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The Role of Within-Trip Dynamics in Unplanned Versus Planned Purchase Behavior

The recent surge in the importance of shopper marketing has led to an increased need to understand the drivers of unplanned purchases. The authors address this issue by examining how elements of the current shopping trip (e.g., lagged unplanned purchase, cumulative purchases) and previous shopping trips (e.g., average historical price paid by the shopper) determine unplanned versus planned purchases on the current trip. Using a grocery field study and frequent-shopper-program data, the authors estimate competing models to test behavioral hypotheses using a hierarchical Bayesian probit model with state dependence and serially correlated errors. The results indicate that shoppers with smaller trip budgets tend to exhibit behavior consistent with a self-regulation model (i.e., an unplanned purchase decreases the probability of a subsequent unplanned vs. planned purchase), but this effect reverses later in the trip. In contrast, shoppers with medium-sized trip budgets tend to exhibit behavior consistent with a cuing theory model (i.e., an unplanned purchase increases the probability of a subsequent unplanned vs. planned purchase), and this effect increases as the trip continues. The article concludes with a discussion of implications for research and practice.

Keywords: shopper marketing, in-store decision making, self-regulation, cuing theory, autocorrelated probit models

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Consumers are increasingly able to avoid or tune out advertising in traditional media, and thus, shopper marketing has experienced marked gains in resources at consumer packaged goods firms (Hein 2008; Lucas 2012). Unplanned purchases are an important outcome of shopper marketing 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. Recent research has examined budget deviation (Stilley, Inman, and Wakefield 2010a), browsing and shopping (Hui, Bradlow, and Fader 2009), social influences (Zhang et al. 2014), and factors that influence unplanned purchases and spending (Bell, Corsten, and Knox 2011; Hui, Inman, et al. 2013; Inman, Winer, and Ferraro 2009).

Despite the recent increase in research focused on the factors that drive unplanned purchases, significant gaps remain. For example, prior research on in-store decision making has employed a survey-based, overall trip–level approach. That is, unplanned purchase behavior has largely been studied as a static behavior that remains constant throughout the duration of the trip (Bell, Corsten, and Knox 2011; Inman, Winer, and Ferraro 2009; Park, Iyer, and Smith 1989). In this research, we address this issue using a unique data set that merges frequent-shopper-program (FSP) data with a field study in a supermarket setting.

Our research extends prior research on in-store decision making by examining within-trip dynamic effects on unplanned versus planned purchase behavior. Recent research in sequential choice has shown that prior decisions and choices can influence subsequent decisions (e.g., Dhar, Huber, and Khan 2007; Khan and Dhar 2006; Vohs and Faber 2007), suggesting that unplanned purchase behavior probably does not remain constant throughout the trip. These findings prompt the question of what this pattern might be and how it might evolve during the trip. Two theories of interchoice behavior are pertinent to this question. On the one hand, most prior research on in-store decision making has applied self-regulation theory to predict that an unplanned purchase will *decrease* the probability of the subsequent purchase being unplanned, because shoppers try to exert self-control and avoid yielding to temptation (e.g., Stilley, Inman, and Wakefield 2010a). As self-regulation resources become depleted, it is more difficult to maintain self-control (Muraven and Baumeister 2000), and this effect may actually reverse later in the trip. On the other hand, a typical grocery store is rife with potential cues

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that may spur shoppers to recall items that they did not plan to buy (Inman and Winer 1998). To the extent that shoppers are receptive to such in-store cues, cuing theory (Lynch and Srull 1982) predicts that an unplanned purchase will *increase* the probability of the subsequent purchase being unplanned because the unplanned selection may cue other forgotten needs.

Relatedly, we examine whether choosing a hedonic (vs. utilitarian) item influences the subsequent purchase decision. Understanding how prior purchases within a shopping trip affect the nature of subsequent purchases is important for designing in-store programs and store layout. We also assess whether a consumer's past purchase history can be used to help differentiate which items will be planned versus unplanned on the current shopping trip. This is of increasing interest to retailers and manufacturers alike, given the importance of getting on the shopping list (Symphony IRI Group 2012). Inman, Winer, and Ferraro (2009) begin to address this issue by examining how unplanned purchase likelihood varies with product characteristics such as category interpurchase time. Whereas they were restricted to using population averages, in this article, we leverage FSP data to examine the usefulness of shopper-level FSP information. Specifically, we examine the effect on planned versus unplanned purchases of a shopper's historical average price paid in the category as well as the shopper's frequency and recency of purchases in each product category.

Our research makes two contributions to the literature on in-store decision making and offers useful implications for shopper marketing practice. First, and most important, we show that unplanned purchases during a shopping trip are state dependent, but the nature of this state dependency evolves over the course of the shopping trip and differs between shoppers. Specifically, we assess the conditions under which the carryover effect predictions of self-regulation theory and cuing theory apply and how they evolve during the trip. Stilley, Inman, and Wakefield (2010a) find that consumers have mental budgets for planned and unplanned items. These authors then use self-regulation theory to describe the deviation between total planned and actual spending for the entire shopping trip. In another study, Stilley, Inman, and Wakefield (2010b) extend this analysis and examine the total amount spent on planned versus unplanned items as a function of promotional savings realized before and after the unplanned budget is exhausted. This process again relies on self-regulatory theory. Both these analyses focus on differences between consumers at the overall trip level. In contrast, our research tests whether self-regulation or cuing theory describes shopping behavior during the trip. If self-regulation or cuing theories are valid, we should observe an incremental increase in the probability of making an unplanned versus planned selection on an item-by-item basis within shopper as the trip progresses. This is a core contribution of our research.

Consistent with our predictions, we find that for shoppers with a smaller trip budget (less than \$64 in our data set), an unplanned purchase decreases the probability that the subsequent purchase will be unplanned versus planned, but this effect reverses over the course of the shopping trip. These results are compatible with self-regulation theory (e.g., Baumeister and Heatherton 1996). For shoppers with medium-sized trip budgets (\$64–\$109), an unplanned selection increases the probability that the next selection will also be unplanned, and this effect grows stronger over the course of the trip. This is congruent with cuing theory (Lynch and Srull 1982). Large-trip-budget (>\$109) shoppers do not change their behavior as the result of an unplanned purchase, suggesting that they are not as mindful of whether their selections are planned versus unplanned. We also find that category hedonicity is inversely related to the subsequent likelihood of an unplanned purchase when a shopper makes a planned purchase, offering field evidence of the licensing effect that was not supported by Hui, Bradlow, and Fader (2009).

Secondarily, similar to Kumar et al. (2008), who use customer sales data to select customers for targeting and to assess the optimal allocation of resources to the selected customers, we demonstrate that a shopper's purchase history (commonly available from FSP data) can be used to identify planned versus unplanned purchases on the current trip. We find that unplanned purchases are less likely for higher-priced categories, for categories that are frequently purchased, and for items that have not been purchased recently. These findings are an important first step in being able to (1) develop a tailored shopping list for each shopper on the basis of individual shopping history and (2) add potentially unplanned items to the shopping list.

The remainder of the article 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 versus planned purchase likelihood. We then detail the data and statistical model and present the results. We conclude with a discussion of the implications of our findings for research and practice.

Conceptual Background

We use several streams of research to guide our understanding of a shopper's item-by-item selection of planned versus unplanned items. We begin with self-regulation behavior and cuing theory, followed by a discussion of the licensing effect and the FSP-based variables. 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 has suggested that shoppers have distinct goals for shopping trips (e.g., a "fill-in" trip, a "weekly replenishment" trip; Bell, Corsten, and Knox 2011), plans to purchase specific items and/or brands from a category, and a budget for planned and unplanned items (Stilley, Inman, and Wakefield 2010a, b). Park, Iyer, and Smith (1989, p. 423) 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 before entering the store or as items the shopper recognizes as needs or wants after entering the store. This latter category includes items for which the consumer experiences a sudden, unreflective urge or impulse to buy (Rook 1987). Regardless of whether the item is a forgotten need or a want prompted by the shopping experience, the shopper must balance the desire for many different products while keeping to the substantive and economic goals of the shopping trip.

Dynamics of Unplanned Purchases

Walking through a grocery store, a shopper is confronted with many more unplanned than planned items for potential purchase. Both self-regulation and cuing theory suggest that unplanned purchases are dynamic over the course of the shopping trip. We consider two types of dynamics: (1) carryover effects from earlier purchases on subsequent unplanned versus planned purchases and (2) the change in the probability of making an unplanned versus a planned purchase over the course of the shopping trip. Recognizing the role of self-regulation, Inman, Winer, and Ferraro (2009) identify several strategies a shopper might employ to limit unplanned purchases, including using a shopping list, shopping only in aisles where planned items are located, and limiting the amount of time spent shopping. Stilley, Inman, and Wakefield (2010a) demonstrate that self-regulation concepts such as shopper impulsiveness and resource depletion in the form of how long a consumer has shopped are associated with aggregate unplanned purchases. In contrast, we consider the applicability of self-regulation theory to the sequence of specific selections made by a shopper.

Self-regulation. Baumeister and Heatherton (1996) review the three components of self-regulation. First, there must be a 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 with the desired state. In the context of grocery shopping, the existence of mental trip budgets and consumers' ability to stay reasonably close to those budgets suggests that there is goal setting and monitoring. Stilley, Inman, and Wakefield's (2010a) study shows that shoppers had an average mental budget for the shopping trip of \$58.46 with an average amount spent of \$58.93, while in another study, they report an average budget of \$66.45 and spending of \$69.84 (Stilley, Inman, and Wakefield 2010b).

The third component of the self-regulation model is what Sayette (2004) refers to as "altering responses"—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 shopper makes an unplanned purchase, it will decrease the probability of a subsequent unplanned purchase as the shopper aims to maintain an overall budgetary goal for the trip. In Stilley, Inman, and Wakefield (2010a, b), before beginning their shopping trips, consumers had budgeted \$17.35 and \$20.37, respectively, to unplanned purchases. Because these amounts are less than the amount budgeted for planned items, to stay within the overall budget, an effective altering response would be to resist the attraction of a subsequent unplanned purchase.

However, self-regulation theory suggests that a shopper's ability to stick to budgetary and other shopping objectives may change over time due to self-depletion of regulatory resources. During a shopping trip, shoppers are exposed to numerous environmental factors that have been shown to decrease self-control performance, such as noise (Glass, Singer, and Friedman 1969; Hartley 1973), crowding (Evans 1979; Sherrod 1974), and proximity to a tempting product (e.g., Vohs and Heatherton 2000). As more items are purchased, self-regulation depletion is likely (for a review of self-regulation depletion, see Muraven and Baumeister 2000). This suggests that the likelihood of an altering response decreases as the shopping trip continues.

Will a shopper's behavior change when he or she exceeds the expected expenditures on a shopping trip? To avoid going over the trip budget by a greater amount, shoppers may stick to their enumerated list and forgo any additional unplanned purchases. However, if resource depletion increases as the trip progresses, this decreases self-control and increases the probability of goal abandonment (Cochran and Tesser 1996; Soman and Cheema 2004). Thus, at some point in the shopping trip, an unplanned selection may actually increase the probability that the next selection will be unplanned as opposed to planned.

Cuing theory. Park, Iyer, and Smith (1989) suggest an alternative to self-regulation theory. They argue that more active cognitive processing during the shopping trip will lead to more unplanned purchases because 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 (vs. planned). That is, cuing theory suggests the opposite of the altering response proposed by self-regulation theory.

The longer a shopper is in the store and exposed to more items, the greater the probability that the shopper will be exposed to items that cue a forgotten want or need. Stilley, Inman, and Wakefield (2010a) report that time in the store is positively related to unplanned purchasing (moderated by the shopper's mental budget for unplanned purchases), but they attribute this finding to self-regulation resource depletion. However, previous analyses were conducted at the trip level—and therefore, between consumers—whereas our research focuses on within-consumer analysis and how planned versus unplanned purchasing changes over the course of the shopping trip.

Both cuing theory and self-regulation theory suggest that the effect of an unplanned purchase will change over the course of the shopping trip and that unplanned versus planned purchases are more likely later in the trip. Cuing theory implies that an unplanned purchase will trigger other wants and needs, leading to an increased probability that the next selection will be unplanned as opposed to planned. As the shopping trip progresses, more needs are cued and more unplanned purchases are made. Self-regulation theory suggests that shoppers will engage in altering responses to stick to the substantive and economic goals of the shopping trip. In this case, an unplanned purchase will increase the probability of a planned purchase on the next selection as the shopper reverts back to planned purchases. However, as the result of resource depletion, the reaction to making an unplanned purchase should change as the shopping trip continues. Although both theories predict that an unplanned purchase is more likely to prompt an additional unplanned purchase as the trip progresses, cuing theory and self-regulation theory differ on early reactions to unplanned purchases.

Importantly, we argue that the shopper's purpose for the trip influences whether cuing theory or self-regulation theory explains shopper behavior. Bell, Corsten, and Knox (2011) show that the more abstract the goal of the shopping trip, the greater the total number of unplanned purchases. To the extent that a shopper has a well-defined purpose, such as shopping for immediate consumption or for meals for the same day (Bell, Corsten, and Knox 2011), the shopping trip will be more goal directed, and we expect the self-regulation model to be more descriptive. However, when a shopper is on a larger shopping trip with less well-defined goals, he or she should be more open to in-store cues (i.e., cuing theory better fits this behavior). In our analysis, we use each shopper's overall a priori planned budget for the shopping trip as a proxy for the shopping goal to test our prediction that the dynamics of unplanned purchases differ between shoppers.

The Licensing Effect

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 regarding potential carryover effects. Our examination of the literature suggests that the less hedonic an item is, the more likely the shopper should be to buy an unplanned versus a planned item on the subsequent purchase.

According to the licensing effect (Khan and Dhar 2006), making a virtuous decision licenses people 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 something that is healthy vs. tasty), which suggests that deciding to purchase a healthy but less tasty alternative should lead to increased likelihood of subsequently selecting a more hedonic, unplanned item. Likewise, Fishbach and Dhar (2005) find that when consumers have conflicting goals that they pursue over time, even perceived lack of progress on the focal goal (e.g., eating healthy) can lead to disengagement. 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 willpower remaining to resist making an unplanned purchase on the next selection.

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

Shopper-Level FSP-Based Factors

Retailers' FSPs enable them to track shoppers' purchases over time. The FSP data from the retailer that participated in this study capture category and brand purchased, price paid, quantity purchased, and date of purchase. Whereas Inman, Winer, and Ferraro (2009) use 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 and the frequency and recency of category purchase. We discuss predictions for each of these factors in the following subsections.

Average purchase price. Recent research by Stilley, Inman, and Wakefield (2010a, b) shows that shoppers have mental budgets, or spending expectations, for grocery trips and try to avoid exceeding these amounts. Even though there may be some room in the shopper's 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). In addition, 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 as opposed to a planned basis.

Frequency and recency. To plan purchases in advance, consumers must be able to cognitively recognize the need or want. Consumers tend to have difficulty retrieving all of 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). However, this effect may be tempered by the amount of time that has elapsed since the last purchase. Items that have been purchased relatively recently may not need to be "restocked," and such purchases may be opportunistic and unplanned. In contrast, items that have not been purchased for a relatively long time are more likely to be purchased on a planned versus unplanned basis as a result of the consumer noting the household's exhausted inventory of that item.

Empirical Test

Data

The data we use to test our behavioral hypotheses are from a field study first discussed by Stilley, Inman, and Wakefield

(2010b). Our analysis differs from theirs in that their analysis focuses on cross-sectional differences in the total amount spent as a function of how much of the budget is still available, whereas our research focuses on the individual-level sequence of planned and unplanned purchases. A random sample of 400 customers from two grocery stores located in a southwestern U.S. city were intercepted as they entered the supermarket and asked to participate in a marketing research study. We define an unplanned purchase as one that was not planned before the consumer entered the store. We follow the procedures of prior researchers (Hui, Huang, et al. 2013; Inman, Winer, and Ferraro 2009; Kollat and Willet 1967; Park, Iyer, and Smith 1989), 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 return for their participation. They were asked what items they intended to buy, how much they expected to spend on the planned purchases, and how much they expected to spend overall (i.e., their overall trip budget). Furthermore, shoppers were asked how often they shop for groceries, how frequently they visit the focal store, and whether they were shopping for a particular occasion on the current trip. Planned versus unplanned purchases were determined by comparing responses in the preshopping survey with shoppers' 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 cart. This method records the specific order in which items were selected and allows for 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 receipts, 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) offer more details, including evidence that the research methodology did not alter the average amount shoppers spent. Specifically, they compare each shopper's spending on the survey trip with spending on similar trips using the FSP data and report that the difference between the amount spent on the day of the survey and the preceding six-month mean is not statistically significant ($F = 1.70$). For the purposes of our study, a demand effect would manifest itself as a shopper deliberately changing the sequencing of planned versus unplanned items. Although participants were instructed to scan items as they selected them, they were given no indication that the sequence of planned versus unplanned items was relevant. Because the aggregate amount spent was not different between this trip and previous trips, it seems unlikely that shopping behavior changed. Although it is theoretically possible that shoppers systematically changed the sequence of planned and unplanned items while keeping their overall spending unchanged, this seems unlikely. However, we cannot definitively rule out demand effects, and this is a potential limitation of the current methodology, which we discuss further in the conclusion.

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 three 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, 1,807 items represented duplicate universal product codes (UPCs; e.g., two cans of tomatoes, several loaves of bread) for the same shopper. Because our analysis focuses on sequential effects, we removed these duplicate UPCs removed from the data set 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.

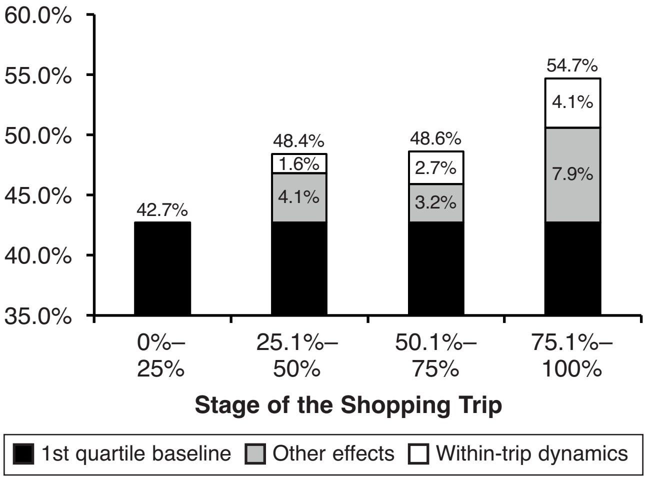
Model

In our data, we observe the sequence of selections by each shopper, and our goal is to determine whether systematic factors are associated with whether a selection is planned or unplanned. In this sense, our analysis is similar to that performed by Inman, Winer, and Ferraro (2009), but our focus is on dynamic factors within the shopping trip. Our conceptual discussion provides theoretical support for our thesis that the propensity to make an unplanned (vs. planned) purchase should change over the course of the shopping trip. Figure 1 illustrates the proportion of selections that are unplanned at different stages of the trip. In the first quarter of the shopping trip, 42.7% of the selections are unplanned, but among the fourth quarter of selections, 54.7% are unplanned. This model-free evidence suggests that selecting planned versus unplanned items is dynamic. Figure 1 also previews one of our key findings, showing that the incre-

TABLE 1
Purchase Behavior

	Original Data	Removed Duplicate UPCs
Number of respondents	328	328
Number of purchases	9,988	8,181
Percentage unplanned	52.7%	53.9%
Number of duplicate UPCs	1,807	—
Percentage unplanned	47.5%	—
Average number of purchases	30.5	24.9
Distribution of Purchases		
Maximum	158	109
75th percentile	39	32
Median	24	20
25th percentile	16	14
Minimum	7	2

FIGURE 1
Proportion of Selections That Are Unplanned at Different Stages of the Shopping Trip with Modeled Sources of Increase



mental increase from within-trip dynamics grows over the course of the shopping trip.

Our approach is to model planned versus unplanned purchases as a function of variables that describe the product, within-trip dynamics, and FSP variables. Our dependent variable is binary, indicating whether the nth selection for person i is planned ($y_{in} = 0$) or unplanned ($y_{in} = 1$). Our analysis is restricted to determining whether there are systematic differences between the selection of planned and unplanned items in a shopping trip. We define and measure all variables without knowing whether the current selection is planned or unplanned, but they are conditioned on observing a selection. A different analysis designed to predict whether an unplanned purchase is made at all (an unconditional analysis) would require a different modeling approach and significantly more information. We return to this topic when discussing further research. Our statistical model is given by

$$(1) \qquad y^*_{in} = \beta_{io} + \beta_i' x_{in} + \gamma_i y_{i,n-1} + \delta' z_{in} + \varepsilon_{in},$$

$$\varepsilon_{in} = \phi\varepsilon_{i,n-1} + \nu_{in}, \text{ where } \nu_{in} \sim N\left(0, \sigma^2_\nu\right),$$

$$y_{in} = 1 \text{ if } y^*_{in} > 0, \text{ else } y_{in} = 0,$$

where x_{in} is a vector of independent 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 versus planned purchase. The vector β_i, the intercept β_{i0}, 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.

Consistent with Inman, Winer, and Ferraro (2009), our model conceptualizes the selection of a planned versus unplanned item as a function of the attributes of the product but not of competing products. An item is either planned or unplanned, but the selection of an unplanned item does not preclude the selection of some other planned (or unplanned) item on a subsequent selection. Whereas the choice of Folger's coffee typically precludes the choice of Maxwell House coffee, the selection of an unplanned can of coffee does not preclude the subsequent selection of a planned bag of flour. Thus, our model is not comparable to discrete brand choice models in which the explanatory variables include not only the selected brand's variables but also the values of other brands in the consideration set. Rather, it is closer in spirit to purchase incidence models in which, conditional on a shopping trip, the purchase in a product category is a function of that product category's characteristics in a given week but not the characteristics of other product categories (see, e.g., Gupta 1988). We discuss the shopping zone variables, error structure, and heterogeneity after reviewing the independent variables summarized in Table 2.

Independent Variables

Cumulative spending. Stilley, Inman, and Wakefield (2010b) 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 include the natural logarithm of cumulative spending on unplanned purchases to control for a self-imposed budget on unplanned purchases; we expect the effect of cumulative unplanned spending to be negative.

We also consider the effect of cumulative spending on planned items, which can play two roles. First, as a consumer gets planned items and uses up the budget allocated to those purchases, it is more likely that any remaining selections will be unplanned. Second, as the shopping trip progresses, consumers are exposed to more cues and self-regulation resources are likely to become depleted, increasing the likelihood of making unplanned versus planned purchases. We therefore expect the coefficient of the natural logarithm of cumulative planned purchases to be positive, although we cannot definitively conclude whether it is due to the exhaustion of the planned budget, self-regulation resources, or cues in the environment.

Product-related factors. In line with previous empirical research, we include several variables related to the product and/or product category. We expect shoppers to avoid making unplanned versus planned purchases of items that are priced above their historical average price. An item might be above its average price because of a price increase or because the item is frequently on sale but not on this particular shopping trip. An item is designated as having a "higher price" if its current price is at least 10% above its historical average. We discuss "on sale" items when we review the results. Furthermore, Inman, Winer, and Ferraro (2009) show that product category hedonicity has a significant impact on unplanned purchase probability. Product categories were assigned a hedonic score on the basis of the hedonicity ratings reported by Wakefield and Inman (2003) and were then mean centered; more utilitarian goods have a negative score, while more "fun" items have a positive

TABLE 2
Independent Variables

Variable	Predicted Sign	Operationalization
Ln(Planned Cumulative $\$_{n-1}$)	+	The natural log of total amount spent on planned items up to the previous selection. We calculated this by matching prices to the sequence of items selected from the handheld scanner. Shoppers indicated what items they planned to buy in the preshopping survey, which allowed for identification of planned and unplanned items.
Ln(Unplanned Cumulative $\$_{n-1}$)	–	The natural log of total amount spent on unplanned items up to the previous selection
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.
Higher Price	–	Equal to 1 if the current price is 10% higher than the average price of that UPC in the past six months; otherwise equal to 0
y_{n-1}	+/–	Lagged dependent variable equal to 1 if the previous selection was unplanned; otherwise equal to 0
Ln(nth purchase) × y_{n-1}	+	Interaction term between the natural log of the number of items selected so far and whether the previous selection was unplanned. n indicates the first, second, third, … selection by a shopper.
Over trip budget	+	Equal to 1 when the cumulative purchases exceed the stated budget from the preshopping survey; otherwise equal to 0
Hedonic_{n-1}	–	The mean-centered hedonicity of the previously selected item
$\text{Hedonic}_{n-1} \times y_{n-1}$	N.A.	Interaction term between the mean-centered hedonicity of the previously selected item and the lagged dependent variable
Ln(PC Mean Price)	–	Natural log of the mean price of items purchased in the product category by the shopper in the past six months. If there are no purchases, Ln(PC Mean Price) set = 0.
Ln(PC Frequency)	–	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 Ratio)	+	Natural log of how many days it has been since the shopper's last purchase in the product category, divided by the product category's average interpurchase time. If no purchase in the last six months, recency is set = 180.

Notes: N.A. = not applicable.

score. We expect the coefficient of the hedonicity variable to be positive (i.e., hedonic items are more likely to be unplanned rather than planned).

Lagged purchase. 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 1981b), 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. For a shopper to stick to an overall budget and shopping goals, self-regulation theory implies that a shopper will return to planned items after making an unplanned selection. However, if an unplanned purchase cues another forgotten want or need, a subsequent selection is more likely to be unplanned than planned. As mentioned previously, we expect that self-regulation theory will describe shoppers with smaller trip budgets and, therefore, the coefficient on the lagged dependent variable will be negative. For larger-trip-budget shoppers, we expect a positive coefficient on the lagged dependent variable consistent with cuing theory.

Importantly, we test our thesis that the reaction to choosing an unplanned item changes over the course of the shopping trip. A shopper's desire or ability to stick to his or her original shopping goals may be depleted as the shopping trip progresses, so the strategy of deliberately selecting a planned item after making an unplanned selection may be abandoned at some point. Cuing theory also suggests that the shopper's active cognitive processing will lead to more recognized wants or needs as the shopping trip progresses. We test this using an interaction between the lagged dependent variable and the natural log of the cumulative number of selections made up to the current selection. For this test, the cumulative number of selections represents the length of the shopping trip; using the log of the cumulative number of selections limits the correlation between this variable and the log of cumulative spending on planned items.[1] An alternative would be to use the amount of time between entering the store and the current selection, which would require a "time stamp" from the handheld scanner. Unfortunately, this measure is not available in our data.

[1]The correlation between Ln(Planned Cumulative $\$_{n-1}$) and Ln(nth purchase) × y_{n-1} is .23. We also included the main effect for Ln(nth purchase) in the model, but it was not statistically significant; therefore, we removed it. Model coefficients and the substantive results do not change when Ln(nth purchase) is included in the model.

Formally, our measure of resource depletion and cognitive processing accords more effect to the actual deliberation and choosing of products rather than merely being in the store. However, we expect the two measures (cumulative time and cumulative selections) to be highly correlated.[2] Both cuing theory and self-regulation theory imply that the coefficient on this interaction term will be positive. Similarly, we expect that after a shopper exceeds the stated budget for the shopping trip, the cumulative effect of being exposed to many cues and/or resource depletion will lead to increased purchases of unplanned as opposed to planned items. We test this expectation by including a dummy variable equal to 1 for selections made after the trip budget is exceeded (and equal to 0 before that point); we expect the coefficient of the dummy variable to be positive.

The licensing effect suggests that the purchase of a low-hedonic item will give the shopper "permission" to indulge and select a more "fun" item with a higher hedonicity rating. Because unplanned items are more likely to have higher hedonicity ratings (Inman, Winer, and Ferraro 2009), this suggests that purchasing an item with a low hedonicity rating will increase the probability that the subsequent item will be unplanned. To test this prediction, we lag the aforementioned hedonicity variable 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, its coefficient should be negative. Furthermore, to test whether this effect is influenced by whether the previous item was planned or unplanned, we include the interaction between lagged hedonicity and y_{n-1}.

We constructed individualized shopping variables by analyzing the previous six months' FSP shopping history for each respondent. For each product category for each individual, we computed the average price paid in the category, the number of times a purchase was made, and the recency (in number of days) of the last purchase. We transformed the recency variable to recognize that some purchase categories are consumed more quickly than others (e.g., the interpurchase time for milk is typically shorter than for maple syrup). For each product category in our data, we calculated the average interpurchase time. We computed the ratio of the shopper's recency to the average interpurchase time for the given product category. The natural logs of these variables were then merged into the current shopping trip data. We expect the coefficient on price to be negative, indicating that higher-priced items are more likely to be planned. Similarly, we expect the coefficient on frequency to be negative, indicating that more frequently purchased items are more likely to be planned. The coefficient on recency should be negative, indicating that items purchased a relatively longer time ago are more likely to be planned as a result of exhausting a household's existing stock. Table 2 summarizes the variables and the expected coefficients.

Shopping Zone Variables, Error Structure, and Heterogeneity

The self-regulation and cuing models imply that the selection of a planned or unplanned item is not independent of a shopper's prior selections. In addition to the independent variables already discussed, other effects, such as environmental factors (e.g., store layout), might induce sequential effects in planned/unplanned purchase behavior. For example, being in the cookies aisle might result in more unplanned purchases than being in the produce section. Similarly, the purchase of hamburger meat may cue the unplanned need for ketchup and prompt the shopper to go to the condiments aisle and make a selection. Furthermore, store managers may deliberately lay out the store to encourage unplanned purchases; excluding variables that capture this effect may lead to an endogeneity problem. We control for store layout by including shopping zone dummy variables that capture the area of the supermarket in which the current selection is made (for a similar approach, see Hui, Bradlow, and Fader 2009) as well as the previous selection. Our data are from two stores with different layouts. In the first store, we identified and coded 34 distinct shopping zones, whereas the second was coded into 24 shopping zones. The shopping zones typically coincide with the aisles in the supermarket, meat or dairy sections, checkout, and special displays.

Even after including the independent variables and shopping zone variables, there may be other unaccounted-for environmental factors that result in correlations between selections. Our model captures these factors through serially correlated error terms, represented as a first-order autoregressive process and the parameter ϕ. When $|\phi| < 1$, the sequence of selections is stationary in the sense that the influence of previous selections dies off in an exponential manner (see, e.g., Franses 1998; 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.

In the context of a utility-maximizing discrete choice model, Seetharaman (2004) offers a useful typology of dynamic effects. We do not formulate the model in terms of the "utility" of a planned versus an unplanned purchase, but there are some direct parallels in terms of the behavioral interpretation. As we have noted, the lagged dependent variable captures "state dependency" in the form of the shopper altering his or her behavior or being cued to another forgotten want or need as the result of making an unplanned purchase. Lagged hedonicity and shopping zone variables capture characteristics of the previous purchase that may affect the shopper's propensity to make a planned

[2]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 endogenous because purchasing more unplanned items entails spending more time in the supermarket. However, this is not a concern in the current study because our unit of analysis is the item-by-item selection process rather than the aggregate number of purchases.

versus unplanned purchase, analogous to Seetharaman's (2004) carryover effects of marketing variables. The autocorrelated error (ACE) is a form of "habit persistence" that captures effects on the shopper that are not observed by the researcher. In our model, we posit that the habit persistence results from environmental or other factors that influence the probability of making a planned or unplanned purchase, which decay over time.[3]

Stewart (2006) offers a straightforward introduction to the random-effects probit model with ACEs and a lagged dependent variable. Keane (1997) provides a more elaborate example in the context of brand choice. As noted previously, the coefficient on the lagged dependent variable will be used to test whether and how shoppers alter their shopping behavior as the result of making an unplanned selection. Whether the average γ_i is greater or less than 0 will provide evidence regarding 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 example, if there is positive autocorrelation, but it is not modeled, the value of γ will have an upward bias.

To compare models with and without ACEs, we parameterize the error variance term in Equation 1 as $\sigma_v^2 = (1 - \phi^2)$. Note that, in an ACE regression, the full error covariance matrix is given as the following (Judge et al. 1988, p. 387):

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

which is consistent with our latent variable structure in Equation 1. For a probit model, the usual way to identify the model is to set $\sigma_v^2 = 1$; with $\phi = 0$, the error covariance matrix is simply the identity matrix. However, with $\sigma_v^2 = 1$ and $|\phi| > 0$, the diagonal elements in Equation 2 are greater than 1, resulting in an increase in the error variance. Increasing the error variance reduces model fit statistics. We set $\sigma_v^2 = (1 - \phi^2)$ so that the diagonal elements in Equation 2 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 ACEs.

We adopt a Bayesian approach for inference and estimation, which has a bearing on how we model heterogeneity and test for differences between shoppers' goals or plans for the trip. In panel data, state dependency may arise as a result of not properly accounting for heterogeneity (Heckman 1981b). Equation 1 includes fixed parameters across the sample as well as individual-level heterogeneity. Heterogeneity is modeled as $[\beta_{i0}, \{\beta_i\}, \gamma_i] \sim N_p(\overline{\beta}, \Sigma)$, which is a multivariate normal distribution for the stacked vector $[\beta_{i0}, \{\beta_i\}, \gamma_i]$. 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 in simulated data with individual-level ϕ_i. Similarly, because each respondent often made only one selection or no selections in a particular shopping zone, we pooled the effects of the shopping zone variables across respondents. The prior on ϕ is uniform U(–1, 1); we use conjugate but diffuse priors for δ, Σ, and $\overline{\beta}$ (full details appear in the Web Appendix). Allowing for individual-level parameters (particularly on the intercept term) controls for differences in the purpose of the trip (Bell, Corsten, and Knox 2011; Knox, Bell, and Corsten 2011); individual differences such as using a list, gender, and payment type (Inman, Winer, and Ferraro 2009); impulsivity (Stilley, Inman, and Wakefield 2010a); and other person/trip factors that have been shown to influence the amount of unplanned purchasing at the trip level.

As noted previously, shoppers' plans or goals for the trip may determine whether the self-regulation or cuing model best describes their behavior. Because we do not have explicit information regarding the purpose of the trip analogous to the measures used by Bell, Corsten, and Knox (2011), we use the total amount that the shopper planned to spend before entering the supermarket as a proxy for the shopper's plans. We take smaller trip budgets to indicate more targeted and goal-oriented shopping trips, whereas larger trip budgets indicate less well-defined goals such as "major trip, weekly or less often," as used by Bell, Corsten, and Knox. The amount each shopper planned to spend on the shopping trip ranged from a minimum of \$7 to a maximum of \$400, with a median of \$50 and an average of \$66.45. As we described previously, we predict that the self-regulation model will characterize smaller-trip-budget shoppers, whereas the cuing model will characterize shoppers with larger trip budgets.

Models with individual-level heterogeneity must consider whether the random effects are correlated with the independent variables included in the model (Wooldridge 2010). In models estimated with maximum likelihood, in which the random effects are integrated out of the likelihood, failure to account for the correlation can result in endogeneity. In our Bayesian model, the individual-level parameters are not integrated out of the likelihood function, so there is not the same endogeneity problem. However, it still might be the case that the individual-level effects are a function of variables either included or not included in the model. To address this possibility, we allow for heteroskedasticity in the model intercept terms between shoppers. Our approach follows that of Bresson, Hsia, and Pirotte (2011), who introduced the model in the context of a linear regression model with panel data and individual-level heterogeneity. As they note, heteroskedasticity could arise as a result of differences between shoppers (e.g., income) or because the individual-level parameters are correlated with the independent variables.

In the full model, the distribution of heterogeneity is represented as

[3]We do not include a term for lagged utility, as Seetharaman (2004) does for his utility-maximizing model. We include geometric decay only for the ACE, or "habit persistence."

$$\beta_{i0} \sim N\left(\theta_0' w_i, \sigma_i^2\right), \text{ and} \tag{3a}$$

$$\left[\{\beta_i, \gamma_i\}\right] \sim N_{p-1}(\theta w_i, \Delta), \tag{3b}$$

where Equation 3a represents a regression equation with an individual-level variance term to capture the heteroskedasticity. Equation 3b is a multivariate normal regression, and the vector w_i includes an intercept term and the mean-centered budget for shopper i. Our model differs from that of Bresson, Hsia, and Pirotte (2011) in that we include explanatory variables in the distribution of heterogeneity and our base model is a correlated probit as opposed to a linear regression. The Web Appendix reports full details of the model.

There are several possible sources of endogeneity in our model. Endogeneity occurs when the independent variables are correlated with the error term. First, as Heckman (1981a, p. 102) notes, if there is serial correlation in the error terms, the lagged dependent variable will be correlated with the error term. We address this in our model by explicitly modeling the ACE term with $\phi\varepsilon_{i,n-1}$, where ν_{in} is assumed to be the i.i.d. error term. Second, if relevant variables are omitted from the model and those variables are correlated with the included independent variables, this can lead to an endogeneity problem. We believe the most likely sources of omitted variables are environmental occurrences that vary in different parts of the store (e.g., product assortment, end-of-aisle displays, shelf notices). As noted previously, we control for these factors by including shopping zone dummy variables for the current and lagged selection. If these variables are correlated with the other independent variables (i.e., the z variables are correlated with the x variables), we would expect to observe a significant change in the parameter estimates between models with and without the shopping zone variables. As we have discussed, another possible source of endogeneity occurs if the random intercept terms are correlated with the independent variables (i.e., between β_{i0} and the x variables). Given our hierarchical Bayes model, we do not believe this is a concern, but there could still be unaccounted-for variables determining the difference between the random effects. We model this through the heteroskedasticity in the upper level of the hierarchical Bayes structure in Equation 3a. Despite controlling for these possible sources of endogeneity, it still may be the case that the x variables are correlated with the ν variables. This is ultimately an empirical issue, and we know of no formal statistical test that would apply in our model structure. However, our model does allow for an empirical estimate of the realized values of ν—call them $\hat{\nu}$—and we test to determine whether the independent variables are correlated with the realized error terms.

Data augmentation facilitates estimating the model parameters using Markov chain Monte Carlo methods without relying on high dimensional integration. We ran Markov chain Monte Carlo chains for 10,000 iterations and used a sample of every 10th from the last 5,000 for model inferences. We assessed convergence by inspecting the time series plots of model parameters and reestimating 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 calculate 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). To calculate the LMD, we need 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 ACEs. We use the GHK to simulate probabilities even in models without correlated error terms to control for noise resulting from the simulation.

Results

We estimated four models. The purpose of the first three is to determine the effect of various independent variables as well as whether we need to include ACEs. Model 1 includes the cumulative spending variables and the product category hedonicity as well as whether the item is priced higher than in previous weeks. Model 2 subsumes Model 1 and adds shopping trip dynamics, and Model 3 subsumes Model 2 and adds the shopping zone variables. The final model uses the best of the preceding models, tests the effect of planned budget on the model dynamics, and incorporates heteroskedasticity into the distribution of heterogeneity. We estimated Models 1–3 with and without ACEs. Table 3 presents parameter estimates and fit statistics. We estimated the LMD for Models 1–3, and it favors the model with the highest value; for the full model, we used posterior predictive model checking to assess the adequacy of the model.

Models 1–3. First, we note that in all three instances, the models with the ACE structure fit better than those without. In Models 2 and 3, the coefficient for the lagged dependent variable or state dependence went from negative and statistically significant (–.272 and –.275, respectively) to not significant when the ACEs were eliminated from the model, illustrating the potential biasing effect of excluding correlated error terms in models of sequential choice. The autocorrelation coefficient is positive in all three models (.346, .228, and .126) but is smallest in Model 3, in which the current and lagged shopping zone variables capture some of the unexplained carryover between selections.

The LMD of –4,845.4 favors Model 2 with the ACEs but without the shopping zone variables; this specification is used in the full model. With the possible exception of the autocorrelation coefficient, we note the similarity in the parameter estimates between the models with and without the shopping zone variables; this suggests that including the shopping zone variables does not affect the correlational structure between the X_n variables and the error term. However, if the independent variables are correlated with the error term, this could indicate that sources of endogeneity still remain in the model. For each observation, we calculated the empirical estimate of the error term $\hat{\nu}_{in}$ from Equation 1 and calculated the correlation coefficient between it

TABLE 3
Model Comparison: Posterior Means

	Model 1		Model 2		Model 3		Full Model	
	ACE	Non-ACE	ACE	Non-ACE	ACE	Non-ACE	Intercept	Budget
$\bar{\beta}_0$ Intercept	–.319**	–.288**	.248**	.188**	.037	–.004	.306**	.000
$\bar{\beta}_1$ Ln(Planned Cumulative $\$_{n-1}$)	.274**	.146**	.250**	.236**	.277**	.274**	.361**	.000
$\bar{\beta}_2$ Ln(Unplanned Cumulative $\$_{n-1}$)	–.131**	.000	–.217**	–.239**	–.231**	–.246**	–.376**	.001
$\bar{\beta}_3$ Hedonic	.090**	.086**	.118**	.119**	.155**	.107**	.107**	.001
$\bar{\beta}_4$ Higher price	–.114**	–.140**	–.131**	–.140**	–.124*	–.124*	–.153**	.000
$\bar{\gamma}$ y_{n-1} (state dependency)			–.272**	–.108	–.275**	–.134	–.221*	.006**
$\bar{\beta}_6$ Ln(nth purchase) × y_{n-1}			.154**	.213**	.200**	.216**	.161**	–.002**
$\bar{\beta}_7$ Over trip budget			.224**	.218**	.150*	.164*	.256**	–.003
$\bar{\beta}_8$ Hedonic$_{n-1}$			–.164**	–.179**	–.185**	–.196**	–.179**	.001
$\bar{\beta}_9$ Hedonic$_{n-1}$ × y_{n-1}			.189**	.185**	.206**	.214**	.203**	.000
$\bar{\beta}_{10}$ Ln(PC Mean Price)			–.132**	–.135**	–.184**	–.184**	–.149**	.001
$\bar{\beta}_{11}$ Ln(PC Frequency)			–.204**	–.206**	–.254**	–.257**	–.223**	.000
$\bar{\beta}_{12}$ Ln(PC Recency Ratio)			–.046*	–.052*	–.064**	–.065**	–.048*	.000
ϕ autocorrelation coefficient	.346**	—	.228**	—	.126**	—	.187**	
Significant Shopping Zone Variables								
Current zone					18/58	20/58	Distribution of σ_i^2	
Lagged zone					5/57	3/57	25th = .213, 50th =	
LMD	–5,167.6	–5,252.5	–4,845.4	–4,904.1	–5,050.5	–5,107.3	.360, 75th = 1.058	

*Indicates that 90% of the posterior mass is away from 0—that is, the estimate is significant at the 90% level.
**Indicates that 95% of the posterior mass is away from 0—that is, the estimate is significant at the 95% level.
Notes: Log-marginal density favors the model with the highest number. PC = product category.

and each of the independent variables. Across the posterior distribution of the parameters, none of the correlation coefficients was significantly different from 0 at a 95% level,[4] which provides additional evidence that endogeneity is not a major concern in the model.

Full model. The right-hand side of Table 3 contains the parameter estimates from the full model, which is Model 2 with planned budget as an explanatory variable for the other parameters and heteroskedasticity on the individual intercepts. We first discuss model fit and evidence of heteroskedasticity and then turn to the substantive interpretation. In the full model, the first observation for each shopper had to be dropped (unlike Models 1–3); therefore, we did not calculate the LMD, because comparison with the earlier models would not be meaningful. Rather, we use the posterior distribution of model parameters, generate planned and unplanned purchases for each shopper, and then compare the distribution of unplanned purchases with the actual data. This is a form of posterior model checking in which a salient aspect of the original data is compared with predictions from the model; systematic departures suggest that the model is not adequate (for an extended discussion and references, see Gilbride and Lenk 2010). In our case, the number of unplanned purchases made by each shopper is not directly modeled but is an ancillary statistic.

Figure 2 and Table 4 show that the mean and median of the predicted unplanned purchases (13.8 and 9.0) match very closely with the actual distribution (13.4 and 9.0). Figure 2 shows that there is some tendency to overstate the fre-

FIGURE 2
Posterior Predictive Model Check: Distribution of Unplanned Purchases

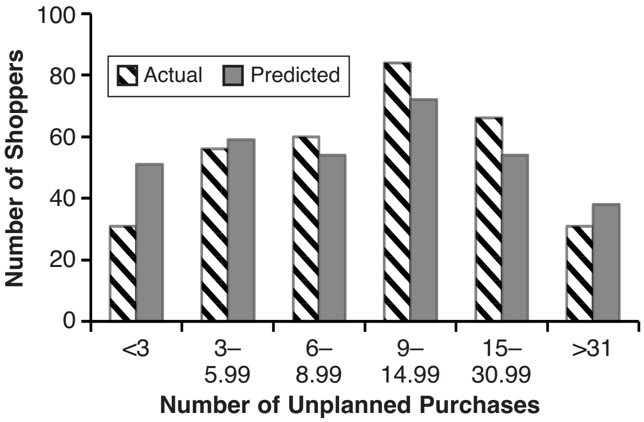


TABLE 4
Posterior Predictive Model Check: Summary Statistics for Unplanned Purchases

	Number of Unplanned Purchases Across Shoppers	
Percentile	Actual	Predicted
25th	5.0	4.5
50th	9.0	9.0
75th	17.0	18.0
Average	13.4	13.8

[4]Consistent with the tables, in the text we refer to a parameter as being "significant" when 95% of its posterior mass is away from 0.

quency of unplanned purchases for the very highest and lowest part of the distribution. Across the 328 shoppers, the predicted number of unplanned purchases was higher than the actual in 50.3% of the cases and lower in 49.7%, and the correlation between the predicted number of unplanned purchases per shopper and the actual number was .995. We believe that this provides evidence that the full model is adequate. With regard to heteroskedasticity, as the bottom right-hand side of Table 3 shows, the 25th percentile of σ_i^2 is .213, whereas the 75th percentile is 1.058, suggesting that there are differences in the error variance of the model intercept across shoppers.

In the "Full Model" columns in Table 3, the parameter estimates for the "Intercept" column can be interpreted as the effect of the corresponding independent variable when the overall budget for a shopper is equal to the sample mean. For example, the coefficient for Ln(Unplanned Cumulative $\$_{n-1}$) would be calculated as $\beta_2 = -.376 + .001 \times \text{Budget}_i$, where Budget_i is the mean-centered budget for shopper i. However, for all variables except the lagged dependent variable (y_{n-1}) and the interaction between the lagged dependent variable and cumulative purchases (Ln(nth purchase) $\times$ y_{n-1}), budget adds no explanatory power, and attention can be focused on the column labeled "Intercept." So, in the example for Ln(Unplanned Cumulative $\$_{n-1}$), $\beta_2 = -.376$ because the coefficient for the "Budget" column is not statistically different from 0.

The parameters for unplanned cumulative spending (negative), category hedonicity (positive), and higher-priced items (negative) are consistent with previous research. One might expect that items on sale or on promotion would increase shoppers' probability of making an unplanned versus planned purchase. We tested several operationalizations of these variables but did not find a statistically significant relationship. Although Inman, Winer, and Ferraro (2009) did not have a "promotion" variable, they found a significant impact for displays, which presumably coincided with products that were on promotion; however, not all items on promotion are likely to have a display. Our data did not have information on displays beyond that captured in the shopping zone variables.[5] It may be the case that many shoppers used weekly inserts or circulars to construct their shopping lists before entering the store, muting the overall impact of promotions on prompting unplanned versus planned purchases. Gupta (1988) finds that regular prices and price cuts have no impact in his purchasing timing model. He concludes that shoppers who did not plan on making a purchase in a category may not pay attention to prices.

Our results show that the propensity to make unplanned as opposed to planned purchases is dynamic and differs between shoppers with varied shopping plans. The coefficient on planned cumulative spending ($\bar{\beta}_1 = .361$) is positive and significant, indicating that as the shopping trip progresses, unplanned items become more likely to be selected than planned items. However, because the coefficient for unplanned cumulative spending is negative ($\bar{\beta}_2 = -.376$), the overall impact is not clear. There is support for the cumulative effect of shopping cues and/or resource depletion toward the end of the shopping trip. When shoppers exceed their stated trip budget ($\bar{\beta}_7 = .256$), they are more likely to make unplanned rather than planned purchases. As we note subsequently, the impact of the nth selection when the previous item was unplanned requires special attention to interpret its impact. Although the model-free evidence in Figure 1 indicates that unplanned versus planned selections increase over the course of the shopping trip, this may be due to hedonicity or other factors unrelated to how long the shopper has been making selections in the supermarket.

To test whether unplanned versus planned purchases become more likely as the shopping trip progresses, we used only the dynamic variables in our model to predict the probability of making an unplanned versus planned selection. Specifically, we used the variables ln(Planned Cumulative $\$_{n-1}$), ln(Unplanned Cumulative $\$_{n-1}$), y_{n-1}, ln(nth purchase) $\times$ y_{n-1}, and Over trip budget together with the individual-level betas estimated from the full model. In this simulation, the values of all other variables were set to 0. Integrating over the posterior distribution of model parameters, we find the probability of making an unplanned versus planned purchase is 9.6% higher during the last quarter of selections than during the first quarter of selections, and the probability increases in each quartile. This result controls for the hedonicity of items, FSP variables, and whether the item is at a historically higher price. In other words, the 9.6% increase is attributable to the within-trip dynamics as opposed to the characteristics of the product. Figure 1 illustrates this result: the observed increase in unplanned versus planned purchases over the course of the shopping trip is allocated to within-trip and "other" sources using the model-based results. Focusing on the fourth quartile, unplanned versus planned purchases increases to 54.7% compared with 42.7% in the first quartile. Of the 12-percentage-point increase, 7.9 percentage points are attributed to other factors, such as the hedonicity of the product (e.g., candy in the checkout aisles). However, 4.1 percentage points of the increase are due to within-trip dynamics; that is, each purchase in the last part of the shopping trip is 4.1 percentage points more likely to be unplanned due to within-trip dynamics. Although within-trip dynamics are not the only or largest source of the increase in unplanned versus planned purchases, they are substantively important, and this is the first research to quantify their magnitude.

The interpretation with regard to state dependency is more nuanced. Because Budget is statistically significant in the distribution of heterogeneity, the state-dependency variable must be calculated as $\gamma = -.221 + .006 \times \text{Budget}_i$ and the interaction term as $\beta_6 = .161 - .002 \times \text{Budget}_i$. To investigate the implications of the relationship between trip budget and state dependence, we examined the posterior distribution of the parameters. Recall that Budget_i is mean-centered, so this variable will be negative for shoppers who plan to spend less than the sample average (\$66.45). For shoppers with a planned overall budget of less than \$64 (or 61% of the sample), the state-dependent variable γ is statisti-

[5]We also estimated the full model with the shopping zone variables, and the substantive results are the same.

cally significant and negative, while the interaction term β_6 is positive and statistically significant.[6] This means that for shoppers with a below-average trip budget (whom we call "smaller-trip-budget" shoppers), an unplanned purchase initially decreases the probability that the next selection will be unplanned and increases the probability that it will be planned. That is, self-regulation theory applies. However, as the shopping trip progresses (as measured by the cumulative number of selections n), this effect eventually reverses. We report details of these calculations in Table 5.

For shoppers planning on spending between \$64 and \$109 (27% of the sample), γ is not statistically significant, but β_6 is positive and statistically significant. This means that for these medium-trip-budget shoppers, an unplanned purchase always increases the probability that the next item will be unplanned versus planned; that is, cuing theory applies. Moreover, this effect grows larger as the shopping trip progresses. For large-trip-budget shoppers with a trip budget greater than \$109 (12% of the sample), neither γ nor β_6 is statistically significant, indicating that an unplanned purchase has no impact on whether the next selection is either planned or unplanned at any point in the shopping trip. We summarize these conclusions in Table 5.

Self-regulation theory suggests that shoppers will attempt to stick to their planned versus unplanned purchases by adopting altering responses but that depletion of their self-regulation resources may result in the abandonment of those plans. This model best describes the shoppers who planned to spend a smaller-than-average amount and presumably had more targeted shopping goals. For shoppers planning to spend between \$64 and \$109, unplanned purchases always increased the probability of another unplanned purchase, and this effect increased over the shopping trip. These results are consistent with cuing theory. For large-trip-budget shoppers, the selection of planned or unplanned purchases had no impact on subsequent selections, although the dynamics of cumulative planned and unplanned spending as well as being over budget had identical impacts. It may be that these large-trip-budget shoppers are not mindful of when they make a planned versus unplanned purchase and therefore do not change their behavior. These results have implications for

[6]Because our probit model is inherently nonlinear, caution must be used in interpreting interaction terms such as β_6 and β_9. Following the results of Ai and Norton (2003) and Greene (2010, p. 292), and using the posterior means, the interaction between Ln(nth purchase) and y_{n-1} is positive as long as β_6 is positive. The interaction between Hedonic_{n-1} and y_{n-1} is also positive given the values of β_8 and β_9.

TABLE 5
Overall Trip Budget and Dynamics of Unplanned Purchases

A: State Dependence Calculations: Full Model

$\bar{\gamma}y_{n-1} + \bar{\beta}_6$ ln(nth purchase)] × y_{n-1} =	$\bar{\gamma}$ = –.221 + .006Budget_i
[$\bar{\gamma} + \bar{\beta}_6$ ln(nth purchase)] × y_{n-1}	$\bar{\beta}_6$ = .161 – .002Budget_i
	Budget_i = mean-centered overall budget
	Mean overall budget = \$66.45

B: Representative Examples

Overall Budget	nth Purchase	$\bar{\gamma}$	$\bar{\beta}_6$ln(nth Purchase)	Net State Dependency
\$50	2	–.32	.13	–.19
	5	–.32	.31	–.01
	10	–.32	.45	.13
\$75	2	n.s.	.10	.10
	5	n.s.	.23	.23
	10	n.s	.33	.33
\$110	—	n.s.	n.s.	n.s.

C: Summary of Effects

Overall Budget	Proportion of Sample	Dynamics of an Unplanned Purchase
<\$64	61%	Early in the trip, an unplanned purchase decreases the probability that the next selection will be unplanned versus planned. This effect reverses as the shopping trip progresses.
\$64–\$109	27%	An unplanned purchase always increases the probability that the next selection will be unplanned versus planned. This effect grows larger as the shopping trip progresses.
>\$109	12%	An unplanned purchase has no effect on whether the next selection will be planned or unplanned at any point in the shopping trip.

Notes: n.s. = not significant at the 95% level.

both theory development and management practice, which we discuss in the next section.

The licensing effect posits that engaging in a necessary but difficult task gives the actor "permission" to engage in a more hedonic activity that may deviate from his or her ultimate goal. In the context of shopping, we interpret this to mean that buying a utilitarian item that is low in hedonicity will give the shopper permission to make an unplanned rather than a planned purchase on the next selection. We find that this effect holds for planned, but not for unplanned, purchases. When the previous selection was planned (y_{n-1} = 0) and a utilitarian product, coefficients $\overline{\beta}_8$ and $\overline{\beta}_9$ show that this increases the probability that the next item will be unplanned [–.179 × (–lagged hedonicity) + .203 × (–lagged hedonicity) × (0) > 0]. However, when the previous selection was unplanned (y_{n-1} = 1), there is no licensing effect (i.e., –.179 + .203 is not statistically different from 0).

The results with the FSP variables are consistent with our prediction and suggest that historical information about shoppers' purchases can be used to help identify planned versus 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 than unplanned. These results are consistent with a resource-planning view, in which shoppers invest more time and cognitive resources in planning big-ticket items. We also find that more frequently purchased items are more likely to be planned than infrequently purchased items. Finally, when the time since last purchase is relatively long, ln(Recency_Ratio) > 0, the item is more likely to be purchased on a planned as opposed to unplanned basis.

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 to draw correct inferences. Although prior research has demonstrated that more time spent shopping is related to the aggregate amount of unplanned purchases (e.g., Park, Iyer, and Smith 1989), our analysis is the first to show that the propensity to make unplanned versus planned purchases increases over the course of the shopping trip. As shoppers spend more of their budget on planned items, the probability of making unplanned versus planned purchases increases, but this is moderated by the amount budgeted for unplanned purchases. For smaller-trip-budget and medium-trip-budget shoppers, the selection of an unplanned item later in the shopping trip increases the probability that the next item will be unplanned rather than planned. After a shopper exceeds the planned budget for the shopping trip, unplanned purchases become more likely.

Our findings also shed light on when a self-regulation model of shopping behavior versus a cuing model is more likely to apply. We find that only shoppers with below-average trip budgets engage in the altering response of avoiding an unplanned purchase after making an initial unplanned purchase. This altering response is the key theoretical difference between the self-regulation model and the cuing model. In contrast, shoppers with the largest spending plans do not seem to pay attention to planned versus unplanned purchases on an item-by-item basis—or if they do, it does not alter their immediate shopping behavior. Knowing when a shopper is amenable to suggestions for other unplanned items has direct managerial implications.

The use of a list may affect a shopper's self-regulation actions, resource depletion over the course of the shopping trip, or reliance on store-based shopping cues. Shoppers who use a list have larger planned budgets ($75.20) than those who do not ($62.72), indicating that large-trip-budget shoppers may be using a list as a coping mechanism. We tested this by including a "list" variable as an explanatory variable in the distribution of heterogeneity in the full model. However, it did not have a statistically significant impact on shopping dynamics.

The finding that, for a shopping trip, shoppers can articulate what items they plan to buy, make a budget, and stay reasonably close to that budget suggests that shopping is a goal-directed activity. This research shows that selecting planned versus unplanned items does not occur at random during a shopping trip even after controlling for category-specific and environmental factors. However, neither self-regulation theory nor cuing theory is adequate to explain the behavior of all shoppers because individual-specific plans for the trip have a bearing on the most applicable model.

We also find support for the licensing effect for all shoppers. We find that category hedonicity has an immediate impact on the probability that a purchase will be unplanned versus planned, but our results also document a dynamic impact. The immediate impact is consistent with the findings reported by Shiv and Fedorikhin (1999). The dynamic impact supports the licensing effect, wherein a utilitarian selection gives the shopper permission to make an unplanned purchase in the next selection (Khan and Dhar 2006) but, according to our results, does so only when the previous selection was planned. The antecedent condition of "sticking to the plan" seems to be important for the licensing effect in this context. Whereas Hui, Bradlow, and Fader (2009) find some support for the licensing effect with regard to browsing behavior, our results show a relationship between making a planned, less hedonic selection and then making an unplanned purchase. This discrepancy in findings may be attributed to our scaled measurement of item hedonicity and our focus on the item-by-item selection process, whereas Hui, Bradlow, and Fader employed a more coarse, dichotomous measure regarding whether the entire basket was primarily hedonic versus utilitarian.

Managerial and Consumer Welfare Implications

The results of our research have several implications for managers and consumers. First, the results suggest that at some point in a shopping trip, an unplanned selection increases the probability that the next selection will be unplanned versus planned, and this effect grows larger as the shopping trip continues. Our analysis is restricted to estimating systematic differences between planned and unplanned purchases. However, if we assume that some of the unplanned purchases are net additions to the shopping cart, the economic benefit to the retailer of an unplanned purchase is not limited to the current selection but has a carryover effect. In our data, consumers planned on spending \$20.37 on unplanned items but actually spent \$34.59 on average. This benefit is tempered by the finding that shoppers were still reasonably close to their overall budget (\$66.45 planned compared with \$69.84 actually spent). Retailers should be able to get the largest benefit by offering unplanned items to shoppers later in their trips, particularly when the budget for unplanned items has not been exhausted. That said, we also find that shoppers who have exceeded their trip budget and are still making purchases are prone to make unplanned purchases. In-store sampling or other in-person promotions should be located more deeply in the trip.

The licensing effect suggests that an effective merchandising strategy would be to mix low- and high-hedonic items. The purchase of a low-hedonic item gives the shopper permission to make an unplanned purchase, and high-hedonic items are more likely to be unplanned as opposed to planned purchases. However, the licensing effect pertains only to planned purchases, which highlights the benefits that might accrue to more detailed tracking information obtained through mobile shopping apps. A simple mobile app such as the Scan It! app used by Stop & Shop grocery stores in the U.S. Northeast might offer to keep track of shoppers' budgets by asking them to input their shopping list and trip budget before beginning their shopping trip. Shoppers would scan each item with their phone as they put it into the basket, and the app could track whether the item was planned or unplanned. The app would let shoppers know how much they have spent on planned and unplanned items and how much of their overall budget remains.

In addition, with this information and geographic tracking within the store, the retailer can make more targeted suggestions. For example, the app could alert the shopper to nearby unplanned items following a planned purchase. Furthermore, incorporating the effect of trip budgets, for smaller-trip-budget shoppers, suggestions for unplanned items should wait until after several selections have already been made; for medium-trip-budget shoppers, suggestions can start from the beginning of the shopping trip. When a shopper selects a planned, low-hedonic product, a nearby high-hedonic product might be suggested and/or a coupon offered for the item. Coupon offers or product suggestions should be more frequent as the shopping trip progresses as long as the shopper has money left in the shopping budget. Clearly, a balance would need to be struck so that offers are not so frequent as to annoy shoppers.

Conversely, consumers should be mindful of their greater propensity to make unplanned purchases as their shopping trip unfolds. Although our research does not investigate whether 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 versus planned purchases throughout the shopping trip. That is, making and monitoring a mental budget (or using a shopping app) 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.

Limitations and Further Research

The statistical model we used in this research analyzed item-by-item selections to determine whether there are systematic differences between planned and unplanned purchases. Formally, we model Pr(Planned|Selection) and Pr(Unplanned|Selection), the probability of making a planned versus unplanned purchase given that a selection has been observed (i.e., something was put into the shopping basket). Ultimately, retailers are interested in maximizing the total number of purchases, planned and unplanned, which would be given by Pr(Planned|Selection) × Pr(Selection) and Pr(Unplanned|Selection) × Pr(Selection). Our research demonstrates that dynamic factors affect the selection of planned versus unplanned items and suggests that attempts to model whether the consumer will make a planned, an unplanned, or no selection need to consider similar dynamics. That is, modeling Pr(Selection) would have to use information collected throughout the shopping trip as opposed to only using information observed when a selection was made.

The presence of a significant autocorrelation coefficient suggests that additional behavioral research should be done to more thoroughly explicate the dynamics in shopper purchasing behavior. First, although 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 stand-alone unplanned items and would require a comprehensive analysis of cross-purchases to determine complementary categories. Such a "network analysis" of unplanned purchases is a fertile direction for further research.

The expected effects of self-regulation theory pertain to smaller-trip-budget shoppers, whereas cuing theory is more applicable to medium-trip-budget shoppers. Those with the largest spending plans did not react to unplanned purchases. Lee and Ariely (2006) argue that shoppers begin their trip with fuzzy shopping goals that become more concrete as the trip progresses. To the extent that goal concreteness is related to differential cuing of unplanned items, this may be part of the underlying process. Notably, it may be the case that goal concreteness does not change over the course of the shopping trip for shoppers with larger budgets. This would explain our finding that the carryover effect of unplanned purchases on the subsequent purchase is stable throughout the trip and is an intriguing topic for further research.

Two other methodological limitations warrant additional attention. First, because shoppers were interviewed before the shopping trip, it is possible that they altered the sequence of planned versus unplanned selections in response to telling the researchers their shopping plans. An alternative methodology would be to interview shoppers as they exit the store and ask them to identify which items were planned or unplanned; however, respondents may be reluctant to admit how many or which items were unplanned (i.e., socially desirable responding). Thus, whether "pre-" or "post-" interviewing shoppers is preferable is an open question. Second, our data set did not include information on which items were on display; because previous research has shown that displays are positively related to making unplanned purchases, this may result in an omitted variable bias and may be related to why the price and "on sale" variables were not significant. Because the current analysis conditions on a selection being made and focuses on dynamic effects, we do not believe that the exclusion of promotion variables alters our basic conclusions. Nonetheless, further research should include and test promotion variables.

In conclusion, our research shows that making planned versus unplanned purchases is a dynamic process that is influenced by the last item purchased, the stage of the shopping trip, and shoppers' goals for the shopping trip. Our research shows that an individual shopper's prior history can be used to identify items more likely to be bought on a planned versus unplanned basis. To the extent that customized shopping lists can be created that enhance customer satisfaction and loyalty, proprietary FSP data have the potential of creating a sustainable competitive advantage because they cannot be duplicated by other retailers. Furthermore, our findings can be used to help determine the order in which shoppers' prior purchases are displayed in the retailer's mobile app, with categories with the highest likelihood of unplanned purchase being higher on the list. Indeed, this may present another revenue opportunity for retailers because they can auction the order in which previously purchased items are displayed, akin to Google AdWords. That is, consumer packaged goods firms could bid to get their product higher on the list and could weight their bid by the probability of the purchase being planned.

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WEB APPENDIX

The Role of Within-Trip Dynamics In Unplanned Versus Planned Purchase Behavior

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WEB APPENDIX: ESTIMATION ALGORITHM

To estimate the serially correlated probit model described in the paper we rely on Bayesian methods using data augmentation. Data augmentation and exploiting conditional relationships greatly simplifies estimation. Our approach draws heavily on the presentation by Huang and Shen (2002). The model for each item selected is:

(A1)
$$y_{in} = 1 \text{ if } y_{in}^{*} > 0, \text{ else } y_{in} = 0$$
$$y_{in}^{*} = \beta_i' x_{in} + \varepsilon_{in}$$
$$\varepsilon_{in} = \phi \varepsilon_{i,n-1} + \nu_{in} \quad \text{where } \nu_{in} \sim N(0, 1-\phi^2)$$

where y_{in} = 1 if the n^{th} purchase of shopper i is unplanned and for each shopper we observe n_i purchases. The vector x_{in} contains an intercept, explanatory variables, and any lagged terms including $y_{i,n-1}$ to represent state dependence. Unlike other time series models in the literature, we have a finite shopping sequence with a definitive beginning and ending. For the first unplanned purchase, we set $y_{i,0}$ = 0. However, we assume environmental factors up to the first purchase may have an impact on subsequent behavior and assume ε_{i0} ~ N(0,1). The remainder of the model hierarchy is given by:

(A2)
$$\beta_i \sim N_p(\overline{\beta}, V_\beta)$$
$$\overline{\beta} \sim N_p(0, 100 I_p)$$
$$V_\beta \sim IW(p+3, (p+3) I_p)$$
$$\phi \sim Uniform(-1,1)$$
)

where p is the dimension of x_{in}, N_p signifies a multivariate normal distribution of dimension p, IW is the Inverse Wishart distribution, and I_p is an identity matrix of dimension p. Let X_i represent the stacked matrix of $\{x_{in}'\}$ and y_i the vector of observed outcomes. The algorithm is initialized with the estimates:

$$\beta_i = (X_i^{'}X_i)^{-1}X_i^{'}y_i \text{ for each } i$$

$$\varepsilon_{in}^{*} = y_{in} - \beta_i^{'}x_{in} \text{ for each } i \text{ and } n$$

and φ=0. The following steps describe an MCMC chain with the posterior distribution of all model parameters as the stationary distribution.

1. Draw $y_{in}^{*} \mid y_i, \varepsilon_i^{*}, \beta_i, \phi$ for each i and n

   If $y_{in} = 1$, $y_{in}^{*} \sim TN(\mu_{in}, \tau_{in}^{2}, y_{in}^{*} > 0)$,

   if $y_{in} = 0$, $y_{in}^{*} \sim TN(\mu_{in}, \tau_{in}^{2}, y_{in}^{*} < 0)$ where TN indicates a truncated normal distribution.

   If n=1, $\tau_{i1}^{2} = 1-\phi^{2}$ and $\mu_{i1} = \phi\varepsilon_{i2}^{*} + \beta_i^{'}x_{i1}$;

   if $1<n<n_i$ $\tau_{in}^{2} = \dfrac{1-\phi^{2}}{1+\phi^{2}}$ and $\mu_{in} = \dfrac{\phi\varepsilon_{i,n-1}^{*}}{1+\phi^{2}} + \dfrac{\phi\varepsilon_{i,n+1}^{*}}{1+\phi^{2}} + \beta_i^{'}x_{in}$;

   if $n = n_i$ $\tau_{in}^{2} = 1-\phi^{2}$ and $\mu_{in} = \phi\varepsilon_{i,n-1}^{*} + \beta_i^{'}x_{in}$.

   Compute $\varepsilon_{in}^{*} = y_{in}^{*} - \beta_i^{'}x_{in}$.

   Note that these distributions can be obtained by re-writing the latent variables as:

$$\begin{aligned}
&y_{i1}^{*} = \beta_i^{'}x_{i1} + \phi\varepsilon_{i0} + \nu_{i1} \\
&y_{i2}^{*} = \beta_i^{'}x_{i2} + \phi\left(y_{i1}^{*} - \beta_i^{'}x_{i1}\right) + \nu_{i2} \\
&y_{i3}^{*} = \beta_i^{'}x_{i3} + \phi\left(y_{i2}^{*} - \beta_i^{'}x_{i2}\right) + \nu_{i3} \\
&etc.
\end{aligned}$$

   and recognizing that the draw of y_{in}^{*} involves both y_{in}^{*} and $y_{i,n+1}^{*}$ and therefore $\varepsilon_{i,n-1}^{*}$ and $\varepsilon_{i,n+1}^{*}$.

2. Draw $\beta_i \mid y_i^{*}, \phi$ for each i

   Compute $z_{i1}^{*} = y_{i1}^{*}$ and $x_{i1}^{*} = x_{i1}$.

Compute $z_{in}^* = \dfrac{y_{in}^* - \phi y_{i,n-1}^*}{\sqrt{1-\phi^2}}$ and $x_{in}^* = \dfrac{x_{in} - \phi x_{i,n-1}}{\sqrt{1-\phi^2}}$ for remaining n_i.

$$\beta_i \sim N_p\left(b, D\right)$$

$$D = \left(V_\beta^{-1} + X_i^{*}{}' X_i^*\right)^{-1}$$

$$b = D\left(X_i^{*}{}' z_i^* + V_\beta^{-1}\bar{\beta}\right).$$

3. Draw $\phi|\{y_i\}$, $\{\varepsilon_i^*\}$, $\{\beta_i\}$

   Because $\phi \sim$ Uniform(-1,1), we use a random walk Metropolis-Hastings algorithm which, conditional on the $\{\varepsilon_i^*\}$ is straightforward to compute. Let $\phi_{(o)}$ be the current draw and $\phi_{(c)} = \phi_{(o)} + \eta$ be candidate where $\eta \sim N(0, \sigma^2)$ and σ^2 is chosen so that the acceptance rate is approximately 50%.

   Define $\xi_{i1}^{(c)} = \beta_i' x_{i1}$ and $\xi_{in}^{(c)} = \beta_i' x_{in} + \dfrac{\phi^{(c)}\varepsilon_{i,n-1}^*}{\sqrt{1-\phi^2}}$, then the likelihood for shopper i is given by

   $L_i^{(c)} = \prod_{n=1}^{n_i}\left[\Phi\left(\xi_{in}^{(c)}\right)\right]^{y_{in}}\left[1-\Phi\left(\xi_{in}^{(c)}\right)\right]^{(1-y_{in})}$ where $\Phi(\ )$ represents the standard normal cumulative distribution. Define $L_i^{(o)}$ analogously.

   Then, accept the candidate or new draw of $\phi_{(c)}$ with probability:

$$\min\left(\frac{\prod_{i=1}^{I} L_i^{(c)}\chi(-1<\phi_{(c)}<1)}{\prod_{i=1}^{I} L_i^{(o)}\chi(-1<\phi_{(o)}<1)}, 1\right)$$ where $\chi()$ is the indicator function.

Draws of $\bar{\beta}$ and V_β are standard and details can be found in references such as Rossi, Allenby, and McCulloch (2005). Changes for the model with shopping variables are straightforward and are not detailed here.

Full Model with Individual Level Variance

In the Full Model, the distribution of heterogeneity is given by:

$$\beta_{i0} \sim N(\theta_o' w_i, \sigma_i^2)$$

(A3)

$$[\{\beta_i\}, \gamma_i] \sim N_{p-1}(\theta w_i, \Delta)$$

Where θ_o is vector, σ_i^2 is an individual level scalar for the variance, θ is a matrix of regression coefficients, and Δ is a covariance matrix. We specify priors as:

$$\theta_o \sim N_2(0, 100 I_2)$$

$$\sigma_i^2 \sim IG(\frac{4}{2}, \frac{1}{2})$$

(A4)

$$vec[\theta] \sim \mathrm{N}_{2\times(p-1)}(0, 100 I_{2\times(p-1)})$$

$$\Delta \sim IW((p-1)+3, ((p-1)+3) I_{2\times(p-1)})$$

Here IG represents the Inverse-Gamma distribution. With modifications for the probit model and the explanatory variables in the distribution of heterogeneity, the model follows that of Bresson, Hsia, and Pirotte (2011).

1. Draw $y_{in}^* \mid y_i, \varepsilon_i^*, \beta_i, \phi$ for each i and $n > 1$

   This step is the same as for the earlier model, but no value is drawn for y_{i1}^*

2. Draw $\beta_i \mid \beta_{io}, y_i^*, \phi$ for each i

   Compute $z_{in}^* = \dfrac{y_{in}^* - \phi y_{i,n-1}^*}{\sqrt{1-\phi^2}} - \beta_{i0} x_{in,1}^*$ and $x_{in}^* = \dfrac{x_{in} - \phi x_{i,n-1}}{\sqrt{1-\phi^2}}$ for each $n_i > 1$.

   $$\beta_i \sim N_p(b, D)$$

   $$D = \left(\Delta^{-1} + X_i^{*\prime} X_i^*\right)^{-1}$$

   $$b = D\left(X_i^{*\prime} z_i^* + \Delta^{-1} \theta w_i\right).$$

Draw $\beta_{io} \mid \beta_i, y_i^*, \phi$ for each *i*

Compute $z_{in}^* = \frac{y_{in}^* - \phi y_{i,n-1}^*}{\sqrt{1-\phi^2}}$ and $x_{in}^* = \frac{x_{in} - \phi x_{i,n-1}}{\sqrt{1-\phi^2}}$ for each $n_i > 1$.

$\beta_{io} \sim N\left(b, d\right)$

$$d = \left(\frac{\sigma_i^2}{t_i \sigma_i^2 + 1}\right)$$

$$b = d\left(t_i\left(\overline{y}_i^* - \overline{x}_i^*{}'\beta_i\right) + \frac{w_i'\theta_o}{\sigma_i^2}\right).$$

Here $t_i = n_i - 1$

3. Draw $\phi \mid \{y_i\}, \{\varepsilon_i^*\}, \{\beta_i\}$

   Again, this draw is the same as above but excludes the first observation for each shopper.

4. Draw $\sigma_i^2 \mid \beta_{io}, \theta_o, w_i$

   $$\sigma_i^2 \sim IG\left(\frac{t_i + 4}{2}, \frac{1 + t_i\left(\beta_{io} - w_i{}'\theta_o\right)}{2}\right)$$

5. Draw $\theta_o \mid \{\beta_{io}\}, \{\sigma_i^2\}, \{w_i\}$

   $\theta_o \sim N_p\left(b, D\right)$

   $$D = \left(100 I_2^{-1} + \sum_{i=1}^{N} \frac{w_i' w_i}{\sigma_i^2}\right)^{-1}$$

   $$b = D\left(\sum_{i=1}^{N} \frac{w_i'\beta_{io}}{\sigma_i^2} + 100 I_2^{-1} \times 0\right).$$

Draws of θ and Δ are standard and details can be found in references such as Rossi, Allenby, and McCulloch (2005).