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## Snap Coupons: Investigating Mobile Coupon Adoption, Use, and Value

Paul Mills and César Zamudio

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## Report Summary

By 2016, 44.5% of marketers are expected to use mobile coupons and 40% of U.S. smartphone users are predicted to redeem mobile coupons. Most research to date has focused on “push” coupons delivered by manufacturers and retailers. Here, Paul Mills and César Zamudio use commercial data to examine redemption behavior and mobile platform use of “pull” coupons, in particular, coupons delivered at the point of purchase, which they call “snap” coupons.

They analyze data from 171 supermarket shoppers who scanned 1,624 grocery items, generating 10,174 coupons across five major product categories. The dataset comprises shopper characteristics such as basket size and total expenditure, store trip patterns, and coupon characteristics for the scanned or focal product as well as for rival coupons in the set.

Using cluster analysis, logistic, and linear regression, they offer a rich picture of pull coupon adoption and use with three key managerial implications.

First, rather than evaluating coupons in isolation, consumers evaluate pull coupons by comparing the focal coupon to a set of rival coupons, based on “set size,” the number of coupons shown after scanning. A focal coupon is more likely to be redeemed when compared to few (2 to 4), or many (9 to 12), coupons. This suggests that brand managers should assess the likely number of competitors on such coupon platforms before committing to participate.

Second, shoppers evaluate coupons by comparing a coupon’s net price in relation to the range and distribution of net prices for rival brands. This is consistent with range theory, which predicts that customers evaluate prices considering the entire range of prices for competing alternatives. This suggests that brand managers and retailers should consider the net prices of competing brand coupons, and not only their own, when assigning coupon value.

Third, cluster analysis reveals three pull coupon user segments. The first segment consists of platform adopters, who scan consistently over 42 weeks. The remaining two are non-adopter segments: users who heavily use the platform for novelty, then stop; and users who slowly discontinue platform use.

Importantly, this novelty segment is as valuable as the larger adopter segment in terms of store expenditure. This suggests that promotional efforts to encourage platform adoption across the board may not be an appropriate strategy. Instead, it may be beneficial to intervene at critical points after adoption to encourage novelty users to become adopters.

*Paul Mills is a Ph.D. candidate and César Zamudio is Assistant Professor of Marketing and Entrepreneurship, both in the College of Business Administration, Kent State University.*

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## **Introduction**

In 2014, 319 billion print, or “traditional” coupons for consumer-packaged goods valued at roughly \$513 billion were distributed in the United States (Inmar.com, 2015). Given their ubiquity, the use of traditional coupons has inspired a rich marketing literature (e.g., Narashimhan, 1984; Blattberg and Neslin, 1990; Danaher et al. 2015). Although this research has generated valuable insights, retailers and brand managers face new challenges as new coupon formats emerge: paper coupons are still the dominant format for delivering coupons, yet electronic delivery of digital coupons is one of the fastest growing delivery mechanisms (emarketer.com, 2014). By 2016, 44.5% of marketers are expected to use mobile coupons as part of their strategy, and 40% of U.S. smartphone users will redeem a mobile coupon (Trueship.com, 2015). Accordingly, retailers are expected to increasingly use mobile coupons as a key marketing tactic (Shankar et al. 2010), and the need to better understand customer’s “experiences and the consumer path to purchase” (MSI Priority RP1) when utilizing mobile coupons is critical. Given the growing importance of electronic coupons, the extent of the applicability of insights derived from traditional coupon research into the mobile coupon context also remains an open question (Chiou-Wei and Inman, 2008).

This report concerns coupons delivered to a consumers’ cell phone or other mobile device. Mobile coupon researchers have examined the determinants of mobile coupon use (Dickinger and Kleijnen, 2008; Jayasingh and Eze, 2012), factors influencing mobile coupon redemption rates (Banerjee and Yancey, 2010; Khajehzadeh et al. 2014), and profiles of mobile coupon users (Im and Ha, 2012). A major limitation of research into mobile coupons is that data from commercial mobile coupon systems remains scarce, thus prior studies have generally relied on consumer surveys or laboratory experiments, and report consumers’ stated intentions to use or redeem mobile coupons (Khajehzadeh et al. 2014). Consequently, current mobile coupon research has focused on impediments to consumers’ adoption of mobile coupons (e.g., Dickinger and Kleijnen, 2008) as opposed to behavior after consumers adopt such a platform.

Mobile coupon research has focused on two modes of coupon delivery: “push” delivery, in which coupons are delivered without consumers requesting them, and “pull” coupons, where consumers explicitly request a mobile coupon. Most research to date focuses on push delivery (e.g., Dickinger and Kleijnen, 2008; Khajehzadeh, et al., 2014) as opposed to pull delivery (Unni and Harmon, 2007).

Our report adds to extant understanding of mobile coupons by addressing the limitations above. We use observational data to investigate post-adoption mobile coupon behavior using a sample of 171 supermarket shoppers who redeemed 1,121 mobile coupons across five product categories. We focus on a unique type of pull coupon, which, because of their instantaneous delivery at the point of purchase, we term a “snap coupon.” Consumers initiate snap coupon delivery by scanning a product’s UPC barcode and receive a coupon for the product scanned as well as a set of coupons for other products that are close substitutes.

The major takeaways of our report are the following. First, we discover managerially relevant user segments based on scanning behavior over time. We find three major segments: (1) *platform adopters* (72.5% of users), who scanned at a consistent rate over shopping trips (a maximum of 42) in the investigated time period, (2) *novelty users* (15.2% of users), who exhibited a strong initial use of the platform, but stopped scanning after approximately fifteen shopping trips; and (3) *dwindling users*, (12.3% of users), who exhibit an opposing pattern - initial interest followed by a sharp reduction in scanning activity per trip until usage stops in the vicinity of the fifteenth trip. Importantly, novelty users, who did not exhibit sustained platform adoption, are as valuable as platform adopters as measured by average basket dollar value and number of items purchased. In contrast, dwindling users are less valuable when using the same measures. We suggest market intelligence efforts to employ this information in individual consumer targeting.

Second, since consumers receive a set of competing mobile coupons, as opposed to a single coupon, we address whether the characteristics of this coupon set (i.e., number of coupons and competitors coupon prices) influence coupon redemption for the focal product (the one scanned by consumers to initiate delivery). Investigating coupon sets is new to the literature, and we present preliminary evidence of the optimal conditions for coupon redemption given the characteristics of the coupon set. We find that both the size of the coupon set and the composition of the set in terms of rival products’ prices influence the likelihood that a shopper will redeem a coupon for the item they scan. Interestingly, the effect of coupon set size is U-shaped, with smaller, and larger, coupon sets motivating the highest probability of redemption. Thus, these results may serve brand managers to determine whether they may want to participate in a snap coupon platform where coupon sets are shown to consumers, conditional on their number of likely competitors.

The remainder of the report is organized as follows: Section 2 presents an overview of the relevant literature on mobile coupons, focusing particularly on studies of post-adoption behavior and literature on pull mobile coupons. Section 3 presents the report's industry setting. Section 4 presents our data and provides descriptive statistics. Section 5 presents our results. Section 6 concludes with managerial implications and Section 7 acknowledges some limitations and suggests further research directions.

## **Overview of the Literature**

A mobile coupon is a digital coupon sent either by email, or using a mobile application, to a consumer's mobile device such as a mobile phone, smart phone, tablet, or personal digital assistant (Dickinger and Kleijnen, 2008). Mobile coupons are rapidly gaining consumer acceptance and retailers are increasingly using mobile couponing as a promotional marketing tool (Shankar et al., 2010). Firms use mobile coupons for a variety of reasons including strengthening relationships with consumers (Friedrich et al., 2009), extending their reach to a broader consumer audience (Balasubramanian et al., 2002), and increasing redemption rates compared to conventional methods (Shankar and Balasubramanian, 2009). Research into mobile coupons can be classified into two major streams: pre-adoption studies versus post-adoption studies, and mode of delivery (push vs. pull) studies. This report uniquely addresses the area of post-adoption of pull coupons (see Table 1).

### **Pre-adoption studies**

Research on mobile coupons has relied on survey and experimental data to measure the attitudes or intentions of consumers who have not yet adopted a mobile coupon platform. These studies extend the Technology Acceptance Model (TAM), which suggests that intentions to adopt a new technology are directly or indirectly driven by attitude, perceived usefulness, and ease of use (Bagozzi et al., 1992; Davis, 1989).

Research into pre-adoption has uncovered determinants of and barriers to adoption of coupons. Hsu et al. (2006) find that the perceived usefulness of mobile coupons is most influential in determining intended use. Dickinger and Kleijnen (2008) report that ease of use (in terms of redemption effort) is the main determinant of attitude towards mobile coupons. However, redemption effort also negatively influences the perceived benefits of coupon adoption. Similarly, fear of unwanted spam can threaten a customer's perception of control and negatively affect the intention to use mobile coupons (Dickinger and Kleijnen, 2008). Additional

pre-adoption studies have identified additional factors that positively impact consumer's attitudes and intentions toward adopting mobile coupons, such as customizing the content or the timing of coupon delivery (Bacile and Goldsmith, 2011), increasing coupon content relevance (Rau et al., 2011) and enhancing source credibility (Jayasingh and Eze, 2012).

Overall, pre-adoption studies consistently predict that customers are more likely to use mobile coupons that are delivered in a timely fashion and provide customized, relevant content. However, while participants in pre-adoption studies often report being unfamiliar with, or disinterested in using mobile coupons, we focus instead on post-adoption behavior of pull coupon users who are already chosen to download an app in the store that will deliver the coupons and thus are prone to mobile coupon use.

### **Post-Adoption Studies**

To date, the scarcity of data from commercial mobile coupon platforms has made it difficult to observe the behavior of mobile coupon users. Among the few studies that incorporate such data, whether the format and content of mobile coupons influences the probability of redemption is investigated by Kondo et al. (2007) in the context of service coupons. They find that designing the coupon so that it requires action on the part of the mobile user significantly increases redemption. Banerjee and Yancey (2010) find that the effect of mobile coupon delivery timing on coupon redemption is moderated by product category. For utilitarian products (e.g. meals), timing had no effect on redemption rate, but for hedonic purchases (e.g. desserts) the effect of coupon timing was significant with coupons sent earlier in the day resulting in greater redemption compared with coupons sent later in the day. Coupon value had no effect on redemption rate in Banerjee and Yancey's (2010) work.

Whereas the above studies examine the redemption of push coupons, this report examines the influence of an additional action; the shopper's decision to scan a product's bar code. In addition, post-adoption studies have examined the use of mobile coupons to purchase products with a high service component such as restaurants and hair salons, limited to a single brand, and for products and services consumed at the time of purchase (e.g., Unni and Harmon, 2007). This empirical setting limits the opportunity to observe mobile coupon use across multiple competing brands in several grocery categories.

*Push vs. pull mobile delivery.* This report adopts Unni and Harmon's (2007) definition of a pull mobile coupon: those sent to the consumer's mobile device immediately upon an explicit request or shortly thereafter on a one-time basis. We also adopt Paavilainen's (2002) definition of push mobile coupons: those sent at a time other than when the customer requests them, and where the promotional offer is either generic to the consumer or based on previously stated product preferences.

As compared to push coupons, pull coupons address important concerns about mobile coupon adoption found in prior studies including consumers' concerns regarding spam and unwanted promotions (Scharl et al. 2005; Dickinger and Kleijnen, 2008), perceived control (Shankar et al., 2010), relevancy of coupon content (Simonson, 2005), and the cost of searching for, clipping, and using coupons (Bonnici et al., 1996; Putrevu and Ratchford, 1998). With that said, mobile coupons may present new costs to consumers such as loss of sense of control regarding who sends them mobile coupons, how many they will receive, and when they will receive them (Scharl et al., 2005). Dickinger and Kleijnen (2008) and Achadinha et al., (2014) find that fear of unwanted coupons, loss of consumer control, and irritation with uninvited electronic clutter (spam) undermine consumers' positive attitude toward mobile coupons.

To the best of our knowledge, the only published study on pull mobile coupons is Unni and Harmon (2007). The authors measure the attitudes and intentions of undergraduate students towards a hypothetical mobile coupon service and find that pull mobile coupons are significantly more attractive than push coupons. As noted earlier, a disadvantage of their study is that it does not investigate actual pull coupon redemption behavior. Our study addresses this gap by examining how consumer, coupon, and brand characteristics influence the redemption of pull mobile coupons in a supermarket setting using observed data.

## **Empirical Setting**

The study was conducted in a 40,000 square-foot, full-service supermarket in a community of 2,205 households in northeastern Ohio. The store, which sells approximately 35,000 different products, is located about eight miles from the closest competitor, which does not distribute grocery advertising in the same market. Private discussion with store management revealed that although some portion of local consumers may choose to shop at another supermarket, their customers are unlikely to shop regularly at other supermarkets. The third-

party app developer that provided data for our study delivers snap coupons for five major product categories: bread (e.g., loaf bread, buns, bagels, and breadcrumbs), carbonated soft drinks, salty snacks (e.g., potato chips, pretzels, popcorn, tortilla chips, etc.), breakfast cereals, and bulk-size pet food. Each category comprises an entire side of a supermarket aisle, with a total of 923 grocery products from 54 manufactures across all categories (Table 2).

Data was collected from 171 shoppers who downloaded the app, requested, and received snap coupons from at least one of the products in the five categories. Figure 1 illustrates the process of product scanning, brand choice and coupon redemption examined in this study, and compares it to a scenario where consumers do not have the opportunity, or who chose not to scan and request snap coupons.

Shoppers downloaded a free smartphone app (Apple or Android) developed by the third party app developer. The smartphone app required customers to register by providing basic demographic information including their gender and age, with an option not to report. On arriving at the store, shoppers could scan the bar code of any product in the five categories using their own smartphone or a loaner available at the store's customer service desk. Scannable products were identified with point-of-purchase LED displays promoting snap coupon availability<sup>1</sup>. Scanning triggered the delivery of a snap coupon for the scanned product (which we call focal product), followed by a list of coupons (termed "coupon set") for similar products, arranged in order of descending value. To create coupon sets of manageable size, each of the 923 products was assigned to a subcategory of close substitute products determined by the third-party app developer. For example, a 2-liter bottle of Coca Cola was assigned to a subcategory containing five other brands of 2-liter colas. 164 subcategories were available with an average of 5.6 products per subcategory. Thus, a coupon set from one of the subcategories was generated each time a consumer scanned, with the first coupon in the set being for the scanned product, followed by the other coupons in the set in order of decreasing face value.

The value of each of the coupons were a function of two factors: the product's retail price and, when available, the consumer's prior purchase history. The following example (illustrated in Figure 2) describes how coupon values were calculated. The minimum coupon value for any

<sup>1</sup> When a customer scanned an item in a major product category that did not offer mobile coupons, the customer received a message informing them that no coupons are available for items in that product category. The purpose of scanning was stated to be exclusively to receive coupons, not to receive additional product information.

product was zero<sup>2</sup> and the maximum was 30% of the product's retail price. For example, if a product retailed for \$4.00, coupons for that product could range from a few cents to \$1.20. The first time a customer scanned a product, all values in the coupon set were initialized at one-half of the maximum coupon value. For example, for the products illustrated in Figure 2, since each has a retail price ( $P_A$ ,  $P_B$ ) of \$4.00, initial coupons values ( $C_A$ ,  $C_B$ ) on Trip #1 would be \$0.60. Coupon values on subsequent shopping trips would be determined by the customer's product purchase from their last shopping trip. If the customer had chosen Product A on Trip #1, the coupon value for Product A on Trip #2 would be reduced, and the coupon value for Product B would be increased. The new coupon value is determined by incrementing or decrementing one half of the range between the previous coupon and the minimum or maximum coupon value. The algorithm for the display order of coupons and their value was determined by the app developer.

At checkout, the point of sale system is synchronized with the mobile application by scanning a bar code at the cash register. All coupons chosen by the consumer are redeemed when the cashier processes a product from the customer's shopping cart for which a mobile coupon was offered.

### **Data Description**

Data was collected at multiple different levels. Consumer-level data contains characteristics of the sample of 171 shoppers who used the mobile snap coupon app. Trip-level data contains the full history of shopping trips in which scanning was observed, purchases and basket size for each trip, coupon redemption, and times of the day/week where trips occurred. Scan-level data contains information generated every time a coupon was requested. Coupon-level data includes information that occurred as a consequence of the scan – namely, the generation of a coupon for the focal product, competing products, and the characteristics of each coupon within the coupon set. The variables used in our study are defined in Table 3 and their descriptive statistics are presented in Table 4.

<sup>2</sup> Although the minimum value of \$0.00 was used to calculate initial coupon values, when coupons reached a level of approximately 2% of MSRP, the value was not decreased further so that a small coupon was always offered for all items in the coupon set.

### **Consumer-level variables**

A summary of customer demographics is provided in Table 4. The typical shopper profile as reported by supermarket management indicates that nearly 75% of shoppers are female and is in their mid to late forties. Self-reported data from shows that female shoppers outnumber male shoppers by nearly 2:1 (93 female, 46 male), although a portion of shoppers (20.5%) chose not to report their gender. The average age of shoppers is 48.7 years. Thus, the app users age and gender strongly corresponded with that of the average shopper. Our study shows that older shoppers are quite prone to use pull coupons: we find that 76.5% of the mobile app users are 40 years old or more. This age is higher than that of participants in earlier pre-adoption studies. For example, the average age of participants in the Dickenger and Kleijnen (2008) study was 26.7 years. Examining coupon adoption with a broader age range of consumers may be important considering that the importance of adoption determinants of mobile marketing services varies by age. For example, usefulness is considered more important by consumers aged 25–34 and speed of use is more appreciated by younger consumers (Pagani 2004).

### **Trip-level variables**

Customers in the study visited the store 797 times – a “trip” was defined as whenever a consumer was observed to check out at the cash register after scanning. Trip-level data allowed us to determine consumers’ intensity of scanning over multiple trips, which can serve as proxy for likelihood of adoption, to the extent that a consumer decides to scan continuously over a number of trips. For investigating snap coupon platform adoption, we focus on both the time elapsed between trips, and the intensity of scanning over consumers’ trip history from the first time the platform was used. Thus, we consider each customer’s first shopping trip as the first time a scan was observed, and compute trip data for that customer as more scans were observed.

Panel 1 of Figure 3 charts the intensity of scanning for consumers in our dataset. The horizontal axis denotes consumers’ trips, aggregated in groups of three trips – that is, trips 1-3, trips 4-6, and so on. The first trip is denoted as the first time a consumer scanned a product. The vertical axis denotes the average number of scans within each group of trips. As can be seen, the average amount of scanning per trip group remained relatively consistent over the period of observation. A similar, relatively consistent behavior is observed in terms of redemption of any

coupon in the coupon set over time. Redemptions exclusively for the focal product scanned exhibit an identical pattern, and are not shown.

### **Scan-level variables**

Shoppers scanned 1,553 grocery items, generating 9,758 mobile coupons or 6.3 coupons for every item scanned. The frequency distribution of the number of coupons shown to consumer per scan (that is, coupon set size) is shown in Figure 4. Items in some categories were scanned more frequently than in other categories. For example, shoppers scanned items in the bread category most frequently, with 38.5% of overall scans, while bulk pet food represents only 2.3% of overall scans (see Table 5).

Shoppers in our sample redeemed a total of 1,121 coupons. This means that an item was purchased 72.2% of the time an item was scanned. Of the coupons redeemed, most were for the product that the customer chose to scan. However, 48 coupons (4.3% of redeemed coupons) were for rival products that were not scanned but were presented as alternatives in the coupon set.

### **Coupon-level variables**

Although coupon values are determined according to the algorithm described in the outset, the average coupon value was approximately \$0.63. Table 6 shows that while most of coupons redeemed are for the focal product scanned, considerable heterogeneity was observed across product categories. For example, while 1.9% of the coupons redeemed for breakfast cereals are for items other than the item scanned, product switching accounts for over 6.2% of redemptions among salty snack products. Table 7 lists the top 20 redeemed coupons. Bread was the most frequently scanned product (38.5%) and bread coupons were the most frequently redeemed (14 of the top 20 coupons). The top three redeemed coupons are for store brands. Consequently, third-parties or retailers interested in designing snap coupon platforms should include both store and national brands in the coupon sets shown to consumers.

The dataset described above provides an initial glimpse into how a mobile coupon platform may be adopted. It also shows how it may be used to scan and redeem coupons for focal and rival products, and whether behavior related to the mobile platform may be ultimately associated with outcomes such as basket size and basket dollar value.

## **Taxonomy of Mobile Adopters Using Scanning Intensity Over Time**

Identifying consumers' patterns of mobile platform use is useful to discover unobserved adoption patterns. These patterns are extracted from the data following a procedure adopted from Powers et al. (1998). The authors investigate patterns of academic research publication by tracking marketing scholars for a 20-year period from the time they graduate. Analogously, here, we track each shopper from their first scan to request a snap coupon up until the last time each shopper was observed to scan.

Individual shopper patterns of mobile platform use were assembled in groups of three trips, as in Panel 1 of Figure 3. These patterns were then analyzed using hierarchical, within-groups clustering using correlations and absolute scanning frequency as similarity measures (Powers et al. 1998). Three major adopter segments emerged from the analysis and these adoption patterns are shown in Panel 2 of Figure 3. The first segment, *platform adopters* (124 customers, 72.52% of total) is the largest, and shoppers within this segment appear to have adopted the platform successfully, as exhibited by their average number of scans over time. Sustained scanning was observed for a maximum of 42 trips – however, since 97% of consumers were observed to make 27 trips or less, only data for a maximum of 27 trips is shown. The second segment, *novelty users* (26 customers, 15.20% of total) initially scans 2-3 items per trip then surges to 6 scans per trip after 6 trips. However, this group stops using the app after fifteen trips. Finally, the third segment, *dwindling users* (21 customers, 12.28% of total) represents a somewhat contrasting case, with initial mobile platform use close to the average of other segments, but with reduced scanning around trips 10 to 15, after which use of the app ceases. A caveat of this clustering segmentation approach is that the analysis is aggregate – in other words, some consumers from the adopter group may have dropped use of the platform before the maximum number of trips elapsed. However, on average, consumers who were identified to be in the platform adopter segment should be expected to be more likely to demonstrate sustained use of the mobile coupon application. The same qualification applies to the remaining two segments.

## **Determinants of Coupon Redemption**

Table 8 shows the results of modeling the likelihood of redeeming a coupon for the focal product by using a logistic regression applied to scan-level data. Note that this likelihood

depends on the characteristics of the coupon for the focal product as well as those of the rival products, which are highly correlated. Thus, due to our focus on what consumers observe in their screen after scanning, and the high correlation above, we do not focus on the characteristics of each particular coupon but of the coupon set. The dependent variable is whether redemption of the coupon for the focal product occurred. Independent variables include characteristics of the *whole* coupon set faced, as well as other controls. Keep in mind that, because results shown derive from a logistic regression, odds ratios are shown alongside these estimates to aid interpretation. The odds ratio measures the specific percentage of increase/decrease to the odds of redemption given the independent variable in question, where ratios above 1 indicate an increase to the odds of redemption whereas ratios below 1 indicate a reduction.

Two models are estimated. Model 1, termed the *holistic information* model, assumes that consumer redemption of a particular coupon is a function of processing information of all coupons within the set. This model further assumes that consumers process information about the set on the basis of the central tendency and spread of the price of the items within the set, and the value (that is, the savings) provided by the coupons within the set. In contrast, Model 2, termed the *rival information* model, instead assumes that consumer process set information by focusing on the characteristics of coupons other than the coupon for the focal product.

When comparing the results of both models, the results suggest that the overall average values and distribution of coupon values for all coupons in the set do not influence the redemption decision (top part of Model 1 - All in Set), but that considering the coupon for the focal product independently of the set of rival coupons does have a significant influence on redemption (Model 2 - Rivals). Specifically, we find that the probability of redeeming a coupon for the focal product increases as the prices of the rival products increase (because the odds ratio is greater than 1, measured at 1.41), but decreases as the standard deviation, or spread, in prices among rival products increases (due to the odds ratio being lower than 1, measured at .66). In addition, we also find that shoppers are less likely to redeem a coupon for the focal product as the value of the coupons for rival products increases.

The influence of rivals' prices is somewhat expected, as when the average price of rivals increases, so does the price of the focal product, and high-priced products on sale may be likewise highly desirable. Similarly, as the value of rival coupons increases, these become more desirable, and thus a coupon for the focal product should be expected to be redeemed with less

frequency. However, the result that rival price spread reduces redemption of coupons for the focal product is less straightforward, and may indicate that consumers feel less motivated to redeem a focal product coupon when rival products shown are from different price ranges, perhaps making comparisons harder or increasing the need to browse through the coupons shown, which may cause fatigue. Thus, a focal product is best served by being placed in coupon sets where its value is high and where the price spread among rivals is the lowest; focal products in high-price categories are expected to also be redeemed with more frequency after controlling for the above.

We also find that as coupon set size increases, shoppers are less likely to redeem a coupon for the item they scanned, and that this effect is a marginally significant U-shaped curve, in which relatively small and relatively large set sizes are related to a higher probability of promotion. This calculation includes *only* the effect of set size (Figure 5). One should expect small set sizes to lead to a higher probability of redemption, as there is less information to process. As to the larger set sizes, while one would expect choice overload to diminish the probability of redemption (Iyengar and Lepper, 2000), it may be that the increased number of options may motivate consumers to search more in the hopes of finding a coupon for a substitute product they may be interested in (Weitzman, 1979), leading to higher overall redemption. However, remember that the price spread of the coupon set diminishes the probability of redemption: consequently, the positive effect on redemption due to a focal product appearing on a larger set could be negated if the price spread among rivals is too high. Note that the qualitative nature of this effect is robust across both the holistic and the rival information models.

Finally, regarding the controls used, we find that their effects are robust to both specifications. Evening shoppers are less likely to redeem coupons for the focal product, but that weekend shoppers are more likely to do so. This information may be valuable to retailers and brand managers as they seek to expand their understanding of lifestyle segmentation to mobile platform use. Prior research has found strong day of the week effects and has suggested that price sensitivity, choice patterns and shopper's response to promotions may differ by shopping day (Kahn and Schmittlein, 1989). Nighttime shoppers have also been found to purchase baskets of similar composition, but smaller size than daytime shoppers (Geiger, 2007). Segmenting consumers by shopping time and day may allow brand managers and retailers to optimize promotions to leverage these differences across lifestyle segments.

## **Determinants of Trip Outcomes**

Lastly, a linear regression model was used to capture whether the information displayed to consumers across scans during a shopping trip may be related to the total dollar value of a consumer's basket and the total number of items purchased during the trip. As discussed above, we focus on the information of rival products presented to consumers during a particular scan. Since 78.9% of consumers may have scanned more than once during a single trip, we aggregate the rival information shown in a coupon set across scans as well. For example, if, in a given trip, a consumer scanned for a snap coupon in two separate occasions, and faced an average rival coupon value of \$3.50 during the first scan and \$4.50 on the second, the average rival coupon value across scans (that is, the grand mean) would be \$4. In addition, we consider the adoption segment to which each consumer in the sample belongs to. The effect on total basket dollar value and size of belonging to the novelty or dwindling segment is assessed, when compared to the adopter segment. Finally, respondents' demographics (gender and age) were included as controls. Due to multicollinearity concerns, since the coupon values and associated product prices are closely related, we include the prices of the products shown in the coupon set, and not the coupon values in the trip-level regressions. The mean variance inflation factor (VIF) of the variables in the regression (excluding the set-size quadratic term) is 3.39.

Table 9 shows the results of modeling the outcome of shopping trips with respect to two measures: the total amount spent on the shopping trip (column 1) and the size of the shopper's basket in terms of the total number of items purchased (column 2). This table provides insight into the effect of mobile coupon use on broader measures of shopper behavior beyond coupon redemption. Consistent with the findings regarding the taxonomy of mobile coupon users in Section 5.1, we find that outcomes differ across platform adopter segments. In each individual trip, dwindling users spend less and purchase fewer items than those in the adopter segment, while novelty users spend an equal amount of dollars and purchase an equal amount of items, on average, as compared to the adopter segment.

Managerially, this result is quite significant for two reasons. First, dwindling users appear to be small-basket shoppers and therefore may not be worth pursuing with a mobile platform. Second, and most important, novelty users seem to be on par with adopters in terms of their dollar value and items purchased. As a consequence, managers involved in the deployment of a mobile platform may find it worthwhile to spend resources in supermarket intelligence efforts to

track adoption, and to motivate novelty consumers to continue using the platform around (1) the vicinity of the sixth trip, when adoption appears to change its trajectory and (2) the vicinity of the fifteenth trip, in which there seems to be the highest risk of consumers abandoning use of the platform. This suggestion implies that consumers need be tracked individually, on the basis of their trips, and not solely on the basis of a timeline beginning with the time a mobile pull coupon platform is launched.

Regarding the rest of the variables, consistent with findings at the coupon-redemption level, shoppers are influenced by how the prices and the price distributions of rival products compare to their focal brand. As the overall average price of rival products increases, so does both amount spent on their shopping trip and the number of items purchased, which indicates that these trips involve consumers interested in higher-priced items. However, this effect is dampened as the standard deviation in the prices of rival products increases. This result is robust across different size coupon sets.

Our data includes shopping behavior across multiple shopping trips ( $M=3.84$  trips per shopper,  $SD=5.23$ ) enabling us to observe not only changes in the intensity of mobile coupon use described above, but whether the effects of mobile coupon use on shopping behavior persists over time as well. Table 9 shows that as the interval between shopping trips where coupons are used increases, shoppers buy fewer items and spend less. This result suggests that scanning intensity, not only in terms of the volume of scans, but also in terms of the recency of scanning, influences shopping outcomes. Thus, retailers and brands may find it beneficial to encourage shoppers to use mobile coupons on a frequent basis, such as by promoting a popular item as a “scan of the week.”

## **Conclusions**

This research provides the uncommon opportunity to observe how shoppers use mobile coupons in an actual shopping setting. The post-adoption empirical setting for this study enables us to observe when a shopper scans a grocery product, what coupon they receive for focal and rival substitute products, whether they choose to redeem a coupon and which coupon they choose, as well as the overall contents of their shopping cart in terms of items and dollar value of the basket. Scanning behavior is observed over time.

Several takeaways from this study have important implications for retailers and brand managers. First, the use of the mobile coupon platform is not restricted to a niche, or small group, of consumers, but is rather spread across different types of shoppers. We find that mobile coupon use is equally high for older shoppers as for younger shoppers, regardless of gender. This provides encouraging empirical evidence that older shoppers are willing and able to adopt mobile coupon technology.

Second, our analysis reveals different segments of mobile coupon users based on their use of the mobile coupon application over time. The largest segment of customers adopted the platform and continued to scan and redeem coupons at a steady rate over shopping trips. However, two other segments emerged. First are *novelty users*, shoppers who appear to enjoy the novelty of the application, but who discontinue using the platform after initially high scanning behavior. The third segment, *dwindling users*, consists of those shoppers whose use dwindles steadily as they use the platform. Importantly, whereas dwindling users appear to be small-basket, low-value shoppers, novelty users' spending and items purchased are on par with the larger adopter group. This suggests that promotional efforts to encourage platform adoption "across the board" may not be an appropriate strategy. Instead, retailers and brand managers may find it beneficial to develop a strategy to intervene with additional promotions or messaging at critical points during adoption (in particular, in the vicinity of the third and fifteenth trips) to encourage use of mobile coupons such that novelty users become adopters. Care should be exercised, such that promotional efforts do not target consumers whose scanning patterns approximate that of dwindling users, whose value may not be worth pursuing.

Third, our research examines a setting in which shoppers consider which coupons to redeem from among sets of competing coupons rather than evaluating coupons in isolation. These consumers appear to evaluate coupons by comparing the coupon for the focal brand to the set of rival coupons based on features such as the price and price distribution of rival brands, and the average value of coupons in the set, *exclusive* of the focal product coupon. This result points to the importance consumers place on coupons for the item scanned as a reference for evaluating competing offers. The study of such coupon sets is new in the literature, and reveals that the probability of redeeming a coupon is related to set size in a U-shaped fashion, such that observing a small, or large, amount of coupons to compare with the focal product seems to

motivate redemption. Thus, we believe that further study into coupon sets and how consumers may process such information for the purposes of redemption may be illuminating.

Finally, we find evidence that while redemption decisions do not vary with customer characteristics such as age or gender, redemption is affected by the time when customers shop. Evening shoppers are less likely to redeem coupons for the focal product, and weekend shoppers are more likely to do so. This may also be useful information to retailers and brand managers who wish to optimize their coupon targeting strategy.

### **Limitations and Future Research**

Although our data provides some interesting and novel insights, we are only able to observe a relatively small number of shoppers (N=171) purchases in five major categories. As more data becomes available, future research will provide an opportunity to examine both the robustness of these findings, and to expand the use of the platform to a larger base of shoppers, more categories, and to observe trends in coupon use over an extended period of time. This platform also has some limitations imposed by the design of the mobile application and by the third party developer.

In addition, the voluntary registration form in the third-party mobile app provided only a limited scope of self-reported customer information such as age and gender. Since the app users cannot be tied to other sources of shopping data, and since the store does not use a shopper loyalty card system, we have no information about the shoppers purchase history outside of their use of the mobile coupon app, nor do we observe the behavior of shoppers who do not adopt the mobile coupon system for comparison purposes. Further investigation that considers both a sample of adopters, and a sample of non-adopters, and compares them, could shed further light into mobile coupon use and adoption. Finally, investigating the determinants of non-adoption, that is, the time until the platform is no longer used, would also be valuable for managers considering to launch a mobile coupon platform in the presence of the three segments uncovered in this report.

Finally, the mobile app developer determined the price algorithm used in this study. While the platform does provide the opportunity to observe redemption in a dynamic price setting, we are unable to manipulate the parameters of such algorithm.

Given that a number of different adoption clusters were found, it may be that tailoring the price algorithm to produce the greatest redemption across each segment may prove valuable in further increasing overall mobile platform adoption and coupon redemption.

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**TABLE 1**  
**Relevant Mobile Coupon Literature and Contribution of this Report**

	<b>Push delivery</b>	<b>Pull delivery</b>
<b>Pre-adoption studies</b>	Hsu et al. (2006) Dickinger and Kleijnen (2008) Jayasingh and Eze (2009) Bacile and Goldsmith (2011) Rau et al. (2011) Im and Ha (2012) Jayasingh and Eze (2012) Khajehzadeh et al. (2014) Achadinha et al. (2014)	Unni and Harmon (2007)
<b>Post-adoption studies</b>	Kondo et al. (2007) Banerjee and Yancey (2010)	<b>This Report</b>

**TABLE 2**  
**Manufacturers of Brands Available for Scanning**

Andy Capp's	General Mills, Inc.	PepsiCo
Arnold Bakers Inc.	Heartland	Pik-Nik
Ballreich's	H-K Anderson	Post Foods, LLC
Cape Cod Potato Chips Inc.	IAMS	Procter & Gamble
Contadina	Jones Snack Chips	Shearer's Snack Foods
Cotton Club Bottling	Kraft Foods, Inc.	Snyder of Berlin
Dad's Pet Food	Kariba Farms	Snyder's Of Hanover, Inc.
Delallo	Kashi International	Stacy's Pita Chip Company
Del Monte Pet Food	Kellogg Company	Sunshine Pet Food
Dr. Pepper/Seven Up, Inc.	Luzianne	TGI Friday's
Drake	Malt O Meal	The Coca-Cola Company
Entenmann's	Mars Candy Co	The Quaker Oats Company
Faygo Bottling	Kentucky Kernel	Troyer Farms
Food Club Pet Food	Mediterranean Snacks	Uncle Ray's Chip Company
Frito-Lay, Inc.	Nickles Bread Company	Value Time
Fry Crisp	Nunn-Better Pet Food	VIGO
Fryin' Magic	Old London	Walnut Creek
Full Circle	Orlando	Yoder's Snack Foods

*These manufacturers supply items in the five categories studied in this report:*

1. Bread (including loaf bread, buns, bagels, bread crumbs)
2. Breakfast cereal
3. Carbonated soft drinks
4. Salty snacks (including potato chips, pretzels, popcorn, tortilla chips)
5. Bulk size pet food

**TABLE 3**  
**Customer and Coupon Characteristics Studied**

<i>Consumer-Level Variables</i>		
<b>Variable</b>	<b>Measurement</b>	<b>Description</b>
Gender	Binary	Female, Male, Not reported. Self-reported.
Age	Continuous	Customer's age in years. Self-reported.
Adopter segment membership	Discrete	Dummy set. Membership in the three adopter segments: (1) platform adopters, (2) novelty users, and (3) dwindling users.
<i>Trip-Level Variables</i>		
Number of trips	Continuous	Count of all customer shopping trips where at least one coupon was redeemed.
Number of scans per trip	Continuous	Number of products scanned on any trip where at least one coupon is redeemed.
Total spending per trip (Basket dollar value)	Continuous	Dollar value of the shoppers basket on any trip where at least one coupon is redeemed.
Number of items bought per trip (Basket size)	Continuous	The total number of items purchased on any trip where at least one coupon is redeemed.
Days since last trip	Continuous	Days elapsed since the last observed trip: takes the value of 0 for consumers' first trip.
Evening	Discrete	1= If purchase is made after 5 PM; 0=otherwise.
Weekend	Discrete	1= If Saturday or Sunday; 0=otherwise.
<i>Scan-Level Variables</i>		
Product category	Discrete	Five categories: Bread, breakfast cereals, snacks, soft drinks, and bulk pet food.
Focal product price	Continuous	Retail price in dollars of the product scanned.
Coupon set size	Continuous	Number of coupons presented to the shopper upon scanning the focal product.
Price (All or Rivals)	Continuous	The average price of products in either the entire coupon set (All) or the coupon set of Rivals only.
Std. Dev of Price (All or Rivals)	Continuous	The standard deviation of prices for products in the entire coupon set (All) or the coupon set of Rivals only.
Coupon Value (All or Rivals)	Continuous	The average value of coupons in either the entire coupon set (All) or the coupon set of Rivals only.
Std. Dev of Coupon Value (All or Rivals)	Continuous	The standard deviation of coupon values for products in the entire coupon set (All) or the coupon set of Rivals only.
Redemption rate, overall	Continuous	The ratio of the number coupons redeemed to the number of products scanned.
Redemption rate, focal product	Continuous	Ratio of the number coupons for the focal product redeemed to the number of products scanned.
<i>Coupon-Level Variables</i>		
Coupon for focal product	Binary	1=Coupon is for the target product scanned, 0=Coupon is for a substitute item in the coupon set
Coupon value	Continuous	Total savings, in dollars, for each coupon presented

**TABLE 4**  
**Descriptive Statistics for the Snap Coupon Dataset**

<i>Consumer-Level Variables</i>				
<b>Variable</b>	<b>Mean Or Pct.</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
Female shopper	53.8%	-	-	-
Male shopper	25.7%	-	-	-
Age (years)	48.7	14.4	16	76
Adopter segment member	72.5%	-	-	-
Novelty segment member	15.2%	-	-	-
Dwindling segment member	12.3%	-	-	-
<i>Trip-Level Variables</i>				
Number of trips	4.48	6.31	1	42
Number of scans per trip	2.56	1.78	1	14
Total spending per trip (dollars)	40.34	42.66	0.89	457.99
Number of items bought per trip	14.31	14.71	1	174
Days since last trip	70.36	67.30	1	327
Time of trip, daytime	75.6%	-	-	-
Time of trip, evening	24.4%	-	-	-
Day of trip, weekday	60.5%	-	-	-
Day of trip, weekend	39.5%	-	-	-
<i>Scan-Level Variables</i>				
Focal product price (dollars)	3.43	2.08	0.99	24.29
Coupon set size	6.28	1.73	2	13
Price, All products in set (dollars)	3.49	1.87	0.79	21.82
Std. Dev. of Price, All products in set (dollars)	0.68	0.47	0.00	6.37
Coupon value, All products in set (dollars)	0.62	0.33	0.12	4.31
Std. Dev. Coupon value, All products in set (dollars)	0.18	0.14	0.00	1.29
Price, Rivals only (dollars)	3.54	0.86	2.09	12.75
Std. Dev. of Price, Rivals only (dollars)	1.00	0.89	0.21	9.85
Coupon value, Rivals only (dollars)	0.67	0.19	0.32	2.27
Std. Dev. Coupon value, Rivals only (dollars)	0.25	0.16	0.03	2.26
Redemption rate (overall)	72.2%	-	-	-
Redemption rate (focal product)	69.1%	-	-	-
<i>Coupon-Level Variables</i>				
Coupon value (dollars)	0.628	.382	.02	5.40

When discrete variables are shown in the above table, percentages are used instead of means.

**TABLE 5**  
**Coupon Scanning and Redemption by Category**

<b>Category</b>	<b>Items Scanned</b>	<b>% of All Scans</b>	<b>Coupons Presented</b>	<b>Coupons Redeemed</b>	<b>Coupons Redeemed/ Items Scanned</b>
Bread	598	38.5	3,881	449	75.1
Cereal	226	14.6	1,273	154	68.1
Salty Snacks	346	22.3	1,988	261	75.4
Carbonated Drinks	348	22.4	2,425	235	67.5
Bulk Pet Food	35	2.3	191	22	62.9
<b>Total</b>	<b>1,553</b>		<b>9,758</b>	<b>1,121</b>	<b>72.2</b>

**TABLE 6**  
**Product Switching Behavior**

<b>Category</b>	<b>Total Redemptions</b>	<b>Redemption Focal Product</b>	<b>Percent Switch</b>
Bread	449	434	3.3%
Breakfast Cereal	154	151	1.9%
Salty Snacks	261	245	6.2%
Carbonated Soft Drinks	235	224	4.7%
Bulk Pet Food	22	19	13.6%
Overall	1,121	1,073	4.28%

**TABLE 7**  
**Top Coupons by Redemption**

<b>No.</b>	<b>% of Total</b>	<b>Description</b>	<b>Brand</b>	<b>\$ Retail</b>	<b>\$ Coupon</b>	<b>Savings as % of Price</b>
1	3.80	Hot dog buns 8 CT	Store	1.39	0.18	12.9%
2	3.80	White bread 20 OZ	Store	1.39	0.19	13.7%
3	3.40	Hamburger buns 8 CT	Store	1.39	0.20	14.4%
4	2.10	Tortilla chips	National	4.29	0.58	13.5%
5	2.02	Italian bread 20 OZ	National	2.59	0.39	15.1%
6	1.86	English muffins 6 PK	National	3.99	0.53	13.3%
7	1.70	Italian bread	National	2.79	0.41	14.7%
8	1.62	Tortilla chips	National	4.29	0.48	11.2%
9	1.62	Wheat bread 20 OZ	National	2.59	0.42	16.2%
10	1.54	White bread 16 OZ	Store	0.99	0.14	14.1%
11	1.54	Wheat bread	National	2.99	0.37	12.4%
12	1.38	Wheat bread 20 OZ	Store	1.99	0.31	15.6%
13	1.38	White bread 20 OZ	National	2.59	0.21	8.1%
14	1.13	Tortilla chips	National	3.99	0.59	14.8%
15	1.13	Soda, 12 CT	National	5.19	0.52	10.0%
16	1.05	Potato chips	National	3.99	0.36	9.0%
17	0.97	Whole wheat	National	2.69	0.45	16.7%
18	0.97	Light wheat bread	National	2.39	0.40	16.7%
19	0.89	Soda 12 CT	National	5.19	0.99	19.1%
20	0.81	Wheat buns	National	2.89	0.41	14.2%

**TABLE 8**  
**Determinants of Redemption of Focal Coupon**

	<b>Model 1</b>		<b>Model 2</b>	
	<i>Holistic information</i>		<i>Rival information</i>	
	<b>Estimate</b>	<b>Odds ratio</b>	<b>Estimate</b>	<b>Odds ratio</b>
Average Price (All in Set)	-.01 (.17)	.99 (.16)	-	-
Price Std. Dev. (All in Set)	-.04 (.23)	.96 (.23)	-	-
Average Value (All in Set)	-.49 (1.07)	.61 (.66)	-	-
Value Std. Dev. (All in Set)	.65 (1.23)	1.92 (2.37)	-	-
Average Price (Rivals)		-	<b>.34**</b> (.16)	<b>1.41**</b> (.22)
Price Std. Dev. (Rivals)	-	-	<b>-.41***</b> (.16)	<b>.66***</b> (.10)
Average Value (Rivals)	-	-	<b>-1.46**</b> (.63)	<b>.23**</b> (.15)
Value Std. Dev. (Rivals)	-	-	.87 (.78)	2.39 (1.86)
Coupon Set Size	<b>-.41*</b> (.23)	<b>0.67*</b> (.16)	<b>-.39*</b> (.23)	<b>0.67*</b> (.16)
(Coupon Set Size) <sup>2</sup>	<b>.03*</b> (.02)	<b>1.03*</b> (.02)	<b>.03*</b> (.02)	<b>1.03*</b> (.02)
Age	-.000 (.00)	1.00 (.00)	.00 (.01)	1.00 (.01)
Male	.13 (.13)	1.14 (.15)	.17 (.13)	1.19 (.16)
Evening	<b>-.35**</b> (.139)	<b>0.70**</b> (.097)	<b>-.34**</b> (.139)	<b>.71**</b> (.099)
Weekend	<b>.27**</b> (.12)	<b>1.31**</b> (.16)	<b>.26**</b> (.12)	<b>1.30**</b> (.16)
Constant	<b>2.31**</b> (.76)	-	<b>1.94*</b> (.81)	-

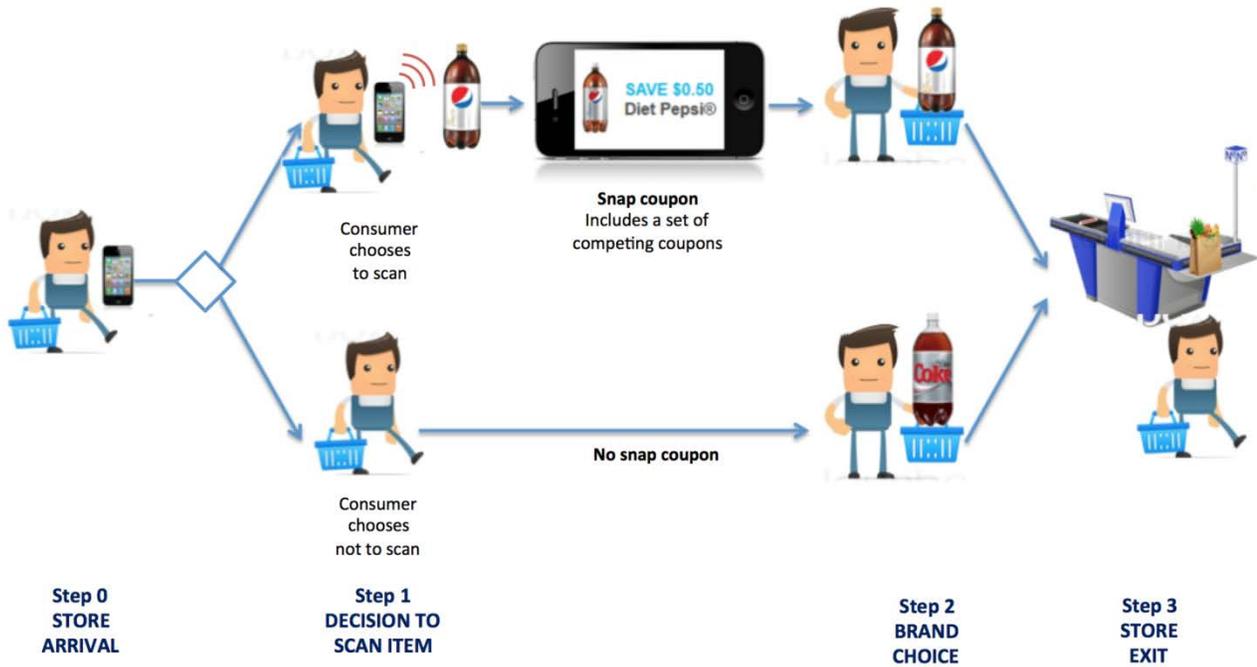
N=1,351 scans. Significant estimates marked with \*\*\* (99%), \*\* (95%) or \* (90%). The odds ratio measures the percentage increase/decrease to the odds of redemption along a particular variable. Ratios above 1 indicate increased odds of redemption whereas ratios below 1 indicate a reduction.

**TABLE 9**  
**Determinants of Trip-Level Outcomes**

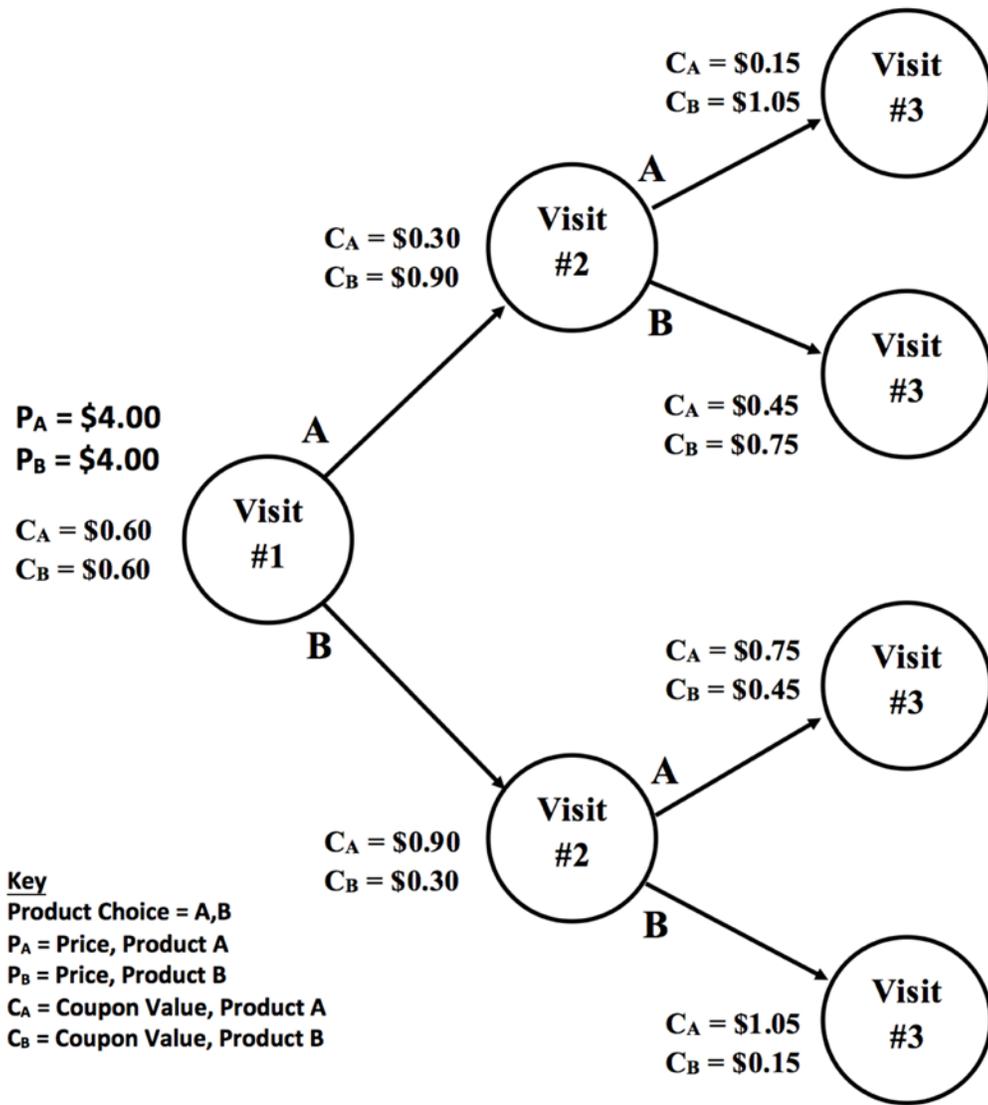
Variable	(1) Spending per Trip	(2) Items per Trip
Novelty Segment Member	10.02 (12.12)	1.13 (2.16)
Dwindling Segment Member	<b>-11.29***</b> (3.57)	<b>-4.54***</b> (1.33)
Coupon Set Size	-2.53 (6.61)	.88 (1.66)
Coupon Set Size <sup>2</sup>	.20 (.50)	-.08 (.11)
Days Since Last Trip	<b>-.09***</b> (.03)	<b>-.04***</b> (.01)
Average Price (Rivals)	<b>7.03***</b> (1.57)	<b>2.09***</b> (.53)
Price Std. Dev. (Rivals)	<b>-8.30***</b> (2.33)	<b>-2.96***</b> (.63)
Age	<b>.10**</b> (.05)	<b>.03**</b> (.02)
Male	-7.20 (7.16)	<b>-4.57**</b> (1.37)
Evening	-2.29 (5.24)	-.84 (1.42)
Weekend	1.92 (5.06)	1.53 (1.43)
Constant	<b>41.63*</b> (21.36)	<b>11.98*</b> 6.76

N= 508 (spending per trip); N= 490 (items per trip). Significant estimates marked with \*\*\* (99%), \*\* (95%) or \* (90%). Robust standard errors.

**FIGURE 1**  
**Scanning, Coupon Redemption, and Checkout Process**

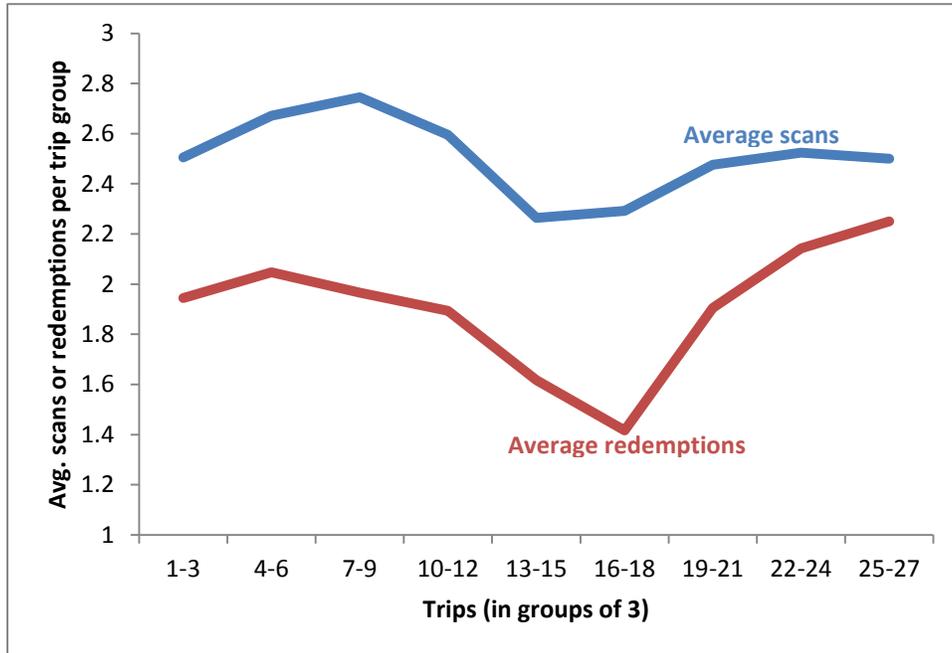


**FIGURE 2**  
**An Example of History Based Coupon Values**

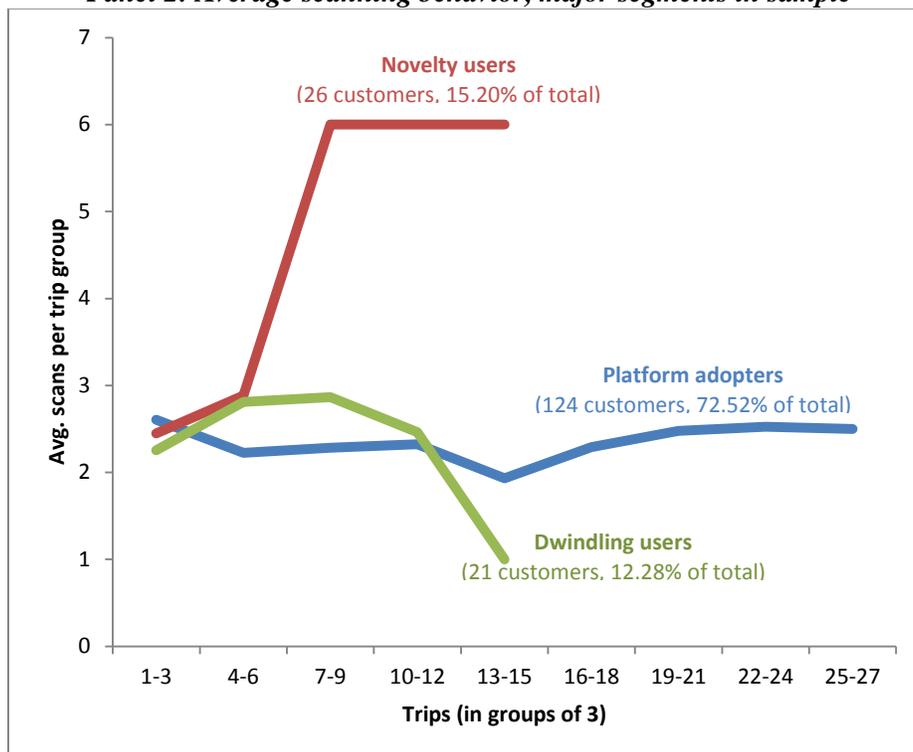


**FIGURE 3**  
**Adoption (Scanning) Patterns of the Mobile Platform**

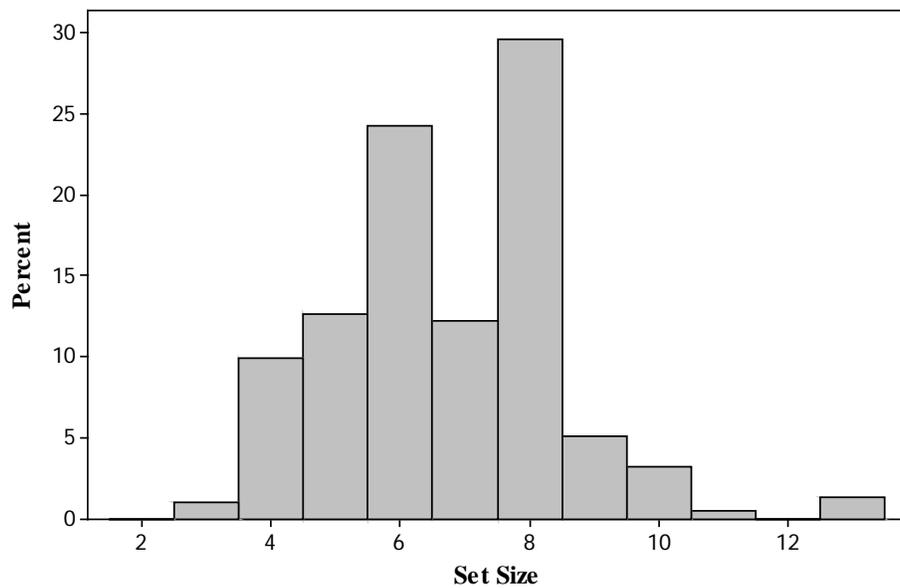
*Panel 1: Scanning and redemption behavior over time*



*Panel 2: Average scanning behavior, major segments in sample*



**FIGURE 4**  
**Coupon Set Size Distribution across all Subcategories**



**FIGURE 5**  
**Coupon Redemption vs. Coupon Set Size**

