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Dynamic Conversion Behavior at E-Commerce Sites

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This paper develops a model of conversion behavior (i.e., converting store visits into purchases) that predicts each customer's probability of purchasing based on an observed history of visits and purchases. We offer an individual-level probability model that allows for different forms of customer heterogeneity in a very flexible manner. Specifically, we decompose an individual's conversion behavior into two components: one for accumulating visit effects and another for purchasing threshold effects. Each component is allowed to vary across households as well as over time. *Visit effects* capture the notion that store visits can play different roles in the purchasing process. For example, some visits are motivated by planned purchases, while others are associated with hedonic browsing (akin to window shopping); our model is able to accommodate these (and several other) types of visit-purchase relationships in a logical, parsimonious manner. The *purchasing threshold* captures the psychological resistance to online purchasing that may grow or shrink as a customer gains more experience with the purchasing process at a given website. We test different versions of the model that vary in the complexity of these two key components and also compare our general framework with popular alternatives such as logistic regression. We find that the proposed model offers excellent statistical properties, including its performance in a holdout validation sample, and also provides useful managerial diagnostics about the patterns underlying online buyer behavior.

Key words: stochastic models; e-commerce; online purchasing conversion; buyer behavior
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1. Introduction

Purchasing conversion rates, defined as the percentage of visits that result in purchases, are a primary focus of attention for many online retailers. With typical conversion rates rarely exceeding 5%, e-commerce managers are struggling to understand conversion behavior at their sites. Despite the vast amounts of data available online, few efforts have been made to explore conversion behavior beyond just reporting overall, store-level conversion rates and looking for improvements over time. This paper aims to more closely examine online purchasing conversion rates by developing a model that explicitly addresses the differences across shoppers as well as dynamics over time.

Before we develop our model, it is important to highlight some of the unique characteristics of online conversion that may impact any modeling and analysis efforts. First, customer behavior online is, in some important respects, different from that in other environments. Second, the data available online are also unique and necessitate special considerations in any in-depth empirical study. We discuss some of the key differences that highlight the need for a unique online conversion model.

Online Customer Behavior

One of the most salient characteristics that differentiates online and offline shopping behavior is the low "transportation costs" required to visit a virtual store. In studies of offline shopping behavior, one key component of modeling a customer's store choice and purchasing decision is the costs—both tangible and psychological—associated with traveling to one or more stores (Dellaert et al. 1998). In contrast, it is essentially costless for a customer to visit an online store site. This has several effects on observed behavior. First, because the costs are much lower, online shoppers may be more likely to visit a store without any intention of buying. In the offline world, where the shopper incurs costs just by taking the time and effort to visit a store, it is less likely that he will "waste a trip" and not buy. As a result, we observe lower conversion rates online. Second, the low cost of visiting a website also makes the shopper more likely to delay a purchasing decision and return later to buy. In the offline world, by contrast, there are very limited economies of scale for follow-up trips, so shoppers may rush to closure to avoid incurring more travel costs. For these reasons, we are more likely to see online shoppers making multiple trips to the same

store for a single purchasing decision, even for lower-involvement purchasing decisions.

In general, there may be a wide spectrum of shopping behaviors observed at a given online store. Janiszewski (1998) dichotomizes offline shopping behavior into *exploratory* or *directed* search. Moe (2003) extends this dichotomy and presents a taxonomy of behaviors for online shoppers at a retail site. Specifically, store visits can be sorted into four groups based on the shopper's motivations for entering the store and the purchasing horizon. One group, *directed buyers*, exhibits goal-directed search behavior: They have a specific product purchase in mind when entering the store and, as a result, are unlikely to exit the store without a purchase. A second group, *search/deliberation visitors*, also exhibits goal-directed search behavior, but unlike the directed buyers, they only have a general product category in mind when entering the store. For these shoppers, purchasing may occur after a series of store visits as they gather more information during each store visit. In stark contrast, *hedonic browsers* tend to enter a retailer with no product or even product category in mind. Instead, any purchase that may or may not occur is a result of the in-store experience and the stimuli encountered—seemingly a random or "impulse" occurrence to an outside observer. The final group consists of *knowledge-building visitors*, who have no intention of buying and are simply in the store to gather information about the products available. In other words, there may be a group of visitors who are inherently nonbuyers, no matter how stimulating the shopping environment may be. The implication of this taxonomy for any modeling effort is that we must develop a flexible model that can accommodate each of these behaviors accordingly. The conversion model proposed in this paper will do just that.

Because our model features such a general (but well-grounded) structure, it can be applied to many different types of products. For instance, the nature of grocery purchasing is such that it is very unlikely for a customer to enter the store and exit without any purchases. On the other hand, it is very likely for a shopper to enter a car dealership and exit without buying. One objective of this paper is to develop a model that can be applied across a broad array of purchasing contexts.

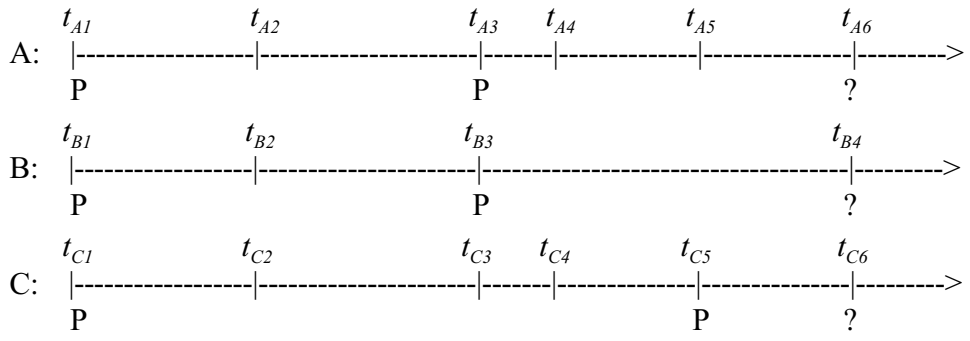
Using Online Click-Stream Data

Typical offline field data tend to capture only purchasing events. Nonpurchase data, e.g., visit characteristics, are either completely ignored or need to be gathered through self-report or controlled experiments, which tend to be inaccurate and not easily generalizable. Online click-stream data, however, capture both types of information in a complete, timely, and accurate manner.

Furthermore, because click-stream data encapsulate so much detail about each individual's behavioral history, the datasets are often large and cumbersome. The size of these datasets—and the difficulty in manipulating them—is frequently underestimated by many marketing researchers. When dealing with such large datasets, parsimony and efficiency are important characteristics when constructing statistical models for this environment. Our stochastic model of conversion behavior can be estimated relatively easily and quickly with a closed-form likelihood function, while still allowing for multiple sources of heterogeneity and nonstationarity. One limitation of click-stream data is the difficulty in obtaining user-identifying characteristics, such as demographics. Though several research firms collect such information from their panel of participants, most online retailers are reticent to collect or utilize such data because of privacy concerns. Therefore, we incorporate heterogeneity into our model only through stochastic distributions around the key behavioral parameters, although customer characteristics (and other covariates) can easily be introduced in the future.

Illustration of Conversion Behavior Dynamics

To illustrate the research problem, consider three individuals (see below) with the following behavioral histories, where t_{ij} denotes the time of individual i's jth visit and P indicates visits during which a purchase took place.



Individual A visited this particular store five times prior to t_{A6} and purchased twice, once at t_{A1} and again at t_{A3}. If this customer comes back to the store again at t_{A6}, what is her probability of purchasing during that visit? Two nonpurchase visits have occurred since the last purchase at t_{A3}, compared to only one prior to that. What effect, if any, do these visits have on influencing purchase, and has that effect changed since the last purchase? The visits at t_{A4} and t_{A5} may have positive effects that accumulate toward a purchase (e.g., learning more about a certain product that the shopper intends to buy), and thus may increase the likelihood of buying at t_{A6}. On the other hand, past visits may have no relation to future purchasing behavior—purchasing may be a stochastic result of the current visit alone.

Now examine individual B—his purchasing history is identical to that of A, but his visiting behavior is different. At t_{B4}, is person B more or less likely to purchase than A at her t_{A6}? There may be a trade-off between the higher baseline probability of purchasing that B appears to have (two purchases over three visits, compared to two purchases over five visits for A) versus the positive visit effects (as noted in the previous paragraph) from which A may have benefitted. Therefore, when modeling conversion probabilities we must consider the potential effect of visits in conjunction with any Bayesian updating of a customer's latent purchasing tendencies as we observe a series of visits and purchases (or lack thereof) over time.

In addition to the role that past visits have on purchasing, past purchase patterns may also affect future conversion behavior. Consider individual C, with a visiting history identical to that of A. The only difference is the timing of past purchases. How will this affect C's purchasing probability at t_{C6}? One could argue that because a purchase just occurred at t_{C5}, person C is less likely to purchase at t_{C6}, implying the existence of a hiatus between purchase events. However, individual C might be more likely to purchase again soon if a recent purchase experience is very salient, and therefore influential in reducing purchasing-related anxiety. To go one step further, what would be the effect of a third purchase (at, say, t_{C3}) on future behavior? Would it help or hurt the probability of a purchase at t_{C6}?

2. Model Development

These stylized illustrations and our broader discussion of online shopping point out the need for six key components in a model of conversion behavior:

1. *Baseline probability of purchasing*. For each individual, there is a baseline probability of purchase at each visit, independent of his recent purchase/visit patterns. This baseline reflects the overall extent to which visits are purchase directed for each customer.

2. *Positive visit effect on purchasing*. Each visit has its own stochastic impact (assumed to be nonnegative), and as the effects of these visits accumulate, the probability of purchase increases over time. In other words, as a shopper makes more visits, she will be increasingly likely to purchase in subsequent visits, depending on the magnitude of these visit effects on purchasing.

3. *Negative purchasing-threshold effect on purchasing*. Purchasing propensity can be negatively affected by an individual's level of purchase-related anxiety toward a given retailer. For example, shoppers new to a site may be risk averse and reluctant to provide personal information, such as credit card numbers, home addresses, etc., to an unknown vendor as part of the transaction process. Putsis and Srinivasan (1994) also conceptualize a framework in which buying probabilities are a result of visit effects and purchasing-threshold levels, but they focus their attention primarily on a descriptive analysis of the factors that affect prepurchase deliberation time.

4. *Heterogeneity in visit effects and purchase thresholds*. Any well-specified model of choice behavior must accommodate differences across customers. In this case, we expect that the two components just described (visit effects and purchasing thresholds) will vary in magnitude across households.

5. *Evolving effects over time*. The magnitudes of the visit effects and purchasing threshold may evolve over time as the customer gains experience with the shopping environment. For example, repeated visits to a website may have smaller effects on purchasing as the shopper gets used to the environmental stimuli and becomes less persuaded by content that has been seen often in the past (Park et al. 1989). Purchasing thresholds may shrink as shoppers gain familiarity through repeated purchases, thereby making future purchasing more likely (Beatty and Ferrell 1998). On the other hand, someone may be likely to buy at an early visit (to see what the process is like), but as the novelty wears off with repeated purchases, he may feel increasing resistance against making a purchase.

6. *Hard-core never-buyers*. Finally, there may be a segment of shoppers who use the retail site more as an informational reference than as a retailer, and therefore have no intention of ever buying at the website. Therefore, our model will incorporate a component that can separate these individuals out from the conversion process that applies to everyone else.

We first develop the *static conversion model*, which ignores the evolutionary effects and the hard-core never-buyers noted in Steps 5 and 6 above. We combine the behavioral elements from Steps 1–4 in the

following manner. Let p_{ij} be the probability of individual i purchasing at visit j:

$$p_{ij} = \big(\text{net effect of visits since last purchase } (V_{ij})\big) \Big/ \big(\text{net effect of visits since last purchase } (V_{ij}) + \text{purchasing threshold } (\tau_{ij})\big). \quad (1)$$

This basic structure is identical to a framework first proposed by Schmittlein and Morrison (2003), who analyzed the dynamics in the success rate of in vitro fertilization (IVF) as patients go from one IVF attempt to another. Like their model, we will separate out Bayesian updating from previous nonpurchase visits (or IVF failures, in their case) from "learning effects" that may arise from one visit to the next. However, unlike the Schmittlein and Morrison model, our proposed conversion model will also allow for nonstationarity resulting from previous purchases (successes) in addition to any nonstationarity from any previous nonpurchases (failures). Also, unlike Schmittlein and Morrison, we will model multiple purchasing cycles and allow learning effects to carry over from one purchasing cycle to the next. These differences will allow us to accommodate aspects of online shopping that do not arise in the IVF setting. Nevertheless, the fact that the same basic framework can be successfully applied for contexts as different as IVF trials and online purchasing says a great deal about its robustness and versatility.

Like Schmittlein and Morrison (2003), we assume that the net visit effect, V_{ij}, consists of two components: a baseline propensity to buy (v_{i0}) that applies at every visit, and the incremental effects (m_{ij}) that accumulate across all visits that have occurred since the last purchase. In a customer's first purchasing cycle, for example,

$$V_{ij} = v_{i0} + m_{i1} + m_{i2} + \cdots + m_{ij} \quad (2)$$

for household i who has made j (nonpurchase) visits. A large baseline effect (v_{i0}) relative to the magnitude of visit impacts (m_{ij}) allows for the existence of directed buyers, whereas larger visit effects allow for more of a search/deliberation process. Purchases resulting from hedonic browsing visits would be associated with a low baseline (v_{i0}) and incremental visit effects (m_{ij}) with a low mean but high variance. This would allow for impulse buying with relatively little visit-to-visit accumulation.

To accommodate these different forms of heterogeneity, we assume that the baseline purchasing propensity v_{i0} is gamma distributed across the customer population with shape parameter r_v and scale parameter γ. We acknowledge that there are many different sources of heterogeneity that can affect these baseline purchasing propensities, such as demographic characteristics. However, because many click-stream datasets do not include adequate covariate information, we incorporate heterogeneity strictly as unobserved random effects that follow a flexible probability distribution. Specifically, we assume that the visit impacts, as well as the purchasing thresholds, vary across customers in accordance with a gamma distribution, such that $m_{ij} \sim \text{gamma}(\mu, \gamma)$ and $\tau_{ij} \sim \text{gamma}(r_\tau, \gamma)$.[1] The resulting purchasing probability is therefore a ratio of two gamma random variables, or a beta-distributed random variable:

$$\begin{aligned} f(p_{ij}) &= \frac{v_{i0} + m_{i1} + m_{i2} + \cdots + m_{ij}}{v_{i0} + m_{i1} + m_{i2} + \cdots + m_{ij} + \tau_{ij}} \\ &= \frac{\text{gamma}(r_v + j\mu, \gamma)}{\text{gamma}(r_v + j\mu + r_\tau, \gamma)} \\ &= \text{beta}(r_v + j\mu, r_\tau). \end{aligned} \quad (3)$$

Using Bayes Theorem, we can update this probability from visit to visit at the individual level, using the information we have about each customer's visit/purchase history. If individual i has made x_{ij} prior visits which include n_{ij} purchases (up to but not including visit j), it is easy to show that

$$\begin{aligned} \mathbf{Pr}(\text{purchase}_{ij} \mid x_{ij}, n_{ij}) &= \mathbf{E}[p_{ij} \mid x_{ij}, n_{ij}] \\ &= \frac{r_v + j\mu + x_{ij}}{r_v + j\mu + r_\tau + n_{ij}}. \end{aligned} \quad (4)$$

A special case of this static conversion model deserves explicit mention. If we allow for no accumulation of visit effects (i.e., $\mu = 0$), then this specification collapses down into the well-known beta-binomial choice model. This will be a natural benchmark for us to compare all of our models against.

Evolving Visiting Effects. Thus far, we have assumed that the gamma distribution governing the impact of visits remains stationary over time with parameters μ and γ. While the impact of successive visits may accumulate over time, we have not allowed for any trends in this stochastic process. We therefore extend the model to allow for the possibility that the influence of store visits (m_{ij}) will increase, decrease, or stay the same depending on the shopper's history with the site.

Several studies have proposed that customers process information more efficiently as they learn about a new environment (Alba and Hutchinson 1987, Johnson and Russo 1984), thereby decreasing the

[1] Because the sum of the baseline effect and the visit impacts are compared against the threshold to determine purchasing propensity, it is reasonable to assume that they are measured on the same scale, and thus the distributions governing these three effects share the same scale parameter γ.

number of visits required to accumulate a sufficient amount of information to purchase. However, it can also be argued that shoppers are less affected by the store environment as they become more acclimated to it (Park et al. 1989), thereby increasing the number of visits needed to persuade them to buy. The model proposed in this paper will not predetermine the direction of these learning effects; instead, we will allow for dynamics that can increase or decrease the magnitude of visit effects over time. In doing so, the model will provide a measure for the evolutionary process that may (or may not) be occurring.

We approximate the customer's experience with the site with the number of times she has previously visited the site and implement the evolutionary trend through the shape parameter governing the incremental visit effects, m_{ij} (Schmittlein and Morrison 2003). Therefore, we assume $m_{ij} \sim \text{gamma}(\mu_j, \gamma)$, where $\mu_j = \mu_0 k^j$, and thus the net effect of visits for the first purchase cycle then becomes

$$V_{ij} \sim \text{gamma}(r_v, \gamma) + \text{gamma}(\mu_0 k^1, \gamma) + \text{gamma}(\mu_0 k^2, \gamma) + \cdots + \text{gamma}(\mu_0 k^j, \gamma). \quad (5)$$

The parameter k ranges from zero to infinity and characterizes how visit impacts evolve as customer familiarity increases. If k equals one, there is no evolutionary effect; the stochastic process governing m_{ij} is a simple stationary one. If k is less than one, visits tend to become less influential over time, while if k is greater than one, visits tend to become more influential as customers evolve. However, despite the upward or downward trend on the shape parameter, each successive draw of m_{ij} is still a random variable, thereby allowing any particular visit to have an unusually high or low impact. This allows for the possibility of impulse purchases, albeit with different probabilities, at any given visit.

Across multiple purchases, (8) generalizes to

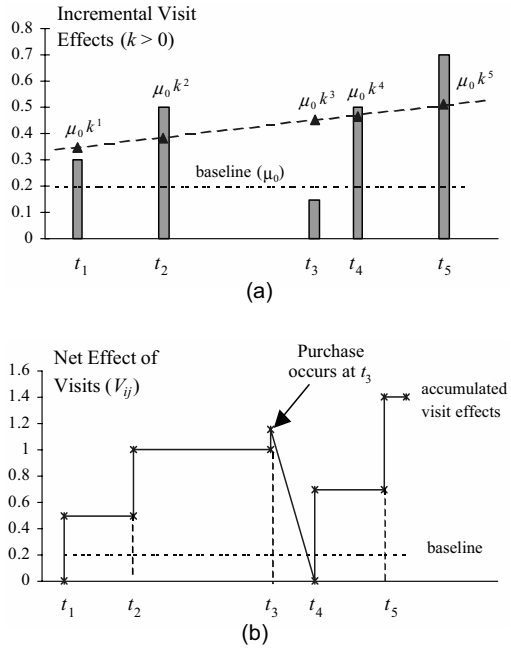
$$V_{ij} \sim \text{gamma}\left(r_v + \sum_{u=lp+1}^{j} \mu_0 k^u, \gamma\right), \quad (6)$$

where lp indicates the visit during which the last purchase occurred. If customer i has not yet been observed making a purchase, then all past visits would contribute to V_{ij}, or $lp = 0$.

Figures 1a and 1b illustrate how the net effect of visits can accumulate over a customer's history. Assuming that visit effects evolve such that $k > 0$, incremental visit effects will stochastically vary about a mean, which itself is evolving (see Figure 1a). From visit to visit, these incremental effects accumulate until a purchase is made, at which time the net effect is reset to zero (see Figure 1b).

Evolving Purchasing Thresholds. Under the static model, the purchasing threshold for household i, τ_{ij}, was specified as a gamma-distributed random variable with shape parameter r_τ and scale parameter γ to account for customer heterogeneity. It did not vary over time. However, a customer's purchasing threshold may evolve depending on his or her past behavior, or more specifically, past purchasing experiences (Beatty and Ferrell 1998).

Figure 1 (a) Incremental Visit Effects; (b) Net Effect of Visits



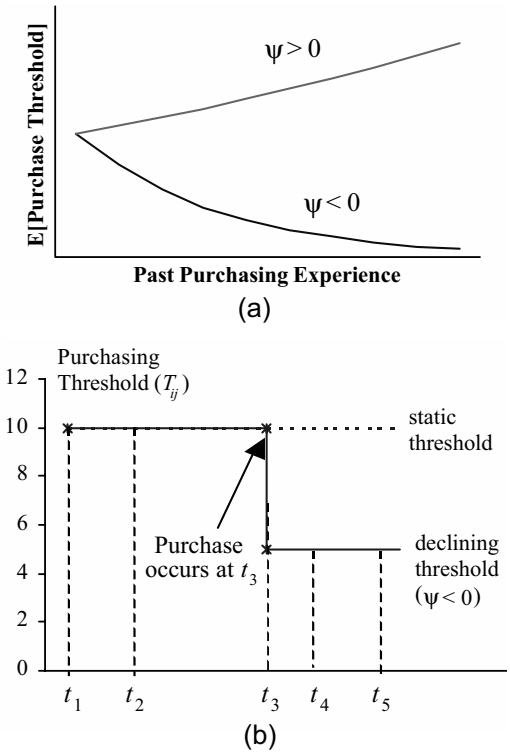
In much the same way that visit impacts are allowed to evolve over time, we implement the evolution of purchasing thresholds through the shape parameter:

$$\tau_{ij} \sim \text{gamma}(r_\tau \exp\{\psi x_{ij}\}, \gamma), \quad (7)$$

where r_τ captures the initial purchasing threshold, ψ is a parameter that governs the magnitude and direction of the dynamic process, and x_{ij} is the number of purchases that customer i has made, up to (but not including) visit j. This specification for the shape parameter allows the threshold to either increase, decrease, or remain constant, depending on the sign of the evolutionary parameter, ψ. If ψ equals zero, the purchasing-threshold distribution remains stationary with a shape parameter of r_τ regardless of past purchasing experiences. If, however, ψ is less than zero, thresholds decline as the customer gains purchasing experience with the retailer, and she becomes more likely to buy at future visits.[2]

[2] For both the evolving visit effects and the evolving purchasing thresholds, we experimented with discount factors that would allow these effects to diminish based on the amount of actual time between successive visits/purchases. However, this addition did not significantly improve the fit or predictive accuracy of the model.

Figure 2 (a) Threshold Dynamics; (b) Evolving Purchasing Threshold



Figures 2a and 2b illustrate how the purchasing threshold can evolve as a function of past purchasing events. Notice that, depending on ψ, this threshold can increase or decrease (Figure 2a). Assuming $\psi < 0$ such that purchasing increases future conversion probabilities, the threshold changes after each purchase as seen in Figure 2b. Whether or not a purchase occurs is the stochastic result of a conversion probability derived from the combination of visit effects (Figure 1b) and the purchasing threshold (Figure 2b).

Hard-Core Never-Buyers. The final component of the model is an element that Schmittlein and Morrison (2003) do not consider. In many situations, there may be a set of shoppers who visit a store to look around but have absolutely no intention of ever buying anything there. We assume that these "hard-core never-buyers" comprise a fraction, $(1-\pi)$, of the population. This parameter will affect our specification of p_{ij} such that if a customer's history contains no purchases ($x_{ij}=0$),

$$f(p_{ij} \mid x_{ij}=0) = (1-\pi) + \pi \frac{V_{ij}}{V_{ij}+\tau_{ij}+n_{ij}}. \quad (8)$$

If, however, customer i had purchased in the past and therefore proven herself not to be a never-buyer, then the probability of buying at all subsequent visits is simply

$$f(p_{ij} \mid x_{ij}>0) = \frac{V_{ij}+x_{ij}}{V_{ij}+\tau_{ij}+n_{ij}}. \quad (9)$$

The resulting likelihood function can be written as

$$L = \prod_{i=1}^{N}\prod_{j=1}^{I_i} [\mathbf{Pr}(\text{purchase}_{ij})]^{I_{ij}} \cdot [1-\mathbf{Pr}(\text{purchase}_{ij})]^{\bar{I}_{ij}}$$
$$= \prod_{i=1}^{N}\prod_{j=1}^{I_i} \mathbf{E}[p_{ij}]^{I_{ij}} \cdot (1-\mathbf{E}[p_{ij}])^{\bar{I}_{ij}}, \quad (10)$$

where I_{ij} is a 0/1 variable indicating whether or not customer i actually makes a purchase at visit j. Parameter estimation is performed using ordinary maximum likelihood procedures. We utilize the MATLAB programming language on a standard desktop PC. In this setting, the complete model requires a few minutes to obtain optimal estimates for its parameters. This estimation procedure is quite robust; we have seen no evidence of local optima or other irregularities.

3. Data

We use click-stream panel data collected by Media Metrix, Inc., covering the browsing habits of approximately 10,000 households whose Internet behavior was recorded over time. This firm recorded the sequence and timing of all URLs viewed by each panel member. We examine the panel's shopping behavior at a leading online bookstore, Amazon.com, from March 1, 1998, through October 31, 1998. We observe 4,379 panelists who made at least one visit, collectively covering a total of 11,301 visits.

Purchase is defined as any visit during which a purchase occurred. Many online stores utilize a specific Web page that acts as a purchase confirmation after an order has been submitted. Those visits in which the panelist saw the "confirm-order" page of the store's website were identified as purchase visits. The number of units purchased and the total amount spent were not considered in this analysis.

Table 1 summarizes the visiting and purchasing dynamics at Amazon.com. All measures seem to indicate that site performance is improving from the first four-month period to the next. The conversion rate is increasing, the numbers of visitors and buyers are increasing, and so on; however, these aggregate measures do not account for the inflow of new shoppers and the dropout of existing shoppers, so they may mask the true underlying dynamics that are occurring at the individual level (Moe and Fader 2003). When we examine the same statistics while accounting for the entering and exiting of shoppers, a very different pattern emerges. Table 2 shows the conversion rate statistics only for those shoppers who seemed to be active throughout the entire data period, i.e., those who made one or more visits to the store in both the first two months and the last two months of the

Table 1 Summary of Visiting and Purchasing at Amazon.com

	All 8 months	Months 1–4	Months 5–8
Number of visitors	4,379	2,645	2,756
Number of buyers	851	459	544
Number of visits	11,301	5,238	6,025
Number of purchases	1,573	689	885
Conversion rate (%)	13.9	13.2	14.7
Visits/visitor	2.58	1.98	2.19
Purchases/buyer	1.85	1.50	1.63
Purchases/visitor	0.36	0.26	0.32

data period. This illustrative subsample avoids any problems due to censoring, and thus provides a better view of individual-level dynamics. Contradicting the (apparently) increasing conversion rates for the entire sample as seen in Table 1, this group's conversion rates are actually decreasing over time. Therefore, without modeling behavior at the individual level, e-commerce managers can easily draw incorrect conclusions. Our model accounts for these individual-level patterns, and therefore provides a better indication of differences across households as well as the dynamics over time.

4. Results

As a start, the full (six-parameter) conversion model was estimated across the entire eight months of Amazon.com data (see Table 3, Row 1). From the model results, there are three main dynamics we are looking to identify. First is the influence of visits. The model indicates that visits do have effects, above and beyond the baseline, which accumulate and increase purchasing probabilities as indicated by a relatively large $\mu_0 = 0.276$ when compared to the baseline, $r_v = 0.062$. Second is the evolving effect over time. That is, does the incremental effect of each visit systematically evolve as the shopper gains experience? In this case, k is less than one, suggesting that subsequent visits have a diminishing (but still positive) impact on purchasing behavior as the shopper makes more visits to the site. Third, how do past purchases affect the purchasing threshold? According to the full model, it seems that purchasing thresholds increase as a function of previous purchasing experiences ($\psi = 0.117$), perhaps due to the decreasing novelty of buying online.

Table 2 Conversion Rate Summary for Active Amazon.com Shoppers Only

	Months 3–4	Months 5–6
Conversion rate (%)	26.0	20.8
Number of visits	757	472
Number of purchases	197	98

Taken together, the two latter dynamics suggest that conversion probabilities are decreasing over time, at least for this particular site during this particular time period. Once again, this contradicts the aggregate trends (Table 1), but is supported by the pattern seen in Table 2.

Table 3 also shows the parameter estimates and fit statistics for several nested models, all the way down to the simple two-parameter beta-binomial. There is little distinction, from a statistical perspective, between the full model and one with no threshold dynamics ($\psi = 0$, in Row 2). Both models offer similar in-sample fit statistics as well as out-of-sample validation results (to be discussed in the next section). For consistency, we will stick with the full model for the subsequent discussion.

5. Alternative Models and Benchmarks

We compare the performance of our proposed conversion model to a wide range of established benchmarks along several dimensions: (1) in-sample log-likelihood, (2) holdout log-likelihood, and (3) predictive accuracy for an individual's next visit. When we estimate the proposed model using only the first half of the dataset, we obtain a log-likelihood for the holdout sample of $-2{,}330.0$. Additionally, the proposed conversion model predicts a 14.7% conversion rate for a set of holdout visits (described in greater detail at the end of this section), compared to the actual conversion rate of 15.7—a relative error of only 6.3%.

Benchmark 1—Logistic Regression. We use a logistic regression model that incorporates recency and frequency measures as explanatory variables. The dataset used for the logistic regression model is identical to that used by the conversion model. We model the probability of purchasing in each session as a function of: (1) the number of past visits, (2) the number of past purchases, (3) the number of visits since the last purchase, (4) time elapsed (in days) since the last visit, and (5) time elapsed (in days) since the last purchase. The fit of the model (LL $= -4{,}367.79$, BIC $= 8{,}791.55$) is vastly inferior to that of the conversion model—even the beta-binomial achieves a superior log-likelihood (LL $= -4{,}308.03$, BIC $= 8{,}632.83$). We also estimated a latent-segment logistic regression to better accommodate customer heterogeneity. When we expand the model to include multiple segments, we find only two distinct segments: one large segment (72%) that responds very little to past purchases and one (28%) that is very sensitive to past purchase behavior (i.e., if you have purchased in the

Table 3 Parameter Estimates for Conversion and Nested Models at Amazon.com

	r_v	μ_0	k	r_τ	ψ	π	LL	BIC
1. Full model	0.062 (0.021)	0.276 (0.026)	0.932 (0.014)	2.314 (0.086)	0.117 (0.016)	0.790 (0.024)	−4,264.25	8,578.81
2. Visit effect: evolving accumulation (no threshold dynamics)	0.155 (0.037)	0.317 (0.035)	0.918 (0.016)	3.159 (0.177)	**0**	0.777 (0.025)	−4,266.17	8,574.26
3. Visit effect: static accumulation (no threshold dynamics)	0.099 (0.038)	0.436 (0.205)	**1**	4.047 (0.018)	**0**	0.904 (0.029)	−4,279.06	8,600.04
4. Threshold dynamics only	1.348 (0.072)	**0**	**1**	8.782 (0.120)	0.234 (0.032)	0.868 (0.040)	−4,299.44	8,632.42
5. Beta-binomial	0.613 (0.015)	**0**	**1**	4.436 (0.040)	**0**	**1**	−4,308.03	8,632.83

Note. The numbers in bold indicate the values at which the parameters were fixed, and standard errors for the parameter estimates are presented in parentheses.

past, you are more likely to purchase again in the future). Adding a third segment does not add appreciably to the fit of the model. Although the latent-segment model improves upon the single-segment logistic regression (LL = −4,285.50, BIC = 8,692.30), it still provides a far poorer fit than the conversion model.

Benchmark 2—Duration Models. The basic idea here is to reframe the modeling situation from a repeated choice question (*"will you buy at the next visit?"*) into a timing problem (*"how many visits need to occur before you make your next purchase?"*). Duration models have been commonly used in marketing to examine offline grocery store purchasing and can easily be extended to the online purchasing conversion problem. Seetharaman and Chintagunta (2003) provide an excellent review of these models and the many methodological options that exist when implementing them. Specifically, they discuss the application of a discrete-time model to examine purchasing conversion by assuming that store visits occur at regular weekly intervals. In our case, however, we know the times of the actual visits, so we do not need to make any assumptions about them. Additionally, Seetharaman and Chintagunta recommend the use of *cause-specific competing risks models* to incorporate a shopper's recent history of visits and purchases. Specifically, a different timing process is employed based on the customer's recent visiting (and purchasing) history. Based on the findings of Seetharaman and Chintagunta, we applied a discrete-time, cause-specific duration model to our online conversion dataset. We primarily used the log-logistic specification.[3] Estimated as a cause-specific model, it requires four parameters—one (γ, α) pair to be used for intervisit times that follow a nonpurchase visit, and a separate pair for spells that follow purchase visits. When estimated on the entire data period, the model provides a log-likelihood of −4,419.47 and a BIC of 8,872.47.[4] Compared to the other benchmarks we examined, this model fares the worst in terms of in-sample fit.[5]

Although the log-logistic timing model provides an appropriate benchmark for our proposed conversion model, it falls short in several significant ways. First, as mentioned earlier, most timing models (when applied in the purchase incidence context) assume that visits occur at regular weekly intervals. This may be a reasonable assumption for offline grocery shopping, but is unlikely to extend to other environments. The proposed conversion model, on the other hand, deals with conversion on a visit-by-visit basis rather than assuming a fixed time interval for store visits. This is possible in the online environment because visits, in addition to purchases, are fully observable (a significant benefit of click-stream data over store scanner data). Additionally, our proposed conversion model incorporates an individual's entire observed history of purchases and nonpurchases, whereas the cause-specific timing model only accounts for the outcome of the visit immediately preceding the current visit. Finally, our proposed conversion model also explicitly captures learning effects that accumulate across visits and purchase cycles. The aforementioned differences enable the proposed conversion model to allow for different types of shopping behaviors (e.g.,

[3] Seetharaman and Chintagunta (2003) tested a number of different baseline specifications and found that log-logistic and expo-power outperformed all others and were comparable to each other, with the log-logistic model fitting better for some product categories and the expo-power model fitting better for others. We estimated the cause-specific competing-risks expo-power model, which requires six parameters. Although its LL of −4,418.55 is slightly better than that of the log-logistic, its BIC of 8,886.55 is worse, so we did not pursue this model any further.

[4] The parameter estimates for the log-logistic duration model are as follows: $\gamma_{\text{purchase}} = 0.517$, $\alpha_{\text{purchase}} = 1.191$, $\gamma_{\text{nonpurchase}} = 0.255$, $\alpha_{\text{nonpurchase}} = 1.693$.

[5] We also estimated a log-logistic model with multiple support points to better accommodate heterogeneity. This provided a slight improvement in the log-likelihood (−4,411.47), but after accounting for the nine parameters it requires, its BIC value (8,898.41) does not justify the need for the additional latent segment.

searching, browsing, etc.)—a unique contribution of the conversion model over any of the benchmark models proposed in this paper.

Benchmark 3—Beta-Binomial. We also considered the beta-binomial, a special case of the proposed conversion model, as another benchmark. Like the proposed model, it incorporates a Bayesian shrinkage estimate that combines the parameters of the population's beta heterogeneity distribution with each household's own distinct visiting and purchasing history, but it is a purely stationary model: It does not accommodate any of the dynamic aspects (e.g., learning) that are central to the full conversion model.

Benchmark 4—Historical Conversion Rates. Finally, we use a simple projection of historical (observed) conversion rates, a common measure used in practice. Each panelist's predicted buying probability for future visits is simply the number of purchases divided by the number of visits in the calibration period. Though this method is very easy to implement, it is severely limited in its ability to accurately predict behavior for relatively inactive individuals. For example, an individual who made one purchase in one visit in the estimation period would be said to have a predicted conversion rate of 100% for future visits, an unlikely outcome.

Results of Benchmark Comparisons. Table 4 compares each of the benchmark models with the conversion model. Column 3 provides the holdout likelihoods generated by applying the parameter estimates resulting from the first half of the data to the holdout sample. Based on these measures, we find that the dynamic conversion model outperforms each of the benchmark models offered.

We also examine predictive validity by estimating each model on the first half of the data and predicting purchasing probabilities for every household's first visit in the holdout period. Of the 1,022 panelists who made visits in both the model estimation period and the forecasting period, 759 of them did not buy at all in the first four months. Of these 759 shoppers, 10.7%, or 81 individuals, actually made a purchase in their next visit. Using historical conversion rates, all of these 759 shoppers would have been dismissed as having 0% conversion probabilities in the future. The beta-binomial model, with its more lenient shrinkage estimates, predicts that 9.1% of the observed nonbuyers would buy in their next visit.

Table 4 **Benchmark Comparisons**

	In-sample LL	In-sample BIC	Holdout LL	Predicted conversion rate (%) (Actual = 15.7%)
Conversion model	−4,264.25	8,578.8	−2,330.0	14.7
Logistic regression (one segment)	−4,367.8	8,791.6	−2,474.7	19.2
Logistic regression (two segments)	−4,285.5	8,692.3	−2,360.5	14.2
Proportional hazards model	−4,419.5	8,872.5	−2,442.6	18.2
Beta-binomial	−4,308.0	8,632.83	−2,343.4	13.0
Historical conversion rate	NA	NA	NA	13.8

By allowing for the accumulation of visit effects, the conversion model mirrors the actual future conversion far more closely, estimating that 11.1% of the historical nonbuyers would buy in their next visit. As a result, those shoppers who may be "written off" by the competing benchmark models because of low observed conversion probabilities in the past would not be so easily dismissed by the conversion model. Some of these shoppers were apparently building up towards a future purchase, and the proposed model seems to capture these shopping dynamics fairly well.

Overall, of the 1,022 next visits for which we predict purchasing, 160 visits actually resulted in a purchase, leading to a 15.7% conversion rate for this select group of panelists. The average predicted purchasing probability across these 1,022 visits as calculated by the conversion model is 14.7%, a relative error of only 6.3%. Compared to the average purchasing probabilities according to the historical conversion rates (13.8%), the beta-binomial (13.0%), the single-segment logistic regression (19.2%), the two-segment logistic regression (14.2%), and the log-logistic model (18.2%), the conversion model provides the most accurate overall conversion predictions.

6. Conclusions

The Internet has provided e-commerce managers with an abundance of data that can be used for analyses of online buying behavior. The objective of this paper was to carefully investigate one of these metrics—conversion rates. Our model allows for a more valid and useful examination of conversion behavior than can be provided by a simple aggregation of the number of visits and purchases. We illustrated that aggregate measures can offer highly misleading conclusions. Our model avoids these errors by directly addressing heterogeneity across customers as well as dynamics over time. Because customers have different reasons for visiting a retail site, it is important to understand and account for various patterns in the relationship between visiting and purchasing. These patterns are often overlooked but are addressed explicitly in our conversion model. We highlighted the role of two model components in particular (accumulating visit effects and purchase thresholds) and

showed how these elements (taken together and separately) contribute to the model's logical basis and strong empirical performance.

The research problem of examining conversion probabilities is very complex, and several issues are still unexplored. For example, we have ignored the different activities that take place *within* each visit. The sequence of pageviews (e.g., duration, type of pages examined, etc.) could have a great influence on the likelihood that a customer will buy in any given visit. Likewise, we have ignored other possible covariates such as demographics, panelist behavior at other sites, and site design characteristics. However, our model provides a fairly general platform to build in some of these measures in future research. It will be interesting to hypothesize (and empirically test) how these explanatory factors will impact the various components of the model. For instance, demographics may be expected to exert their influence on the baseline propensity to buy (v_{i0}), within-session measures may drive the incremental effect of each visit (m_{ij}), and site design characteristics may show up through the purchase threshold (τ_{ij}). The important point is that our model captures the key behavioral elements underlying the conversion process and can be readily adapted for theory testing using richer datasets as they become available.

In addition, we have defined our modeling problem by taking as given the pattern of customer visits to the focal website. However, as other papers have shown (e.g., Moe and Fader 2003, Roy 1994), purchasing behavior may differ depending on the visiting patterns of the individual in question. Therefore, further extensions of this model could also develop a fully integrated model that captures both behavioral phenomena (visits and conversion) and the two-way interplay between them. However, in the same way that scanner-data researchers first chose to understand (and build separate models for) brand choice, category incidence, and purchase quantity (Gupta 1988) before creating fully integrated models (Bell et al. 1999, Chiang 1991, Chintagunta 1993), we feel that the same type of modular approach is warranted here. We believe that our conversion model is a useful first step in this direction and encourage future researchers to build upon it.

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