

## WEB APPENDIX

### Perception Spillovers Across Competing Brands: A Disaggregate Model of How and When

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#### Model Estimation

##### A.1 Heterogeneity

To account for physicians' unobserved heterogeneity, we adopt a random coefficient approach. Accordingly, we assume that  $\beta_i \sim N(\beta_0, \sigma_\beta^2)$  and  $\rho_i \sim N(\rho_0, \sigma_\rho^2)$ .

##### A.2 Model Likelihood

Given our model formulation, and under the common assumption of *i.i.d.* extreme value error terms, we obtain the familiar multinomial logit model (McFadden 1973). The choice probability can then be written as:

$$(\text{Pr}_{ijt} | \theta) = \frac{e^{E[U_{ijt}]}}{\sum_J e^{E[U_{ijt}]}} \tag{A.1}$$

where  $\text{Pr}_{ijt} | \theta$  is the probability that the physician  $i$  prescribes drug  $j$  at time  $t$ . This probability is conditional on the parameter vector  $\theta$ , which includes the physicians' quality perceptions, their risk aversion, their sensitivity to detailing efforts, and the underlying heterogeneity in the detailing sensitivity and risk aversion coefficients.

The likelihood of observing physician  $i$  making the observed prescriptions is given by the following:

$$L_i(\theta) = \int \prod_{t=1}^{T_i} \prod_{j=1}^J (\text{Pr}_{ijt} | \theta)^{K_{ijt}} f(\theta) d\theta. \tag{A.2}$$

Referring to Equation (A.2), the log-likelihood across all observations of all physicians,  $LL(\theta)$ , is given by:

$$LL(\theta) = \sum_{i=1}^I \log(L_i(\theta)). \tag{A.3}$$

##### A.3 Simulated Maximum Likelihood

The log-likelihood for each individual physician is a function of conditional probabilities. To compute the log-likelihood we need to integrate the conditional probabilities over the state space of the parameters. Hence, we estimate the Bayesian learning model via simulated maximum likelihood (see Train 2003 for details).

#### A.4 Variable Formulation and Initial Conditions

The detailing stock at time  $t$  for a brand  $j$  and physician  $i$ ,  $Det_{ijt}$ , is defined as per the Nerlove-Arrow (1962) formulation:

$$Det_{ijt} = d_{ijt} + \lambda_d Det_{ijt-1}. \quad (A.4)$$

where  $\lambda_d \in [0,1]$  is the carry-over parameter of detailing and  $d_{ijt}$  is the number of detailing visits that physician  $i$  received from the sales representatives of drug  $j$  in the month prior to prescription occasion  $t$ . This formulation makes detailing a stock variable, which is then a function of the flow of current and past detailing, and allows us to account for carry-over effects of detailing. Based on past research in the context of pharmaceutical industry, we set  $\lambda_d = 0.7$  (Narayanan, Manchanda and Chintagunta 2005). We do not estimate  $\lambda_d$  so as to reduce the computational burden. We tested for alternative values of the parameter and find the same substantive results.

Finally, to mitigate the initial conditions problem associated with learning models in general and the use of the detailing stock variable, we use the first six months to initialize the levels of past consumption experience and the level of detailing. We note however that for three of the five drugs (Prozac, Lustral and Seroxat) we observe the full history prescription and detailing history from the time of their introduction.

#### A.5 Identification

##### *Prior Variances*

One of the identification problems associated with Bayesian learning models is that the prior variance, the detailing signal variance ( $\sigma_m^2$ ), and the patient feedback signal variance ( $\sigma_v^2$ ) are only identified up to a multiplicative constant. Following prior literature (e.g. Erdem 1998; Narayanan, Manchanda and Chintagunta 2005) we solve this identification problem by setting the initial quality variance of each drug to one, in the basic learning models without spillovers (Model 3).

When testing for spillovers from an incumbent drug to a new entrant drug, we use the posterior variance of an already existing drug as the prior variance of the new drug (for the drugs present in the market from the beginning of the time period under analysis we follow the *same constraint* as before and set the prior variance to one). Accordingly, for Model 4 where we test for the presence of spillovers across dissimilar drugs (from Dothiepin or Amitriptyline to Fluoxetine), we set the prior quality variance of Dothiepin and Amitriptyline to be equal to one. In contrast, for the new entrant drug Prozac (Fluoxetine molecule) we set this variance to be equal to the posterior variance of Dothiepin or Amitriptyline at the time Prozac enters the market, computed using Equation (8).

For Model 5, which tests for the presence of spillovers across similar drugs (from Prozac to Lustral and Seroxat), similar to the approach described above, we set the prior quality variance of Lustral and Seroxat to be equal to the posterior quality variance of Prozac at the moment

Seroxat and Lustral entered the market. For all the remaining drugs, so as to compare with the basic learning model we use the standard constraint: prior quality variance constrained to one.

Note that when we constrain the prior quality variance to one, this prior quality variance is common across all individuals. However, when we use the posterior variances of the drugs to test for prior perception spillover effects, the prior is specific to drugs and individuals (as their previous experience with the existing drugs will determine their posterior quality variances).

That is why we allow for individual and brand specific subscripts in  $\sigma_{ij}^2(0)$ .

#### *Prior Means*

Previous research has assumed prior quality means to be constant across brands and individuals. In the basic learning model that does not account for spillovers effects, as before, we assume prior means to be the same across all individuals and brands (and this is the prior mean reported in the basic learning model). However, when we test for spillovers from an incumbent drug to a new entrant drug, the prior mean of the new drug is set to be the same as the posterior mean of a particular incumbent drug. In that case, the prior quality means for the drugs benefiting from spillovers will be individual and brand specific because the individual's experience with the drugs will determine their posterior quality means (and that is why we have individual and brand specific subscripts in  $\bar{Q}_{ij}(0)$ ). This is similar to the logic behind the constraints of the prior quality variances described previously.

#### *Quality Levels*

We further note that the absolute levels of the qualities ( $Q_j$ ) have no meaning as such (Erdem and Keane 1996, p. 13). The levels can be scaled up or down by adding a constant to the attribute scale. It is the *difference* in the quality levels between the brands that matters. Following the work of Erdem (1998) and Erdem, Zhao and Valenzuela (2004) we impose the following constraint (which helps the interpretation of these terms):

$$\sum_{j=i}^J Q_j = 0. \tag{A.5}$$

where  $Q_j$  is true mean quality of the drug  $j$  and  $J$  is the number of drugs (five in our case).