MARKETING DECISION MAKING AND ITS DOWNSTREAM EFFECTS ON CONSUMER BEHAVIOR

by

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STATEMENT OF DISSERTATION APPROVAL

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ABSTRACT

Marketers invest significantly in generating consumer action, with curiosity one of many ways to pique interest. This is the topic of our first essay, in which we discuss how discounted price displays arouse curiosity, thus affecting information search behavior. This essay moves beyond the assumption that any prediscounted price will elicit the same consumer response and considers four moderating factors, including i) absolute price, ii) dispositional curiosity, iii) expected price and iv) drive states such as hunger. In a series of examinations, we propose that higher (lower) prices generate greater (less) curiosity. Findings inform psychology-based accounts of curiosity and provide implications for marketers in understanding pricing's effect on information seeking.

Essays 2 and 3 explore the long-term impact of a referral on sender and receiver behavior. Marketers have long sought to harness the influence of existing customers, with much literature focusing on a referral's worth. While prior research has extensively examined referral value, less is known about how the specific information within the referral itself differentially influences behavior. Thus, Essay 2 focuses on the degree of customization within the referral, examining for both senders and receivers the influence of custom (sender-generated) versus standard (company-generated on behalf of sender) referrals. To test our predictions, we utilize email referrals from retail customers and

compare purchase behavior between these referral types, testing the underlying theories of spotlight effect and reciprocity.

In our third essay, we ask whether the act of referring changes long term purchase behavior of referrers. Extensive literature has proved the value of customers acquired through referral efforts of existing customers. However, while much is known about the incremental value of referrals, less is known about the intervening role of the referral itself. Therefore, in our research we seek to understand how a referral influences future sender behavior and ask whether the act of referring results in an increase, decrease, or consistency in purchases for senders. We explore opposing predictions based on i) dissonance and ii) market mavens and explore these predictions through an empirical examination of transaction data, offering implications for marketers and theorists alike.

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ESSAY 1: HOW DISCOUNTED PRICE DISPLAYS AFFECT INFORMATION SEARCH BEHAVIOR

Introduction

Marketers invest significantly in implementing tactics aimed at generating consumer interest in their offerings. One popular method involves price displays that seek to arouse intrigue in the “bargain” or “deal” for a particular product. For example, the electronics retailer Best Buy offers online daily deals that feature the regular, prediscounted price for a given product. In order for consumers to see the special price—that is, to learn of the magnitude of the deal being offered—the consumer is encouraged to first place the item into their virtual shopping cart. Similarly, various products offered on the online auction site eBay show the prediscounted price with a strikethrough (e.g., $~~38.99~~), with the special price being displayed only at checkout. Despite marketers’ common usage of this tactic to generate what we refer to as price curiosity—that is, the ability to pique consumer interest from price displays—no known research explores the different factors that might influence this interest and, hence, consumer action.

In this research, we examine the effect of price curiosity on consumer action. Specifically, we explore two alternate accounts. The first, which we coin as the “marketer’s intuition” account, relies on a heuristic commonly used in marketing whereby the lowest prediscounted price will generate the greatest action. That is, this account posits that consumers will be most interested in seeing “how low can it go” in terms of price. The second account—a psychology-based account on curiosity—suggests that the less predictable outcome may generate greater interest. That is, it implies that a higher prediscounted price would be more likely to arouse greater curiosity than lower prices. Just as a story with multiple endings may increase a reader’s intrigue, this account suggests that a higher price—which includes a greater number of possible prices—will be viewed with greater interest.

Importantly, this essay moves beyond the assumption that any prediscounted price will elicit the same response from consumers and asks four key questions that explore various moderating factors of curiosity. First, what is the effect of absolute price; that is, would a high price or low price result in greater curiosity? Second, given the heterogeneous nature of curiosity, what might be the role of one’s dispositional curiosity? Third, how might one’s price expectation—that is, their expected price and acceptable price range for a given product—influence curiosity? Finally, with curiosity theorized to be a homeostatic drive similar to such drives as hunger or thirst, could one’s price curiosity be affected by manipulating such factors? To answer these questions, we begin with a marketplace test that measures consumer response to actual emails that include—among other factors—the strikethrough price. Then, to test for theoretical underpinnings in a more controlled setting, we use eye tracking for process evidence, which also examines the moderating role of one’s dispositional curiosity. A subsequent lab study examines the moderating role of expected price and price range across various products. Finally, we seek to validate the drive-based accounts of curiosity through a controlled lab study examining the role of hunger in one’s propensity to engage in curiosity-seeking behaviors.

This research has many theoretical and practical implications for consumers and managers alike. From a theoretical perspective, our research further informs the role of the gap in one's knowledge in generating curiosity. Second, we are able to support our hypothesis with process evidence of curiosity through the use of eye tracking. Third, our research informs extant literature's discussion on the drive-based role of curiosity and its similarity to other innate drive states such as hunger. From a practical perspective, we are able to provide marketers with valuable insights regarding the role of price in piquing consumer interest. This has significant implications for marketers in understanding the effect of high and low price points on the consumer's desire to seek additional information, and in enabling sharper predictions of consumer response to an offer based on the factor of price.

In the section that follows, we begin with a review of existing literature on curiosity and information search behavior in marketing. Based on these extant theories, we then build our theoretical framework. Subsequently, we present real world data and controlled lab studies to test our research propositions and then conclude with a general discussion including implications for marketers and theorists alike.

Theoretical Review

Past research suggests that curiosity arises when one's desire to know surpasses their current knowledge for a given topic (Loewenstein 1994). Hence, it can be understood as a knowledge or information gap between one's existing and desired information states. Whenever there is a perceived gap between these two states, curiosity is aroused that motivates one to search for information that can close the gap. While there are many viewpoints on what fuels curiosity, early theorists viewed it as being influenced by both internal drives and external states. That is, it is conceived as a homeostatic drive—similar to one's hunger (Dashiell 1925; Nissen 1930) in that it that will intensify in magnitude if left unsatisfied—and is also viewed as stimulus-induced drive state that can be induced by external (environmental) stimuli. Panksepp (1998), for example, discusses the role of curiosity as part of an animal's Seeking system, which—along with the Rage, Fear, and Panic systems—is responsible for survival. Specifically, the Seeking system is what makes animals eagerly explore the environment around them. In humans, it is believed to be the system that is responsible for one's curiosity, including intellectual pursuits (Panksepp 1988). Given that it is treated as more of a drive state, it has also been suggested that if curiosity is left unexplored, it will intensify and only diminish after the appropriate level of information is found that can assuage (or appear to assuage) the drive. Such an increase in one's curiosity intensity is directly related to one's ability to close the information gap. Curiosity is theorized to follow an inverted U-shape when considered across one's knowledge gap. Generally, when the knowledge gap is narrower, low curiosity ensues. As the knowledge gap increases, curiosity begins to increase. However, after a certain point, a further increase in the knowledge gap results in decreased levels of curiosity. For example, as noted by Piaget (1969), a very low discrepancy between what one knows and what one desires to know would result in an effortless, automatic retrieval of information. Hence, low curiosity would be aroused as the narrow information gap can be eliminated with little-to-no effort. On the other end of the knowledge gap, when the knowledge gap is perceived as extremely wide, it will quite possibly prohibit one from pursuing additional information. Thus, in the case of a wide information gap, one may exhibit low curiosity and neglect to seek new information. This is attributed to the depletion of cognitive resources associated with the increased perceived effort that is required in one's attempt to close a wide knowledge gap. As discussed by Loewenstein (1994), consider an individual that knows the capitals of 47 of the 50 state capitals versus an individual that knows only three of the 50. It is theorized that the individual knowing 47 of the capitals is more likely to frame their situation as not knowing three capitals. Applying the knowledge gap principle to this example, the individual's narrow knowledge gap may trigger the feeling that his or her knowledge of the state capitals is already sufficient. Thus, curiosity for knowing the final three state capitals may not be worth his or her effort. As for the latter person, given the extremity of their knowledge gap in only knowing three of the 50 state capitals, it is suggested that this individual would be more likely to view the knowledge gap as too wide to traverse. Thus, the very wide gap could serve as a deterrent to curiosity-fulfilling behaviors. These examples illustrate how the magnitude of the knowledge gap influences one's decision to engage in (or defer on) additional information seeking.

Pertinent to marketing, extant research has considered the importance of curiosity in capturing consumers' attention or in keeping them engaged. Curiosity has been considered an essential component of information search in that it enables consumers to learn more about the environment around them (Steenkamp and Baumgartner 1992). Because curiosity can motivate individuals to seek more information to confirm or refute their hypotheses (Klayman and Ha 1987), it is no surprise that curiosity is a commonly employed tactic in engaging consumers. We find marketers implementing various tactics that are aimed at piquing consumer interest by presenting only part of the story or message. These tactics have proven to positively influence the consumer's desire to seek additional information. For example, "mystery ads"—that is, those ads in which the brand is not identified until the latter part of an ad—were found to be more effective in producing memory associations than less mysterious ads, attributed in part to one's curiosity (Fazio, Herr, and Powell 1992). Furthermore, prior research and its usage of curiosity as an impulsivity manipulation suggests a strong linkage between one's curiosity and subsequent behavior. For example, Hartig and Kanfer (1973) examined the effect of temptation on impulsive behaviors by informing children to resist peeking at a "surprise" toy offering for an extended period in an experimental setting. The latency of a child's transgression—that is, the time it took for the child to give way to their curiosity—was subsequently measured across various conditions.

Summarizing early research on curiosity (Hebb 1955; Hunt 1963; Piaget 1969), three common propositions resonate, showing that curiosity i) reflects an individual's natural tendency to seek and to make sense of the world, ii) is triggered by violated expectations between what one knows and what one seeks to know, and iii) follows an inverted U-shaped relationship in accordance to the magnitude of the information gap. Subsequent research has validated these propositions, showing that vague (versus detailed) information can increase one's interest and learning via curiosity, but only when the knowledge gap is at a moderate level. For example, in one study, Menon and Soman (2002) varied the level of information presented in an advertisement for a digital camera and directly solicited responses on participants' curiosity, interest, involvement, and intent for the product. Results confirmed that a higher degree of curiosity comes from a moderate (versus a wide or a narrow) knowledge gap. Finally, Dijk and Zeelenberg (2007) provide additional insights through what was coined as the "sealed-package paradigm," whereby the presence of "hints" (information) was shown to increase one's willingness to pursue options with uncertain outcomes. In this research, participants were more likely to opt for a mystery package (versus known monetary remuneration) for their participation in a lab study when they were given just a small amount of additional, but still incomplete, information about the product.

Thus far, we have mainly discussed extant literature's view on the various stimulus-based determinants of curiosity. Literature has also provided valuable insights relative to the underlying physiological factors affecting one's curiosity. Within the human Seeking system—which is the emotional system responsible for human's interest and eagerness to explore—a very important driver of curiosity is the neurotransmitter dopamine. Research has explored how curiosity is affected by one's dopamingergic activity, which has been shown to help control the brain's reward and pleasure systems. Specifically, increased dopamine activity has been shown to be strongly associated with one's curiosity. It is believed that these dopamine circuits promote curiosity—that is, states of eagerness and directed purpose—in humans and animals alike (Panksepp 1998; Silvia, and Kashdan 2009). For example, when the human Seeking system becomes underactive—commonly associated with aging—a form of depression results that is believed to result in less eagerness to explore (i.e., less curiosity). This is corroborated by medical research among Alzheimer's patients, which has linked reduced levels of dopamine to a general lack of curiosity and unwillingness to explore the environment around them (Cross et al. 1981). With the drive for food being one of the most prevailing behaviors within the Seeking system, it should come as no surprise that dopamine is believed to regulate food intake. In Volkow et al. (2002), it is discussed how the expectation of food increases dopamine activity. Specifically, their research showed that food stimulation—i.e., the thought or possibility of food—in combination with a drug known to increase the amount of dopamine in the synapse resulted in higher self-reported measures of "hunger" and "desire for food." Similarly, Piech et al. (2009) discuss food stimuli's role in increasing dopamine and subsequent motivational arousal, with results suggesting the ability of food-related cues to induce hunger.

In addition to identifying determinants of curiosity, research has also identified ways to measure one's curiosity. An individual's eye movements and fixations have been shown to correlate strongly with general interest and attention to stimulus that is found to be more curious or novel (Berlyne 1958). For example, Loftus and Mackworth (1978) show that "informative stimuli"—e.g., stimuli with a low a priori probability of making an appearance—results in greater focus. Specifically, they show that novel (which they refer to as highly informative) stimulus (e.g., the unexpected appearance of an octopus within a picture of a rural farm landscape) is found faster, looked at more often and viewed with longer duration than expected (i.e., uninformative) stimulus. Similarly, medical research on the effects of aging and dementia among Alzheimer's patients demonstrated less visual attention (i.e., less eye fixation) to novel stimulus and a greater deterioration of visual exploratory activity (versus a matched control). From this, researchers concluded that diminished curiosity could be measured via eye tracking methods (Daffner et al. 1992), with less focus on novel stimulus representing less curiosity.

Theoretical Conceptualization

Let us consider the example of a consumer receiving information in the form of an email including various products offered at discounted prices. Within this email, each product is presented at the nonpromoted retail price. That is, the price is displayed at its original (full) price with a strikethrough line running through it, indicating to the consumer that the new price is at some point below its original (e.g., $~~70~~). In such an instance, two possible outcomes could occur, with each driven by a different theoretical mechanism. The first, referred to in our introduction as the "marketer's intuition" account, relies on a heuristic commonly used in marketing whereby the lowest (prediscounted) price will generate the greatest action. That is, this account suggests that consumers will be more likely to seek additional information in hopes of learning (and being delighted by) just how much the already low price could be reduced. The second account—which stems from psychology-based accounts on curiosity—suggests that the less predictable outcome is likely to generate greater interest. That is, it posits that a higher prediscounted price would be more likely to arouse greater curiosity than lower prices. We next discuss each of these accounts (i.e., marketer's intuition and psychology-based) in greater detail.

Extending the example from the prior paragraph, if the marketer's intuition account holds, we would expect to find greater curiosity for a lower strikethrough price, all else equal. As previously alluded to, this is attributed to the consumer's interest in seeking the best deal. If the strikethrough price is already low, this account would suggest an increased interest for the consumer in seeing how low the price could go. Consider a product with an acceptable consumer price range \$70–\$90.[1] When featured with the message “is regularly \$70”—that is, when featured at the lower end of the \$70–\$90 price range—the marketer’s intuition account would suggest greater excitement versus a price at the higher end of the range. This excitement—driven by the low absolute starting price—would be expected to result in greater information search. Conversely, if the psychology-based account holds true, we would expect to find greater curiosity at the higher end of this price range (e.g., “is regularly \$90”). We attribute this effect to the differential in the knowledge gap that we expect when a product is featured at a high or low price, with higher prices creating a wider knowledge gap in light of the greater number of absolute unknowns in terms of alternate price points. Returning to our price example, a product that is featured with the message “is regularly \$90” includes more alternate price points in the absolute versus a product featured as “is regularly \$70.” From this, the sheer number of alternate price points for the \$90 offering is likely to result in an increased knowledge gap that could result in greater curiosity.

After testing which of the competing accounts shows greater curiosity (that is, the marketer’s intuition account or the psychology-based account), we then seek to explore three additional moderating factors. First, for the prevailing account, we expect to find process evidence that is consistent with increased curiosity. For this, we turn to eye tracking methodology. Relying on extant literature’s findings that increased fixation occurs with more novel stimulus (Berlyne 1958), we expect to find greater eye fixation on stimulus theorized to generate greater curiosity. For example, if the psychology-based account were to hold, we would expect to find that higher (lower) strikethrough prices

[1] Importantly, this assumes that the price falls within some acceptable range and conveys comparable quality to consumers. That is, it is expected that marketers, in establishing the strikethrough price, take into account the acceptable price range for a given product.

result in higher (lower) eye fixations on the price stimulus, all else equal. Second, in order to test for the presence of the knowledge gap, we seek to examine the moderating roles of expected price and price range for a given product. This allows us to see if an individual's price expectation and their acceptable price range results in the knowledge gap reaching a point whereby information is no longer sought. Third, with extant literature's view of curiosity as a homeostatic drive (similar to hunger), we would expect to find increased curiosity-seeking behaviors in conjunction with an intensified seeking system—specifically, via increase in one's desire to satiate their hunger. That is, we would expect to find that food stimulation results in behaviors consistent with greater information seeking. To test this proposition, we implement a food-stimulation manipulation prior to measuring the effect of price curiosity.

We next describe the different methods aimed at testing our propositions. First, we utilize data from an online retailer to examine whether high versus low strikethrough prices result in greater curiosity and subsequent information search. We then present a series of lab studies to i) corroborate our findings and ii) help test the underlying process in a more controlled setting.

Marketplace Test for Price Curiosity

In our first examination, we seek to measure the effect of a high versus low strikethrough price on curiosity in a real-world marketplace setting. Our data were from an online retailer, including over 3 months of daily emails sent to existing members. Each email featured one main product and 2–3 supplemental product offers. Each of these offers included the product image along with a brief description. Moreover, each product was promoted using strikethrough price. All products included a button reading as "Check it Out," enabling the consumer to click through to learn more about a given product. Importantly, this provided us with the opportunity to measure one's propensity to seek additional information about a given product, which we utilize as our main dependent measure. Revisiting the alternate accounts from our theoretical predictions, if the marketer's intuition account holds, we should find greater click-through from lower strikethrough prices. If it is the curiosity account that holds, we should see the opposite—that is, greater click-through from higher strikethrough prices.

Method

Eighty-one emails over a span of 91 days were analyzed, which comprised a total of 322 product offers sent to 905 existing customers that previously opted-in to receive daily deals from the online retailer. As previously noted, upon opening the email, consumers could click on one of approximately three to four offers (each featuring price with the strikethrough and an accompanying text description) to learn about the actual discounted price. Key variables include consumer clicks on the offer, the strikethrough price as well as controls such as feature order and accompanying text. In order to account for customer-specific heterogeneity, a longitudinal panel data model—i.e., a random effects logistic regression—was run. Panel data present an advantage in enabling the researcher to observe the repeated outcomes from the same economic units (i.e., customers) over time (Arellano and Bonhomme 2012). A random effects model assumes that the individual (in our case, customer-specific) effects are uncorrelated with the model's predictors (Allison 2009). In our case, the availability of customer-specific longitudinal data allows us to control for unobservable characteristics that could be correlated with the initial variables in our model. Thus, our aim in this analysis is to account for the unobserved differences that likely exist among customers and the fact that those differences may change over time.

In this examination, we predict a customer's click-through probability as a function of the strikethrough price (log-transformed to induce linearity), whether or not it was the lead feature (dichotomized as 1 = lead feature, 0 = secondary feature) and the accompanying text. For this latter measure, the accompanying text, we measure its descriptiveness. Past research on linguistics, which measures a message's overall "emotiveness" (Piskorski, Sydow, and Weiss 2008) can be used to understand the effect of product description as a moderator. In short, the emotiveness measure is the ratio of modifiers (i.e., adverbs and adjectives) to content words (i.e., nouns and verbs), with higher emotiveness equating to more descriptive text. The model is noted in Equation 1.

$$\Pr\left(\mathrm{Click}_{\mathrm{ip}} = 1 \,\middle|\, \mathrm{LogPrice}_{\mathrm{p}}, \mathrm{Lead\ Feature}_{\mathrm{p}}, \mathrm{Text}_{\mathrm{p}}\right) \tag{1}$$

$$= \frac{e^{\beta_0 + \beta_1 1\mathrm{LogPrice}_{\mathrm{p}} + \beta_2 \mathrm{Lead\ Feature}_{\mathrm{p}} + \beta_3 \mathrm{Text}_{\mathrm{p}}}}{1 + e^{\beta_0 + \beta_1 1\mathrm{LogPrice}_{\mathrm{p}} + \beta_2 \mathrm{Lead\ Feature}_{\mathrm{p}} + \beta_3 \mathrm{Text}_{\mathrm{p}}}}$$

Results

Before running our main analysis, we first ensured that the random effects model (versus a fixed effects model) is appropriate by running a Hausman test. Based on the results ($\chi 2$ = .12, *p* = .98), we fail to reject the null hypothesis that the random effects (versus fixed effects) model is the preferred approach and thus proceed with our planned analysis. The results show a significant effect from price, indicating a greater probability of clicks for higher-priced offers ($\beta_{LogPrice}$ = .09, z(905) = 2.62, $p < .04$). Furthermore, as one might expect, lead features (versus secondary features) are more likely generate clicks ($\beta_{LeadFeature}$ = 1.25, z(905) = 23.17, $p < .01$). For text emotiveness, we find no main effect from increased or decreased text descriptiveness (β_{Text} = -.05, z(905) = -1.29, $p <$ .20). In interpreting the results from the model, a 10% increase in strikethrough price predicts a .38% increase in the probability of a click. Figure 1 illustrates for the main product offer the effect of low price (at the 10^{th} percentile of prices) versus high price (at the 90^{th} percentile of prices) on the probability of a click-through.[2]

Discussion

Thus far, we find evidence for increased price curiosity from high (versus low) prices. While we control for such factors of customer heterogeneity and text emotiveness, we acknowledge the multitude of exogenous influences from such factors as one's dispositional curiosity, the product category, one's price threshold, etc. We therefore pose two key questions in seeking to further validate our findings. First, what might suggest that curiosity is at play; that is, what process evidence might exist in support of the curiosity account? Second, with this analysis limited to a specific product category, might the same effect occur via random assignment of high and low prices across multiple product categories? Given these questions, we planned further studies to test for the generalizability of the effect and its underlying mechanism. In the sections that follow, we discuss our approach.

[2] Results are illustrated for lead feature products. A similar main effect emerges for secondary products.

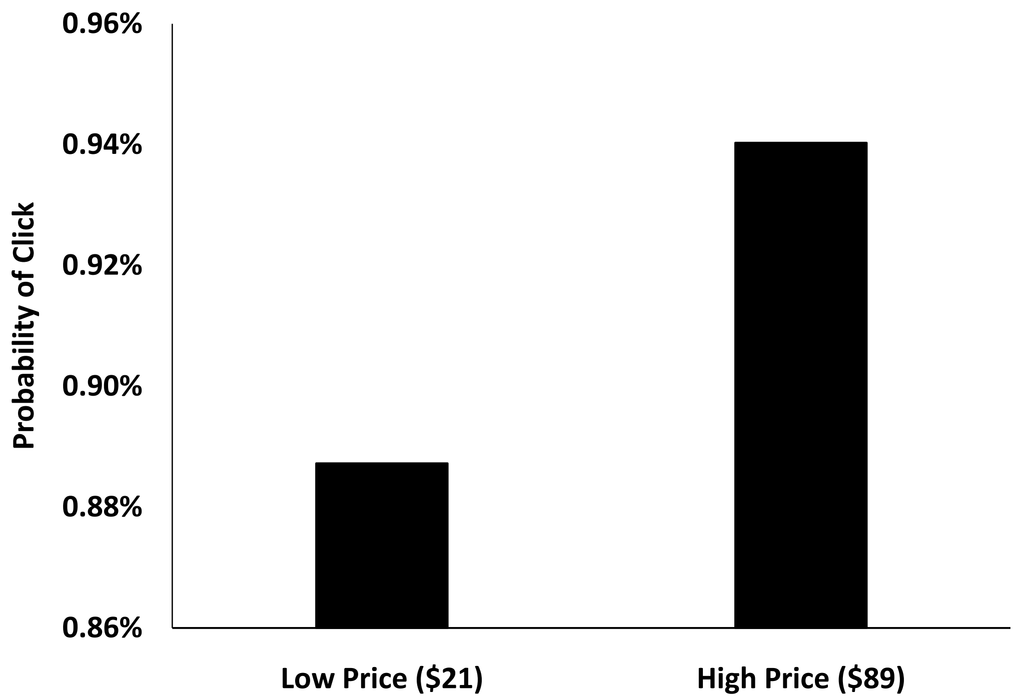


Figure 1: Marketplace Test Results Show Greater Click-Through for High Price

Test for Process Evidence in a Controlled Setting

Thus far, we find evidence that a higher strikethrough price results in greater information-seeking behaviors, which we attribute to increased curiosity. The results of the email data reveal that the outcome predicted by the psychological mechanism seems to be at work. To test the mechanism further and to generalize the results, we conducted this current study to gather process evidence in a more controlled setting. For this we use eye tracking. This allows us to i) control for one's dispositional curiosity by measuring their response (eye fixation) to extant stimulus and then to ii) examine eye fixation on product and strikethrough price stimuli. Importantly, in this test we also extend the assessment to include multiple product categories varying both in price and in price range.

As discussed in our theoretical background, prior research has shown that people tend to focus on what they find to be novel or curious (Berylne 1958; Starker and Bolt 1990). For example, Daffner et al. (1994) attributed one's lack of exploratory eye movements to decreased novelty seeking and curiosity among participants (Alzheimer's patients). Therefore, in the context of our prior examination, we posit that higher price points—which we theorize to result in greater curiosity—should receive more visual attention relative to lower price points, all else equal.

Method

In this study, we employ the use of a portable eye tracking device in order to capture participants' eye movement data for on-screen stimuli. The device's ability to track pupil movement provided access to data that revealed exactly when, where, and for how long a given participant looked at the on-screen stimuli. From this, we measured participants' ocular fixation for on-screen stimuli, which we next describe.

Sixty-one undergraduate students were recruited in return for partial course credit to take part in the study. After the initial explanation about the experimental procedure involving eye tracking, participants were equipped with the eye track device and seated at a computer. Participants were first presented with stimulus from past research known to result in greater attention linked to one's curiosity. Borrowed from research in experimental psychology (Berlyne 1958, 1960), the intention of this preliminary exercise was to establish one's dispositional or chronic level of curiosity based on the premise that "novel" stimulus results in greater eye fixation, similar to the effect from increased curiosity. To establish this dispositional measure of curiosity, a total of 16 screens were presented to participants. These consisted of eight screens including novel stimuli in the form of varying shapes. Each of these eight screens was separated by an interstitial or calibration screen that included two intersecting lines for which participants were instructed to focus on the center. The first screen that was displayed for the participant included the calibration—that is, the intersecting lines. After a countdown of approximately 7 seconds, the first set of shapes appeared. Each set included two images. This sequence—that is, the intersecting lines screen followed by the shapes screen—continued for approximately 2.5 minutes. For this part of the exercise, participants were instructed only to focus on the center of the intersecting lines within those screens and that they were free to look wherever they chose when the subsequent shapes screen appeared.

From this exercise, we segue into the main part of our study; that is, the method used to test our dependent measure of eye fixations on product and price stimuli. Participants, during the above referenced initial briefing, were instructed that products may or may not appear on the screen after the shapes exercise. All participants—at the conclusion of 16 screens for the novel stimuli presentation—were randomly assigned to a high or low price condition. In the high (low) condition, participants were first presented with the intersecting lines and then presented with a screen that included a product image/logo followed by a high (low) strikethrough price. This process continued for each of six products featured with a strikethrough price that was at a value above (below) the marketplace's expected price.[3] The six selected products were aimed at providing a mix

[3] High and low prices were based on an online assessment for the high and low prices being featured for a given product, providing us with a reasonable range of prices for the purposes of this study.

of high and low price ranges. For example, a high price range example included a 32” LED HDTV, which, on average, costs approximately $299. In this example, participants were either presented with a strikethrough price of $429 or $159 for the high or low price conditions, respectively. As an example of the low range product, a streaming video service was featured as $5.99 (low price) or $9.99 (high price). The list of products and prices are noted in Appendix A. Our key dependent measure for this part of the study is ocular fixation. From this, and based on results from our marketplace examination, we expect to find greater fixation for high (versus low) price condition, which we attribute to increased curiosity.

Results

In our model, we predict total (log) fixations as a function of the price condition (dichotomous), dispositional curiosity (continuous), and their interaction. All else equal, higher prices resulted in greater fixations ($\beta_{HighPrice} = 8.10$, $z(61) = 2.17$, $p < .04$). Also, as expected, as dispositional curiosity increased, so did price stimulus fixation ($\beta_{DispositionalCuriosity} = 2.07$, $z(61) = 5.61$, $p < .001$). That is, more curious individuals were likely to focus on any stimulus, all else equal. Finally, we find a significantly negative price x dispositional curiosity interaction ($\beta_{HighPrice \times DispositionalCuriosity} = -1.89$, $z(61) = -2.2$, $p < .04$), telling us that as one’s dispositional curiosity increases, fixations decrease for high (versus low) prices. Figure 2 illustrates these effects by showing total predicted eye fixations between the high and low price conditions at low and high levels of dispositional curiosity (i.e., the 10^{th} and 90^{th} percentiles, respectively).

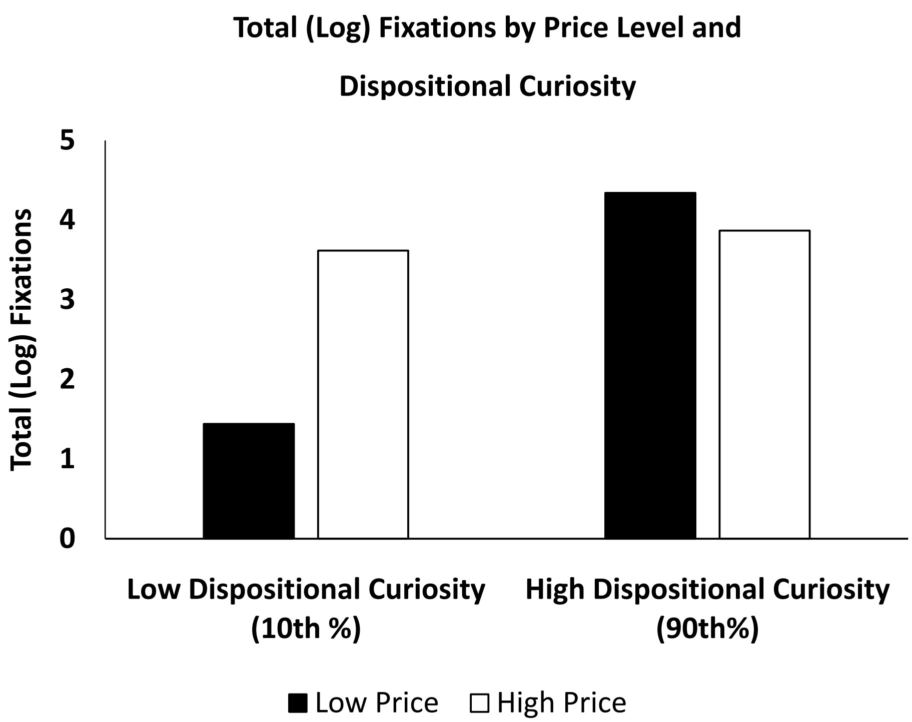


Figure 2: Test for Process Evidence

Discussion

Results suggest that individuals with lower dispositional curiosity tend to focus more on higher prices. This is the expected finding from our initial marketplace examination, which we also attribute to curiosity. However, among those individuals with high dispositional curiosity, we find signs of a ceiling effect, whereby highly curious individuals tend to fixate more on the product stimulus irrespective of price. That is, these findings suggest that highly curious individuals are less affected by high versus low price, and these individuals are likely to seek additional information, irrespective of price.

However, our measure of price—based on an examination of the range of prices found in the marketplace—may not necessarily reflect “high” or “low” prices for each individual consumer. That is, it is quite possible that a price that we had classified as high could be viewed as a low by one consumer and high by another. Moreover, while we find process evidence for increased curiosity, the eye track method—which provided limited interaction for participants with the mouse and keyboard—was not conducive to measuring the behavioral-based measure of clicks. Therefore, in the next study, we seek to address these limitations.

Measuring the Moderating Role of Expected Price and Price Range

While we find process evidence for increased curiosity for high price, it could be argued that our measure of "high" and "low" price is a subjective value; that is, while it is based upon marketplace prices, it is not necessarily reflective of a "high" or "low" price relative to a given consumer's expected price range. Moreover, our test for process evidence is based on eye tracking, a protocol that precluded us from measuring a behavioral-based measure such as click-through (e.g., total clicks, as measured in our marketplace test). Therefore, in this study, we begin with the price stimuli from the eye tracking study and then rely on a behavioral-based measure of clicks as our dependent measure. This is important because it enables the key predictor of price—previously labeled as "high" versus "low"—to be measured at the individual level on a continuous (versus dichotomous) basis.

Method

Participants (n = 257) were undergraduate students recruited in return for partial course credit to take part in an online-administered study. After participating in unrelated survey tasks, participants were asked to take part in a short exercise involving product choice. Participants were randomly assigned to one of the two price conditions noted in the eye track study (high versus low absolute price). Five of the six selected products from the previous eye tracking study (noted in Appendix A) were presented to consumers,[4] albeit in a different fashion that we discuss in the following paragraph.

For the main procedure of the study, participants were presented in succession five different products chosen from our eye tracking study (TV, tablet computer, laptop, cloud storage and streaming video). Participants were first instructed that they would ultimately be asked to provide their estimates of the actual prices for each of these products and that by exploring the product information made available to them on subsequent screens, they could obtain details that might help them in making these estimates. Participants were then instructed that they could simply click on any product that they wished to learn more about. For each of the five products, participants could click one of two buttons to either i) obtain additional product information (e.g., description, features, information on comparable products) or ii) proceed to the next page without receiving this information. Appendix B provides an example of this interface for one of the product offerings (the 32" LED HDTV). For any of the presented products, by clicking for product information, participants were then presented with various features and benefits as well as the opportunity to learn about related products. In the survey, participants were also asked to state for each product the following details: i) the lowest price at which they expect to find this (or a similar) product, ii) the highest price that they expect to find for this (or a similar) product, and iii) their best estimate of the average price at which each product is offered.

[4] The headphone product (see Appendix A) from the eye track study was excluded, as this product resided well above the price range for other products in the category. Specifically, the lack of comparable products at this price range—which was part of our study protocol—warranted exclusion of this product.

In our analysis, we aim to examine the effects of expected price and price range on a consumer's propensity to seek additional information. Thus, for our dependent measure we predict the probability of click-through, with key predictors including the individual-specific factors of relative price, price range, and the interaction of these two measures. The measure of relative price is simply the ratio of the strikethrough price to the individual's expected retail price. For example, a strikethrough price of $20 in the context of an individual's expected price of $10 would yield a relative price measure of (20/10 =) 2. The variable of price range was a measure of the participant's maximum expected price minus their minimum expected price. For comparability across the various products that were tested, this measure was standardized with a mean of zero and a standard deviation of one.

Results

The dependent variable of click-through probability was predicted as a function of relative price, price range, and their interaction. For the predictor of relative price, we find that increases in relative price (i.e., the actual-to-expected price ratio) result in a lower probability of click-through ($\beta_{RelativePrice} = -.11$, $z(1017) = -2.05$, $p < .05$), all else equal. For the price range of a given product (i.e., the maximum minus the minimum expected price) there is no significant main effect. Our main interest was in the influence of the interaction of relative price and price range—that is, to examine whether the effect of relative price one's curiosity varies in accordance to price range. Importantly, we find a significantly negative relative price x price range interaction ($\beta_{RelativePrice\ x\ PriceRange} = -.14$, $z(1017) = -2.29$, $p < .03$). In interpreting this interaction, a positive effect on click-through probability occurs for high-priced products that have a narrow price range. However, when the price range is wider, this effect is reversed. In Figure 3, we illustrate the effect of these findings by showing click-through probability at the 10^{th} and 90^{th} percentiles of both relative price and price range. Specifically, for products with narrower price ranges, we find the expected pattern (i.e., consistent with our prior examinations) of increased click-through for higher prices. However, for products with wide price ranges, higher prices result in less interest in the form of click-through.

Discussion

Thus far, the marketplace examination and our test for process evidence (eye tracking) both revealed findings suggesting greater curiosity amid higher prices. In this current study, we find this to be the case for products with a narrow price range. However, we find a reversal of this effect when the price is range is wider. These findings lend credence to the inverted U-shaped knowledge gap curve as discussed in the theoretical background. In briefly revisiting the knowledge gap, it is viewed as the gap between what the consumer knows and what the consumer seeks to know. Moreover, it is theorized that a knowledge gap that is too narrow or too wide may prohibit one from seeking additional information, as it is not deemed as being worthy of the consumer's effort. Specifically, we find evidence that wider price ranges amid higher-priced products run the risk of creating a knowledge gap that is too wide for the consumer to seek action to close the gap.

In light of these results—specifically in the case of the high-priced product with a wide price range—we next ask whether increasing one's curiosity could increase one's

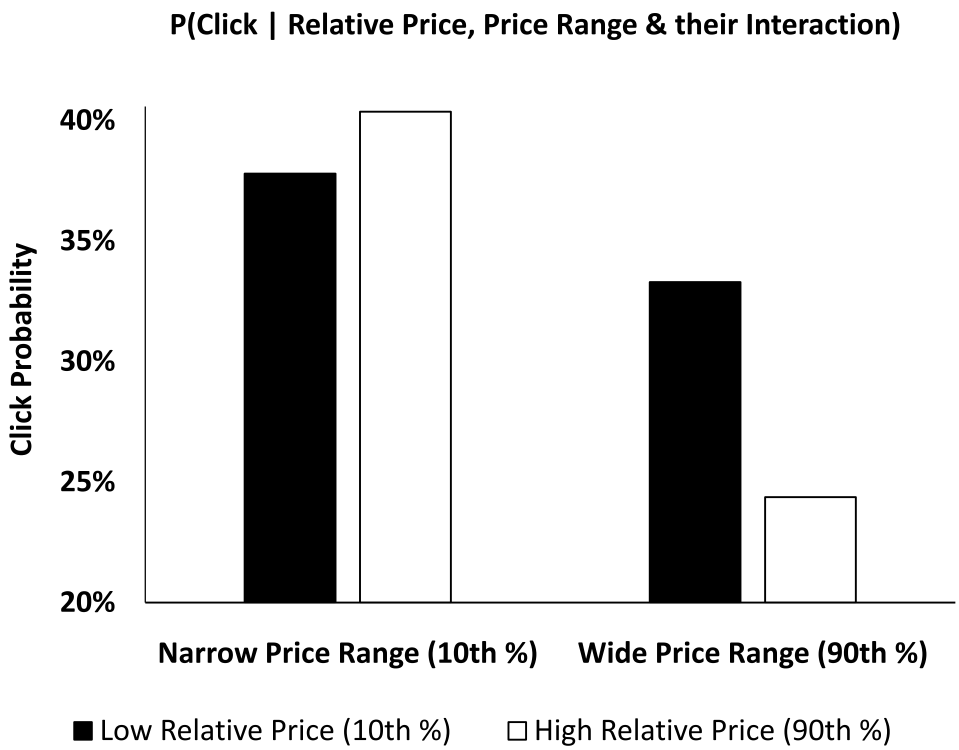


Figure 3: The Moderating Role of Expected Price and Price Range

propensity to seek additional information. If we are able to induce curiosity among participants, might they show a greater propensity to seek additional information amid a wide knowledge gap? In our next study, we seek to measure effect of increased curiosity, which we aim to achieve by way of hunger inducement.

<u>Hunger Manipulation Lab Study</u>

To build upon our prior findings, our next study is aimed at measuring the effect of increased curiosity among participants. We aim to do this by controlling for one's level of hunger, a factor believed to affect curiosity. In brief, hunger has been linked to dopamingergic activity—that is, the release of dopamine. As discussed in our theoretical background, the desire for food (as tested through food stimulation) would be expected to produce greater hunger. This desire is believed to increase dopamine activity, which we theorize would equate to greater action aimed at "feeding" one's curiosity. From this, we expect to find a more pronounced effect on curiosity behavior (in the form of click-through) in the presence of hunger inducement.

Given our above hypothesis, we find it important to note a potential alternate account stemming from extant research briefly introduced in our theoretical review. Just as an increase in the knowledge gap may ultimately inhibit one's desire to seek additional information, findings from Piech et al. (2009) suggest that an increase in hunger could negatively affect one's cognitions and subsequent ability to seek additional information. Specifically, their research theorizes that an increase in hunger ultimately impedes one's cognitive flexibility via "gross increase in distractibility." In their research, hunger inducement via food-related cues—in addition to increasing participants' self-reported hunger—resulted in a significantly greater number of participant errors in a target stimulus identification task. Thus, counter to the theory that increased hunger amplifies one's seeking system and subsequent information search behavior, it is possible that hunger inducement will negatively affect cognitive ability and thus reduce one's information seeking. In the presence of this account, we would expect that the abovementioned "increase in distractibility" would preclude one from seeking additional information based on strikethrough price. That is, if this account were to hold, we would find no effect from the factors of price and price range (presented in our prior study) due to the increased cognitive competition resulting from hunger inducement. In the next section we explore the method used to test our hypothesis.

Method

In this study design, we seek to induce food stimulation—via extant method adapted from brain imaging research (Volkow et al. 2002)[5]—prior to our implementation of the main protocol of the prior study. Participants (n = 183), asked to take part in a short exercise involving product choice, were undergraduate students recruited to our lab study in return for partial course credit. The study was offered on one of two consecutive days, with participants in the control condition (n = 95) taking part on day one, and participants in the food manipulation condition (n = 88) taking part on day two.[6] In both conditions, participants were briefed in a room that was separated from the one in which they completed the survey. During this briefing, they were instructed that they would first take part in a 5–10 minute exercise at a table at the front of the room, and then they would be seated at a computer for the main part of the study. Before entering the room, participants were instructed that there may or may not be other items on the table when they are initially seated. The study administrator indicated that this was due to the fact that other groups were using the lab that day and therefore instructed participants to try their best to just complete the task at hand, irrespective of what else was on the table. Upon being escorted into the lab, participants were first seated at a set of connected tables in front of the room and followed written instructions to complete a word completion task. This task was approximately 8 minutes in length, subsequent to which participants were—as a group—instructed that they could take a seat a computer to complete the main part of the survey.

[5] Specifically, the proposed approach is adapted from what is previewed on page 176 of Volkow et al. (2002).
[6] This study design ensured that there was no spillover effect from the food manipulation condition. This minimized the risk of hints or aromas from the food manipulation condition entering into the control condition test.

We next describe the differences between the two test conditions. In the test condition (with no food manipulation), the center of the table included various writing utensils and stacks of papers. In the food manipulation condition, the very same word completion task and table setup was encountered, although the center of the table was adorned with indulgent baked goods and treats. Moreover, the aroma in the room was enhanced by warming of the various treats and also included the (hidden) effects from candles of various tempting scents (e.g., vanilla, sugar cookie, caramel). Finally, participants in this condition were told that they would be allowed to taste a small sample before exiting the survey. Key to this method—as adapted from Volkow et al. (2002)—is the lure of the food more so than the sampling; that is, the aroma and possibility of a small taste was intended to trigger a yearning or hunger for food and not to satiate. Examples of the lab setup for the food manipulation condition are noted in Appendix C. In sum, the two study constructs were identical with the exception of the presence or absence of the assorted desserts.

As for the main part of the study—that is, the computer administered portion—the product choice exercise was the same protocol implemented in the previous study, with the exception being that this study was implemented in the lab (versus being administered online). Thus, subsequent to the table exercise, the study continued by measuring clicks on the various product stimuli and gathering responses on expected price and price range. Finally, as an additional control, participants were asked to provide their responses to hunger rating questions borrowed from extant literature (Friedman, Ulrich, and Mattes 1999). This includes four 9-point bipolar scales that measure for the current time a participant's claimed i) level of hunger, ii) desire for food, iii) amount they could eat, and

iv) fullness. These items are summed (with item (iv) reverse-scaled) to provide a hunger score for each participant. In sum, the food stimulation manipulation and the claimed hunger questions provide us with the ability to not only induce, but also to validate, one's hunger level preceding the price curiosity exercise.

In our analysis, subsequent to a simple manipulation check, we first seek to examine the control condition in order to validate our prior (online-administered) study. We then examine the results of the food manipulation. For each condition, we predict click-through probability as a function of relative price, price range, and their interaction. In the section that follows, we discuss findings from the above study design.

Results

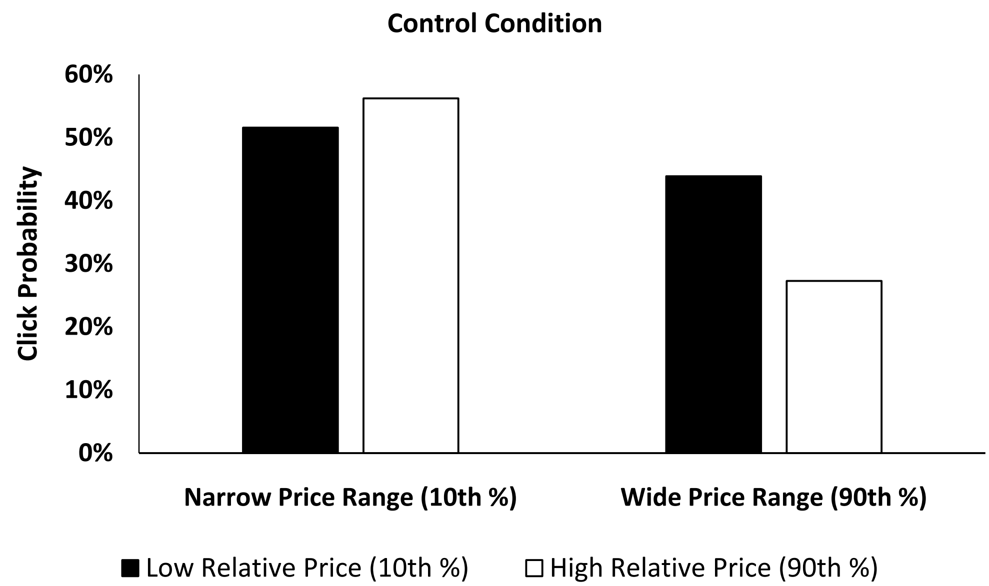
First, in order to confirm that the food manipulation resulted in our expected increase in claimed hunger, we begin with a manipulation check via one-sided t-test. Results confirmed our hypothesis, with significantly greater hunger in the food manipulation (M = 21.7, SD = 7.9) versus control (M = 19.5, SD = 8.5) condition ($t(183) = 1.76$, $p < .04$). Similar to the previous study, the dependent variable of click-through probability was predicted as a function of relative price, price range, and their interaction. In the control condition, results exhibit a similar pattern to the prior study. That is, we find moderate significance for the predictor of relative price, whereby an increase in price results in a lower probability of click-through ($\beta_{RelativePrice} = -.14$, $z(377) = -1.80$, $p < .08$). Also, there is no significant main effect for price range, consistent with the prior study. Finally, we find a moderately significant (negative) relative price x price range interaction ($\beta_{RelativePrice\ x\ PriceRange} = -.33$, $z(377) = -1.87$, $p < .07$). Within the food manipulation condition, however, we see different results—that is, we find no evidence of the effects of relative price nor price range. Subsequent to the food manipulation, the model reveals only a moderately significant intercept value ($\beta_{Intercept} = -.24$, $z(349) = -1.70$, $p < .10$).

In Figure 4, we illustrate the effect of the above findings by showing click-through probability at the 10th and 90th percentiles of both relative price and price range for each condition. It should be noted that the control condition mirrors the results of our prior study (see Panel A of Figure 4 versus Figure 3)—that is, for products with narrow price ranges, we find increased click-through for higher prices. However, for products with wide price ranges, higher prices result in a lower probability of click-through. In panel B of Figure 4 (the food manipulation condition), we see no differences between products based on price and price range.

Discussion

We first find that in our control condition we are able to replicate the results of our prior study. That is, we find that higher prices result in increased curiosity for products with a narrow price range and that this effect is reversed when the price is range is wider. Within the food inducement condition, however, we expected to find a pronounced effect on curiosity behavior in the form of increased click-through probability. While we find evidence of a successful hunger manipulation, results from the food condition show that the main effects vanish relative to the other examination. While deviating from our hypothesis, these findings do lend credence to the alternate account described in our study introduction. That is, amidst greater hunger, it is plausible that the

A)



B)

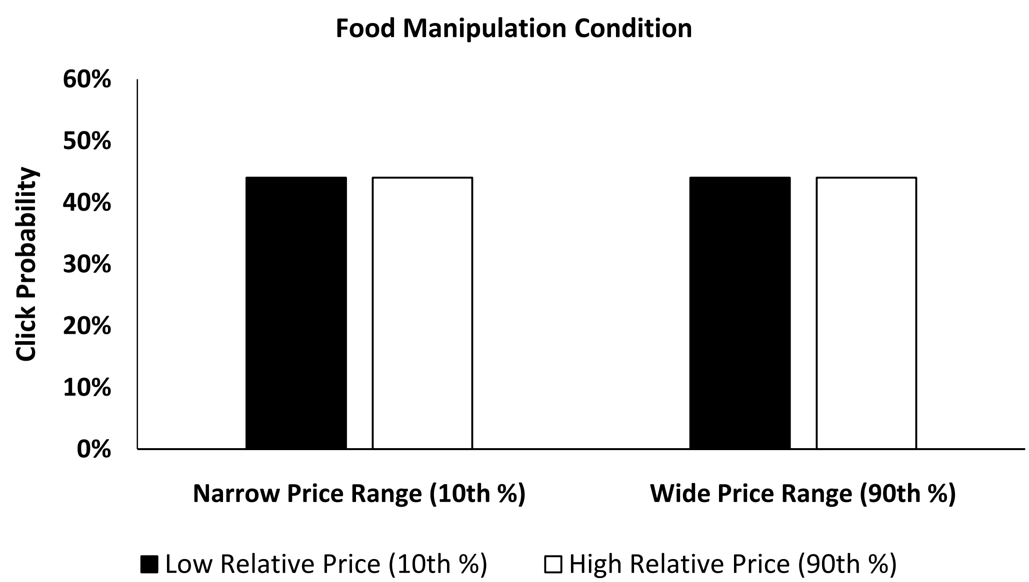


Figure 4: Hunger Manipulation Lab Study. A) Control Condition: Amid Narrow Price Range, High Price Equates to Greater Click-Through; Effect Reverses Amid Wide Price Range. B) Food Manipulation Condition: No Effect, Suggesting Presence of the "Impairment of Cognitive Flexibility" Account

impairment of cognitive flexibility results in less of an ability or desire to engage in additional information seeking. As discussed in this study's introduction, in the presence of this effect we would expect to find no effect from the factors of price and price range (presented in our prior study), which is precisely what we witnessed. Thus, we feel this study provides evidence supporting the drive-based accounts of curiosity. Just as increased levels of hunger may reach a point that inhibits one's ability to forage for food, it is possible that this could also ultimately inhibit the degree to which one seeks information in the environment.

General Discussion

In this essay, we present evidence that higher prices increase consumers' curiosity. We see this in the form of a behavioral-based measure of click-through, which indicates greater consumer desire to seek more information amid higher strikethrough prices. With the numerous exogenous factors influencing one's ultimate response to a marketing message, we supplemented these real-world findings with three lab studies aimed at measuring the effect of curiosity in more controlled settings. Our first approach sought to measure the underlying process of curiosity while extending beyond a single product category. From this, we found that higher prices resulted in greater curiosity-related processing mechanisms (via increased eye fixation), all else equal. In this same study, we measured one's dispositional curiosity, finding an attenuation of the main effect amid highly curious participants. Our second lab study showed an effect on curiosity stemming from differences in relative price and price range, and provided evidence that products with high relative price and a wide price range run the risk of attenuating one's curiosity. This attenuation is attributed to the knowledge gap becoming too wide for a consumer to attempt to close it, consistent with psychology-based accounts of curiosity. Finally, in our third lab study, after successful hunger inducement, we find an effect on one's information-seeking behaviors, which helps to inform drive-based accounts from extant literature that relates curiosity to such states as hunger or thirst.

This research holds several theoretical and practical implications. Theoretically, it is among the few explorations that consider the role of prices on arousing curiosity in the marketplace. Although past research has discussed the similarity of curiosity to a drive state, there is, to the best of our knowledge, no empirical evidence to support this proposition. In this research, we show that curiosity does behave like a drive state and shows similar downstream influences. Moreover, we demonstrate that price variance has an interesting influence on curiosity, with greater variance in price expectation resulting a differential effect relative to low variance in price expectation. In sum, we are able to inform extant psychology-based theory on curiosity while contributing to marketing literature on the role of the relationship between price and product information. This provides unique insight into the way in which price and product information—and its position along the knowledge gap continuum—affects one's curiosity.

This research also holds many implications in the marketplace, both to managers and to consumers. For instance, these findings provide valuable insights for marketers on the downstream effects of how price is displayed. Specifically, based on the product's relative price and price variance, these findings can inform marketers on the optimal way in which price information is communicated to the consumer. That is, depending on the expected retail price and the range of prices for the product, we are able to provide guidance for marketers in determining the appropriate price display enabling optimal consumer response (via increased curiosity). Thus, our research provides a framework for marketers in their structuring of price displays aimed at increasing consumer information search.

THE LONG-TERM IMPACT OF A REFERRAL ON SENDER AND RECEIVER BEHAVIOR

Introduction: Referral Behavior and Its Marketing Impact

Companies have long sought to use the influential power of existing customers by way of their recommendations to friends and family, known as referral marketing. In the two essays that follow, we examine the long-term impact of referral marketing from both the sender and receiver perspective. Referral marketing plays a critical role in a brand's marketing mix, and is used across a variety of categories. Brands offering such programs apply to news publications (The Economist), satellite television (DirecTV), banking (Bank of America), mobile communications (T-Mobile, Virgin, AT&T), retail (Costco), and consumer goods (diapers.com). Given its prevalence in the market and importance in driving firm value, it is of no surprise to find that marketers and theorists alike seek to understand more about the long-term effect that a referral has on the referrer (i.e., the sender) as well as the newly-acquired friend or family member (i.e., the receiver).

Existing literature has provided findings that help in measuring the effect of referral marketing. The ability to measure customer response in the form of net present value provides valuable insights for marketers in understanding the true value of a referral (Kumar et al. 2010). Moreover, the ability to model a customer's probability of survival based on their prior purchase patterns (Fader, Hardie, and Lee 2005) provides the opportunity to examine the long-term performance of referral marketing from both the sender and receiver perspective.

In addition to presenting our findings on sender and receiver behavior, we also test the possible theoretical mechanisms underlying such behavior. In Essay 2, we first discuss reciprocity and the spotlight effect to explain the impact of a referral on sender and receivers. In Essay 3, we examine the intervening effect of a referral on the purchase behavior of senders. We utilize dissonance theory as well as the concept of market mavens and opinion leadership to determine which of these theoretical mechanisms underlie our observed effects.

In the sections that follow, we review theories pertinent to referral marketing and its measurement, which apply to the two essays that follow it. We first present the extant theory on referrals, as well as the modeling of individual-level factors such as customer lifetime value (which we refer to henceforth as CLV) and the computation of a customer's probability of being active. We then proceed to our second essay, where we highlight the theoretical domains of reciprocity and the spotlight effect, followed by our testing of these theories. Finally, in our third essay, we begin with a review of literature related to dissonance as well as market mavens and opinion leadership and conclude with research aimed at confirming the theories likely at play in explaining our results.

Theorectical Review on Referral Behavior

Literature on Customer Referrals

In the areas of referral marketing, extant research is plentiful. Common to this is the intuitive but no less valuable finding that increased value comes from customers that are referred. Referrals come in a number of varieties; that is, they can come from customers or noncustomers alike and can be customer-initiated or company-initiated (Buttle 1998). Customers that refer others have been likened to noncompany sales personnel in that their efforts in garnering new business for the firm can provide them with earnings in the form of rewards or discounts (Kumar et al. 2010). Invaluable methodologies have been developed to quantify the value of these consumers, which we review in detail at a later point within this theoretical review.

Existing research also shows how a referral can be affected by such factors as reward magnitude and the strength of the relationship between the sender and receiver. For example, in an experiment manipulating various factors of reward programs for electronic devices, referral likelihood was shown to increase in the presence of a reward program. In this same study, strength of the brand as well as the strength of the tie between sender and receiver was shown to have an effect on total referrals (Ryu and Feick 2007). Specifically, Ryu and Feick (2007) introduced the counterintuitive finding that weaker (versus stronger) brands with weaker (versus stronger) sender and receiver ties are more likely to garner a greater number of referrals. Additional research contributing to this learning focused on the reward offered for a referral from members of an online mall site (senders) to prospective customers (receivers). In this large-scale field experiment, the magnitude of the financial incentive was shown to be positively related to the total number of referrals sent as well as the total new customers and purchases from the referral (Ahrens and Coyle 2013).

Moreover, research has investigated the optimal mix of the referral reward and the product price based on the customer's willingness to recommend, providing guidance for marketers in structuring referral and/or reward programs (Biyalogorsky, Gerstner, and Libai 2001). The method of acquisition in customer referral has also been explored, proving to be a key factor in determining the value of a referral. For example, research has compared customers acquired via word-of-mouth (WOM) to those acquired through more traditional firm-induced marketing messages. In this research—among customers in the internet domain— Villanueva, Yoo, and Hanssens (2008) showed that WOM-acquired customers are nearly twice as valuable over the long term. Furthermore, prior research has distinguished between "endogenous" (customer-generated) and "exogenous" (firm-induced) WOM among both customers and noncustomers alike to better understand its effects. Results of a field experiment for a national restaurant chain showed that exogenous (firm-induced) WOM drives higher sales and that the customer's level of involvement—e.g., brand loyalists versus switchers—influences the effectiveness of WOM on the receiver (Godes and Mayzlin 2009). Specifically, it was shown that WOM-driven sales were higher for less loyal (versus highly loyal) customers, providing unique insights relative to perceived credibility of the sender. In the sections that follow, we continue with a more detailed examination of the modeling methods used in referral marketing.

Modeling Customer Purchases and Survival Probability

In this section, we review some methods that enable researchers to predict the survival likelihood of a particular customer, a key component of the research that we present in the balance of our essays. The importance of this methodology is amplified in the presence of a noncontractual customer setting, whereby the time at which a customer becomes “inactive” is an unobservable event (Reinartz and Kumar 2000). Prior research in this area has mainly focused on predicting i) the probability of survival for a given customer at time *T* and ii) the number of future purchases in light of their prior purchase history. Additionally, predictions for future purchases are used in such calculations as CLV, an area that we will later explore.

Schmittlein, Morrison, and Colombo’s (1987) influential work on counting and identifying active customers discusses at length two dimensions, which include the customer’s transaction opportunity (as continuous or discrete) and the type of relationship that the customer has with the firm (contractual versus noncontractual). Historically, continuous opportunities for transactions in a noncontractual setting—e.g., consumer purchases in a retail shopping environment—have received significant attention from those modeling customer-specific survival probabilities (Fader and Hardie 2009). Central to this work is the above referenced seminal work from Schmittlein, Morrison, and Colombo (1987) on the Pareto/NBD Model, which enables the calculation and identification of those individual customers that are active, as well as the prediction of future individual-level transactions. Given our intended use of this model—which we discuss at greater length in the section that follows—key extensions to the basic Pareto/NBD are worth noting here. Importantly, research has extended to include time-invariant covariate effects (Abe 2008; Fader and Hardie 2007) as well as an examination based on average spend per transaction. (Fader, Hardie, and Lee 2005; Schmittlein and Peterson 1994).

The Pareto/NBD Model

The Pareto/NBD is based on five key assumptions: i) customer purchases are made according to a Poisson process with purchase rate λ, ii) customer lifetime is exponentially distributed with death rate of μ, iii) the purchase rate λ follows a gamma distribution across all customers, iv) customer death rates μ are distributed to different gamma distributions across customers, and v) the distributions of purchase rates λ and death rates μ are assumed to be independent of each other. The Pareto/NBD model has four parameters in r, α, s, and β that characterize the purchase/death process for customers.

In addition to the parameter values (r, α, s, and β), the model is reliant on basic pieces of information including the recency of a given customer's last purchase and the frequency of their total purchases. The primary notation for recency and frequency is (x, t_x, T), which is summarized as follows: x indicates the number of transactions occurring from time zero through time T, and t_x is the time of the last transaction (which is greater than zero and less than or equal to T). The best fitting parameters are estimated via maximum likelihood, which maximizes the sum of the log-likelihood for each individual customer based on frequency (x), recency (t_x) and total time (T). From this, as noted in Schmittlein, Morrison, and Colombo (1987), the probability that an individual customer is still active at T based on their recency and frequency (x, t_x, T) is $P(\text{alive} \mid x, t_x, T)$. Also of interest is the expected number of transactions in the future time horizon of t periods, which is noted as $E[X(T, T+t) \mid x, t_x, T]$. In summarizing the key elements of the Pareto/NBD model, we begin with the likelihood function for a randomly-chosen consumer with purchase history ($X = x$, t_x, T), which is expressed as

$$L(r, \propto, s, \beta \,|X = x, t_x, T) \tag{2}$$

$$= \frac{\Gamma(r + x)\alpha^r \beta^s}{\Gamma(r)} \times \left\{\frac{1}{(\alpha \,+\, T)^{r+x}(\beta \,+\, T)^s} + \left(\frac{s}{r + s + x}\right) \mathrm{A}_0\right\},$$

where for α ≥ β

$$A_0 = \frac{{}_2F_1(r + s + x, s + 1; r + s + x + 1; \,\frac{\alpha - \beta}{\alpha + t_x}}{(\alpha + \, t_x)^{r+s+x}}$$

and for α ≤ β

$$A_0 = \frac{{}_2F_1(r + s + x, r + x; r + s + x + 1; \,\frac{\beta - \alpha}{\beta + T}}{(\alpha + \, t_x)^{r+s+x}}.$$

The probability that a given customer is alive is stated as

$$P(\text{active}\,|r, \alpha, s, \beta, X = x, t_x, T) \tag{3}$$

$$= \left\{1 + \frac{\mathrm{s}}{r + s + x} \,(\alpha + T)^{r+x}\, (\beta + T)^s \,\mathrm{A}_0\right\}^{-1},$$

with the expected number of transactions for a consumer in (T, T + t] expressed as

$$E(Y(t)|X = x, t_x, T, r, \alpha, s, \beta) = \tag{4}$$

$$= \frac{(r+x)(\beta+T)}{(\alpha+T)(s-1)} \left[1 - \left(\frac{\beta + T}{(\beta + T + t)}\right)^{s-1}\right]$$

$$\times \; P(\text{active} \mid r, \alpha, s, \beta, X = x, t_x, T)\,.$$

Customer Lifetime Value and Customer Referral Value

Existing research has provided valuable modeling tools for marketers that enable individual-specific measurement of CLV, allowing marketers to more wisely invest in specific customers. Venkatesan and Kumar (2004), for example, have shown that customers selected on the basis of current CLV provide marketers with greater profit relative to customers chosen on other customer-based measures. In brief, while CLV is certainly not a "one size fits all" approach,[7] it can be generalized as the present value of expected cash flows from a customer (Fader and Hardie 2014). In Equation 4 below, we examine more closely the calculation of CLV that is applicable to ongoing, noncontractual purchase settings such as retail shopping. Specifically, this begins by measuring for customer *i* the expected net cash flow based on number of purchases and transaction value, conditional on customer *i* being alive. That is, past purchases for a specified period are analyzed, with predictions made for a specified future time period based on the time horizon of interest. This value is then multiplied by survival probability, and discounted to reflect a net present value, formally expressed as

$$\text{CLV}_i = \sum_t \; (\text{expected net cash flow}_t \mid \text{alive}) \times \text{P}(\text{alive}_t) \times (\text{discount factor}_t). \tag{5}$$

[7] Regarding the varying definitions of CLV, see Fader and Hardie (2014) for a healthy discussion on this topic.

Notably, existing research has examined as part of a customer's lifetime value (CLV) what is classified as customer referral value (CRV), which is one component of a total customer's total equity (see Kumar, Peterson, and Leone 2007; Kumar et al. 2010). In brief, CRV takes into account for a given sender a discounted cash flow value of the total lifetime value of the customers that were acquired through that particular sender's actions. For example, if an individual customer's lifetime value is $100, and he or she refers a customer that ends up with a lifetime values of $200, this latter value would be used to calculate CRV (based on a specified discount rate). Prior research has shown that the value of sender's referrals—that is, their CRV—is higher than the sender's CLV. For example, Kumar, Peterson, and Leone (2007) examined both CLV and CRV within the financial services and telecom industries, with analysis yielding CRVs that were 1.78 and 4.28 times higher than CLVs for referring customers (i.e., senders).

In the next section, we introduce our second essay. This extends our previous preview of extant literature's contributions in referral marketing and explores the possible theoretical mechanisms underlying referrals from both the sender and receiver perspective.

ESSAY 2: THE INFLUENCE OF A CUSTOM (VERSUS STANDARD) MESSAGE ON SENDERS AND RECEIVERS OF MARKETING REFERRALS

Introduction

Marketers have long sought to harness the influential power of customers in garnering new business, with countless tactics implemented in both the online and offline space. One such example implores consumers to "Tell your friends about *The Economist*, get a free month!," and goes on to proclaim to customers that "When a friend signs up, you get a free month! It's that easy, so start spreading the news." These types of word-of-mouth communications, a key aspect of referral marketing, are estimated to be the primary factor in 20 to 50% of all purchasing decisions (Bughin, Doogan, and Vetvik 2010). Moreover, as noted in the theoretical review preceding this essay, referral tactics are an important source of new business with tremendous sales implications. While prior research has examined at great length the source of the referral, it tends to treat the structure of the referral as equal; that is, less is known about how the specific information within the referral itself could influence ongoing purchases. In our research, we focus on the degree of customization of the referral, and we explore whether all referrals are equally likely to lead to an increase in purchases. Specifically, we focus on whether the referral is accompanied by a custom (sender-generated) or a standard (boilerplate) message from the sender, and we ask: Are all referrals—e.g., customized and standardized messages alike—perceived in the same fashion by the receiver? Or, does it happen that a receiver is more likely to alter their behavior—i.e., make a purchase—when the sender delivers a customized (versus standardized) referral message? And, what effect might we see from the sender when the message is customized (versus standardized)?

In the case of customized referrals and messages directly from companies, it is possible that consumers feel that they are special and hence, purchases and loyalty may be more likely to follow. But in the case of receiving customized referrals from friends, we do not expect the mere presence of "feeling special" to be a factor, and we posit that other factors could influence purchases stemming from a customer's referral to their friend. To preview applicable theory, the existing domains of reciprocity and spotlight effect would suggest greater purchase likelihood after receiving a customized message. The former theory deals with a sense of obligation on behalf of consumer to return or pay forward to others the goods or services provided to them. The latter theory pertains to the overestimated belief that the self's actions are being observed by others. We believe that both of these effects are factors in one's response to the receiving *and* sending of a custom referral, both of which have immense implications for companies. Specifically, instead of assuming equal impact for all referrals, marketers can better understand the importance—and quantify the value—of customized referrals from a consumer to their friend. To test our research predictions, we utilize email referrals sent by existing customers (senders) of an online retailer and we categorize these referrals based on whether they are structured in a customized versus standardized fashion (with the specific method being discussed in a later section). We then compare the purchase behavior of senders and receivers of these two message types in testing the underlying theories.

In the sections that follow, we present our theoretical conceptualization, including a review of extant theories and our predictions. This is followed by a discussion of our research approach and findings that test our hypothesis. We then conclude with a discussion of implications for marketers and theorists alike.

Theoretical Review

In order to understand how receivers and senders are likely to respond to referrals, we consider extant work on reciprocity and the spotlight effect. These theories discuss how both the receiver and sender of a message may be likely to respond to a referral gesture. Specifically, they review how the receiver may feel obligated to signal to the sender his or her thanks, and how the sender's actions may be influenced by the (erroneous) belief that his or her referral actions are under scrutiny. Each of these is discussed in the sections that follow.

Reciprocity

In the most general sense, reciprocity is a societal norm whereby individuals feel an obligation or sense of duty in repaying goods or services provided for them (Gouldner 1960). An important aspect of reciprocity is the dual benefit for the "sender" and "receiver" of the good or service; that is, it results in a mutually gratifying outcome for both parties (Malinowski 1932). The most common form of reciprocity is captured by the simple principle "you scratch my back, and I'll scratch yours." That is, in the standard form of reciprocity, one party (e.g., Party A) provides a benefit to another party (Party B) with the expectation of the favor being returned. This form of reciprocal altruism is defined as an exchange between the same two individuals that result in a net benefit for both (Trivers 1971).

Reciprocity need not be directly concentrated on exchanges between Parties A and B; that is, it can be indirectly experienced between multiple parties. In comparison to direct reciprocity, indirect reciprocity follows a much less intuitive general principle that "you scratch my back and I'll scratch someone else's" (Nowak and Sigmund 2005). Indirect reciprocity is generalized as being upstream or downstream. For example, within the concept of indirect upstream reciprocity, Party A first helps Party B, who in turn may be motivated to help Party C, which can extend indefinitely (Boyd and Richardson 1989; Nowak and Sigmund 2005; Pfeiffer and Killingback 2005). As for indirect downstream reciprocity, Party A, in their providing of aid to Party B, is aided by their reputation in helping others. Thus, Party C chooses to help Party A as a result of becoming aware of their prior acts of altruism toward Party B (see Nowak and Sigmund 2005).

Spotlight Effect

In this section, we discuss the theory behind one's belief that their future actions are under greater scrutiny by friends or acquaintances. In the context of referral marketing, consider a sender delivering a referral to a friend or family member. It is plausible that the act of referring triggers the feeling that their recent purchase behavior—that is, whether or not they have engaged in purchases since referring someone—are under scrutiny by the receiver. This phenomenon, whereby people overestimate the degree to which their actions are being noticed by others, is commonly referred to as the spotlight effect (Gilovich, Medvec, and Savitsky 2000).

Central to this research on the spotlight effect is the finding that people tend to overvalue the level of attention that others are paying to them. Research has shown, for example, that people consistently overestimate the salience of their contributions in group exchanges and settings. Specifically, participants—in taking part in a group discussion on a current social/policy issue—overestimated such factors as remarkable commentary and time spent talking, and they underestimated such negative factors as speech errors and offensive comments. Effect of the spotlight is further exemplified by related research from Gilovich, Kruger, and Medvec (2002), which consistently showed participants' tendencies to overestimate how their actions and performance would be noticed by others. Specifically, one's own measures of their physical appearance and competitive performance confirmed their tendencies to overestimate the degree to which others take note. Taking into account this theory on spotlight effect and the preceding overview of reciprocity, we now turn to our theoretical predictions.

Theoretical Predictions

In the context of a referral, the spotlight effect suggests that individuals may overestimate how the act of their referral reflects on them as a person, resulting actions that may otherwise not be taken. Furthermore, reciprocity suggests that individuals may feel a sense of duty or obligation to repay a benefit (i.e., favor) extended to them. Thus, in the example of a sender, irrespective of their perception of themselves,[8] it is plausible that the act of referring another customer could amplify the degree to which they perceive

[8] Some consumers may see themselves as having greater influence and marketing expertise. These consumers, referred to in literature as "market mavens," possess greater knowledge of products and a greater likelihood to share this information with others (see Feick and Price 1987) for more information.

their actions to be under scrutiny. This feeling of "being in the spotlight" could ultimately lead to differences in sender's future purchasing behavior. As for the case of the receiver, we propose an effect attributed to reciprocity. That is, it is possible that the receipt of a message from a friend plays a role in motivating receivers to act on the invitation to extent their appreciation for the invite. Here we propose an effect attributed to upstream reciprocity; that is, an effect whereby the receiver behaves in a way that signals to the sender his or her gratitude for the referral.

As it pertains to the proposed effect of message type on both sender and receiver behavior, we propose that a custom (versus standard) message will result in greater value from the sender and receiver's perspective, all else equal. We continue to attribute these expected results to the presence of the spotlight effect for the sender, as well as the sense of reciprocity that we theorize stems from the receipt of a custom (versus standard) message. More specifically, we expect that one's feeling of being "in the spotlight" will be amplified in the presence of a custom versus standard message. That is, we posit that senders and receivers of customized (one-to-one) messages will behave differently than senders and receivers of one-to-many messages. Thus, we expect to find that customized, one-to-one messages result in greater overall value from both the sender and receiver's perspective in the form of transactions, predicted survival and purchase frequency as well as projected customer value.

In the sections that follow, we present findings from a real-world data set that examines the impact of a standard versus custom message on sender and receiver transaction value. We then further validating these findings by modeling predicted survival, purchase frequency, and total customer value.

Data Description

In testing the abovementioned theoretical accounts, we turn to data from an online retailer, spanning 200 weeks of customer-level transaction activity between March 2010 and January 2014. In addition to sales measures on per-customer basis, these data importantly afforded us the opportunity to identify senders and receivers of marketing referrals sent by existing customers (via email) to prospective customers. Moreover, among those senders and receivers of referrals, we were able to identify a given referral as being custom or standard. In the context of this data set, existing customers—in their act of referring other customers—typed in recipients' email addresses from a company landing page and then could either (a) proceed to send their invite with a standard, boilerplate message provided by the company or (b) type a personal message to their chosen recipient(s). Having an ability to discern whether the email mirrored or deviated from the boilerplate, company-generated copy, we then coded for each customer whether or not they were a sender or receiver, and whether or not the invitation (sent or received) was custom or standard. Specifically, a custom message was one that differed from the text structure of the standardized boilerplate text that was prepopulated for the sender.

Next, we summarize the composition of our data. As noted in Panel A of Table 1, a total of 38,467 people received invitations from 6,754 existing customers (senders), with the lion's share being standard (versus custom) invitations. In total, sender referrals resulted in 1,690 receivers taking action (i.e., becoming a member). In Panel B of Table 1, we see that—among these 1,690 receivers that became a member—a total of 827 made purchase(s) during the data collection period (based on referral efforts of one of the 6,754 senders). Moreover, Panel B breaks down the activity of all 21,046 customers that made

Table 1: Key Measures for Senders and Receivers

A)

	Receiver action from all Invitations Sent		
	Not Joined	**Joined**	*Total*
Standard Invitation	31,361	1,338	*32,699*
Custom Invitation	5,416	352	*5,768*
Total	*36,777*	*1,690*	*38,467**

** A total of 6,754 senders, each sending ~5.7 invitations*

B)

	Breakdown of All Customers			
	Total	***Senders***	***Receivers***	***All Other***
n	*21,046*	*6,754*	*827*	*13,905*
Number of Trans	4.97	7.35	5.88	3.84
Trans Value	$98.81	$98.85	$109.26	$98.16
Number of Invites	n/a	5.69	n/a	n/a

C)

	Among Purchasers		
	Custom	***Standard***	*Total*
Senders	*3,340*	*3,414*	*6,754*
Receivers	*179*	*648*	*827*

purchases over the 200 weeks of data and shows the activity of senders and receivers on these same measures. In Panel C of Table 1, we see that among the 6,754 customers that sent a referral, we find a nearly equal split between custom and standard invites (at 49% and 51%, respectively). As for the 827 receivers making purchases, 179 are attributed to custom invitations and 648 to standard invitations. Given this summary data, we next seek to empirically examine the effect of message type on key sales measures for senders and receivers.

<u>Measuring Transaction-level Data</u>

As noted in the previous section, from our data we are able to isolate custom versus standard senders and receivers through access to all referrals sent from existing customers of an online retailer to their chosen recipients. To preliminarily test our proposed effects attributed to spotlight effect and reciprocity, we begin with an examination of key purchase measures, which we next discuss.

Method

We begin with an examination of receiver response to a referral. For this, our dependent measure is the probability that a receiver ultimately joined as a function of receiving a custom versus standard invite. We then continue with an examination of key transaction-level measures for both senders and receivers, whereby we examine the difference between custom and standard referrals on key measures of transactions per consumer and average transaction value as well as the average number of invitations sent. In the presence of our proposed effect attributed to a sender's sense of being in the spotlight, we should find initial evidence for greater value from custom (versus standard) referrals. Moreover, in the presence of the proposed effect from reciprocity on receiver behavior, we should find greater response to custom (versus standard) invites.

Results

Before examining any differences in sales, we first sought to understand whether custom versus standard invitations had an effect on whether or not a receiver ultimately joined or made a purchase. Thus, in two separate logistic regressions, we predicted one's propensity to join and then to make a purchase as a function of whether the invitation was standard or custom. In subjecting the dependent measure of joined (1 = joined, 0 = not joined) to logistic regression, we find that the receiver of a custom message is 52% more likely than the receiver of a standard message to join (β_{Unique_Invite} = .42, z(38466) =

6.824, $p < .001$). Similarly, we find that those receiving a custom invitation are 83% more likely than those receiving a standard invitation to ultimately make a purchase ($\beta_{Unique\_Invite} = .61$, $z(38466) = 4.194$, $p < .001$). However, among those receivers ultimately joining, this effect is attenuated. That is, we see no statistical increase in a receiver's propensity to purchase once they have joined.

To further examine the above findings, we next examine the effects of custom versus standard invitations on sender and receiver purchase behavior. To address this, we predicted average transaction value (ATV) as a function of message type; that is, we examined separately for senders and receivers the effect of a custom versus standard invitation message. Among senders, as noted in Figure 5, we find that those sending unique invitations have an ATV of $102.53, whereas those sending standard invitations spend an average of $95.71. This difference is significant ($\beta = 6.82$, $t(1, 6669) = 4.238$, $p < .001$). Among receivers, the difference in ATV is insignificant; that is, we find no difference in average purchase dollars based on whether the customer was acquired via custom or standard invitation.

To continue our examination of key transaction measures, we next compare custom to standard messages on total transactions for both senders and receivers. Among senders, we see a pattern similar to Figure 5, with a significantly greater number of transactions for custom versus standard invites ($\beta = 2.93$, $t(1, 6752) = 9.21$, $p < .001$). Among receivers, we continue to see a nonsignificant effect. A summary of these results is noted in Table 2, which also includes a comparison of the total number of invitations sent by custom and standard senders. It should be noted that no statistical difference exists between the total number of invitations sent by custom versus standard senders.

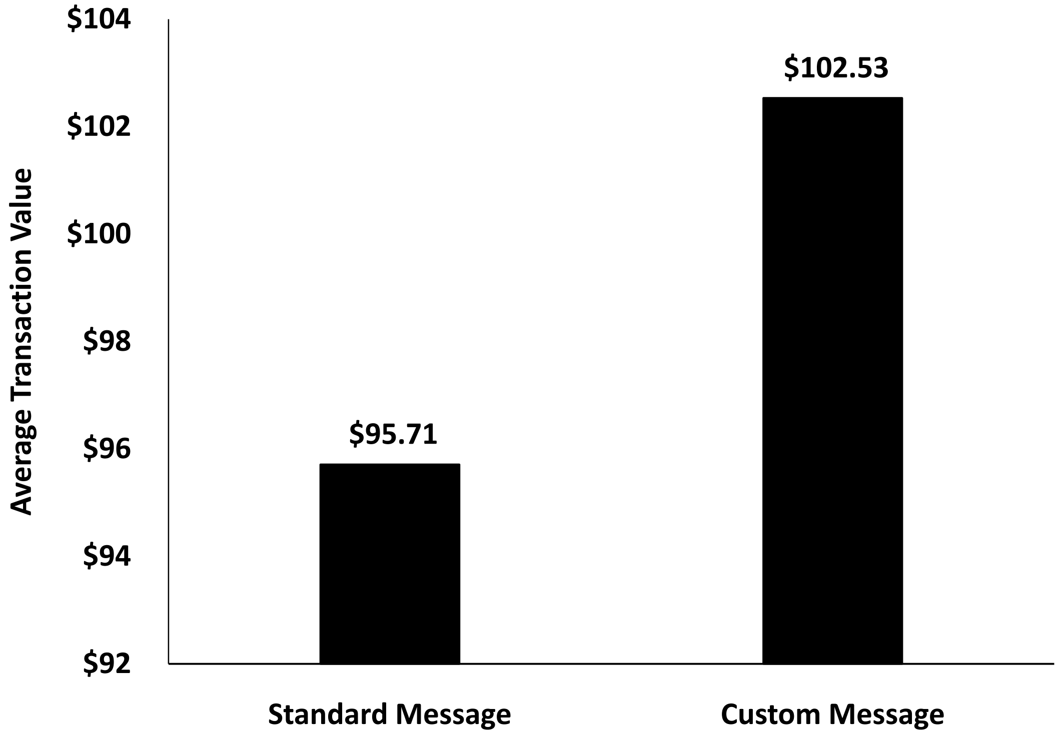


Figure 5: Average Transaction Value—Greater ATV for Custom (vs. Standard) Senders

Table 2: Summary of Key Measures between Custom and Standard Invites

	Senders			***Receivers***		
	Custom		***Standard***	***Custom***		***Standard***
n	*3,340*		*3,414*	*179*		*648*
Avg # of Transactions	8.86	***	5.93	6.34	n/s	5.76
Avg Transaction Value	$102.53	***	$95.71	$106.23	n/s	$110.10
Avg Total Invites Sent	5.48	n/s	5.90	n/a		n/a

**** Denotes significant difference (p < .001) between Custom & Standard Invites; n/s = not significant*

Discussion

Results provide initial evidence that the value of a custom (versus standard) invitation is greater from both the sender and receiver's perspective. For senders, we see this in the form of greater transactions and average transaction value for custom (versus standard) invitations, which we attribute to the spotlight effect.[9] For receivers, we find greater probability to join and to make a purchase upon receipt of a custom (versus standard) invitation. However, among receivers that ultimately join, we find no statistical differences in their probability of making a purchase nor any differences in their transaction measures. Thus, we see initial evidence that our hypothesized effect for receiver behavior attributed to reciprocity only applies to the receiver's initial actions of joining and making a first purchase.

With this initial evidence in hand, we next examine in greater detail the long-term effects of a custom (versus standard) message. Borrowing from the extant methods reviewed in our theoretical background, we implement a more rigorous analysis of our existing data. Specifically, we extend this analyses to include the key measures of a customer's probability of being active as well as their predicted number purchases, culminating with total customer value.

Modeling Customer Value via Pareto/NBD

In this section, we further examine the effects of a custom (versus standard) message by implementing a more rigorous analysis pertaining to customer value. Mainly,

[9] With no statistical difference in the number of invitations sent by custom versus standard senders, we continue to attribute our effect to the spotlight effect. If the differential had been significant, one could posit that the increased response was simply due to the increased prominence of custom (vs. standard) messaging.

our intent is to more specifically calculate sender and receiver worth by modeling i) each customer's probability of remaining as a customer based on their recency and frequency of all purchases (see Fader, Hardie, and Lee 2005) and ii) their predicted number of purchases as part of overall customer value. Building upon our previous findings, in addition to validating the worth of senders and receivers, we decompose sender and receiver purchase behavior based on the presence of custom or standard messages. We predict greater value for senders (versus nonsenders), which we attribute to senders' feelings of being "in the spotlight." Moreover, within senders, we expect to find greater value in the presence of a custom (versus standard) referral. Among receivers, our aim is to examine the worth of a custom versus standard referral, whereby we expect greater overall value based on and receivers' sense of reciprocity. An overview of the method is presented below, followed by results and a discussion of our findings.

Method

Using the Pareto/NBD method outlined in our theoretical background, we model for each customer the probability of remaining active, their predicted number of purchases, and their resulting customer value. From this, we compare these key measures between customers as a function of the factors previously examined; i.e., we compare between custom and standard invitations from both the sender and receiver perspective. In this analysis, we use the same customer-specific data from our prior examination. The data provided us with 200 weeks of data for over 21,000 customers, including data on each customer in the form of when they joined and purchased as well as the frequency and total dollar value of these purchases. From this method, our aim is to project customer activity over 1 year. Thus, we chose to calibrate our model with 148 weeks of data with a 52 week holdout to assess model fit.

Revisiting the Pareto/NBD model, based on frequency (x), recency (t_x), and total time (T), the best fitting parameters are estimated via maximum likelihood, which maximizes the sum of the log-likelihood for each individual customer. From this, we obtain the probability that an individual customer is still active at T (i.e., $P(\text{alive} \mid x, t_x, T)$) based on their recency and frequency. Also of interest is the expected number of transactions in the future time horizon of t periods, which is noted as $E[X(T, T+t)|x, t_x, T]$. After projecting purchase activity for each customer over the 1 year period, we then multiply average transaction value based on calibration period purchases by the above values of survival (e.g., $P(\text{alive} \mid x, t_x, T)$) and expected transactions ($E[X(T, T+t)|x, t_x, T]$), yielding our customer value measure. In the section that follows, we highlight the results of our model.

Results

For our analysis, we begin with an overview of model fit.[10] First, as noted in panel A of Figure 6, actual purchases from the calibration period transactions were shown to result in an adequate fit with the modeled transactions. Moreover, panel B of Figure 6 provides further evidence of acceptable model fit; that is, while the actual purchases in the 52 week holdout include a few jumps (e.g., the spike near week 160), we see adequacy in the direction and magnitude of the modeled versus actual sales in the holdout period. Thus, we proceed to our main analysis of the key components of customer value.

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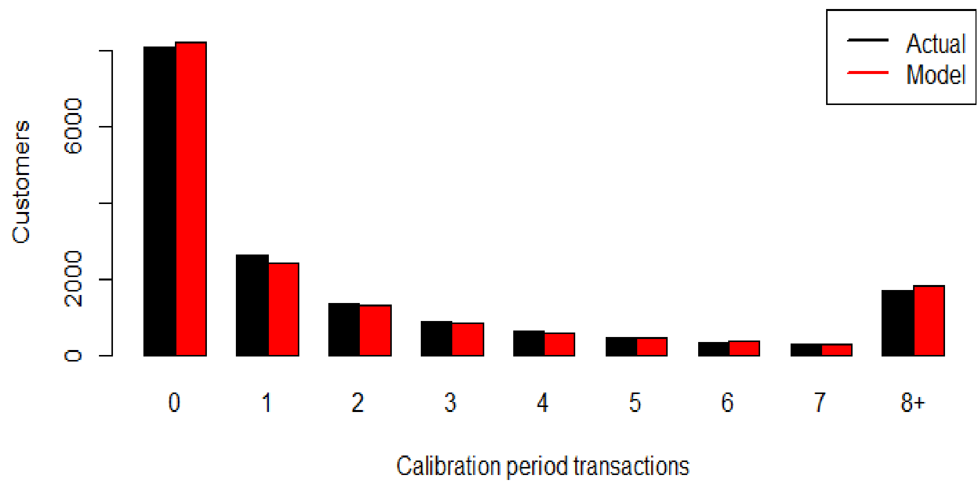
[10] We include all 21,000+ customers in this model, as our goal is to compare differences between projected values based on such groupings as senders versus nonsenders, custom versus standard senders, etc.

A)



B)

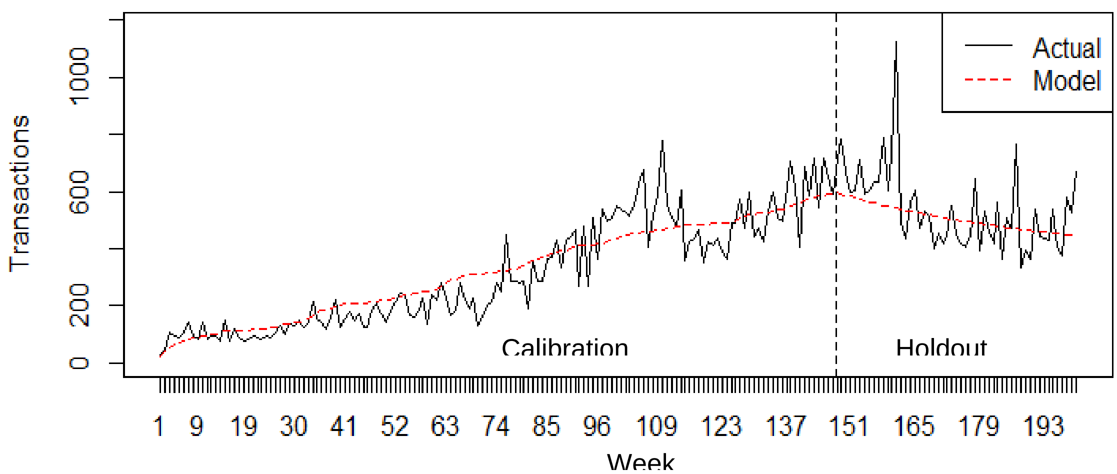


Figure 6: Pareto/NBD Model Fit. A) Calibration: Actual versus Modeled Transactions. B) Calibration & Holdout: Weekly Incremental Transactions (Actual vs. Modeled)

We begin with a macro assessment of sender and receiver behavior. For senders (versus nonsenders), we find significantly greater survival rate, purchases, and customer value, with details noted in Panel A of Table 3. Among receivers, however, modeled buyer behavior is significantly lower than nonreceivers. That is, we find significantly lower survival probability, predicted purchases and customer value; see Panel B of Table 3. We next examine the effect within groups based on whether the mode of referral was custom versus standard. For custom (versus standard) senders, we find significantly greater performance on our key measures (see Panel C of Table 3). As for modeled behavior of receivers (Panel D of Table 3), we find no significant differences based on whether the received referral was custom or standard.

Discussion

Results of this examination corroborate our initial findings from the average transaction value by showing significantly greater performance for custom (versus standard) messages among senders. This effect holds on all three key measures of survival, predicted purchases and customer value, which we attribute to the spotlight effect. As a caveat to these findings, we find it important to acknowledge that the message delivery type is self-selected by the consumer, and it is plausible that custom senders could simply be “better” customers than standard senders. However, given our finding of no statistical differences in the number of invitations sent between custom and standard senders, we continue to attribute our effect to the presence of spotlight effect, and we revisit this point in our concluding discussion.

As for results among receivers, we find that overall value is lower than

Table 3: Average Transaction Value

Between Groups: Significantly Greater Performance Among Those Sending & Receiving

A)

	Senders vs. Nonsenders					
	Senders	**Nonsenders**	**△**	**DF**	**p**	
P(Alive)	.544	.519	.025	16228	<.001	***
Predicted Purchases	2.37	1.34	1.03	16228	<.001	***
Customer Value	$256.20	$139.82	$116.39	16228	<.001	***

B)

	Receivers vs. Nonreceivers[1]					
	Receivers	**Nonreceivers**	**△**	**DF**	**p**	
P(Alive)	.424	.534	-.11	16228	<.001	***
Predicted Purchases	1.20	1.73	-.53	16228	<.001	***
Customer Value	$130.24	$184.44	-$54.19	16228	<.001	***

Within Groups: Greater Performance for Custom Messages; No Effect Among Receivers

C)

	Senders					
	Custom	**Standard**	**△**	**DF**	**p**	
P(Alive)	.563	.525	.04	5849	<.001	***
Predicted Purchases	2.75	1.96	.78	5849	<.001	***
Customer Value	$301.36	$208.15	$93.21	5849	<.001	***

D)

	Receivers				
	Custom	**Standard**	**△**	**DF**	**p**
P(Alive)	.453	.416	.04	797	< .20
Predicted Purchases	1.39	1.15	.24	797	< .36
Customer Value	$140.18	$127.41	$12.77	797	< .69

**** Denotes significant difference (p < .001) between groups of interest*

nonreceivers on all key measures. Moreover, we find no effect from the receipt of a custom versus standard invite. Thus, we lack evidence for our hypothesized effect of increased response from custom receivers. In sum, our findings suggest that receivers tend to respond to sender messages with lower than average performance than nonreceivers, irrespective of whether the received message is custom or standard. In examining this effect among receivers, it is quite possible that we are witnessing these results due to the fact that receivers are joining merely as an appeasement or a signal of thanks to the sender, which would still be a form of reciprocity, albeit with a different outcome. To further explore this possibility, we revisit the findings presented as part of our first examination in this essay, where it was found that custom receivers were 52% more likely to join and 83% more likely to make a purchase than standard receivers. These results, in conjunction with the findings of the current study, still point to reciprocity, but importantly highlight that this reciprocity is short-lived. That is, a custom receiver's greater propensity to respond to the initial invite does not appear to sustain.

General Discussion

In this research, we ask whether referral type has an impact on the purchase behavior of the sender and receiver. Based on theory pertaining to the spotlight effect and reciprocity, we posit that custom (versus standard) referrals will have a greater effect on both sender and receiver behavior. To test our theory, we preliminarily examined transaction measures of custom versus standard senders and receivers and extended this analysis with a model-based examination of key components of customer value (from predictive modeling based on Pareto/NBD) across these very same customers. For senders, we find significantly greater performance across the board, with a more pronounced effect when a custom (versus standard) message is sent. In light of the similar invitation activity between custom and standard senders (in the form of number of invitations sent), we do not feel that custom senders are simply better or more active customers; however, with message type (custom versus standard) being self-selected by consumers, a randomized field study design would allow us to further examine this effect.

As for receivers, we find that one's propensity to join and make a purchase is higher when the received message is custom (versus standard), although we do not see this translate to greater performance on our transaction or model-based measures. Taken together, these findings support our hypothesis that the act of sending a custom (versus standard) referral has an impact on both senders and receivers, albeit with a less sustainable effect for the latter group. That is, we continue to posit that reciprocity is at play in a receiver’s response, although results suggest that this applies only to a receiver’s initial activity with the company (e.g., the act of joining and making an initial purchase).

From a theoretical perspective, our findings inform existing research pertaining to referral marketing and predictive modeling of customer value, whereby we uniquely show how the specific information within the referral itself can influence purchase behavior and customer value. Moreover, we feel these findings uniquely incorporate consumer behavior theories stemming from spotlight effect and reciprocity. Results also provide practical implications for marketers in seeking to understand the optimal drivers of referral programs. In our research, by focusing on the degree of customization of the referral and its effect on purchases, our findings give cue to marketers in optimizing referral programs. Specifically, a marketer’s incorporation of customized messaging elements in referral programs can help to increase the overall response to a given referral.

ESSAY 3: CAN THE ACT OF REFERRING CHANGE THE LONG-TERM PURCHASE BEHAVIOR OF REFERRERS?

Introduction

Much marketing literature has proved the value of customers that are acquired through the referral efforts of existing customers. Referrals are considered important because it is hoped that a referral will increase sales by persuading receivers to act on the sender's message via ongoing purchases. Further illuminating the importance of referrals, past research has suggested that a sender's customer lifetime value (CLV) should not simply include the value of an individual customer's purchases, but should also include the value of the people that this customer referred over his or her lifetime. For example, Kumar et al. (2010) measured customer referral value (CRV) in addition to CLV in calculating a customer's worth to the firm. In calculating a given customer's total value, CRV takes into account the value of all newly-acquired customers stemming from that customer's successful referrals over the lifetime of the customer. This research has provided valuable insights for marketers in understanding the true value of a referral on a per-customer basis.

However, while we know much about how much value referrals add, in our research we seek to learn more about the intervening role of a referral and how it might influence future purchase behavior of the sender. That is, we ask in our research whether the act of referring a product to another individual would result in an increase, decrease, or consistency in purchase behavior on behalf of the sender. In examining extant theories, we find two opposing predictions based on i) dissonance reduction and ii) market mavens and opinion leadership.

Theoretical Review

Cognitive Dissonance

The theoretical domain of dissonance can inform how a referral may affect sender behavior. As discussed in Festinger's (1957) seminal work, dissonance is introduced when an individual holds psychologically inconsistent cognitions. It is viewed as a physiologically uncomfortable arousal state—that is, a conflict of cognitions—whereby one is driven to undergo cognitive change to reduce the conflict. Similar to our innate desires to reduce such factors as hunger or thirst, individuals will attempt to reduce dissonance, resulting in preservation of a consistent, stable self (Aronson 1992).

Mainly, there are two necessary conditions for an individual to experience dissonance. This includes i) the possibility of aversive consequences and ii) a personal sense of responsibility for those consequences on behalf of the individual (Cooper and Fazio 1984). Regarding the first necessary condition of aversive consequences, the behavior in question must minimally introduce the possibility of an adverse event. That is, the individual's action runs the risk of triggering an event that would not be preferred by that person. In the context of our example of a sender of a referral, this aversive event could entail being questioned by a receiver as to why a referral would be sent by someone that does not even purchase the product for him or herself. As for the second necessary condition of personal responsibility, this simply means that an individual must be in control of triggering the behavior or action and thus able to accept responsibility. For example, a customer extending a referral invitation to a friend or family member, through their initiation of the message—is responsible for the message in that he or she personally extended it.

Opinion Leaders and Brand Mavens

The important role that some consumers can play in influencing the behaviors of other consumers is informed by existing research on opinion leaders and brand mavens. While these two groups are distinct from each other, opinion leaders and mavens are rather similar as it relates to their overall high level of brand awareness as well as their increased propensity to try more brands (Elliot and Warfield 1993).

Opinion leaders are generally defined as individuals that exert a disproportionate amount of influence on the decisions of others within a specific product or category (Flynn, Goldsmith, and Eastman 1996). One's status as an opinion leader has been shown to positively relate to one's overall awareness, shopping, and purchase behavior. For example, in the wine category, opinion leaders were shown to be heavier consumers, providing evidence of one's status as an opinion leader resulting in an overall greater level of consumption.

Market mavens, while similar to opinion leaders in their ability to influence, are more expansive in their knowledge of different kinds of products, with their influence extending beyond product features to such factors as where to shop and where to find a deal (Feick and Price 1987). In addition to providing evidence for maven's increased propensity to gather marketplace information, research has shown evidence of greater experimental buying behavior via higher unaided and aided recall of brands as well as larger consideration and trial sets (Elliot and Warfield 1993). Additionally, mavens have been shown to be "smart shoppers" when it comes to seeking and disseminating knowledge about deals. For example, participants of a grocery shopping survey showed that those high on the market maven scale gave away four times as many coupons as those scoring low on the market maven scale (Price, Feick, and Guksy-Federourch 1998).

Theoretical Predictions

Much research on dissonance reduction has shown that individuals seek to maintain internal consistency between their beliefs and actions. Whenever there is an imbalance, psychological distress is triggered, resulting in actions aimed at reducing this dissonance. For example, it is possible that the sender's act of referring a friend or family member might trigger a cognition similar to "*I think that my friend would like this product, so I'm going to recommend that they try it*." This cognition raises the possibility of creating conflict for the sender, as it may be incongruent with cognitions regarding her recent purchase activity. That is, dissonance could be aroused in the presence of a concurrent, conflicting cognition that recognizes the possibility of one feeling the spotlight effect of their recommendation. For example, the sender could state to herself, "*I'm recommending that my friend(s) try this product, but I haven't tried it myself as of late. I don't want to be accused of recommending something that I'm not familiar with.*"

Applying the above example to the context of a sender, if the referral is personally crafted and delivered to the recipient, then the responsibility clearly falls on the sender.[11] Moreover, an inconsistency may surface in the mind of the sender if their recent purchase behavior is inconsistent with their recent act(s) of referring. That is, if a customer that has recently sent a referral to a friend has not made a purchase in quite some time, he or she may experience dissonance between the recent act of referring and the recent trend of making no purchases. To reduce this dissonance, the sender may feel implored to make purchases, thus minimizing the discrepancy between the conflicting behaviors of purchasing and referring. Hence, dissonance theory would predict greater purchases by the sender *after* the point at which a referral occurred.

On the other hand, research on market mavens and opinion leadership suggests that certain individuals refer products because they like spreading information about products and categories of interest; that is, their status as the subject-matter expert, or information guru, is an innate need for them. Purchasing, however, is not a necessary condition for mavens to refer products. It is thus plausible that senders may simply be more likely to hold status as a market maven or opinion leader. In the sole presence of this effect, we would expect to find no change between the upstream and downstream actions of the sender based on a referral. That is, if our effect is due *solely* to one's status as a market maven or opinion leader, we would expect to find equally strong sales both before and after the point at which a referral occurs.

In the sections that follow, we first present preliminary findings from an empirical examination of sales data for an online retailer. These data allow us to examine the precise point of a referral and whether this results in any significant changes in

[11] If, for example, a message was sent on behalf of the sender from the company or brand, this may not be the case.

downstream (i.e., postreferral) sales from the sender. We then extend this model to more specifically monetize the pre- and postreferral value of a sender in terms of his or her CLV.

Analysis of the Referral as an Intervention

To initially test our competing accounts—that is, the dissonance and maven accounts—we begin with an examination of customer transactions over time. Specifically, we identify the precise point of referral for a sender—treating this event as an intervention—which allows us to compare prereferral to postreferral transaction behavior for customers. In the presence of the dissonance account, we should find that postreferral behavior exceeds that of prereferral. That is, we should find greater value from senders after the intervening effect of the referral. Alternatively, if our effect were to be attributed solely to the maven account, we would expect to find no difference between prereferral and postreferral purchase behavior.

Data and Variables

To measure the sender's behaviors before and after the point of the referral, we examined sales patterns for senders with the point of referral identified for each individual. To do this, we began with the data set described in Essay 2, which consisted of 200 weeks of purchase data spanning from March 2010 to January 2014. Importantly, these data allowed us to examine the day at which a given customer referred someone, allowing us to examine prereferral to postreferral behavior. In structuring our data for analysis, we focus on the 6,754 customers that sent a referral (the average number of purchases for this group, as noted in Table 1 of Essay 2, was 7.35). We first centered the variable of purchase occasion, *Purch_Ctr*, with the point of the referral rescaled as purchase number 0 for a given sender. For example, a *Purch_Ctr* measure of 3 would equate to the third purchase *after* a referral was sent. On the other hand, a *Purch_Ctr* measure of -3 would represent the third purchase *before* a customer's referral was sent. We then added a dichotomized intervention variable, where for the centered purchase occasion variable *Purch_Ctr* for customer *i*

$$Intervention_i = \begin{cases} 1 \; if \; Purch\_Ctr_i \; \geq 0 \\ 0 \; if \; Purch\_Ctr_i \; < 0 \, . \end{cases}$$

From this, we compare average transaction value between prereferral and postreferral periods—specifically, as a function of purchase occasion, the referral intervention and their interaction. In the next section we present results.

Results

Based on the above described referral data, a repeated measures ANOVA predicted average transaction value (ATV) as a function of purchase occasion number, the dichotomous referral intervention variable and their interaction. We begin with the significant intercept of \$104.56 (β_0 = 104.56, t(1, 49759) = 105.18, p < .001), which would indicate sender ATV immediately preceding their point of referral (i.e., *Purch_Ctr* = 0 and *Intervention* = 0). We next explore the effect of *Purch_Ctr*, whereby results indicate a significant main effect for purchase occasion, with each additional purchase resulting in a lower average transaction value, in dollars (β_{Purch_Ctr} = -.13, t(1, 49759) =

-3.53, $p < .001$). Interpreting this, a consumer's third purchase would be 13 cents less than their second and 26 cents less than their first purchase. As for the effect of the referral itself (i.e., *Intervention*), we see a significantly positive main effect, with the point of the referral resulting in an approximate $2 increase in ATV ($\beta_{Intervention} = 1.97$, $t(1, 49759) = 2.04$, $p < .001$). Finally, for the interaction between *Purch_Ctr* and *Intervention*, we find that each purchase subsequent to the point of a referral results in a significantly greater ATV. Specifically, we find that each postreferral purchase results in an increase in ATV of $0.46 ($\beta_{Purch_Ctr \times Intervention} = .46$, $t(1, 4. 49759) = 8.39$, $p < .001$). A visual representation of this effect is noted in Figure 7, which displays ATV for a hypothetical customer making seven purchases over their lifetime (chosen due to its proximity to the mean number of purchases made by senders—that is, $M_{Senders} = 7.35$).

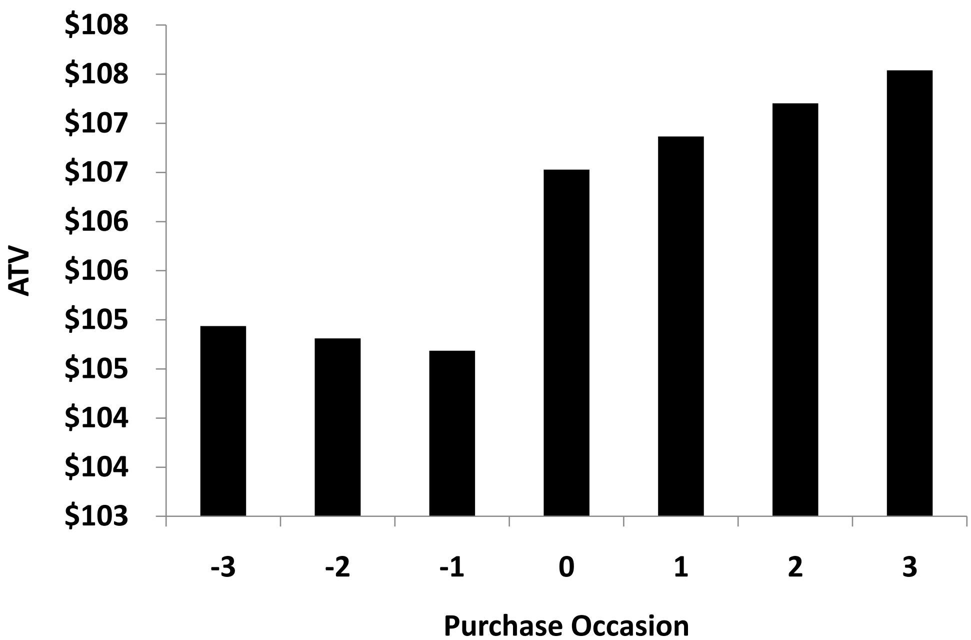


Figure 7: Analysis of the Referral as an Intervention—Sender ATV Increases Postreferral

Discussion

In this analysis, we provide preliminary evidence that the point of a referral results in an increase in postreferral behavior. Results suggest that the act of referring serves as an intervention for senders, whereby we see a disproportionate increase in their purchase patterns after the point of sending a referral. Specifically, we see this in the form of increased ATV, which is also shown to increase over each purchase occasion following a referral. These results are consistent with the theoretical account of dissonance reduction, whereby we posit that senders engage in increased purchases postreferral in order to justify their personal promotion of the company/brand to friends or family.

However, ATV is merely one variable and does not adequately capture the total value of a given customer. That is, these findings are based on a singular measure of average dollars and fail to take into account such factors as frequency and/or recency of purchases. Thus, in the next section, we seek to extend this analysis through a more rigorous decomposition of CLV that compares prereferral and postreferral customer value. In the section that follows, we discuss in greater detail the method employed.

CLV Decomposition: Pre- versus Postreferral

While the prior analysis provides evidence for greater postreferral value from senders in the form of average transaction value, it does not fully capture customer activity over the duration of our data. Thus, our objective in this examination is to calculate total customer value on a prereferral and postreferral basis and compare these two measures. To do this, we compute for senders a time-adjusted prereferral and postreferral dollar value derived from the CLV method reviewed in our theoretical background. Based on this method, we decompose this CLV measure into a prereferral and postreferral component, which is importantly adjusted to reflect a comparable net present value for each customer. In the presence of the dissonance account, which is what our prior (intervention) analysis suggested, we would expect to find that postreferral CLV exceeds that of prereferral. Alternatively, if the maven account were to prevail, we would find no difference between the aforementioned pre- and post-CLV measures.

Methodology

In this examination, we utilize the same data set from Essay 2, spanning 200 weeks of customer transaction detail between March 2010 and January 2014. As a brief recap, these data allowed two important measures in i) identification of senders of referrals and ii) isolation of the day at which a referral occurred. For the purposes of our analysis, we subsequently focused on those senders that made at least one purchase after the point of a referral, which identified 2,268 customers (34% of all senders) making 36,324 purchases (73% of all sender purchases).[12] In order to monetize pre-to-post value of a sender, we revisit the CLV calculation presented in Equation 4, which for a given customer takes the net present cash flow from purchases multiplied by the customer's probability of being active. With our current examination focusing retrospectively (versus prospectively) on actual (versus predicted) purchases, we treat survival as a certainty, with pre and postreferral CLV from Equation 4 revised to reflect a pre- and postvalue for each consumer (in Equations 5 and 6, respectively) as follows:

[12] There were 6,754 senders in total, making 49,857 purchases. For the purpose of our analysis, we focus on those making at least one postreferral purchase, which comprised 2,268 customers making 36,324 purchases.

$$\text{Pre CLV}_i = \sum_{t \leq 0} (\text{actual cash flow}_\text{t}) \times \text{P}(\text{alive}_\text{t}) \times (\text{discount factor}_\text{t}) \text{ and} \tag{6}$$

$$\text{Post CLV}_i = \sum_{t > 0} (\text{actual cash flow}_\text{t}) \times \text{P}(\text{alive}_\text{t}) \times (\text{discount factor}_\text{t}). \tag{7}$$

To illustrate the above equations, consider the following actions of a hypothetical customer within a given year: he/she became a customer on January 1 with a $100 purchase, then made a $90 purchase on March 1, and a $50 purchase on March 15 before referring a customer on March 30. Postreferral, let us assume this customer made a total of three $150 purchases on the first days of the next 3 months of April, May, and June. In this instance, pre-CLV is the cash flow generated from all purchases occurring *before* their point of referral ($100, 90, $50), with each purchase discounted back to January 1. As for post-CLV, each of the 3 purchases of $150 are also discounted back to January 1. With our data consisting of actual (versus predicted) purchases, we treat survival as a certainty and thus P(alive$_t$) = 1. As for (discount factor$_t$) in Equations 5 and 6, this is comprised of discount rate *d* based on *j* days since joining for a given customer and calculated as

$$(\text{discount factor}_\text{t}) = \frac{1}{(1+d)^j} \ . \tag{8}$$

The discount rate *d* in Equation 7 was established by benchmarking the weighted average costs of capital in comparable industries, which was 8% annually.[13] This method was employed for each of the 2,268 customers, with each customer's output consisting of two

[13] The discount rate was adjusted to a daily rate for Equations 5 and 6 (as all other time variables were daily).

key values from Equations 5 and 6 in the form of pre-CLV and post-CLV. Subsequent to calculating these two values, we examine pre-CLV versus post-CLV via two-sided t-test and present our findings in the section that follows.

Results

A two-sample t-test was performed that compared pre-CLV (from Equation 5) to post-CLV (from Equation 6). Results highlight a significant difference between the pre- and postvalues, with post-CLV being over \$200 greater than pre-CLV (M_{Pre} = \$803.99, M_{Post} = \$1,008.30, Δ = \$204.31, t(2268) = -3.092, *p* < .001). These findings—which are illustrated in Figure 8—are consistent with the pattern that emerged in our prior (intervention) examination whereby we see a positive postreferral effect on sender purchase behavior.

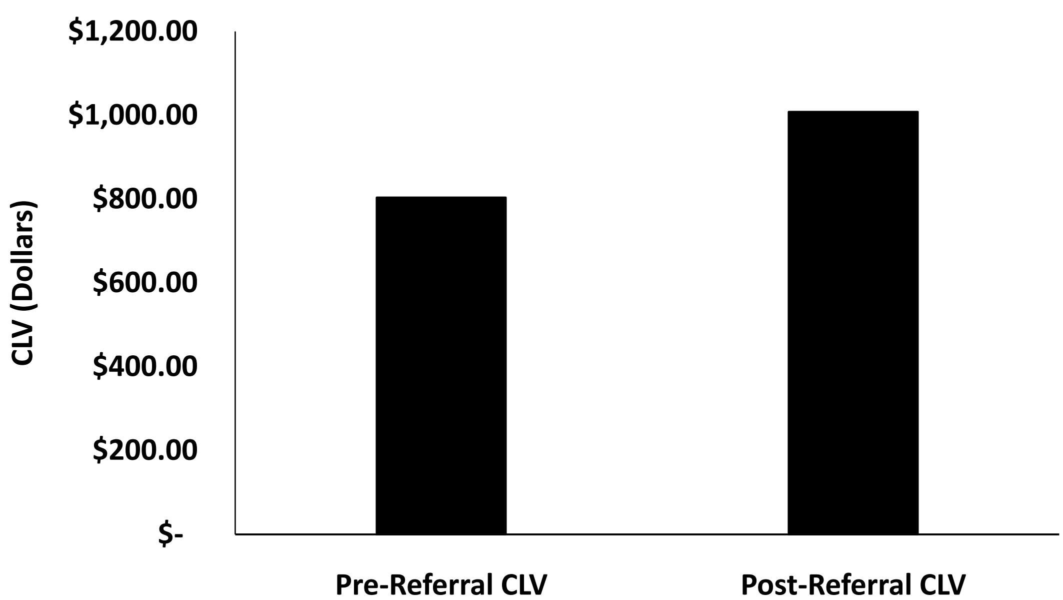


Figure 8: CLV Composition—For Senders, Greater Value Postreferral

Discussion

In this examination, we provide further evidence for the positive effect of a referral on future sender behavior. Similar to our intervention analysis, we see a disproportionate increase in consumers' purchase patterns *after* the point of sending a referral. Importantly, we see this in the form of a decomposed CLV that compares actual prereferral versus actual postreferral value. This evidence of significantly higher postreferral CLV is consistent with our theory of dissonance reduction, whereby we continue to posit that senders engage in increased purchase behavior in order to justify their referral actions.

General Discussion

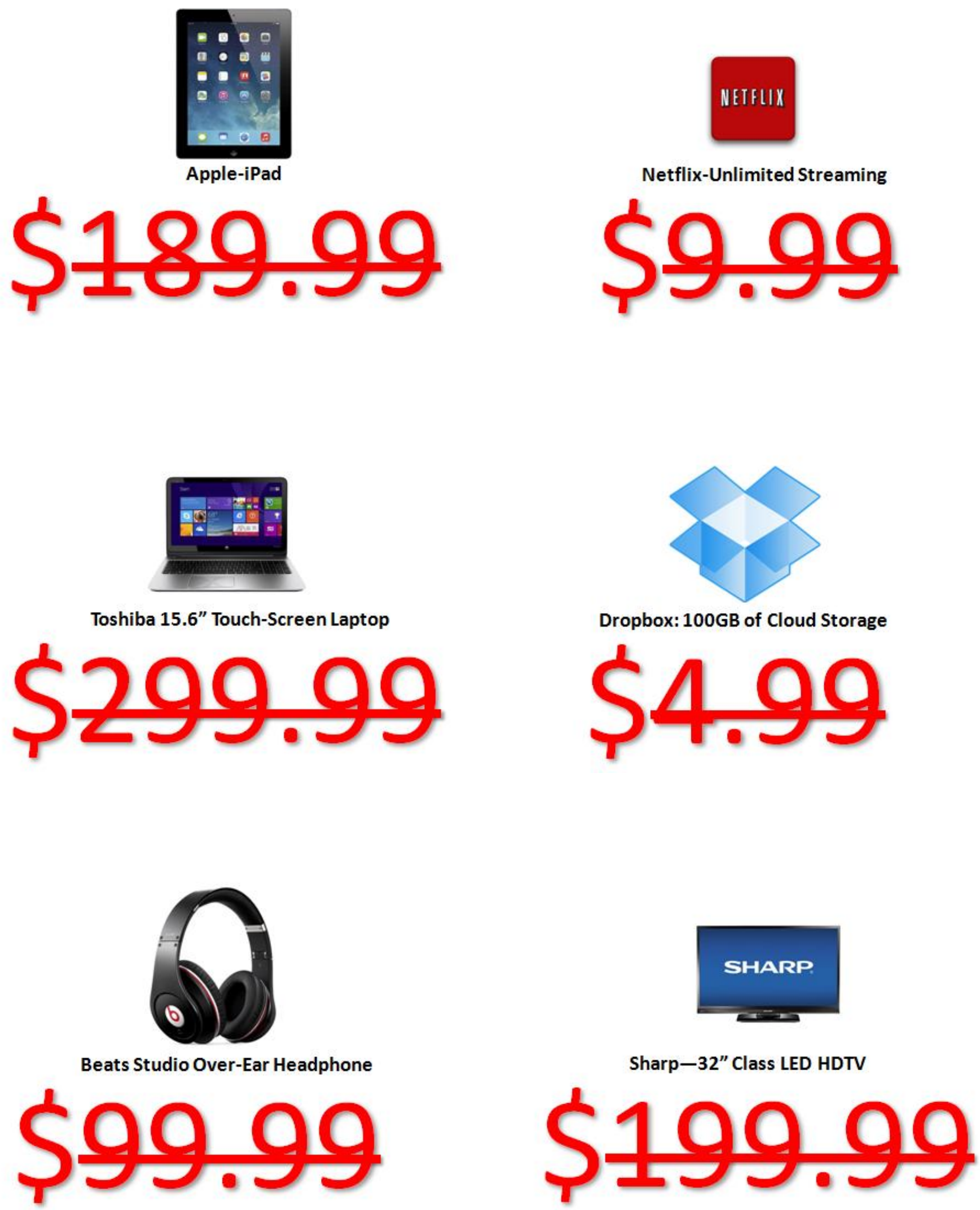
In this research, we ask whether the act of referring a product increases, decreases, or leaves unchanged the purchase behavior of the sender. From extant theory, we find alternate predictions stemming from dissonance reduction and market mavens. In the account of dissonance reduction, it is expected that the sender would engage in additional purchases in order to reduce conflict between the act of referring and making purchases for him or herself. Alternatively, if the sender's referral behavior is attributed to his or her status as a market maven, then this individual's purchase behavior should remain at comparable levels both before and after the point of referral. In our research, we find evidence that the referral itself serves as a point of intervention that results in an increase in average transaction value for the sender. We then validate these findings with a more rigorous analysis based on a decomposition of CLV into pre- and postreferral measures. We feel that these findings offer unique implications for theorists and marketers alike, which we discuss in the paragraph that follows.

From a theoretical perspective, this research informs existing theories and models pertaining to the value of a customer referrals. We feel that our findings uniquely inform this literature by providing insights relating to how the act of the referral itself serves as a point of intervention that results in a significant change in postreferral sender behavior. From a marketing practitioner's perspective, our research provides valuable insights that aid marketing managers in understanding the lasting impact of a referral on the subsequent purchase behavior of the sender. This has immense implications for marketers in optimizing long-term sales.

APPENDIX A

STIMULUS FOR EYE TRACKING STUDY

Low Price Condition[14]



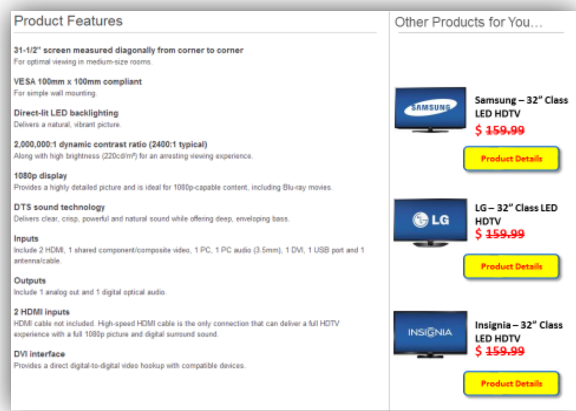
[14] For the High Price condition, prices were as follows: $309.99 for the tablet, $24.99 for streaming video, $799.99 for the laptop, $11.99 for cloud storage, $299.99 for headphones, and $429.99 for the TV.

APPENDIX B

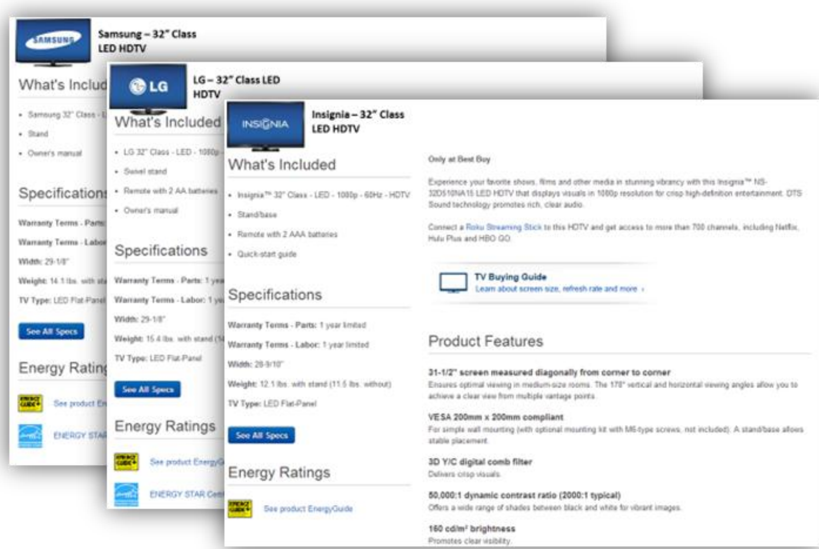
STIMULUS EXAMPLE FOR CONTROLLED LAB STUDY

A) Main Product Stimulus

B) Depth of Interaction Page 1



C) Depth of Interaction Pages2–4



APPENDIX C

STIMULUS EXAMPLE FOR FOOD MANIPULATION CONDITION


SEAT AT FRONT TABLE
WORKING ON THE TASK
FEW MINUTES YOU WILL BE INSTRUCTED
TO A COMPUTER TO FINISH THIS STUDY
(AND TAKE SAMPLE) AS YOU LEAVE
HUNGRY?
A SMALL SAMPLE
ON YOUR WAY OUT
(AFTER THE STUDY)

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