ESSAYS ON TWO NOVEL PRICING MECHANISMS

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1. OVERVIEW

Pricing has been identified as a cornerstone of the marketing mix (Winer, 2005), and novel pricing mechanisms can help firms differentiate themselves from others in their industry (Sawhney, Wolcott, and Arroniz, 2006). Innovative pricing is a strategic tool that captures greater customer value through creative forms of differentiated pricing, and increasing purchase intentions by engaging customers in the pricing process (J. Raju and Zhang, 2010). Notable examples of novel pricing techniques are automatic markdowns by Filene’s Basement (Fournier and Avery, 2011), name your own price strategy popularized by Priceline (T. Wang, Gal-Or, and Chatterjee, 2009), and the retail club pricing model adopted by Sam’s Club and Costco (Kim and Choi, 2007). General Motors “No Haggle” pricing policy for its’ Saturn automobiles was so appealing that customers were willing to pay higher prices to avoid the unpleasant hassle of negotiation (Zeng, Dasgupta, and Weinberg, 2008). Some companies consider their innovative pricing strategies so important they seek patent protection for them. For example, Uber filed for a patent on their surge pricing policy (Decker and Saitto, 2014).

While pricing research has been strongly influenced by economic principles, academic research has also explored the psychological aspects of pricing on consumers behavior (Krishna, 2009; Winer, 2005). For example, studies of price fairness (e.g., Xia, Monroe, and Cox, 2004), and differences in how consumers construct reference prices (e.g., Tradib Mazumdar, Raj, and Sinha, 2005), show that emotions and biases lead consumers to act in a manner that fails to maximize their economic outcome.

My dissertation proposal examines behavioral responses to pricing through two novel pricing mechanisms: mobile coupons where coupon values are based on each shopper’s redemption history, and pay-what-you-want (PWYW) pricing, where consumers are allowed to
pay any price they choose (Kim, Natter, and Spann, 2009). Both pricing mechanisms provide differentiated prices based on consumer heterogeneity and the opportunity to actively engage in the price setting process. For example, coupon values in my study are set according to whether shoppers are brand-loyal, or deal-prone by examining their purchase history, whereas in PWYW pricing, differences in an underlying personality trait, anticipated guilt, determine what price customers pay.

Customers who are engaged in price setting focus more attention on purchase implementation (i.e., ‘how to buy’) rather than on purchase evaluation (i.e., ‘whether to buy’) leading to higher purchase intentions (Chandran and Morwitz, 2005). Consumers who participate actively in price setting enjoy a greater sense of control and prefer participative pricing over fixed pricing (Decker and Saitto, 2014). PWYW pricing allows customers to exercise some control over the final price. In this regard, PWYW pricing is beneficial to sellers because it invites consumers to become active participants in the price-setting process rather than merely passive price takers.

The setting for my mobile coupon study offers a related set of benefits. Recipients of traditional paper coupons, or so called “push” mobile coupons, who play little role in determining the content or timing of delivery of coupons (Unni and Harmon, 2007). However, the consumers in my study actively participate in the transaction process by scanning product barcodes as they shop to receive coupons creating greater customer engagement in the purchasing process (Kalyanam and McIntyre, 2002). Engaged shoppers are likely to purchase more items, more often than non-engaged shoppers (Shankar et al., 2016). Since shoppers in my study are rewarded with discounts for their efforts, in-store pull coupons provide an element of gamification to the shopping process, which improves the effectiveness of mobile marketing by
increasing customer engagement in the shopping process (Hofacker, De Ruyter, Lurie, Manchanda, and Donaldson, 2016).

**Essay One**

Essay One analyzes the behavior of supermarket shoppers who scan a product’s barcodes using a smartphone app. Upon scanning, a shopper receives a coupon for the item they scanned as well as a set of coupons for direct competitors in the same category. Coupon values generated by the mobile app are based on each shopper’s purchase history. If a shopper redeems a coupon for a given brand, the coupon value for that brand is reduced on their next visit, while the coupon values for competing brands increase. This targeted couponing feature allows me to observe distinctive profiles for brand-loyal and deal-prone shoppers based on switching behavior over time, a powerful tool for retailers and brand managers who wish to set coupon values based on heterogeneity in shopper brand preferences.

Targeting coupon values according to consumer preferences also helps overcome the concern that competitive couponing is predicted to result in a discount war between competing brands (Corts, 1998). This concern is assumed to be valid when all consumers receive coupons of equal discount depth. However, the literature leaves open the possibility that competing coupons may be profitable when coupon values are customized according to an individual consumer’s willingness to pay (Cheng and Dogan, 2008; Shaffer and Zhang, 1995). This concern is particularly valid when consumer purchase histories can be consulted at the time a price offer is made and with goods characterized by repeat, frequent purchases such as grocery purchases (Acquisti and Varian, 2005). Thus, this research, examines coupon values for high frequency
products during grocery shopping, and thus provides a suitable context for examining competing coupons within a setting amenable to competing coupons.

I model the determinants of redemption including coupon value, price range, coupon set size, and brand loyalty to explain what strategies consumers use to choose among multiple coupons. A latent class analysis uncovered two consumer segments driven by heterogeneity in consumer loyalty. Members of the first segment, (70% of shoppers), appear brand-focused and employ an internal (memory-based) reference price strategy common to evaluating single coupons. However, members of the second segment, (30% of shoppers), focused on price comparisons using a comparative stimulus-based (price range) strategy and are more likely to switch brands if offered greater incentives. Over several months, as consumers gained experience with mobile coupons, brand loyalty diminished for both segments, but average brand loyalty declined less steeply over the same period for members of the brand-loyal segment than for members of the deal-prone segment. These findings, new to the literature, provide guidance for managers who wish to set customized coupon values to achieve specific redemption goals. My results have broader implications for applying price comparison tools that are becoming increasingly popular with online retailers like Google and Amazon.

**Essay Two**

Essay Two examines PWYW pricing, a mechanism that allows customers to set the price they pay. A reasonable concern with allowing consumers to set prices is that they will act selfishly at the expense of firms. However, robust empirical evidence shows that most consumers pay something, although there is a good deal of variance in the price consumers choose (Kim et al., 2009). My dissertation does not focus on the question of whether PWYW is profitable,
(although there are other motives for offering PWYW such as to induce product trial, garner publicity, or sell complementary products) (Groening and Mills, 2017). Instead, I explore how consumers approach price setting.

One suggested explanation for the observed differences in the PWYW prices is that they are due, in part, to an individual propensity toward feeling guilty for paying too little (Regner and Barria, 2009) since guilt constrains unfair behavior in exchanges (Rabin, 1993). Thus, consumers who have a greater tendency to anticipate the negative effects from guilt would result pay more to avoid this cost (Cialdini, Kallgren, and Reno, 1991). While the role of guilt in explaining consumer PWYW pricing has been suggested by prior researchers (e.g., Regner and Barria, 2009), little work has tested the influence of guilt empirically.

I examine the role of guilt using two scenario-based PWYW experiments, an incentive compatible PWYW field experiment, and data from a large PWYW field study. I find that consumers with higher levels of anticipated guilt pay more than those with less anticipated guilt. The presence of social norms of fairness (e.g. equality, equity, need and reciprocity) negatively moderates the influence of anticipated guilt on PWYW prices. When norms of fairness are more salient, and consumers can follow the norm, the individual’s level of anticipated guilt has little influence. However, when norms of fairness are less salient, how to act can be more ambiguous, and the consumer’s moral compass plays a stronger role in decision making. These findings have managerial implications for firms who are considering PWYW for settings where there are few strategic motives to induce payment (Groening and Mills, 2017). Firms can increase payments using appeals that emphasize social norms to make anticipated guilt more salient particularly in settings where they have little strategic power.
To investigate the generalizability of this result beyond opportunism in PWYW pricing, I test the same model in two other settings where consumers can act opportunistically: returning used merchandise (i.e., “wardrobing”) and internet movie piracy. I find that the same pattern of results holds in both instances. Thus, I find that the personal trait of anticipated guilt plays a potentially important but conditional role in deciding a range of opportunistic consumer behaviors.

In *Smart Pricing: How Google, Priceline and Leading Businesses Use Pricing Innovation for Profitability* (2010), Jagmohan Raju and Z. John Zhang conclude that “to be smart about pricing, you have to know, first of all, what kind of customers you are dealing with,” (p.202). My dissertation investigates how consumer behavioral responses to two novel pricing mechanisms; pay what you want, and customized mobile coupons. In Essay One, I investigate differences in consumer behavior between brand-loyal and deal-prone supermarket shoppers when they can choose among competing mobile coupons. In Essay Two, I explore how differences in consumer’s propensity to experience guilt, conditional on the salience of social norms, influences how selfishly they behave first using PWYW pricing and then in other settings that provide an opportunity for them to act with self-interest. Thus, this research provides insights about how unobserved differences in motivation and personality among customers drive their purchase behavior.
2. ESSAY ONE
Scanning for Discounts: Investigating Mobile Coupon Adoption and Redemption

2.1 Introduction

In 2016, nearly 308 billion print or “traditional” coupons were distributed in the U.S. (Inmar.com 2017), with 81% of consumers using coupons regularly (Carter 2016). Given their ubiquity, traditional coupons have inspired a rich marketing literature (e.g., Blattberg and Neslin 1990). However, marketers face new challenges with the advent of mobile coupons delivered to consumers’ mobile devices. Mobile coupons are used by 33% of millennials, and constitute the fastest-growing coupon segment (eMarketer). Given their growing popularity, firms are expected to increasingly use mobile coupons (Shankar, et al. 2010).

While mobile and print coupons share characteristics and goals, mobile coupons offer unique capabilities (Table 1). Mobile technology reduces the effort required to search for, clip, and save coupons (Dickinger and Kleijnen, 2008; Shankar and Balasubramanian, 2009). Coupon content and value can be customized (Fong, Fang, and Luo, 2015; Shankar et al., 2010; Tanner, 2014), and individuals can interact with the sender electronically (Kalyanam and McIntyre, 2002; Shankar et al., 2010). Mobile platforms can notify the sender when a consumer has viewed or redeemed a coupon, which can be tracked to individual behavior over time (Danaher, Smith, Ranasinghe, and Danaher, 2015; Shankar, Inman, Mantrala, Kelley, and Rizley, 2011). The content and timing of mobile coupon delivery can be determined by the sender (push coupons) or triggered by an explicit request (pull coupons) (Dickinger and Kleijnen, 2008; Unni and Harmon, 2007).

____________________________
Insert Table 1 about here
____________________________
Although mobile coupons research has produced important findings, several gaps concerning key differences between traditional and mobile coupons remain. For example, most studies examine the decision to redeem a coupon at a single point in time. This does not provide information about long-term coupon adoption or how mobile coupon use changes over time. In addition, despite mobile technology’s ability to facilitate the search for, and comparison of, multiple brands, coupons have generally been studied monopolistically, as isolated, individual offers. And, although marketers have shown keen interest in the benefits of in-store decision making (e.g., Hui, Inman, Huang, and Suher, 2013), studies have yet to examine the role of in-store mobile coupons delivered at the “first moment of truth” (Nelson and Ellison, 2005).

This article addresses these gaps and makes three contributions to the mobile coupons literature. First, by analyzing a unique longitudinal dataset of mobile grocery coupon use, I find that “pull” in-store mobile coupons resulted in a sustained pattern of coupon adoption. Shoppers in this study engaged in a relatively high rate of brand switching when they received a coupon for an alternative product when compared to the redemption rate of unsolicited traditional print coupons (Inmar 2016), or the reported redemption rate of “push” mobile coupons (e.g., Danaher et al., 2015; Fong et al., 2015). Consistent with prior findings (Heilman, Nakamoto, and Rao 2002; Thompson 1997), pull mobile coupons users exhibited larger basket sizes and spending per trip, adding to a growing body of evidence challenging the theoretical notion that competitive couponing inevitably results in an unprofitable prisoner’s dilemma (Besanko, Dubé, and Gupta, 2003; Fong et al., 2015).

Second, in this study, consumers request coupons by scanning a product’s bar code, triggering delivery of a coupon for the item scanned, as well as for closely competing products. This allows us to examine mobile coupon redemption in the context of competing coupons, a
setting new to the mobile coupon literature, but also popular with retailers such as Amazon and Google who recommend products and prices to shoppers. Relying on reference price (Mazumdar, Raj, and Sinha 2005) and range theory (Janiszewski and Lichtenstein 1999), I find that when some consumers evaluate a set of competing coupons, the likelihood of redeeming a coupon for the scanned product depends less on coupon value (a reference-point strategy) than on coupon set characteristics, such as the range of competing prices (a stimulus-based strategy). Brand loyalty moderates the attractiveness of coupon value, such that value plays a weaker role for loyal consumers. This finding extends the literature on range theory to a setting where consumers’ decisions are based on a range of discounted prices. Redemption is also shaped by the number of competing coupons, with the likelihood of redemption being highest when the set is small, containing fewer alternatives, or large, when comparing coupons is effortful. These findings imply that managers have a good deal of latitude in targeting redemption rates by setting coupon values conditional on the number of competitors, consumer loyalty, and the desired degree of aggressiveness, rather than simply offering large coupon values that potentially erode profits.

Third, I observe coupon use over repeated shopping trips, in contrast to prior research, and thus capture changes in redemption behavior that emerge as shoppers gain experience with coupons, and to answer whether mobile coupon use can be sustained over time. Latent class analysis uncovers two consumer segments that use different coupon choice strategies. The first segment is brand-focused (71.1% of shoppers) and chooses coupons using a reference point strategy. The second segment is deal-prone (28.9% of shoppers) and chooses coupons using a stimulus-based strategy by comparing discounts across products in the set. Both segments redeemed coupons in a sustained fashion over several months. While loyalty declined gradually,
the decline was less pronounced for the brand-focused segment. This suggests that contrary to possible concerns that only a handful of deal prone shoppers would use pull mobile coupons in the long-term, I find a sizeable mixture of both deal-prone and brand-loyal shoppers, who continue to redeem coupons after months of use.

The empirical setting of this study is also noteworthy. This is the first study of mobile coupons for groceries, and in-store coupon delivery at the point of purchase, or ‘first moment of truth’ (Hui et al., 2013; Nelson and Ellison, 2005). It also investigates pull mobile coupon redemption beyond permission-based or location-based delivery (Fong, Fang, and Luo 2015; Molitor, Reichart, and Spann 2016). This is especially relevant given consumers preference for pull coupons (Unni and Harmon, 2007) and the emergence of mobile marketing applications that leverage the advantages of pull delivery (Smutkupt, Krairit, and Esichaikul, 2010).

2.2 Mobile Coupon Literature

As data from actual mobile coupon use is scarce, most research has relied on scenario-based surveys and experiments that measure attitudes toward, and intention to use mobile coupons using TAM-like models (e.g., Dickinger and Kleijnen 2008). Prior studies examine which consumer, coupon, and environmental characteristics promote or inhibit prospective mobile coupon use. Table 2 provides an overview of this research stream and key takeaways.

| Insert Table 2 about here |

Many of these studies treat adoption as a single, dichotomous event in time. Yet, a persistent concern for mobile application developers is the attrition rate that plagues mobile app use (Clark, 2010), since a large portion of consumers abandon mobile apps after a few uses.
(O’Connell, 2016). Thus, a static view of coupon use offers little insight into how temporal factors affect technology preferences (Burke 2002), or whether shoppers will continue to use mobile coupons in a manner attractive to firms. This study uses panel data collected from months of repeated coupon use to examine patterns of adoption and changes in redemption behavior over time.

2.2.1 **Push versus pull delivery**

Most prior research has examined mobile coupons that are “pushed” to consumers, thus relegating the mobile device to the role of an electronic newspaper despite its interactive capabilities. Although mobile marketing research has focused on push distribution (Barnes and Scornavacca, 2004), coupons are more effective when triggered by an explicit request from the consumer, and shoppers prefer pull coupons because they are timely, relevant, and less prone to spam (Unni and Harmon, 2007). Consumers are willing to trade the convenience of having content pushed to them for the freedom of customizing coupon content and delivery (Guo, Marston, and Chen, 2015). The emergence of mobile applications designed for pull marketing (e.g., ShopSavvy, BuyVia, and ScanLife) “makes it likely that pull campaigns will play a greater role in the future of mobile marketing” (Smutkupt, Krairit, and Esichaikul 2010, p. 134).

Whereas prior studies provide evidence of the acceptance of location- and permission-based forms of pull coupons, in this article I examine a broader class of pull coupons—namely, as defined by Guo et al (2015), coupons intended for one time use for which the consumer explicitly controls the content and timing of delivery. This definition embraces Kalyanam and McIntyre’s (2002) view of interactivity. They note “a mobile consumer who is in the supermarket and receives…a coupon message about Cheerios while walking past the box on the shelf would not constitute digital interaction (since the communication is one-way). But a two-way device that…the consumer uses to enable in-store activities would be” (p. 492).
2.2.2 In-Store Coupons

Several papers have found beneficial outcomes of targeting consumers based on their proximity to competing retailers (Danaher et al., 2015; Fong et al., 2015; Luo, Andrews, Fang, and Phang, 2013). However, no paper yet examines the in-store mobile coupons, despite the importance of in-store promotion on decision making at the “first moment of truth” (Ailawadi, Beauchamp, Donthu, Gauri, and Shankar, 2009; Hui et al., 2013; Inman, Winer, and Ferraro, 2009). In some respects, in-store mobile coupons are similar to “peel-off” package coupons and coupons dispensed at the shelf that provide same-trip discounts. These surprise in-store coupons have been found to be both profitable, and attractive to manufacturers (Dhar, Morrison, and Raju 1996). Therefore, determining whether in-store mobile coupons are used sustainably and by valuable customers are important questions for managers.

To motivate their use, coupon values are often set high enough to compensate for the effort required to search for, save, and redeem them (Henderson, 1985). Location-based coupon studies have leveraged this aspect of couponing (Fong et al., 2015; Luo et al., 2013). By minimizing differences in effort, in-store coupons provide a setting that allows us to examine the role of small coupon values on adoption and redemption behavior.

2.2.3 Competing Coupons

The few empirical studies that examine competing coupons have focused on coupons from competing retailers, such as coupons from pizza restaurants distributed in coupon books (Raghubir, 2004), or location-based mobile coupons for movie chains, restaurants and other retailers (Fong et al., 2015; Luo et al., 2013; Molitor et al., 2016). Thus, coupons for competing substitute products remain largely unexplored. One possible reason is the prediction that engaging in competitive couponing will result in an unprofitable prisoner’s dilemma (Corts, 1998). However, the literature leaves open the possibility that competing coupons whose values
are customized according to an individual consumer’s willingness to pay may be profitable (Cheng and Dogan, 2008; Shaffer and Zhang, 1995), particularly when consumer purchase histories can be consulted at the time a price offer is made and with goods characterized by repeat, frequent purchases such as groceries (Acquisti and Varian, 2005). Recent empirical evidence suggests that contrary to this prediction, targeted competing coupons may be both financially profitable (Besanko et al., 2003; Pancras and Sudhir, 2007) and beneficial to the firm in a number of other ways (Venkatesan and Farris, 2012). This study examines mobile coupons with targeted values for competing brands at a single retailer. This topic, new to the coupon literature, also informs the more general emerging literature on recommendation engines and price comparison tools becoming popular with online retailers such as Amazon and Google.

2.3 Conceptual Development

I examine the theoretical literature that shapes expectations about how consumers will evaluate sets of competing coupons, and how I expect this behavior to change over time. This leads to the six predictions summarized in Table 3.

2.3.1 Competitive couponing: from one coupon to sets of coupons

Studying competing coupons is important because customized coupons can be profitable for manufacturers and retailers. Shaffer and Zhang (1995) evaluate a policy of sending traditional coupons to customers of a rival firm (offensive targeting) to increase sales and to a firm’s own customers (defensive targeting) to counteract a rival’s coupons. They demonstrate that competitive couponing can be beneficial if coupon values are customized by offering larger
discounts with offensive coupons and smaller discounts for defensive coupons. For example, higher discounts were shown to be optimal for targeting customers near a competitor’s location while smaller discounts were optimal for targeting customers near the firm’s own location (Fong et al. 2015; Luo et al. 2013), bolstering the idea that firms can benefit from competitive couponing without eroding profits if they can target coupons appropriately.

2.3.2 Forces shaping mobile coupon redemption

Single coupons: the role of coupon value

Consumers often judge the attractiveness of a given price by comparing it with an internal reference price (IRP) remembered from a prior shopping occasion (Krishnamurthi, Mazumdar, and Raj 1992; Mazumdar et al. 2005). These comparisons influence decision making (Kalyanaram and Winer 1995), such that prices lower than the IRP are perceived favorably and prices above the IRP are viewed negatively (Winer 1988). This model is based on adaptation-level theory (Helson 1964) in which the consumer’s IRP is the adaptation level formed by shopping experiences (Kalyanaram and Winer 1995). By extension, when a consumer considers a coupon, the focal price is the net or discounted price and the adaptation level is their memory of prior prices (Niedrich, Sharma, and Wedell 2001). Coupons with high values provide a deeper discount, making focal prices more attractive (Lichtenstein, Netemeyer, and Burton 1990) and positively influence product choice and redemption rates (Leone and Srinivasan 1996).

Therefore, although I expect coupon values to influence purchase behavior, in economic terms, coupon value is expected to be inconsequential, since the effort required to search, save, and redeem mobile coupons is small compared to traditional print coupons. Thus, I predict:

**Prediction 1:** Coupon value will have a significant but negligible effect on the likelihood for redeeming a coupon for the product scanned.
2.3.3 Multiple coupons: the role of price comparisons

Some consumers judge prices contextually, employing a stimulus-based reference (SBR) price based on comparisons made across a set of observed prices (Moon, Russell, and Duvvuri 2006). The SBR price forms on each purchase occasion when the consumer observes the shelf prices of competing brands (Mazumdar and Papatla 2000). Analogously, I conjecture that a similar SBR could form when consumers assess a set of coupons displayed on their smartphones. Previous research on SBR price posits that consumers evaluate prices according to their relative position on a scale defined by the lower and upper bounds of the range of other prices (Janiszewski and Lichtenstein 1999; Moon and Voss 2009). This range forms when the consumer considers the range of prices at the time of purchase (Rajendran and Tellis 1994) and can explain why the effect of a competitive coupon is stronger when price ranges are large rather than small (Raghubir 2004). While range theory has been applied to retail prices (Janiszewski and Lichtenstein, 1999; Moon and Voss, 2009), and to comparisons of product attributes (Yeung and Soman, 2005), this tests range theory in a new setting where buyers are asked to consider the effect of promotional discounts when comparing prices. Thus, I predict:

**Prediction 2.** The location of a products net price within the set of net prices (NPR) will influence redemption. A coupon that results in a price low in the net price range will more likely to be redeemed than a coupon which results in a price high in the price range.

In sum, I expect not only coupon value, but also the relative position of the discounted price within a range of other net prices resulting from the set of coupons to influence redemption.

2.3.4 The moderating effect of brand loyalty

Some consumers are considered brand loyal in that they purchase the same product repeatedly from the same brand, regardless of a competitor’s actions or changes in the environment (Jacoby and Kyner 1973). By contrast, deal-prone consumers show a general inclination to use
promotional deals such as buying on sale or using coupons and are more likely to switch between brands (Lichtenstein, Netemeyer, and Burton 1995).

Brand loyalty influences consumers’ tendency to redeem coupons (e.g., Raju, Srinivasan, and Lal 1990) and how they evaluate coupon attractiveness (Mazumdar and Papatla 1995). Prior studies have found a robust negative association between coupon redemption and brand loyalty and that loyalty attenuates consumers’ responses to coupon value (Mittal 1994). Brand loyal consumers are more inclined to redeem coupons for their favorite brand, and that increasing coupon values has a smaller impact on the redemption rates of loyal consumers (Shoemaker and Tibrewala, 1985). This suggests that customers who have previously redeemed coupons for a particular brand are more likely to redeem coupons for that brand on subsequent visits, but that coupon value has a smaller impact on their decision than it has on less brand loyal consumers. I predict:

**Prediction 3.** Brand loyalty will (negatively) moderate the effect of coupon value on redemption such that coupon value will have less influence on the behavior of highly brand loyal consumers compared with less loyal consumers.

**2.3.5 Coupon set size**

Even when facing simple choices, consumers find decision making more difficult as the number of choices increases (Iyengar and Lepper 2000). One explanation is the cognitive burden imposed by making comparisons: while more choices offer benefits, they also imply additional costs (Scheibehenne, Greifeneder, and Todd 2010). If the perceived marginal cost of comparing prices exceeds the benefit, consumers may forgo comparisons (Schwartz 2004). If benefits increase more slowly than costs, set size imposes a U-shaped influence on consumers’ overall utility (Reutskaja and Hogarth 2009). Sets with few coupons, while easy to process, provide fewer benefits, while large sets require comparing the net price of each product with others in the
set. Presenting a set of alternatives may expand the consumer’s consideration set, particularly for those who are more brand loyal (Tradib Mazumdar et al., 2005). However, consumers may be unwilling to expend this effort, leading them to simply redeem the coupon for the product they scanned (Scheibehenne et al. 2010). Thus, I predict:

**Prediction 4.** Coupon set size will exert a U-shaped, effect on the redemption rate for a focal coupon. Shoppers are expected to be more likely to redeem a (default) coupon for a product they scan when the size of the coupon set is either very small, or very large.

### 2.3.6 Loyalty over Time

Whether current sales promotions influence repeat purchase behavior is an important question for manufacturers and retailers. Empirical studies that have examined changes in brand loyalty over time have reported mixed results (c.f., Dawes, Meyer-Waarden, and Driesener, 2015; Dekimpe, Steenkamp, Mellens, and Abeele, 1997). In settings with high levels of sales promotion, Rothschild (1987) proposes that behavioral learning theory should cause an overall decline in brand loyalty, particularly among closely related products. Thus, I predict:

**Prediction 5.** Aggregate brand loyalty will diminish over time for all consumers.

However, this finding ought not to apply equally to all consumers. Lal and Padmanabhan (1995) suggest that two segments of shoppers exist: a brand-loyal segment of consumers with low probability of switching and a segment that is more deal-prone and tends to switch because of price. Dekimpe et al. (1997) suggest that prior empirical findings showing an overall decline in brand loyalty might best be explained by decomposing the customer sample into different segments. My dissertation tests this suggestion explicitly by tracking repeat purchases over time while manipulating the consumers’ promotional environment. I propose:

**Prediction 6.** Brand loyalty will decrease, on average, for all consumers. However, brand loyalty will decrease more sharply for those consumers who are classified as deal-prone than for those consumers characterized as brand-focused.
2.4 Empirical Setting and Data Description

I conducted this study in a 40,000 square-foot supermarket in northern Ohio. The store sells approximately 35,000 different products (stock-keeping units [SKUs]) and is located approximately eight miles from its nearest competitor. Although some customers also shop at other stores, management believes that its store is the primary store for grocery shopping for its customers. Consumers downloaded a free smartphone app developed by a third-party developer by visiting the app store, or scanning a QR code on posters located throughout the store. This installation process required only a few minutes. Upon arriving at the store, consumers could scan the bar code of any product in five categories (bread, carbonated soft drinks, salty snacks, breakfast cereals, and bulk-size pet food) using their phone. Scanning triggers the delivery of a set of coupons consisting of a coupon for the focal product and coupons for several substitute products. Consumers could choose products they prefer and redeem coupons at checkout.

To create coupon sets of manageable size, the app developer assigned each SKU to a subcategory of close substitutes. For example, a 2-liter bottle of Diet Coke was assigned to a subcategory with five other 2-liter diet cola SKUs. For the 923 different scannable products, 163 subcategories were created, averaging 5.6 SKUs per subcategory. Upon scanning any product, consumers received coupons for all brands in that product’s subcategory. Coupon value was set by the developer as a function of consumers’ purchase history, with frequently redeemed coupons showing progressively smaller values (for details, see the Appendix 1).

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1 Although coupon sets sometimes contained different varieties (e.g., flavors) of a particular product, to discourage shoppers from “gaming the system” the coupon sets did not contain different package sizes of the same product.
2.4.1 Sample characteristics and representativeness

In total, 171 consumers scanned at least one product. According to the supermarket management, these consumers represent 15–20% of their customer base; (Appendix 2 provides descriptive statistics). The store tracks average consumer measures such as demographics (age and gender), shopping habits (day of the week and time of day), and purchase outcomes (number of items and spending per trip). To ensure the representativeness of the sample, Appendix 3 compares these metrics for my sample, the average store shopper, and surveys of average shoppers across the United States. Regarding gender, female consumers outnumber male consumers (93 women, 46 men), with a proportion of consumers (approximately 20%) not reporting their gender. In addition, the average age of consumers is 48.9 years. Thus, the app users’ age and gender appear to correspond to the average of all shoppers.

2.4.2 Variables used in the study

Dependent variable: Focal coupon redemption. I define focal coupon redemption as whether the coupon for the scanned brand was redeemed following each scan. The alternative to redemption was either redeeming a coupon for another product or not redeeming any coupon from the coupon set at all.

Independent variable (1): Coupon value. Regarding coupon value, the average for all coupons is $0.62. As described above and detailed in Appendix 1, coupon values are set on each shopping visit according to the customer’s redemption history.

Independent variable (2): Net Price Range (NPR): Following Janiszewski and Lichtenstein (1999), I define the net price range (NPR) of coupon c in coupon set h during scanning occasion j as

\[
NPR_{chj} = \frac{NP_{cj} - LNP_{hj}}{HP_{hj} - LNP_{hj}},
\] (1)
where NP_{cj} is the net price of the focal product (i.e., the product’s shelf price less the coupon’s value), LNP_{hj} denotes the lowest net price of a product in coupon set h, and HNP_{hj} denotes the highest net price of a product in coupon set h. This measure captures the percentile value (between 0 and 1) of the focal product’s net price within the range of net prices for the coupons offered. It represents is a “psychologically transformed” representation of coupon value that captures the location of a focal product’s net price within the range of net prices available to consumers (Moon and Voss 2009). A high value for NPR reflects a price that is relatively costlier and less attractive and thus should result in lower redemption.

*Independent variable (3): Coupon set size.* I define coupon set size as the number of coupons a consumer receives after scanning a product (including both the focal and competing coupons). I observe a range of coupon set sizes, with an average set size of 6.28 coupons.

*Independent variable (4): Loyalty.* Finally, I construct a behavioral measure of loyalty for each scan j of product i at time t, specified as

$$LOY_{ijt} = \frac{\text{Number of purchases of product}_{ijt}}{\text{Number of opportunities to purchase product}_{ijt}}.$$  \hspace{1cm} (2)

This measure is based on the percent-of-purchases approach developed by Cunningham (1956) and is favored for its simplicity of calculation and interpretation (Jacoby and Kyner 1973; Mellens, Dekimpe, and Steenkamp 1995). This measure isolates the effect of observed prices on the likelihood of redemption in the models by controlling for brand preference as an explanation for the results. In my data, a consumer is considered to be completely loyal on their first purchase of a brand. I update this loyalty measure on each subsequent occasion where the customer creates an opportunity to purchase the product again.
2.5 Approach to Analysis

2.5.1 Determinants of coupon redemption.

I model the likelihood of redeeming a coupon for the focal product on each scanning occasion using a panel logistic regression model, and control for unobserved consumer heterogeneity using a random-effects specification. The dependent variable is the binary choice of whether or not to redeem the coupon for a focal product. For each consumer $i$ on trip $t$, the dependent variable for each scan $j$ of a focal product is

$$Y_{ijt} = \begin{cases} 1 & \text{if the coupon for the focal product is redeemed} \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (3)

This latent variable includes the covariates discussed previously, and its basic specification is

$$Y_{ijt}^* = \beta_0 + \beta_1 \text{SETSIZE}_{ijt} + \beta_2 \text{FV}_{ijt} + \beta_3 \text{NPR}_{ijt} + \beta_4 \text{LOY}_{ijt} + c_i + \epsilon_{it},$$ \hspace{1cm} (4)

where

\begin{align*}
\text{SETSIZE}_{ijt} &= \text{coupon set size observed upon scanning}, \\
\text{FV} &= \text{focal value of the focal product’s coupon}, \\
\text{NPR} &= \text{net price range of the observed coupon set}, \\
\text{LOY} &= \text{the brand loyalty measure, and} \\
\epsilon_{it} &= \text{i.i.d. logistic}
\end{align*}

In the specification, $c_i$ denote unobserved individual effects, distributed $N(0, \sigma_c^2)$. I maximize the panel-level log-likelihood from this specification using adaptive Gauss–Hermite quadrature (Wooldridge 2010). Note that the specification in Eq. 3 only shows main effects, the empirical application includes interactions as well.
2.5.2 Investigating unobserved consumer segments

In addition to the analysis above, I identify latent, emerging consumer segments by analyzing redemption data over time via a latent class, finite mixture panel logistic regression (Finch and French, 2015). The finite mixture for redeeming a focal coupon can be specified as

\[ H(Y|X, \Theta) = \sum_{s=1}^{S} \pi_s(\alpha) P(Y|\beta_s(X)) \]  (5)

where \( Y \) and \( X \) denote the observations of the dependent and independent variables, respectively; \( \Theta \) collects the relevant parameters in the model, which are \( \alpha \), the propensity to belong to each of \( s = 1, \ldots, S \) latent class segments to be found in the data (\( S \) is specified \textit{a priori}) and \( \beta_s \), which indicate parameters \( \beta_0 \) through \( \beta_5 \) above, now being segment-specific; \( \pi_s(\alpha) \) denotes the probability of being a member of segment \( s \); and \( P(Y|\beta_s(X)) \) is the likelihood of redeeming the focal coupon. Maximization is conducted using an E-M approach (Leisch 2004).

This approach allows us to capture potentially unobserved consumer segments. Note that since the tendency to be classified into a segment is determined by \( \alpha \) and, since there are no covariates in the segment probability specification, this propensity is informed by time-varying redemption patterns, because I measure coupon redemptions scan by scan. As such, the latent class segment memberships captured in the data can capture redemption patterns over time.

2.6 Results

2.6.1 Mobile coupon app patterns of use

I first explore the adoption of the pull mobile coupon app by addressing whether pull coupons delivered in-store through consumers’ smartphones would be used sufficiently in a retail environment, how would the level of scanning, and conversion to coupon redemptions compare to traditional coupons, and can these patterns can be sustained over time.
During the period of study, 171 consumers downloaded the app and redeemed a coupon at least once, indicating high engagement. 75.4% of scans resulted in redemption, suggesting that consumers found value in using the app beyond mere novelty. Approximately 91.5% of redeemed coupons were for the scanned product; the remaining 8.5% were competing coupons for another brand. While this rate may seem relatively low, it should be considered in context, as it is substantially higher than the average redemption rate of 0.38% for print coupons (Inmar 2016), or 1.06% for push mobile coupons (Danaher et al., 2015). Thus, the redemption rate for a competing pull coupon is substantially more likely to be redeemed than an unsolicited push coupon.

A reasonable concern is that these favorable metrics might quickly dissipate over time. To investigate whether coupon use occurred in a sustained fashion, I tracked consumers trip by trip. Consumers made 611 trips to the supermarket, where a *trip* captures a visit in which the consumer scanned at least one product. I identify each consumer’s first trip by detecting the first time a scan occurred and then compute trip data for each consumer according to his or her subsequent scanning behavior. Of the 171 customers who used the app at least one time, 102 customers, (59.6%) continued to use the app on several shopping occasions.

Figure 1A illustrates the use of pull mobile coupons for these 102 consumers. The horizontal axis indicates time since each consumer’s first scan, for each customer (arranged along the vertical axis). Each bubble represents a shopping trip where the consumer scanned. The size of the bubble is proportional to the number of scans. These 102 consumers scanned on 7.72 shopping trips over an average of 119.8 days, with a mean of 2.72 scans per trip. The main takeaway is that the majority of users appear relatively consistent both in the regularity and in
intensity of scanning, suggesting that customers are likely to use a pull mobile coupon app in a sustained fashion.

2.6.2 Determinants of Coupon Redemption

Having established that pull mobile coupons were used sufficiently and sustainably over time, I next investigate the determinants of coupon redemption. Table 4 presents logistic regression results, providing regression estimates and odds ratios, where ratios above 1 indicate an increase in the odds of redeeming a coupon for the focal product and ratios below 1 indicate a reduction.

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Insert Table 4 about here

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Pricing and redemption

I first examine the effect of coupon value on the likelihood of redemption. Model 1a examines the main effect of coupon value, which is not significant (b = -0.002, p > .10), whereas Model 1b examines the moderating effect of brand loyalty. When I account for this key variable, the main effect of coupon value turns significant (b = .042, p < .01) consistent with Prediction 1, and I also find a negative interaction between coupon value and brand loyalty (b = -5.190, p < .01). Although higher coupon values increase redemption likelihood overall, the influence is smaller for consumers who are more brand loyal, consistent with Prediction 3.

Models 2a and 2b investigate the role of price comparisons (NPR) on redemption. The location of the focal product’s net price in the coupon set’s price range significantly influences redemption likelihood (b = -.560, p < .01). As the relative price increases, the coupon becomes less attractive, and the likelihood of redemption falls. The odds ratio associated with NPR (.57) means that as proposed by Prediction 2, on average, a consumer is approximately 40% less likely
to redeem a coupon for a product at the low than at the high end of the NPR. Model 2b finds only a marginally significant interaction between brand loyalty and NPR \( (b = -0.938, p = 0.092) \).

As studies show that some consumers use a reference price (IRP) approach to evaluate prices while others use a price range strategy, Models 3a and 3b estimate the likelihood of coupon redemption by incorporating the joint effects of coupon value and NPR on redemption likelihood. The results indicate that the effect of NPR is significant \( (b = -0.541, p < 0.01) \) while the main effect of coupon value is not \( (b = -0.001, p > 0.10) \). Model 3b, which incorporates brand loyalty interactions, again shows that coupon value influences redemption, but the effect is negatively moderated by brand loyalty \( (b = -4.873, p < 0.01) \). As noted, I find no significant interaction between brand loyalty and NPR \( (b = -0.787, p > 0.10) \); consumers who rely on NPR appear to compare current prices with little regard for their purchase history.

**Coupon set size and redemption**

Table 4 captures the effect of coupon set size on redemption via the set-size and set-size-squared terms. Across all models, I find the predicted U-shaped effect \( (p < 0.05) \). The lowest probability of redemption occurs with moderately sized sets of around six coupons. Consumers are more likely to redeem a focal coupon when sets are substantially smaller or larger than six coupons. This is consistent with Prediction 4, which posits that while consumers prefer variety, too many options lead to a decreased motivation to choose.

**2.6.3 Setting strategic coupon values**

The combination of coupon value, NPR, brand loyalty, and coupon set size provides a set of decision variables managers can use to optimize coupon redemption. Figure 5 uses the estimates in Model 3b to compute the predicted probability of redeeming a focal coupon under different conditions. Panel A shows the probability of redeeming a focal coupon for various combinations
of coupon value and NPR. The green-shaded areas represent the highest probabilities of redemption and the red areas the lowest. As coupon values increase, the probability of redemption increases as well. However, this panel also illustrates how NPR can amplify or attenuate the effectiveness of a given coupon. For example, if a manager offers a $0.50 coupon, the result is the most competitive net price within the set (NPR = 0), with a probability of redeeming that coupon of 41.0%. However, if the same coupon results in the least competitive price (NPR = 1), the probability of redemption drops to 20.7%, a reduction of 20.3%. For this reason, the optimal conditions occur when coupon value ranges between $0.50 and $0.80 and, at the same time, when NPR varies between 0.0 and 0.4. Consequently, managers must consider the distribution of prices for competitive couponing and select coupon values accordingly.

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Insert Figure 5 about here

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Given the importance of NPR, panel B of Figure 5 illustrates the redemption probabilities for various combinations of set size and NPR (holding coupon value constant at its mean of $0.62 for illustrative purposes). The shading pattern reflects the U-shaped effect of size on redemption. As the figure shows, redemption improves when either small sets (e.g., 2–4 coupons) or large sets (e.g., 10–12 coupons) are offered, as evidenced by the higher redemption probabilities for those sizes. The NPR dimension again suggests that offering a very competitive coupon is beneficial. However, a very competitive coupon might still suffer from low redemption when it is located in a medium-sized set. For example, a highly competitive coupon (NPR = 0) has a redemption probability of 57.2% when offered in a set of three coupons, but only of 46.3% when in an average size set of six coupons—a reduction of 10.9%.
Panel C of Figure 5 shows how to set coupon values according to consumer loyalty. For any coupon value, loyal consumers (rightmost columns) are more likely to redeem a coupon than less loyal consumers (leftmost columns), consistent with a main effect of loyalty. For low levels of loyalty, coupon value has a pronounced effect on redemption likelihood. For example, as coupon values rise from $0.05 to $0.80, redemption for the least loyal customers increases from 6.8% to 71.8%. By contrast, for the most loyal customers, changes in coupon value have almost no effect on redemption rate, due to the interaction of coupon value with loyalty. Since the consequence of defensive targeting is that loyal consumers are offered smaller discounts, high-value coupons are not available to them and were omitted.

2.6.4 Redemption over time and emerging consumer segments
As noted earlier, the literature suggests that some consumers are brand-loyal and others deal-prone. Two customer journeys illustrate this point. Figure 2A depicts the shopping history of a 45-year-old male consumer over 7 trips in which he continued to scan Cool Ranch Doritos chips, receiving coupons for that product as well as five competing products including other flavors of Doritos and other flavored tortilla chips. Shelf prices for these products ranged from $2.96 to $3.64. As Figure 2A shows, this consumer consistently purchased Cool Ranch Doritos, even though the history-based pricing algorithm generated coupons with very low values for his preferred brand. After the seventh trip, the coupon value for Cool Ranch Doritos was $0.07 while the highest competing coupon value was $1.29. In this case, this consumer is clearly a loyal consumer of Cool Ranch Doritos.

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Insert Figure 2 about here
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This behavior contrasts with the journey of a 42-year-old woman, depicted in Figure 2B. This consumer shopped the rippled potato chips subcategory, which offers six competing brands. Four of these had shelf prices between $2.37 and $3.39 per 16 oz. bag, while the other two were discount brands, priced at approximately $1.00. Unlike the previous loyal consumer, she scanned Snyder potato chips on 8 of 9 trips but redeemed a coupon for this product on only 3 occasions, switching to the higher-priced Shearer’s after the first visit, after Shearer’s coupon value increased enough to make switching attractive. On the third trip, she purchased a higher-priced brand but also purchased a discount brand (perhaps revealing an unplanned purchase triggered by a high-value coupon). Overall, this consumer’s journey is consistent with a value conscious shopper’s concern with paying low prices, subject to product quality (Lichtenstein et al. 1990).

To account for this additional source of consumer heterogeneity, I applied a latent class logistic regression model as described in the analytical approach. Table 5 presents results using the specification of the best-fitting model in the redemption analysis (Model 3B, Table 4). For parsimony, I omit the day control variables – findings, however, are robust to including these.

Insert Table 5 about here

I find that a two-segment solution fit the data best, as indicated by the BIC criterion. Consistent with Prediction 1, members of the brand-focused segment relied on coupon value to determine redemption \( (b=0.041, p<0.01) \). As in the previous panel data results, brand loyalty again positively influenced the likelihood to redeem a coupon \( (b=0.060, p<0.01) \), and (negatively) moderated the effect of coupon value. Coupon value mattered least for the most brand loyal shoppers \( (b=-5.170, p<0.01) \), again consistent with Prediction 3. For this segment, the location of the product’s net price in the range of net prices (NPR) was not a significant factor \( (p>0.10) \). In keeping with
Prediction 2, the deal-prone segment appeared to make redemption decisions based on price comparisons (NPR). The higher the net price was in the price range, the less likely the consumer was to redeem the coupon ($b = -3.022, p<.01$). Members of this segment were not influenced by coupon value ($p>.10$) unless extremely brand loyal, in which case there was again a negative interaction ($b= -4.840, p<.05$) as predicted.

The demographics of these two segments are similar, consisting of approximately 25.4% males ($z= -1.10, p>.10$) and the average age was about 48.7 years ($t=1.68, p=.10$). However, their redemption behavior was quite different. Although, on average, consumers redeemed a focal coupon about 91% of the time, brand-focused shoppers redeemed the focal coupon 92.1% of the time, while deal-focused shoppers redeemed a focal coupon only 88.4% of the time. These findings suggest that while targeting by demographics is not an effective strategy, the ability to target to shoppers based on their likelihood of switching is potentially important.

Figure 5B illustrates how consumer loyalty evolves over time for each consumer segment. Here, the horizontal axis indicates time, starting with the app launch. Both segments exhibit high initial loyalty, possibly because consumers begin using the app by scanning their favorite products. Over time, the average loyalty across both segments diminishes slowly, and then begins to diverge more noticeably. The brand-focused segment remains relatively brand loyal (around 70%), while the more deal-prone segment declines considerably, to just under 50%. This finding illustrates that while some consumers are deal-prone shoppers who tend to redeem the highest value coupons, others will take advantage of any coupon, even one of very low value, for their preferred brands.

Although the data do not allow us to compare coupon shoppers with non-coupon shoppers, as shown in Table 3, mobile coupon users in this study purchased more items on
average per trip (2 items) and spent more ($4.15) than the average customer, a result consistent with studies of traditional in-store coupons (Heilman et al. 2002; Thompson 1997).

2.7 General Discussion
This research provides an uncommon opportunity to observe how consumers use mobile coupons over time. I contribute to the literature by focusing on how consumers choose from among competing coupons delivered to them as they shop. These findings also inform a broader literature on how consumers evaluate alternatives presented to them by mobile apps and recommendation engines common to online retail web sites such as Amazon and Google.

Unlike memory-based price strategies (IRPs) used to assess individual coupons, evaluating coupon sets leads some consumers to adopt a comparative, stimulus-based, strategy (SBR) that depends on the product’s price in relation to others. While range theory has been applied to retail prices (Janiszewski and Lichtenstein, 1999; Moon and Voss, 2009), and measures of product attributes (Yeung and Soman, 2005), to the best of my knowledge this is the first test of range theory in a setting where buyers consider the effect of promotional discounts when making price range comparisons. The number of coupons in the set also matters. Although not entirely robust, I find some evidence indicating that the number of competing coupons influences redemption through a U-shaped effect consistent with choice overload models.

The data reveals that shoppers can be divided into two segments. The first segment consists of brand-focused shoppers who consider the value of single coupons, and are more likely to redeem a coupon of any value, even after many shopping trips and when coupon values are very low. The second segment consists of deal-focused consumers who make price comparisons across substitute brands, and are more likely to switch when a coupon makes a product more attractive relative to others in the set. Finally, I find that brand loyalty evolves
differently over time across these two segments. While on average, brand loyalty diminished for all customers, loyalty declined substantially less for brand-focused customers than it did for the deal-prone segment of shoppers.

**2.7.1 Managerial implications**

*Can pull coupons be beneficial?*

The question of the potential benefits of in-store pull mobile couponing should be addressed along several dimensions. The first concern is whether pull mobile coupons are redeemed broadly enough. Consumers in this study redeemed a coupon 75.4% of the time, substantially higher than the single-digit rates typical of print coupons (Musalem, Bradlow, and Raju 2008) and other forms of mobile coupons (e.g., Danaher et al. 2015; Fong et al. 2015; Luo et al. 2013). Unlike conventional redemption rates, however, 75.4% reflects the likelihood of redeeming a coupon conditional on requesting one. This measure is akin to redemption rates for electronic coupons that are expressed as the ratio of coupons redeemed to the number of coupons actually downloaded from the internet. In such cases, redemption rates as high as 58.9% are observed (Alpar and Winter 2014). However, the 75.4% response also reflects consumers’ preference for pull coupons (Unni and Harmon 2007; Watson, McCarthy, and Rowley 2013). Another driver of the high redemption rate is that reducing the expiration period of mobile coupons increases redemption rates substantially (Danaher et al. (2015). In this study, shoppers have only 2 hours to redeem a coupon before it expires.

The second concern is whether pull mobile coupons are profitable. As there is little motivation to offer coupons to consumers who are willing to purchase products without a discount (Raghubir 2004), firms must differentiate between new and loyal customers to avoid giving away profits. This could mean that offering high coupon values to shoppers already
holding the product in their hands could undermine pull mobile coupons as a means of expanding sales, hurting profits as well. A number of authors have argued that competitive couponing leads to a prisoner's dilemma in which profits for competing firms erode (Cheng and Dogan, 2008; Shaffer and Zhang, 1995).

While this profit concern is justifiable for traditional coupons, for which consumers customarily receive equal discounts, in-store coupons can be profitable if coupon values can be customized according to consumers’ willingness to purchase the product (Cheng and Dogan 2008; Shaffer and Zhang 1995). In fact, Besanko, Dubé, and Gupta (2003) show that the prisoner’s dilemma does not arise in an empirically calibrated model of competition, noting, “Targeted pricing need not generate the prisoner’s dilemma… in contrast to the findings of theoretical models. Fong et al (2015) find that properly segmenting customers may lead to profitable results that leaves competing manufacturers better off, stating “By experimentally varying the discount depth, we evaluate how cannibalization creates an incentive to offer different prices to competitively targeted customers and customers near the focal location,” a method also shown to be profitable by Dubé, Fang, Fong, and Luo (2017).

This suggests that the profit concerns outlined above can be avoided using mobile targeting. As to the question of when such targeting is attractive, technology that enables price conditioning is attractive when consumer purchase histories can be used to determine coupon values for frequent purchases such as groceries (Acquisti and Varian, 2005) and “can lead to competitive advantages through personalized enhanced services…making price discrimination feasible” (p. 380). Although behavior tracking and coupon customization are not feasible with traditional coupons, they can be accomplished with a digital platform (Cheng and Dogan 2008). For example, Fong et al. (2015) and Molitor et al.(2016) show that high coupon values can
effectively target customers located far from a retailer while low coupon values are sufficiently attractive to consumers located near the retailer. Thus, varying discount depth allows firms to defend loyal customers from poaching using low value coupons, while offering high-value coupons induces trial and brand switching for customers who buy from rivals (Cheng and Dogan 2008; Shaffer and Zhang 1995). In this article, I observe that loyal customers redeem coupons worth only a few cents (Fig. 2, panel A) while deal-focused consumers require coupons of commensurately higher value (panel B). Behavior-based pricing mechanisms would allow marketers to target these two segments with customized coupons. As Figure 5 shows, firms have latitude in determining what coupon value to select based on parameters such as the number of competing brands, the target consumer’s brand loyalty, and how aggressive they wish to be. Accordingly, they can select a discount depth that suits their redemption goals.

A third concern is the potential benefits of pull mobile couponing for retailers. Apart from increases in brand or category sales, in-store coupons lead to improved overall store sales (Thompson 1997). In this study, mobile coupon users also spent and purchased more than the average store shopper. This finding corroborates the notion that offering even loyal customers in-store coupons has benefits for retailers. For example, Heilman and Rao (2002) find that a $1 in-store surprise coupon increases basket size by 11–12% and overall spending by $7.68. Shoppers in the current study saved an average of $1.83 using coupons but spent $4.15 more per trip than the average shopper, suggesting this difference is even larger when compared with non-mobile coupon users. As retailers play an influential role in prescribing in-store promotions such as shelf space, slotting allowances, displays, double coupons, and other promotions (Ailawadi et al. 2009), I expect them to encourage suppliers to engage in competitive couponing. Mobile
coupons can also be used to promote private-label and store-brand products. It is noteworthy that 5 of the top 20 most frequently redeemed coupons in this study were for store-brand products.

Lastly, while I focus on the short-term economic gains from competing coupons, recent evidence indicates coupons have additional benefits, even when offered to existing customers, including enhancing customer loyalty (Dodson, Tybout, and Sternthal 1978), inducing stockpiling and accelerated purchases (Neslin, Henderson, and Quelch 1985), providing customer intelligence (Grewal et al. 2011), increasing product awareness and knowledge (Raghubir, Inman, and Grande 2004; Srinivasan, Leone, and Mulhern 1995), increasing sales after coupon expiration (Banerjee et al. 2011; Sahni, Zou, and Chintagunta 2014), generating sales lift from non-coupon users (Srinivasan et al. 1995; Venkatesan and Farris 2012), and leading to cross-category sales (Sahni et al. 2014). As the customer profiles in Fig. 2 illustrate, in-store mobile coupons provide a location-based, time-sensitive opportunity to create touch points that significantly influence the customer journey (Lemon and Verhoef 2016).

In summary, customized coupons provide a new tool to engage in competitive pricing. Recognizing this, firms have begun using personalized prices online (e.g., Staples) or in store (e.g., Sears) (Tanner 2014), and more are expected do so (Mikians et al. 2012), as firms consider targeted coupons an effective means to implement targeted pricing, rather than risk stirring up resentment by using surcharges (Tanner 2014). This potential has prompted two start-up firms (Insight Market Data, and aMobileCoupon) to offer mobile in-store customized coupons.

2.8 Limitations and Future Research
This study provides new insights by analyzing actual use of mobile coupons, but several limitations remain. First, the data comes from a supermarket in a small town with few nearby competitors. While this provides a well-controlled experimental environment, one concern might
be the generalizability of the findings to more competitive settings. Research on the effects of pricing and promotions on supermarket store choice shows that only a small fraction of consumers are knowledgeable about competitive prices (Dickson and Sawyer 1990; Monroe and Lee 1999) and that few consumers switch stores as a result of price policies or specials (Von Freymann 2002). Neither unadvertised (Walters and MacKenzie 1988) nor advertised (Walters 1991) price discounts have an appreciable effect on inter-store traffic. These findings are supported by industry statistics, which show that approximately 96% of supermarket shoppers nationally reported having a primary grocery store in which they routinely shop for their groceries (Brown 2015). Moreover, the two questions addressed herein (i.e., how customers choose among competing coupons and how their adoption behavior evolves over time) seem less prone to influences of inter-store competition than other questions might be. Thus, even if gathered in a somewhat monopolistic setting, I expect these results to be generalizable to supermarkets in a more congested location, and omitting competing supermarkets seems insufficient grounds for rejecting these results (Shugan 2002). However, future research questions might benefit from a more competitive empirical setting.

Second, I was unable to collect data from consumers who did not adopt the mobile coupon app, which may have represented a valuable control group. Prior adoption studies have faced similar obstacles (e.g., Im, Bayus, and Mason 2003; Manchanda, Xie, and Youn 2008) and proposed implementing a hazard model to avoid this difficulty (e.g., Prins and Verhoef 2007; Thompson and Sinha 2008). Hazard models estimate the time to adoption and treat non-adopters as those who have not yet made an adoption decision. However, I treat adoption not as a dichotomous event but as a measure that reflects a consumer’s intensity of use over time. Further investigation should compare adopters and non-adopters to provide additional insights.
Third, while I attempt to control for the influence of brand loyalty, the effects of brand loyalty may nevertheless be confounded by the pricing algorithm used by the third-party app developer to compute coupon values. Future work with an updated version of the app might have greater ability to control for confounding effects of price and prior purchases.

Finally, the coupon sets were designed to focus on choices between close substitutes. Future research might examine coupon sets designed with other goals in mind. Offering coupons for complementary products (e.g., a coupon for salsa when tortilla chips are scanned) might require consumers to shop across different aisles. This would allow researchers to examine whether pull mobile coupon apps lead to increases in unplanned spending (Hui, et al. 2013).
Table 1. Comparison of Traditional and Mobile Coupon Features

<table>
<thead>
<tr>
<th>Coupon Feature</th>
<th>Traditional Coupons</th>
<th>Mobile Coupons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Targeted / Customizable&lt;sup&gt;a,b&lt;/sup&gt;</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Identifiable to the Shopper&lt;sup&gt;c,d&lt;/sup&gt;</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Effort Required by the Shopper&lt;sup&gt;e,f&lt;/sup&gt;</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Interactivity&lt;sup&gt;a,g&lt;/sup&gt;</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Behavior Tracking&lt;sup&gt;c,d&lt;/sup&gt;</td>
<td>Limited</td>
<td>High</td>
</tr>
<tr>
<td>Delivery&lt;sup&gt;c,h&lt;/sup&gt;</td>
<td>Push</td>
<td>Push or Pull</td>
</tr>
</tbody>
</table>

<sup>a</sup> Shankar et al. (2010); <sup>b</sup>Fong et al. (2015); <sup>c</sup> Shankar et al. (2011); <sup>d</sup> Danaher (2015); <sup>e</sup>Dickinger and Kleijnen (2008); <sup>f</sup>Shankar and Balasubramanian (2009); <sup>g</sup>Kalyanam and McIntyre (2002); <sup>h</sup>Unni and Harmon (2007);
<table>
<thead>
<tr>
<th>Authors/Date</th>
<th>Outcome</th>
<th>Independent Variables</th>
<th>Method and Data Details</th>
<th>Key Managerial Takeaways</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unni and Harmon</td>
<td>Perceived benefits</td>
<td>Distribution (push/pull)</td>
<td>Lab experiment</td>
<td>• Both advertising type and distribution matter, but their joint effect only occurs in terms of perceived value: if managers choose a push distribution, consumers would value promotional content more than brand content. However, for pull distribution, consumers would value both types of content equally.</td>
</tr>
<tr>
<td></td>
<td>Perceived value</td>
<td>Advertising type (brand/promotion)</td>
<td>N=153 college students with no previous knowledge of location-based advertising</td>
<td>• Moreover, the perceived value of deployed location-based advertising is higher for pull distribution regardless of its type (brand or promotion), which suggests that consumers perceive more value when content is pulled rather than pushed.</td>
</tr>
<tr>
<td></td>
<td>Privacy concerns</td>
<td></td>
<td>Four (brand and promotion × push and pull) location-based ad stimuli</td>
<td>• As privacy is also found to be more salient with the more intrusive push distribution, the study suggests pull distribution is more adequate for location-based advertising. However, managers can consider push distribution when deploying promotional content.</td>
</tr>
<tr>
<td></td>
<td>Intention to try mobile platform</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dickinger and Kleijnen</td>
<td>Attitude toward mobile coupons</td>
<td>Economic benefit</td>
<td>Online survey</td>
<td>• Major reason for potential new users of mobile coupons is perception of economic benefit; major barriers are redemption effort and lack of control.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Redemption effort</td>
<td></td>
<td>• Successful deployment of mobile coupons for new users should (1) stress economic benefit; (2) explain that benefit, in relation to effort, is a net positive; and (3) clarify that the user will be in control, minimizing spam.</td>
</tr>
<tr>
<td></td>
<td>Intention to redeem</td>
<td>Perceived control</td>
<td></td>
<td>• Intention to redeem mobile coupons not associated with redemption of traditional coupons. Therefore, these two coupon types may attract different market segments, and managers should not assume that targeting heavy traditional coupon users will adopt mobile coupons.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Fear of spam</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Social norms</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Past coupon use</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Banerjee and Yancey</td>
<td>Redemption rate</td>
<td>Coupon value (Hi/Lo)</td>
<td>Observational secondary data</td>
<td>• For utilitarian products, highest redemption rate occurs with high-value coupons framed as a free item, e.g., a BOGO coupon. Timing is not significant.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Discount framing (discount/free items)</td>
<td>N=74 mobile coupon campaigns</td>
<td>• For hedonic products, timing determines redemption, with redemption rates being four times larger when the coupon is delivered no later than noon.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Product category (utilitarian (meals)/hedonic (desserts))</td>
<td>SMS (smartphone text message) mobile coupon campaigns from Midwestern mobile marketing firm</td>
<td>• Managers should not make timing, value, and framing decisions independently, especially for utilitarian coupons. The study’s small sample size also suggests carrying out prior testing of hedonic coupon designs in particular before deployment.</td>
</tr>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Delivery timing (noon and earlier/afternoon)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Banerjee et al.</td>
<td>Intention to redeem</td>
<td>Ad claims (objective/subjective)</td>
<td>Field experiments</td>
<td>• Mobile coupons create lagged positive effects for non-redeemers.</td>
</tr>
<tr>
<td></td>
<td>Recognition (product, attribute, price)</td>
<td></td>
<td>Two studies with two waves each (N=196; N=81; N=180; N=114)</td>
<td>• Customers may have higher memory, associated with higher purchase intention, and actual increases in future purchases.</td>
</tr>
<tr>
<td></td>
<td>Purchase intention (actual/future)</td>
<td></td>
<td>Midwest fast-food chain coupons</td>
<td>• These effects are moderated by gender, age, and possibly distance to/availability of the product.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• Managers can use mobile campaigns to boost new product trials and build awareness and knowledge of new product features, attributes, and specifications.</td>
</tr>
<tr>
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</tr>
<tr>
<td>Im and Ha</td>
<td>Adoption clusters</td>
<td>Coupon use frequency</td>
<td>Survey study</td>
<td>• Consumer segments based on their personal innovativeness in information technology (PIIT) were found (innovators, early majority, late majority and laggards).</td>
</tr>
<tr>
<td></td>
<td>Attitude towards mobile coupons</td>
<td>Mobile phone use behaviors</td>
<td>N=623 U.S. adult consumers</td>
<td>• Perceived ease of use and enjoyment of mobile coupons are not different across segments. However, these segments are different in terms of usefulness, attitudes, and intentions to use mobile coupons, with more innovative segments exhibiting a higher level of these traits.</td>
</tr>
<tr>
<td></td>
<td>Behavioral intention</td>
<td>Personal Innovativeness in IT (PIIT)</td>
<td>Traditional and mobile coupons</td>
<td>• If available, managers deploying coupons to new prospective users can preemptively gather PIIT data to identify and target consumers more likely to adopt mobile coupons (i.e., those with a higher PIIT).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Perceptual variables: usefulness, ease of use, enjoyment, subjective norm, risk, compatibility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Authors/Date</td>
<td>Outcome</td>
<td>Independent Variables</td>
<td>Method and Data Details</td>
<td>Key Managerial Takeaways</td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------------------------------</td>
<td>------------------------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| Molitor et al. (2013) | • Coupon choice/ redemption rate (by clicking on coupon) | • Distance to store  
• Coupon ranking (by distance/random) | Field experiment  
• N=354,662 clicks from 3,965 German mobile users  
• 3,218 different mobile coupons from 3,544 different stores in 372 cities | • Increasing distance to store by 1 kilometer decreases response rates between 2.0% and 4.7%.  
• Scrolling down one rank leads to a reduction in response rates from 4.4% to 5.2%.  
• Consumers make tradeoffs between distance and coupon value: a value increase of 1% is equivalent to a distance reduction of 92–230m.  
• Managers deploying mobile coupons should establish coupon values that make transportation costs worth it. This decision is most important when coupons are ranked randomly, and thus distance differences can be exacerbated. |
| Reichhart et al. (2013) | • Response rate  
Conversion rate | • Channel (e-mail/SMS)  
Observational secondary data  
• N=37,382 German mobile and computer users  
Campaign with a 67% discount for a downloadable PC software | Field experiment  
• N=12,625 mobile phone users  
• 50% off movie ticket SMS coupons  
Survey study  
• N=414 smartphone users  
• SMS message scenario | • Coupons delivered via SMS underperform e-mail in response rate (visiting the website that the coupon links) by ~20.43% However, coupons delivered via mobile outperform e-mail in conversion rate (purchasing the product after visiting the website) by +81.96%.  
• Therefore, deployment of mobile coupons in different channels may serve a strategic purpose: managers interested in boosting visits should deliver mobile coupons via e-mail, and if interested in boosting sales should deliver mobile coupons via SMS. |
| Luo et al. (2013) | Field experiment  
• Redemption rate  
Survey study  
• Purchase intention | Field experiment  
• Distance  
• Time  
Survey study  
• Construal level  
• SMS intrusiveness  
• Purchase impulsiveness  
• Price consciousness  
Survey study  
• N=37,382 German mobile and computer users  
Campaign with a 67% discount for a downloadable PC software | Field experiment  
• N=12,625 mobile phone users  
• 50% off movie ticket SMS coupons  
Survey study  
• N=414 smartphone users  
• SMS message scenario | • Near-distance and same-day mobile coupons are more likely to result in purchases.  
• For mobile coupon deployment for users close to a movie theater, a same-day coupon results in a 76% increase in the odds of purchasing as compared with a two-day prior coupon.  
• However, for users far from the theater, a one-day prior coupon results in a 9.5 times increase in the odds of purchasing when compared with a same-day coupon, or a 71% increase when compared with a two-days prior coupon.  
• Thus, managers should deploy mobile coupons that are strategically timed depending on consumers’ distance to a target location, if known. |
| Danaher et al. (2015) | • Redemption rate | • Walking distance to store  
• Coupon value  
• Format (dollar, percentage)  
• Expiration length  
• Product type (snack foods, menswear, shoes)  
• Redemption history  
• Coupon display order  
• Price threshold | Field experiment  
• N=8,534 mall shoppers in large Western country  
• 3 randomly selected mobile coupons among a possible total of 134 delivered per mall visit  
• Coupons from 38 stores | • Consumers redeem mobile coupons based on a tradeoff between distance and coupon value: an increase of 100 meters in walking distance to the store must be offset by an 11% increase in coupon value.  
• A higher minimum price threshold, a bundled discount format, shorter expiration lengths and coupons placed at the top of a coupon list increase the probability of redemption.  
• Consumers who have redeemed a mobile coupon previously are 21% more likely to redeem in the future as compared with those who have not.  
• Deployment of mobile coupons in environments with walking travel distance can be optimized given the above determinants, and should focus on motivating consumers to redeem once, at which point further redemption is more likely. |
| Fong et al.(2015) | • Redemption rate | • Location (focal, competitive, benchmark)  
• Discount depth (20%/40%/60%)  
• Timing (delayed/real time) | Field experiment  
• N=18,000 coupon recipients  
• Movie theater coupons | • When deploying mobile coupons in a competitor’s location, the larger the discount depth, the larger the redemption rate, with 60% depth exhibiting the largest increase.  
• Interaction between locational targeting and discount depth: high discounts are optimal for the competitive location, medium discounts for the focal location.  
• Competitive locational targeting generates incremental sales without cannibalizing profits.  |
Table 3. Predicted Outcomes

<table>
<thead>
<tr>
<th>No.</th>
<th>Prediction</th>
<th>Finding</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Coupon Value will be positively associated with redemption, but in economic terms, in-store coupon values will have only a small influence on redemption.</td>
<td>Supported. Main effect of coupon value is n.s. (Model 1A and 3A) but positive and significant in the interaction model (1B and 3B). The economic impact is low (b=.039–.042) (See Section 2.6.2 and Table 4)</td>
</tr>
<tr>
<td>2</td>
<td>When consumers evaluate coupon sets, Price Range (NPR) will have a significant influence on coupon redemption.</td>
<td>Supported. The effect of NPR is negative and significant in Models 2 and 3. The economic impact is high (b &gt; -.50) (See Section 2.6.2 and Table 4)</td>
</tr>
<tr>
<td>3</td>
<td>Brand Loyalty will (negatively) moderate the effect of Coupon Value and NPR, since promotional prices matter less for more brand loyal consumers</td>
<td>Supported. Brand loyalty has a strong main effect in all Models. The interaction is negative and strong (Models 1B and 3B). (See Section 2.6.2 and Table 4)</td>
</tr>
<tr>
<td>4</td>
<td>Coupon set size will assert a nonlinear (U-shaped) influence on redemption of a coupon for the product scanned. Redemption rates are greater when the set size is either very small or very large.</td>
<td>Partially Supported. Redemption of a focal coupon is lowest for medium sized coupon sets (i.e., approximately 6 coupons.) (See Section 2.6.2 and Table 4)</td>
</tr>
<tr>
<td>5</td>
<td>Overall, brand loyalty will decrease over time as consumers use, and learn about the promotional price targeting system.</td>
<td>Supported. Average brand loyalty diminished over time for all consumers (See Section 2.6.4 and Figure 1B)</td>
</tr>
<tr>
<td>6</td>
<td>While overall brand loyalty will decrease with time, consumers can be segmented according to the strategy they use to assess the attractiveness of coupons. Brand loyalty for the deal prone segment of consumers will diminish more than for the product focused segment of consumers.</td>
<td>Supported. Latent class model reveals a two segment solution. Segment 1 (71% of consumers) are product focused, and loyalty decreased to approximately 70%, while for consumers in Segment 2, (comparison shoppers), brand loyalty fell to approximately 50%. (See Section 2.6.4 and Figure 1B)</td>
</tr>
</tbody>
</table>
Table 4. Likelihood of redeeming a coupon for the focal product

<table>
<thead>
<tr>
<th></th>
<th>Coupon Value</th>
<th>Price Range</th>
<th>Coupon Value &amp; Price Range</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1a</td>
<td>Model 1b</td>
<td>Model 2a</td>
</tr>
<tr>
<td><strong>(SE)</strong></td>
<td>Odds Ratio</td>
<td>Odds Ratio</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td><strong>Weekend_Day</strong></td>
<td>.504** (.210)</td>
<td>.485** (.165)</td>
<td>.459** (.213)</td>
</tr>
<tr>
<td><strong>Weekend_Eve</strong></td>
<td>.374 (.278)</td>
<td>.418 (.286)</td>
<td>.358 (.280)</td>
</tr>
<tr>
<td><strong>Weekday_Day</strong></td>
<td>.319 (.200)</td>
<td>.327 (.205)</td>
<td>.313 (.202)</td>
</tr>
<tr>
<td><strong>Set size</strong></td>
<td>-.464* (.248)</td>
<td>-.446* (.229)</td>
<td>-.518** (.255)</td>
</tr>
<tr>
<td><strong>Set size²</strong></td>
<td>.039** (.019)</td>
<td>.036** (.019)</td>
<td>.042** (.019)</td>
</tr>
<tr>
<td><strong>Brand loyalty</strong></td>
<td>.023*** (.003)</td>
<td>.047*** (.004)</td>
<td>.023*** (.003)</td>
</tr>
<tr>
<td><strong>Coupon value</strong></td>
<td>-.003 (.002)</td>
<td>.042** (.007)</td>
<td>- .002 (.002)</td>
</tr>
<tr>
<td><strong>NPR</strong></td>
<td>-.560*** (.170)</td>
<td>-1.317*** (.245)</td>
<td>-.541*** (.172)</td>
</tr>
<tr>
<td><strong>Value × Loyalty</strong></td>
<td>-5.189*** (.763)</td>
<td>-4.873*** (.006)</td>
<td>-5.189*** (.772)</td>
</tr>
<tr>
<td><strong>NPR × Loyalty</strong></td>
<td>-.938* (.557)</td>
<td>-2.555 (.590)</td>
<td>-9.38* (.575)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>.049 (.839)</td>
<td>-1.879 (.889)</td>
<td>.470 (.868)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>1,552 1,552</td>
<td>1,552 1,552</td>
<td>1,529 1,529</td>
</tr>
<tr>
<td><strong>Log-likelihood</strong></td>
<td>-857.25 -833.77</td>
<td>-845.37 -843.94</td>
<td>-844.98 -820.16</td>
</tr>
<tr>
<td><strong>Pseudo-R²</strong></td>
<td>5.3% 8.2%</td>
<td>5.4% 5.5%</td>
<td>5.6% 8.5%</td>
</tr>
</tbody>
</table>

* p<.10, ** p<.05, *** p<.01. Random-effects specification used. b There are 23 occurrences where NPR=0, which were dropped from Models 3a/b. Estimating Models 1a/b and 2a/b also dropping these 23 observations produced nearly identical results.
Table 5. Likelihood of redeeming a coupon for the focal product
Latent Class Model (Based on Model 3B, Table 4)

<table>
<thead>
<tr>
<th></th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta ) (SE)</td>
<td>( \beta ) (SE)</td>
</tr>
<tr>
<td>Set Size</td>
<td>-0.393 (.332)</td>
<td>-0.354 (.379)</td>
</tr>
<tr>
<td>Set Size(^2)</td>
<td>0.032 (.025)</td>
<td>0.030 (.029)</td>
</tr>
<tr>
<td>Loyalty</td>
<td>0.060*** (.007)</td>
<td>0.003 (.011)</td>
</tr>
<tr>
<td>Focal Value</td>
<td>0.042*** (.007)</td>
<td>0.030 (.019)</td>
</tr>
<tr>
<td>NPR</td>
<td>0.166 (.581)</td>
<td>-3.022*** (1.150)</td>
</tr>
<tr>
<td>Loyalty x Value</td>
<td>-5.170*** (.810)</td>
<td>-4.840** (2.225)</td>
</tr>
<tr>
<td>Loyalty x NPR</td>
<td>-0.354 (.742)</td>
<td>3.178** (1.289)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.314 (1.236)</td>
<td>1.304 (1.504)</td>
</tr>
<tr>
<td>N (% of Total)</td>
<td>1,144 (71.1%)</td>
<td>385 (28.9%)</td>
</tr>
<tr>
<td>BIC (2 segments)</td>
<td>1797.172</td>
<td></td>
</tr>
<tr>
<td>BIC (3 segments)</td>
<td>1847.339</td>
<td></td>
</tr>
<tr>
<td>BIC (4 segments)</td>
<td>1901.005</td>
<td></td>
</tr>
</tbody>
</table>

\*p<.10, \**p<.05, \***p<.01.
Figure 1. Adoption, scanning and average customer loyalty over time.

1A. Scanning occurrences over time (Note: bubble diameter is proportional to number of scans)

1B. Average brand loyalty over time by latent class segment
Figure 2. Scanning and redemption example

2A: Brand loyal consumer

2B: Brand switching consumer
Figure 3. Illustrative probability matrices for selecting optimal coupon values

### 3A: Effect of coupon value and NPR

<table>
<thead>
<tr>
<th>Coupon Value</th>
<th>0.0</th>
<th>0.1</th>
<th>0.2</th>
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<td>45.7%</td>
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### 3B: Effect of NPR and coupon set size

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<th>12</th>
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<td>28.6%</td>
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<td>43.3%</td>
<td>41.0%</td>
<td>38.4%</td>
<td>36.1%</td>
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<td>31.7%</td>
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<td>37.2%</td>
<td>35.0%</td>
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<td>28.3%</td>
<td>26.3%</td>
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<td>41.7%</td>
<td>39.4%</td>
<td>37.1%</td>
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<td>32.6%</td>
<td>30.5%</td>
<td>28.5%</td>
<td>26.5%</td>
</tr>
<tr>
<td>NPR</td>
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<td>50.5%</td>
<td>48.5%</td>
<td>46.0%</td>
<td>43.4%</td>
<td>41.2%</td>
<td>39.0%</td>
<td>36.6%</td>
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<td>32.1%</td>
<td>30.1%</td>
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<tr>
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<td>52.4%</td>
<td>49.9%</td>
<td>47.5%</td>
<td>45.0%</td>
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<td>40.2%</td>
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### 3C: Effect of loyalty and coupon value

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<th>Most Loyal</th>
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<td>$0.10</td>
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<td>11.8%</td>
</tr>
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<td>$0.15</td>
<td>10.5%</td>
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</tr>
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<td>$0.20</td>
<td>12.9%</td>
<td>16.9%</td>
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</tr>
<tr>
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<td>23.7%</td>
</tr>
<tr>
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<td>36.9%</td>
</tr>
<tr>
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<tr>
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</tr>
<tr>
<td>$0.80</td>
<td>71.8%</td>
<td>74.2%</td>
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Appendix 1. Example of history-based price setting mechanism

In this illustrative example of the history-based pricing mechanism, Product A and Product B are assumed (for the sake of simplicity) to both have a regular shelf price = $4.00. The minimum coupon value is $0.00 and the maximum coupon value is always capped at 30% of a product’s shelf price or $1.20 in this example. Initial coupon values are always set to 50% of the maximum coupon value (i.e., $0.60 for Product A and $0.60 for Product B). If a coupon is redeemed on Visit #1, the face value is reduced by 50% on the next visit. If a coupon for a competing product is redeemed, the value is increased by 50% on the following visit. For instance, if the shopper in this example purchases Product B using a $0.60 coupon on Visit #1, they will receive a $0.90 coupon for Product A on Visit #2, and a $0.30 coupon for Product B on their second visit.
Appendix 2. Descriptive statistics for the mobile coupon data set

<table>
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<th>Consumer Data</th>
<th>Mean/Pct</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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<tr>
<td>Female shopper</td>
<td>53.8%</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Male shopper</td>
<td>25.7%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Age (years)</td>
<td>48.7</td>
<td>14.4</td>
<td>16</td>
<td>76</td>
</tr>
<tr>
<td>Adopter segment member</td>
<td>72.5%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Novelty segment member</td>
<td>15.2%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Dwindling segment member</td>
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<td>0.382</td>
<td>0.02</td>
<td>5.40</td>
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<tr>
<td>Focal product price (dollars)</td>
<td>3.43</td>
<td>2.08</td>
<td>0.99</td>
<td>24.29</td>
</tr>
<tr>
<td>Coupon set size</td>
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<td>1.73</td>
<td>2</td>
<td>12</td>
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<tr>
<td>Price, all products in set (dollars)</td>
<td>3.49</td>
<td>1.87</td>
<td>0.79</td>
<td>21.82</td>
</tr>
<tr>
<td>Coupon value, all products in set (dollars)</td>
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<td>0.33</td>
<td>0.12</td>
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<td>1.0</td>
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<tr>
<td>Redemption rate (overall)</td>
<td>72.2%</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Redemption rate (focal product)</td>
<td>69.1%</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<table>
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<td>42</td>
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<tr>
<td>Number of scans per trip</td>
<td>2.56</td>
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<tr>
<td>Total spending per trip (dollars)</td>
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<td>28.66</td>
<td>0.99</td>
<td>107.50</td>
</tr>
<tr>
<td>Number of items bought per trip</td>
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<td>14.71</td>
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<td>Categories scanned per trip</td>
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<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Weekday- evening shopper</td>
<td>24.4%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Weekend-daytime shopper</td>
<td>60.5%</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Weekend-evening shopper</td>
<td>39.5%</td>
<td>-</td>
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<td>-</td>
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N=171 consumers, N=1,553 scans, N=611 trips. When discrete variables are shown, percentages are used instead of means.
## Appendix Table 3. Sample Representativeness

<table>
<thead>
<tr>
<th></th>
<th>Shoppers in Study</th>
<th>Store Shoppers</th>
<th>National Comparison</th>
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<tbody>
<tr>
<td>Age</td>
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<td>45-50</td>
<td>47.0^a</td>
</tr>
<tr>
<td>Gender % female</td>
<td>66.9%</td>
<td>65%</td>
<td>64.0%^a</td>
</tr>
<tr>
<td>Weekend shoppers</td>
<td>43.7%</td>
<td>35%</td>
<td>32.6%^a</td>
</tr>
<tr>
<td>Peak shopping hours</td>
<td>11 AM, 2 PM, 4 PM</td>
<td>11 AM, 4 PM</td>
<td>11 AM, 4 PM^a</td>
</tr>
<tr>
<td>Trips per week</td>
<td>2.1</td>
<td>1.75</td>
<td>1.6-1.7^b</td>
</tr>
<tr>
<td>Avg. spending / trip</td>
<td>$41.65</td>
<td>$37.50</td>
<td>34.00^c</td>
</tr>
<tr>
<td>Items / trip</td>
<td>15.5</td>
<td>13.5</td>
<td>15.1^b,d</td>
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</tbody>
</table>

3. ESSAY TWO
Opportunistic Consumers: Following the Crowd or their own Moral Compass?

3.1 Introduction

Traditionally, marketing research assumes that companies have the sole power to set prices, and create policies for services (e.g., shipping and merchandise returns) with little input from customers (Wirtz and McColl-Kennedy, 2010). Thus, research typically has viewed ethical decision making through the lens of the firm (Bobkoff, 2013). For instance, Home Depot does not raise the price of shovels during snow storms or electric generators during power outages because they do not wish numerous stakeholders to perceive them as greedy or taking advantage of those in need. In fact, Home Depot wishes to establish and maintain long-term relationships with its customers. Opportunistic pricing behavior would affect its legitimacy standing, and be detrimental to its long-term existence.

Yet, in recent years, innovation and technology have given consumers the ability to assert greater control in their relationships with firms. Consumers are able to use the internet to engage in unfair treatment of firms (Rezabakhsh, Bornemann, Hansen, and Schrader, 2006). Moreover, as firms increasingly invite consumers to co-create the product, so to have firms invited them to co-create pricing; such as eBay auctions, Priceline’s name-your-own-price for hotels (NYOP), and Radiohead’s pay-what-you-want album release (PWYW).

Opportunistic customer adversely affect a firm’s bottom line through lost profits, employee dissatisfaction, added stress, and burnout, creating an indirect burden on the firm’s well-behaved customers (Fisk et al., 2010). Thus, researchers should consider not only how firms may behave opportunistically, but also how consumers behave in situations that allow them to act opportunistically. As a result, researchers have begun to investigate how consumers respond
to circumstances that provide them with power to act opportunistically (Berry and Seiders, 2008; Fisk et al., 2010). For instance, consumers take advantage of online returns policies (Piron and Young, 2000) and service guarantees (Wirtz and McColl-Kennedy, 2010), download entertainment illegally (Jambon and Smetana, 2012), hack company websites or share passwords to obtain internet content (McMahon and Cohen, 2009), and post untruthful reviews (Short, 2012). This research adds to the literature that focuses on issues beyond pure economic self-interest such as personality and situational factors to explain consumer behavior (Fisk et al., 2010; O’Fallon and Butterfield, 2005).

Consumers have both selfish and unselfish motivations (Dodge, Edwards, and Fullerton, 1996). While some people might cheat, the magnitude of their dishonesty is often low relative to the maximum potential amount they could obtain through cheating (Mazar, Amir, and Ariely, 2008). For instance, a majority of PWYW customers paid something for the rock band Radiohead’s In Rainbows album (Stillman, 2007).

This paper advances consumer opportunism research by investigating the role of guilt in consumers’ ethical decision making. I use the focus theory of normative conduct and a negative state relief model, to hypothesize that a personality variable, guilt proneness, plays a pivotal, but contingent, role in explaining opportunistic behavior (Cialdini, Darby, & Vincent, 1973). I argue that consumers decide whether to engage in opportunistic behavior by considering the anticipated negative effect of guilt, and modify their actions to minimize anticipated guilt (Cialdini et al., 1973). When social norms of fairness are available, heuristics, or scripts that guide the consumer’s decision making process are primed (Bicchieri, 2005). When norms of fairness are less salient, consumers rely on a deliberative approach, and consider standards of
fairness that guide their own moral compass. Thus, the saliency of norms of fairness may negatively moderates the effect of individual guilt proneness on consumer opportunism.

I test these hypotheses in four laboratory studies and a field experiment by manipulating the saliency of social norms of fairness. Specifically, I examine distributive-based principles of equality, need, and equity, and an intentions-based principle, reciprocity. The findings are robust across a range of behaviors that range from acceptable, to questionable to completely unacceptable where consumers may behave opportunistically (purchases where the customer can pay what they want, cheating on merchandise returns, and online piracy) (Dootson, Johnston, Beatson, and Lings, 2016).

This paper contributes to a broader literature that examines the role of guilt in marketing relationships beyond guilty consumption or the use of guilt in promotional appeals (Coulter and Pinto, 1995). Specifically, the finding that the effect of anticipated guilt is contingent is of value for theory and practice. In terms of theory, this result helps reconcile prior contradictory findings about consumer opportunism. For example, two recent studies measured the influence of guilt on PWYW prices, and offer seemingly conflicting findings. Data from customers at a German zoo suggests that avoiding guilt was a strong factor in how much customers paid (Kunter, 2015), while guilt had low explanatory power in predicting prices for online music downloads (Regner, 2015). My results reconcile these two findings - the zoo customers were not provided with salient norms while music customers were provided with a salient social norm. In terms of managerial practice, managers should not assume that guilt appeals alone will result in greater consumer compliance without also considering the moderating influence of information that cues social norms. Similarly, differences in the salience of fairness might explain conflicting evidence.
regarding the effectiveness of guilt appeals used by the recording industry to combat music piracy (Haines and Haines, 2007; Lyonski and Durvasula, 2008).

3.2 Conceptual Framework and Hypothesis Development

3.2.1 Opportunistic consumer behavior

Some researchers define opportunism as “self-interest with guile” implying deceit (Williamson, 1979). However, in this conceptualization, while deceit may be present, it is not a prerequisite for opportunistic behavior. Thus, I define opportunism as behavior that exploits circumstances in self-interest, especially without regard to moral principles or others' interests. As an example, if a restaurant allows patrons to pay what they want for lunch, some customers may choose to pay nothing. Their opportunistic behavior, while self-interested and exploitative, is not deceitful. This definition of opportunism is similar in use to other terms that have been applied to capture consumer self-interested behavior (e.g. deviant, dysfunctional, aberrant, unethical, immoral, and inappropriate) (Fisk et al., 2010). For example, Lee (2015) defines one form of opportunistic consumer behaviors as purchasing products with the intent to return them after use. Bhargave & Guha (2010) refer to low pay-what-you-want-price offers as opportunistic.

Consumers have no cause to feel guilty from engaging in the behavior unless they feel that they have committed a transgression (Baumeister, Stillwell, and Heatherton, 1994; L. Watson and Spence, 2007). Consistent with this view, opportunistic consumer behavior has been shown to produce outcomes that are described as ‘unfair’ by consumers (Fisk et al., 2010). For example, Osmonbekov & Gruen (2013) find that opportunistic behavior (such as taking an inequitable share of benefits) leads to perceived unfairness on the part of customers.

Moreover, some opportunistic behaviors are more egregious than others. Individuals may deem some consumer behaviors as wrong but acceptable, others as unacceptable but perhaps
justifiable, and still others as unacceptable under any circumstances (Dootson et al., 2016). For example, 93% of survey respondents reported that switching price tags is unacceptable, but only 45% of respondents considered lying about a child’s age in order to pay a lower admission to an event unacceptable (Dootson et al., 2016).

This work examines opportunistic consumer behavior in three settings (PWYW, illegal downloads, and merchandise returns) that vary in the degree of license the firm grants to the consumer to act selfishly. At one extreme, PWYW pricing gives the consumer a great deal of discretion in determining their behavior because a PWYW policy invites the customer to pay any amount including nothing. Consumers are not violating the terms of a PWYW policy even if paying low amounts or nothing at all violates its spirit.

On the other hand, while firms craft merchandise return policies to allow genuinely dissatisfied customers to return merchandise, consumers can exploit this policy by purchasing a product, using it, and then returning it for a full refund (Piron and Young, 2000). As an example, a recent public radio story documented the abuse of a “100% satisfaction” return policy offered by L.L. Bean, a well-known sporting goods and apparel retailer (Bobkoff, 2013). Some music fans purchased tents for a 3-day outdoor festival, and returned the tents after the event, full of dirt and mud, for a full refund. These customers behaved opportunistically by taking advantage of the retailer’s return policy. In other words, firms are not inviting consumers to return all products, whereas in PWYW firms are inviting all levels of payment.

Finally, while online piracy of music, movies and software is prevalent, it is clearly not sanctioned by the firm under any conditions (Lee, 2015). Thus, consumers that pirate products are exhibiting opportunistic and illegal behavior.
Consumers may use contextual factors and techniques to justify their opportunistic behavior and mitigate anticipated guilt, such as denial of responsibility, denial of injury, denial of victim, condemning the condemners and appealing to higher loyalties (Harris and Dumas, 2009). Consumer’s perceptions of an opportunistic act can also be influenced by situational factors (Dootson et al., 2016; Fisk et al., 2010). For example, people may judge cheating a prosperous person less harshly than cheating a needy person of the same amount (De Bock, Vermeir, and Van Kenhove, 2013). Similarly, illegal music downloading is most unacceptable when artists are described as receiving profits and least unacceptable when researchers described the industry as receiving revenue from missed music sales (Jambon and Smetana, 2012).

The frequency and level of unethical consumer behavior depends on individual personality variables such as honesty or shame, and contextual variables such as social norms (Fisk et al., 2010; Wirtz and Kum, 2004). Opportunistic behavior often produces unfair outcomes that violate social norms (Fisk et al., 2010), and thus arouses guilty feelings (Antonetti and Baines, 2015). Thus, guilt, social norms, and their interaction affect a consumer’s level of opportunistic behavior.

3.2.2 Guilt: The Cost of Acting Opportunistically

Past research has consistently found that individual personality variables and situational variables influence the levels and frequency of opportunistic behavior O’Fallon & Butterfield, 2005). In this study, I examine anticipated guilt (also called guilt proneness or guilty conscience), an individual personality trait that indicates a person’s propensity to experience guilt when engaging in a range of opportunistic behaviors (Cohen, Wolf, Panter, and Insko, 2011). For example, research has shown that anticipating guilty feelings increases PWYW amounts for zoo admission (Kunter, 2015), two-thirds of consumers who engaged in returning
used merchandise reported feelings of guilt (Piron and Young, 2000) and, pirates of online music and movies use a variety of neutralization techniques to minimize guilty feelings associated with illegal downloads (Moore and McMullan, 2009).

Guilt is an unpleasant emotional state associated with transgressions (Baumeister, Stillwell, and Heatherton 1994). Individuals who believe they have benefited unfairly may seek to redistribute gains in order to achieve more equitable outcomes because of their feelings of guilt (Walster, Berscheid, and Walster, 1973). In other words, by imposing a negative cost, guilt provides a motivational force for consumers to behave in acceptably and to avoid behaving unacceptably (Tangney, 2003; L. Watson and Spence, 2007).

When guilt is experienced as a response to an explicit act, it is referred to as reactive guilt (Rawlings, 1970). Prior studies have demonstrated that reactive guilt experienced by customers after committing transgressions leads to reparative action. For instance, Dahl et al. (2005) find that when consumers become socially connected to sales people and then fail to make a purchase, guilty feelings motivate them to take reparative actions such as increasing the amount they would be willing to spend on a subsequent visit. Steenhaut and Van Kenhove (2005) examine whether relationship commitment and reactive guilt cause consumers’ to report the error when they receive too much change from a cashier.

However, guilt can also have an inhibitory effect. Guilt that arises from consideration of a potential violation of one's internal standards is referred to as anticipated guilt (Cotte, Coulter, and Moore, 2005). Anticipated guilt can occur when individuals consider taking advantage of another person even if that person is not physically present. Even anonymous internet interactions have been found to cause anticipated guilt (Dahl et al., 2005). Guilt proneness is a personality trait that captures the likelihood of experiencing guilt for violating internalized moral
standards (Mosher, 1980). Those individuals who are more guilt prone are more likely to behave fairly when they anticipate the negative effects of guilt (Cohen et al., 2011).

The negative state relief model (Cialdini et al., 1973) predicts that the anticipation of guilt produces an unpleasant emotional state from which individuals seek relief by acting in a manner that reduces those feelings (Kugler and Jones 1992).

Research has examined the influence of anticipated guilt on behavior in many settings. Restaurant customers may weigh paying a small tip against the anticipated guilt from violating the tipping norm (Conlin, Lynn, and O’Donoghue, 2003); charitable contributions are influenced by donors’ anticipated guilt (Basil, Ridgway, and Basil, 2008), and participants in bargaining games are motivated to avoid the negative cost of guilt by adhering to norms of fairness in allocating resources (Jakiela 2011). Anticipated guilt has been shown to reduce adversarial behavior (M. R. Cunningham, Steinberg, and Grev, 1980), illegal file downloading (X. Wang and McClung, 2012), the level of one-sided offers in bargaining scenarios (Nelissen, Leliveld, Van Dijk, and Zeelenberg, 2011), and the tendency of buyers to take advantage of sellers when receiving an incorrect amount of change (Steenhaut and Van Kenhove, 2006). Therefore, I predict that:

H1: Higher levels of guilt proneness will result in less opportunistic consumer behavior than lower levels of guilt proneness.

3.2.3 Social norms: Following the rules of society

Social norms are rules of behavior that a group or society considers acceptable, and violating these norms can result in sanctions from the group (Lapinski and Rimal, 2005). Social norms are important to decision making because they provide guidance when the correct course of action is unclear. When consumers are uncertain about what behavior is acceptable, they are more likely to accept the social proof afforded by norms (Charness, 1993). I focus on norms of
fairness associated with exchange relationships (outcome-based norms and intentions-based norms) (Aggarwal and Larrick, 2012).

The first set of fairness norms, outcome-based norms, focuses on the distribution of allocations among the participants. Three principles important to distributive fairness are equity, equality, and need (Deutsch, 1975). The norm of equity assesses fairness based on whether each exchange partner receives benefits proportional to their contributions. However, other outcome-based norms are appropriate under different circumstances, such as whether equal allocations or allocations based on need are the fairest (Aggarwal and Larrick, 2012).

Intentions-based norms form the second set of fairness norms. These norms focus on exchange partner’s motives (Falk, Fehr, and Fischbacher, 2008). The most common intentions-based norm is the norm of reciprocity, which prescribes that individuals are obligated to treat others as others treat them. Bagozzi (1995) suggests that reciprocity is central to coordinating mutual actions in marketing relationships and an essential feature of self-regulation. Fair reciprocation of an act can promote future exchange while taking advantage of trusting partner can seriously undermine the relationship (Pillutla, Malhotra, and Murnighan, 2003). In settings, such as cheating on merchandise return policies, unfair customers exploit the seller’s trust by failing to adhere to the spirit of the policy (Berry and Seiders, 2008).

The focus theory of normative conduct predicts that individuals are more likely to conform to social norms when the norm is made more salient (Kallgren et al., 2000). Salient norms prime behavioral scripts that offer a cognitive shortcut, or heuristic that guides consumer behavior (Bicchieri, 2005; Bicchieri and Chavez, 2010). In the absence of such heuristics, customers might use a more deliberative route to decision making (Bicchieri, 2005). In interviews with consumers, Dootson (2016) finds that “participants unanimously agreed the
saliency of an individual’s moral standards determined the likelihood of an individual performing a DCB (Deviant Consumer Behavior)” (p. 765). Thus, I predict:

**H2:** Greater salience of social norms of fairness will result in less opportunistic behavior than lower salience of norms of fairness.

### 3.2.4 The moderating effects of social norms

Studies of the effect of anticipated guilt on opportunistic behavior have produced equivocal results. For example, while prior studies have conceptualized the role of guilt in PWYW pricing (Chao, Fernandez, and Nahata, 2014; Regner and Barria, 2009), two recent studies present conflicting results about the influence of guilt on opportunistic behavior (Kunter, 2015; Regner, 2015). Survey data from PWYW customers at a German zoo suggests that avoiding guilt was a strong factor in how much customers paid (Kunter, 2015), while survey data from an online music web site found guilt had low explanatory power in predicting prices (Regner, 2015). However, while the music customers were provided with a suggested minimum amount, the zoo customers were intentionally not provided with any reference price. In other words, a social norm was present (music downloads) guilt affected opportunistic behavior, but when the social norm was absent (zoo) then guilt did not affect the level of opportunistic behavior.

Thus, I argue that a salient social norm provides consumers social proof of fairness that allows them to focus on fair behavior with less effortful processing (Bicchieri, 2005; Cialdini and Goldstein, 2004). By focusing on the normative behavior deemed fair by others, consumers may be less likely to consider their own standards of conduct and the guilt associated with violating those internalized standards. However, when social norms are not salient, it may be more difficult for consumers to determine what behavior is considered fair, forcing them to rely more on their own standards and the guilt anticipated if they violate them (Bicchieri, 2005;...
Levine, Bitterly, Cohen, and Schweitzer, 2015). In other words, in the absence of social norms, personal traits, such as anticipated guilt, that guide a consumer’s moral compass are more likely to play a role in determining whether they engage in opportunistic behaviors.

Prior studies of consumer opportunism support for this prediction. For example, Wirtz and Kum (2004) find that personality, situational variables, and their interaction influence the level of cheating on service guarantees. Specifically, reducing the risk of detection increased cheating behavior of highly moralistic people more strongly than for those with low morality, since people with higher levels of cheating behavior were less influenced by changes in the risk of detection. Levine et al. (2015) examine the effect of the saliency of trust on the influence that guilt-proneness had on the outcome of a behavioral trust game. The interaction between the experimental manipulation of the saliency of trust, and guilt-proneness suggests that when the act of trust is salient, guilt-proneness appears to matter less. Higher salience of trust may cause even low guilt-prone individuals to anticipate feeling guilty if they violate an exchange partner’s trust. Levine et al. (2015) conclude that individual differences in guilt-proneness may matter more when trust is less salient than when expectations are explicitly stated. Specifically, I expect that the effect of guilt proneness on opportunistic behavior will moderated by the saliency of a social norm, such that the influence of guilt proneness will be weak when a social norm is more salient, and will be strong when a social norm is less salient. Thus, I predict:

**H3:** The salience of social norms negatively moderates the effect of guilt proneness on opportunistic consumer behavior, such that guilt proneness matters less when social norms are more salient.

Figure 1 illustrates the proposed theoretical model of opportunistic consumer behavior. In each of four experiments, I test whether the saliency of norms of fairness associated with four different values (equality, equity, need, and reciprocity) moderates the effect of guilt proneness
on the extent to which participants will engage in a variety of opportunistic consumer behaviors.

3.3 Experimental Studies

In this article, I examine the effects of four different social norms of fairness on opportunistic consumer behavior by manipulating the saliency of the social norm experimentally in five different studies. In Study 1, I first examine whether an outcome-based norm of fairness based on equality influences how much participants in a PWYW setting pay for a birthday cake. I operationalize the social norm as the average amount others paid for a similar cake. This socially-constructed reference price provides social proof of a fair price. In Study 2, I investigate another outcome-based norm of fairness, based on need, which I operationalize by manipulating the wealth of the “victim” in an online movie piracy experiment. Study 3 tests the influence of the norm of equity in a PWYW setting. I operationalize the social norm by manipulating whether the customer must disclose their willingness to pay to the seller. In PWYW, since the buyer sets the price, they dictate the outcome for themselves and the seller. The equity of the buyer’s decision depends, in part, on their value for the product, captured by how much they would normally be willing to pay for it (WTP), and their payment (Price). The ratio of these two values (Price/WTP) captures fairness (Jang and Chu 2012). Disclosing their willingness to pay provides the seller with information about both their cost (their price) and benefit (their WTP), and exposes the equitableness of their decision. In Study 4, I observe the effects of an intentions-based norm of fairness on consumers’ likelihood of returning used clothing to a department store. I operationalize the norm by manipulating the seller’s motive for implementing the returns policy. Finally, Study 5 is a field experiment that tests the model in a real-world PWYW
purchase setting where I manipulate the presence of a social norm of fairness by providing some customers with a reference price in the same manner used in Study 1. Taken together, these five studies provide a rigorous test of the theoretical model using four different social norms of fairness, across three different types of opportunistic behavior, using scenario-based and field experiments.

3.3.1 Pretest

Testing the moderating effect of social norms requires manipulating whether information given to consumers provides them with social proof about what behavior is acceptable. A pretest confirmed that the proposed manipulations have significantly different measures of social acceptability.

One hundred six Amazon Mechanical Turk workers (61% male, 39% female) received a small amount of compensation for participating in an online survey. The participants were asked to rate the social acceptability of decisions under four different settings: 1) buying a cake under PWYW pricing, 2) pirating a movie from an online web site, 3) purchasing a buffet lunch under PWYW pricing, and 4) returning used merchandise to department store. For each of these settings the participants were provided with two alternative conditions. In the PWYW birthday cake scenario, one condition provided a social reference price (i.e., the average price paid by others) while the other did not. In the online piracy setting, the one condition described a financially needy movie distributor while in the other condition the distributor was described as well-off. In the case of the PWYW buffet lunch, in one condition the participant must disclose to the seller that they reap a large benefit from the price they pay, while in the second condition this information is kept private. Finally, in the case of returning used merchandise, in one condition the store’s motive for their return policy is described as beneficent, while in the other condition the motive is described as a selfish one. In each case the participants rated the social acceptability of an action on a 5-point scale (ranging from 1= Completely Unacceptable to 5= Completely Acceptable).
The results of the pretest are presented in Table 1. Across all four scenarios, the proposed manipulations resulted in significantly different assessments of the average social acceptability of the behaviors described in the alternative experimental conditions.

3.3.2 Study 1 – An equality-based norm of fairness

This study examines whether customers act opportunistically in a PWYW scenario. Allowing customers to choose their price creates a moral dilemma, since consumers want to attain the greatest material gain possible by paying nothing while avoiding the anticipated negative effects of guilt that come from acting selfishly. Thus, guilt prone individuals must decide what price is sufficiently fair. In this experiment, I provide one group of participants with a salient social norm – a reference price indicating the average price paid by others. This information provides social proof regarding the fair price. A second group receives no information regarding the average price paid by other, and thus there is no salient clue as to a fair price. I test the effect of anticipated guilt (H1), a norm of fairness based on equality (the average price paid by others) (H2), and their interaction (H3), on PWYW prices.

Method.

I recruited Amazon Mechanical Turk workers from the United States (n=140) to participate in an online study in exchange for a small fee (Appendix 3 summarizes the characteristics of participants in Studies 1 through 4). I dropped eight participants (5.7%) from the study either because they failed the manipulation check (n=2), or because of outliers or inconsistencies in their responses (n=6), such as PWYW amounts greater than their willingness
to pay, resulting in 132 valid responses. I presented the participants with a scenario in which they considered purchasing a cake for an upcoming birthday party from a bakery using PWYW pricing. The survey then instructed the participants to imagine paying for the cake by depositing their payment into an opaque box located near the exit of the store. In the Reference Price Present condition, participants were informed via a sign posted next to the payment box that other customers had paid an average of $10 for the cake. In the No Reference Price condition, participants did not have a posted sign. Participants in both treatments were told that their payment was anonymous and they would not revisit the bakery in the future to minimize the possible influence of self-presentation motives for payment amount. A manipulation check confirmed that participants understood that their payments were anonymous and they would not return to the bakery in the future. After entering their payment amount, the survey asked participants to report the price they expected to pay for the cake prior to arriving at the bakery. This step accounts for the possible effects of a customer’s internal reference price compared with the external reference price.

The Guilt-Negative-Behavior-Evaluation (Guilt-NBE) scale, (see Appendix 2), is used to assess anticipated guilt (an emotional trait) rather than reactive guilt (an emotional state) (Cohen et al., 2011). Individuals with high Guilt-NBE scores have been found less likely to make unethical decisions in exchanges with others (e.g., Bracht & Regner, 2013). I controlled for the gender of the participant since some prior studies have shown it to affect guilt proneness (Cohen et al., 2011).

Results

Table 2A compares the means for guilt proneness, the expected price, and PWYW amount for each condition. Table 2B presents the main effects (Model 1) and the interaction
(Model 2) of regressing PWYW payments on guilt proneness, the salience of the social norm, and their interaction.

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Insert Figure 1 about here

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Guilt proneness significantly predicts PWYW prices in both the main effects model (b=.558, p < .01) and interaction model (b=.763, p<.01), providing support for Hypothesis 1. Contrary to the prediction of Hypothesis 2, participants in the Reference Price Present group who were provided with a salient social norm paid significantly less money on average (M=$12.60) than participants in the No Reference Price group who were not provided with this information (M=$16.73, M_diff=-4.13, t=3.058, p<.01). While this result seems surprising at first, the price that participants expected to pay provides a possible explanation. While there no significant difference in the expected price of the birthday cake between the two experimental groups (M_diff=.13, t=.085, p>.10), customers in both groups expected to pay much more for the cake than the reference price ($10). Providing an average price lower than the expected price allowed participants in the Reference Price Present group to pay an amount comparable to what others paid but less money than they otherwise might have been willing to pay. Thus, providing a low reference price can potentially lead to greater unfair behavior. By contrast, members of the No Reference Price group had to rely upon their own judgment, and acted selfishly; paying less money than the price they expected to pay. I found a significant, positive effect of expected prices (b=.360, p<.01) but no effect of gender on PWYW payments.

The interaction model, Model 2, has an adjusted R^2 value of 36.9%, an improvement of 2% over the main effect model (34.9%). As predicted by Hypothesis 3, there is a significant
negative interaction between guilt proneness and the presence of the fairness norm (b= -0.529, p<.05) as illustrated in Figure 2. The effect of guilt proneness on PWYW payments was greatest in the No Reference Price condition where no social norm of fairness based on equality was present. When a reference price is salient, participants with high guilt proneness paid $2.26 more than participants with low guilt proneness ($13.62 versus $11.36). Without a reference price, high guilt prone participants paid $7.36 more than their low guilt prone counterparts ($20.90 versus $13.54); a much larger difference.

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Insert Figure 2 about here

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Discussion

Study 1 finds evidence that participants who are more guilt prone pay higher PWYW prices as predicted by Hypothesis 1. However, contrary to Hypothesis 2, the presence of a salient social norm resulted in significantly lower payments, but this main effect became insignificant in the interaction model. Since the $10.00 reference price was substantially lower than customer expected to pay, participants in the reference price present condition may have felt they had license to pay much lower prices. While participants in the reference price absent condition also paid less than they expected. In the absence of external information, these participants had to rely solely on internal judgement regarding what price to pay. Finally, as evidenced by Figure 2, and consistent with the prediction of Hypothesis 3, the saliency of a social norm negatively moderated the effect of guilt proneness on opportunistic consumer behavior. The effect of guilt proneness had a larger effect on those for whom the social norm was less salient than for those who could simply rely on the reference price for making their pricing decision.
3.3.3 Study 2 – A need-based norm of fairness

The preceding study examined how social norms and guilt affect opportunism in a context where the seller invited customers to pay any price they wanted. Yet, sellers do not allow some opportunistic behaviors under any circumstances. For example, providers of online content such as music, movies, and video games, are subject to unauthorized illegal downloading of their products (i.e., piracy). Study 2 examines how guilt proneness and social norms influence the likelihood that a consumer will pirate online content. I test the effect of anticipated guilt (H1) and the effect of another outcome-based norm of fairness associated with need, by manipulating the perceived financial neediness of the seller (H2) on the participant’s likelihood to engage in movie piracy. In addition, I also examine the interaction of anticipated guilt and need (H3).

Method

Amazon Mechanical Turk workers from the United States (n = 185) were recruited to participate in an online study in exchange for a small fee. Six participants (3.2%) were dropped from the study for failing manipulation checks; resulting in 179 valid responses. The survey instructed participants to imagine visiting an online web site to download a movie they want to watch. Participants were told that the price of the movie was one they were willing to pay. Next, the survey asked them to imagine that as they were about to download the movie they discovered another web site where they could pirate the movie (i.e., download it free). The instructions reminded the participants that piracy is unauthorized and illegal.

To test the moderating effect of need, I manipulated the perceived neediness of the seller by randomly assigning participants to two experimental groups. Members of the Low-Need group, (n=90), were told that the movie was produced by a large production company with a recent string of blockbuster hits, while those in the High-Need group, (n=89) were told that the
movie was produced by a small independent filmmaker just trying to make it in the business. All participants were then asked to report the likelihood that they would pirate the movie on a 7-point scale (anchored by 1=Not at All Likely to Pirate and 7=Very Likely to Pirate). Since evidence suggests an association between past participation in piracy and intention to pirate in experiments (Grolleau and Mzoughi, 2008) I controlled for prior piracy behavior by asking participants whether they have previously downloaded electronic content (e.g., movies, games, music). Next, guilt proneness was measured using the Guilt-Negative-Behavior-Evaluation (Guilt-NBE) scale used in Study 1. The gender of the participant was recorded as a control, since females have been shown to have higher guilt proneness scores in some online experiments (Cohen et al., 2011).

Results

Table 3 provides results of regressing the likeliness of piracy on guilt proneness, the presence of the social norm, and their interaction along with the controls variables. Model 1 presents the main effects and Model 2 includes the interaction. The adjusted $R^2$ for Model 2 is 33.7%.

A large portion (67.6%) of participants reported that they had pirated digital content in the past. Although this proportion was the same across the two treatments ($z=0.691, p>.10$), those who reported a prior history of pirating content indicated that they were significantly more likely

\footnote{While some bias from self-reported illegal behavior might occur, participants were reminded that their survey responses are anonymous and that the researchers use no identifiable information.}
to pirate the movie (b=2.211, p<.01). The average likelihood of pirating the movie in the Low-Need treatment was (M=4.20) and is significantly higher than the likelihood of pirating among those in the High-Need treatment (M=3.55), (t=1.99, p<.05). As in Study 1, I find that gender has an insignificant effect on the likelihood of piracy (b=.035, p>.10).

As shown in Table 3, Model 1, I find a significant, negative main effect of guilt proneness on piracy (b=-.090, p<.05). The negative sign of the coefficient means that participants with higher levels of guilt proneness are less likely to pirate the movie, supporting Hypothesis 1. Second, as predicted by Hypothesis 2, the participants’ intentions to pirate have a significant positive effect on the perceptions of the seller’s financial need (b=.658, p<.05).

Table 3, Model 2 shows the moderating effect of saliency of the social norm of fairness. The effect of guilt proneness becomes insignificant, but the effect of need remains statistically significant in Model 2. The saliency of the seller’s need negatively moderates the effect of a consumer’s guilty proneness on the likelihood of pirating (b=-.130, p< .05), supporting Hypothesis 3. The negative coefficient for this interaction means that the influence of anticipated guilt on the intention to pirate a movie is more pronounced when the seller is described as having greater financial need, and less consequential when consumers are told that the seller has a low level of financial need. Figure 3 illustrates the results of this interaction. While the effect of guilt is pronounced for the Low-Need treatment group, the highest guilt prone consumers are equally unlikely to pirate the movie regardless of the seller’s financial need.

Insert Figure 3 about here
Discussion

The results of this study follow a similar pattern to the results found in Study 1 using a different opportunistic behavior, piracy, and a different outcome-based norm of fairness based on need. First, I find that participants with high levels of guilt proneness will less likely to engage in piracy compared with participants having low levels of guilt proneness, supporting H1. Next, I find that participants will be less likely to engage in piracy when the salience of need is high compared to when the salience of need is low, supporting H2. However, in the low-need case, guilt proneness has a negligible effect on a participant’s intention to pirate since, consistent with the pretest results, consumers feel that stealing from the poor is unacceptable. By contrast, when the seller is well-off, how consumers should act is less clear, as demonstrated in the pre-test findings, and the personality variable of guilt proneness plays a stronger role in determining whether they choose to pirate the movie, as predicted by H3.

3.3.4 Study 3 – An equity-based norm of fairness

The goal of this study is to examine the effects of another outcome-based norm of fairness, the norm of equity, on opportunistic behavior in a PWYW price setting. The norm of equity prescribes that neither partner to a transaction should benefit disproportionately compared to the other. I manipulate the salience of the norm of equity by requiring some participants to disclose to their willingness to pay for a lunch to the restaurant. The ratio of Price/WTP captures fairness (Jang and Chu 2012). Therefore, disclosing their willingness to pay provides the seller with information about both their cost (their price) and benefit (their WTP), and exposes the equitableness of their decision. Disclosing this information reveals both their cost (the price they offer) and their benefit (e.g. their WTP), thereby exposing the equitableness of their decision. This increasing the salience of the social norm compared to a second experimental group who
are not required to disclose their value for the meal. I test the effect of anticipated guilt (H1) and the saliency of the norm of equity (H2) on a consumer’s PWYW payment amount.

Method

This study uses a single-factor design in which a customer must either disclose their WTP, a measure of the product’s value, to the seller or keep this information private. I recruited Amazon Mechanical Turk workers from the United States (n = 120) to participate in an online study in exchange for a small fee. Eleven participants (9.1%) were dropped from the study because they failed manipulation checks (n=5), or they had inconsistencies in their responses (n=6) such as PWYW amounts that exceeded their willingness to pay); leaving 109 valid responses. Participants were randomly assigned to one of two experimental groups; Reveal WTP or Private WTP. In both treatments, participants were asked to imagine purchasing lunch in a distant city at a buffet restaurant that they had not previously visited. All participants were told that the restaurant allows diners to pay-what-they-want for lunch. In the Private WTP treatment, to control for self-presentation motives, the participants were told that their payment is anonymous, and they would not return to this restaurant. A manipulation check was used to confirm that they understood that their payments and WTP were anonymous and they would not return to the restaurant in the future. Participants imagined paying for their meal by placing their money into an envelope and depositing it in an opaque metal box near the exit. In the Reveal WTP scenario, the participants had to disclose, in writing, to the seller, their WTP for the meal along with the amount they chose to pay by writing this information on the outside of their payment envelope, (although their payments would be anonymous). The participants in this Reveal WTP group entered their PWYW amount and their WTP amount. By comparison, Participants in the Private WTP condition were not asked to imagine writing anything on their
payment envelope. They were only asked to imagine putting their money into the envelope and dropping it into the payment box. Following this, they were asked to enter their payment amount and then asked to report their willingness to pay for the meal to the experimenter, as a control. Importantly, those in the Private WTP condition were not asked about their WTP until after they made their payment and were not asked to report this to the seller; whereas, in the Reveal WTP condition the participants were asked to consider both their WTP and payment amount before making their payments and to report their WTP to the seller. All participants then completed the Guilt-Negative-Behavior-Evaluation (Guilt-NBE) measure used in Studies 1 and 2, and to report their gender, since females have been shown to have higher guilt proneness scores in some online experiments (Cohen et al., 2011).

Finally, although payments in each group were anonymous, members of the Reveal WTP condition were required to disclose information that might affect their self-image or concerns about the image they projected to others. To control for image concerns as a possible explanation for any differences in payments, all participants completed the Image Management (IM) and Self Deceptive Enhancement (SDE) subscales of the Balanced Inventory of Desirable Responding (BIDR) (Paulhus, 1991) included in Appendix 1.

Results

Table 4A compares the means for the PWYW amount, guilt proneness, WTP, and the BIDR measures for both experimental groups. Table 4B provides results of testing the model in Figure 1 by regressing PWYW payments on guilt proneness, the presence of the social norm, and their interaction as well as WTP and the control described above. The adjusted \( R^2 \) for Model 2 is 54.1\%, a 1.4\% improvement over the main effects only model (Model 1).
As predicted, there is a significant difference in PWYW amounts between the two treatment groups (Table 4A). Participants who were required to reveal their WTP, and thus the equity resulting from their decision, paid an average of $1.52 more for lunch than those participants who were not asked to reveal their WTP (t=2.17, p<.05). This difference is striking considering there is no statistically significant difference in the average WTP for the meal between these two groups (t=.803, p>.10). Nor is there any significant difference in the guilt proneness, impression management, or self-deception enhancement scores between the two treatment groups (p>.10).

As shown in Table 4B, the controls, (gender, self-deception enhancement, and impression management) do not have a significant effect on prices in either the main effects or moderation models. In support of H1, guilt proneness is positively associated with higher PWYW payments in the main effects model (b=.107, p<.01) and in the interaction model (b=.237, p<.01). Consistent with H2, increasing the saliency of the norm of equity (by asking participants to reveal their WTP to the seller) decreases opportunism, increasing the amount participants pay in the main effects model (b=1.344, p<.01), and the interaction model (b=5.897, p<.05).

The interaction in Table 4B and illustrated in Figure 4 shows that increasing the salience of the norm of equity negatively moderates the effect of guilt proneness on the PWYW amounts (b=-.192, p<.05) supporting H3. For participants who were not required to reveal their WTP (Private WTP condition), as individual guilt proneness increases, the average PWYW payment increases
by $2.70, from $8.85 to $11.55. However, for those who are required to reveal their fairness (Reveal WTP condition), the influence of guilt proneness is weaker, with PWYW payments increasing only $0.51, from $11.35 to $11.86 as predicted by Hypothesis 3.

Discussion

The results of this study replicate the pattern of results found in the prior two experiments using a third norm of fairness, equity. Again, I find that participants with high guilt proneness were less likely to act opportunistically in paying for lunch than those with low guilt proneness, supporting H1. Consistent with H2, even though members of both experimental groups had the same WTP for their meal, participants were less likely to act opportunistically when the equity norm more salient even when controlling for impression management concerns. When the norm of equity more salient, the impact of anticipated guilt on PWYW prices was weaker than when participants could conceal their fairness and had greater temptation to act opportunistically, guided by their conscience, as predicted by H3.

3.3.5 Study 4 – A reciprocity-based norm of fairness

This study examines how guilt proneness influences opportunistic behavior in the presence of an intentions-based norm of fairness, reciprocity. To examine how reciprocity influences ethical decision making, this study manipulates a store’s motive for offering a merchandise return policy. I test the effect of anticipated guilt (H1) and the salience of the fairness motive of the seller (H2) and their interaction (H3), on a consumer’s likelihood of RETURNING used merchandise.

Method

Amazon Mechanical Turk workers form the United States (n = 135) were recruited to participate in an online study in exchange for a small fee. Nine participants (6.6%) were dropped
from the study because they failed manipulation checks; resulting in 126 valid responses. The survey prompted the participants to imagine that they had to attend an out of town wedding. When they arrived, they discovered that they forgot to pack dress shoes and that they decided to buy a pair of shoes at a local department store. After wearing the shoes for the weekend, they realize the store has a “100% Satisfaction Guarantee” policy and although they were completely satisfied with the shoes, the shoes could be returned for a full refund. The instructions further stated that since the participant had worn the shoes the store will not be able to resell them. Participants were randomly assigned to one of two experimental groups. Participants in the Beneficent Motive (high salience) group were informed that the store offers a return policy to be fair to customers so those who are genuinely dissatisfied with their products can return them. Member of the Sales Motive (low salience) group were told that the store offers this policy to promote sales, without mentioning fairness. Following these statements, a manipulation check confirmed that the participant understood the store’s motive for implementing the returns policy. Then, all participants reported their likelihood to return the worn shoes to the store using a 7-point Likert-type scale (where 1= extremely unlikely and 7= extremely likely). Guilt proneness was measured using the Guilt-Negative-Behavior-Evaluation (Guilt-NBE) measure used in the prior studies and the gender of the participant used as a control since females have been shown to have higher GASP scores in some online experiments (Cohen et al., 2011).

Results

Of the 135 participants, 9 (6.7%) failed the manipulation check, resulting in 126 participants. Table 5 provides results of testing the model in Figure 1 by regressing the likelihood of returning the worn merchandise on guilt proneness, the salience of the social norm (Model 1),
and their interaction (Model 2). The adjusted $R^2$ for Model 2 is 21.8%, an improvement of 1.9% over Model 1.

As predicted by Hypothesis 1, guilt proneness has a significant negative effect on opportunistic behavior in both the main effects model ($b=\ -0.163$, $p<.01$) and in the interaction model ($b=\ -0.241$, $p<.01$). Participants with higher guilt proneness were less likely to return the used shoes than those with low guilt proneness. Saliency of the norm fairness has a significant, negative effect on reducing opportunistic behavior in both the main effects model ($b=\ -0.785$, $p<.01$) and in the interaction model ($b=\ -3.457$, $p<.05$). The negative coefficient means that when the norm of fairness is salient participants were less likely to return used merchandise, supporting Hypothesis 2. Gender does not significantly influence the outcome in either model.

As predicted by Hypothesis 3, and illustrated in Figure 5, there is a significant negative interaction between guilt proneness and the salience of the reciprocal norm of fairness concerning the sellers’ motive for their returns policy ($b=\ -0.119$, $p<.05$). Individual guilt proneness makes less of a difference when the seller’s motive for the policy is to be fair ($M_{diff}=1.25$) than when fairness is not salient ($M_{diff}=2.47$). Interestingly, the most guilt prone participants are equally unlikely to return worn shoes in either case.

The results indicate when the norm of fairness was made more salient by introducing a beneficent motive for the returns policy, the influence of anticipated guilt was weaker than when
a selfish explanation for the returns policy was offered. Therefore, the effect of guilt proneness on opportunistic consumer behavior was negatively moderated by the strength of the reciprocity norm, such that guilt proneness mattered more when the norm of reciprocity was less salient, as predicted by Hypothesis 3.

Discussion

This study examined an intentions-based motive of fairness, reciprocity, on consumers’ moral behavior. As in each of the prior studies, this experiment finds that participants with high levels of guilt proneness will less likely to engage in opportunistic consumer behavior compared with participants with low levels of guilt proneness, supporting H1. Similarly, I found that when consumers were prompted to consider the retailer’s expectations for fairness as a motive for their returns policy they were less likely to return worn shoes, supporting H2. Finally, the saliency of the retailer’s expectations of fairness negatively moderated the effect of guilt proneness on the likelihood of returning used clothing such that guilt proneness mattered more to those who may not have thought about the retailer’s expectations of fairness, supporting H3.

3.3.6 Study 5 – A PWYW field experiment

The preceding scenario-based experiments exhibit a common pattern of results: when social norms of fairness are more salient to consumers, those norms moderate the influence of their guilty conscience on the likelihood of engaging in opportunistic behaviors. This study tests this result through an incentive-compatible field experiment. The experimental design replicates the hypothetical framework used in Study 1 in a real-world setting. Customers pay whatever price they want for an inexpensive meal using their own money. I manipulate the presence of a social norm of fairness by providing some customers with the price others paid for the meal.

Pretest
To determine the appropriate social reference price, I conducted a pretest, by surveying 42 undergraduate students, familiar with the café. The survey participants were asked to (anonymously) disclose the amount they would be willing to pay for the pizza plus beverage meal if they could pay any price they wanted. The average stated price was $0.81. In order to test whether the reference price alters the amount customers would normally pay without one; a slightly higher, fictitious $0.90 reference price was used.

Method

Participants were customers of a student-run campus café. The café serves lunch and snacks to students at a large northeastern Ohio university. A popular menu choice is a meal consisting of a slice of pizza and a cold beverage. The normal fixed price for this meal is $1.50.

Over two consecutive days, the Café offered a PWYW pricing scheme. The change in pricing was described to customers as a 2-day promotion using signs placed in the café. One purpose of providing this explanation was to minimize the possibility that customers might strategically pay more to induce the café to continue offering the PWYW pricing policy (Mak, Zwick, Rao, and Pattaratanakun, 2015). Diners were asked by the café staff to complete an anonymous, four question survey to complete their purchase. The four questions were the Guilt-Negative-Behavior-Evaluation scale used in the prior studies (Cohen et al., 2011). Since regular customers might respond differently than infrequent customers, customers were also asked to report how often they purchase pizza at the café on a 4-point scale (ranging from less than once per week to four times per week).

Customers were randomly assigned to one of two treatment groups. Members of the first (no reference price) group were provided with the information described above. Members of the second (reference price) group were provided with additional information that “on average, other
customers paid 90¢.” This additional information was hand-written next to the location where customers were asked to record their PWYW price. Cashiers collected the form and charged the amount the customer elected to pay.

Results

Of 72 customers that participated in the experiment, 2 participants did not complete the survey, resulting in 70 valid observations (36 in the no-reference price condition and 34 in the reference price condition). Table 6A compares the means for guilt proneness, the PWYW amount, and the average frequency of purchase for both groups. The average level of anticipated guilt was not statistically different between both groups (t = 1.59, p>.10). The average price paid by members of the no-reference group ($0.88), is significantly higher than the average price ($0.64) paid by participants who were provided with a $0.90 social reference price (t=1.98, p=.052).

Table 6B presents main effects (Model 1) and the interaction (Model 2) of regressing PWYW payments on guilt proneness, the salience of the social norm, and their interaction. The adjusted R² for Model 2 is 36.91%, an improvement of 13% over Model 1.

As predicted by Hypothesis 1, guilt proneness had a significant main effect on opportunistic behavior in both the main effects model (b=.041, p<.01) and in the interaction model (b=.101, p<.01). Participants with higher guilt proneness were likely to pay higher PWYW prices. Making the social norm more salient by presenting a reference price had a significant main effect on PWYW price for the interaction model (b= 1.892, p<.01) but only a marginally significant effect in the main effects Model 1 (b= -.192, p=.096).
As predicted by Hypothesis 3, and illustrated in Figure 6, there is a significant negative interaction between guilt proneness and presence of the social norm of fairness ($b = -0.093$, $p < .01$).

*Insert Figure 6 about here*

The effect of anticipated guilt on PWYW prices is weaker when the buyers have information about what price others consider fair, then when they must decide for themselves what price is fair as predicted by Hypothesis 3.

*Discussion*

As in each of the prior online studies, this field experiment also found that participants with higher guilt proneness were less likely to engage in opportunistic behavior compared with those with lower levels of guilt proneness, supporting H1. Interestingly, customers who were told that others paid an average of $0.90 paid significantly less than those who were not given any information about what others consider a fair price ($t = 1.98$, $p = .052$). An explanation for this result may be that customers who were provided with an external reference price ($0.90) used that information to anchor their payment decision. However, those who were not provided with any social reference price may have relied on the regular ($1.50) retail price to choose the amount they paid. Since participants reported having purchased pizza frequently in the past, they are likely to have a well-established internal reference price of $1.50. This explanation is consistent with prior empirical findings that an external reference close to, or higher than an internal reference price, resulted in payments lower than the respective external reference price (Soule and Madrigal, 2014), and that customers with high internal reference prices pay more under PWYW than customers provided with external reference prices (Johnson and Cui, 2013).
Thus, as in the prior scenario based studies, I find evidence that when consumers are prompted to consider what price is “fair” by examining the response of others, they are less likely to behave opportunistically by paying very low prices, supporting H2. Finally, introducing the social norm of fairness negatively moderated the effect of guilt proneness on the amount customers paid such that the consumer’s level of guilt proneness mattered when they were provided with information about social expectations of fairness, supporting H3.

3.4 General Discussion

Opportunistic behavior of consumers has become more important as innovation and technological developments have given more power to consumers in their relationships with firms. Therefore, studying conditions that trigger a wide range of unethical consumer behaviors is an important avenue for marketing research (De Bock et al., 2013). This paper helps advance an understanding of under what circumstances consumers are likely to engage in opportunistic behavior. For instance, consumers can take advantage of new participative pricing mechanisms such as PWYW (J.-Y. Kim et al., 2009) or use unethical tactics such as sniping or shill bidding practices in online auctions (Marcoux, 2003).

The consistent pattern of results across four scenario-based studies and a field experiment helps explain consumers’ ethical decision making and robustly supports the hypotheses. First, increases in anticipated guilt lead to lower levels of opportunistic behavior (H1). Second, increasing the salience of concerns for social norm of fairness reduces opportunistic behavior (H2). Third, salient norms minimize (negatively moderate) the effect of anticipated guilt on opportunistic behavior (H3). That is - in situations where norms are not salient, consumers must decide how to behave by turning to their own moral compass rather than following the behavior of others.
I test a theoretical model (Figure 1), based on the Negative State Relief model (Cialdini et al., 1973), in three different settings where consumers could act opportunistically: PWYW purchases, merchandise returns, and online piracy. These settings vary in the degree of license the seller grants the consumer to exploit their relationship. At one extreme, sellers who offer PWYW pricing do not encourage customers to pay low prices, but do not forbid it (Kim et al., 2009). Returns policies have characteristics of both settings since firms often explain the intent of the policy, but may turn a blind eye to abuses by unethical customers (Berry and Seiders, 2008). However, firms are resolute that piracy is unacceptable and unlawful. Thus, the behaviors selected for this paper span a range from acceptable to questionable to unacceptable (Dootson et al., 2016).

The focus theory of normative conduct predicts that consumers will be more likely to conform to social norms when those norms are more salient (Cialdini, Reno, and Kallgren, 1990). I test this prediction by manipulating the saliency of (1) equality (information about what others paid for a birthday cake in a PWYW experiment), (2) need (the wealth of the seller in an online movie piracy experiment), (3) equity (whether buyers reveal their willingness to pay for lunch in a PWYW experiment), and (4) reciprocity (by manipulating the seller’s motive in a merchandise returns experiment). In each case, increasing the saliency of norms of fairness increased the likelihood consumers acted fairly. These norms span both outcome–based and intentions-based norms of fairness, providing a robust test of the effect of the focus theory of normative conduct (supporting H2).

This paper contributes to a broader literature that examines the role of guilt in marketing relationships. Although research has long investigated the potential of consumer guilt to predict and shape behavior (e.g., Lascu, 1991), most research has focused on consumption guilt, and
guilt in promotional appeals (e.g., Antonetti & Baines, 2015). For example, researchers have studied consumers’ guilty feelings when they consider purchasing unhealthy foods or hedonic goods (e.g., Khan & Dhar, 2010; Wansink & Chandon, 2006), buying environmentally harmful products (Peloza, White, and Shang, 2013), and post-consumption guilt from impulse purchases (e.g., Cole & Sherrell, 1995). Guilt has also been well-researched in the context of advertising appeals (e.g., Coulter & Pinto, 1995), social marketing (e.g., Brennan & Binney, 2010) and for stimulating charitable donations (Basil et al., 2008). However, understanding the influence of a consumer’s guilty conscience when dealing with firms has received relatively little attention.

I focus on how anticipated feelings of guilt determine whether consumers engage in unethical conduct. This extends a prior literature that investigates how (reactive) guilt experienced by customers after committing transgressions leads to reparative action. For instance, Dahl et al. (2005) find that when consumers and sales people become socially connected, failure to make a purchase causes guilt, which motivates the consumer to take reparative actions such as increasing the amount they are willing to spend on subsequent visits. Steenhaut and Van Kenhove (2005) examine how relationship commitment and feelings of guilt determine consumers’ reparative actions when they receive too much change from a cashier. Opportunism drives less committed consumers to keep the money, while guilt-related feelings lead highly committed consumers to report the mistake. By contrast, these findings demonstrate the inhibitory power of consumer guilt, and provides insight into how firms might avert harmful behavior by opportunistic customers.

An important managerial implication of this findings is that guilt is not an elixir that should take for granted. Even guilt prone customers can be influenced by contextual factors that moderate the effects of their anticipated guilt. This insight helps reconcile contradictory results in
prior studies of ethical behavior. For example, Kunter (2015) found that guilt had a significant positive effect on the PWYW price customers offered for admission to a German zoo. By contrast, Regner (2015) found that guilt had little explanatory power on PWYW offers for music downloads. This result suggests that the salience of social norms might explain the differences in these findings. By design, social norms were not salient in Kunter’s (2015) study, since the zoo removed reference prices from the customers view, while in Regner (2015) musicians explicitly suggested a minimum donation amount for music downloads.

One practical implication of these results is consumers will be less likely to anticipate guilt when norms of fairness are salient. Piron & Young (2000) reported that one-third of the participants in their survey of retail borrowers failed to express feelings of guilt, and provided other reasons for their behavior. The authors suggest, “It is conceivable that such rationalizations are but a thin veil to cover guilt” (p. 30). However, it is also possible that the setting failed to evoke guilt. Perhaps social norms were available to consumer so that their anticipated guilt was not activated. Several studies have found that simple cues such as signs with images of watchful eyes lead to prosocial behavior such as reduced littering (Ernest-Jones, Nettle, and Bateson, 2011) and increased charitable donations (Ekström, 2012). Thus, firms could amplify concerns for fairness using situational cues/norms. There are other scenarios in addition to the ones that I investigated in this paper where consumer opportunism is present. For example, the internet enables consumers to post untruthful product reviews in exchange for compensation (Short, 2012). Social media allowed consumers to sabotage a co-production initiative by posting anti-SUV videos to a site created by the Chevrolet to disseminate user-generated content about their 2007 Chevy Tahoe SUV (Ertimur and Venkatesh, 2010).
3.5 Limitations and Future Research

Numerous studies have documented cultural influences on ethical consumer behavior (e.g., Rawwas, Swaidan, & Oyman, 2005). For example, Hofstede’s cultural Individualism-Collectivism index was found to be a significant predictor of software piracy rates across different countries (Depken and Simmons, 2004; Yang and Sonmez, 2007). These authors do not conjecture about whether cultural differences in guilt proneness might account for this result. Thus, I used only U.S. participants to control for cultural differences in these experiments. Although this might limit the generalizability of this results, it avoids potential confounds due to unmeasured cultural differences.

Prior research has found that guilt proneness varies across countries (Wong and Tsai, 2007), and that compared with collectivist countries, individualistic countries are characterized by a guilt culture (Fougère and Moulettes, 2007). Therefore, people from individualistic societies have been predicted to experience greater guilt from acting selfishly (Hofstede, 2011). For instance, students from an individualistic country anticipated stronger feelings of guilt from cheating on an exam than students from a collectivist country (Stipek, 1998), and consumers from individualistic countries have higher levels of anticipated guilt when making environmentally unfriendly purchasing decisions than for those from collectivistic countries (Onwezen, Bartels, and Antonides, 2014).

To illustrate the plausibility of this idea, I obtained data from a large multi-cultural PWYW field trial. This data cover two weeks of payments of consumers who paid whatever price they wanted to download a computer video game. The game, which was a popular and best-seller normally sold for $20. During the PWYW trial, 82,592 consumers from 50 countries downloaded the game (with a minimum 30 purchases per country). I have illustrated the average
price paid, by country, in Appendix Figure 5A, and the percentage of customers who paid zero for the game in Appendix Figure 5B. The average price paid for the game was $2.11, but varies considerably from country to country. For example, Turkish customers (N=689) paid the lowest average price of $0.20, while the average Swiss customer (N=279) paid $4.82. There are equally dramatic differences between these two countries in the percentage of free-riders (i.e., those who paid nothing for the game other than a small PayPal transaction fee that does not benefit the video game manufacturer). In Turkey, 88.7% of the customers paid zero, while in Switzerland, only 10.4% of the customers engaged in free-riding. Turkey is also a country with a very low measure of Cultural Individualism (Hofstede IC index=37) compared to Switzerland (Hofstede IC index=68). An initial examination of this data revealed that the Hofstede Individualism-Collectivism Index for each country is a significant, positive predictor of the average PWYW price (b=.014, p=.011, Adj. $R^2$=11.19%) providing evidence that greater cultural guilt proneness is associated with higher PWYW payments. Although the nature of this data does not allow a rigorous analysis of this model, the example highlights the potential importance of future research that investigates guilt-related cultural differences.

In summary, three different consumer settings using four different norms of fairness provide a picture that guilt and social norms act together to influence consumer opportunism, and that the role of guilt is contingent on information that consumers use to make ethical decisions. I hope these insights provide avenues for further research that will build on upon these findings.
<table>
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<tr>
<th>Setting</th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>M₁</th>
<th>M₂</th>
<th>t-stat</th>
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<tr>
<td>PWYW</td>
<td>No Reference Price</td>
<td>Posted Reference Price</td>
<td>3.76</td>
<td>3.21</td>
<td>3.34***</td>
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<tr>
<td>Piracy</td>
<td>Small Financially Needy Provider</td>
<td>Large Well-Off Provider</td>
<td>2.28</td>
<td>2.95</td>
<td>3.57***</td>
</tr>
<tr>
<td>PWYW</td>
<td>Disclose Equity</td>
<td>Conceal Equity</td>
<td>3.23</td>
<td>2.74</td>
<td>2.75***</td>
</tr>
<tr>
<td>Returns</td>
<td>Beneficent Motive</td>
<td>Selfish Motive</td>
<td>2.63</td>
<td>3.00</td>
<td>1.86*</td>
</tr>
</tbody>
</table>

N = 42, ***p<.01, **p<.05, *p<.10
Table 2A

<table>
<thead>
<tr>
<th>Variable</th>
<th>Social Reference Price</th>
<th>No Social Reference Price</th>
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<tr>
<td>PWYW Price</td>
<td>12.60</td>
<td>16.73</td>
<td>3.058***</td>
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<tr>
<td>Expected Price</td>
<td>23.77</td>
<td>23.90</td>
<td>0.085</td>
</tr>
<tr>
<td>Guilt Proneness</td>
<td>22.03</td>
<td>23.12</td>
<td>-1.307</td>
</tr>
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</table>

N = 132, ***p<.01, **p<.05

Table 2B
Study 1. Regression Results. Moderating Effects of an Equality Based Norm of Fairness on Guilt Proneness. (DV = PWYW Price)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β (SE)</td>
<td>β (SE)</td>
</tr>
<tr>
<td>Guilt Proneness</td>
<td>.558***</td>
<td>.763***</td>
</tr>
<tr>
<td></td>
<td>(.120)</td>
<td>(.150)</td>
</tr>
<tr>
<td>Reference Price</td>
<td>-4.795***</td>
<td>7.209</td>
</tr>
<tr>
<td>Present (1=Yes)</td>
<td>(1.133)</td>
<td>(5.520)</td>
</tr>
<tr>
<td>Expected Price</td>
<td>.351***</td>
<td>.360***</td>
</tr>
<tr>
<td></td>
<td>(.064)</td>
<td>(.063)</td>
</tr>
<tr>
<td>Guilt x Reference</td>
<td>- .529**</td>
<td>H3 ✓</td>
</tr>
<tr>
<td>Price</td>
<td>(.238)</td>
<td></td>
</tr>
<tr>
<td>Gender (1 = Male)</td>
<td>-.138</td>
<td>-.287</td>
</tr>
<tr>
<td></td>
<td>(1.140)</td>
<td>(1.125)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-3.844</td>
<td>-8.481</td>
</tr>
<tr>
<td></td>
<td>(3.129)</td>
<td>(3.723)</td>
</tr>
</tbody>
</table>

Adjusted R²: .349 .369

N=132, ***p<.01, **p<.05, unstandardized coefficients
Table 3
Study 2. Regression Results. Moderating Effects of a Need Based Norm of Fairness on Guilt Proneness. (DV = Likelihood of Piracy)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>β (SE)</td>
<td></td>
<td>β (SE)</td>
<td></td>
</tr>
<tr>
<td>Prior Piracy (1=Yes)</td>
<td>2.211**</td>
<td>(.306)</td>
<td>2.285***</td>
<td>(.305)</td>
</tr>
<tr>
<td>Guilt Proneness</td>
<td>-0.090**</td>
<td>(.031)</td>
<td>-0.036</td>
<td>(.040)</td>
</tr>
<tr>
<td>Low-Financial Need Treatment (1=Yes)</td>
<td>0.658**</td>
<td>(.279)</td>
<td>3.470**</td>
<td>(1.349)</td>
</tr>
<tr>
<td>Guilt x Low-Financial Need</td>
<td></td>
<td></td>
<td>-0.130**</td>
<td>(.061)</td>
</tr>
<tr>
<td>Gender (1 = Male)</td>
<td>-0.035</td>
<td>(.282)</td>
<td>-0.104</td>
<td>(.281)</td>
</tr>
<tr>
<td>Intercept</td>
<td>4.014**</td>
<td>(.773)</td>
<td>2.878***</td>
<td>(.933)</td>
</tr>
<tr>
<td>R²</td>
<td>0.319</td>
<td></td>
<td>0.337</td>
<td></td>
</tr>
</tbody>
</table>

N=179, ***p<.01, **p<.05, *p<.10
Table 4A

<table>
<thead>
<tr>
<th>Variable</th>
<th>WTP Private</th>
<th>WTP Revealed</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWYW Price</td>
<td>7.74</td>
<td>9.26</td>
<td>2.167**</td>
</tr>
<tr>
<td>WTP</td>
<td>10.60</td>
<td>11.13</td>
<td>.803</td>
</tr>
<tr>
<td>Guilt Proneness</td>
<td>23.62</td>
<td>22.79</td>
<td>.946</td>
</tr>
<tr>
<td>Impression Management</td>
<td>7.73</td>
<td>7.05</td>
<td>.815</td>
</tr>
<tr>
<td>Self-Deception Enhancement</td>
<td>5.94</td>
<td>6.75</td>
<td>.995</td>
</tr>
</tbody>
</table>

N = 109, ***p<.01, **p<.05, *p<.10

Table 4B
Study 3. Regression Results. Moderating Effects of Equity Based Norm of Fairness on Guilt Proneness. (DV = PWYW Price)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 β (SE)</th>
<th>Model 2 β (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guilt Proneness</td>
<td>.107** (.049)</td>
<td>.237*** (.081)</td>
</tr>
<tr>
<td>WTP</td>
<td>.719*** (.074)</td>
<td>.737*** .074</td>
</tr>
<tr>
<td>Reveal WTP (1=Yes)</td>
<td>1.344*** (.504)</td>
<td>5.897** (2.314)</td>
</tr>
<tr>
<td>Guilt Proneness x Reveal WTP</td>
<td></td>
<td>-.192** (.095)</td>
</tr>
<tr>
<td>Impression Management</td>
<td>.032 (.070)</td>
<td>.039 (.069)</td>
</tr>
<tr>
<td>Self-Deception Enhancement</td>
<td>-.019 (.065)</td>
<td>-.025 (.064)</td>
</tr>
<tr>
<td>Gender (1 = Male)</td>
<td>-.652 (.514)</td>
<td>-.812 (.512)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-1.575 (1.525)</td>
<td>-4.681** (2.153)</td>
</tr>
</tbody>
</table>

Adjusted R² .527 .541

N=109, ***p<.01, **p<.05, *p<.10
Table 5
Study 4. Regression Results. Moderating Effects of a Norm of Reciprocity on Guilt Proneness. (DV = PWYW Price)

<table>
<thead>
<tr>
<th></th>
<th>Model 1 β (SE)</th>
<th>Model 2 β (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guilt Proneness</td>
<td>-.163*** (.030)</td>
<td>-.241*** (.050)</td>
</tr>
<tr>
<td>Fairness Motive (1=Yes)</td>
<td>- .785*** (1.133)</td>
<td>-3.457** (1.420)</td>
</tr>
<tr>
<td>Guilt x Fairness Motive</td>
<td></td>
<td>-.119** (.062)</td>
</tr>
<tr>
<td>Gender (1 = Male)</td>
<td>-.083 (.306)</td>
<td>-.076 (.302)</td>
</tr>
<tr>
<td>Intercept</td>
<td>6.509*** (.811)</td>
<td>8.282*** (1.221)</td>
</tr>
</tbody>
</table>

Adjusted R² .199 .218

N=126, ***p<.01, **p<.05, *p<.10
Table 6A

<table>
<thead>
<tr>
<th>Variable</th>
<th>Social Reference Price</th>
<th>No Social Reference Price</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWYW Price</td>
<td>0.64</td>
<td>0.88</td>
<td>1.978**</td>
</tr>
<tr>
<td>Guilt Proneness</td>
<td>21.38</td>
<td>23.08</td>
<td>1.598</td>
</tr>
</tbody>
</table>

N = 70, ***p<.01, **p<.05, *p<.10

Table 6B
Study 5. Regression Results. Moderating Effects of Equality Based Norm of Fairness on Guilt Proneness. (DV = PWYW Price)

<table>
<thead>
<tr>
<th></th>
<th>Model 1 ( \beta ) (SE)</th>
<th>Model 2 ( \beta ) (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guilt Proneness</td>
<td>.041*** (.013)</td>
<td>.101*** (.020)</td>
</tr>
<tr>
<td>Reference Price Present</td>
<td>-.192* (.114)</td>
<td>1.892*** (.554)</td>
</tr>
<tr>
<td>(1=Yes)</td>
<td></td>
<td>H2 ✓</td>
</tr>
<tr>
<td>Guilt x Reference Price</td>
<td></td>
<td>-.093*** (.024)</td>
</tr>
<tr>
<td>Prior Purchase Frequency</td>
<td>-.168*** (.062)</td>
<td>-.159*** (.057)</td>
</tr>
<tr>
<td>Intercept</td>
<td>.281 (.342)</td>
<td>-1.129 (.482)</td>
</tr>
</tbody>
</table>

| Adjusted R\(^2\)          | 23.87%                    | 36.91%                    |

N=70, ***p<.01, **p<.05, *p<.10
Figure 1
Conceptual Model of the Effects of Guilt Proneness and Salience of Social Norms of Fairness on Opportunistic Consumer Behavior.

Salience of Norms of Fairness:
- Equality
- Need
- Equity
- Reciprocity

Guilt Proneness $\rightarrow$ H1 $\rightarrow$ Opportunistic Behavior

H2

H3
Figure 2
Study 1. Interaction between an Equality-Based Norm of Fairness and Guilt Proneness.
Figure 3
Study 2. Interaction between a Need-Based Norm of Fairness and Guilt Proneness.
Figure 4
Study 3. Interaction between an Equity-Based Norm of Fairness and Guilt Proneness.
Figure 5
Study 4. Interaction between a Reciprocity-Based Norm of Fairness and Guilt Proneness.
Figure 6
Study 5 (Field Experiment). Interaction between an Equality-Based Norm of Fairness and Guilt Proneness.
Appendix 1

Paulhus BIDR Social Desirability Scale, Version 6
Self-Deceptive Enhancement (SDE): Sum of Items 1 – 20

Scoring: 1= Not at all True, 7=Very True, add one point for every '6' or '7'
Reverse scored items: 2,4,6,8,10,12,14,16,18,20.

1. My first impressions of people usually turn out to be right.
2. It would be hard for me to break any of my bad habits.
3. I don't care to know what other people really think of me.
4. I have not always been honest with myself.
5. I always know why I like things.
6. When my emotions are aroused, it biases my thinking.
7. Once I've made up my mind, other people can seldom change my opinion.
8. I am not a safe driver when I exceed the speed limit.
9. I am fully in control of my own fate.
10. It's hard for me to shut off a disturbing thought.
11. I never regret my decisions.
12. I sometimes lose out on things because I can't make up my mind soon enough.
13. The reason I vote is because my vote can make a difference.
14. My parents were not always fair when they punished me.
15. I am a completely rational person.
16. I rarely appreciate criticism.
17. I am very confident of my judgments
18. I have sometimes doubted my ability as a lover.
19. It's all right with me if some people happen to dislike me.
20. I don't always know the reasons why I do the things I do.

Appendix 2

Guilt Negative Behavior Evaluation (Guilt NBE) Subscale of the Guilt Shame and Proneness (GASP) Scale (Cohen et al. 2011)

Scoring: 1= Very Unlikely, 2= Unlikely, 3= Somewhat Unlikely, 4=Undecided, 5= Somewhat likely, 6= Likely, 7=Very Likely. The Guilt NBE is scored by averaging the four items below.

1. After realizing you have received too much change at a store, you decide to keep it. What is the likelihood that you would feel uncomfortable about keeping the money?

2. You secretly commit a felony. What is the likelihood that you would feel remorse about breaking the law?

3. At a friend’s housewarming party you spill red wine on their new cream-colored carpet. You cover the stain with a chair so that nobody notices your mess. What is the likelihood that you would feel that the way you acted was pathetic?

4. You lie to people but they never find out about it. What is the likelihood that you would feel terrible about the lies you told?

Appendix 3

Scenario-Based Studies:
Sample Size and Participant Characteristics

<table>
<thead>
<tr>
<th>Measure</th>
<th>Study 1 Equality</th>
<th>Study 2 Need</th>
<th>Study 3 Equity</th>
<th>Study 4 Reciprocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Amazon mTurk workers recruited</td>
<td>142</td>
<td>185</td>
<td>120</td>
<td>135</td>
</tr>
<tr>
<td>Dropped due to Manipulation Checks</td>
<td>2</td>
<td>6</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>Dropped due to Outliers/Inconsistency</td>
<td>8</td>
<td>n/a</td>
<td>6</td>
<td>n/a</td>
</tr>
<tr>
<td>Total Valid Responses</td>
<td>132</td>
<td>179</td>
<td>109</td>
<td>126</td>
</tr>
<tr>
<td>Valid responses/Total Responses (%)</td>
<td>94.3%</td>
<td>96.7%</td>
<td>90.8%</td>
<td>93.3%</td>
</tr>
<tr>
<td>Gender Composition (Male%)</td>
<td>53.8%</td>
<td>54.2%</td>
<td>59.6%</td>
<td>51.0%</td>
</tr>
<tr>
<td>Age 18-25 (%)</td>
<td>20.5%</td>
<td>17.3%</td>
<td>11.9%</td>
<td>11.3%</td>
</tr>
<tr>
<td>Age 25-35 (%)</td>
<td>35.5%</td>
<td>44.1%</td>
<td>41.3%</td>
<td>35.7%</td>
</tr>
<tr>
<td>Age 35-50 (%)</td>
<td>28.8%</td>
<td>23.5%</td>
<td>28.4%</td>
<td>34.5%</td>
</tr>
<tr>
<td>Age 50+ (%)</td>
<td>15.2%</td>
<td>15.1%</td>
<td>18.4%</td>
<td>18.5%</td>
</tr>
</tbody>
</table>
## Appendix 4

### Scenario-Based Studies: Description of Manipulation and Data Integrity Checks

<table>
<thead>
<tr>
<th>Study</th>
<th>Manipulation Check(s)</th>
<th>Other Data Integrity Criteria</th>
</tr>
</thead>
</table>
| 1     | (1) Participant understands their payment is anonymous.  
       | (2) Participant understands they will not return to the bakery in the future.        | (1) PWYW offer is \( \leq \) WTP  
       |                                             | (2) WTP is within +2 SD of mean                                      |
| 2     | Participants understand movie pirating is unauthorized.                               | N/A                                                               |
| 3     | (1) Participant understands their payment is anonymous.  
       | (2) Participant understands they will not return to the restaurant in the future.   | (1) PWYW offer is \( \leq \) WTP  
       |                                             | (2) WTP is within +2 SD of mean                                      |
| 4     | Participant understands the motive is to promote fairness / to promote sales depending on treatment. | N/A                                                               |
Appendix 5

Appendix Figure 5A
Average PWYW Price Paid by Country for Video Game Purchases.
Appendix Figure 5B
Percent of PWYW Customers Paying Zero by Country for Video Game Purchases.

[Bar chart showing the percent of PWYW customers paying zero by country for video game purchases]
4. CONCLUSION

This dissertation addresses one of the fundamental components of the marketing mix – pricing (McCarthy and Perreault, 1993). While early research on pricing focused on economic principles, my work contributes to literature on behavioral pricing that explores how psychological aspects of pricing influence consumer behavior by addressing two major themes in behavioral pricing: 1) how consumers construct and use reference prices to judge the attractiveness of a price, and 2) how perceptions of fairness influence consumer behavior (Krishna, 2009; Winer, 2005).

Marketers use a variety of price reduction strategies such as price reductions ("sales"), rebates and coupons to motivate consumers to try new products, switch brands, accelerate purchases and expand category sales (Neslin, 2002). Sales are price reductions in which all consumers receive the same discount (Davis, Inman, and McAslister, 1992). Firms can also offer rebates; a price reduction that relies on price discrimination after the sale, since only those customers willing to follow the rebate procedures receive a discount, and only after they pay full price (Chen, Moorthy, and Zhang, 2005). Coupons are a means of price discrimination prior to purchase, since only those customers willing to expend the added effort of using a coupon receive a discount upon payment (Narasimhan, 1984). Although firms can offer comparable economic benefits using any of these price reduction strategies, consumers respond differently to sales, rebates and coupons since they affect consumers in ways other than providing an economic incentive (Raghubir et al., 2004).

Essay 1 examines how consumers use reference prices to judge the attractiveness of price reductions in a new context. Prior empirical research has focused on the use of individual coupons that are “pushed” to consumers (Dickinger and Kleijnen, 2008). When assessing
individual coupons, consumers adopt a memory-based, or so-called internal reference price (IRP) strategy and evaluate coupons by comparing the current price to prices paid in the past (Tradib Mazumdar et al., 2005). My dissertation examines a new setting in which consumers evaluate a set of competing pull mobile coupons. Evaluating a set of coupons prompts some consumers to use an IRP strategy while other shoppers apply a comparative strategy, (called a stimulus-based reference price or SRP) to make choices (Moon and Voss, 2009). Coupon values in my study are assigned based on a customer’s redemption history. When a customer redeems a coupon for a particular item, on the next trip, the coupon value for that item is reduced and coupon values for competing products in the category are increased. This pricing mechanism allows me to examine redemption choices in a dynamic pricing environment.

I segment consumers according to which strategy (IRP or SRP) they use, and model how coupon value, number of competing coupons, range of prices for competing brands, and consumer brand loyalty determine redemption behavior. While my research examines mobile coupon use, the findings may be useful to marketers interested in a broader range of settings where consumers receive information about competing brands such as price comparison tools and recommendation engines used by retailers such as Google and Amazon.

Within the broader behavioral pricing literature, price fairness has important status since firms’ profits are constrained by the fear that they will be accused of exploitation such as price gouging or taking unfair advantage changes in demand by raising prices or cutting wages (Kahneman, Knetsch, and Thaler, 1986) and because consumer satisfaction is influenced by perceptions of price fairness (Bolton, Warlop, and Alba, 2003). For example, customers became outraged when they discovered that Amazon.com was selling the same DVD at different prices to different customers (Adamy, 2000)
Since firm’s have traditionally had the power to set prices, most studies have examined price fairness from the perspective of the firm (Xia et al., 2004). However, by using internet or mobile technology to reduce information asymmetry, consumers gain knowledge, and become more likely to take advantage of companies (Rezabakhsh et al., 2006).

Essay 2 addresses a gap in the price fairness literature by empirically testing whether the individual trait of anticipated guilt, together with information about social norms, predicts whether consumers will act fairly in settings where they may behave opportunistically. In the realm of price fairness, PWYW provides a window into how fairly consumers respond when they become the price setters (Jang and Chu, 2012). I find that anticipated guilt, contingent on the salience of social norms, plays a significant role in how much customers choose to pay, and that guilt matters more when consumers are less certain about what amount is socially acceptable. I show that these findings are robust across a range of other opportunistic behaviors such as abusing merchandise return policies and engaging in computer piracy.
5. REFERENCES


