Web Appendix to Accompany

Quantifying the Benefits of Individual Level Targeting in the Presence of Firm Strategic Behavior

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The purpose of this Web Appendix is to briefly discuss the sensitivity analysis to the various model assumptions that are summarized in Section 6 of the paper. Sections 4 and 5 of the paper show the importance of incorporating firm strategic behavior, as ignoring it results in biased estimates and hence a biased comparison between targeting strategies. However, an important concern for any study that incorporates a "supply side" model in estimating demand model parameters is that the FOC not be mis-specified (this issue is discussed in detail in a recent set of review papers on structural modeling - including Chintagunta et al. (2006); Bronnenberg, Rossi and Vilcassim (2005); Chintagunta, Kadiyali and Vilcassim (2004); Kadiyali, Sudhir and Rao (2000)).[1] To ensure that the FOC is not mis-specified, in this section, we provide a summary of how we test key assumptions in the proposed model – (1) profit maximization at the physician versus the segment level in the *estimation* model; (2) profit maximization versus sales maximization; (3) heuristic versus strategic detailing levels; (4) marginal costs of detailing that are estimated from the data rather than assumed a priori; (5) myopic vs. forward-looking detailing decisions; and (6) a different heterogeneity specification.

Estimation model assumes segment level targeting rather than physician level targeting

We assume that the firm *targets at the segment level* in setting detailing and then simulate the profitability from targeting at the individual level. To illustrate this, out of the two segment level models that we estimated (see Section 5), we pick the one that uses decile based segmentation. Our results show that, on average, the increase in profits from targeting at the individual level is 18% relative to targeting at the segment level. We consider this result to be close enough to the 23% obtained with the

[1] Another approach to address this problem would be to use instrumental variables. While it may be tempting to do this, the solution may not be much better than the problem. As Bronnenberg, Rossi and Vilcassim (2005) note (p. 24), "Because of the problems with the specification of the supply side, there is growing sentiment to eliminate this part of the model and deal with possible endogeneity problems through instrumental variables. This solution, however, may simply be replacing one possible source of specification error with another. There are no general methods of ascertaining whether an instrumental variable is valid." In addition, as mentioned earlier, it is hard to find an instrumental variable to "proxy" for the detailing variable, since such an instrument needs to vary across physicians, brands and time periods.

individual level profit maximization assumption i.e., the gains to targeting are robust to the assumption on whether targeting in the detailing happens at the individual level or segment level.

Sales versus profit maximization

Given that contact with physicians involves the sales force, it may be the case that the true data generating process is based on local sales maximization (reflecting the behavior of individual salespeople if incentives are based on sales quotas). We therefore estimate a model that takes sales maximization as the given objective (details on the model are available from the authors on request). We then compute an out of sample fit metric to examine how well a model based on this assumption recovers the data. As can be seen from the RMSE measures reported in Table 1, a model generated under this assumption fits the data poorly relative to our assumed model specification.

Heuristic versus strategic decision making

In the proposed model while accounting for strategic behavior, we assume firms target at the individual physician level. There are at least two other ways to describe how firm makes its detailing decisions: targeting at the segment level and using the heuristic rule as discussed by Manchanda, Rossi and Chintagunta (2004). Here we compare the three models by checking their relative model fits. For that, we estimate all the three models using data from the first 11 quarters, and then conduct a hold-out sample test, predicting the number of details for the final quarter. The RMSEs for the predicted details with the observed data are listed in Table 1, which shows that the proposed model (targeting at the individual level) predicts the best.

---------- Insert Table 1 about here ----------

Marginal cost estimates

One benefit of incorporating firm strategic behavior in the modeling process is that the model allows us to obtain the marginal cost of detailing. Based on those cost estimates, we can conduct different policy experiments and compare profits under different scenarios (Chintagunta, Kadiyali

and Vilcassim (2004)). To ensure that our results are not sensitive to the estimated marginal costs, we conducted a robustness check by comparing the profit gains for both the proposed approach and the approach that ignores firms' strategic behaviors under different cost values (Table 2).

---------- Insert Table 2 about here ----------

In the base model, we use the estimated marginal cost of detailing in comparing the profit gains of individual level targeting vs. segment level targeting. As we have seen before, the profits gains are 23% using the proposed approach and 5% using the approach that ignores firms' strategic behaviors. We then fix the cost of detailing for all brands at $100, the typical value used in the industry. The profit gains with this cost assumption are 22% and 4% under the proposed and the approach that ignores firms' strategic behaviors respectively. Similar results are obtained when we compare the profits under the highest cost of detailing estimated in the data for all brands ($120) as well as the lowest ($80). Thus, across a wide range of costs, assumed and/or estimated, the computed profit gains only vary by a trivial amount.

Non-myopic behavior

First, we carry out a simulation using our estimated parameters to determine the impact of being forward-looking on profits. We focus on a subset of 100 physicians (we do this to reduce computation time). Specifically, each firm is assumed to maximize its expected discounted profits from an individual physician, while considering all the competitors' strategies. For computational simplicity, we assume an infinite time horizon. By solving this dynamic game among the four firms, we find the optimal detailing level at each time period for all the competing firms. Using these optimal detailing solved from this dynamic game, we evaluated the total profits over 100 quarters (we use a quarterly discount rate of 0.975). The results show that if the companies and the salespersons had been forward looking when they set detailing levels, given the estimated parameters for each individual physician, their overall profits could be improved by 8%. Thus, these results

suggest that a forward-looking firm is likely to be better off than one that engages in myopic behavior (assuming no additional costs).

Second, to carry out the estimation of the model parameters under the assumption of forward looking firms, we first solve for detailing levels assuming that firms are engaged in a two-period repeated game. In order to estimate the model using full information likelihood method (equation (10)), we need to obtain the analytical solution for the distribution of detailing. However, this is not feasible given our demand model specifications. So, we first change the log-reciprocal operationalization of detailing to a more standard log-log demand model, and solved for the detailing distribution analytically under a sub-game perfect equilibrium assumption. While details are not reported here, using the estimates from this model, we predicted detailing levels, and computed the RMSE of predicted and actual detailing. We find this to be 2.9, which is much higher than the RMSE for the proposed model, which is 1.5 (see table 11). This suggests that the proposed model describes the data better than the two-period look-ahead model, although it does not rule out the possibility that a fully dynamic model might describe the observed data better.

Different heterogeneity specification

We have assumed a specific heterogeneity distribution in our model (the Gaussian distribution). This implies that firms think of physician as being located on a continuum with respect to the prescription and detailing parameters. However, it is indeed possible that firms classify physicians into segments based on their response parameters. We therefore implement a latent class model on our data. Specifically, we estimate the parameters of a latent class model with joint prescriptions and detailing decisions at the segment level, where the parameters are now segment specific. We compare the prediction of this model with our proposed model using a holdout sample as described before. The RMSE of the predicted detailing using the parameter estimates from the latent class model is 5.5 as opposed to the RMSE of 1.5 (Table 11) from the proposed model. This suggests weaker support for the latent class model relative to the proposed model.

References

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Table 1: RMSE for hold-out sample tests

Assumptions of firm strategic behavior	RMSE of predicted and actual detailing
Target at the individual level	1.5
Target at the segment level	4.0
Sales Maximization	4.9
Heuristic	3.2
Latent class model	5.5

Table 2: Profit gains for both approaches using different cost values

Cost values used ($)	Proposed approach (%)	Approach that ignores firms' strategic behaviors (%)
Base model	23	5
Cost = $100	22	4
Cost = $120	22	5
Cost = $80	21	4