stage of the online shopping journey for e-commerce. A scarcity nudge can be effective for consumers with a deliberative mindset in the early stage but less beneficial in encouraging them to commit to the short-listed products left in the carts in the late shopping stage. However, a price discount can break this noncommitment
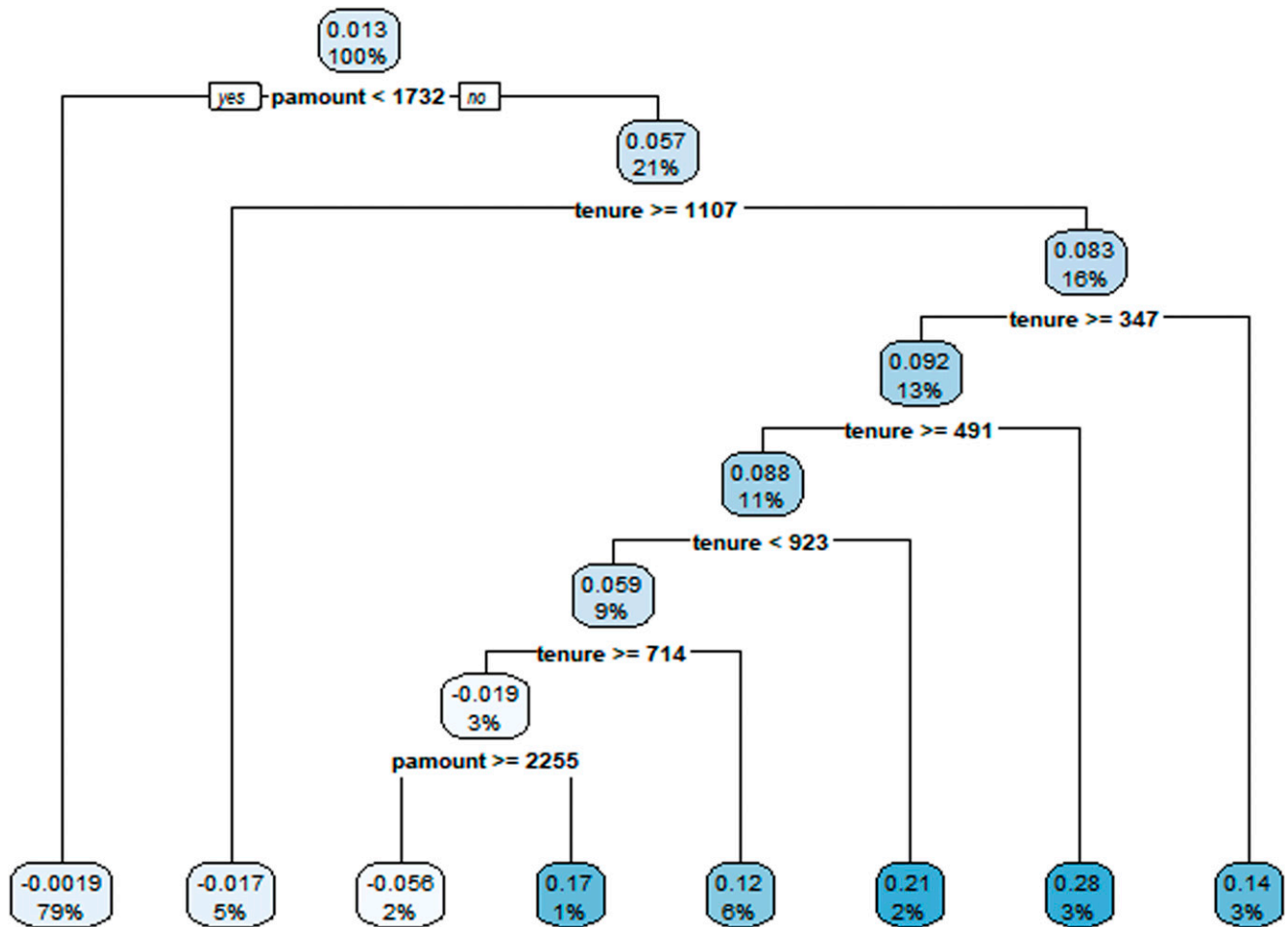
by providing customers in an implemental mindset with the economic maxim: "Why not buy now; it is cheap." We also contribute to the literature on cart abandonment (Close and Kukar-Kinney 2010, Egeln and Joseph 2012), which has largely focused on the drivers of carts using survey-based "soft" subjective data, by investigating sales outcomes of carts with field experiment-based "hard" objective data. Furthermore, we go beyond simple direct effects toward a moderated and relative model to pinpoint more effective e-commerce targeting and ECT designs.

We also contribute to the scarcity literature (Balachander et al. 2009, Zhu and Ratner 2015) by demonstrating the interactive effects of scarcity and ECT on sales demand. Our results add real-world evidence to support previous conceptual research (Folkes et al. 1993, Shah et al. 2012, Mehta and Zhu 2015). Our evidence indicates that, as an attention grabber, a scarcity message can induce consumers to take immediate actions in response to fear of missing out. More importantly, our results extend current knowledge by noting that the call-for-action effect of a scarcity message is weak for consumers when they have decided what to buy as it is not highly instrumental for checking out the short-listed products in carts. A plausible reason is that a scarcity message might invoke disbelief of, and consumer annoyance toward, the claimed product shortage: customers may feel doubtful if the scarcity message is ubiquitous throughout their online shopping journey, that is, from capturing their awareness at the beginning to urging purchases at the end. In such a scenario, the scarcity message may become a cliché and lose its urgency effect ultimately (e.g., vip.com).

Our findings also extend the literature on price incentives. Consistent with previous findings that price discounts can increase consumer purchases in the short-term (Blattberg and Neslin 1990, Rossi et al. 1996, Alba et al. 1999), we found that an ECT design with a price incentive as a value enhancer can boost purchases of the products left in digital carts. However, the same price incentive is not effective for deliberating consumers without carts before they have established concrete shopping goals. This is because they may view discounts as low-quality signals given the possible information asymmetry between buyers and sellers at the beginning of the online shopping journey. This line of reasoning also adds to the literature on the limits of price incentives (Jedidi et al. 1999, Kopalle et al. 1999, Aydinli et al. 2014) by recognizing a new context: digital carts in e-commerce targeting.

Additionally, our findings contribute to the literature by demonstrating the relative effects of price incentives versus scarcity nudge across shopping goal stages. Previous studies have rarely contrasted the effects of price incentive and scarcity, let alone the

Figure 7. (Color online) Heterogeneous Effects for Scarcity vs. Incentive ECT Designs with Empty Carts

Note. pamount, purchase amount.

role played by shopping goal stages that can flip the pattern of their relative effects. Our key contribution in this respect is to ascertain their comparative effectiveness in early versus late shopping stages per the two-stage shopping goal theory (Lee and Ariely 2006): a scarcity message is more effective in the early stage without carts, whereas price incentives are more effective in the late stage with loaded carts.
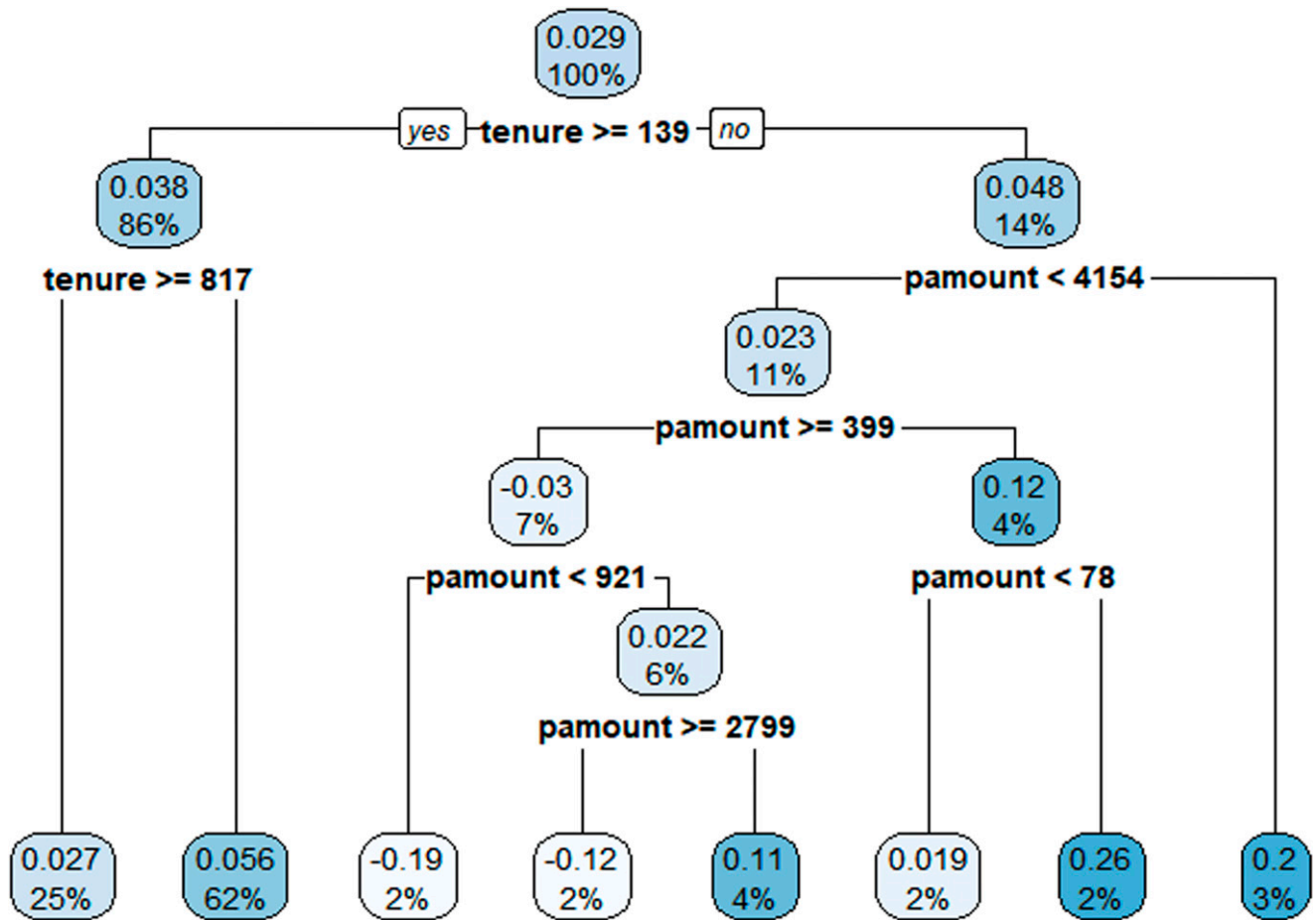
Managerial Implications
Given that the average abandonment rate for an e-commerce shopping cart is as high as 69% with approximately $4.6 trillion of products unpurchased, managers have a strong interest in ECT. Instead of aimlessly targeting users at large, our findings suggest that it is more rewarding for managers to implement ECT than e-commerce targeting without carts. In the precart stage, people browse sites with abstract shopping goals. By contrast, when customers enter the at-the-cart stage with concrete shopping goals yet leave before completing the transaction, they may have strong purchase intentions but become

distracted or navigate to other sites to compare prices before making a purchase (Garcia 2018). In this sense, the at-the-cart stage is exactly the moment to run targeted win-back promotions in e-commerce. With ECT, managers can target interested customers and turn these would-be buyers into real buyers for effective cart recovery management, thus spending their e-commerce budget wisely with amplified returns on investment.

Moreover, managerial actions call for an appropriate match between shopping goal stages (i.e., the status of customers' digital carts) and ECT designs (i.e., monetary and nonmonetary). ECT with a price incentive can help attain higher returns in the late stage. However, the same incentive is ineffective in the early stage, that is, undesirable outcomes despite good intentions. Our findings have implications for firms that thrive on the abundant provision of discounts (e.g., Ross.com). For example, highlighting economic sacrifice (e.g., presenting discounts all the time) could boomerang, leading to low-quality perception and harmed brand equity. Furthermore, McCall et al. (2009)

Figure 8. (Color online) Heterogeneous Effects for Incentive vs. Scarcity ECT Designs with Digital Carts

Note. pamount, purchase amount.

and Mela et al. (1998) identified strategic customers who would intentionally save coupons or search for discounts at the checkout, causing delay and inconvenience. Strategic customers may also create digital carts and intentionally delay their purchases to get a discount. In this situation, the reason for creating carts is to await a coupon deal from the company. Our setting is different because, in our first-stage experimental design, the company solicits cart creation. Our design isolates the effects of company-solicited carts from confounding factors and alternative explanations, such as the organic shopping processes of customers, various marketing promotion channels, seasonality, market competition, and other unobservable factors. Far-sighted managers should differentiate strategic customers from nonstrategic ones using carting habit data and target nonstrategic customers with monetary incentives for more incremental purchases.

E-commerce managers should note that, when consumers have not yet created carts and are uncertain of their shopping goals, a scarcity message might be an effective tactic. However, this scarcity nudge may be less effective in driving immediate actions if implemented in the late stage. In other words, e-commerce firms can deploy scarcity nudges (e.g., "Ends tonight" or "Only two left") to create a sense of urgency, but this effect is lessened when customers have an implemental mindset with digital carts. Therefore, we recommend that firms be cautious when using scarcity messaging in ECT designs; they are advised to display out-of-stock situations or limited time deals when customers browse the websites without carts in a deliberative rather than an implemental mindset. However, when deploying scarcity messaging, practitioners should be truthful and only warn of insufficient inventory when the inventory is actually insufficient. With the application of real-time stock inventory and automatic product recommendations on e-commerce sites, customers may discover accurate information regarding how many products retailers have left. If online retailers lie about insufficient stock and claim that the stock of a product is low when it is not actually so, customers may question the integrity of these retailers and distrust them. Thus, although claiming scarcity can compel customers to purchase and induce more conversions, retailers

should not deceive customers and ought to avoid irresponsible claims of scarcity in e-commerce.

Finally, e-commerce managers may face an inherent trade-off between costly price incentives and costless scarcity messages in financial budgeting. When does it benefit the firm to use the more potent but costly price incentives? When should a firm use costless urgency-based scarcity messages? The different mindsets (i.e., deliberative versus implemental) in the online shopping journey constitute a key factor in understanding which type of promotion is more effective. Stores, for example, generally aspire to leverage economic sacrifice or call-to-action urgency to promote sales growth. However, customers may perceive discounts as signals of low quality or may be insensitive to the urgency. Our findings suggest that managers should ensure that they implement ECT with appropriate designs in the right shopping goal stage. E-commerce managers can lower financial budgets while increasing returns if they align ECT promotions with consumers' mindsets and shopping goal stages. In particular, firms can leverage a costless scarcity message for e-commerce targeting in the early shopping goal stage when customers' digital carts are empty and then roll out an ECT design with price incentives in the late shopping goal stage with digital carts.

Limitations

Our research has several limitations that indicate avenues for future research. First, it examines only two forms of ECT design—scarcity message and price incentive. Thus, in the future, other ECT designs, such as charity appeals, should be explored. Second, our research was limited to one retail company from one industry. Many digital companies use personalized targeting by adopting recommendation engines based on customers' previous browsing histories, purchase histories, and even purchase funnel positions. More research is required to test the generalizability of our findings to other e-commerce contexts and to examine the effects of cart targeting by providing complementary products and sending email, SMS, or mobile notifications to omnichannel customers. Furthermore, our data did not address strategic customers in carting behavior. Thus, future research could investigate when and how to target strategic users who create carts and intentionally delay the purchase of products left in the carts to receive coupons and promotional deals from the company.

Conclusion

In conclusion, our research is an initial step toward conceptualizing a framework for ECT and testing the relative and moderated effects of scarcity and price incentives. This is anticipated to stimulate further scholarly work in the pivotal field of e-commerce.

Endnotes

[1] Online shopping cart abandonment is an e-commerce term used to describe customers who add products to their online shopping carts but pause before completing the purchase. Cart abandonment is definitely a possible reason for customers to leave their loaded carts without completing checkout (because of either losing interest in the selected products or switching to another store), but it is also possible that customers are taking a break from their shopping (either transitioning across devices or waiting to add more items and checkout for a single shipment). Xu et al. (2017) have termed the temporal "breaks" in customer online shopping processes as "micromoments" that provide a critical opportunity for retailers to move customers along their shopping journey.

[2] See https://www.clickz.com/how-these-11-brands-are-nailing-cart -abandonment-emails/112960/ and https://www.pinterest.com/ pin/567523990515390512/.

[3] Baymard Institute. 40 Cart Abandonment Rate Statistics. https:// baymard.com/lists/cart-abandonment-rate.

[4] We acknowledge an anonymous reviewer for this insight.

[5] We are grateful to an anonymous source for bringing this theory to our attention.

[6] Our model does not focus on the direct effects of scarcity message and price incentive because these are intuitive and have already been addressed in the literature.

[7] Targeting with digital carts refers to the ability to target the overt interests of shoppers who have short-listed products in their digital carts. By contrast, targeting without digital carts here refers to the situation of being unable to utilize product preferences for targeting because of an empty cart rather than the case of choosing to ignore cart information when it is actually available.

[8] See https://www.emarketer.com/Article/Mobile-Email-Most -Likely-Drive-Purchase/1008512.

[9] We acknowledge one reviewer for making this suggestion.

[10] Our modeling analyses support the notion that the first-stage solicitation indeed has a statistically significant effect ($p < 0.01$) on the carting outcome as presented in Table 3 (panel for the first-stage results). This effect may not be as significant as like generation after the survey conducted by Mochon et al. (2017) because cart creation is more complicated than like generation. First, receivers may check out immediately after creating the cart. This set of observations is absorbed by purchases after the first-stage invitation, and their cart status on April 2 is again empty although first-stage invitation has impacted their cart creation behavior. Second, given SMS ads are employed by this retailer quite frequently (every week); the effect is usually not that large. Nevertheless, as shown in Figure 4, the first-stage company invitation still made some difference to cart creation.

[11] One may be concerned that, if the effect only lasts for one week, companies may not need to worry about choosing one or the other ECT design. However, any purchase is a good source of revenue for managers. Also, the effects are statistically significant and economically meaningful as stated subsequently. For instance, if managers optimize the promotions each week, e-commerce revenue is boosted significantly. This tends to accumulate each week, month, and year and promotes more successes. However, if the managers use incorrect

targeting and fail to match ECT designs with consumer shopping goal stages, the monetary incentive is ineffective in the early stage of the online shopping journey. This budget waste also tends to accumulate each week, month, and year and promotes more failures.

[12] Our data confirmed that, before the first-stage SMS, the cart status and number of products carted were not significantly different between receivers and nonreceivers (all $ps > 0.10$), thus supporting the similar cart creation behavior between nonreceivers and receivers before the first stage of the experiment.

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