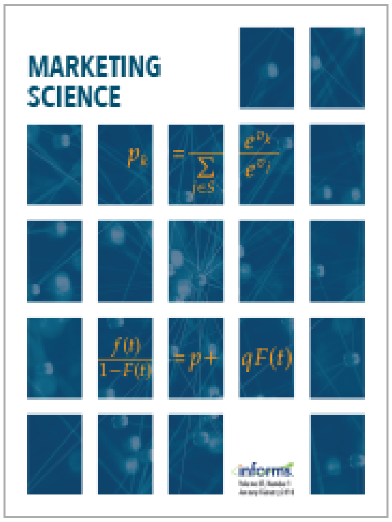


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

On the Profitability of Stacked Discounts: Identifying Revenue and Cost Effects of Discount Framing

Necati Ertekin, Jeffrey D. Shulman, Haipeng (Allan) Chen

informs
http://pubsonline.informs.org/journal/mksc/

MARKETING SCIENCE
Vol. 38, No. 2, March–April 2019, pp. 317–342
ISSN 0732-2399 (print), ISSN 1526-548X (online)

On the Profitability of Stacked Discounts: Identifying Revenue and Cost Effects of Discount Framing

Necati Ertekin,[a] Jeffrey D. Shulman,[b] Haipeng (Allan) Chen[c]

[a] Leavey School of Business, Santa Clara University, Santa Clara, California 95053; [b] Michael G. Foster School of Business, University of Washington, Seattle, Washington 98195; [c] Gatton College of Business and Economics, University of Kentucky, Lexington, Kentucky 40506

Contact: nertekin@scu.edu, https://orcid.org/0000-0003-3704-0797 (NE); jshulman@uw.edu, https://orcid.org/0000-0001-5288-3421 (JDS); allanchen@uky.edu, https://orcid.org/0000-0002-6057-8395 (HAC)

Received: January 6, 2017
Revised: January 9, 2018; July 23, 2018; September 17, 2018
Accepted: September 25, 2018
Published Online in Articles in Advance: April 4, 2019

https://doi.org/10.1287/mksc.2018.1137

Abstract. Previous research demonstrates that stacked discounts increase retail revenue. For instance, a retailer should sell more products by offering "20% off, plus an extra 25% off" than by offering an economically equivalent single discount of "40% off." We conduct multimethodology research to investigate a potential downside of offering stacked discounts: Can stacked discounts disproportionately increase retailer costs from product returns? We incorporate insights from prior behavioral work and develop an analytical model to generate predictions about how stacked discounts affect retail sales and return performance. Next, we conduct a laboratory experiment to provide evidence for our theory in a controlled environment. Subsequently, we empirically test our predictions under real market conditions using six-year transactional data from promotional events at a national jewelry retailer. Finally, drawing upon the empirical estimates, we conduct a numerical study to assess the impact of stacked discounts on retail profitability. Our analytical model and the empirical results identify the inherent tradeoffs associated with stacked discounts and demonstrate the cost structures under which stacked discounts will decrease firm profitability despite an increase in initial sales. We conclude by discussing implications for retailers in assessing the impact of how they frame their price discounts.

History: Yuxin Chen served as the senior editor and Scott Neslin served as associate editor for this article.
Supplemental Material: Data files are available at https://doi.org/10.1287/mksc.2018.1137.

Keywords: stacked discounts • product returns • framing effect • pricing

1. Introduction

For a variety of reasons, retailers often choose to offer discounts. One of the most attractive discount types for consumers is a percentage discount (e.g., 40% off) (MarketingCharts 2014). Two different percentage-discount strategies are frequently encountered in the marketplace: Consider a retailer that offers a percentage discount worth $40 for a product with an original price of $100. The retailer can frame the discount either as a *single discount* (i.e., 40% off) or as an economically equivalent sequence of two percentages (hereafter *stacked discounts*; i.e., 20% off, plus an extra 25% off). Retailers such as Macy's, JCPenney, Kohl's, Toys"R"Us, and Barnes & Noble frequently use the strategy of stacked discounts for their price promotions (Figure 1). The use of stacked discounts has been reported for jewelry, outdoor equipment, kids' wear, home decoration, and even upscale fashion retailers (e.g., Bloomingdale's or Saks Fifth Avenue),[1] and holiday seasons have brought news media encouraging consumers to look for stacked discounts (ABC News 2014).

The phenomenon of stacked-price discounts was first investigated by Chen and Rao (2007). The authors found that a stacked-price discount increases sales volume compared with the economically equivalent single-price discount. They attribute this effect to consumers focusing on the face value of the percentages and mistakenly adding up the two sequential discounts, in effect ignoring the differences in the base dollar values for the two percentages, a feature that makes stacked discounts different from any other types of discounts. Feng and Cai (2015) recently demonstrated that the positive effect of stacked discounts relative to economically equivalent single discounts may go beyond the focal, promoted products and emerge in consumers' perception of a retailer's overall prices as well.

Prior research thus suggests that by stacking percentage discounts, a retailer may affect consumer price perceptions and increase sales relative to framing the same price discount as an economically equivalent single-percentage discount. Based on these results, retailers are likely to continue or expand the use of stacked discounts as one of their promotional tactics. Yet, retail decisions to use this tactic may be premature because prior research treats the consumer purchase decision as terminal, when in reality consumers are faced with another decision after purchase: whether to

Marketing Science, 2019, vol. 38, no. 2, pp. 317–342, © 2019 INFORMS

Figure 1. (Color online) Examples of Stacked Discounts

keep or return a product they purchased. Product returns are common, with rates as high as 35% (Guide et al. 2006), and most commonly occur due to product mismatch with customer preference (Ferguson et al. 2006, Douthit et al. 2011) because consumers make the purchase decision with uncertainty about the utility derived from the product and make a return decision after this uncertainty is resolved. A return is commonly viewed as a result of this two-stage process (e.g., Anderson et al. 2009, Shulman et al. 2010). From this perspective, retail tactics that affect the consumer purchase decision in the first stage, such as stacking discounts, have the potential to influence the consumer return decision in the second stage. Thus, recommendations as to whether to use stacked-percentage discounts are incomplete without consideration of how such a pricing tactic affects both purchases and returns.

Returns are costly to manage for retailers. In fact, an astounding $260 billion in sales were returned to U.S. retailers in 2015 (National Retail Federation 2015), corresponding to a 4%–6% profit loss for retailers and manufacturers (Richardson 2004, Douthit et al. 2011). Managers today are actively involved in identifying factors that influence returns at the point of purchase (Douthit et al. 2011). In the current research, we investigate how price-discounting strategies could affect returns, an important issue that has attracted little attention in the literature. In particular, we conduct multimethodology research to understand the implications of stacked discounts on consumers' initial purchases, their subsequent returns, and overall retail profitability.

Our research consists of four steps. First, using insights from prior behavioral work, we develop an analytical model of the two-stage process driving returns (i.e., purchase decision and subsequent return decision) and derive theoretical predictions about how consumer behavioral responses to a retailer's discount-framing decision affect the retail sales and return performance. Next, we conduct a laboratory experiment to provide evidence for our theory in a controlled environment. Third, using a novel proprietary data set that includes 3,191,080 stock keeping units (SKUs) offered with either of the two discount framings across 1,057 different stores during 249 different promotional events at a national jewelry retailer, we develop an econometric model to empirically test our analytical predictions under real market conditions. Finally, by using empirical estimates from the econometric model, we conduct a numerical study to assess the impact of stacked discounts on retail profitability. With this multimethodology approach, we aim to attain a substantive convergence regarding the theoretical relationship between stacked discounts and retail sales, returns, and profitability.

Our multimethodology research allows us to make several contributions to the literature. First, we show that previous research overstates the positive impact of stacked discounts on a firm's profitability. Our research uniquely identifies a tradeoff associated with stacked discounts in that they may increase not only the initial sales but also the return rates. As a result, stacking discounts may decrease retail profitability compared with offering the economically equivalent single discount under certain cost structures. Second, we demonstrate in the laboratory experiment that the effect of stacked discounts is driven by consumer price misperception associated with stacked discounts. Furthermore, by corroborating this finding, we demonstrate in the retail data set that the effect of stacked discounts is moderated by the channel in which the promotion is offered (i.e., online versus offline). Unlike physical store customers, online customers are able to see the final price of a discounted product before completing a transaction. Thus, for online promotional purchases, consumer price judgments are likely to be the same under both discount framings. Hence, stacked discounts do not have a measurable impact on sales or return rates for online stores compared with the economically equivalent single discounts.

As secondary contributions, this paper is also the first to (1) nest the prior experimental findings in a two-stage analytical model with consumer uncertainty and (2) confirm the prior experimental findings regarding stacked discounts on purchases (Chen and Rao 2007) with a large observational data set. With these contributions, we aim to boost confidence for the impact of stacked discounts on initial sales and to provide validity for our predictions and findings regarding the impact of stacked discounts on returns.

The findings have implications for retailers in assessing the impact of how they frame their price discounts. In particular, our results demonstrate that, in contrast to the previous literature that supports an unconditional use of stacked discounts (Chen and Rao 2007, Feng and Cai 2015), retailers should avoid using stacked discounts in certain situations.

We organize the rest of this paper as follows. In Section 2, we position our work with respect to the relevant literature. In Section 3, we develop an analytical model to predict the impact of stacked discounts on sales and returns. We empirically test our predictions in a laboratory experiment in Section 4 and using retail data in Section 5. In Section 6, we conduct a numerical study to demonstrate the conditions under which stacked discounts will decrease or increase profitability relative to an economically equivalent single discount. We conclude the paper with managerial and theoretical insights in Section 7.

2. Literature Review

In this section, we first review previous literature on stacked discounts and consumer biases relevant to processing percentages. We subsequently review prior literature on product returns.

2.1. Stacked Discounts

Promotional discounts are heavily studied in the marketing literature (e.g., Neslin 1990, Sun et al. 2003, Ailawadi et al. 2014, Montaguti et al. 2016). We position our work with respect to the stacked-discounts stream of the promotions literature. Chen and Rao (2007) are the first to document the effect of stacked discounts on consumer purchases. Their laboratory and field experiments document a systematic error in how consumers process sequential percentage changes. Specifically, because of the misuse of whole-number strategies, consumers erroneously add up sequential percentages (e.g., 20% off, plus an extra 25% off) and arrive at the wrong conclusion about their overall effect (i.e., 45% off, instead of the actual 40% off). This research thus provides a behavioral underpinning for the prevalent use of stacked discounts in the retail market. More recent research has studied the effect of stacked discounts on retail price image, concluding that stacked discounts could enhance consumer perception of retailers' overall prices (Feng and Cai 2015).

Similar errors have been documented in how consumers process percentages in other contexts. For example, the price difference between \$10 and \$15 is perceived to be bigger when the latter is described as 50% more than the former, as compared with when the former is described as 33% less than the latter (Kruger and Vargas 2008). A bonus pack of "50% more free" is preferred to the economically equivalent price discount of "33% off" (Chen et al. 2012). A reduction in cost (e.g., 50% less gas consumption) is perceived to be the same as an economically inferior increase in benefit (e.g., 50% more miles driven per gallon) (Mohan et al. 2015).

This stream of research has also identified boundary conditions for the erroneous processing of percentages. For example, the advantage of stacked discounts over the economically equivalent single discount can be mitigated when consumer numeracy or motivation is high, correct calculation is easy, or the fallacy associated with directly adding up percentages is obvious (e.g., 70% off plus 45% off, leading to a negative price) (Chen and Rao 2007, Kruger and Vargas 2008). Similarly, the incorrect comparison of percentages diminishes when the comparison occurs on absolute scales (e.g., dollar versus percentage) or when the difference between the price increase and decrease is small (Kruger and Vargas 2008). Also, the perceived difference between a cost reduction and an economically inferior benefit increase (50% less gas consumption versus 50% more miles driven per gallon) becomes smaller when standard rates (e.g., miles per gallon) are provided (Mohan et al. 2015).

In summary, previous research has examined how consumers process information expressed in percentage terms and how this processing affects sales. We contribute to this literature by providing predictions and evidence on how consumer return decisions are affected by percentage discounts framed as stacked discounts.

2.2. Product Returns

Product returns is an area of growing interest among scholars in marketing and operations management. There is a body of analytical work that focuses on a firm's optimal decisions. A set of papers looks at the optimal refund showing how firms balance the refund's effect on the return cost with its effect on initial sales quantity and selling price (e.g., Davis et al. 1995, 1998; Hess et al. 1996; Shulman et al. 2011; McWilliams 2012; and Akcay et al. 2013). Shulman et al. (2009) identify conditions for when a firm should and should not invest in making sure consumers are informed about the product fit prior to their purchase as a means of reducing returns. Ofek et al. (2011) look at a competing retailer's service provision and decision to open an online channel in light of product returns. A body of work also looks at how a manufacturer should set up the contract with its retailer in light of the downstream effect of its policy on consumer returns (e.g., Su 2009, Shulman et al. 2010, Xu et al. 2015). Altug and Aydinliyim (2016) examine how refunds affect consumers' decisions to defer purchase until inventory clear-out prices are offered. Alptekinoglu and Grasas (2014) find how product returns affect a retailer's product assortment decisions.

A second set of papers focuses on consumer behavior as it relates to product returns. For instance, Wood (2001) studies the effect of return policy leniency on decision deliberation time and product ratings. Bechwati and Siegal (2005) show that sequential versus simultaneous presentation of products affects product returns. Janakiraman and Ordonez (2012) study the relation between return deadlines and return rates.

Recent empirical work has modeled consumer product return behavior. Anderson et al. (2009) develop a structural model to estimate an individual's return cost and run policy simulations to identify the effects of increasing return costs on consumer behavior. Bower and Maxham (2012) study how fee versus free returns affect postreturn spending. Petersen and Kumar (2009) identify how consumer factors such as whether the purchase is a gift, external factors such as whether the purchase is made during the holiday season, and firm factors such as whether the item is on sale affect the rate of product returns. For example, the authors show products purchased on sale (i.e., lower-priced items) are less likely to be returned than products purchased at regular prices. Shulman et al. (2015) validate analytical predictions that partially, but not fully, resolving consumer uncertainty about product fit prior to purchase can increase product returns. Ertekin et al. (2019) focus on return prevention factors during a purchase and examine how service quality factors such as salesperson competence and store environment influence subsequent consumer return behavior. Ertekin (2018) demonstrates how retailers can use store labor during an in-store return event to convert returns into exchanges and to increase future purchases.

In summary, analytical, behavioral, and empirical studies have examined how consumers respond to firm strategies to manage product returns. We contribute to this literature by introducing the retail strategy of stacked discounts as another potential driver of consumer returns.

3. An Analytical Illustration of Stacked Discounts

In this section, we develop predictions from an analytical model regarding how stacked discounts affect initial sales quantity and product returns. Consistent with prior literature (e.g., Anderson et al. 2009; Shulman et al. 2010, 2015), we model consumer return behavior as a result of a two-stage decision process in which consumers first must decide whether to buy under uncertainty about product fit and then must decide whether to return the purchased product after the uncertainty has been resolved. Consistent with the literature on stacked discounts (e.g., Chen and Rao 2007), we model the consumers' calculation of price in the presence of stacked discounts to follow a whole-number strategy in which the perceived price systematically deviates from the actual price. In the following subsection, we define the model parameters. Subsequently, we solve the model and formalize its predictions.

The purpose of this model is to predict how stacked discounts affect product returns. This is the first model in the literature to speak to this issue. To demonstrate the validity of this model, we also predict the effect of stacked discounts on initial sales quantity. For face validity, the latter prediction should be consistent with prior behavioral work. Together, these predictions allow for an opportunity to test whether the multiple aspects of our unified theory of purchases and returns can be empirically supported as they relate to stacked versus economically equivalent single discounts.

In our model development, we consider static purchasing behavior for several reasons. First, static purchasing behavior is suitable particularly for infrequent purchases (Erdem and Keane 1996) when choices made in the previous periods do not serve as reference and do not causally affect a consumer's current utility (Chintagunta et al. 2006). In this regard, the jewelry purchases we study are infrequent. In our six-year-long data obtained from the subject retailer, 65% of customers have a single purchase, 97% of all customers have less than five purchases, and only 6% of customers purchased the same product the second time. Thus, making purchase decisions based on past purchases is unlikely for the majority of customers. Second, static purchasing behavior is also suitable when customers are not forward-looking (Erdem 1996, Chintagunta et al. 2006). Forward-looking behavior for jewelry purchases (e.g., postponing the purchase of a necklace for St. Valentine's Day to Mother's Day or Christmas due to forward-looking expectations about future lower prices) is unlikely. Third, static purchasing behavior is suitable if uncertainty about product quality or brand image is low, and, hence, consumer learning is not an important component of the choice process (Erdem and Keane 1996, Chintagunta et al. 2006). Considering that our empirical results are consistent between product categories for which quality uncertainty is low and those for which quality uncertainty is high, consumer learning about quality or brand appears to have negligible impact for jewelry purchases.

3.1. Model Definitions

Consider a product that offers consumer i utility of ownership equal to $U_i = \mu_i + \psi_i$ where μ_i denotes the component of utility known prior to purchase and ψ_i denotes the component of utility unknown at the time of purchase. Consumers rationally anticipate that ψ_i will be drawn from a distribution described by cumulative distribution function $F(\psi_i)$ and probability density function $f(\psi_i)$. Consumer heterogeneity in μ_i is captured by a continuously differentiable distribution with cumulative distribution function $G(\mu_i)$ and probability density function $g(\mu_i)$.

Consider discount percentages $a \geq 0$ and $b \geq 0$ that can be stacked to yield a net price of $p_n = p_o(1-a)\cdot(1-b)$, where p_o denotes the original price. Consistent with the empirical findings of Chen and Rao (2007), consumers mistakenly use a whole-number strategy in judging the overall effect of the stacked discounts to be the sum of the individual values. We denote the perceived stacked discount price by $p_s = p_o(1-a-b)$. Let $\gamma \doteq p_n - p_s = abp_o$ denote the difference between the actual net price and the consumer judgment of the price. Notice that if either $a = 0$ or $b = 0$ (i.e., single discount), then $\gamma = 0$ and consumers' price judgments are accurate.[2]

In the stage 1 purchase decision, consumers decide whether to buy in order to maximize their expected utility. If a consumer does not buy, he or she is left with the outside option that can be interpreted as either abstaining from purchase or purchasing a different product from another retailer. In the interest of parsimony, we normalize the expected utility of the outside option to zero.[3] In the stage 2 return decision, consumers decide whether to keep or return in order to maximize their actual utility. Consistent with the practice at major retailers and the firm we study, we assume the retailer has a full refund policy. If a consumer opts to return a purchase in stage 2, this consumer gets p_n refunded, but experiences a hassle cost denoted by h. The stage 1 expected utility accounts for the anticipated possibilities that the product will be kept or returned. In the following subsection, we solve the model via backward induction.

3.2. Model Analysis

In the following analysis, we demonstrate the effect of γ on product sales and returns. A consumer who computes the discounted price to be p_s will anticipate keeping the product if the utility from keeping it is greater than the utility from returning it (i.e., $\mu_i + \psi_i - p_s > -h$). Thus, for a given μ_i, a consumer anticipates that the probability of making a return, conditional on a purchase being made, equals $F(p_s - h - \mu_i)$. In other words, the consumer anticipates returning a purchased product if and only if the unknown component of utility turns out to be sufficiently low (i.e., $\psi_i < p_s - h - \mu_i$). We integrate over the possible values of ψ_i to calculate the expected utility of purchasing the product, given a perceived stacked-discount price of p_s.

$$E[utility\_of\_purchase|\mu_i] = \int_{p_s-h-\mu_i}^{\infty} (\mu_i + \psi - p_s)\, f(\psi)d\psi - \int_{-\infty}^{p_s-h-\mu_i} h\, f(\psi)d\psi. \qquad (1)$$

We first aim to demonstrate how stacked discounts affect the number of initial purchases. Consumers will make a purchase if $E[utility\_of\_purchase|\mu_i] \geq 0$. Thus, there exists a threshold on the observed utility component $\hat{\mu}$ such that consumers buy if and only if $\mu_i > \hat{\mu}$. Substituting $p_s = p_n - \gamma$ into Equation (1), we can define $\hat{\mu}$ by

$$Y \doteq \int_{p_n-\gamma-h-\hat{\mu}}^{\infty} (\hat{\mu} + \psi - p_n + \gamma)\, f(\psi)d\psi - \int_{-\infty}^{p_n-\gamma-h-\hat{\mu}} h \cdot f(\psi)d\psi = 0.$$

We can sign the comparative static $\partial\hat{\mu}/\partial\gamma < 0$ using the implicit function theorem and the fact that $\partial Y/\partial\hat{\mu} = \partial Y/\partial\gamma$. Recall that γ represents the difference between the actual price and the perceived price when consumers use a whole-number strategy in judging the discounted price. Given the distribution of μ_i, the percentage of the consumer population who makes a purchase is equal to $1 - G(\hat{\mu})$. The number of initial purchases will be equal to the consumer population size multiplied by $1 - G(\hat{\mu})$. Because $G(\mu_i)$ is a continuous, increasing, and differentiable function, we can make the following prediction.

Prediction 1. *The number of initial purchases will be an increasing function of the difference between the actual net price and the consumer judgment of the price, γ, which implies there will be a greater initial sales quantity when there is a stacked discount than when there is an economically equivalent single discount.*

Prediction 1 is consistent with the prior literature examining the effect of stacked discounts on sales (Chen and Rao 2007) and serves as a sanity check on the model. The intuition for the prediction is relatively straightforward; if consumers calculate the selling price to be lower, there will be more consumers who will anticipate earning enough value to justify buying the item. The only new element to this prediction is that our model shows that the sales-increasing effect empirically established in Chen and Rao (2007) continues to hold when consumers have uncertainty regarding their utility of owning the product and anticipate a possibility of returning the purchase.

We now turn our attention to the return probability. Figure 2 presents representative information from a receipt given to customers after a purchase at the retailer under the study.[4] Like many retailers, the firm we study requires the original receipt to issue a refund for a returned product. Thus, we assume consumers will actually be informed of the true price p_n prior to a return decision. For a return to occur in stage 2, a purchase must have occurred in stage 1. In other words, a return will actually occur if both the ex ante unknown utility component turns out to be sufficiently low to merit returning the item ex post (i.e., $\psi_i < p_n - \mu_i - h$) and the ex ante known utility component is sufficiently high to merit purchasing initially (i.e., $\mu_i > \hat{\mu}$). From the retailer's perspective, the rate at which initial purchases are returned is thus given by $Pr(\psi_i < p_n - \mu_i - h | \mu_i > \hat{\mu})$. Integrating $Pr(\psi_i < p_n - \mu_i - h | \mu_i)$ over all $\mu_i > \hat{\mu}$, we get a return rate equal to

$$Return\ Rate = \int_{\hat{\mu}}^{\infty} \int_{-\infty}^{p_n - \mu_i - h} f(\psi) g(\mu) d\psi d\mu. \qquad (2)$$

Equation (2) implies that, holding all else constant, the return rate is decreasing in $\hat{\mu}$ [i.e., $\partial Return\ Rate / \partial \hat{\mu} < 0$ if $g(\hat{\mu} \neq 0)$]. Also notice that there is no direct effect of γ on the return rate. Rather, there is an indirect effect of γ on the return rate by the fact that $\partial \hat{\mu} / \partial \gamma < 0$. Thus, we make the following prediction.

Prediction 2. *The return rate will be an increasing function of the difference between the actual net price and the consumer judgment of the price, γ, which implies the return rate will be higher with stacked discounts than with an economically equivalent single discount.*

Prediction 2 is new to the literature. The intuition for this prediction is as follows. A higher γ attracts more customers to make a purchase initially. However, the additional consumers who are attracted by the lower calculated price have lower values of μ_i. In other words, the additional sales arising from stacked discounts come from consumers who would otherwise not buy at the actual net price because the ex ante expected utility is not high enough. After purchase, a consumer who realizes a low actual utility (i.e., ψ_i is low) will decide to return the product if the refund net of any return hassle exceeds the actual utility of keeping the product. A consumer with a low ex ante known utility component value (i.e., low μ_i) is more predisposed to have a low actual utility of keeping the product. Therefore, the additional consumers who are attracted to buy due to the stacked discount have a higher likelihood of returning their purchase. As a consequence, stacked discounts increase the rate of returns.[5]

In summary, our model is the first to make a prediction of how stacked discounts affect product returns. The model confirms the prior prediction about stacked discounts and initial order quantity, although it develops this prediction while uniquely accounting for ex ante consumer uncertainty and anticipation of the possibility of making a return. The model presents a unified theory of how stacked discounts relative to equivalent single discounts affect purchase and return behavior, thereby confirming and extending prior research.

Figure 2. A Representative Purchase Receipt with Stacked Discounts

```
04/18/05 17:05      1492   TRANS#:   222764
095210,   REG#: 01

                     SALE
Qty
------------------------------------------------------------
1   BB14K  WG  11/2  CTW PR                 2860.00
    001     16467573
    Mkdn  5    30.1%  x  2860.00  =          861.00-
    Mkdn  6     5.0%  x  1999.00  =          100.00-
                                            -----------
                       Item Subtotal:       1899.00
------------------------------------------------------------
                          Subtotal          1899.00
                          Tax  8.5000%       161.42
                          Total             2060.42
```

4. Laboratory Experiment

In this section, we describe the method and results from a controlled laboratory experiment to provide empirical evidence for the predictions derived from our theoretical model.

4.1. Method

A total of 253 Amazon mturkers participated in the study for a nominal payment. We used a one-factor (discount format: *single*, *stacked*) between subject design. Participants were randomly assigned to one of the two experimental conditions. They were asked to imagine that they were shopping for jewelry and liked a necklace demonstrated with a picture and limited information. They were told that the regular price was \$1,000, but there was a single discount of 40% off for the single discount condition or stacked discounts of 20% off plus an extra 25% off for the stacked-discount condition. Participants indicated their purchase intention of the discounted necklace on a seven-point scale. They were then asked to estimate the final price. After that, they were told to imagine they bought the necklace, provided more pictures as well as additional product descriptions (to facilitate utility uncertainty resolution), shown the receipt with the actual dollar amount of the discount (to mimic the reality and the analytical model where consumers are informed of the true price prior to a return decision), and asked to indicate their return intention on a seven-point scale. Lastly, they estimated the final price again.[6] Appendix A provides stimuli and all measures for the experiment.

4.2. Results

A one-way (discount format: *single*, *stacked*) analysis of covariance (ANCOVA) was conducted on purchase intention. We found that the effect of discount format was significant. Participants in the stacked-discount condition were more likely to purchase the jewelry than those in the single-discount condition ($M_{stacked} = 4.70$, $M_{single} = 4.46$, $F(1, 244) = 4.60$, $p = 0.033$), supporting Prediction 1.

A similar one-way ANCOVA was then conducted on return intention. Purchase intentions were used as an additional covariate to capture the probability of return conditional on purchase. We found that participants who were more likely to buy the jewelry in the first place were less likely to return it ($\beta = -0.44$; $t = 6.02$, $p < 0.001$). The effect of discount format was significant. Supporting Prediction 2, participants in the stacked-discount condition were more likely to return the jewelry than those in the single-discount condition ($M_{stacked} = 4.01$, $M_{single} = 3.78$, $F(1, 243) = 3.96$, $p = 0.048$).

We then linked the higher return intention in the stacked (versus single) discount condition to overestimation of discounts. Recall that participants estimated price twice: once before and once after they saw the receipt (i.e., $pe1$ and $pe2$, respectively). The difference between the two estimates (i.e., $pe2 - pe1$) was used to capture overestimation of the price discounts. Not surprisingly, there was an overestimation of the total discount in the stacked-discount condition ($pe2 - pe1 = \$53.57 > 0$, $t_{125} = 8.60$, $p < 0.001$), but not in the single-discount condition ($pe2 - pe1 = -\$0.42 < 0$, $t_{118} = 0.137$, $p > 0.1$). A moderation analysis revealed a significant interaction effect between discount format and discount overestimation ($\beta = 0.012$, $t = 2.08$, $p = 0.038$), such that (1) return intention was not significantly different between the two conditions when there was no overestimation and (2) the effect of stacked discounts relative to the economically equivalent single discount on return intention increased in discount overestimation.

To summarize, in a controlled laboratory experiment, we found that stacked discounts increased sales, replicating earlier work (Chen and Rao 2007). More critical to our purpose, stacked discounts also increased returns relative to an economically equivalent single discount. The moderation analysis supports the theory that the increase in returns from stacked discounts is driven by the magnitude of price misestimation. Overall, the laboratory experiment results provide empirical evidence for the analytical predictions derived from our theoretical model.

5. Empirical Application

Having established the proposed effect of stacked discounts on customer purchases and returns in a controlled laboratory experiment, in this section we use retail data to provide empirical support for our theory under real market conditions. In the following two subsections, we describe the data, our empirical setting, and the analysis methods. Then, we formulate our econometric model, present the results, and conduct a series of robustness checks to verify that our findings persist across an array of alternative specifications and explanations.

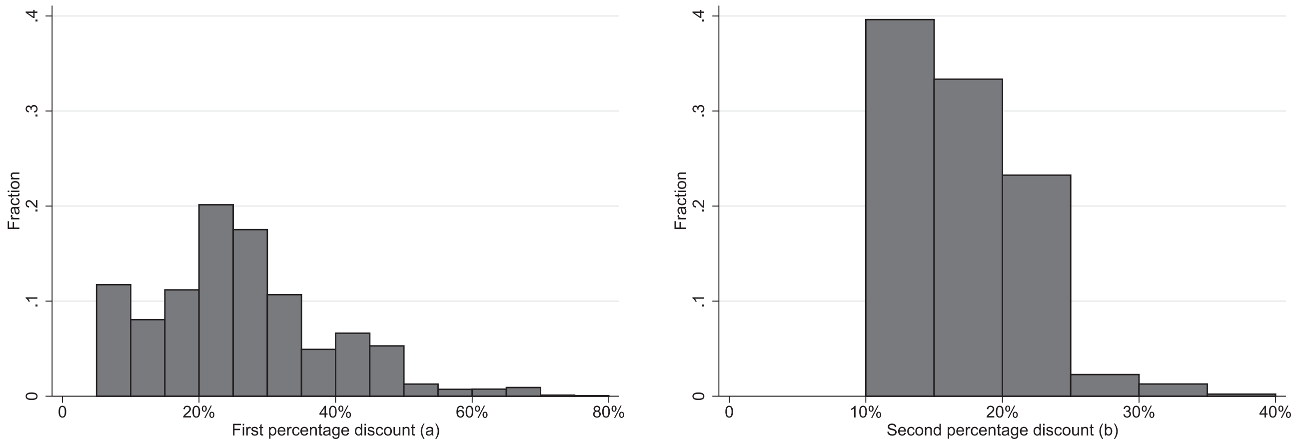
5.1. Empirical Setting and Data

To illustrate the impact of stacked discounts on sales and returns, we consider an application to a national jewelry retailer. The retailer sells jewelry, including women's jewelry, men's jewelry, and watches. It operates more than 1,000 stores located in shopping centers in the United States and Canada under five different brand names. The retailer has a full refund policy for all returned items with an average return rate of 14.8%. It operates its stores centrally such that the headquarters makes operational decisions including inventory, pricing, and promotions to strictly ensure the consistent price at a given time across all stores.

The retailer offers promotional pricing discounts typically for two-thirds of a year based on a predetermined annual promotion calendar. The sales generated from promotional products account for 42% of the annual revenue at the retailer, a figure that can be considered consistent with the U.S. retail industry (Smith and Agrawal 2017). Price promotions can be applied to certain stock keeping units or certain product categories. All pricing promotions during a promotional event are offered as percentage discounts such as "Up to 60% off for selected diamond rings" or "25% off regular + 10% off additional for all watches." Figure 3 demonstrates the distributions of discount percentages used at the retailer. It is likely that a product that is offered with a discount during a promotional event can later be offered with a different discount or at its original price. Considering that jewelry items arrive at stores with preprinted price tags and the retail stores are not able to replace the price tags in-store, the final net prices of jewelry items are not displayed on the price tags. Rather, when promotional pricing is in effect, as directed by the headquarters office, all stores use the same window displays and in-store displays to inform customers about the promotion.

The raw data consist of item-level transactions from all retail outlets for the six-year period between August 2009 and July 2015. During this period, we identify 249 promotional events in which the retailer uses both

Figure 3. The Distributions of Single Discount and Stacked Discounts at the Retailer



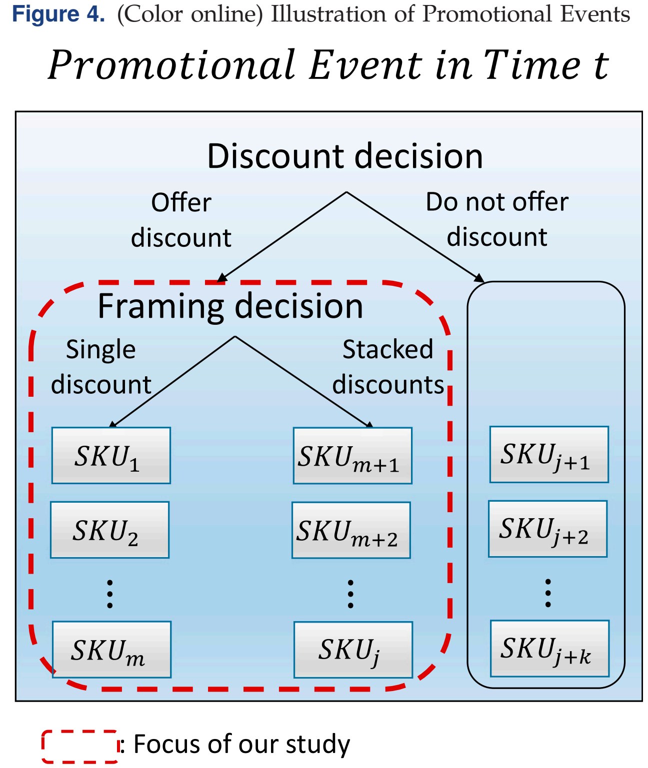
single-percent discount framing and stacked-percent discount framing. We illustrate a promotional event in Figure 4. For a promotional event, the retailer exercises two decisions for SKUs: (1) whether to offer a discount; and (2) if the decision is to offer a discount, whether to frame the discount as a single-percent discount or as a stacked-percent discount. Note that the first decision is a result of a typical price-optimization problem in which the retailer aims to maximize her sales. We do not focus on this decision. Rather, given that the first stage decision is to offer a discount, we focus on how the retailer should frame that discount.

Using the discount codes in the data, we are able to identify the number of discounts and the reason for each discount applied to a transaction. The retailer offers 14 additional discounts (e.g., employee discount, customer service discount, military discount, etc.) that are (1) not related to the theory we study (i.e., customers make math error when calculating the percent discounts) and (2) available throughout the year. Because we focus on framing percentage discounts offered only during a promotional event, we remove all transactions with these additional discounts. To ensure that we observe product returns and past sales/return rate for a given SKU, we limit our analysis to the time period between August 2010 and April 2015. By doing so, we aim to remove any issues with left-censoring or right-censoring of data (Petersen and Kumar 2015).

5.2. Analysis Methods

We want to establish a causal relationship between discount framing and sales/return rates using observational data. Thus, we use the potential outcomes causal model (Rubin 2005), also known as the Rubin causal model, a counterfactual framework pioneered by Rubin (1974). In our setting, framing a discount offered on a product as a single-percent discount and framing the same discount on the same product as stacked-percent discounts represent the two conditions under which we expect different sales and return rates (i.e., potential outcomes). The potential outcomes framework has proven to be useful when randomization is impractical (Wooldridge 2010). The model assumes that for every condition defined in a study, each subject has a different potential outcome depending on their "assignment" to a condition. However, causal inference in such studies has a missing data problem [described as the "fundamental problem of causal inference" (Holland 1986)] because one can never observe all potential outcomes at once, and, therefore, one or

Figure 4. (Color online) Illustration of Promotional Events



more of the potential outcomes is always missing. The potential outcomes causal model is used to recover consistent estimators of the parameters from observational data when only one of the potential outcomes can be observed. Potential outcomes estimated by this model are expressed in the form of counterfactual conditional statements, which state what would be the case conditional on a prior event occurring.

The potential outcomes causal model is notably suitable for our empirical setting for two main reasons. First, when a discount with a certain framing is offered for a given product during a promotional event, by the company policy, all stores follow the same discount-framing strategy. For instance, if a wedding ring is offered with a 40% discount, the same offer will be present in all stores, and none of the stores will offer a different discount framing (e.g., 20% off, plus an extra 25% off) for the same ring. Thus, it is not possible to observe both conditions at once and one of the potential outcomes is always missing. Second, as illustrated in Figure 4, each promotional event can be considered an experiment in which the retailer (1) assigns some SKUs to the stacked-discounts condition and other SKUs to the single-discount condition and (2) simultaneously observes the potential outcomes (i.e., sales and returns) from both conditions for the same time period (i.e., the duration of the promotional event).

One may consider that SKUs that are offered at their original prices during a promotional event would serve as a reference condition to SKUs that are offered with either a single discount or stacked discounts. As demonstrated in Figure 4, SKUs with no discount are segregated from SKUs with any type of discount as a result of two sequential decisions (i.e., discount decision and framing decision). Ignoring this feature and estimating a model comparing SKUs with no discount to SKUs with any type of discount will result in a confounded effect that commingles both the discount decision and the framing decision. Therefore, consistent with the focus of our study, in a given promotional event, we remove all SKUs with no discount and only compare SKUs offered with a single discount to SKUs offered with stacked discounts. This process generates a data set with 3,191,080 SKUs (in the price range of \$6.99 and \$27,199) that are offered with either of the two discount framings across 1,057 different stores during 249 different promotional events. A potential concern of removing SKUs with no discount is selection. SKUs with any type of discount may systematically be different from SKUs with no discount, resulting in biased estimates. However, as we detail in the next section, our econometric model identifies the causal effect of stacking-percent discounts by differencing the two potential outcome models, one for a single discount and one for stacked discounts. Considering that factors that may generate the systematic difference between SKUs with no discount and SKUs with any type of discount will be present for both single-discounted SKUs and stacked-discounted SKUs, such factors will cancel out when differencing the two potential outcome models. Hence, the potential selection concern due to removing SKUs with no discount is trivial for our study.

Even though the potential outcomes causal model helps us test a causal relationship between discount framings and sales/return rates, we conduct extra analyses and follow a three-step methodology to strengthen our results. First, we measure the effect of stacked discounts by using an endogenous potential outcomes causal model with selection on unobservables. Next, to minimize the inherent differences between products that are offered with a single discount and products that are offered with stacked discounts, we use a propensity-score matching between the two groups. Finally, we conduct multiple robustness checks to validate our conclusions and address alternative explanations. We detail these methods next.

5.3. Econometric Specifications

We aim to identify the impact of stacked discounts relative to an economically equivalent single discount on sales and return rate of 3,191,080 SKUs offered during promotional events. We use the indicator $Stacked_{ij}$ to denote whether SKU j is offered with stacked discounts ($Stacked_{ij} = 1$) or with an economically equivalent single discount ($Stacked_{ij} = 0$) during promotional event i. Let ($Sales_{ij0}$, $Sales_{ij1}$) and ($ReturnRate_{ij0}$, $ReturnRate_{ij1}$) be the two potential outcomes for SKU j in a store during promotional event i for the logarithm of sales quantity and return rates, respectively. $Sales_{ij0}$ ($ReturnRate_{ij0}$) and $Sales_{ij1}$ ($ReturnRate_{ij1}$) denote the natural log of the number of items sold (return rate) in a store during promotional event i when SKU j is offered with a single discount and with economically equivalent stacked discounts, respectively. For each SKU, the retailer can realize either $Sales_{ij0}$ ($ReturnRate_{ij0}$) or $Sales_{ij1}$ ($ReturnRate_{ij1}$). Then, the two potential outcome equations and the potential outcomes model can be defined as

$$Y_{ij0} = \lambda_0 + \boldsymbol{X}'_{\boldsymbol{ij}}\boldsymbol{\beta_0} + \epsilon_{ij0}, \tag{3}$$

$$Y_{ij1} = \lambda_1 + \boldsymbol{X}'_{\boldsymbol{ij}}\boldsymbol{\beta_1} + \epsilon_{ij1}, \tag{4}$$

$$Y_{ij} = (1 - Stacked_{ij}) \times Y_{ij0} + Stacked_{ij} \times Y_{ij1}, \tag{5}$$

where Y denotes *Sales* when estimating the sales model and *ReturnRate* when estimating the return rate model, $\boldsymbol{X_{ij}}$ is a set of covariates related to ($Sales_{ij0}$, $Sales_{ij1}$) and ($ReturnRate_{ij0}$, $ReturnRate_{ij1}$), λ_0 and λ_1 are parameters, and ϵ_{ij0} and ϵ_{ij1} are error terms. Equations (3) and (4) represent the potential outcome equations with the assumptions of being linear in parameters, $E(\epsilon_{ijs}) = 0$, and $E(\epsilon_{ijs}|\boldsymbol{X_i}) = 0$ such that $s \in \{0, 1\}$. Equation (5) states the observational rule of the model and Y_{ij} indicates the realized outcome. Let $\boldsymbol{\lambda_x} = E(\boldsymbol{X_{ij}})$ and $\boldsymbol{\beta} = \boldsymbol{\beta_1} - \boldsymbol{\beta_0}$. If we assume $E(\epsilon_{ij}|\boldsymbol{X_{ij}}, Y_{ij}) = E(\epsilon_{ij0} + Stacked_{ij}(\epsilon_{ij1} - \epsilon_{ij0})|\boldsymbol{X_{ij}}, Stacked_{ij}) = 0$, by substituting Equations (3) and (4) into (5), we get

$$E(Y_{ij}|\boldsymbol{X_{ij}}, Stacked_{ij}) = \lambda_0 + (\lambda_1 - \lambda_0)Stacked_{ij} + \boldsymbol{X'_{ij}\beta_0} + Stacked_{ij}(\boldsymbol{X_{ij}} - \boldsymbol{\lambda_x})\boldsymbol{\beta}, \qquad (6)$$

where $\delta = (\lambda_1 - \lambda_0) + (\boldsymbol{X_{ij}} - \lambda_x)\beta$ represents the causal effect of stacked discounts relative to an economically equivalent single discount on sales/return rate and is the parameter of interest for our paper.

Equation 6 assumes no differences in distributions of covariates that are related to both the potential outcomes and the treatment assignment. In other words, the assignment of SKUs to the two conditions (i.e., offering a single discount or offering stacked discounts) is randomized across products. Clearly, this is a fairly brave assumption, as there might be multiple explanations for why the retailer chooses a certain discount framing for a product. For instance, the retailer may use stacked discounts to clear out products that stand on the shelf for a long time. A relationship between the preference of discount framing and the sales/return rate outcome implies that δ estimated from Equation (6) might be biased (Wooldridge 2010). Therefore, we need to account for endogeneity due to nonrandom assignment of discount framings by explicitly modeling the endogenous variable $Stacked_{ij}$ and embedding an endogenous treatment assignment correction into Equation (6). We model the assignment process with a latent utility framework as follows:

$$Stacked^*_{ij} = \theta_0 + \boldsymbol{Z'_{ij}\theta} + \upsilon_{ij}, \qquad (7)$$
$$Stacked_{ij} = \begin{cases} 1 & if\ Stacked^*_{ij} > 0 \\ 0 & \text{otherwise,} \end{cases}$$

where $Stacked^*_{ij}$ is the unobserved benefit the retail derives by offering SKU j with stacked discounts relative to offering it with an economically equivalent single discount during promotional event i, $\boldsymbol{Z_{ij}}$ is a set of observed covariates related to the retailer's propensity to offer stacked discounts, and υ_{ij} is an unobserved error component. We account for endogeneity due to nonrandom assignment of discount framings by using the estimated inverse-probability weights obtained from Equation (7) in Equation (6). Note that the goal of treatment-assignment correction is different from estimating δ (Wooldridge 2010). The treatment-assignment equation aims to correct $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$ in Equation (6), which indexes $E(Y_{ij}|\boldsymbol{X_{ij}})$ in the population. By contrast, in estimating δ, we identify the causal effect of stacked discounts on sales and return rates. When we assume $E(\epsilon_{ijs}|\boldsymbol{X_{ij}}, \boldsymbol{Z_{ij}}) = E(\epsilon_{ijs}|\boldsymbol{Z_{ij}}) = E(\epsilon_{ijs}|\boldsymbol{X_{ij}})$ and $E(\epsilon_{ijs}|Stacked^*_{ij}) = 0$, by estimating Equations (6) and (7) simultaneously, we can obtain an unbiased estimator for δ.

Practically, even though this approach accounts for the endogeneity due to nonrandomization of discount-framing assignment using observable covariates, it assumes that the unobservable factors in Equations (6) and (7) are not correlated, which is known as the conditional-independence assumption (Wooldridge 2010). Yet, some unobservables may violate this assumption. For instance, inventory, demand, and quality are among the factors the subject retailer considers when choosing the discount framing for promoted products. One can argue that customers will be more likely to return products that are low in inventory, have low demand, or are low quality. Because we are not able to observe these factors, the conditional-independence assumption will be violated. Hence, $E(\epsilon_{ijs}|Stacked^*_{ij}) \neq 0$. In particular, using Equation (7) and $E(\epsilon_{ijs}|\boldsymbol{Z_{ij}}) = 0$, one can show that $E(\epsilon_{ijs}|Stacked^*_{ij}) = \upsilon'_{ij}\boldsymbol{\pi_s}$ [where π_s denotes the coefficient on the control function term that is estimated for each potential outcome equation, as shown in Equation (8)], adding a second endogeneity to our model. Thus, we need to modify our econometric model to address endogeneity due to such unobservables.

As suggested by Wooldridge (2010), we use a control-function approach to address endogeneity due to unobservables. We obtain the control function term $\hat{\upsilon}_{ij}$ as the difference between $Stacked_{ij}$ and our estimate of $E(Stacked_{ij}|\boldsymbol{Z_{ij}})$ from Equation (7) (i.e., residuals from the treatment assignment model).[7] Hence, in this approach, $\hat{\upsilon}_{ij}$ represents the consistent estimate of the unobservables and can be used to compute the following equation to obtain an unbiased estimate of δ:

$$E(Y_{ij}|\boldsymbol{X_{ij}}, \upsilon_{ij}, Stacked_{ij}) = \lambda_0 + (\lambda_1 - \lambda_0)Stacked_{ij} + \boldsymbol{X'_{ij}\beta_0} + Stacked_{ij}(\boldsymbol{X_{ij}} - \boldsymbol{\lambda_x})\boldsymbol{\beta} + \pi_0\upsilon_{ij} + (\pi_1 - \pi_0)Stacked_{ij}\upsilon_{ij}, \qquad (8)$$

where $\delta = (\lambda_1 - \lambda_0) + (\boldsymbol{X_{ij}} - \lambda_x)\beta + (\pi_1 - \pi_0)\boldsymbol{\upsilon_{ij}}$. Although it is advisable to have instrument(s) in $\boldsymbol{Z_{ij}}$ for identification, technically, Equations (6) and (8) are still identified, even if the covariates in $\boldsymbol{X_{ij}}$ and $\boldsymbol{Z_{ij}}$ are the same so long as Equation (7) is a nonlinear model, and thus the mapping from Z_{ij} to $\text{Prob}(Stacked_{ij} = 1 \mid Z_{ij})$ is nonlinear (Wooldridge 2010). Our parametric identification relies on the nonlinearity of the treatment assignment model because $\boldsymbol{X_{ij}}$ and $\boldsymbol{Z_{ij}}$ are the same in our model.

We specify Equations (6) and (8) as linear models when estimating the *Sales* model and fractional probit models when estimating the *ReturnRate* model. We specify Equation (7) as a probit model. As we demonstrate in Section 3, sales and returns are interrelated, suggesting the error terms in the *Sales* models are likely to be correlated with the error terms in the *ReturnRate* models. Thus, we integrate the *Sales* and *ReturnRate* models by parameterizing a correlation (i.e., ρ) between the error term in Equation (3) [Equation (4)] in the *Sales* model with the error term again in Equation (3) [Equation (4)] in the *ReturnRate* model. We use Stata'a generalized method of moments (GMM) estimator for the simultaneous estimation of equations (Stata-Corp. 2016). Our estimation uses the starting values computed by minimizing the objective function of each equation outside the GMM estimator. The results are identical, with 10 different sets of starting values. They are also robust to scaling of covariates for our sample data. We control for heteroscedasticity and nonindependence of observations from the same promotional event by clustering standard errors at the promotional event level.

5.4. Control Variables

We use a rich set of control variables in our analysis. The set of covariates $\boldsymbol{X}$ in the potential outcome equations includes product-specific, promotional event-specific, and store-specific control variables that are potentially related to the outcome variables. For product characteristics, we include the logarithm of the discounted price of a product (*FinalPrice*) because more expensive products are more likely to be returned (Hess and Mayhew 1997). We also include the logarithm of the dollar value of total discount (*Discount*), as previous research shows customers may be sensitive to both the absolute price and the discount from the regular price (Jedidi et al. 1999, Anderson et al. 2009). Note that by including these two variables, we can attribute the sales or return rate difference between two products that have the same *FinalPrice* and *Discount* during a promotional event—one is framed as stacked discounts and the other is framed as economically equivalent single discount—to the difference in discount framing. We control for the demand, quality, and inventory level of a product using three proxies. *PastSale* represents the logarithm of the number of items sold between the beginning of the data set (i.e., August 2009) and the beginning of a promotional event. *PastReturnRate* represents the return rate of *PastSale*. *Shelflife* represents the number of days between a product's first sales transaction observed in the data and the start day of a promotional event. We also include indicator variables for product categories (*ProdCat*) to control for differences in sales and return rates across different product categories.

For promotional events, we include an indicator to identify whether the promotional event includes a holiday (e.g., Christmas or Mother's Day) (*Holiday*), the length of the promotional event in days (*PromoDays*) because sales should increase as the promotional event lasts longer, and *Month* and *Year* indicators to control for seasonality. For store characteristics, we use *StoreSize* as the logarithm of the total square feet of a store, *BrandName* indicators to identify the brand name under which a store operates, sales volume group (*SalesVolume*) defined by the retailer for each store as an ordinal variable ranging from one to six where one represents the lowest and six represents the highest sales volume group, and indicator variables for the quality of a mall (*Mall*) in which the retail store is located. We use *Mall* to control for the quality and the competitive environment of the mall in which a store is located and for potential economic differences in population across stores. Lastly, we also include fixed effects for the geographic locations of stores (*Location*).

Table 1 provides descriptive statistics and the correlation matrix for the variables used in the analysis for single-discounted products (*Stacked* = 0) and stacked-discounted products (*Stacked* = 1). With a variance inflation factor score mean of 1.92 and a range between 1.03 and 3.93, below the rule-of-thumb cut-off of 10 (Neter et al. 1996), there is little evidence of multicollinearity.

5.5. Results

The reliability of estimated parameters from our econometric models depends on whether the parametric assumptions of potential outcomes causal framework are satisfied. Thus, before we present the results, we first examine the parametric assumptions required for potential outcomes causal models as described in Appendix B. Overall, our analysis shows that the required parametric assumptions are satisfied for our data set. We next present the results from the three different econometric specifications for the integrated sales and return rate models in Table 2. Model 1 presents the results from Equation (6) that ignores the nonrandomization of treatment assignment. Note that we estimate two different models. POM-0 represents the estimation of Equation (3) for products offered with a single discount during a promotional event. POM-1 represents the estimation of Equation (4) for products offered with stacked discounts during a promotional event. Model 2 presents the results from the simultaneous estimation of Equation (6) for sales and return rate models along with Equation (7). This model is the potential outcomes causal model with treatment assignment on observables. Finally, Model 3 presents the results from the simultaneous estimation of Equation (7) along with Equation (8) for sales and return rate models. This model is the endogenous potential outcomes causal model with treatment assignment on unobservables. In all three models, δ is estimated to be the difference between the predicted margin of outcome variable in model POM-1 and the predicted margin of outcome variable in model POM-0.

Model 3 estimates four coefficients on the control function term (denoted as π_s in Table 2) in each of the potential outcome models based on the premise that

Table 1. Descriptive Statistics and Correlation Matrix

	Stacked = 0		*Stacked* = 1												
Variable	Mean	Standard deviation	Mean	Standard deviation	1	2	3	4	5	6	7	8	9	10	11
1. *Sales*	0.71	0.29	0.75	0.09	1.00										
2. *ReturnRate*	0.11	0.31	0.13	0.31	0.01	1.00									
3. *FinalPrice*	5.10	1.17	5.60	1.03	−0.03	0.09	1.00								
4. *Discount*	3.66	1.52	4.91	1.16	0.02	−0.07	0.53	1.00							
5. *PastSale*	6.28	2.06	6.32	1.87	0.04	−0.02	0.05	−0.05	1.00						
6. *PastReturnRate*	0.11	0.08	0.12	0.07	−0.19	0.11	−0.42	0.32	0.02	1.00					
7. *ShelfLife*	487.69	350.88	559.26	353.92	−0.09	0.00	−0.14	0.18	0.59	0.03	1.00				
8. *PromoDays*	11.57	8.43	11.58	5.01	0.02	0.01	0.09	−0.06	−0.01	−0.01	0.06	1.00			
9. *Holiday*	0.28	0.44	0.27	0.49	0.02	0.01	−0.06	0.07	0.04	−0.04	−0.05	−0.30	1.00		
10. *StoreSize*	7.43	0.24	7.45	0.26	0.00	0.01	0.01	0.07	−0.10	0.00	−0.01	−0.00	−0.01	1.00	
11. *Stacked*					0.09	0.02	−0.22	0.42	−0.01	0.06	0.10	−0.31	0.13	0.04	1.00
Sample size (N)	1,497,578		1,693,503												

the unobservable factors in the assignment model and in each of the potential outcome equations are correlated. The test on the joint significance of these coefficients generates a statistic (denoted as "χ^2 for endogeneity" statistic in Model 3) to assess the null hypothesis of no endogeneity due to unobservables. Any significant test result implies the presence of endogeneity due to unobservables and necessitates the use of Model 3 over Model 1 that ignores endogeneity due to unobservables (Wooldridge 2010). With a significant χ^2 statistic, we reject the null hypothesis and choose Model 3 over Model 1. To the best of our knowledge, there is no standard test used to choose between Model 2 and Model 3, as finding the

Table 2. Potential Outcomes Causal Model Results

	Model 1		Model 2		Model 3	
Variable	POM-0	POM-1	POM-0	POM-1	POM-0	POM-1
Sales model						
Effect of *Stacked* on *Sales*: δ	0.038*** (0.004)		0.041*** (0.004)		0.049*** (0.012)	
FinalPrice	−0.01*** (0.002)	−0.00*** (0.001)	−0.01 (0.006)	−0.00 (0.004)	−0.02*** (0.004)	−0.00 (0.003)
Discount	0.00*** (0.001)	0.00* (0.001)	0.01* (0.002)	0.01** (0.002)	0.01*** (0.002)	0.00 (0.004)
Other Controls	Included		Included		Included	
π_s					−0.35** (0.117)	0.05* (0.020)
ReturnRate model						
Effect of *Stacked* on *ReturnRate*: δ	−0.003 (0.006)		0.032** (0.011)		0.050*** (0.014)	
FinalPrice	0.10*** (0.029)	0.15*** (0.034)	0.13** (0.046)	0.12* (0.062)	0.11*** (0.004)	0.12*** (0.007)
Discount	−0.01 (0.023)	−0.05* (0.020)	−0.04 (0.040)	−0.02** (0.005)	−0.01*** (0.002)	−0.00 (0.008)
Other Controls	Included		Included		Included	
π_s					−0.07*** (0.018)	−0.11*** (0.016)
Assignment model			Included		Included	
Observations (N)	3,191,080		3,191,080		3,191,080	
ρ	0.02***	0.09***	0.02***	0.09***	0.01***	0.10***
χ^2 (d.f.) for endogeneity					78.57 (4) ***	

Note. Robust standard errors clustered at promotional events are presented in parentheses.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

right treatment effect model is still an ongoing research (e.g., Rolling and Yang 2014). However, considering that (1) the two models generate consistent insights and (2) the conditional-independence assumption in Model 2 is highly likely to be violated, as we are not able to observe some factors the retailer might consider when making the discount-framing decision (e.g., inventory, demand, and quality), for all practical reasons, we choose Model 3 over Model 2 and use it to interpret our findings.

In Table 2 under Model 3, the estimated δ in the *Sales* model is 0.049 ($p = 0.000$). This suggests framing a discount as stacked-percentage discounts increases sales quantity by 4.9% relative to framing the same discount as a single-percent discount, supporting Prediction 1. This result is consistent with the experimental findings in Chen and Rao (2007) and establishes credibility on our results for the rest of the analysis.

With respect to return rates, we find the estimated value of δ in the *ReturnRate* model is 0.05 ($p = 0.000$). We also find the predicted potential outcome mean when $Stacked = 0$ (i.e., when a discount is framed as single) is 0.11 (not displayed in Table 2). Together, these two results imply that framing a discount as stacked discounts relative to the economically equivalent single discount increases the return rate by 5 percentage points (from 0.11 to 0.16), providing support for Prediction 2.[8]

Having identified the causal effect of stacked discounts on sales and return rates, we now empirically examine whether this effect is indeed driven by γ as described in Predictions 1 and 2. To do so, we assess the effect of γ on the relationship between stacked discounts and sales/return rates. As described in Section 3.1, we operationalize γ as the difference between the actual net price and the consumer judgment of the price such that $\gamma \doteq p_n - p_s = abp_o$. Ideally, we should conduct the analysis by interacting γ with $Stacked_{ij}$ in Equation (8). However, γ does not vary when $Stacked_{ij} = 0$, as, theoretically, it always equals zero for SKUs offered with a single discount. Therefore, γ and $Stacked_{ij}$ contain redundant information, and the interaction cannot be tested due to collinearity. Alternatively, we divide products offered with stacked discounts into four subgroups based on the quartiles of the ranked set of γ such that the first (fourth) subgroup includes SKUs with a γ that falls in the first (fourth) quartile. Next, we generate four different subsets by combining each subgroup with single-discounted SKUs. Finally, we estimate Model 3 within each subset. Table 3 demonstrates the estimated δ for each subset. We observe that, consistent with Predictions 1 and 2, the effect of stacked discounts on sales and return rates increases in γ, further supporting our theoretical explanations.

5.6. Robustness Checks

In this section, we check the robustness of our results. We find that our main results and insights from the interaction effect analysis remain the same across all robustness checks. In the interest of brevity, we demonstrate only the results for the main model rather than for each quartile of γ separately.

5.6.1. Propensity-Score Matching. In our study, the assignment of discount framing to a product is not random. Even though from an econometric-modeling perspective we address this issue by explicitly modeling treatment assignment in Equation (7), we check the robustness of our results using the counterfactual causal analysis as suggested by the literature (Rosenbaum and Rubin 1983, Dehejia and Wahba 2002). In particular, we use propensity-score matching between products offered with stacked discounts and products offered with single discounts to minimize the inherent differences between the two groups. We note that matching not only provides an alternative estimate for the effect of the discount-framing decision, but also restricts the range of analysis.

Rosenbaum and Rubin (1983) define propensity score as the conditional probability of having one condition rather than the other condition, given the observed covariates. Propensity-score matching summarizes the observed characteristics of each SKU into a single-index variable (i.e., the propensity score), which enables us to generate a subset of products that have similar propensity scores and therefore little bias in the observed covariates. Under the matching assumption, the only difference between stacked-discounted products and single-discounted products is the discount framing. Hence, the average treatment effect obtained from the propensity-score matching can be attributed to the discount framing.

We conduct propensity-score matching as described in Appendix C and obtain a subsample of 2,446,647 observations that consist of similar products with respect to their observed covariates. This process matches 80.3% of stacked-discounted products to single-discounted products. The average treatment effect estimated through propensity-score matching (i.e., the difference in the mean outcome variable between the stacked-discounted products and the single-discounted products in the matched sample) is 0.039 ($p = 0.000$) for *Sales* and 0.036 ($p = 0.000$) for *ReturnRate*. Note that the average treatment effect in propensity-score matching is estimated based on observable covariates. Hence, the propensity-score matching estimates are comparable to Model 2 estimates (in Table 2) that are obtained by using the potential outcomes causal model with treatment assignment on observables. From this

Table 3. The Interaction Effect of γ on δ

		The range of γ			
		First quartile	Second quartile	Third quartile	Fourth quartile
Sales model	δ	0.023*	0.048***	0.056**	0.067***
		(0.011)*	(0.011)*	(0.021)*	(0.016)*
ReturnRate model	δ	0.022*	0.042***	0.062***	0.074***
		(0.009)*	(0.013)*	(0.009)*	(0.017)*
Observations (N)		1,917,578	1,924,708	1,917,153	1,924,475

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

perspective, we find the estimated effects of stacked discounts are consistent with our main findings. To examine how hidden bias due to unobservables would influence the estimates in propensity-score matching, we take a further step and estimate Model 3 using the matched subset of data. We find that the estimated effects of stacked discounts on sales ($\delta = 0.063$, $p = 0.000$) and return rates ($\delta = 0.059$, $p = 0.000$) are consistent with our main finding, suggesting that (1) the potential effect of inherent product differences is negligible and (2) our results are even more prominent when we restrict our analysis to more homogeneous products.

5.6.2. Customer Profile. To this point, we have not considered the potential difference in customer profile between single-discounted purchases and stacked-discounted purchases. One may argue that the estimated effect might be attributed to the customer profile differences between the two groups. Even though the potential outcomes causal model with treatment assignment on unobservables aims to address such differences that are not captured in the regression model, here, we take a further step and utilize the transaction-level data to address potential differences in customer profile between the two groups. In particular, we operationalize five variables to represent the average RFM (recency, frequency, and monetary value) related to sales and returns for discounted products. *PastPurchaseFreq* (*PastReturnFreq*) represents the average of past-purchase (return) frequency [i.e., frequency of all purchases (returns) made up to one year prior to promotional event *i*] of all customers who purchase SKU *j*. *PastPurchaseValue* (*PastReturnValue*) represents the average of the logarithm of dollar value of past purchases (returns) of all customers who purchase SKU *j*. *PromoSensitivity*, measured as the average ratio of past discounted purchases to all past purchases of all customers who purchase SKU *j* during promotional event *i*, represents customer tendency to purchase on promotion. In addition, in both models, we include three variables, denoted as *CustomerDemographics* in Table 4. *Gender* is the ratio of all female customers to all customers who purchase product *j* during promotional event *i*. *Age* is the average age group (i.e., an ordinal variable ranging between 1 and 13) of all customers who purchase product *j* during promotional event *i*. *HHIncome* is the average household income group (i.e., an ordinal variable ranging between 1 and 9) of all customers who purchase product *j* during promotional event *i*.

Table 4 demonstrates the results from all models with the additional customer profile variables. In general, we find the estimated coefficients confirm our expectations regarding the relationship between sales/return rates and RFM metrics. For instance, consistent with past research, we find sales are positively associated with customer past returns (Petersen and Kumar 2009) and customer past spending (Reinartz and Kumar 2003). With respect to returns, our results suggest that products are more likely to be returned when customers are frequent returners (Petersen and Kumar 2015) or when they shop less often with the retailer. We can also infer that promotion-sensitive customers are likely to prefer single-discounted products over stacked-discounted product, suggesting that they have more accurate promotion perceptions than regular customers. Although the results contribute to our understanding of how RFM metrics influence sales and return rates for each of the two discount framings, our insights with respect to the discount-framing effect on sales and return rates remain the same. Thus, we conclude that our results are robust to the exclusion of customer profile metrics.

5.6.3. Seasonality Due to Holidays. With this robustness check, we aim to rule out two alternative explanations. First, even though we control for temporal effects with three indicator variables (i.e., *Holiday*, *Month*, and *Year*), our results might possibly be driven by the outliers in sales and return rates typically observed during the holiday season. One can argue that because stacked discounts are more likely to be offered during holiday seasons and returns are more likely to occur during these times, our model might mistakenly attribute the outliers in sales and returns to stacked discounts. To address this, we remove all purchases made during a holiday season (i.e., 1,083,557 observations with *Holiday* = 1) and run Model 3 after excluding the *Holiday* variable. We find that the magnitudes of the estimated

Table 4. Potential Outcomes Causal Model Results with Customer Profile Controls

	Model 1		Model 2		Model 3	
Variable	POM-0	POM-1	POM-0	POM-1	POM-0	POM-1
Sales model						
Effect of *Stacked* on *Sales*: δ	0.033*** (0.006)		0.035*** (0.005)		0.045*** (0.012)	
PastPurchaseFreq	0.01** (0.003)	0.00 (0.000)	0.01** (0.004)	-0.00 (0.000)	0.00* (0.002)	-0.00 (0.000)
PastPurchaseValue	0.06*** (0.006)	0.01*** (0.002)	0.08*** (0.010)	-0.00 (0.001)	0.04*** (0.004)	0.01*** (0.002)
PastReturnFreq	0.05*** (0.010)	0.00 (0.001)	0.06*** (0.013)	0.00 (0.002)	0.04*** (0.009)	-0.00 (0.001)
PastReturnValue	0.02*** (0.005)	–0.00 (0.001)	0.02*** (0.006)	0.00** (0.001)	0.02*** (0.004)	0.00 (0.001)
PromoSensitivity	0.36*** (0.035)	0.07*** (0.010)	0.45*** (0.055)	0.01 (0.007)	0.26*** (0.024)	0.07*** (0.010)
CustomerDemographics	Included		Included		Included	
Other Controls	Included		Included		Included	
π_s					–0.21* (0.095)	0.04** (0.014)
ReturnRate model						
Effect of *Stacked* on *ReturnRate*: δ	–0.003 (0.007)		0.035* (0.016)		0.053*** (0.016)	
PastPurchaseFreq	–0.04** (0.014)	–0.01 (0.006)	–0.00* (0.002)	–0.00 (0.001)	–0.01*** (0.001)	–0.01 (0.000)
PastPurchaseValue	–0.02 (0.022)	0.00 (0.020)	–0.00 (0.006)	–0.00 (0.005)	–0.00 (0.004)	–0.00 (0.003)
PastReturnFreq	0.16*** (0.039)	0.01 (0.026)	0.06*** (0.014)	–0.00 (0.006)	0.04*** (0.009)	–0.00 (0.004)
PastReturnValue	0.01 (0.017)	0.04* (0.014)	0.01 (0.006)	–0.01 (0.006)	–0.00 (0.003)	0.01** (0.003)
PromoSensitivity	0.28* (0.123)	0.06 (0.126)	0.01 (0.039)	–0.01 (0.033)	0.04 (0.021)	0.01 (0.020)
CustomerDemographics	Included		Included		Included	
Other Controls	Included		Included		Included	
π_s					–0.09*** (0.014)	–0.10*** (0.013)
Assignment Model			Included		Included	
Observations (*N*)	3,191,080		3,191,080		3,191,080	
χ^2 (d.f.) for endogeneity					56.42 (4) ***	

Note. Robust standard errors clustered at promotional events are presented in parentheses.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

effects of stacked discounts on sales ($\delta = 0.042$, $p = 0.000$) and return rates ($\delta = 0.044$, $p = 0.000$) slightly decrease, yet are consistent with our main findings, ruling out this explanation.

Second, a holiday-specific product (e.g., Santa Claus earring) can be offered with stacked discounts right after the holiday is over. In this case, one can argue that customers who purchase a holiday-specific product after the holiday may return this product simply because the product is outdated, not because it is offered with stacked discounts. Hence, the observed effect on sales and return rates might be due to a product being outdated. We address this by removing all purchases made two weeks after a holiday and running Model 3 using the remaining 2,240,826 observations. The results ($\delta = 0.039$, $p = 0.004$ in the *Sales* model and $\delta = 0.040$, $p = 0.000$ in the *ReturnRate* model) imply that even though post-holiday sales may potentially explain some of the estimated effects in the main model, a substantial amount of the estimated δs can still be attributed to the offer of stacked discounts, further strengthening our results.

5.7. Falsification Test of the Theory

We demonstrate with the laboratory experiment in Section 4 that when consumers' price judgments are accurate, discount framing does not have a measurable impact on sales and returns, suggesting that our theory is falsified when price misperception does not vary with the discount type. In this section, we conduct a falsification test of the theory using retail online channel data.

The retailer operates three online stores. Because of the company's consistent pricing strategy, during a promotional event, online stores also offer the same promotion for selected products as physical stores do. Similar to physical stores that advertise a promotional event using in-store displays, online stores display the details of a promotional event (e.g., "Save 20%–40% off all bridal") on the main page of their websites. However, unlike physical stores, online stores display the final price of a discounted product along with the product detail information. Thus, for online promotional purchases, consumer price judgments should be accurate regardless of the discount framing in effect, suggesting that our theory must be falsified for online sales.

During the 249 promotional events used in the physical stores analysis, we identify 165,145 SKUs that are offered with either of the two discount framings. We replicate our analysis using the sales and return rates for 165,145 SKUs and demonstrate the results in Table 5. We do not include the control variables specific to physical stores (i.e., *StoreSize*, *Mall*, *Location*, and *SalesVolume*) in this analysis.

The significant χ^2 statistic that tests for endogeneity suggests that Model 3 is the appropriate model to make inferences. We find that the impact of stacked discounts on sales and return rates is insignificant in the online setting, supporting our expectations regarding the falsification of the theory for online stores.[9] This suggests that displaying the final net price of a promotional product to consumers prior to a purchase prevents potential price misperception due to miscalculation. In such cases, stacked discounts are not different from economically equivalent single discounts for retail sales and return performance.

6. Profit Implications of Stacked Discounts

The analytical predictions and empirical findings show that, when the final price is not displayed to customers, framing a price promotion as stacked-percent discounts, relative to a single-percent discount, will increase sales and returns. This suggests that simply looking at the effect on sales quantity overstates the impact of stacked discounts on profitability. Consider the following profit function that is commonly used in

Table 5. Potential Outcomes Causal Model Results for Online Stores

	Model 1		Model 2		Model 3	
Variable	POM-0	POM-1	POM-0	POM-1	POM-0	POM-1
Sales model						
Effect of *Stacked* on *Sales*: δ	0.004 (0.004)		−0.015 (0.013)		0.008 (0.012)	
FinalPrice	−0.01*** (0.002)	−0.06*** (0.005)	−0.05 (0.065)	−0.04*** (0.004)	−0.01 (0.011)	−0.08* (0.034)
Discount	0.05*** (0.002)	0.13*** (0.004)	0.08** (0.029)	0.11*** (0.004)	0.06*** (0.010)	0.07*** (0.011)
Other Controls	Included		Included		Included	
π_s					0.29* (0.126)	−1.05*** (0.193)
ReturnRate model						
Effect of *Stacked* on *ReturnRate*: δ	0.002 (0.003)		−0.002 (0.006)		−0.008 (0.035)	
FinalPrice	0.12*** (0.006)	0.13*** (0.019)	0.11*** (0.007)	0.28*** (0.043)	0.13*** (0.014)	0.14*** (0.029)
Discount	−0.05*** (0.005)	−0.00 (0.014)	−0.05*** (0.005)	−0.05 (0.034)	−0.04*** (0.012)	−0.00 (0.017)
Other Controls	Included		Included		Included	
π_s					0.23*** (0.064)	0.12* (0.052)
Assignment model			Included		Included	
Observations (N)	165,145		165,145		165,145	
χ^2 (d.f.) for endogeneity					43.71 (4)***	

Note. Robust standard errors clustered at promotional events are presented in parentheses.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

the literature (e.g., Shulman et al. 2009, 2010; Su 2009; McWilliams 2012): $\Pi = q_s(p_n - c + ReturnRate(s - p_n))$ where c represents the procurement cost, q_s represents the quantity sold, s represents the salvage value obtained from a returned unit, and *ReturnRate* corresponds to the aggregated probability a purchase is returned as a percentage of q_s. Combining our empirical findings with the profit expression uncovers a novel tradeoff. On the one hand, stacked discounts increase profit due to the increase in unit margin over more initial sales. On the other hand, stacked discounts decrease profit due to the increase in return rate as more units that are procured at a procurement cost c will be salvaged as a returned unit only at a value of s. In this section, we examine the impact of stacked discounts on retail profitability in light of this tradeoff.

We compare the retail profit under the stacked-discounts scenario to that under the single-discount scenario over a wide range of parameter values for γ, c, s, and *ReturnRate*. Consistent with our empirical analysis on the interaction effect of γ (i.e., the difference between the actual net price and the consumer judgment of the price), we consider four different ranges for γ: first quartile, second quartile, third quartile, and fourth quartile. Note that p_n can be a multiplier in the profit function so long as c and s are defined as percentages of p_n. Thus, we normalize p_n to 1 and consider a continuous range of (0, 1) for c and s. Although a high value of c may represent a product with a high procurement cost, the normalization of p_n implies a higher value of c may also represent a product that is sold at a price close to its original procurement cost. Because q_s is also a multiplier in the profit function, we normalize q_s to 1 for the single-discount scenario. For the stacked-discounts scenario, we assume q_s increases by the estimated percentage (see Table 6) obtained from the interaction effect analysis of γ on the sales quantity. For instance, when the retailer offers stacked discounts such that γ falls in the first quartile, $q_s = 1.023$ (i.e., initial purchase quantity with stacked discounts is 2.3% more than the initial purchase quantity with an economically equivalent single discount). Prior literature demonstrates return rates range from 4% to 35% across industries (Rogers and Tibben-Lembke 1998, Guide et al. 2006). Thus, to capture industry-specific differences in return rates, we consider four different values for *ReturnRate*: 5%, 15%, 25%, and 35%. We use these values for the single-discount scenario. For the stacked-discounts scenario, we calculate *ReturnRate* using the estimated percentage increase (see Table 6) obtained from the interaction effect analysis of γ on the return rate model in Section 5.5. Note that the numbers reported in Table 6 do not represent the estimated return rates. Rather, they can be considered the percentage increase in return rate when changing the discount framing from single discount to stacked discounts. For instance, a retailer with a 5% return rate under a single-discount scenario will face a 6% return rate [i.e., 5% × (1 + 20%)] under a stacked-discounts scenario when γ falls in the first quartile.

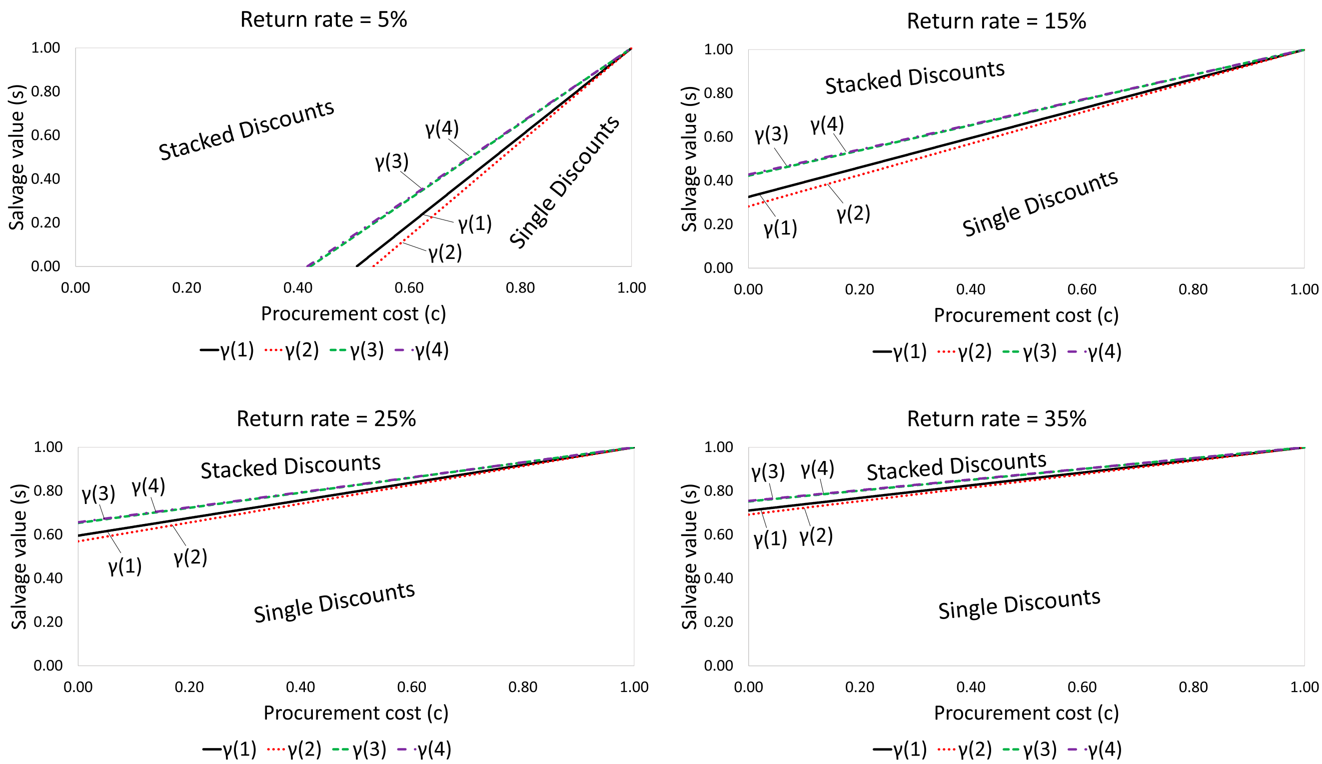
Figure 5 demonstrates the results of the numerical study with four panels. Each panel represents a different value for *ReturnRate*. Within each panel, the horizontal and vertical axes show the values of c and s, respectively. On each panel, the solid line corresponds to a γ value in the first quartile, the line with round dots (…) corresponds to a γ value in the second quartile, the line with square dots (- -) corresponds to a γ value in the third quartile, and the line with dash dot (– -) corresponds to a γ value in the fourth quartile, such that, offering stacked discounts is more profitable for retailers than offering an economically equivalent single discount for parameter values that fall above a line and vice versa.

Figure 5 indicates that there are cost structures such that offering stacked discounts would decrease retail profitability relative to offering an economically equivalent single discount. First, stacked discounts become less profitable than single discounts as c increases (i.e., as the procurement cost approaches the net price) because this limits the gains associated with the increased sales that stacked discounts generate. This implies that retailers should refrain from offering stacked discounts when operating with thin margins. Second, stacked discounts become less profitable as s decreases (i.e., as the value from salvaging a returned unit diminishes relative to the net price) because this increases the loss associated with the increased return rate that stacked discounts generate. This implies that retailers should refrain from offering stacked discounts when they obtain low salvage value from returned products. Third, stacked discounts become less profitable as the return rate increases. This suggests that stacked discounts can be a viable strategy, particularly for retailers with low return rates (e.g., furniture retailers, the auto parts industry, and the household chemicals industry) and should be cautiously assessed for retailers

Table 6. Estimated Increase in Sales Quantity and Return Rates

	The range of γ			
	First quartile	Second quartile	Third quartile	Fourth quartile
Increase in sales quantity	2.3%	4.8%	5.6%	6.7%
Increase in return rate	20%	38%	56%	67%

Figure 5. (Color online) Profitable Discount Strategy for Retailers



with high return rates (e.g., catalog retailers, apparel stores, and the consumer electronics industry).

Finally, we observe that stacked discounts do not necessarily become more profitable as γ increases. This can be explained by the tradeoff we identify. The variable γ has two contradicting effects on profit. First, as γ increases, sales increase (i.e., the positive effect on profit). Second, as γ increases, return rate increases (i.e., the negative effect on profit). If the positive effect compensates its negative effect (as in the case when γ increases from first quartile to second quartile), stacked discounts become more profitable as γ increases. Otherwise (as in the case when γ increases from second quartile to fourth quartile), single discounts become more profitable. These observations indicate that stacked discounts can be a profitable strategy, even when the difference between the actual net price and the consumer judgment of the price is low. This is in contrast to what one can infer from the existing literature (e.g., Chen and Rao 2007) that stacked discounts are more beneficial to retailers when consumer errors in price judgment are more severe (i.e., when γ is large) and further testifies to the unique value of considering the effect of stacked discounts on returns. In general, our numerical study suggests that retailers should consider the cost of returns, characterized by c, s, and *ReturnRate*, when making their discount-framing decisions.[10] We caution that, even though the profitability implications related to c, s, and *ReturnRate* are likely to be generalizable, the implications related to γ are conditional on the magnitude of the treatment effect estimates presented in Table 6. A different set of estimates on another data set may yield different managerial insights with respect to γ. Nevertheless, our research illustrates the importance of considering the discount format (and the resultant γ) in firm's profitability decisions and provides a useful approach to identify the contingencies of when to use single or stacked discounts as the appropriate promotional tactics.

In conclusion, although framing a final price as a result of stacked discounts can increase initial sales quantity, profitability can be diminished. Although the relationship between profitability and the severity of consumer errors in price judgment is likely to be retail-specific, our analysis suggests several generalizations. If the seller's profit margin or salvage value is sufficiently low, then the negative effect of stacked discounts outweighs the positive effect. The same is true for items that suffer from already high return rates. Therefore, the prescription from prior research for retailers to deploy stacked discounts should be taken with caution when their profit margin is thin, return costs are high, or salvage value of returned products is low.

7. Managerial Insights and Conclusion

This paper confirms and extends prior research on stacked discounts. We first build an analytical model to develop predictions regarding how stacked discounts affect retail sales and return rates. We empirically validate these predictions in a controlled laboratory experiment as well as using a large-scale retail data set. Combined, the converging evidence across multimethods shows that prior research overstates the advantages of stacked discounts. Although we confirm prior experimental findings that stacked discounts increase initial sales quantity, we uniquely identify a novel tradeoff relating to stacked discounts: Stacked discounts also increase return rates.

Both the analytical model and the empirical findings give insight into the process. Prior literature has shown that stacked discounts lead to a miscalculation of the actual price due to a whole-number strategy of incorrectly adding the discount percentages together. Our analytical model predicts that initial sales quantity and subsequent returns increase as the difference between the perceived price calculated using the whole-number strategy and the actual price increases. The empirical evidence validates these predictions. Thus, as stacked discounts create a greater disparity between the miscalculated price and the actual price, they will attract more customers to buy initially, but these customers are those whose ex ante known component of utility would be too low to buy without miscalculating the price. As such, the consumers attracted by stacked discounts are more likely to have ex post actual utility that is below the refund offered. Therefore, stacked discounts increase the likelihood that a purchase is ultimately returned.

The experimental study illustrates that the disparity between the miscalculated price and the actual price is the primary driver explaining the effect of stacked discounts. Consistent with this conclusion, we find in the retail data set that stacked discounts, compared with the economically equivalent single discounts, do not affect online sales and return rates. This arises because, unlike physical-store customers, online customers are able to see the final price of a discounted product before completing a transaction, suggesting that consumer price judgments are likely to be the same under both discount framings for online promotional purchases.

The practical implication is that, when accounting for the increase in returns, stacked discounts have less desirable consequences than previously stated. More importantly, there are cost structures for which prior literature would suggest that firms offer stacked discounts when in fact doing so would diminish profitability. For instance, in contrast to the existing literature (e.g., Chen and Rao 2007) implying that stacked discounts are more beneficial to retailers when consumer errors in price judgment are more severe, we demonstrate that stacking discounts may be a less profitable discount tactic than offering an economically equivalent single discount when this error is more severe. We note that such cases are possible when consumer errors in price judgment amplify the cost of returns more than the additional margins obtained from the increased initial sales. Otherwise, the severity of consumer errors in price judgment is likely to benefit the retailer more with stacked discounts than with single discounts. Consumers are likely to make such errors when discounts are large (e.g., holiday season sales), consumer education level is low, or the shopping environment distracts consumers from focusing on the price calculations (e.g., during busy holiday-shopping seasons when the stores are crowded and consumers have to make multiple purchases). From this perspective, our study suggests that, before determining their promotional tactic in such cases, retailers should first conscientiously evaluate how consumer purchase and return behavior changes in response to an increase in potential price miscalculation with stacked discounts and then make their discount-framing decision accordingly.

With respect to cost structures, we illustrate how the procurement cost and the salvage value on product returns relative to the selling price affect whether stacked discounts increase or decrease profitability. In particular, the negative consequence of stacked discounts outweighs the positive effect when returns are costly or when initial sales earn the retailer a low unit margin. We also show that stacked discounts might be more disadvantageous to companies with already high return rates.

Lastly, we also highlight that the effect of stacked discounts may depend on the channel in which the discount is offered as well as the demonstration of the discount. For online purchases, a typical procedure is to demonstrate the final price of a product before customers confirm the transaction. Hence, consumer price judgments are likely to be accurate, even with stacked discounts. This situation can also arise in physical stores if the final price of a stacked-discounted product is displayed on the price tag. In such cases, efforts and investments into examining the profitability of stacked discounts may be unnecessary, as the two discount framings should be equivalent with respect to their effects on sales and return rates. For other cases, our study suggests that managers should carefully assess their cost structures and consumer characteristics before implementing stacked discounts. From this perspective, our study could be considered limited to retailers that do not demonstrate the final price of a discounted product prior to a purchase. Another limitation of our study is that we do not consider a potential signaling effect of the discount-framing decision because the empirical data suggest that the signaling effect of stacked discounts is unlikely for the jewelry retailer. However, it is possible that such an effect might exist for other product categories. Thus, future research can examine the effect of stacked discounts on profitability when consumers infer various signals from stacked discounts. Lastly, a theoretical implication of our research is that among the customers who purchase stacked-discounted products, two distinct segments exist: (1) customers who would have bought anyway even if the discount is framed as a single discount and have a return rate of R, and (2) customers who are attracted only by stacked discounts and have a return rate of αR, where $\alpha > 1$. Thus, even though retailers can attract a new segment through framing promotional discounts as stacked discounts, potentially, it is also the high return rate of this new segment that can make stacked discounts less profitable than their economically equivalent single discounts. Future research can extend our study to empirically identify these two segments.

Acknowledgments
The authors thank Professor Yuxin Chen, the associate editor, and anonymous reviewers for constructive feedback throughout the review process. This paper improved significantly as a result of their guidance.

Appendix A. Stimuli for the Laboratory Experiment
Stimulus and measures for the stacked-discount condition:

Initial information	Imagine you are shopping for jewelry, and you found a necklace you like. 1/2 CT. T.W. Journey Diamond Double Pendant in 10K White Gold 
Price	Here's what you see on the price tag. Regular Price $1000 20% off plus an extra 25% off *final price given at checkout
Purchase intention	Would you buy it? 1 = very unlikely; 7 = very likely
*pe*1	Assuming no tax, what is the price consumers have to pay when they purchase this jewelry?
Postpurchase information	Imagine you bought the jewelry, and got the following information: 1/2 CT. T.W. Journey Diamond Double Pendant in 10K White Gold Beautifully crafted in 10K white gold, this unique design features a pathway lined with diamonds in graduating sizes, representing the road taken. A border of smaller accent diamonds adds even more sparkle to this remarkable design. Radiant with 1/2 ct. t. w. of diamonds, this pendant suspends from an 18.0-inch box chain that secures with a spring-ring clasp. 
Receipt	Here's the receipt. Take a careful look at the receipt. Regular Price $1000.00 Take 20% off; Take an extra 25% off -$400.00 You paid $600.00
Return intention	Do you want to keep it, or do you want to return it? 1 = definitely keep it; 7 = definitely return it
*pe*2	Remember how much you paid for the jewelry?

(Continued)

Socially desirable responding measures (1 = true; 0 = false)	I always accept others' opinions, even when they don't agree with my own. I never hesitate to help someone in case of emergency. When I have made a promise, I keep it—no ifs, ands, or buts. I always stay friendly and courteous with other people, even when I am stressed out. I always eat a healthy diet.
Demographics	Gender: 1 = male; 2 = female Have you ever bought jewelry? 1 = yes; 2 = no Are you interested in buying jewelry soon? 1 = yes; 2 = no
Hypothesis-guessing	What do you think the researcher is trying to find out?

The stimulus and measures are the same for the single-discount condition as the stacked-discount condition, except for the following:

Price	Here's what you see on the price tag. Regular Price $1000 40% off *final price given at checkout
Receipt	Here's the receipt. Take a careful look at the receipt. Regular Price $1000.00 Take 40% off -$400.00 You paid $600.00

Appendix B. Examining Parametric Assumptions for Econometric Models

In order to consistently estimate δ in Equation (6), the potential outcome equations must be correctly specified. A consistent estimator of δ using the simultaneous estimation of Equations (6) and (7) or using the simultaneous estimation of Equations (7) and (8) requires either the potential outcome equations or the selection model to be correctly specified, a property known as "doubly robust" (Wooldridge 2010). In addition, all three estimators require the overlap assumption (i.e., the assumption that ensures each product could receive any treatment assignment) (Wooldridge 2010). In this section, we aim to (1) assess the specification of both the potential outcome equations and the selection model and (2) examine the overlap assumption.

We define base sales and return rate models using the equation $E(Y_{ijs}|\boldsymbol{X}_{ij}, Stacked_{ij} = s) = \boldsymbol{X}'_{ij}\boldsymbol{\beta}_s$. We estimate the base models for each potential outcome in isolation using all covariates other than $Stacked_{ij}$. Table B.1 presents the results obtained from the base models under the "Base sales models" and "Base return models" columns. The $Stacked = 0$ and $Stacked = 1$ columns represent the base models for single-discounted products and stacked-discounted products, respectively. All the covariates have the expected signs and are mostly significant. For instance, consistent with past research (Jedidi et al. 1999, Anderson et al. 2009), an increase in *FinalPrice* or a decrease in *Discount* is associated with an increase in return rate. Model fit statistics (R^2 and Wald χ^2) indicate good fit in all models.

The "Assignment model" column in Table B.1 presents the results obtained from the treatment assignment model specified in Equation (7). We find that, except for *Holiday*, all the covariates in the assignment model are significant and have the expected signs. With a significant model fit statistic (Wald χ^2) and an 83.4% accurate classification of the membership for the two conditions (i.e., framing as a single discount or as stacked discounts), we conclude that our assignment model mainly captures the retailer's discount-framing decision.

The estimated models in Table B.1 are specified as linear, fractional probit, and probit models. Normality of residuals in these models is necessary to obtain accurate coefficients. We find that the residuals from these models follow normal distribution. Considering the model fit statistics and the normality of residuals, we conclude that the potential outcome models and the treatment assignment model are correctly specified.

The overlap assumption is violated when the estimated densities of the probability of getting each treatment level have relatively little mass in the regions in which they overlap and have too much mass around 0 or 1 (Busso et al. 2014). We examine this assumption by plotting in Figure B.1 the estimated kernel density of propensity scores (i.e., the probability that a product is framed as stacked discounts) obtained from the treatment assignment model. The figure displays that neither discount-framing type has too much mass near 0 or 1, and the two estimated densities have most of their respective masses in regions in which they overlap each other. Thus, there is no evidence that the overlap assumption is violated. Overall,

Table B.1. Baseline Sales/Return Models and Treatment Assignment Model Results

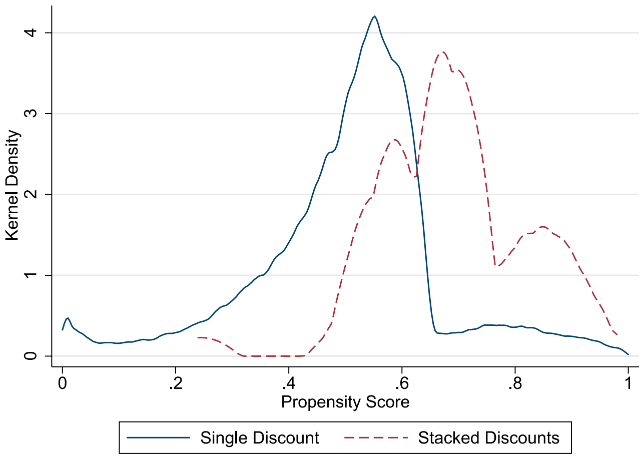
	Base sales models		Base return models		
Variable	*Stacked* = 0	*Stacked* = 1	*Stacked* = 0	*Stacked* = 1	Assignment model
FinalPrice	−0.02***	−0.00***	0.11***	0.11***	−0.65***
	(0.004)	(0.001)	(0.006)	(0.006)	(0.043)
Discount	0.01***	0.00***	−0.01***	−0.00***	0.87***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.041)
PastSales	0.00***	0.01***	−0.01**	−0.01***	−0.02**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.008)
PastReturnRate	−0.07***	−0.02***	1.36***	1.30***	−0.03***
	(0.009)	(0.003)	(0.055)	(0.041)	(0.007)
ShelfLife	−0.00***	−0.00***	−0.00***	−0.00*	0.00**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PromoDays	0.00***	0.00***	0.00	0.00*	−0.07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)
Holiday	0.01*	0.00*	0.02**	0.02***	0.05
	(0.005)	(0.002)	(0.005)	(0.006)	(0.174)
StoreSize	0.00	0.00***	0.04***	0.01	
	(0.001)	(0.000)	(0.009)	(0.009)	
ProdCat, Month, Year, BrandName	Included		Included		Included
SalesVolume, Mall, Location	Included		Included		
Sample size	1,497,578	1,693,502	1,497,578	1,693,502	3,191,080
R^2	0.44	0.34			
Wald χ^2			872,683***	1.11e+09***	3,960***

Note. Robust standard errors clustered at promotional events are presented in parentheses.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

we find the parametric assumptions for potential outcomes causal model are satisfied.

We note that there is a region (i.e., propensity scores less than 0.26) in which the probability of single-discount assignment is positive, whereas the probability of stacked discounts assignment is zero. In Section 5.6.1, we conduct a propensity-score matching and eliminate this region. We demonstrate that when the propensity densities are fully overlapping, our results still hold, suggesting that the difference between single discounts and stacked discounts when propensity scores less than 0.26 has negligible impact for our study.

Figure B.1. Estimated Kernel Density of Propensity Scores



Appendix C. Propensity-Score Matching

We match products offered with a single discount to those with stacked discounts using *FinalPrice*, *Discount*, *PastSales*, *PastReturnRate*, *ShelfLife*, *ProdCat*, *Holiday*, *Month*, and *Year* variables. With these variables, we aim to match products that are in the same product category and similar with respect to (1) their prices and the amount of discounts; (2) the demand, quality, and inventory level; and (3) the timing the discount is offered. Thus, the difference with respect to the outcome variables between the two groups after the matching can be attributed to the discount framing. We estimate the propensity score by using a logistic regression model in which $Stacked_{ij}$ is regressed on the observed covariates. Following Dehejia and Wahba (2002), we utilize radius matching without replacement, using the common support restriction with a narrow caliper range of 0.022. This process matches 1,359,287 stacked-discounted products to 1,087,360 single-discounted products.

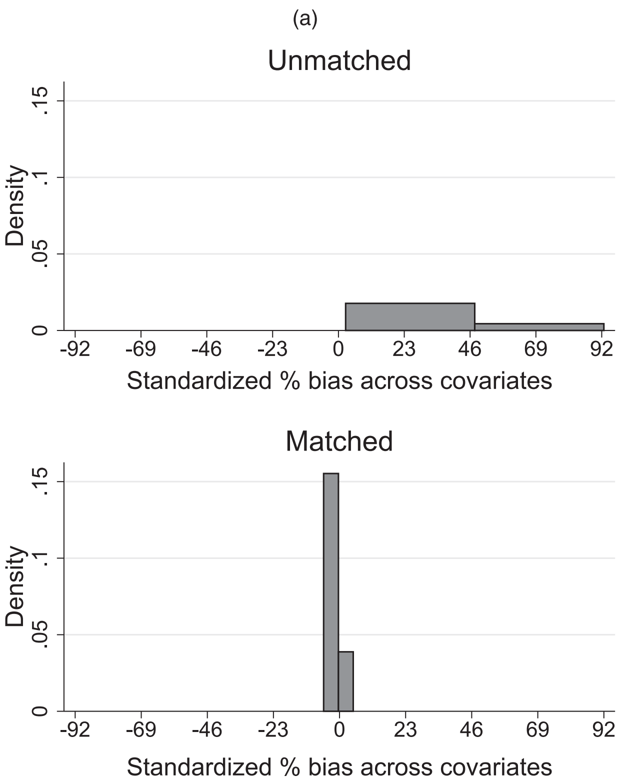
Table C.1 demonstrates the standard balance results obtained from propensity score matching. The *t*-tests that compare the means of continuous variables for the stacked-discounted products (i.e., the column *Stacked* = 1) and the single-discounted products (i.e., the column *Stacked* = 0) before matching demonstrate that the two groups have different distributions of covariates except *PastSales*. As the insignificant *t*-test results indicate, the matching process results in a subset of data in which the distributions of covariates are similar between the two product groups.

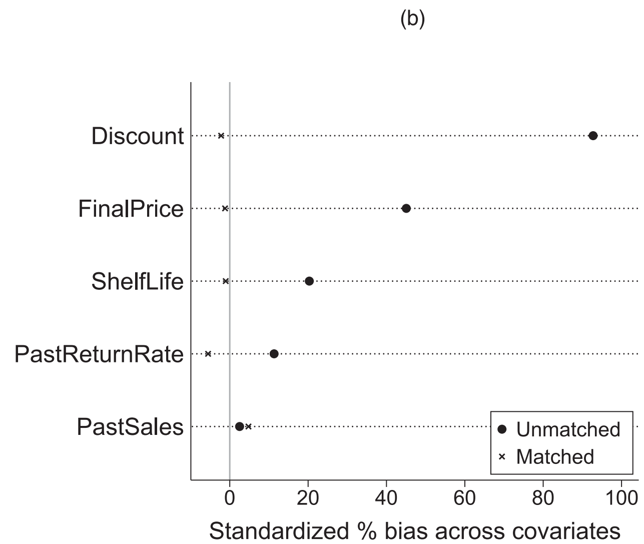
We find the average bias before matching is 34.4%. With propensity-score matching, we achieve an average reduction

Table C.1. Propensity-Score Matching

Variable	Unmatched or matched	Mean: *Stacked* = 1	Mean: *Stacked* = 0	Bias %	|Bias| reduction %	*t*-test: *t*	*t*-test: $p>\|t\|$
FinalPrice	U	5.60	5.10	45.1		403.35	0.00
	M	5.50	5.51	−1.2	97.3	−0.22	0.83
Discount	U	4.91	3.66	92.7		833.63	0.00
	M	4.50	4.53	−2.2	97.6	−0.35	0.73
PastSales	U	6.32	6.28	2.5		0.24	0.83
	M	4.56	4.46	4.8	−90.3	0.51	0.61
PastReturnRate	U	0.12	0.11	11.3		2.03	0.02
	M	0.12	0.13	−5.5	51.1	−1.01	0.31
ShelfLife	U	559.26	487.69	20.3		181.00	0.00
	M	164.81	168.46	−1.0	94.9	−0.15	0.88

Figure C.1. Standardized Percent Bias Before and After Matching

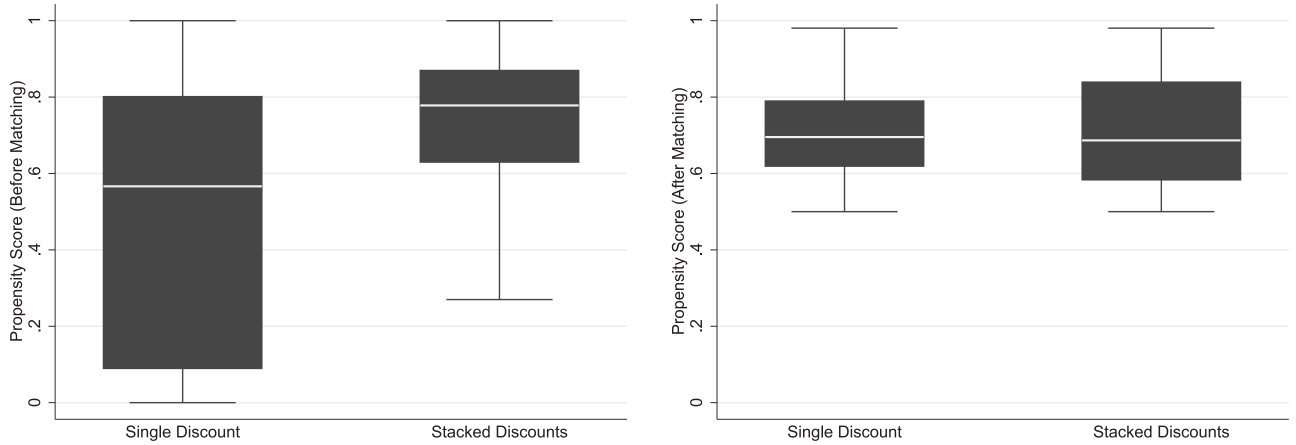




of 91.6% in bias for all covariates, decreasing the average bias to 2.9% as demonstrated in Figure C.1(a). Figure C.1(b) demonstrates the percent bias reduction for each continuous covariate used in the propensity-score matching. Note that, before matching *FinalPrice* and *Discount* are the two covariates that demonstrate the highest disparity between the two groups among all covariates. Our theory regarding the impact of discount framing on sales and return rates is predicated on the assumption that the two products, one is offered with stacked discounts and the other is offered with an economically equivalent single discount, have the same *FinalPrice* and *Discount*. Hence, matching the two groups on these two covariates is critical to obtain a more accurate measure of the discount-framing effect. As demonstrated in Figure C.1(b), we successfully match the two groups on *FinalPrice* and *Discount* as well as on other covariates.

We do not demonstrate the results for indicator variables (i.e., *ProdCat*, *Holiday*, *Month*, and *Year*), even though used in propensity-score matching, because the interpretation for indicator variables is not as straightforward as for continuous covariates. Yet, we note that the propensity scores are obtained from a logistic regression model that also includes indicator variables. Thus, to demonstrate the overall efficiency of propensity-score matching with observable covariates including indicator variables, we provide the box plots of propensity-score distributions for the two groups both before matching and after matching in Figure C.2. The figure

Figure C.2. Propensity Scores Before and After Matching



shows that the propensity-score distributions are different before matching; however, after matching the distributions are almost identical, providing evidence of common support. Overall, we conclude that propensity-score matching identifies stacked-discounted products that are similar to single-discounted products based on observed covariates.

Appendix D. Empirical Support for Insights from the Numerical Study

Note that our assignment model specified in Equation (7) represents the retailer's discount-framing decision process. To provide empirical support for our insights from the numerical study, we modify Equation (7) as follows: First, we use *OriginalPrice*, measured as the logarithm of the original price of a discounted product as a proxy variable for procurement cost c and replace *FinalPrice* with *OriginalPrice*. Second, the salvage value of a product at the subject retailer depends on the type of the contract the retailer signs with the supplier of that product. For instance, depending on the type of the contract, a supplier can fully or partially reimburse the retailer for all returned products. It is also possible that the contract does not allow returns and the retailer has to deal with returned products. Thus, using unique supplier codes that can be associated with SKUs, we include supplier fixed effects in Equation (7) as proxies to salvage value s. Note that *PastReturnRate* in Equation (7) corresponds to the return rate in the numerical study.

We construct the modified discount-framing decision model (i.e., Model D) in four steps by adding variable(s) of interest (i.e., *OriginalPrice*, *PastReturnRate*, and *SupplierFixedEffects*) to the assignment model without those variables (i.e., Model A). We assess the significance of adding additional variables in a model using the log-likelihood ratio (LR) test between the model with the additional variable and the model without the additional variable. We estimate these models using the first half (i.e., early periods) of our data. We demonstrate the results in Table D.1. The significant LR statistics suggest that the key variables of interest improve the model fit at each step. Thus, we use Model D for making inferences. The coefficients of *OriginalPrice* and *PastReturnRate* are both negative, suggesting that stacked discounts are less preferred as procurement cost and return rate (and thus return cost) increase. Model D classifies the membership for the two conditions (i.e., framing as a single discount or as stacked discounts) accurately for 86.4% of all observations. Next, using the estimated coefficients from Model D, we conduct out-of-sample prediction for the second half (i.e., late periods) of our data. We find that Model D is able to accurately predict the subject retailer's stacked-discounts versus single-discount decision during the late periods of our data for 80.9% of all cases. Overall, these empirical findings

Table D.1. Discount-Framing Decision Model Results

Variable	Model A	Model B	Model C	Model D
OriginalPrice		–0.83***	–0.84***	–0.84***
		(0.075)	(0.074)	(0.071)
PastReturnRate			–0.20**	–0.25**
			(0.063)	(0.093)
SupplierFixedEffects				Included
Other Controls	Included	Included	Included	Included
Sample size	1,594,419	1,594,419	1,594,419	1,594,419
Wald χ^2	4,482***	4,837***	4,933***	5,336***
LR (d.f.)		50,272 (1)***	118 (1)***	14,193 (97)***

Note. Robust standard errors clustered at promotional events are presented in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

further provide support for the numerical study insights regarding the impact of procurement cost, salvage value, and return rate on the retailer's discount-framing decision.

Endnotes

[1] See PRNewswire (2015), BusinessWire (2013), PRNewswire (2013), Sloan (2008), and Edelson (2009), respectively.

[2] In practice, consumers may mistakenly calculate the actual net price also with single discounts such that $\gamma > 0$ for single discounts. The model predictions are robust even if we modify our model to include such cases, so long as stacked discounts result in a greater overestimation than single discount, an observation we empirically support in Section 4.

[3] There are two alternatives to modeling a nonzero outside option. The outside option can be a constant $O > 0$ for all consumers or the utility of the outside option can depend on the customer. The latter is equivalent to our model in which μ_i represents the known relative utility (i.e., $\mu_i = \hat{\mu}_i - O_i$ where $\hat{\mu}_i$ is consumer i's known component of utility and O_i is the consumer's expected utility from the outside option). It is straightforward to show that the model predictions are robust to a constant nonzero expected utility from the outside option.

[4] Information from an actual receipt is recreated to preserve anonymity of retailer's identity.

[5] Note that our model assumes a constant marginal utility of money (i.e., consumer price elasticity is constant). Equivalent findings persist if consumers vary in their marginal utility of money. In which case, additional sales arising from stacked discounts would come from consumers with high marginal utility of money (i.e., high price elasticity) who would otherwise not buy at the actual net price and who are more predisposed to have low actual utility relative to the value of the refund. To flexibly allow for this possibility, a more rigorous explanation of our theory is that the additional consumers who are attracted by the lower calculated price have values of μ_i that are lower relative to the marginal utility of money. This intuition allows for the additional consumers gained to have either higher marginal utility of money or lower values of μ_i, each of which has a consistent effect on how sales and returns relate to the miscalculation in price.

[6] We also measured socially desirable responding using items from an existing scale (Stober 2001) to control for its potential effect on return, asked participants to guess the purpose of the study to control for the potential effect of hypothesis-guessing, and measured three types of demographics (i.e., gender, product experience, and product interest). All these were used as covariates in our analysis. We thank an anonymous reviewer for making this suggestion. The qualitative results hold when these measures are not included as covariates.

[7] This type of control function approach is sometimes referred to as the two-stage residual inclusion method and is demonstrated to be consistent for both linear and nonlinear models (Terza et al. 2008). Our insights are consistent even if we obtain the control function term as the generalized residuals of the treatment assignment model (as discussed by Wooldridge 2010).

[8] We acknowledge that an alternative explanation based on Thaler's (1985) segregate gains principle exists for our results. Under this alternative explanation, the segregate gains from stacked discounts could provide transaction utility at the time of purchase. If the return decision ignores the transaction utility and is based solely on the acquisition utility, the same pattern of results obtained in our theory and data could arise. We thank the associate editor for bringing this alternative explanation to our attention.

[9] We replicate the online stores analysis using only customers who shop (and products that are offered) both offline and online. Our results are robust to potential differences in customers and products between online and offline stores.

[10] In Appendix D, we provide evidence that the retailer's decisions of offering stacked discounts are consistent with this analysis.

References

ABC News (2014) Holiday shopping secrets for the best deals revealed. *Good Morning America* (December 15), https://abcnews.go.com/GMA/video/holiday-shopping-secrets-best-deals-revealed-27605945.

Ailawadi KL, Gedenk K, Langer T, Ma Y, Neslin SA (2014) Consumer response to uncertain promotions: An empirical analysis of conditional rebates. *Internat. J. Res. Marketing* 31(1):94–106.

Akcay Y, Boyaci T, Zhang D (2013) Selling with money-back guarantees: The impact on prices, quantities, and retail profitability. *Production Oper. Management* 22(4):777–791.

Alptekinoglu A, Grasas A (2014) When to carry eccentric products? Optimal retail assortment under consumer returns. *Production Oper. Management* 23(5):877–892.

Altug MS, Aydinliyim T (2016) Counteracting strategic purchase deferrals: The impact of online retailers' return policy decisions. *Manufacturing Service Oper. Management* 18(3):376–392.

Anderson ET, Hansen K, Simester D (2009) The option value of returns: Theory and empirical evidence. *Marketing Sci.* 28(3):405–423.

Bechwati NN, Siegal WS (2005) The impact of the prechoice process on product returns. *J. Marketing Res.* 42(3):358–367.

Bower AB, Maxham JG (2012) Return shipping policies of online retailers: Normative assumptions and the long-term consequences of fee and free returns. *J. Marketing* 76(5):110–124.

BusinessWire (2013) Save more on purchases this November with GO Outdoors. Business Wire. Accessed September 16, 2018 https://www.businesswire.com/news/home/20131030006210/en/Save-Purchases-November-Outdoors.

Busso M, DiNardo J, McCrary J (2014) New evidence on the finite sample properties of propensity score reweighting and matching estimators. *Rev. Econom. Statist.* 96(5):885–897.

Chen H, Rao AR (2007) When two plus two is not equal to four: Errors in processing multiple percentage changes. *J. Consumer Res.* 34(3):327–340.

Chen H, Marmorstein H, Tsiros M, Rao AR (2012) When more is less: The impact of base value neglect on consumer preferences for bonus packs over price discounts. *J. Marketing* 76(4):64–77.

Chintagunta P, Erdem T, Rossi PE, Wedel M (2006) Structural modeling in marketing: Review and assessment. *Marketing Sci.* 25(6):604–616.

Davis S, Gerstner E, Hagerty M (1995) Money back guarantees in retailing: Matching products to consumer tastes. *J. Retailing* 71(1):7–22.

Davis S, Hagerty M, Gerstner E (1998) Return policies and the optimal level of "hassle." *J. Econom. Bus.* 50(5):445–460.

Dehejia RH, Wahba S (2002) Propensity score-matching methods for nonexperimental causal studies. *Rev. Econom. Statist.* 84(1):151–161.

Douthit D, Flach M, Agarwal V (2011) A "returning problem": Reducing the quantity and cost of product returns in consumer electronics. Accessed July 1, 2016, http://www.accenture.com/sitecollectiondocuments/pdf/accenture-reducing-the-quantity-and-cost-of-customerreturns.pdf.

Edelson S (2009) Markdowns strike early, cut deep. *Women Wear Daily* 198(8):10.

Erdem T (1996) A dynamic analysis of market structure based on panel data. *Marketing Sci.* 15(4):359–378.

Erdem T, Keane MP (1996) Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Sci.* 15(1):1–20.

Ertekin N (2018) Immediate and long-term benefits of in-store return experience. *Production Oper. Management* 27(1):121–142.

Ertekin N, Ketzenberg M, Heim G (2019) Assessing impacts of store and salesperson dimensions of retail service quality on consumer returns. *Production Oper. Management.* Forthcoming.

Feng S, Cai JZ (2015) The impact of stackable discounts on retail price image. *Internat. J. Bus. Admin.* 6(6):26–35.

Ferguson M, Guide VDR, Souza GC (2006) Supply chain coordination for false failure returns. *Manufacturing Service Oper. Management* 8(4):376–393.

Guide VDR, Souza GC, Wassenhove LNV, Blackburn JD (2006) Time value of commercial product returns. *Management Sci.* 52(8): 1200–1214.

Hess JD, Mayhew GE (1997) Modeling merchandise returns on direct marketing. *J. Direct Marketing* 11(2):20–35.

Hess JD, Chu W, Gerstner E (1996) Controlling product returns in direct marketing. *Marketing Lett.* 7(4):307–317.

Holland PW (1986) Statistics and causal inference. *J. Amer. Statist. Assoc.* 81(396):945–960.

Janakiraman N, Ordonez L (2012) Effect of effort and deadlines on consumer product returns. *J. Consumer Psych.* 22(2):260–271.

Jedidi K, Mela CF, Gupta S (1999) Managing advertising and promotion for long-run profitability. *Marketing Sci.* 18(1):1–22.

Kruger J, Vargas P (2008) Consumer confusion of percent differences. *J. Consumer Psych.* 18(1):46–61.

MarketingCharts (2014) Consumers: Emails with discounts heavily influence purchase decisions. Accessed September 16, 2018, https://www.marketingcharts.com/digital-45559.

McWilliams B (2012) Money-back guarantees: Helping the low-quality retailer. *Management Sci.* 58(8):1521–1524.

Mohan B, Chandon P, Riis J (2015) Percentage cost discounts always beat percentage benefit bonuses: Helping consumers evaluate nominally equivalent percentage changes. *J. Marketing Behav.* 1(1):75–107.

Montaguti E, Neslin SA, Valentini S (2016) Can marketing campaigns induce multichannel buying and more profitable customers? A field experiment. *Marketing Sci.* 35(2):201–217.

National Retail Federation (2015) Consumer returns in the retail industry—Annual return survey. Technical report, National Retail Federation, Washington, DC.

Neslin SA (1990) A market response model for coupon promotions. *Marketing Sci.* 9(2):125–145.

Neter J, Kutner MH, Wasserman W, Nachtsheim C (1996) *Applied Linear Statistical Models* (McGraw-Hill/Irwin, Homewood, IL).

Ofek E, Katona Z, Sarvary M (2011) "Bricks and Clicks": The impact of product returns on the strategies of multichannel retailers. *Marketing Sci.* 30(1):42–60.

Petersen JA, Kumar V (2009) Are product returns a necessary evil? Antecedents and consequences. *J. Marketing* 73(3):35–51.

Petersen JA, Kumar V (2015) Perceived risk, product returns, and optimal resource allocation: Evidence from a field experiment. *J. Marketing Res.* 52(2):268–285.

PRNewswire (2013) Ruum American Kid's Wear promotes fall blowout sale with up to 50% off children's clothing. Accessed September 16, 2018, https://www.prnewswire.com/news-releases/ruum-american-kids-wear-promotes-fall-blowout-sale-with-up-to-50-off-childrens-clothing-229237481.html.

PRNewswire (2015) Celebrate International Women's Day with Angara Jewelry. Accessed September 16, 2018, https://www.prnewswire.com/news-releases/celebrate-international-womens-day-with-angara-jewelry-300045598.html.

Reinartz WJ, Kumar V (2003) The impact of customer relationship characteristics on profitable lifetime duration. *J. Marketing* 67(1): 77–99.

Richardson HL (2004) Point of no returns. *Material Handling Logist.* (June 7), https://www.mhlnews.com/transportation-amp-distribution/point-no-returns.

Rogers D, Tibben-Lembke R (1998) *Going Backwards: Reverse Logistics Trends and Practices* (Reverse Logistics Executive Council, University of Nevada, Center for Logistics Management, Reno).

Rolling CA, Yang Y (2014) Model selection for estimating treatment effects. *J. Roy. Statist. Soc. Ser. B* 76(4):749–769.

Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1): 41–55.

Rubin DB (1974) Estimating causal effects of treatments in randomized and nonrandomized studies. *J. Ed. Psych.* 66(5): 688–701.

Rubin DB (2005) Causal inference using potential outcomes. *J. Amer. Statist. Assoc.* 100(469):322–331.

Shulman JD, Coughlan AT, Savaskan RC (2009) Optimal restocking fees and information provision in an integrated demand-supply model of product returns. *Manufacturing Service Oper. Management* 11(4):577–594.

Shulman JD, Coughlan AT, Savaskan RC (2010) Optimal reverse channel structure for consumer product returns. *Marketing Sci.* 29(6):1071–1085.

Shulman JD, Coughlan AT, Savaskan RC (2011) Managing consumer returns in a competitive environment. *Management Sci.* 57(2): 347–362.

Shulman JD, Cunha M Jr, Clair JKS (2015) Consumer uncertainty and purchase decision reversals: Theory and evidence. *Marketing Sci.* 34(4):590–605.

Sloan C (2008) Bottomless pit of promotions. *Home Textiles Today* (October 13), http://www.hometextilestoday.com/article/431980-bottomless-pit-of-promotions/.

Smith SA, Agrawal N (2017) Optimal markdown pricing and inventory allocation for retail chains with inventory dependent demand. *Manufacturing Service Oper. Management* 19(2): 290–304.

Stata-Corp (2016) *Stata Statistical Software: Release 14.2* (StataCorp LP, College Station, TX).

Stober J (2001) The social desirability scale-17 (SDS-17): Convergent validity, discriminant validity, and relationship with age. *Eur. J. Psych. Assessment* 17(3):222–232.

Su X (2009) Consumer returns policies and supply chain performance. *Manufacturing Service Oper. Management* 11(4): 595–612.

Sun B, Neslin SA, Srinivasan K (2003) Measuring the impact of promotions on brand switching when consumers are forward looking. *J. Marketing Res.* 40(4):389–405.

Thaler R (1985) Mental accounting and consumer choice. *Marketing Sci.* 4(3):199–214.

Terza JV, Basu A, Rathouz PJ (2008) Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling. *J. Health Econom.* 27(3):531–543.

Wood SL (2001) Remote purchase environments: The influence of return policy leniency on two-stage decision processes. *J. Marketing Res.* 38(2):157–169.

Wooldridge JM (2010) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, Cambridge, MA).

Xu L, Li Y, Govindan K, Xu X (2015) Consumer returns policies with endogenous deadline and supply chain coordination. *Eur. J. Oper. Res.* 242(1):88–99.