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Inertial Disruption: The Impact of a New Competitive Entrant on Online Consumer Search

The objective of this article is to examine the impact of a new competitive entry on online consumer search behavior. The authors use store visitation as a measure of online search and decompose a shopper's tendency to search a given Web site into a baseline search preference for that site and an inertial effect of visiting that site. They find that inertia is an important driver in search behavior and is easily disrupted by a new competitive entry. This is a new and significant finding that contributes to the competitive entry literature. The authors develop a Bayesian model of search that separates the role of baseline search preference and inertia on store visitation and captures the effect of a new competitive entry. They apply this model to Internet clickstream data for the online bookstore market, in which they focus on the entry of Borders.com in 1998.

Keywords: e-commerce, competitive entry, clickstream data, online search, hierarchical Bayesian models, consumer inertia

Consumer search has always been considered an important stage in the decision-making process and has been the focus of extant research in both online and offline environments (e.g., Brynjolfsson and Smith 2000; Johnson et al. 2004; Moorthy, Ratchford, and Talukdar 1997). Recently, research on consumer search has increasingly focused on the online environment (Brynjolfsson and Smith 2000; Johnson et al. 2004; Lynch and Ariely 2000; Morwitz, Greenleaf, and Johnson 1998). With access to rich Internet clickstream data, researchers have been able to observe individual-level search behavior and to study more carefully any search dynamics that may exist. For example, Johnson and colleagues (2004) model the nonstationarity found in online search behavior and show how the size of search sets changes as consumers gain experience. In their article, they focus on the gradual changes in search patterns found in an evolving Internet environment. In this article, we study how search is affected by a disruptive market change—namely, that of a new competitive entry. Specifically, we examine shifts in consumer tendencies to search incumbent sites after the new competitor goes online.

The context of our study is the online bookstore market pioneered by Amazon.com in July 1995. Several competitors soon followed, including Barnesandnoble.com in May 1997. In this article, we focus on the entry of Borders.com, a notable new competitor that launched its site in May 1998. Before the Borders.com launch, at least ten incumbent bookstores were established in the market. The entry of Borders, a major competitor in the offline environment, marked a dramatic change in the online market and thus provides a rich context for us to study the effects of competitive entry on consumer search.

Existing research on competitive entry has primarily focused on challenges facing the new entrant. Far fewer studies have taken the perspective of the incumbent competitors. Kalra, Rajiv, and Srinivasan (1998) examine incumbent response to new competitive entries. However, the focus of their study is on the incumbent's time to respond to the new competitor rather than the effect of the new competitor on its customers and their behavior.

A few studies have examined the impact of a new competitor on the behavior of existing customers. In an experimental setting, Lehmann and Pan (1993) find that new competitors have the effect of shifting consideration sets toward dominating, compromise, and assimilated brands while steering them away from extreme brands. Van Heerde, Mela, and Manchanda (2004) model the effect of product innovation on price elasticities of existing customers at the store level. Finally, Mahajan, Sharma, and Buzzell (1993) provide a diffusion model approach to assess how a new entrant can affect potential market size for the category and incumbents.

The objective of this article is to examine the impact of a new competitive entry on consumer search behavior. We consider the consumer's store visitation decision of whether to visit specific store sites. We develop a model that enables us to better understand the factors that drive a shopper's search behavior by decomposing search behavior into a baseline search preference and inertial effect (while considering dynamics over time and consumer heterogeneity). The model then captures and describes the change in behavior resulting from a new competitive entry. We apply our model to Internet clickstream data for the online bookstore market, in which we focus on the entry of Borders.com in 1998.

The results of our proposed model provide new insights into online consumer search behavior and the impact of a

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new competitive entry. Whereas Lehmann and Pan (1993) document the effect of a new competitive entry on preferences, we offer evidence that inertia plays an important role in online search and is easily disrupted by a new competitive entry. This is a new and significant finding that contributes to the competitive entry literature. We also test the effect of several behavioral covariates (observable from clickstream data) on postentry behavior and find that inertial behavior has a far greater influence on a person's response to a new competitive entrant than other measures of search behavior.

Conceptual Framework

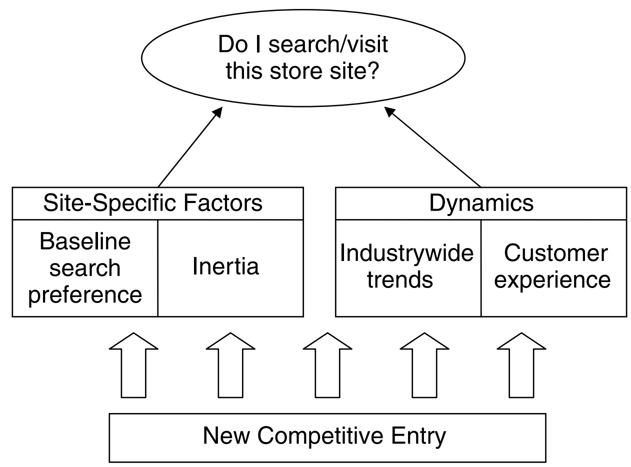
Online Search Behavior

In our study of online search behavior, we focus on store visitation. Much of the existing research (in both the academic and the industry literature) has addressed this aspect of search (see Johnson et al. 2004; Moe and Fader 2004; Summers 2007). Table 1 provides descriptive statistics pertaining to how a competitive entry affects store visitation. The first column provides the percentage of sessions that include a visit to each given site. The next two columns show the same metric for the preentry and postentry periods.

With the entry of Borders.com, Amazon.com, the market leader, experienced a slight decrease in visitation, while Barnesandnoble.com and Books.com experienced increases. This indicates that a competitive entry does not affect all incumbents equally, a pattern previously documented in context effects literature (Huber, Payne, and Puto 1982; Lehmann and Pan 1993).

The purpose of this article is to investigate further the different ways a new competitive entry can affect customer online search behavior and thus affect the incumbents. To this end, we discuss several factors that can potentially influence online search behavior and the potential effect of a new competitive entry on these factors. Figure 1 presents an overview.

FIGURE 1
Overview of Factors Influencing Search



Influence of Site-Specific Effects on Online Search

Various factors draw shoppers to visit a given store site. For example, the store design, recommendation engines, customer reviews, and product assortment can all influence the customer's search experience at a site. As a result, customers may have preferences for including specific store sites in their search set. At the same time, some shoppers are simply creatures of habit and will search a given site simply because they searched that site the last time. Previous studies have shown that such inertial effects exist and are separate from any preferences held by the consumer (Roy, Chintagunta, and Haldar 1996).

Therefore, in this article, we decompose a consumer's intention to search a site into a baseline search preference and an inertial effect. Both baseline search preferences and inertial effects are specific to a given store site. The baseline search preference refers to the shopper's preference for searching a particular site (it indicates nothing about the shopper's preference to buy from that site), whereas the inertial effect represents habits. That is, how much of a shopper's decision to search a given site is because the shopper searched the site the last time and is returning out of habit? Subsequently, we discuss how we model these separate constructs in greater detail.

Influence of Dynamic Effects on Online Search

Although inertia can be considered a dynamic effect, we also consider additional dynamic effects that result from increased experience with online search either at the market level or at the individual customer level. Two potential dynamic effects may exist. First, there are industrywide trends that affect market-level behavior. As the online retail

TABLE 1
Average Incidence Percentage by Site in the Calibration Sample

Site	Entire Data Period (N = 18,408)	Preentry Period (N = 6186)	Postentry Period (N = 12222)
Amazon.com	.839	.845	.836
Barnesandnoble.com	.131	.112	.141
Books.com	.032	.027	.035
Others	.042	.062	.032
Borders.com	.027	N.A.	.042

Notes: N.A. = not applicable.

market grows and matures, online search behavior may exhibit some predictable trends. Overall search would be expected to increase as the online retail environment matures and the general population becomes more comfortable with computers, the Internet, and e-commerce. Alternatively, as the market matures, a clear market leader may emerge, leading to increased search of larger sites and decreased search of smaller sites. The true effect of industrywide dynamics is an empirical question that we address herein.

Second, at the individual customer level, existing research has shown empirically that as a person gains search experience within a given online category, the breadth of search across store sites actually decreases (Johnson et al. 2004). In other words, as consumers learn to search over time, they actually search less. Therefore, in this article, we consider both industrywide and individual-specific sources of dynamics.

Consumer Heterogeneity

Consumer heterogeneity plays an important role in our study. Any approach we take in studying the impact of a new competitive entry must address the issue of consumer heterogeneity. We do this by using a Bayesian modeling approach to accommodate unobserved heterogeneity in search preferences and inertial effects. We also include a set of covariates to capture the effects of observed heterogeneity on search behavior, which we discuss in greater detail when we develop the model.

The Effect of a Disruptive Market Event: Competitive Entry

A new competitive entry is a disruptive market event that can affect several, if not all, of the factors we mentioned previously. Lehmann and Pan (1993) show that a new competitor can shift consumer preferences for incumbent sites toward the dominating brands and away from the extreme brands. By extending their finding to the online retailing context, we would expect consumer search preferences to increase for the market leader and decrease for the smaller sites when a new competitor enters.

Van Heerde, Mela, and Manchanda (2004) also study the effect of a disruptive market event. Specifically, they examine the impact of a product innovation and show how consumer preferences around the time of the new product introduction are more variable. In other words, a disruptive market event can induce consumers to reevaluate their preferences and behaviors. In the online retailing context, this might mean that search preferences become more volatile. One outcome of this may be that inertial effects are disrupted when consumers pause to reevaluate the market.

Similar disruptive effects may also be observed in the dynamic effects. The dynamic effects we discuss in this section reflect trends, regardless of whether they are industrywide or within-individual trends. A disruptive market event, such as a new competitive entry, could easily change the course of these trends. For example, we discussed that as consumers gain experience, they tend to search across fewer sites, partly because they have developed certain preferences and habits. However, when a new competitor enters the market, the competitive landscape changes and forces consumers to question whether their preferences and habits in the preentry environment are still valid in the postentry environment.

Data

We obtained the data used in this study from MediaMetrix, an Internet audience measurement service. MediaMetrix monitors Web site usage for a panel of households that have agreed to have their clickstream behavior recorded. For this study, we use only the clickstream data related to shopping behavior in the online bookstore category, as defined by MediaMetrix. This resulted in a collection of ten Web sites at the start of our data period. This set of Web sites is similar to those used by others who have conducted research in this category (e.g., Johnson, Bellman, and Lohse 2003; Johnson et al. 2004).

We focus on the 30-month period from July 1997 to December 1999. During this period, an 11th online bookstore, Borders.com, was launched in May 1998.[1] This event split the data into a 10-month preentry period and a 20-month postentry period. Other significant launch dates include Barnesandnoble.com, which was launched in May 1997, just before the start of our data set, and Amazon.com, which was launched much earlier in July 1995.

The raw data collected by MediaMetrix is at the click-by-click level. That is, each URL a given household views is recorded along with a time stamp. MediaMetrix aggregates this click-by-click data up to the session level for each individual household. We further aggregate the data up to the daily level such that sessions initiated on the same day are considered one session, a procedure that Johnson and colleagues (2004) use. This resulted in a data set consisting of 11,980 households that conducted a total of 53,082 sessions. For each session, the sites visited are recorded in our final data set and used for the visitation model we present in the next section.[2]

A limitation of using panel data for longitudinal studies is panel churn. To control for churn (and to ensure model identification), we include in our final data set only households that shopped in the online bookstore category at least once before and at least once after Borders.com entered. This reduced our data set to 2389 households, accounting for 22,389 sessions. In addition, there are several sites with low choice incidence.[3] We pool these sites together for our analysis into an "Other" group. Our final set of sites that we model consists of Amazon.com, Barnesandnoble.com, Books.com, Other, and Borders.com.

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[1]The original launch date was set for January 1998, but the actual launch was delayed to allow for additional testing of the Web site (*Forbes* 1998).

[2]We also developed and estimated a model to examine the number of pages viewed at each site. Because the results of this page-view model were similar to those of the visitation model, we focus only on the visitation model.

[3]Store sites included in the "Other" category are Altbookstore.com, Books-A-Million, Booksnow.com, BookZone.com, Powells.com, Superlibrary, and Wordsworth.com.

Modeling Approach

The first step in our model development is to construct a model that captures a shopper's tendency to search a given Web site and to decompose that tendency into a baseline search preference, an inertial effect, and observed dynamics. After constructing this underlying model, we can then introduce model components to capture consumer heterogeneity and any changes that result from a new competitive entrant.

Conditional on a search session occurring, we model the search of each Web site as a multivariate binary incidence to account for consumers searching one or more than one Web site during each search session.[4] We observe person i's decision of whether to search Web site j on session k and denote it as y_{ijk}, where $y_{ijk} = 1$ indicates a search and $y_{ijk} = 0$ indicates no search. This observed decision, y_{ijk}, is determined by a latent search intention, y^*_{ijk}, where the superscript PRE stands for preentry observations and the superscript POST stands for postentry observations:

$$\text{(1a)} \quad y_{ijk}^{PRE} = 1 \text{ if } y_{ijk}^{PRE*} > 0, \text{ and } y_{ijk}^{PRE} = 0 \text{ if } y_{ijk}^{PRE*} \le 0;$$

$$\text{(1b)} \quad y_{ijk}^{POST} = 1 \text{ if } y_{ijk}^{POST*} > 0, \text{ and } y_{ijk}^{POST} = 0 \text{ if } y_{ijk}^{POST*} \le 0.$$

In each period, the latent search intention for a given site is driven by the consumer's underlying search preference for that site, an inertial effect, and observed dynamics. In each period, this can be represented as follows:

$$\text{(2a)} \quad \text{Preentry period: } y_{ijk}^{PRE*} = \theta_{ijk}^{PRE} X_{ijk}^{PRE} + \beta_{j1}^{PRE}\text{Time}_{ik} + \beta_{j2}^{PRE}\text{Session}_{ik} + \varepsilon_{ijk}^{PRE}, \text{ and}$$

$$\text{(2b)} \quad \text{Postentry period: } y_{ijk}^{POST*} = \theta_{ijk}^{POST} X_{ijk}^{POST} + \beta_{j1}^{POST}\text{Time}_{ik} + \beta_{j2}^{POST}\text{Session}_{ik} + \varepsilon_{ijk}^{POST},$$

where X_{ijk} includes a site-specific intercept representing the baseline search preference and a lag term, $y_{ij,k-1}$, representing the inertial effect. Time_{ik} and Session_{ik} capture observed dynamics. The Time_{ik} covariate indicates the day on which the search k takes place (for the first search session observed in our data set, Time = 1) and can capture industrywide dynamics. The Session_{ik} covariate measures the number of sessions in which the consumer searched for books before the given search k and captures individual-specific dynamics that result from increased experience. Note that Session_{ik} is individual specific, not site specific, and counts the number of bookstore searches conducted by person i regardless of the sites searched. In the preentry period, we model each of j = 1, 2, …, J – 1 incumbent sites. In the postentry period, we model j = 1, 2, …, J sites, where the Jth site is the new competitive entrant.

We specify the error terms as follows:

$$\text{(3a)} \quad \varepsilon_{ijk}^{PRE} \sim MVN(0, R^{PRE}), \text{ and}$$

$$\text{(3b)} \quad \varepsilon_{ijk}^{POST} \sim MVN(0, R^{POST}),$$

where R^{PRE} is fixed to be a 4×4 correlation matrix and R^{POST} is fixed to be a 5×5 correlation matrix, as in a standard multivariate binary probit model.

We also allow for heterogeneity in the preentry period as follows:

$$\text{(4)} \quad \theta_i^{PRE} = \overline{\theta^{PRE}} + \eta_i^{PRE},$$

where θ_i^{PRE} is a $2(J - 1) \times 1$ vector indicating person i's preferences and inertial effects for the J – 1 sites before the competitive entry and $\overline{\theta^{PRE}}$ is the average baseline search preferences and inertial effects for the J – 1 sites before the competitive entry.

After the new competitor enters the market, baseline search preferences and inertial effects are expected to shift. To capture this shift, we model the baseline search preferences and inertial effects in the postentry period as follows:

$$\text{(5)} \quad \theta_i^{POST} = \alpha_j{}'S_i + \Gamma\theta_i^{PRE} + \eta_i^{POST},$$

where θ_i^{POST} is a $2J \times 1$ vector indicating baseline search preferences and inertial effects for the J sites after the competitive entry, S_i is a vector of observed individual-specific covariates (including a constant), and Γ is a $2J \times 2(J - 1)$ transition matrix to be estimated.

To elaborate further, the Γ transition matrix represents the influence of preentry parameters on postentry preferences and inertial effects. For example, the first row of the Γ matrix measures the influences of baseline search preferences and inertial effects for the J – 1 sites before entry on the baseline search preference for site 1 after entry. The J + 1th row of the Γ matrix measures the influences of baseline search preferences and inertial effects for J – 1 sites before entry on the inertial effect for site 1 after entry.

We include the individual-specific covariates (S_i) to control for any observed heterogeneity in individual search patterns. Rather than using demographic characteristics of individual visitors, which are typically unavailable from clickstream data, we develop a set of behavioral covariates derived from each person's historical behavior in the preentry period. The first set of covariates characterizes people as one of three search types: (1) nonsearchers, (2) variety searchers, and (3) within-session searchers.[5] Nonsearchers are people who limit their search set to just one site. In addition, they visit the same site session after session. Variety searchers also limit their search set to just one site. However, unlike the nonsearchers, they vary the site from session to session. Finally, within-session searchers are people who visit multiple sites within the same search session. We include only the indicators for variety searchers and within-session searchers in S_i for identification purposes. In addition, the search type effect appears only in the postentry period. Because search type is measured using preentry data, we cannot include it as a covariate in the preentry model. Instead, we capture any individual differences that may be associated with search type in the preen-

[4]We consider each visit to a given Web site a search of that site.

[5]The ability of these measures to accurately reflect a person's search type is dependent on the amount of individual search history contained in the data. This may be limited.

try period as unobserved heterogeneity. The second set of covariates includes measures of recency and frequency. We define recency as the number of days between the last preentry visit and the date of competitive entry. We measure frequency as the number of visits made in the preentry period. We realize that this is a left-censored measure, but it serves as a proxy given our data constraints.

To complete the specification of θ_{ijk}, η_i^{PRE} and η_i^{POST} are random components for preentry and postentry search preferences, which are assumed to be independent across people and normally distributed:

$$\eta_i^{PRE} \sim MVN(0, \Sigma^{PRE}), \text{ and} \tag{6a}$$

$$\eta_i^{POST} \sim MVN(0, \Sigma^{POST}), \tag{6b}$$

where the Σ^{PRE} and Σ^{POST} matrices represent heterogeneity across people and are diagonal. This concludes our specification of the visitation model.

The likelihood specified is complex because it involves higher-order multidimensional integrals, which make the classical inference difficult. We use the Bayesian framework to make inferences about the unknown parameters. Specifically, we use a combination of the Gibbs sampler, the Metropolis–Hastings random walk algorithm, and data augmentation to obtain a sample of parameter draws from their joint posterior distribution (see the Appendix). Another advantage of the Bayesian estimation approach is that the estimates of individual consumer baseline search preferences and inertial effects are a by-product from the Markov chain Monte Carlo algorithm but are treated as nuisance parameters and integrated out under the classical inference approach. These individual-level estimates are valuable in helping understand heterogeneous consumer search patterns, which we demonstrate subsequently in this article.

Results

Preentry Parameter Estimates

We begin by discussing the individual parameter estimates resulting from the visitation model. Subsequently, we integrate the individual elements of the model and discuss the overall implications for incumbent competitors facing a new competitive entry. Table 2 presents all parameter estimates associated with the preentry period.

The first two columns (θ^{PRE}) decompose the latent search intention toward a given site into a baseline search preference and an inertial effect. The next two columns provide the dynamic effects, and the final two columns (Σ^{PRE}) represent the degree of variance, or heterogeneity, found in these measures across shoppers. The state dependence parameters provided in Column 2 are significant and positive, suggesting behavioral inertia. These results indicate that the role of inertial effects in a shopper's overall intention to search a given site is important, highlighting the value of separating baseline search preferences from inertial effects.

Although these inertial parameters are significantly and substantially different from zero, we caution the reader against interpreting the absolute magnitude of the estimated parameters because of the highly nonlinear nature of the multivariate probit model. Instead, we focus on measures of sensitivity that assess the influence of lag search on current search probability. Specifically, we measure sensitivity as the percentage change of predicted search probability on a given Web site from the case without a lag search incidence to the case with a lag search incidence on the same site. Table 3 reports the lag search sensitivity in the preentry period for each site and indicates that the smaller sites (6.156 for Books.com and 2.198 for Others) are more affected by inertia than the larger sites (.114 for Amazon.com and 1.491 for Barnesandnoble.com). We discuss these results further when we compare preentry behavior with postentry behavior.

The model also reveals significant dynamics in consumer search behavior. The dynamics captured by the Time covariate indicate general trends in the online bookstore market. As time passes, consumers increasingly include Amazon.com in their search sets ($\beta^{PRE}_{AM,1}$ = .122), while the presence of Barnesandnoble.com in search sets decreases ($\beta^{PRE}_{BN,1}$ = –.226). This trend may reflect increased branding efforts on the part of Amazon.com. The dynamics with respect to Barnesandnoble.com can be better understood by also examining the Session covariate.

The coefficients for the Session covariate are negative for Barnesandnoble.com ($\beta^{PRE}_{BN,2}$ = –.179) and Books.com

TABLE 2
Preentry Results

	$\overline{\theta^{PRE}}$		Dynamics		Σ^{PRE}	
	Baseline Preference	**Inertial Effect**	**Time**	**Session Count**	**Baseline Preference**	**Inertial Effect**
Amazon.com	**.939**	**.469**	**.122**	–.076	**.288**	**.225**
	(.039)	**(.051)**	**(.033)**	(.045)	**(.041)**	**(.041)**
Barnesandnoble .com	**–1.455**	**.545**	**–.226**	**–.179**	**.224**	**.384**
	(.038)	**(.096)**	**(.035)**	**(.054)**	**(.043)**	**(.099)**
Books.com	**–2.352**	**.852**	–.043	**–.132**	**.360**	**.386**
	(.056)	**(.144)**	(.054)	**(.062)**	**(.059)**	**(.112)**
Other	**–2.047**	**.533**	–.033	.053	**.519**	**.392**
	(.077)	**(.144)**	(.051)	(.058)	**(.101)**	**(.125)**

Notes: Elements in bold are significant at p = .10.

TABLE 3
Preentry Inertial Effect Measured by the Lag Search Sensitivity

Amazon.com	.114
Barnesandnoble.com	1.491
Books.com	6.156
Other	2.198

Notes: Lag search sensitivity = [P(lag_search = 1) – P(lag_search = 0)]/P(lag_search = 0).

($\beta^{PRE}_{BK,2}$ = –.132) and insignificant for Amazon.com and Other sites. The overall negative effect of Session is consistent with the existing literature on online search, which reports that as consumers gain experience searching in a given category, they tend to include fewer store sites in their search set. The negative Session coefficients for Barnesandnoble.com and Books.com indicate that as consumers gain experience in this category, they become less likely to search these two sites. This implies that the shopping experiences at these sites may not fare as well as their competitors, and as a result, these sites are suffering the consequences of shrinking search sets.

The Transition Matrix

When a market disruption (e.g., new competitive entry) occurs, baseline search preferences and inertial effects shift as a function of the transition matrix according to Equation 5. Table 4 presents all estimated elements of the transition matrix, Γ. To simplify our discussion of the results, we focus on two quadrants: (1) the impact of preentry search preferences on postentry search preferences (upper-left-hand quadrant) and (2) the impact of preentry inertial effects on postentry inertial effects (lower-right-hand quadrant). The other two quadrants effectively serve as control variables and are not the focus of our study.

The diagonal elements of the matrix indicate the influence of the preentry value on the postentry value for a given measure. For example, in the upper-left-hand quadrant of the matrix, the baseline search preferences for Amazon.com in the postentry period are independent of the baseline search preferences in the preentry period because the value of Γ_{11} is insignificantly different from zero. However, the postentry baseline search preferences for Amazon.com's competitors are greater if preentry values are higher, as indicated by the positive values for these sites along the diagonal. This suggests some degree of preference reinforcement for these sites when the new competitor enters.

The off-diagonal elements suggest a negative influence of preentry search preference for the market followers on postentry preference for the market leader, Amazon.com. For example, shoppers who prefer to search Barnesandnoble.com and/or Books.com are likely to have lower search preferences for Amazon.com in the postentry period (Γ_{12} = –.338, Γ_{13} = –.382). Other off-diagonal values among the incumbent competitors are insignificantly different from zero. This suggests that if a shopper holds a strong preference for searching one of the existing market followers, he or she is less likely to shift search preferences toward another incumbent site in the postentry period.

TABLE 4
Transition Matrix (Γ)

	Preentry Baseline Search Preference				Preentry Inertial Effect			
	AM	BN	BK	OT	AM	BN	BK	OT
Postentry Baseline Search Preferences								
Amazon.com (AM)	–.194	**–.338**	**–.382**	–.200	**1.287**	**–.435**	**–.863**	**–.751**
	(.160)	**(.111)**	**(.181)**	(.268)	**(.219)**	**(.129)**	**(.249)**	**(.140)**
Barnesandnoble.com (BN)	–.035	**.656**	–.108	.126	**–.700**	.158	**.847**	.147
	(.154)	**(.200)**	(.154)	(.123)	**(.259)**	(.132)	**(.092)**	(.185)
Books.com (BK)	.031	–.571	**.852**	.178	–.485	**.898**	**.714**	–.338
	(.288)	(.310)	**(.239)**	(.325)	(.398)	**(.365)**	**(.238)**	(.251)
Other (OT)	–.181	.253	.105	**.550**	**–.711**	**.414**	.248	–.351
	(.206)	(.184)	(.185)	**(.142)**	**(.309)**	**(.192)**	(.180)	(.289)
Borders.com	.080	.174	**.365**	.235	**–.780**	.001	**.416**	–.253
	(.189)	(.189)	**(.144)**	(.137)	**(.253)**	(.213)	**(.160)**	(.222)
Postentry Inertial Effects								
Amazon.com (AM)	**.316**	**–.292**	.242	–.081	**.553**	.210	–.006	**.787**
	(.156)	**(.133)**	(.147)	(.182)	**(.247)**	(.158)	(.245)	**(.191)**
Barnesandnoble.com (BN)	.246	–.079	**.399**	.124	–.820	.331	.160	**.813**
	(.194)	(.175)	**(.173)**	(.184)	(.256)	(.214)	(.246)	**(.182)**
Books.com (BK)	.485	.621	**1.363**	.002	–.668	.007	**.647**	.396
	(.626)	(.540)	**(.461)**	(.380)	(1.141)	(.511)	**(.293)**	(.898)
Other (OT)	.749	–.439	.530	–.269	–.465	–.530	–.605	**.845**
	(.534)	(.480)	(.401)	(.238)	(.495)	(.426)	(.544)	**(.334)**
Borders.com	.430	–.272	.299	–.205	**–.871**	.578	**.466**	**.965**
	(.348)	(.368)	(.199)	(.260)	**(.284)**	(.367)	**(.292)**	**(.253)**

Notes: The values represent posterior means. Posterior standard deviations appear in parentheses. Elements in bold are significant at $p < .05$.

The lower-right-hand quadrant of the matrix represents the influence of preentry inertial effects on postentry inertial effects. For Amazon.com and Books.com, the positive estimates indicate that the competitive entry reinforces any preentry inertial effects they experience (Γ_{65} = .553, Γ_{87} = .647). Several off-diagonal elements in this quadrant are significantly positive, indicating that higher inertial effects for a given site in the preentry period may enhance postentry inertial effects. However, these parameter estimates should not be interpreted in isolation. Because of the negative intercept terms associated with postentry inertia (see Table 5), the net result is actually a decline in inertial effects in the postentry period. The positive elements in the transition matrix only serve to mitigate that decline. Subsequently in this section, we integrate the various parameter estimates and discuss the overall impact of the competitive entry on search behavior.

From the perspective of the new entrant, Borders.com draws customers from those who prefer to search Books.com (Γ_{53} = .365). The customers attracted from Books.com are also highly inertial (Γ_{57} = .416). Conversely, Amazon.com customers with high levels of preentry inertia for Amazon.com are less likely to prefer Borders.com (Γ_{55} = –.780).

Postentry Parameters

The transition matrix is not the only model component that drives postentry behavior. Table 5 presents the remaining parameter estimates that affect postentry search behavior. The only significant direct effects of search type on postentry behavior are evident in the baseline search preferences for Books.com and Others. People who have historically been variety searchers in the preentry period are more likely to include Books.com in their postentry search sets. Those who have historically been within-session searchers are more likely to include the Other sites in their postentry search sets. Although these are noteworthy results, they are not our focus here. Likewise, recency and frequency measures also have mixed effects. Most coefficients are insignificant, and those that are significant do not exhibit consistent or predictable patterns. As a result, we treat these estimates as merely control measures to accommodate observed customer heterogeneity and not any sort of predictive variable.

The dynamic effects in the postentry period are more insightful, especially compared with the preentry dynamic effects. In the postentry period, Time dynamics provide a positive effect on postentry search intentions for Barnesandnoble.com and negative effects on all other incumbents. In other words, in the postentry period, industrywide trends are favorable for Barnesandnoble.com. This is in contrast to the negative effect of Time on Barnesandnoble.com and the positive effect of Time on Amazon.com in the preentry period. The transition matrix already indicated that Barnesandnoble.com benefits from a one-time, sudden effect on search intentions after the launch of Borders.com. In addition, the Time coefficient suggests that the launch of Borders.com leads to a positive trend in search intentions for Barnesandnoble.com as well ($\beta^{POST}_{BN,1}$ = .511). Together, these results suggest that the entry of Borders.com is an event that increases the appeal of Barnesandnoble.com. Although the effect of Session on Barnesandnoble.com is negative ($\beta^{POST}_{BN,2}$ = –.099), it is outweighed by the effect of Time.

Again, the negative coefficient for Session in the postentry period for Barnesandnoble.com ($\beta^{POST}_{BN,2}$ = –.099) is consistent with the existing online search literature and the preentry results. However, Amazon.com benefits from a positive Session coefficient ($\beta^{POST}_{AM,2}$ = .053). The implication here is that as Internet shoppers gain experience with online book shopping, they are increasingly including Amazon.com in their search sets. Thus, while Barnesandnoble.com benefits from Time dynamics, Amazon.com benefits from Session dynamics in the postentry period.

Table 6 provides estimates for the correlation matrices specified in Equations 3a and 3b. The matrices indicate statistically significant correlations across sites. Specifically, the decision to visit Amazon.com is negatively correlated with the decision to visit its competitors. This is true for both the preentry and the postentry periods and justifies our use of a multivariate binary probit analysis instead of treating the search decision as independent across sites.

Overall Results

Thus far, we have discussed the results of each element of the model one by one. Although it is important to understand how to interpret individual model parameters, it may be more useful to examine the overall change in search behavior from the preentry to the postentry period, especially as it relates to inertial effects. To facilitate this comparison, we calculate the lag search sensitivity for each Web site in the postentry period and then compare the resultant preentry and postentry lag search sensitivity in Table 7. These sensitivities represent the sensitivity of search probabilities to the lag search, which is another way to measure the impact of inertial effect. We stress that these parameter estimates should be converted into sensitivities to facilitate the pre- and postentry comparison. This is because the covariance matrix of the error terms in the multivariate probit model is scaled to be a correlation matrix for identification, and therefore other model parameters are estimated relative to this scale.

Across all sites, the inertial effects decrease significantly after the new competitor enters the market. This suggests that such a market disruption can significantly affect search behavior by disrupting established habits. In other words, visitors who have been habitually shopping at an incumbent Web site are more at risk of defecting after a new competitor enters the market than visitors who have not exhibited such inertial behavior. It could be argued that the decrease in inertial effects in the postentry period can simply be a result of regression to the mean. In other words, high levels of inertia in the preentry period may simply be reverting to a lower mean, resulting in a decrease in inertial effects in the postentry period. However, if regression to the mean were driving the results, the reverse (or increasing inertial effects) would also be true for sites experiencing low levels of inertia in the preentry period. Because the results in Table 7 show that inertial effects decrease across all sites, we are confident that some level of inertial decay is

TABLE 5
Postentry Results

	Intercept	Within-Session Searchers	Variety Searchers	Recency	Frequency	Σ^{POST}
Postentry Baseline Search Preferences						
Amazon.com	**.490**	.131	**.228**	**.101**	.013	**.115**
	(.156)	(.216)	**(.115)**	**(.052)**	(.052)	**(.014)**
Barnesandnoble.com	**–1.316**	–.236	–.089	–.001	.047	**.134**
	(.190)	(.138)	(.095)	(.030)	(.038)	**(.018)**
Books.com	**–3.100**	.095	.282	.053	.010	**.702**
	(.466)	(.302)	(.244)	(.086)	(.071)	**(.163)**
Other	**–.795**	–.117	–.164	**–.158**	**.086**	**.505**
	(.279)	(.203)	(.169)	**(.066)**	**(.040)**	**(.097)**
Borders.com	**–.812**	–.101	–.111	.051	**.084**	**.450**
	(.343)	(.148)	(.129)	(.044)	**(.036)**	**(.083)**
Postentry Inertial Effects						
Amazon.com	**–.624**	.197	–.035	–.124	–.059	**.122**
	(.180)	(.202)	(.109)	(.056)	(.045)	**(.016)**
Barnesandnoble.com	.341	.062	–.298	–.065	–.036	**.279**
	(.449)	(.283)	(.170)	(.063)	(.053)	**(.053)**
Books.com	**2.071**	–.299	**–1.106**	**–.504**	.114	**1.146**
	(1.027)	(.731)	**(.484)**	**(.238)**	(.147)	**(.432)**
Other	.124	.670	.077	–.025	–.045	**.732**
	(.281)	(.517)	(.380)	(.264)	(.083)	**(.269)**
Borders.com	**–1.518**	.090	.185	–.163	–.041	**.477**
	(.264)	(.388)	(.382)	(.148)	(.097)	**(.146)**

	Time	Session Count
Postentry y*		
Amazon.com	**–.281**	**.053**
	(.014)	**(.012)**
Barnesandnoble.com	**.511**	**–.099**
	(.017)	**(.019)**
Books.com	**–.189**	–.023
	(.035)	(.024)
Other	–.040	.008
	(.023)	(.023)
Borders.com	**.041**	**–.058**
	(.019)	**(.024)**

Notes: The values represent posterior means. Posterior standard deviations appear in parentheses. Elements in bold are significant at $p < .05$.

TABLE 6
Correlation Matrices

Preentry	Amazon.com	Barnesandnoble.com	Books.com	Other	Borders.com
Amazon.com	1	**–.182 (.018)**	**–.040 (.017)**	**–.085 (.018)**	
Barnesandnoble.com		1	–.008 (.017)	–.012 (.018)	
Books.com			1	.001 (.019)	
Other				1	
Postentry	**Amazon.com**	**Barnesandnoble.com**	**Books.com**	**Other**	**Borders.com**
Amazon.com	1	**–.162 (.016)**	–.020 (.014)	**–.043 (.017)**	**–.056 (.015)**
Barnesandnoble.com		1	.001 (.016)	–.001 (.016)	–.004 (.016)
Books.com			1	.005 (.014)	.006 (.015)
Other				1	.002 (.015)
Borders.com					1

Notes: The values represent posterior means. Posterior standard deviations appear in parentheses. Elements in bold are significant at $p < .05$.

TABLE 7
Comparison Between Preentry and Postentry Inertial Effect Measured by the Lag Search Sensitivity

	Preentry Inertial Effect	Postentry Inertial Effect
Amazon.com	.114	.018
Barnesandnoble.com	1.491	.400
Books.com	6.156	–.996
Other	2.198	1.184

Notes: Lag search sensitivity = [P(lag_search = 1) – P(lag_search = 0)]/P(lag_search = 0). Inertial effects are statistically significant across all sites.

occurring beyond any potential effects resulting from a regression to the mean. In addition, we observe varying degrees of inertial decay across sites. The decay experienced by the market leaders (Amazon.com and Barnesandnoble.com) is less than that experienced by the market follower (Books.com), a result consistent with the context effect research we discussed previously (Huber, Payne, and Puto 1982; Lehmann and Payne 1993).

The inertial disruption of a competitive entry is a key finding of our model and emphasizes the importance of decomposing customer search behaviors into underlying baseline search preferences and inertial effects. In industries in which this effect holds true, customer bases dominated by people whose search behaviors are strongly influenced by inertia are more at risk in the face of a competitive entry. Incumbent competitors with such customer bases should proactively attempt to identify and target people with large inertial effects in anticipation of a new competitor entering the market.

Model Validation and Simulation

Because a key element of this research is the identification of highly inertial people as likely defectors, it is important that the proposed model can accurately decompose a person's behavior into a baseline search preference and inertial effect and link them to the same person's postentry behavior. We test the model's ability to do this by examining hit rates in a validation sample. We also compare the predictive performance of the proposed model with two benchmark models.

We begin by estimating the model on a calibration sample of 18,408 observations (y_{ijk}^{IN}) based on 2028 people. We saved the remaining 3981 observations (y_{ijk}^{OUT}) from the postentry period based on 361 people for the out-of-sample prediction purposes. For this validation sample, we use their preentry data along with the estimation results from the calibration sample to obtain postentry parameters. We then predict the postentry search behavior of the holdout sample.

The first benchmark model (Model 1) completely ignores the structural change induced by the new competitor's entry. In this validation, we first estimate θ_{ij}^{PRE} (j = 1, 2, 3, and 4) and the other model parameters with the preentry data from the 361 people and let $\theta_{ij}^{POST} = \theta_{ij}^{PRE}$ for incumbent Web sites. For the new entrant, we estimate θ_{ij}^{POST} (j = 5) and the other model parameters with a standard binary probit model estimated on the postentry data in the calibration sample without accounting for any structural change induced by the competitive entry. We then use θ_{ij}^{POST} and the other model parameters to predict the postentry search behavior for the holdout sample.

The second benchmark model (Model 2) completely ignores the search history before the competitive entry for the 361 people in the holdout sample. Instead, we estimate the aggregate-level model parameters with a standard multivariate probit model using the calibration sample and use these parameters to predict the postentry search behavior on the five Web sites for the holdout sample.

Table 8 presents the results of our validation test. Our analysis shows that the proposed model can accurately predict the search incidence of the five Web sites for 3772 of the 3981 observations, for a 94.8% hit rate. This impressive level of predictive accuracy validates the use of the model for the identification of specific people to target.

The performance of the proposed model is also significantly better than that of the benchmarks. Model 1 ignores

TABLE 8
Model Validation

(N = 3981)	Number of Observations Accurately Predicted	Hit Rate
Proposed model	3774	94.8%
Model 1	3567	89.6%
Model 2	3485	87.5%

the structural change due to the competitor's entry and provides accurate predictions for 3563 observations, for an 89.6% hit rate. Model 2 ignores the preentry search history and provides accurate predictions for 3482 observations, for an 87.5% hit rate. This suggests the importance of accounting for both the search behavior before the competitor's entry (θ_{ij}^{PRE}) and the structural change induced by the competitor's entry (Γ) in predicting a consumer's postentry search behavior.

To demonstrate the predictive ability of the model, we simulate postentry visitation behavior on the basis of several preentry behavioral scenarios. For each store site, we simulate the behavior for an existing customer (i.e., $y_{ij,k-1}$) with low inertial effects, mean inertial effects, and high inertial effects in the preentry period. We assume mean values for all other parameters so that the only source of variability between simulated customers is the level of the preentry inertia effect. Using these simulated preentry profiles, we then simulate both pre- and postentry visitation behavior. For the mean shopper, we simply use the $\overline{\theta^{PRE}}$ estimates provided in Table 2 to generate preentry visitation probabilities, postentry parameter estimates, and postentry visitation probabilities. For customers with low inertial effects, we construct a scenario in which the baseline search preference is unchanged but the inertial effect in $\overline{\theta^{PRE}}$ is one standard error below the mean. For customer with high inertial effects, we calculate inertial effects to be one standard error above the mean.

Table 9 provides the difference in pre- and postentry visit probabilities for each customer type at each store site. Across sites and customer types, there is a decline in visit probabilities in the postentry period, an expected outcome when a new competitor enters the market. However, the magnitude of decline varies systematically across customer types. Regardless of the store site, customers with high inertial effects in the preentry period experience a greater decline in visit probabilities in the postentry period. This supports our argument that, all else being equal, highly inertial customers are more vulnerable in the face of a new competitive entry.

Conclusion

In this article, we proposed a model of search behavior in an effort to examine the impact of a new competitor entering the market. In our model, we decompose a person's search intention for a given Web site into a baseline search preference for that site and an inertial effect representing habit, while accommodating dynamics. We then model the impact of a new competitive entry on each of these search drivers. Our objective with the modeling effort was to better understand how the new competitor changed not only overall search behaviors but also site-specific search preferences and inertial effects for the incumbent sites.

A unique aspect of our model is the identification of inertial effects in search behavior. The results show that this inertial effect is substantial. They also show that this effect is vulnerable to a market disruption, such as a new competitive entry. For incumbents in industries with dynamics similar to the one we present herein, the identification of highly inertial customers may serve as a first step to limiting the negative effect of an anticipated competitive entry. However, determining whether or what tools are available to stem the potential attrition of these customers is left for further research. We also encourage additional research on the role of inertia in other market environments. We show that inertia is highly vulnerable to a new competitive entry in the online bookstore market. If this result can be shown to generalize across markets, future marketers facing a potential new competitor can better prepare for (and potentially defend against) the impending market disruption.

It is worth mentioning some limitations of the proposed model and its application. Although our model examines the consumer response to a competitive entry, it does not address the competitor's decision to enter. We would expect such entry decisions to be dependent on the expected consumer response to the entry. A new competitor would enter the market only if it anticipated some level of success in either attracting new customers into the market or stealing

TABLE 9
Simulation Results: $Pr(y^{POST}) - Pr(y^{PRE})$

		Amazon.com	Barnesandnoble.com	Books.com	Other
Nonsearcher	Low inertia	–.79%	–13.48%	–3.93%	–3.48%
	Mean inertia	–.99%	–15.58%	–5.62%	–4.89%
	High inertia	–1.16%	–17.85%	–7.85%	–6.70%
Within-session searcher	Low inertia	–2.28%	–11.75%	–3.93%	–2.05%
	Mean inertia	–2.40%	–13.78%	–5.62%	–3.09%
	High inertia	–2.50%	–16.00%	–7.85%	–4.47%
Variety searcher	Low inertia	–4.05%	–13.09%	–3.93%	–3.27%
	Mean inertia	–4.10%	–15.16%	–5.63%	–4.61%
	High inertia	–4.12%	–17.42%	–7.85%	–6.35%

customers away from the existing competitors. As such, overall consumer search probability and the competitive entry decision are potentially endogeneous. However, because of data limitations, we are not able to model the impact of the competitive entrant and the entry decision simultaneously. In addition, our primary contributions are the decomposition of overall search probabilities into a baseline preference and inertial effects and the finding that inertial effects are disrupted by a new competitive entry. The potential problems that may arise from endogeneity in our study are not likely to be substantial. At the time of the Borders.com entry into the online bookstore market, the Internet was still a rapidly growing environment. Companies raced to enter, often without much thought about strategy or even profitability. This is evident in Borders.com's decision and the delays it experienced in launching the site as it was working out technical difficulties.

Another limitation is a consequence of the nature of the data used in this study. To estimate our model, we use data collected from a panel of volunteers who had all their online behavior recorded. This provides us with search behavior across all sites in this product category. However, Web sites do not have access to this kind of data for their entire customer base. Without knowledge of how customers search across sites, the applicability of the proposed model and its findings is limited. A potential remedy of this problem is to survey customers about their historical search behaviors. A well-designed survey that solicits a characterization of respondents' search patterns could assist in the identification of inertial shoppers.

This research focuses on the effect of a new competitive entry on incumbent competitors and their customers. However, our approach can be applied to other market disruptions as well, such as product modifications, the merging of competitors, or regulatory changes. In addition, a variety of product categories can be studied to identify market characteristics that drive the nature of the effect. Finally, our model can be extended to study the impact of competitive entry on cross–state dependence effects. Overall, the impact of a new competitive entry on the existing customer base is an issue that has tremendous potential but, in general, has been understudied. We hope that this article will stimulate further research in this direction.

Appendix: The Markov Chain Monte Carlo Algorithm

1. Generate y_{ijk}^{PRE*}

$$y_{ijk}^{PRE*} = \overline{y_{ijk}^{PRE*}} + \varepsilon_{ijk}^{PRE};\ \overline{y_{ijk}^{PRE*}} = \theta_{ijk}^{PRE}X_{ijk}^{PRE} + \beta_{j1}^{PRE}\text{Time}_{ik} + \beta_{j2}^{PRE}\text{Session}_{ik}.$$

- If $y_{ijk}^{PRE} = 1$, draw $y_{ijk}^{PRE*} \sim N(\overline{y_{ijk}^{PRE*}} + E_{ijk}, V_{ijk})$, such that $y_{ijk}^{PRE*} > 0$, and
- If $y_{ijk}^{PRE} = 0$, draw $y_{ijk}^{PRE*} \sim N(\overline{y_{ijk}^{PRE*}} + E_{ijk}, V_{ijk})$, such that $y_{ijk}^{PRE*} < 0$,

where E_{ijk} (V_{ijk}) is the conditional mean (variance) of ε_{ijk}^{PRE}, conditioning on $\varepsilon_{ij'k}^{PRE}$ and $j' \neq j$.

2. Generate y_{ijk}^{POST*}

$$y_{ijk}^{POST*} = \overline{y_{ijk}^{POST*}} + \varepsilon_{ijk}^{POST};\ \overline{y_{ijk}^{POST*}} = \theta_{ijk}^{POST}X_{ijk}^{POST} + \beta_{j1}^{POST}\text{Time}_{ik} + \beta_{j2}^{POST}\text{Session}_{ik}.$$

- If $y_{ijk}^{POST} = 1$, draw $y_{ijk}^{POST*} \sim N(\overline{y_{ijk}^{POST*}} + E_{ijk}, V_{ijk})$, such that $y_{ijk}^{POST*} > 0$, and
- If $y_{ijk}^{POST} = 0$, draw $y_{ijk}^{POST*} \sim N(\overline{y_{ijk}^{POST*}} + E_{ijk}, V_{ijk})$, such that $y_{ijk}^{POST*} < 0$,

where E_{ijk} (V_{ijk}) is the conditional mean (variance) of ε_{ijk}^{POST}, conditioning on $\varepsilon_{ij'k}^{POST}$ and $j' \neq j$.

3. Generate θ_i^{PRE}

$$\overline{y_{ijk}^{PRE*}} = y_{ijk}^{PRE*} - \beta_{j1}^{PRE}\text{Time}_{ik} - \beta_{j2}^{PRE}\text{Session}_{ik} = \theta_{ijk}^{PRE}X_{ijk}^{PRE} + \varepsilon_{ijk}^{PRE},$$

$$\theta_i^{POST} = \alpha S_i + \Gamma\theta_i^{PRE} + \eta_i^{POST}, \text{ and}$$

$$\theta_i^{PRE} = \overline{\theta^{PRE}} + \eta_i^{PRE}.$$

Then, generate

$$\theta_i^{PRE} \sim MVN(W_i, P_i),$$

where

$$P_i = \{(\Sigma^{PRE})^{-1} + [X_i^{PRE}(R^{PRE})X_i^{PRE\prime}] + [\Gamma'(\Sigma^{POST})^{-1}\Gamma]\}^{-1} \text{ and}$$

$$W_i = P_i[(\Sigma^{PRE})^{-1}\overline{\theta_i^{PRE}} + X_i^{PRE}(R^{PRE})^{-1}\overline{y_i^{PRE*}} + \Gamma'(\Sigma^{POST})^{-1}(\theta_i^{POST} - \alpha S_i)].$$

4. Generate θ_i^{POST}

$$\overline{y_{ijk}^{POST*}} = y_{ijk}^{POST*} - \beta_1^{POST}\text{Time}_{ik} - \beta_2^{POST}\text{Session}_{ik} = \theta_{ijk}^{POST}X_{ijk}^{POST} + \varepsilon_{ijk}^{POST}, \text{ and}$$

$$\theta_i^{POST} = \alpha S_i + \Gamma\theta_i^{PRE} + \eta_i^{POST}.$$

Then, generate

$$\theta_i^{POST} \sim MVN(W_i, P_i),$$

where

$$P_i = \{(\Sigma^{POST})^{-1} + [X_i^{POST}(R^{POST})^{-1}X_i^{POST}]\}^{-1} \text{ and}$$

$$W_i = P_i[(\Sigma^{POST})^{-1}(\alpha S_i + \Gamma\theta_i^{PRE}) + X_i^{POST}(R^{POST})^{-1}\overline{y_i^{POST}}].$$

5. Generate β^{PRE}

$$\overline{y_{ijk}^{PRE*}} = y_{ijk}^{PRE*} - \theta_{ijk}^{PRE}X_{ijk}^{PRE} = \beta_j^{PRE}z_{ik} + \varepsilon_{ijk}^{PRE}.$$

The prior of $\beta_j^{PRE} \sim MVN(0, 100I)$. Then, generate

$$\beta_j^{PRE} \sim MVN(A_j, B_j),$$

where

$$B_j = [z'z/V_j + .01I]^{-1} \text{ and}$$

$$A_j = B_j[z'(\overline{y^{PRE*}} - E_j)/V_j],$$

where E_{ijk} (V_j) is the conditional mean (variance) of ε^{PRE}_{ijk}, conditioning on $\varepsilon^{PRE}_{ij'k}$ and $j' \neq j$.

6. Generate β^{POST}

$$\overline{y^{POST*}_{ijk}} = y^{POST*}_{ijk} - \theta^{POST}_{ijk}X^{POST}_{ijk} = \beta^{POST}_j z_{ik} + \varepsilon^{POST}_{ijk},$$

where $\beta^{POST}_j \sim MVN(0, 100I)$. Then, generate

$$\beta^{POST}_j \sim MVN(A_j, B_j),$$

where

$$B_j = [z'z/V_j + .01I]^{-1} \text{ and } A_j = B_j[z'(\overline{y^{POST*}} - E_j)/V_j],$$

where E_{ijk} (V_j) is the conditional mean (variance) of ε^{POST}_{ijk}, conditioning on $\varepsilon^{POST}_{ij'k}$ and $j' \neq j$.

7. Generate $\overline{\theta^{PRE}}$

$$\overline{\theta^{PRE}} \sim MVN(W, P)$$

where

$$W = P\left(\sum_{i=1}^{N} \theta^{PRE}_i/N + D_0^{-1}\theta_0\right) \text{ and}$$

$$P = [D_0^{-1} + N(\Sigma^{PRE})^{-1}]^{-1},$$

where $\theta_0 = (0, 0, \ldots, 0)'$ and $D_0 = 100I$.

8. Generate Γ

$$\theta^{POST}_i = \alpha S_i + \Gamma\theta^{PRE}_i + \eta^{POST}_i$$

can be written as

$$\delta = Z\gamma + \eta,$$

where

$$\delta = (\theta^{POST\prime}_1 - \alpha S_1', \theta^{POST\prime}_2 - \alpha S_2', \ldots, \theta^{POST\prime}_N - \alpha S_N')',$$

$$Z = (I \otimes \theta^{PRE\prime}_1, I \otimes \theta^{PRE\prime}_2, \ldots, I \otimes \theta^{PRE\prime}_N)',$$

$$\gamma = vec(\Gamma') = (\gamma_1', \gamma_2', \ldots, \gamma_J')' \sim MVN(0, 100I), \text{ and}$$

$$\eta = (\eta^{POST\prime}_1, \eta^{POST\prime}_2, \ldots, \eta^{POST\prime}_N)'.$$

The posterior distribution of γ is

$$\gamma \sim MVN(\gamma^*, \Omega^*),$$

$$\gamma^* = \Omega^* Z'[I \otimes (\Sigma^{POST})^{-1}]\delta, \text{ and}$$

$$\Omega^* = \left(\{Z'[I \otimes (\Sigma^{POST})^{-1}]Z\} + .01I\right)^{-1}.$$

9. Generate α

$$\theta^{POST}_{ij} = \alpha_j S_i + \Gamma_j\theta^{PRE}_i + \eta^{POST}_{ij}, \quad j = 1, \ldots, 2J,$$

where Γ_j is the jth row of the matrix Γ. Then, generate

$$\alpha_j \sim MVN(W_j, P_j),$$

where

$$P_j = [S_i'S_i(\Sigma^{POST}_j)^{-1} + .01]^{-1} \text{ and}$$

$$W_j = P_i[S_i'(\theta^{POST}_{ij} - \Gamma_j\theta^{PRE}_i)/\Sigma^{POST}_j].$$

10. Generate Σ^{PRE}

$$\Sigma^{PRE}_j \sim \text{Inverted gamma } (a_j, b_j), \quad j = 1, \ldots, 2(J-1),$$

where

$$a_j = s_0 + \frac{N}{2} \; (s_0 = 2), \text{ and}$$

$$b_j = \frac{2}{\sum_{i=1}^{N}(\theta^{PRE}_{ij} - \overline{\theta^{PRE}_j})^2 + 2/q_0} \quad (q_0 = .5).$$

11. Generate Σ^{POST}

$$\Sigma^{PRE}_j \sim \text{Inverted gamma } (a_j, b_j), \quad j = 1, \ldots, 2J,$$

where

$$a_j = s_0 + \frac{N}{2} \; (s_0 = 2) \text{ and}$$

$$b_j = \frac{2}{\sum_{i=1}^{N}(\theta^{POST}_{ij} - \alpha_j S_i - \Gamma_j\theta^{PRE}_i)^2 + 2/q_0} \quad (q_0 = .5).$$

12. Generate R^{PRE}

We define

$$V_{ijk} = y^{PRE*}_{ijk} - \theta^{PRE}_{ijk}X^{PRE}_{ijk} - \beta^{PRE}_{j1}Time_{ik} - \beta^{PRE}_{j2}Session_{ik},$$

$$l(R^{PRE}) \propto |R^{PRE}|^{-n/2}\exp\left(-.5\sum_{i=1}^{N}\sum_{k=1}^{K_i} V_{ik}'R^{PRE^{-1}}V_{ik}\right),$$

$$vec(R^{PRE}) \sim MVN(0, I), \text{ and}$$

$$R^{PRE}_{new} = R^{PRE}_{old} + H, \text{ where } H_{ii} = 0.$$

Then, generate a sequence of i.i.d. standard normal deviates of $w_{12}, w_{13}, \ldots, w_{J-2,J-1}$. Then, generate a deviate d from $N(0, \sigma^2_d)$, such that $-\varsigma/\sqrt{2} < d < \varsigma/\sqrt{2}$, where ς is the smallest eigenvalue of R^{PRE} and σ^2_d is a fine-tune parameter (in our context, $\sigma_d = .05$), and form

$$H_{ij} = \frac{dw_{ij}}{\sqrt{\sum_{j=1}^{J-2}\sum_{l=j+1}^{J-1} w^2_{jl}}}.$$

The candidate R^{PRE}_{new} is accepted or rejected on the basis of the following Metropolis–Hastings acceptance probability:

$$\min\left\{\frac{l(R_{\text{new}}^{\text{PRE}})p[\text{vec}(R_{\text{new}}^{\text{PRE}})]\left[\Phi\left(\frac{\varsigma_{\text{new}}}{\sqrt{2}\sigma_d}\right)-\Phi\left(\frac{-\varsigma_{\text{new}}}{\sqrt{2}\sigma_d}\right)\right]}{l(R_{\text{old}}^{\text{PRE}})p[\text{vec}(R_{\text{old}}^{\text{PRE}})]\left[\Phi\left(\frac{\varsigma_{\text{old}}}{\sqrt{2}\sigma_d}\right)-\Phi\left(\frac{-\varsigma_{\text{old}}}{\sqrt{2}\sigma_d}\right)\right]}, 1\right\},$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

13. Generate R^{POST}

Finally, generate R^{POST} the same way that R^{PRE} is generated in Step 12.

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