What Determines Unplanned Purchases?:

A Model Including Shopper Purchase History and Within-Trip Dynamics

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Abstract

The recent advent of shopper marketing has led to an increased need to understand the drivers of unplanned purchases. This research addresses this issue by examining how past purchases (e.g., average historical price paid by the shopper) and elements of the current shopping trip (e.g., lagged unplanned purchase and cumulative purchases) determine unplanned purchases on the current trip. Using a grocery field study and frequent shopper data, we estimate competing models to test behavioral hypotheses using a Bayesian probit model with state dependence and serially correlated errors. We find that serial correlation in the data must be accounted for in order to draw correct inferences. Results indicate that early in a shopping trip, an unplanned purchase suppresses subsequent unplanned purchase, but this effect reverses over the course of the trip such that an unplanned purchase spurs additional unplanned purchases. Further, factors from previous shopping trips determine unplanned purchases in the current trip, suggesting that retailers can use their frequent shopper program data to create customized shopping lists and improve the targeting of mobile app-based promotions.

Keywords: Shopper marketing; state dependence; autocorrelation; probit models; Bayesian model selection; licensing effect

With consumers increasingly able to avoid or tune out advertising in traditional media, shopper marketing has been gaining in importance to practitioners (Hein 2008; Lucas 2009). Unplanned purchases are an important outcome due to the potential for incremental profits for both retailers and manufacturers. Consequently, in-store decision making has garnered an associated spike in interest in academic research with recent papers examining budget deviation (Stilley, Inman and Wakefield 2010a), browsing and shopping (Hui, Bradlow and Fader 2009) and factors influencing unplanned purchases and spending (Bell, Knox ,and Corstens 2010; Inman, Winer and Ferraro 2009; Hui, Inman, Huang, and Suher 2013).

Despite the recent surge in research focused on better understanding the factors that drive unplanned purchases, two significant gaps still remain. First, prior research on in-store decision making has employed a survey-based, trip-level approach. That is, unplanned purchase behavior has largely been studied as a static behavior that remains constant over the duration of the trip (Bell, Knox ,and Corstens 2010; Inman, Winer and Ferraro 2009; Park, Iyer and Smith 1989). Second, it is an open question as to whether shoppers' past purchase history can be used to help identify which items will be planned or unplanned in a given shopping trip. In this research we address both of these issues using a unique data set that merges frequent shopper program data with a field study in a supermarket setting.

Assuming that unplanned purchase behavior remains constant throughout the trip is a significant limitation given the recent research in sequential choices showing that prior decisions and choices can influence subsequent decisions (e.g., Khan and Dhar 2006; Dhar, Huber, and Khan 2007; Vohs and Faber 2007). Our research extends these earlier findings by examining the dynamic effects within a shopping trip on unplanned purchase behavior. Specifically, we argue that (a) there is a carry-over effect from one purchase to the next and (b) this effect varies over the course of the typical shopping trip. We predict that making an unplanned purchase increases the likelihood of subsequent unplanned purchases early-on in the trip, but that this effect weakens and ultimately reverses later in the trip. Relatedly, we examine whether choosing a hedonic item (versus a utilitarian item) influences the subsequent purchase decision. Understanding how prior purchases within a shopping trip affect the nature of subsequent purchases is quite important for designing in-store programs and store layout.

A second question addressed by this research is whether a consumer's past purchase history can be used to help predict which items will be planned or unplanned on the current shopping trip. This is of increasing interest to retailers and manufacturers, given the recognition of the importance of "getting on the list" (Manke 2011). Inman, Winer, and Ferraro (2009) begin to address this issue by examining how unplanned purchase likelihood varies with product characteristics such as category interpurchase cycle. Whereas Inman, Winer, and Ferraro (2009) were restricted to using population averages, in this paper, we leverage frequent shopper program data (hereafter FSP) to examine the utility of shopper-level FSP information to identify unplanned purchases. Specifically, we examine the effect on unplanned purchases of a shopper's historical average price paid in the category, the variability of prices paid in the category over time, as well as her frequency and recency of purchases in each product category.

Our research makes two important contributions to the literature on in-store decision-making, and offers useful implications for shopper marketing practice. First, we show that unplanned purchases during a shopping trip are state dependent, but that the nature of this state dependency changes over the course of the shopping trip. Specifically, we find that an unplanned purchase made early in the trip <u>suppresses</u> subsequent likelihood of an unplanned purchase, but that this effect reverses as the trip progresses such that an unplanned purchase later in the trip actually increases the likelihood that the next purchase will be unplanned. This reversal supports our thesis that self-control depletion (Vohs and Faber 2007) is likely to occur as the trip progresses and this depletion weakens self-regulation and ultimately enhances the likelihood of unplanned purchases. We also find that category hedonicity is inversely related to the subsequent likelihood of unplanned purchase, offering field evidence of the licensing effect that was not supported by Hui, Bradlow and Fader (2009).

Second, we demonstrate that a shopper's purchase history commonly available from FSP data can be used to identify her unplanned purchases on the current trip. We find that unplanned purchases are less likely for higher-priced categories and for categories that are frequently purchased, but are more likely for categories where the shopper displays a greater historical variability in price paid. These findings are an important first step in being able to develop a tailored shopping list for each shopper based on her shopping history and get potentially unplanned items on the shopping list. In doing so, a retailer will be able to maximize share of wallet and minimize the possibility that the shopper will instead purchase these items in a fill-in trip at another retail location such as a drug store. A better understanding of a shopper's prospective needs should also increase the accuracy and opt-in of targeted in-store promotions via mobile apps (Hui, Inman, Huang, and Suher 2011). These actionable managerial implications should enhance the return on investment for the currently underutilized FSP data.

The remainder of the paper is organized as follows. We first integrate relevant streams of behavioral literature to make predictions regarding the impact of both in-store dynamic effects and shopper purchase history on unplanned purchase likelihood. We then detail the data and statistical model, and present the results. We conclude with a discussion of implications of our findings for research and practice.

HYPOTHESIS DEVELOPMENT

We conceptualize the shopping trip as a goal directed activity requiring self-control and regulation to meet each shopper's desired outcome (Gollwitzer 1999). Hoch and Lowenstein (1991) formulate the consumer's problem as one of conflict between *desire* for goods versus the *willpower* to maintain and achieve broader goals. Research suggests that shoppers have distinct goals for shopping trips (Bell, Corsten, and Knox 2011) such as a "fill-in" or "weekly replenishment," plans to purchase specific items and/or brands from a category, as well as a budget for planned and unplanned items (Stilley, Inman, and Wakefield 2010ab). Park , Iyer, and Smith (1989) define unplanned purchases as "the purchase of a product that was not planned prior to entering the store." Researchers have described unplanned purchases as items the shopper simply forgot to put on the list or enumerate prior to entering the store, as well as items the shopper recognizes as needing or wanting after entering the store. This latter category includes items for which the consumer experiences a sudden, unreflective urge, or impulse to buy the item (Rook 1987). Whether the item is a forgotten "need" or a "want" prompted by the shopping experience, the shopper must exert self-control in selecting which items to purchase while keeping to the substantive and economic goals of the shopping trip.

Dynamic Trip Factors

Walking through a grocery store, a shopper is confronted with many more unplanned than planned items for potential purchase. Recognizing the role of self-regulation, Inman, Winer, and Ferraro (2009) identified several strategies a shopper might employ in order to limit unplanned purchases including using a shopping list, shopping only aisles where planned items are located, and limiting the amount of time spent shopping. Stilley, Inman, and Wakefield (2010a) have demonstrated that self-regulatory concepts such as shopper impulsiveness and resource depletion in the form of how long one has shopped help to predict the amount of aggregate unplanned purchases at the end of the shopping trip. In this research we build on the self-regulatory model to form hypothesis and look for evidence of its applicability in the sequence of specific selections made by a shopper.

Baumeister and Heatherton (1996) review the three components of self-regulation. First, there must be an ideal, goal, or set of standards that represents some desired state. Second, there must be monitoring consisting of some sort of comparison of the current state to the desired state. In the context of grocery shopping, the existence of budgets and consumers ability to stay reasonably close to those budgets suggests that there is goal setting and monitoring. Stilley, Inman, and Wakefield (2010a) found that shoppers had an average mental budget for the shopping trip of \$58.46 and the average amount spent was \$58.93; Stilley, Inman, and Wakefield (2010b) found an average budget of \$66.45 and spending of \$69.84. The third component of the self-regulation model is what Sayette (2004) refers to as "altering responses" which consists of actions taken when the current state falls short of the standard or desired state. The monitoring and response elements of the self-regulation model suggest that when a person makes an unplanned purchase, it will decrease the probability of a subsequent unplanned purchase as the shopper seeks to maintain her overall budgetary goal. In the shopping studies cited above, before beginning their shopping trip, consumers had budgeted \$17.35 and \$20.37 to unplanned purchases. Since these amounts are less that the amount budgeted for planned items, in order to stay within the overall budget, an effective altering response would be to resist the attraction of a subsequent unplanned purchase.

> **H1:** An unplanned selection will decrease the probability that the subsequent selection will also be unplanned.

Several arguments might be advanced as alternate explanations or competing theories. First, one might make a statistical argument of "reversion to the mean." If unplanned purchases (or selections) are less common than planned purchases, then one would expect there to be a negative relationship between an unplanned purchase and a subsequent unplanned purchase; an unplanned selection would be followed by a planned item simply because the number of planned items is greater than the number of unplanned items. However, past research has shown that about one-half or more of all selections in the grocery store are unplanned items. A study conducted by the point of purchase advertising association of 2,300 consumers making 34,000 purchases showed that 60.9% were unplanned (Inman, Winer, and Ferraro 2009) and in the current study 53.9% of the purchases were unplanned. Thus, reversion to the mean can be ruled out as an alternative explanation.

Park, Iyer, and Smith (1989) argue that more active cognitive processing during the shopping trip will lead to more unplanned purchases as the active processing triggers forgotten wants or needs. Consumers have limited processing capability (Miller 1956) and therefore often rely on cues that aid in retrieval from memory (Bettman 1979; Lynch and Srull 1982). The associative network model suggests that an unplanned selection may cue other forgotten needs (Collins and Loftus 1975; Ratcliff and McKoon 1988) and thus increase the probability that subsequent selections will also be unplanned items. However, in our selection-by-selection shopping analysis, this would imply that the cued forgotten need is in close proximity to the previously selected item, or that the shopper goes directly to the area of the store where the cued need is located, and selects it. While these are possible outcomes, they seem less probable. Nonetheless it is empirically testable since the cueing theory implies an opposite outcome than hypothesized in H1.

The “what the hell effect” could also result in an increased likelihood of a subsequent unplanned selection. Small failures with regard to goal progress can lead to complete abandonment of goal pursuit (Cochran and Tesser 1996; Soman and Cheema 2004). This would result in a break-down of the self-regulatory model wherein an unplanned selection would result in a shopper dropping one’s goal to limit unplanned purchases. We do not anticipate that the “what the hell effect” will dominate the shopping experience as it would lead to actual expenditures far outpacing pre-shopping budgets. However, we do think it may play a more specific role which we will return to shortly.

During a shopping trip, shoppers are exposed to numerous environmental factors which have been shown to decrease self-control performance such as noise (Cohen et al. 1980; Glass, Singer and Friedman 1969; Hartley 1973), crowding (Evans 1979; Sherrod 1974) and proximity to a tempting product (i.e., Vohs and Heatherton 2000). Therefore, we posit that self-regulatory depletion is likely to increase as more items are purchased (see Muraven and Baumeister 2000 for a review). We predict that the likelihood of an unplanned purchase will increase as the trip progresses, which we operationalize as the cumulative number of purchases.

> **H2**: The probability of making an unplanned selection will increase as the total number of selections in the shopping trip increases.

Stilley, Inman, and Wakefield (2010a) have demonstrated that time in the store is positively related to unplanned purchasing (moderated by the budgeted amount for unplanned purchases) which they also attribute to self-regulatory resource depletion. However their analysis was conducted at the trip level and therefore between consumers. If the self-regulatory hypothesis is valid, we should see an incremental increase in the probability of making an unplanned selection on an item-by-item basis as an individual shopper’s trip progresses. Our analysis addresses this question.

A related concept is time pressure. Hui, Bradlow, and Fader (2009) argue that perceived time pressure will result in more deliberative shopping: visiting areas of the store which contain only planned product categories and a greater probability of purchasing given that one is in that zone. However, their analysis does not specifically distinguish between planned and unplanned purchases. Park, Iyer, and Smith (1989) argue that time pressure reduces the amount of time available to process and react to in-store stimuli and therefore cues fewer forgotten needs resulting in fewer unplanned purchases. While Park, Iyer, and Smith (1989) specifically manipulate time pressure by giving shoppers a time limit at the beginning of the shopping trip, Hui, Bradlow and Fader (2009) measure the time a shopper spends in the store and assume that there is an implicit time budget. Park, Iyer, and Smith (1989) demonstrate that shopping trips taken under time pressure result in fewer overall unplanned purchases for that trip. In contrast, our analysis focuses on the selection-by-selection choices of shoppers.

Vohs and Faber (2007) show that cognitively taxing activities result in a decrease of self-regulatory resources and an increase in impulsive buying. We postulate that as the shopping trip proceeds, time pressure will prove to be another distraction that depletes self-regulatory resources and results in more unplanned selections. This hypothesis does not necessarily contradict Hui, Bradlow, and Fader's (2009) reasoning since one may be more likely to only visit shopping zones where planned items are located, but purchase additional unplanned items while there.

If the probability of making an unplanned purchase increases as the shopping trip progresses, this would suggest that shoppers are not making implementation intentions. Implementation intentions entail specific goal-directed actions in particular circumstances. Gollwitzer, Fujita, and Oettingen (2004) review the literature on goal intentions and more specifically implementation intentions. In the context of grocery shopping, a goal intention might be "Stick to my budgeted spending on this shopping trip" while an implementaton intention might be "After selecting an unplanned item I will review my basket to make sure I'm not exceeding my budget." Importantly, Gollwitzer, Fujita, and Oettingen (2004) present evidence (p. 219) that implementation intentions successfully preserve self-regulatory resources.

While we certainly do not anticipate that goal abandonment characterizes every instance of an unplanned purchase, goal abandonment should be more likely when self-regulatory resources have been depleted. Earlier we discussed that an unplanned purchase may accelerate the likelihood of a subsequent unplanned purchase due to a "what-the-hell" effect (i.e., Cochran and Tesser 1996; Soman and Cheema 2004). Consumers tend to have increased difficulty complying with regulatory goals, such as restraining spending, when self-control resources are depleted (Vohs and Faber 2007). Decrease in self-control is likely to occur as the trip progresses and this may exacerbate the tendency to engage in "what-the-hell" reasoning. Consequently, we posit an interaction between trip length and the carry-over effect of unplanned purchases.

> **H3**: As the trip progresses, the effect of an unplanned selection on subsequent selections will eventually reverse, such that an unplanned selection will increase the probability that the subsequent selection is also unplanned.

Research has shown that hedonic items are more likely to be unplanned because they yield more positive affect than functional items and therefore are more commonly purchased on impulse (Inman, Winer, and Ferraro 2009; Shiv and Fedorikhin 1999). However, this research is silent as to whether any ensuing effects will occur. Our examination of the literature suggests that the less hedonic an item is, the more likely the shopper is to purchase an unplanned purchase on the subsequent purchase.

According to the licensing effect (Khan and Dhar 2006), making a virtuous decision licenses the individual to subsequently make a more indulgent choice by boosting their self-concept. In the goal literature, Dhar and Simonson (1999) find that consumers tend to balance goals when trading off between two conflicting goals (eating healthy vs. good tasting) which suggests that deciding to purchase a healthy, but less tasty alternative should lead to increased subsequent likelihood of selecting a more hedonic, unplanned item. Likewise, Fishbach and Dhar (2005) find that when a consumer has conflicting goals that they pursue over time, even perceived progress on the focal goal (such as eating healthy) can lead to disengagement from the focal goal. Applying a self-control depletion argument suggests the same outcome. A consumer who exerts self-control in the process of making a virtuous choice will deplete self-control (Muraven and Baumeister 2000) and therefore will have less will power remaining to resist making an unplanned purchase on the next purchase.

Despite the apparent robust support for this hypothesis, Hui, Bradlow, and Fader (2009) did not find that a virtuous basket impacted subsequent likelihood of purchasing a relative vice. They only found weak support for increased shopping of zones that contained vice items. We revisit this issue by considering the more immediate impact of hedonicity of the prior purchase on subsequent likelihood of making an unplanned purchase.

> **H4**: Selection of a virtuous product (low hedonicity) will increase the probability that the subsequent selection is unplanned.

Shopper-Level FSP-Based Factors

Retailers' frequent shopper programs (FSP) enable them to track shoppers' purchases over time. The FSP data from the retailer that participated in this study captures category and brand purchased, price paid, quantity purchased, and date of purchase. While Inman, Winer, and Ferraro (2009) used an industry benchmark to include average interpurchase cycle in their model of unplanned purchase, our use of a shopper's own purchase history to describe the category characteristics is new to the literature. Specifically, we assess the effect of each shopper's average price paid in the category, the variability in price paid in the category over the purchase history, and the frequency and recency of category purchase. Predictions for each of these factors are discussed below.

Average Purchase Price. Recent research by Stilley, Inman and Wakefield (2010a, 2010b) shows that shoppers have mental budgets, or spending expectations, for grocery trips and try to avoid exceeding these amounts. Even though a shopper may have some room in her mental budget for unplanned purchases, making an unplanned purchase can cause feelings of guilt if the purchase is perceived to be excessive (Mukopadhyay and Johar 2007). Further, more expensive items are likely to be more accessible in memory and therefore included on the shopping list. This suggests that shoppers will be more hesitant to purchase expensive items on an unplanned basis.

> **H5**: A shopper's average purchase price within a product category will be inversely related to likelihood of unplanned selection.

Price Variation. A temporary price reduction might prompt a shopper to purchase an otherwise unplanned item. In fact, many consumers tend to shop opportunistically and buy certain items when they are on promotion (Bucklin and Lattin 1991; Fox and Hoch 1995; Gupta 1988; Raju 1992). At the individual level, this tendency to engage in opportunistic purchase behavior would be indicated by greater historical price variance for items within the product category (assuming not all purchases in the category are on sale). At the population level, categories that are more frequently discounted should have higher price variance. Both of these factors lead to the same predicted effect:

H6: A larger within-category variation in a shopper's price paid within a product category will lead to a greater propensity to select that category on an unplanned basis.

Frequency and recency. In order to plan purchases in advance, consumers must be able to cognitively recognize the need or want. Consumers tend to have difficulty retrieving all their grocery needs from memory (Bettman 1979), so items that are more easily recalled are more likely to be planned. For example, Inman, Winer, and Ferraro (2009) argue that frequently purchased products are more likely to be planned because these items are more accessible from memory (Posavac, Sanbonmatsu, and Fazio 1997). Further, including purchase frequency in the model controls for the effect of the number of purchases in the category on variation in price paid (i.e., a shopper who makes a single purchase in the category will exhibit no historical variation in price paid). Memory accessibility theory also suggests that purchase recency will influence the likelihood of the item being unplanned. Riccio, Rabinowitz and Axelrod (1994) report that memory links decay over time. Therefore, purchases that occurred more recently should be more easily retrieved and less likely to be unplanned.

H7: More frequently purchased categories will be less likely to be selected on an unplanned basis.

H8: More recently purchased categories will be less likely to be selected on an unplanned basis.

EMPIRICAL TEST

Data and Model

The data used to test our behavioral hypotheses is from a field study first discussed by Stilley, Inman, and Wakefield (2010b). A random sample of 400 customers from two grocery stores located in a southwestern US city were intercepted as they entered the supermarket and asked to participate in a marketing research study. We define an unplanned purchase as one which was not planned prior to entering the store. We follow the procedures of past researchers (Huang, Hui, Inman, and Suher 2012; Stilley, Inman, and Wakefield 2010a; Inman, Winer, and Ferraro 2009; Park, Iyer, and Smith 1989; Kollat and Willet 1967) asking respondents what product categories they planned to purchase before beginning their shopping trip. Every tenth shopper entering the store (or one every five minutes) was approached and asked to participate in a market research study. Shoppers were offered a $10 incentive for a future shopping trip in order to participate. Respondents were asked what items they intended to buy, how much they expected to spend on these itemized purchases, and how much they expected to spend overall. Planned versus unplanned purchases are determined by comparing responses to the pre-shopping survey to actual purchases.

After completing the entrance survey, respondents were given a handheld scanner and asked to scan the bar code of each item as they placed it into their carts or baskets. This method records the specific order in which items were selected and allows investigation of sequential effects. After completing their shopping trip, respondents provided additional information in an exit interview and the researchers made a copy of their receipt, which provided a record of the price and amount spent on each item. Respondents also provided their frequent shopper card number, providing access to their shopping histories. Stilley, Inman and Wakefield (2010b) provide more details, including evidence that the research methodology did not alter respondents' shopping behavior.

Complete data are available for 328 shoppers who made a total of 9,988 purchases. Approximately 80% of the shoppers were female, the average household size was just under 3 people, and the average total trip budget was $66.45 with $46.08 devoted to planned items and

\$20.37 budgeted for unplanned items. Average total expenditures equaled \$69.84 with \$35.25 spent on planned items and \$34.59 spent on unplanned items. Table 1 displays selected statistics on respondents' purchase behavior. Of the 9,988 purchases, there were 1,807 items which represented duplicate UPC's (e.g., two cans of tomatoes, several loafs of bread) for the same shopper. Since our analysis focuses on sequential effects, these duplicated UPC's were removed from the dataset so as not to confound purchase quantity effects with the selection of planned versus unplanned items. Of the 1,807 duplicate items, 47.5% were unplanned indicating that shoppers were slightly more likely to make multiple purchases of planned items. After removing duplicates, our final data set consists of 8,181 purchases.

============== Table 1 about here =================

Our approach to testing the behavioral hypotheses is to model unplanned purchases as a function of control variables suggested by past research (discussed subsequently), within-in trip dynamic factors, and FSP. Our dependent variable is binary, indicating whether the nth selection for person i is planned ($y_{in} = 0$) or unplanned ($y_{in} = 1$). Our statistical model is given by:

$$
\begin{aligned}
& y_{in}^{*} = \beta_i' x_{in} + \gamma_i y_{i,n-1} + \delta' z_{in} + \varepsilon_{in} \\
& \varepsilon_{in} = \phi \varepsilon_{i,n-1} + \nu_{in} \quad \text{where } \nu_{in} \sim N(0, \sigma_\nu^2) \qquad (1) \\
& y_{in} = 1 \text{ if } y_{in}^{*} > 0, \text{ else } y_{in} = 0
\end{aligned}
$$

Where x_{in} is a vector of control and focal variables for shopper *i* for the nth item selected, z_{in} is a vector of variables indicating a store's specific shopping zones, and y_{in}^{*} is a latent variable representing the propensity to make an unplanned purchase. The vector β_i and the scalar γ_i are individual parameters, while the vector δ and the scalar ϕ are parameters common across respondents. Equation (1) is a probit model with a lagged dependent variable and serially correlated error terms. We discuss the shopping zone variables, error structure, and heterogeneity after reviewing the control and focal variables. Table 2 summarizes the control and focal variables specifically used to test the self-regulatory model.

Control Variables

Stilley, Inman, and Wakefield (2010JM) report that consumers have a mental budget for what they expect to spend overall in a shopping trip as well as how much they expect to spend on unplanned items. We control for cumulative spending on the current trip and cumulative spending on unplanned purchases on the current trip by including the natural logarithm of these variables. These cumulative spending amounts control for the effect of a self-imposed budget and separate out the effect of the number of items purchased from a running total of how much money was spent. We anticipate that the effect of cumulative spending will be positive since additional purchases have some positive probability of being unplanned. However, since shoppers have a mental budget for unplanned items, we expect the effect of cumulative unplanned spending to be negative.

Based on past empirical research we include several variables relating to the product and/or product category. As noted below, we expect that items "on sale" are more likely to be unplanned purchases and include this as a control variable. An item was designated as "on sale" if its list price was 90% of the previous week's list price; this operationalization does not include price discounts taken for coupons. Inman, Russell, and Ferraro (2009) showed that the hedonicity of the product category had a significant impact on the probability that an item is an unplanned purchase. Product categories were assigned a hedonic score based on the methodology of Wakefield and Inman (2003) and mean centered; more utilitarian goods have a negative score while more “fun” items have a positive score. We expect that the coefficient of the “on sale” variable and the hedonicity variable to be positive.

============ Table 2 about here =============

Estimation

Hypotheses 1 to 4 focus on the role of the self-regulatory model in unplanned purchases. The coefficient on the lagged dependent variable y_{n-1} tests the effect of an unplanned purchase on a subsequent unplanned purchase. In the dynamic discrete choice literature (Heckman 1981) this would be labeled "state dependence" or "purchase event feedback" (Haaijer and Wedel 2001). This is consistent with our conceptualization wherein the specific act of making an unplanned purchase changes the intentions of the shopper. If hypothesis 1 is correct, we expect the coefficient on the lagged dependent variable to be less than 0.

The second hypothesis has to do with the depletion of self-regulatory resources over the course of the shopping trip; as self-regulatory resources are depleted we expect more unplanned purchases. We operationalize the length of the shopping trip as the natural logarithm of the cumulative number of selections made up to the current selection (excluding duplicated products). An alternative would be to measure the amount of time between entering the store and the current selection which would require a "time stamp" from the hand-held scanner. Unfortunately is measure is not available in our data. Formally, our measure of resource depletion accords more effect to the actual deliberation and choosing of products rather than merely being in the store. However, we would expect the two measures (cumulative time and cumulative selections) to be highly correlated[1]. In accordance with our second hypothesis, we expect the coefficient for the cumulative number of selections to be positive.

Our third hypothesis is tested by forming an interaction term between the lagged dependent variable, equal to one for an unplanned selection, and the natural log of the cumulative number of selections. We expect this coefficient to be positive indicating that as the shopping trip progresses, depletion of self-regulatory resources will result in "goal abandonment" such that an unplanned purchase will increase the probability that the next purchase will be unplanned. Finally, to test the fourth hypothesis we lag the hedonicity variable described above by one selection. If the purchase of a low hedonic product (hedonicity value less than 0) increases the probability that the subsequent selection is unplanned, then its coefficient should be negative.

Shopping Zone Variables, Error Structure, and Heterogeneity

The self-regulatory model, as well as several of the control variables imply that a shopper's selection of planned or unplanned item is not independent of her past selections. In addition to the control and focal variables in our model, other effects such as environmental factors (e.g., store layout) might induce sequential effects in planned/unplanned purchase behavior. For instance, being in the cookies aisle might result in more unplanned purchases than being in the produce section. We control for these effects by including shopping zone dummy variables indicating which area of the supermarket each selection is made (see Hui et al. 2009 for a similar approach). Our data are from two different stores with different layouts. In the first store, 34 distinct shopping zones were identified and coded while the second was coded into 24

[1]When analyzing differences in unplanned purchases across shopping trips or shoppers as in Bell, Corsten, and Knox (2011) or Inman, Winer, and Ferraro (2009) "time spent shopping" may be endogeneous since purchasing more unplanned items entails spending more time in the supermarket. However this is not a concern in the current study since our unit of analysis is the item-by-item selection process, not the aggregate number of purchases.

shopping zones. The shopping zones typically coincide with the aisles in the supermarket, meat or dairy sections, check-out, special displays, etc.

Even after including the control variables and shopping zone variables, there may be other unaccounted-for environmental factors that result in correlations between selections. Our model captures this through the serially correlated error terms, represented as an AR(1) process and the parameter ϕ. When $|\phi| < 1$, then the sequence of selections is stationary in the sense that the influence of past selections dies off in an exponential manner (see for instance Franses (1998) or Greene (2000)). Note however, that in our situation, the sequence is not indexed by time, but by the order of purchase *n*. If $0<\phi<1$, this results in clusters of planned or unplanned purchases that are not fully explained by the variables in the model, but purchasing behavior ultimately reverts back to this explanatory model. The autocorrelated error is a form of "habit persistence" in that factors not observed by the statistician may still have an impact on future choices; in this case elements not already included in the model, represented by the error term. Seetharaman (2004) offers a useful typology of different forms of habit persistence in dynamic choice models.

Stewart (2006) offers a straightforward introduction to the random effects probit model with autocorrelated errors and a lagged dependent variable. Keane (1997) provides a more elaborate example in the context of brand choice. As noted earlier, the coefficient on the lagged dependent variable will be used to test the first hypothesis. Whether the average γ_i is greater or less than 0 will provide evidence on the role of state dependence in unplanned purchase behavior. However, the estimated value of γ will be biased if other factors result in serial correlation but are not properly modeled. For instance, if there is positive autocorrelation, but it is not modeled, the value of γ will have an upward bias.

In order to compare models with and without autocorrelated errors (ACE), we parameterize the error variance term in equation (1) as $\sigma_\nu^2 = \left(1-\phi^2\right)$. To see why, note that in an ACE regression the full error covariance matrix is given as (Judge, et al. 1988, p.387)

$$\frac{\sigma_\nu^2}{1-\phi^2}\begin{bmatrix} 1 & \phi & \cdots & \phi^{N-1} \\ \phi & 1 & \cdots & \phi^{N-2} \\ \vdots & \vdots & \ddots & \vdots \\ \phi^{N-1} & \phi^{N-2} & \cdots & 1 \end{bmatrix} \qquad (4)$$

which is consistent with our latent variable structure in (1). For a probit model the usual way to identify the model is to set $\sigma_\nu^2 = 1$ and with $\phi = 0$, the error covariance matrix is simply the identity matrix. However, with $\sigma_\nu^2 = 1$ and with $|\phi| > 0$ then the diagonal elements in (4) are greater than 1, resulting in an increase in the error variance. Increasing the error variance reduces model fit statistics. By setting $\sigma_\nu^2 = \left(1-\phi^2\right)$ the diagonal elements in (4) are always equal to 1 regardless of the value of ϕ, ameliorating the increase in variance. The net result is that model fit statistics are more comparable for probit models with and without ACE.

Equation (1) includes fixed parameters across the sample as well as individual level heterogeneity. Heterogeneity is modeled as $[\{\beta_i\}, \gamma_i] \sim N_p\left(\bar{\beta}, \Sigma\right)$ which is a multivariate normal distribution for the stacked vector $[\{\beta_i\}, \gamma_i]$. The error correlation coefficient ϕ is common across respondents because with the relatively short panel structure, we could not obtain stable parameter estimates for the distribution of heterogeneity with individual level ϕ_i. Similarly, since each respondent often made only one or no selections in a particular shopping zone, the effects of the shopping zone variables are pooled across respondents. The prior on ϕ is uniform U(-1,1); conjugate but diffuse priors are used for δ, Σ, and $\bar{\beta}$ (full details can be obtained from the authors). As is typical, parameters from the posterior distribution of heterogeneity (i.e., the $\bar{\beta}$

and $\bar{\gamma}$) will be used to summarize and test hypothesis for effects with individual level heterogeneity. Allowing for individual level parameters (particularly on the intercept term) controls for differences in the purpose of the trip (Knox, Bell and Corsten 2011; Bell, Corsten, and Knox 2011), individual differences such as using a list, gender, payment type, etc. (Inman, Winer, and Ferraro 2009) as well as impulsivity (Stilley, Inman, and Wakefield 2010a) and other person/trip factors which have been shown to influence the amount of unplanned purchasing at the trip level.

We adopt a Bayesian approach to estimating the model. Data augmentation facilitates estimating the model parameters via Markov-chain Monte Carlo (MCMC) methods without relying on high dimensional integration. MCMC chains were run for 10,000 iterations and a sample of every 10^{th} from the last 5,000 was used for model inferences. Convergence was assessed by inspecting the time series plots of model parameters and re-estimating the models with different random seeds. Results with simulated data also confirmed that 10,000 iterations were adequate. All models converged quickly. For model comparison we calculated the log marginal density (LMD) using the importance sampler of Gelfand and Dey (1994) as used in hierarchical models by Lenk and Desarbo (2000) and Gilbride and Lenk (2010). This estimator performed consistently well in the results reported by Gamerman and Lopes (2006). In order to calculate the LMD we needed to estimate the probability of the observed data. For calculating probabilities we use the GHK simulator as suggested in Geweke, Keane, and Runkle (1997) and detailed in Train (2003); Stewart (2006) summarizes its implementation in dynamic probit models with autocorrelated errors. We use the GHK to simulate probabilities even in models without correlated error terms to control for noise resulting from the simulation. Full details of the estimation methodology are available from the authors.

Results

Models were estimated using the control and FSP variables (Model 1), Model 1 plus the trip dynamic factors (Model 2), and Model 2 plus the shopping zone variables (Model 3). In addition, each model was estimated with and without autocorrelated errors. Parameter estimates and fit statistics are presented in Table 3. The LMD statistic favors the model with the highest value and we can see that the models including the trip dynamic factors (-4906.8 and -4952.4) are favored over the base Model 1 with just the control and FSP variables (-5083.8 and -5166.2) as well as the full model (Model 3) including shopping zones (-5006.7 and -4995.4). In the shopping zone models, 22 out of 58 and 24 out of 58 of the shopping zones were statistically significant indicating that in particular areas of the two stores, unplanned purchase were more likely, while in others they were less likely. However, the model fit statistics favor the more parsimonious models without the shopping zone variables.

================ Table 3 about here =================

Models with and without autocorrelated errors provide coherent results. First, all three ACE models have positive autocorrelation coefficients, however it is lowest in Model 3 where the shopping zone variables apparently capture some of the unexplained carry-over between selections. Looking at Model 2, the coefficient for the lagged dependent variable $\bar{\gamma}$ goes from -0.520 in the ACE model to -0.304 in the model without autocorrelated errors; this illustrates the potential biasing effect of not including correlated error terms in models of sequential choice. Note that the LMD favors the ACE model. By contrast, in Model 3 the difference between the estimated $\bar{\gamma}$'s is smaller (-0.395 vs. -0.332) and the LMD fit statistic favors the model without the autocorrelation term. With the exception of the autocorrelation coefficient ϕ and the lagged dependent variable coefficient $\bar{\gamma}$, the values of all the other parameters are remarkably close in models 2 and 3. Since the LMD overall favors the ACE Model 2 with the control and focal variables, we will discuss those results.

The parameter estimates for the control variables were consistent with expectations with two exceptions. Results for category hedonicity (positive), cumulative spending (positive), and unplanned cumulative spending (negative) matched our predictions while promotions had no measurable effect on unplanned purchasing. While Inman, Winer, and Ferraro (2009) did not have a "promotion" variable, they found a significant impact for displays, which presumably coincided with products which were on promotion. Our data did not have information on displays. It may be that some shoppers used weekly inserts or circulars to construct their shopping lists, muting the overall impact of promotions on unplanned purchases. Bell, Corsten, and Knox (2011) found that when shoppers consulted fliers or circulars in the store it increased trip level unplanned purchases, but consulting advertisements before shopping had no effect on unplanned purchases.

The results with the FSP variables are largely consistent with prediction and suggest that historical information about shoppers' purchases can be used to help identify the unplanned purchases on the current trip. Based on prices paid by the individual shopper, product categories with a higher mean price are more likely to be planned purchases while items in categories with greater price variation are more likely to be unplanned purchases, supporting Hypotheses 5 and 6, respectively. These results are consistent with a resource planning view where shoppers invest more time and cognitive resources in planning high ticket items. We also find that more frequently purchased items are more likely to be planned than infrequently purchased items, supporting Hypothesis 7. However, days since last purchase, or recency, does not help to predict unplanned purchases. Thus, Hypothesis 8 is not supported. One potential explanation for this is that purchasing an item recently means that the shopper still has inventory of the item and does not have a need for the product.

The empirical results confirm Hypotheses 1 through 4. As noted earlier, the coefficient on the lagged dependent variable $\overline{\gamma}$ is negative and it is statistically significant indicating that an unplanned purchase decreases the probability that the next selection will be unplanned. This is consistent with shoppers altering their behavior to comply with their overall budget goals. The coefficient for the log of cumulative purchases is 0.293 and different from 0; this means that as the shopping trip progresses and more selections are made, the probability of making an unplanned selection increases. This supports Hypothesis 2. It's important to note that the cumulative number of selections is significant even when controlling for the overall cumulative amount spent and the amount spent on unplanned items. While past research has demonstrated that more time spent shopping is related to the aggregate amount of unplanned purchases (Stilley, Inman, Wakefield 2010a; Inman, Winer, and Ferraro 2009; Park, Iyer, and Smith 1989), our analysis shows that the propensity to make unplanned purchases increases over the course of the shopping trip. One interpretation of the past research would be that on longer shopping trips consumers simply browse more, triggering more unrecognized wants or needs leading to a higher level of unplanned purchasing. If this were the case, one would expect a uniformly higher probability of making unplanned purchases, which in our model would be captured by the heterogeneous model intercept. The fact that unplanned purchasing increases over the course of the shopping trip provides evidence of resource depletion in the self-regulatory model of unplanned purchases.

We also find that the interaction between cumulative selections and the lagged dependent variable is positive and significant, in support of Hypothesis 3. This means that the effect of an unplanned purchase on the next purchase changes over the course of the shopping trip. Using the posterior means of the parameters from the distribution of heterogeneity, these results suggest that after approximately the 11th selection in a shopping trip, an unplanned purchase increases the probability that the next selection will be unplanned; we illustrate this effect in the general discussion. This supports our thesis that shoppers' regulatory self-control weakens as the shopping trip wears on.

The results also offer insight on the dynamic effect of hedonicity on subsequent purchases. The negative value ($\bar{\beta}_{xx}$ = -.063) of lagged hedonicity means that if the previous selection was a utilitarian good (i.e., a hedonicity rating below the mean and therefore less than zero since hedonicity is mean centered), that there is a higher probability that the subsequent selection will be an unplanned item. These data therefore support a licensing effect with regard to unplanned purchases in the sense that purchasing a utilitarian good appears to give the shopper "permission" to make an unplanned purchase on the next selection[2].

DISCUSSION

Our results have implications for marketing theory, consumers, and shopper marketing practice. Specifically, our findings suggest that the role of unplanned purchases on subsequent purchases is dynamic and nuanced, and therefore requires an appropriate statistical model in order to draw correct inferences. Early in the shopping trip, an unplanned purchase decreases the probability that the subsequent purchase will be unplanned. However, as the shopping trip progresses, both in terms of money spent and number of items selected, the probability of making unplanned purchases increases to the point where the relationship reverses and an

[2]The models were also estimated separately for the two different supermarkets in our data set. Although there was some loss of power, the results are similar.

unplanned purchase actually *increases* the probability that the next selection will be unplanned. If shoppers have only a finite number of unplanned needs that are made salient by in-store cues, one would expect either a constant propensity to make unplanned purchases or a decreasing probability over time. The observed pattern of results is most consistent with the argument that self-control resources become depleted over the course of the shopping trip until engaging in unplanned purchases ultimately snowballs into additional unplanned purchases.

Simulation

To illustrate the effect of an unplanned purchase on a subsequent purchase, we conducted a simulation experiment. The model incorporates dynamic effects that change over the course of the shopping trip including cumulative spending and cumulative purchases as well as lagged effects and correlated error terms. Observations are not exchangeable and therefore it is inappropriate to just use the average values of the explanatory variables to illustrate model effects. Rather, we use each shopper's actual sequence of purchases and the posterior distribution of his/her parameter values to estimate the effect of an unplanned purchase on a subsequent selection. Our basic methodology is to look at each respondent's sequence of selections, identify a planned purchase, "change" that to an unplanned purchase and calculate the effect on the subsequent selection, keeping constant all other relevant control and focal variables in the shopper's history.

The model indicates that unplanned purchases are more likely as the cumulative spending increases and as the cumulative number of selections increase, but this is offset by the cumulative amount of unplanned spending. We therefore conduct our simulations at different points in the shopping trip: between selections 5 - 10, 15 - 20, 25 - 30, and finally 35 – 40. Only one selection is changed, but we look at a range of values in order to include as many shoppers as possible; for instance if we just looked at just the 5th selection we would exclude about half the sample since they didn't make an unplanned purchase on the 4th selection.

Figure 1 summarizes our findings. Early in the shopping trip, an unplanned purchase decreases the probability by 0.08 that the subsequent purchase will be unplanned[3], consistent with the negative value of the lagged dependent variable in the statistical model and the idea that shoppers monitor their selections in order to stick to their budgets. However, for shoppers making their 15 – 20th selection, an unplanned selection slightly increases the probability that the next selection will be unplanned by 0.01 and by the 25 - 30th selection this increases to 0.06. By the 35 – 40th selection, the countervailing force of the unplanned spending budget appears to moderate the overall effect somewhat and an unplanned selection increases the probability that the next purchase will be unplanned by 0.07. It is important to note that these effects are not due to store layout since the data includes two different stores with different layouts and that different shoppers making their 5 – 10th selection (for instance) need not be in the same part of the store. Further the hedonicity of the items is controlled in the model so it is not simply the case that shoppers are succumbing to the candy in the checkout aisles. Importantly, the model and simulation based results provide field-based evidence supporting the self-regulatory model of shopping behavior.

Along these lines, we find that category hedonicity has an immediate impact on the probability a purchase will be an unplanned selection, but our results also document a dynamic impact. The immediate impact is consistent with the findings reported by Inman, Winer, and Ferraro (2009) and Shiv and Fedorikhin (1999). The dynamic impact supports the licensing effect wherein a utilitarian selection gives the shopper "permission" to make an unplanned

[3] All the values in Table 1 are statistically different from 0 at a p-value < 0.001; all the values are different from each other at a p-value < 0.05.

purchase in their next selection (Khan and Dhar 2006). Whereas Hui, Bradlow and Fader (2009) find some support for the licensing effect with regard to browsing behavior, our results show a relationship between selecting less hedonic items and then making an unplanned purchase. This discrepancy in findings may be attributed to our scaled measurement of item hedonicity, whereas Hui, Bradlow and Fader (2009) employed a cruder, dichotomous measure regarding whether the entire basket was primarily hedonic vs. utilitarian.

Managerial and Consumer Welfare Implications

The results of our research have several implications for managers and consumers. First, the licensing effect suggests that an effective merchandising strategy would be to mix low and high hedonicity items. The purchase of a low hedonicity item gives the shopper "permission" to make an unplanned purchase and high hedonic items are more likely to be unplanned purchases. Similarly, since unplanned purchases are more likely after a shopper has made numerous selections, special features or items considered an "indulgent splurge" should be positioned later in a shopper's typical shopping path. Similarly, in-store sampling or other in-personal promotions should be located more deeply in the trip. On the flip side, consumers should be mindful of their greater propensity to make unplanned purchases as their shopping trip unfolds. While our research does not investigate whether or not unplanned purchases are "good" or "bad" from a consumer's perspective, we note our finding that the cumulative amount spent on unplanned purchases deters additional unplanned purchases throughout the shopping trip. That is, making and monitoring a mental budget for unplanned purchases during a shopping trip provides the shopper flexibility to react to in-store cues and enjoy the shopping experience while avoiding an unexpectedly large overall expense. Forming implementation intentions on what do when making an unplanned purchase may preserve self-regulatory resources (Gollwitzer, Fujita, and Oettingen 2004) and forestall goal abandonment.

Further, the results from the FSP-based variables suggest that retailers can use individual-level data to create customized shopping lists. For each shopper, it is possible to identify the product categories where he/she purchases most frequently and which contain the “big ticket” items (e.g. those with the higher mean prices). Through a mobile app, a retailer could create a pro forma shopping list for the shopper with these as the default items. Further, alerting the shopper to products that are currently priced below the past prices paid by the shopper could lead her to “plan” on an otherwise “unplanned” item. A better understanding of shoppers’ prospective needs should also increase the opt-in rates of targeted in-store promotions delivered to shoppers via mobile apps for smartphones or at kiosks.

Future Research

The presence of a relatively large autocorrelation coefficient suggests that there is additional behavioral research to be done to more thoroughly explicate the dynamics in shopper purchasing behavior. First, while we characterize items as either planned or unplanned, there may be additional underlying reasons for unplanned purchases that are captured by the autocorrelation. For example, some shoppers may purposefully let the store guide them on dinner plans. For these shoppers, the first unplanned item in a meal plan might stimulate additional unplanned purchases. This effect may vary significantly from the sequential effect of purchasing standalone unplanned items.

Our research shows that, early in the trip, making an unplanned purchase reduces the subsequent likelihood of unplanned purchases but that the probability changes over the course of the shopping trip until the effect reverses. Consumers may have an interest in moderating or controlling any additional unplanned purchases. This research shows that an individual shopper's prior history can be leveraged to identify unplanned purchases in advance of the trip. As already mentioned, this suggests that retailers may be able to use the shopper's history such that items that were going to be unplanned could be incorporated into the shopper's pre- shopping planning. That is, the potential unplanned items could in fact become planned items. To the extent that customized shopping lists can be created that enhance customer satisfaction and loyalty, proprietary FSP data has the potential of creating a sustainable competitive advantage since it cannot be "copied" or matched by other retailers. Additional research should be conducted to determine the feasibility of creating individualized shopping lists, their acceptance among consumers, and the overall profit impact on retailers.

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Table 1
Purchase Behavior

	Original Data	Removed Duplicate UPC's
Number of respondents	328	328
Number of purchases	9,988	8,181
% Unplanned	52.7%	53.9%
# of duplicate UPC's	1,807	----
% Unplanned	47.5%	----
Average # of purchases	30.5	24.9
Distribution of purchases:		
Maximum	158	109
75^{th} percentile	39	32
Median	24	20
25^{th} percentile	16	14
Minimum	7	2

Table 2
Independent Variables

Variable	Predicted Sign	Operationalization
Ln(Cum $\$_{n-1}$)	+	The natural log of total amount spent up to the previous selection. Calculated by matching prices to the sequence of items selected from the handheld scanner.
Ln(Unplanned Cum $\$_{n-1}$)	-	The natural log of total amount spent on unplanned items up to the previous selection. Shoppers indicated what items they planned to buy in the pre-shopping survey, this allowed identification of unplanned items.
Hedonic	+	The mean centered hedonicity of the product category for the selected item based on Wakefield and Inman 2003) survey data. Negative and smaller values indicate more “utilitarian” products while higher values indicate more “indulgent” products.
y_{n-1}	- (H1)	Lagged dependent variable equal to 1 if the previous selection was unplanned, otherwise equal to 0.
Ln(n^{th} purchase)	+ (H2)	n indicates the 1^{st}, 2^{nd}, 3^{rd}, … selection by a shopper.
Ln(n^{th} purchase) × y_{n-1}	+ (H3)	Interaction term between the natural log of the number of items selected so far and whether the previous selection was unplanned.
Hedonic_{n-1}	- (H4)	The mean centered hedonicity of the previously selected item.
Ln(PC Mean Price)	- (H5)	Natural log of the mean price of items purchased in the product category by the shopper in the past six months. If no purchases, Ln(PC Mean Price) set = 0.
Ln(PC Var Price)	+ (H6)	Natural log of the variance in prices paid by the shopper in the product category in the past six months. If variance = 0, Ln(PC Var Price) set = 0.
Ln(PC Frequency)	- (H7)	Natural log of how many times the shopper purchased in the product category in the past six months. If frequency = 0, Ln(PC Frequency) set = 0.
Ln(PC Recency)	- (H8)	Natural log of how many days it has been since the shopper’s last purchase in the product category in the past six months. If no purchase in the last six months, Ln(PC Recency) set = Ln(180).

Table 3
Model Results

	(1)		(2)		(3)	
	ACE	**Non-ACE**	**ACE**	**Non-ACE**	**ACE**	**Non-ACE**
Intercept	0.043	0.082	0.116	0.039	-0.027	-0.067
Ln(cum spend)	**0.343**	**0.237**	**0.174**	**0.170**	**0.219**	**0.224**
Ln(unplanned cum spend)	**-0.294**	**-0.160**	**-0.394**	**-0.396**	**-0.398**	**-0.409**
hedonic	**0.093**	**0.088**	**0.105**	**0.106**	**0.126**	**0.120**
My "on promotion"	-0.093	-0.075	-0.103	-0.072	-0.118	-0.101
Ln(PC_ Mean_Price)	**-0.182**	**-0.184**	**-0.188**	**-0.196**	**-0.192**	**-0.196**
LN(PC _Var_Price)	**0.032**	**0.037**	**0.033**	**0.038**	0.011	0.006
Ln(PC_Frequency)	**-0.173**	**-0.178**	**-0.188**	**-0.184**	**-0.231**	**-0.229**
Ln(PC_Recency)	0.009	0.013	0.008	0.011	-0.022	-0.019
Lagged y			**-0.520**	**-0.304**	**-0.395**	**-0.332**
ln(nth purchase)			**0.293**	**0.253**	**0.230**	**0.210**
ln(nth purchase) X lagged y			**0.221**	**0.278**	**0.232**	**0.278**
Lagged Hedonic			**-0.063**	**-0.080**	**-0.070**	**-0.078**
Autocorrelation coef.	**0.299**	---	**0.256**	---	**0.132**	---
LMD	-5083.8	-5166.2	-4906.8	-4952.4	-5006.7	-4995.4
					2	
			Significant shopping zones:		2/58	24/58

Posterior means are displayed.

Bold figures indicate they are statistically significant at 95% level.

Figure 1
Effect of Unplanned Purchase on Probability of Subsequent Unplanned Purchase