WEB APPENDIX A: MCMC ESTIMATION PROCEDURE

For the estimation, we used the Hierarchical Bayes Markov Chain Monte Carlo (HB MCMC) algorithm that allows for a combination of random and fixed parameters (Train 2003), combined with data augmentation (Tanner and Wong 1987). The data augmentation allows us to sample from ξ_{pjt}^{RX}, ξ_{pjt}^{Req}, ξ_{pjt}^{Det} and ξ_{pjt}^{DTCA}, together with the remaining model parameters.

Let $\{\Omega, \Delta, \mathrm{P}, \Lambda\}$ denote the parameters in the second layer of the prescription, drug request, detailing and DTCA equations, respectively; let φ denote the vector of four overdispersion parameters (α^{RX}, α^{Req}, α^{Det} and α^{DTCA}) from the four NBD equations (see Equation (1)); and let $\{\mathrm{B}, \mathrm{A}, \Gamma, \Phi\}$ denote the population vectors of K random parameters that enter the prescription, drug request, detailing and DTCA equations, respectively. We assigned a diffuse prior for the fixed parameters. For the random parameters, we assumed a multivariate normal distribution with diffuse priors for the population parameters. Specifically, we used a normal prior distribution with high variance for the population means and a diffuse inverted Wishart prior distribution for the population variance [$IW(K, I)$], where I is the identity matrix. The elements in the main diagonal of the variance-covariance matrix, S_ξ, are restricted to be positive and were therefore exponentiated to get a lognormal distribution. The draws from the conditional posteriors for the Gibbs sampling are as follows.

First, we drew from

$$f\left(\{\mathrm{A},\mathrm{B},\Gamma,\Phi\}\middle|\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi},\Sigma_{\mathrm{AB}\Gamma\Phi},\{\Omega,\Delta,\mathrm{P},\Lambda\},\phi,S_\xi\right)\propto\prod_{p,j,t}\begin{bmatrix}\Pr\left(RX_{pjt}\middle|\mathrm{B},\xi_{pjt}^{RX},\Omega,\phi\right)\\ \times\Pr\left(Req_{pjt}\middle|\mathrm{A},\beta_{1p},\xi_{pjt}^{Req},\Delta,\phi\right)\\ \times\Pr\left(Det_{pjt}\middle|\Gamma,\beta_{2p},\xi_{pjt}^{Det},\mathrm{P},\phi\right)\\ \times\Pr\left(DTCA_{pjt}\middle|\Phi,\beta_{1p},\beta_{3p},\alpha_{1p},\xi_{pjt}^{DTCA},\Lambda,\phi\right)\end{bmatrix}\times\Pi_1\left(\{\mathrm{A},\mathrm{B},\Gamma,\Phi\}\middle|\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi},\Sigma_{\mathrm{AB}\Gamma\Phi}\right)$$

using the Metropolis-Hastings algorithm.The first element on the right-hand side is the multiplication of the NBD probabilities for the number of prescriptions, number of drug requests, number of detailing visits and DTCA expenditures.The second element is the normal density.

Second, $\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi}$ and $\Sigma_{\mathrm{AB}\Gamma\Phi}$ were drawn from $f\left(\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi}\middle|\{\mathrm{A},\mathrm{B},\Gamma,\Phi\},\Sigma_{\mathrm{AB}\Gamma\Phi}\right)\sim N\left(\frac{\sum_{p}\{\mathrm{A},\mathrm{B},\Gamma,\Phi\}}{NP},\frac{\Sigma_{\mathrm{AB}\Gamma\Phi}}{NP}\right)$

where NP is the number of physicians, and from $f\left(\Sigma_{\mathrm{AB}\Gamma\Phi}\middle|\{\mathrm{A},\mathrm{B},\Gamma,\Phi\},\{\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi}\}\right)\sim IW\left(K+NP,\frac{(KI+\overline{S})}{K+NP}\right)$

where $\overline{S}=\sum_{p}\left(\{\mathrm{A},\mathrm{B},\Gamma,\Phi\}-\{\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi}\}\right)\left(\{\mathrm{A},\mathrm{B},\Gamma,\Phi\}-\{\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi}\}\right)'$ .Third, we drew from the posterior distribution of the second-level parameters in {Ω, Δ, P, Λ}, using the closed-form solution to the standard linear regression coefficients. Finally, we obtained draws from the four overdispersion parameters using essentially diffuse priors:

$$f\left(\phi\middle|\{\mathrm{A},\mathrm{B},\Gamma,\Phi\},\overline{\mathrm{A}},\overline{\mathrm{B}},\overline{\Gamma},\overline{\Phi},\Sigma_{\mathrm{AB}\Gamma\Phi},\{\Omega,\Delta,\mathrm{P},\Lambda\},S_{\xi}\right)\propto\prod_{p,j,t}\left[\begin{array}{l}\Pr\left(RX_{pjt}\middle|\mathrm{B},\xi_{pjt}^{RX},\Omega,\phi\right)\\ \times\Pr\left(Req_{pjt}\middle|\mathrm{A},\beta_{1p},\xi_{pjt}^{Req},\Delta,\phi\right)\\ \times\Pr\left(Det_{pjt}\middle|\Gamma,\beta_{2p},\xi_{pjt}^{Det},\mathrm{P},\phi\right)\\ \times\Pr\left(DTCA_{pjt}\middle|\Phi,\beta_{1p},\beta_{3p},\alpha_{1p},\xi_{pjt}^{DTCA},\Lambda,\phi\right)\end{array}\right],$$

by employing the Metropolis-Hastings algorithm consecutively.

We let the chain run for 1,000,000 iterations and discarded the first 980,000 as burn-in. We then used every tenth iteration to sample from the posterior distribution. Overall, we estimated 115 parameters. These included 41 random coefficients and 74 fixed coefficients.

WEB APPENDIX B: SIMULATION

We performed two simulations in order to further validate our estimation results. First, we have re-estimated our model using a simulated data set, constructed at the individual patient level in order to validate that our aggregate date still allows us to depict physicians' behavior at the dyadic patient-physician level. Second, we have re-estimated our model using a simulated data set, constructed at the monthly physician level. This simulation exercise allows us to validate that our complex estimation procedure allows us to recover the true underlying parameters at the physician level. We hereby elaborate on the two simulations.

B.1 Patient-Physician-Level Simulation

Our simulation allows us to demonstrate that our aggregate-level estimation reliably reflects the behavior inferred at the dyadic level.

The simulation procedure begins with the construction of a patient-level data set simulating a situation in which a patient's demographic characteristics affect his or her binary outcome both for prescriptions and for requests. For instance, we simulate a situation in which requests from Blacks are accommodated less than requests from Whites. We then check whether, after we aggregate these data to the physician level, the model estimation can depict this situation. The data generation process for the simulated dependent values (prescriptions and requests) is carried out at the patient level, using a logit model. The construction of the data set assumes that physicians draw patients from their DMA (i.e., draw the demographic profile of each of their patients from the demographic distribution of the DMA). Then, for each patient across all physicians in each time period, we compute a **binary outcome** for requests and prescriptions at the brand level, using the logit model. The logit model's parameters are set to depend on the demographic characteristics of the patient. Once we aggregate these data to the physician level, the dependent variables become **count variables**, and therefore we assume an

NBD distribution in our model. For this reason we cannot know the 'true' parameters of the NBD model, and cannot compare them to the estimated parameters. We can, however, compare the direction of influence of the logit parameters to those of the NBD model’s two layers and examine whether our model depicts the dependencies that were set at the patient level.

The simulation includes the following steps:

Step 1 – We simulate a patient-physician matrix for 193 DMAs. For each DMA, we draw a random number of physicians between 5 and 15. For each physician, we then randomly draw the number of patients (between 10 and 50) for each period of our time window (14 in total).

Step 2 – Based on the demographic distributions for the 193 simulated DMAs, we draw a demographic profile for each of the patients. The demographic variables include: Black (dummy), Hispanic (dummy), Asian (dummy), White (dummy), Male (dummy), Income, Age (older than 40 years), Education (with one year or more of college education). In addition, a random 10% of the physicians are defined as specialists.

Step 3 – We draw a set of patient-level parameters ρ_{ij0}, ρ_{1i}, ς_{ij0}, ς_{1i}, using the ordinal relationship that we later expect to recover, e.g.:

$$\rho_{0,White,j} > \rho_{0,Black,j}$$

We also specify an association between ρ_1 and ς_1.

(These four parameters correspond to our model's physician-level parameters β_{0pj}, β_{1p}, α_{0pj}, and α_{1p}, respectively.)

Step 4 – We simulate data on DTCA at the DMA level and on detailing at the physician level. We also draw the corresponding remaining parameters from a multivariate normal distribution.

Step 5 – We calculate the number of requests and prescriptions for each row in our data (i.e., for each patient-physician-time combination). Since, at the dyadic level, request and prescription are binary outcomes, we simulate a binary logit regression and derive choice probabilities for each physician-patient-time combination. Specifically, the probability P_{ijt_Req} that drug *j* is requested by patient *i* at time *t* is specified as a multinomial logit model:

$$(1)\ P_{ijt\_Req} = \frac{e^{V_{jt\_Req}}}{\sum_{j=1}^{J} e^{V_{jt\_Req}}}$$

V_{ij_Req} is specified to be a function of two main elements, as follows:

$$(2)\ V_{jt\_Req} = \varsigma_{ij0} + \varsigma_{i1} DTC_{jt}$$

Once the simulated requests are calculated, the probability P_{ijt_Rx} that drug *j* is prescribed to patient *i* at time *t* is specified as a multinomial logit model:

$$(3)\ P_{ijt\_Rx} = \frac{e^{V_{jt\_Rx}}}{\sum_{j=1}^{J} e^{V_{jt\_Rx}}}$$

V_{ij_Rx} is specified to be a function of four main elements, as follows:

$$(4)\ V_{jt\_Rx} = \rho_{ij0} + \rho_{i1} Req_{jt} + \rho_{i2} Det_{jt} + \rho_{i3} DTC_{jt}$$

Note that for both variables, we define threshold levels such that probabilities below these thresholds are treated as zero outcomes. This step ensures that both for requests and for prescriptions we also get zero values as a visit outcome, and thus it allows for different levels of overdispersion once we aggregate the data to the physician level.

Step 6 – We aggregate the dyadic data on requests and prescriptions to the level of aggregation of our behavioral data.

Step 7 – We use the same estimation procedure on the aggregated data set created in Step 6.

We have repeated steps 1–7 three times, each with a different set of initial values. Although we report here only one set of results, the simulation results in all three simulation exercises were similar to those we report here.

In order to keep the discussion of the estimation results of our model on the simulated data set parsimonious, we concentrate on specific variables that were set at the patient level to have a significant influence on the outcome variables. First, we compare the estimation results of the first- and second-level effects of request on prescriptions with the corresponding values of the patient-level simulated data. Second, we compare the estimation results of the DTCA effect on requests with the patient-level values. Third, we compare the estimation results of the feedback parameters of request accommodation and the base level of request with the patient-level values.

Table A1 presents the initial patient-level mean prescription values for the three simulated brands across demographic groups and among specialists and primary care physicians (PCPs). Columns 2–4 present the mean prescription values for patients who request Brands A–C, respectively. Columns 5–7 present the mean number of prescriptions for patients who do not request Brands A–C, respectively. Columns 8–10 present the ratio between the mean number of prescriptions for patients who request Brands A–C and the mean number of prescriptions for patients who do not request these brands, respectively.

The estimation results of our full model on the aggregated simulated data are in line with these initial patient-level figures. First, the estimated effect of requests is positive (β_{1p} = 0.39, *std.*

= 0.004). The magnitude of the effect, calculated as exp(β_{1p}), also fits the initial values (a ratio of around 1.5).

Table A1: Mean Prescriptions for Patients With and Without Requests Across Demographic Characteristics

	With Request for Respective Brand			*Without Request for Respective Brand*			*With/Without Request Ratio*		
	Brand A	*Brand B*	*Brand C*	*Brand A*	*Brand B*	*Brand C*	*Brand A*	*Brand B*	*Brand C*
White	0.36	0.41	0.42	0.21	0.25	0.16	1.7	1.7	2.6
Hispanic	0.30	0.36	0.38	0.23	0.26	0.20	1.3	1.4	1.9
Asian	0.30	0.34	0.37	0.23	0.26	0.21	1.3	1.3	1.8
Black	0.30	0.35	0.38	0.23	0.27	0.20	1.3	1.3	1.9
Urban	0.35	0.40	0.41	0.21	0.25	0.17	1.7	1.6	2.5
Rural	0.35	0.40	0.41	0.22	0.25	0.17	1.6	1.6	2.4
Over 40	0.34	0.39	0.40	0.22	0.26	0.18	1.6	1.5	2.3
Under 40	0.36	0.41	0.42	0.21	0.25	0.16	1.7	1.7	2.6
Male	0.35	0.40	0.41	0.21	0.25	0.17	1.6	1.6	2.4
Female	0.35	0.40	0.41	0.22	0.25	0.17	1.6	1.6	2.5
Low income education	0.34	0.38	0.40	0.22	0.25	0.17	1.6	1.5	2.3
High income education	0.36	0.40	0.42	0.21	0.25	0.16	1.7	1.6	2.6
Specialist	0.35	0.40	0.41	0.22	0.25	0.17	1.6	1.6	2.4
PCP	0.37	0.42	0.42	0.21	0.24	0.16	1.8	1.7	2.7

Moreover, for the second-level effects of Blacks, Hispanics and Income-Education, zero lies outside the 95% highest posterior density interval of the estimate for the population mean (ω_{12} = -0.15, *std.* =0.03; ω_{13} = -0.10, *std.* =0.03; ω_{15} = -0.01, *std.* = 0.003). Similarly, for the effect of a specialist, zero lies outside the 95% highest posterior density interval of the estimate for the population mean (ω_{11} = -0.02, *std.* =0.01). These results are in line with the initial patient-level differences among patients of different demographic groups presented in Table A1.

We now move to the simulated effect of DTCA on the number of requests. The correlations between the simulated periodic requests at the patient level and the periodic level of DTCA spending for the three brands in our simulated patient-level data are 0.71, 0.53 and 0.43, for Brands A, B, and C, respectively. The estimation results on the aggregated simulated file indicate that the mean estimated effect of DTCA on requests is positive and significant (α_{2p}= 7.08, *std.* = 0.04)[1].

Finally, we simulated a positive feedback effect between a physician's tendency to accommodate requests and the periodic number of patient-level requests directed at that physician. Accordingly, in our data-generating process there is a positive correlation (0.30) between the simulated base-level request at the patient level and the physician's simulated tendency to accommodate requests. The estimated feedback effect on the base level of requests is positive, with zero outside the 95% highest posterior density interval of the estimate for the population mean (δ_{01} = 22.94, *std.* = 1.36).

B.2 Physician Level Simulation

The patient-physician level simulation, while allowing the validation of our model's ability to recover dyadic behavior, does not allow us to evaluate the estimation procedure's ability to recover the true parameters underlying the observed behavior. Therefore, we also performed a simulation in which we estimate equations (1)-(12) using data simulated with known parameters. We then evaluate whether the estimation recovers those parameters. Since β_{1p} is an important parameter in our model, we use one set of simulated data where this parameter equals zero and another in which it is non-zero.

The simulation includes the following steps:

Step 1 – we set values for all second level parameters $\{\Omega, \Delta, \mathrm{P}, \Lambda\}$.

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[1] Note that the DTCA variable was divided by 1,000,000 for parameter scale consistency.

Step 2 – we simulate a physician matrix with eight physician level variables representing the second level variables (specialty and 7 demographic variables) using a random number generator.

Step 3 – we generate the first level parameters that are specified to have a second layer (α_{0pj}, α_{1p}, β_{0pj}, β_{1p}, β_{2p}, β_{3p}, $\boxed{?}_{0pj}$, φ_{0pj},) using the product of the second level parameters and second level variables simulated in Steps 1 and 2 (see Equations 3, 4, 7, 8, 10 and 12).

Step 4 – We generate all other first level parameters using a random number generator. These variables are specified to have a normal distribution.

Step 5 – Since lagged values are used in all four equations of our model, we set initial values for t=0 for prescriptions, detailing and DTCA.

Step 6 – we simulate values for t=1 for all four dependent variables for each physician in our simulated data set. This data generating process is based on the individual level parameters simulated for each physician in Steps 3 and 4 (see Equations 2, 6, 9 and 11), using an NBD data generator. In this step we use the initial values generated in Step 5 as the lagged variables. Moreover, since the dependent variables in our system also serve as independent variables in other equations, we set a fixed order to our data generating process. We first generate DTCA data for each DMA. We then produce request data for each physician, based on the generated current DTCA values, followed by generating physician specific detailing data. Finally we generate Rx data for each physician, based on the values generated for all other variables. Note that competitive Rx is a variable that is determined simultaneously to own Rx. We therefore are not able to include this variable in the simulation.

Step 7 – we repeat Step 6 iteratively for t = 2 ,…, 14. In each iteration we use as the lagged values the generated variables of the previous iteration for all dependent variables for the current data generating process.

Step 8 – we organize the values generated in steps 6 and 7, for each dependent variable at the month-physician-brand level, in one comprehensive data set similar in structure to that of our physician level data set.

Step 9 - We use the estimation procedure presented in the paper on the data set created in Step 8.

Tables A2-A5 present the estimation results of our model using two simulated data sets that are based on steps 1-9 above. In the first simulated data set the value of β_{1p} is set to be with mean zero. In the second simulated data set the value of β_{1p} is set to have a non-zero mean. The fourth column in Tables A2 and A4 present the estimation results of the first layer parameters in both simulation sets (labeled 'Estimated Population Mean' and 'Estimated Population Std.'). The fifth column in Tables A2 and A4 present the values used to simulate the data (labeled 'Simulated Population Mean' and 'Simulated Population Std.'). Tables A3.A-D and A5.A-D present the second layer estimates (labeled 'Estimated Mean and Std.') as well as the actual values used to simulate the first layer parameters of the two simulation sets (labeled 'Simulated Values').

The comparison of the estimated values and simulated values illustrates that our estimation procedure recovers the underlying parameters for the data. Both first and second layer parameters in both simulation sets are similar to the values used to generate the data. In particular we find that our estimation procedure recovers the true value of $\beta_{1p.}$ The simulated values for this parameter are (for simulation 1: Population mean = -0.04, Population std. =1.00;

and for simulation 2: Population mean = 1.50, Population std. =1.00) and the estimated value are (for simulation 1: Population mean = 0.06, Population std. =1.12; and for simulation 2: Population mean = 2.05, Population std. =0.87). Moreover, our estimation procedure recovers the sign and significance of feedback effects among the second layer parameters. These feedback effects are estimated through the coefficients of first layer parameters that are used as second layer variables in the equations for the intercepts of our system of equations. For instance, the simulated values for δ_{01} are 3.00 and 4.00[2], for the first and second simulation runs, respectively, and the estimated values for these effects are (Mean = 1.96, std. = 0.29; and Mean = 4.08, std. = 0.37). Note that in some cases, where the first layer parameter is 'insignificant' (i.e., mean that is very close to zero with large variance) the second layer estimate for its effect also becomes insignificant (see, for instance the effect of β_{3p}, the direct effect of DTCA on prescriptions, on $\varphi_{0\mathrm{pj}}$, the base DTCA level, and the effect of β_{2p}, the effect of detailing on prescriptions, on $\gamma_{0\mathrm{pj}}$, the base detailing level). This result is expected as the 'insignificant' first layer effect also does not affect the data generating process for the other first layer parameter.

Overall this simulation provides us with additional validation for our estimation procedure's ability to recover the true parameters underlying the observed behavior in our data.

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[2] The second layer parameters are constant across physicians

Table A2. First-Layer Estimates – Simulation Set 1

Dependent Variable	***Independent Variables***	***Parameter Symbols***	***Estimated Population Mean (Estimated Population Std.)***	***Simulated Population Mean (Simulated Population Std.)***
Number of Prescriptions Written	*Intercept (Brand A)*	β_{0p1}	-4.73 (1.66)	-5.03 (1.34)
	Intercept (Brand B)	β_{0p2}	-5.67 (1.73)	-6.03 (1.34)
	Intercept (Brand C)	β_{0p3}	-3.64 (1.54)	-4.03 (1.34)
	Drug request	β_{1p}	0.06 (1.12)	-0.04 (1.00)
	Detailing	β_{2p}	-0.02 (0.97)	0.03 (0.23)
	DTCA	β_{3p}	-0.62 (0.79)	-0.03 (0.02)
	Lag DTCA	β_{4p}	-0.02 (0.78)	0.02 (0.71)
	Competitive requests	β_{5p}	-0.06 (0.88)	0.002 (0.22)
	Lag mean prescriptions in DMA	β_{6p}	-0.12 (0.48)	-0.0002 (0.22)
	Lag prescriptions	β_{7p}	0.15 (0.72)	0.20 (0.22)
Number of Requests Received	*Intercept (Brand A)*	α_{0p1}	-7.17 (3.46)	-7.11 (3.00)
	Intercept (Brand B)	α_{0p2}	-8.38 (3.66)	-8.11 (3.00)
	Intercept (Brand C)	α_{0p3}	-6.02 (3.28)	-6.11 (3.00)
	DTCA	α_{1p}	1.41 (0.96)	1.06 (0.43)
	Lag DTCA	α_{2p}	-0.39 (0.74)	-0.10 (0.22)
	Lag prescriptions	α_{3p}	0.40 (0.87)	0.20 (0.07)
Number of Detailing Visits Received	*Intercept (Brand A)*	γ_{0p1}	-3.95 (1.13)	-3.94 (0.47)
	Intercept (Brand B)	γ_{0p2}	-5.06 (1.46)	-4.94 (0.47)
	Intercept (Brand C)	γ_{0p3}	-2.97 (0.93)	-2.94 (0.47)
	Lag prescriptions	γ_{1p}	0.33 (0.18)	0.51 (0.22)
	Lag competitive detailing	γ_{2p}	-0.48 (0.81)	-0.20 (0.22)
	Lag detailing	γ_{3p}	-0.29 (0.90)	-0.0002 (0.22)
Total Dollar Amount Spent on DTCA	*Intercept (Brand A)*	φ_{0p1}	-3.95 (1.30)	-3.81 (0.89)
	Intercept (Brand B)	φ_{0p2}	-5.06 (1.60)	-4.81 (0.89)
	Intercept (Brand C)	φ_{0p3}	-2.97 (1.17)	-2.81 (0.89)
	Lag prescriptions	φ_{1p}	1.02 (0.66)	0.99 (0.22)
	Lag competitive DTCA	φ_{2p}	-0.39 (0.51)	0.0003 (0.07)
	Lag DTCA	φ_{3p}	0.29 (0.62)	0.10 (0.22)

Table A3.A. Requests to Prescriptions: Specialty and Spatial Variation (2nd Layer) – Simulation Set 1

	Prescription Equation Second-Level Coefficients											
	Second -Level Parameters For β_{0jp} – Base Rx			***Second -Level Parameters For β_{1p} - Request Effect***			***Second -Level Parameters For β_{2p} - Detailing Effect***			***Second -Level Parameters For β_{3p} - DTCA effect***		
Variable Name		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**
Intercept Brand A	ω_{001}	-4.83 (1.08)	-5.0	ω_{10}	0.06 (0.18)	0.0	ω_{20}	-0.03 (0.11)	0.0	ω_{30}	-0.63 (0.38)	-0.02
Intercept Brand B	ω_{002}	-5.78 (1.29)	-6.0									
Intercept Brand C	ω_{003}	-3.75 (0.84)	-4.0									
$Spec_p$	ω_{01}	1.57 (0.16)	2.0	ω_{11}	0.08 (0.14)	0.0	ω_{21}	0.05 (0.10)	0.1	ω_{31}	0.01 (0.09)	-0.01
$PerBlack_p$	ω_{02}	-1.29 (0.13)	-2.0	ω_{12}	-0.03 (0.12)	0.0	ω_{22}	-0.04 (0.10)	-0.5	ω_{32}	0.03 (0.09)	-0.05
$PerHisp_p$	ω_{03}	2.51 (0.15)	3.0	ω_{13}	0.01 (0.12)	-0.1	ω_{23}	0.10 (0.10)	0.1	ω_{33}	0.04 (0.08)	0.01
$PerAsian_p$	ω_{04}	2.61 (0.18)	3.0	ω_{14}	-0.23 (0.13)	0.0	ω_{24}	-0.04 (0.08)	-0.4	ω_{34}	-0.05 (0.11)	-0.04
$IncEdu\_F_p$	ω_{05}	-0.36 (0.14)	-1.0	ω_{15}	-0.02 (0.15)	0.0	ω_{25}	0.45 (0.09)	0.5	ω_{35}	-0.02 (0.13)	0.05
$PerOver40_p$	ω_{06}	-0. 83 (0.09)	-1.0	ω_{16}	-0.02 (0.12)	0.0	ω_{26}	0.03 (0.11)	-0.4	ω_{36}	-0.002 (0.08)	-0.04
$PerMale_p$	ω_{07}	-1.56 (0.15)	-2.0	ω_{17}	0.09 (0.13)	0.0	ω_{27}	0.62 (0.13)	0.5	ω_{37}	0.05 (0.08)	0.05
$PerUrban_p$	ω_{08}	-1.48 (0.14)	-2.0	ω_{18}	0.14 (0.14)	0.0	ω_{28}	0.28 (0.10)	0.2	ω_{38}	-0.03 (0.09)	-0.01

Table A3.B. DTCA to Requests: Specialty and Spatial Variation (2nd Layer) – Simulation Set 1

	Drug Request Equation Second-Level Coefficients					
	Second -Level Parameters For α_{0jp} Base Requests			***Second -Level Parameters For α_{1p} DTCA Effect***		
Variable Name		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean[*] (Std.)**	**Simulated Values**
Intercept Brand A	δ_{001}	-7.65 (1.73)	-7.00	δ_{10}	1.38 (0.32)	0.80
Intercept Brand B	δ_{002}	-8.87 (1.99)	-8.00			
Intercept Brand C	δ_{003}	-6.51 (1.47)	-6.00			
Prescription responsiveness to requests (β_{1p})	δ_{01}	1.96 (0.29)	3.00			
$Spec_p$	δ_{02}	-0.07 (0.18)	0.00	δ_{11}	0.55 (0.12)	1.00
$PerBlack_p$	δ_{03}	-0.06 (0.24)	0.00	δ_{12}	0.08 (0.11)	-0.05
$PerHisp_p$	δ_{04}	-0.002 (0.24)	0.00	δ_{13}	-0.04 (0.12)	0.08
$PerAsian_p$	δ_{05}	0.07 (0.21)	0.00	δ_{14}	0.07 (0.10)	0.08
$IncEdu\_F_p$	δ_{06}	-0.13 (0.27)	0.00	δ_{15}	-0.51 (0.11)	-1.00
$PerOver40_p$	δ_{07}	0.01 (0.26)	0.00	δ_{16}	-0.07 (0.12)	0.08
$PerMale_p$	δ_{08}	-0.84 (0.55)	0.00	δ_{17}	-0.62 (0.10)	-0.50
$PerUrban_p$	δ_{09}	-0.39 (0.23)	0.00	δ_{18}	0.74 (0.10)	1.20

Table A3.C. Second-Layer Estimates of the Detailing Equation – Simulation Set 1

		Detailing Equation Second -Level Parameters For γ_{0pj} – Base Detailing	
Variable Name		**Estimated Mean** **(Std.)**	**Simulated Values**
Intercept Brand A	ρ_{001}	-3.93 (0.87)	-4.00
Intercept Brand B	ρ_{002}	-5.05 (1.12)	-5.00
Intercept Brand C	ρ_{003}	-2.96 (0.66)	-3.00
Prescription responsiveness to detailing (β_{2p})	ρ_{01}	0.44 (0.22)	2.00

Table A3.D. Second-Layer Estimates of the DTCA Equation – Simulation Set 1

		DTCA Equation Second -Level Parameters For φ_{0pj}– Base DTCA	
Variable Name		**Estimated Mean** **(Std.)**	**Simulated Values**
Intercept Brand A	μ_{001}	-4.99 (0.89)	-6.00
Intercept Brand B	μ_{002}	-6.23 (1.16)	-7.00
Intercept Brand C	μ_{003}	-4.01 (0.68)	-5.00
Request responsiveness to DTCA (α_{1p})	μ_{01}	1.08 (0.04)	2.00
Prescription responsiveness to requests (β_{1p})	μ_{02}	0.05 (0.03)	0.00
Prescription responsiveness to DTCA (β_{3p})	μ_{03}	-1.05 (0.05)	-2.00

Table A4. First-Layer Estimates – Simulation Set 2

Dependent Variable	*Independent Variables*	*Parameter Symbols*	*Estimated Population Mean (Estimated Population Std.)*	*Simulated Mean (Simulated Population Std.)*
Number of Prescriptions Written	*Intercept (Brand A)*	β_{0p1}	-8.91 (1.74)	-8.53 (0.93)
	Intercept (Brand B)	β_{0p2}	-11.12 (2.53)	-9.53 (0.93)
	Intercept (Brand C)	β_{0p3}	-13.71 (3.11)	-10.53 (0.93)
	Drug request	β_{1p}	2.05 (0.87)	1.50 (1.00)
	Detailing	β_{2p}	0.04 (0.98)	0.03 (0.24)
	DTCA	β_{3p}	0.62 (0.94)	-0.03 (0.02)
	Lag DTCA	β_{4p}	-0.52 (0.87)	0.01 (0.70)
	Competitive requests	β_{5p}	-1.39 (0.93)	-0.0008 (0.22)
	Lag mean prescriptions in DMA	β_{6p}	-0.60 (0.79)	0.002 (0.23)
	Lag prescriptions	β_{7p}	-0.04 (0.67)	0.21 (0.23)
Number of Requests Received	*Intercept (Brand A)*	α_{0p1}	-8.69 (4.41)	-7.99 (3.98)
	Intercept (Brand B)	α_{0p2}	-4.87 (3.75)	-4.99 (3.98)
	Intercept (Brand C)	α_{0p3}	-7.53 (4.28)	-6.99 (3.98)
	DTCA	α_{1p}	1.42 (0.62)	1.06 (0.43)
	Lag DTCA	α_{2p}	-0.29 (0.60)	-0.10 (0.22)
	Lag prescriptions	α_{3p}	0.08 (0.06)	0.20 (0.07)
Number of Detailing Visits Received	*Intercept (Brand A)*	γ_{0p1}	-4.16 (0.80)	-3.94 (0.48)
	Intercept (Brand B)	γ_{0p2}	-5.29 (0.98)	-4.94 (0.48)
	Intercept (Brand C)	γ_{0p3}	-3.01 (0.70)	-2.94 (0.48)
	Lag prescriptions	γ_{1p}	0.33 (0.17)	0.50 (0.22)
	Lag competitive detailing	γ_{2p}	-0.49 (0.90)	-0.21 (0.22)
	Lag detailing	γ_{3p}	-0.42 (0.99)	-0.006 (0.22)
Total Dollar Amount Spent on DTCA	*Intercept (Brand A)*	φ_{0p1}	-3.80 (1.00)	-3.81 (0.89)
	Intercept (Brand B)	φ_{0p2}	-5.09 (1.18)	-4.81 (0.89)
	Intercept (Brand C)	φ_{0p3}	-2.90 (0.99)	-2.81 (0.89)
	Lag prescriptions	φ_{1p}	0.96 (0.63)	1.00 (0.22)
	Lag competitive DTCA	φ_{2p}	-0.32 (0.53)	0.001 (0.07)
	Lag DTCA	φ_{3p}	0.21 (0.65)	0.10 (0.22)

Table A5.A. Requests to Prescriptions: Specialty and Spatial Variation (2nd Layer) – Simulation Set 2

	Prescription Equation Second-Level Coefficients											
	Second -Level Parameters For β_{0jp} – Base Rx			*Second -Level Parameters For β_{1p} - Request Effect*			*Second -Level Parameters For β_{2p} - Detailing Effect*			*Second -Level Parameters For β_{3p} - DTCA effect*		
Variable Name		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**
Intercept Brand A	ω_{001}	-7.77 (0.42)	-7.00	ω_{10}	2.05 (0.16)	1.50	ω_{20}	0.04 (0.18)	0.00	ω_{30}	0.58 (0.26)	-0.02
Intercept Brand B	ω_{002}	-9.98 (0.51)	-8.00									
Intercept Brand C	ω_{003}	-11.57 (0.52)	-9.00									
$Spec_p$	ω_{01}	0.85 (0.26)	1.00	ω_{11}	0.07 (0.14)	0.00	ω_{21}	0.06 (0.23)	0.10	ω_{31}	0.09 (0.15)	-0.01
$PerBlack_p$	ω_{02}	-1.34 (0.23)	-2.00	ω_{12}	0.07 (0.12)	0.00	ω_{22}	-0.01 (0.14)	-0.50	ω_{32}	0.03 (0.13)	-0.05
$PerHisp_p$	ω_{03}	0.54 (0.21)	1.00	ω_{13}	0.03 (0.11)	-0.10	ω_{23}	0.02 (0.13)	0.10	ω_{33}	0.03 (0.12)	0.01
$PerAsian_p$	ω_{04}	0.23 (0.12)	1.00	ω_{14}	0.03 (0.11)	0.00	ω_{24}	0.01 (0.13)	-0.40	ω_{34}	0.05 (0.12)	-0.04
$IncEdu\_F_p$	ω_{05}	-0.91 (0.32)	-1.00	ω_{15}	-0.14 (0.13)	0.00	ω_{25}	-0.04 (0.25)	0.50	ω_{35}	-0.10 (0.15)	0.04
$PerOver40_p$	ω_{06}	-0.31 (0.23)	-1.00	ω_{16}	0.05 (0.12)	0.00	ω_{26}	-0.01 (0.14)	-0.40	ω_{36}	0.06 (0.12)	-0.04
$PerMale_p$	ω_{07}	-1.16 (0.26)	-2.00	ω_{17}	-0.11 (0.12)	0.00	ω_{27}	-0.02 (0.17)	0.50	ω_{37}	-0.07 (0.13)	0.05
$PerUrban_p$	ω_{08}	-1.41 (0.30)	-2.00	ω_{18}	0.09 (0.15)	0.00	ω_{28}	0.05 (0.23)	0.20	ω_{38}	0.06 (0.16)	-0.01

Table A5.B. DTCA to Requests: Specialty and Spatial Variation (2nd Layer) – Simulation Set 2

	Drug Request Equation Second-Level Coefficients					
	Second -Level Parameters For α_{0jp} Base Requests			*Second -Level Parameters For α_{1p} DTCA Effect*		
Variable Name		**Estimated Mean (Std.)**	**Simulated Values**		**Estimated Mean (Std.)**	**Simulated Values**
Intercept Brand A	δ_{001}	-12.54 (1.04)	-14.00	δ_{10}	1.03 (0.20)	0.80
Intercept Brand B	δ_{002}	-8.73 (1.00)	-11.00			
Intercept Brand C	δ_{003}	-11.38 (1.00)	-13.00			
Prescription responsiveness to requests (β_{1p})	δ_{01}	4.08 (0.37)	4.00			
$Spec_p$	δ_{02}	-0.02 (0.32)	0.00	δ_{11}	0.74 (0.14)	1.10
$PerBlack_p$	δ_{03}	-0.46 (0.33)	0.00	δ_{12}	0.08 (0.12)	-0.05
$PerHisp_p$	δ_{04}	-0.16 (0.31)	0.00	δ_{13}	0.04 (0.11)	0.08
$PerAsian_p$	δ_{05}	-0.40 (0.32)	0.00	δ_{14}	0.08 (0.11)	0.08
$IncEdu\_F_p$	δ_{06}	0.08 (0.34)	0.00	δ_{15}	-0.64 (0.15)	-1.00
$PerOver40_p$	δ_{07}	-0.48 (0.32)	0.00	δ_{16}	0.12 (0.12)	0.08
$PerMale_p$	δ_{08}	0.21 (0.32)	0.00	δ_{17}	-0.26 (0.13)	-0.50
$PerUrban_p$	δ_{09}	0.21 (0.33)	0.00	δ_{18}	0.94 (0.15)	2.00

Table A5.C. Second-Layer Estimates of the Detailing Equation – Simulation Set 2

		Detailing Equation Second -Level Parameters For γ_{0pj} – Base Detailing	
Variable Name		**Estimated Mean** (Std.)	**Simulated Values**
Intercept Brand A	ρ_{001}	-4.16 (0.14)	-4.00
Intercept Brand B	ρ_{002}	-5.29 (0.18)	-5.00
Intercept Brand C	ρ_{003}	-3.01 (0.11)	-3.00
Prescription responsiveness to detailing (β_{2p})	ρ_{01}	0.19 (0.08)	2.00

Table A5.D. Second-Layer Estimates of the DTCA Equation – Simulation Set 2

		DTCA Equation Second -Level Parameters For φ_{0pj}– Base DTCA	
Variable Name		**Estimated Mean** (Std.)	**Simulated Values**
Intercept Brand A	μ_{001}	-5.46 (0.25)	-6.00
Intercept Brand B	μ_{002}	-6.75 (0.26)	-7.00
Intercept Brand C	μ_{003}	-4.56 (0.24)	-5.00
Request responsiveness to DTCA (α_{1p})	μ_{01}	1.34 (0.08)	2.00
Prescription responsiveness to requests (β_{1p})	μ_{02}	0.08 (0.08)	0.00
Prescription responsiveness to DTCA (β_{3p})	μ_{03}	-0.02 (0.08)	-2.00

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