# "SOLUTIONS" Problem Set 1: BLP Demand Estimation

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These are my attempt at the first problem set for the second year Ph.D. IO course at NYU with Heski Bar-Isaac and Allan Collard-Wexler in Fall 2007. They are offered as suggested "solutions". All errors are my own.

In this problem set we consider estimating discrete choice demand models from weekly panel data on sales of over-the-counter pain medications in Chicago supermarkets. We have data on the number of customers, product sales, retail prices, wholesale prices (the retailer's costs) in each store each week. We also have access to demographic data on income distributions in the store regions. The standard position normalization of zero utility from the outside good and scale normalization of the i.i.d. logit unobservables  $\epsilon_{ijt}$ are both maintained throughout.

## 1 Logit

We assume that consumers choose among products  $j \in J$  to maximize the utility model

$$u_{ijt} = X_{jt}\beta + \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt}$$

or

$$u_{ijt} = \delta_{jt} + \epsilon_{ijt}$$

where the mean utility from product j in week t is

$$\delta_{jt} = X_{jt}\beta + \alpha p_{jt} + \xi_{jt} \tag{1}$$

Berry (1994) shows how to analyze this model by solving for  $\delta$  as a function of observed market shares, obtaining

$$\delta_{jt} = \ln(s_{jt}) - \ln(s_0)$$

allowing us to consider the linear regression model implied by equation (1).

## 1.1 OLS

OLS regression with X = (price, promotion) will provide consistent parameter estimates under the assumptions that: 1) our utility model is specified correctly (i.e. the function  $\delta(s)$  gives us the true mean utility), and 2)  $E[\xi|X] = 0$  (throughout we will focus on the concern that price could be set as a function of  $\xi_{jt}$ , which are unobservable to the econometrician, but potentially known to the firms). Note that in this model the full variation in the data is used to identify the parameter values.

## **1.2** OLS with product fixed effects

In this case the product-specific fixed effects will absorb any portion of the  $\xi_{jt}$  that are not store/week specific, i.e. now the unobservables should be interpreted as deviations from a product-specific unobservable (the fixed effect). For many cases of interest, this might make the condition  $E[\xi|X] = 0$  more plausible. Note that here we are now only using variation in deviation from product-specific means (i.e. only across stores and time) to identify the parameters on price and promotion.

## 1.3 OLS with product/store fixed effects

This more flexible set of fixed effects account for the mean variation across both products and stores, so we should again alter our interpretation of the  $\xi_{jt}$ to account for this, and the assumption of  $E[\xi|X] = 0$  becomes perhaps yet more plausible. Note, however, that we continue to trade off "robustness" of our mean independence assumption against the fact that now our only source of identifying variation is across time (deviations from product/store-specific means).

## 1.4 Instruments and results

In this data set we have wholesale prices, which are the retailers' costs, but which more importantly might be good proxies for the manufacturers' marginal costs, making them potential instruments for price endogeneity with  $\xi_{jt}$  (we might think that only the markup, and not costs, depends on the unobservable). By similar logic, we could use the "Hausman" instruments of average price in other markets.

Since the arguments for good instruments are largely informal, it is worth thinking hard about if these instruments make intuitive sense. First, note from our discussion above that we are instrumenting for three different unobservables in the three different dummy structures (product-store-week unobservables, product-store-week deviations from product mean unobservables, and product-store-week deviations from product-store mean unobservables). Also, in the retail world, the price has two markups over the manufacturer's marginal cost: 1) the markup the manufacturer charges the retailer, and 2) the markup the retailer charges the consumer. My personal thought is that we might not expect wholesale costs to be very good instruments here because they are actually the price the manufacturer charges the retailer, which has a markup that is likely a function of the unobservable, leaving us with the exact same endogeneity problem we started with. As for the Hausman instruments, we might expect them to be better instruments in the dummy variable regressions where the unobservable is market-specific.

Table 1. Results from Logit Regression					
		OLS			
	(i)	(ii)	(iii)		
Price	-0.0514	-0.3413	-0.3302		
	(0.0025)	(0.0101)	(0.0096)		
Promotion	0.2132	0.3295	0.3290		
	(0.0163)	(0.0126)	(0.0115)		
	(0.0100)	(0.0120)	(0.0110)		
Dummies	_	Brand	Store-Brand		
		Wholesale Co	ost IV		
	(iv)	(v)	(vi)		
Price	-0.0106	-0.0080	-0.0345		
	(0.0027)	(0.0197)	(0.0183)		
Promotion	0 2362	0 4309	0.4195		
1 1011001011	(0.0164)	(0.0138)	(0.0126)		
	(0.0104)	(0.0130)	(0.0120)		
Dummies	_	Brand	Store-Brand		
		Hausman	IV		
	(vii)	(viii)	(ix)		
Drico	0.0511	0 5460	0 5480		
1 1100	(0.00011)	-0.0409	-0.0400		
	(0.0026)	(0.0135)	(0.0122)		
Promotion	0.2133	0.2669	0.2624		
	(0.0163)	(0.0130)	(0.0118)		
- ·			~		
Dummies	_	Brand	Store-Brand		

Looking at the results gives us a much clearer picture of the endogeneity issues and our instrument candidates. The first thing to note is that neither set of instruments seems to move the coefficients the way we would hope in the regressions with no dummy variables, which we anticipated in our discussion above. We do see that adding the product dummies shifts the coefficients quite a bit in the direction of being more reasonable in our OLS regressions, and moving to product-store dummies doesn't have much further effect, suggesting that 1) a lot of endogeneity is at the product mean unobservable level, and 2) there isn't much further endogeneity at the product-store mean level. Looking at the Hausman IV dummy regressions shows that there may, however, be some more endogeneity as the unobservable changes across time, and that the Hausman IV do well at instrumenting for this. Finally, we have the curious results in the cost IV regressions, which give different results for the no dummy regression, and which react quite differently to the addition of dummies than the OLS and Hausman IV cases. After a fair amount of investigation, I can't determine exactly what is causing this, but looking at the variation of wholesale costs within each product, they have on average less than half the standard deviation of prices, which might be enough to lower the identifying variation of the data, especially as we add the dummy variables. Combining this with the fact that wholesale costs move with promotions (the manufacturers pay for at least part of the promotion), we might even be approaching having a rank problem with our data matrix.

### 1.5 Logit elasticities

For the Logit model, the elasticity of demand for product j with respect to a price change in product k is given by (all in a given market t, with the subscript suppressed for convenience)

$$\eta_j^k := \frac{\partial s_j / s_j}{\partial p_k / p_k} = \left(\frac{p_k}{s_j}\right) \frac{\partial}{\partial p_k} \left(\frac{\exp(\delta_j)}{1 + \sum_m \exp(\delta_m)}\right)$$
$$= \frac{p_k}{s_j} \alpha \left(-s_j s_k + \mathbf{1}_{\{k=j\}} s_k\right)$$

The mean own-price elasticities over all markets for the parameter estimates from the three OLS regressions are then

		Logit Model	
Brand (Size)	(i)	(ii)	(iii)
Tylenol (25)	-0.1756	-1.1667	-1.1287
Tylenol $(50)$	-0.2538	-1.6854	-1.6305
Tylenol $(100)$	-0.3603	-2.3935	-2.3155
Advil $(25)$	-0.1522	-1.0110	-0.9781
Advil $(50)$	-0.2642	-1.7556	-1.6984
Advil $(100)$	-0.4190	-2.7848	-2.6941
Bayer $(25)$	-0.1372	-0.9122	-0.8825
Bayer $(50)$	-0.1852	-1.2311	-1.1910
Bayer $(100)$	-0.2037	-1.3535	-1.3094
Generic $(50)$	-0.0990	-0.6580	-0.6366
Generic $(100)$	-0.2283	-1.5176	-1.4682

 Table 2. Mean Own-Price Elasticities

There are a host of general issues with logit substitution patterns which are discussed at length elsewhere. The most important thing to note in our specific results here is how unreasonable the model with no dummy variables is in that the elasticities it implies suggest that the firms are all pricing on an inelastic portion of the demand curve, where increasing price would certainly increase profits.

# 2 Random Coefficients Logit a.k.a. BLP

Here the utility model is

$$u_{ijt} = X_{jt}\beta + \beta_{ib}B_{jt} + \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt}$$

where the random coefficients are  $\beta_{iB} = \sigma_B v_i$  with  $v_i \sim N(0, 1)$ ; and  $\alpha_i = \alpha + \sigma_I I_i$  with  $I_i$  the observed income.

Substituting the full specifications for the random coefficients, and collecting the terms that represent the mean utility of product j, we can rewrite the model as

$$u_{ijt} = \delta_{jt} + \sigma_B v_i B_{jt} + \sigma_I I_i p_{jt} + \epsilon_{ijt}$$

where the mean utility from product j in week t is

$$\delta_{jt} = X_{jt}\beta + \alpha p_{jt} + \xi_{jt} \tag{2}$$

#### 2.1 Parameter estimates

#### Identification and the estimation criterion

Our identifying assumption is  $E[\xi_{jt}^{0'}Z_{jt}] = 0 \quad \forall j, t \text{ for some instruments } Z_{jt}$ and the true unobservables  $\xi_{jt}^0$ . Since we don't know the true unobservables, we will use some estimates  $\xi_{jt}(\theta)$  where  $\xi_{jt}(\theta^0) = \xi_{jt}^0$  at the true parameter values  $\theta^0$ . Our estimator for the parameters will minimize the weighted sum of squares (with the "optimal" weights),

$$\hat{\theta} = \arg\min_{\theta} \xi' Z(Z'Z)^{-1} Z' \xi \tag{3}$$

and to form this criterion function we need two things: Z and  $\xi$ .

#### Calculating $\xi$

1. Equation (2) tells us that  $\xi_{jt} = \delta_{jt} - X_{jt}\beta - \alpha p_{jt}$ . Note X and p are data, but we still need  $\delta$ . Berry (1994) proves that there is a unique vector  $\delta$  that solves  $s_{jt} = \mathfrak{s}(\delta_{jt}) \quad \forall j, t$ . BLP gives us the contraction mapping that allows us to solve for this  $\delta$ ,

$$\delta_{jt}^{(m+1)} = \delta_{jt}^{(m)} + \log(s_{jt}) - \log(\mathfrak{s}(\delta_{jt}^{(m)}, \theta_2))$$

and for this we need to know how to calculate the market shares implied by our model  $\mathfrak{s}(\delta_{it}, \theta_2)$ .

2. The market share implied by our model is the share of consumers who choose good j at time t (where we assume they maximize utility)

$$\mathfrak{s}(\delta_{jt},\theta_2) = \int \int \frac{\exp(\delta_{jt} + \sigma_B v_i B_{jt} + \sigma_I I_i p_{jt})}{1 + \sum_j \exp(\delta_{jt} + \sigma_B v_i B_{jt} + \sigma_I I_i p_{jt})} dF^v(v) dF^I(I)$$

but this integral does not have an analytic solution, so we need to simulate ns "individuals" (for each market t), each characterized by

a pair  $(v_i, I_i)$  drawn from the appropriate distributions, and use the simulator

$$\hat{\mathfrak{s}}(\delta_{jt}) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{\exp(\delta_{jt} + \sigma_B v_i B_{jt} + \sigma_I I_i p_{jt})}{1 + \sum_j \exp(\delta_{jt} + \sigma_B v_i B_{jt} + \sigma_I I_i p_{jt})}$$

where the ns elements of the sum are the probability that individual i chooses product j in market t.

#### Instruments Z

We need some instruments  $Z_{jt}$  that are correlated with our independent variables  $(X_{jt}, B_{jt}, p_{jt})$  but not with the  $\xi_{jt}$ . Here we use wholesale price, average price in other markets, and prices in 30 other markets as instruments for price, and we let the other independent variables be instruments for themselves.

#### Solving for $\hat{\theta}$

With Z and  $\xi$  in hand, estimation comes from solving equation (3) where  $\theta = (\beta, \sigma_B, \alpha, \sigma_I)$  are the coefficients to be estimated. This nonlinear search becomes more complicated as the size of the parameter space grows, so one useful trick worth repeating is to "concentrate out" the linear parameters  $\theta_1 := (\beta, \alpha)$  by imposing the FOC of 2SLS as discussed in the appendix to Nevo (2000) and BLP.

The resulting estimates are

	Logit	Random Coefficients (BLP)
Duin	0 4196	0.4604*
Price	-0.4186	-0.4604*
Promotion	0.3060	0.2995
Tylenol $(25)$	-5.8068	-5.9836
Tylenol $(50)$	-4.9997	-5.1566
Tylenol $(100)$	-4.5983	-4.7555
Advil $(25)$	-6.2712	-6.4562
Advil(50)	-5.8658	-6.0219
Advil $(100)$	-5.4373	-5.6048
Bayer $(25)$	-7.5146	-7.7074
Bayer $(50)$	-7.3817	-7.5548
Bayer $(100)$	-6.3075	-6.4741
Generic $(50)$	-7.1249	-7.0569
Generic $(100)$	-6.5145	-6.4000
$\alpha$	-0.4186	-1.3925
$\sigma_B$		0.7821
$\sigma_I$		0.0877
GMM Objective		363.1
computer time		$4.36 \min$
* For comparison.	this is the :	mean effect of price. $\alpha + \sigma_I \overline{I}$ .

Table 3. Results from BLP

Notice here that the biggest difference in the random coefficients model (versus the logit) is not in the mean effects, but in that it allows for systematic heterogeneity among consumers (which shows up more in substitution effects). This is demonstrated here by the fact that the mean effect of price in the two models is very similar, but the effect can vary quite among individual consumers in the random coefficients case. Note in both cases a good "reality check" we can do here is to verify that our fixed effects are monotonically increasing in price inside the branded and generic categories (since we have a vertical model in this case, which requires this for positive market share).

The addition of the random coefficient on whether or not the product is branded provides another example of how the logit model is restricted in how it can explain variance in outcomes. Note how the product-specific dummy coefficients shift systematically down for the branded products and up for the generic products when we move to the random coefficients model. This is because the random coefficient allows for the fact that there is a subgroup of the population that strongly prefers the branded product, but also a group that doesn't, so it can explain the "branded premium" by both a mean and variance effect, whereas the logit model was restricted to only a mean effect (which forced the mean effect to be larger in the logit).

## 2.2 Elasticities

For a fixed market t the price elasticities for product j with respect to a price change in product k in that same market are given by (dropping the t subscript for convenience)

$$\begin{split} \eta_j^k &:= \frac{\partial s_j/s_j}{\partial p_k/p_k} = \left(\frac{p_k}{s_j}\right) \frac{\partial}{\partial p_k} \left( \int \int \frac{\exp(\delta_j + \sigma_B v_i B_j + \sigma_I I_i p_j)}{1 + \sum_m \exp(\delta_m + \sigma_B v_i B_m + \sigma_I I_i p_m)} dF^v(v) dF^I(I) \right) \\ &\approx \frac{p_k}{s_j} \sum_{i=1}^n (\alpha + \sigma_I I_i) \left( -s_{ij} s_{ik} + \mathbf{1}_{\{k=j\}} s_{ik} \right) \end{split}$$

Our estimates for the elasticities from the random coefficients model and Logit models are shown in Table 4.

 Table 4. Own and Cross-Price Elasticities

Random Coefficients Model (BLP)

	Tylenol (25)	Tylenol (50)	Tylenol (100)	Advil	Advil (50)	Advil (100)	Bayer	Bayer (50)	Bayer (100)	Generic (50)	Generic
Tulonal (25)	1 4002	0.0024	0.0028	0.0008	0.0012	0.0002	0.0006	0.0006	0.0004	0.0004	0.0001
Tylenol $(20)$	-1.4003	2 0280	0.0028	0.0008	0.0013	0.0003	0.0000	0.0000	0.0004	0.0004	0.0001
Tylenol $(50)$	0.0011	-2.0289	0.0029	0.0008	0.0013	0.0003	0.0000	0.0000	0.0004	0.0004	0.0001
A dril (25)	0.0011	0.0034	-2.0110	1 2124	0.0013	0.0003	0.0000	0.0000	0.0004	0.0004	0.0001
Advii $(23)$	0.0012	0.0034	0.0028	-1.2124	0.0013	0.0003	0.0000	0.0000	0.0004	0.0004	0.0001
$\begin{array}{c} \text{AdVII} (50) \\ \text{Adv:l} (100) \end{array}$	0.0011	0.0034	0.0029	0.0008	-2.1948	0.0003	0.0006	0.0006	0.0004	0.0004	0.0001
Advil $(100)$	0.0011	0.0034	0.0030	0.0008	0.0013	-3.3635	0.0005	0.0006	0.0004	0.0004	0.0001
Bayer $(25)$	0.0012	0.0034	0.0028	0.0008	0.0013	0.0003	-1.1631	0.0006	0.0004	0.0004	0.0001
Bayer (50)	0.0011	0.0034	0.0028	0.0008	0.0013	0.0003	0.0006	-1.4212	0.0004	0.0004	0.0001
Bayer $(100)$	0.0011	0.0034	0.0029	0.0008	0.0013	0.0003	0.0006	0.0006	-1.6755	0.0004	0.0001
Generic $(50)$	0.0007	0.0021	0.0018	0.0005	0.0008	0.0002	0.0004	0.0004	0.0003	-0.7330	0.0001
Generic $(100)$	0.0007	0.0022	0.0019	0.0005	0.0008	0.0002	0.0004	0.0004	0.0003	0.0004	-1.8840
					Logit Mo	del					
	Tvlenol	Tvlenol	Tvlenol	Advil	Advil	Advil	Baver	Baver	Baver	Generic	Generic
	(25)	(50)	(100)	(25)	(50)	(100)	(25)	(50)	(100)	(50)	(100)
Tylenol (25)	-1.3525	0.0020	0.0017	0.0005	0.0008	0.0002	0.0003	0.0003	0.0002	0.0004	0.0001
Tvlenol(50)	0.0007	-2.0010	0.0017	0.0005	0.0008	0.0002	0.0003	0.0003	0.0002	0.0004	0.0001
Tylenol $(100)$	0.0007	0.0020	-2.6223	0.0005	0.0008	0.0002	0.0003	0.0003	0.0002	0.0004	0.0001
Advil (25)	0.0007	0.0020	0.0017	-1.1635	0.0008	0.0002	0.0003	0.0003	0.0002	0.0004	0.0001
Advil(50)	0.0007	0.0020	0.0017	0.0005	-2.1750	0.0002	0.0003	0.0003	0.0002	0.0004	0.0001
Advil (100)	0.0007	0.0020	0.0017	0.0005	0.0008	-3.4506	0.0003	0.0003	0.0002	0.0004	0.0001
Bayer $(25)$	0.0007	0.0020	0.0017	0.0005	0.0008	0.0002	-1.1143	0.0003	0.0002	0.0004	0.0001
Bayer $(50)$	0.0007	0.0020	0.0017	0.0005	0.0008	0.0002	0.0003	-1.3734	0.0002	0.0004	0.0001
Bayer $(100)$	0.0007	0.0020	0.0017	0.0005	0.0008	0.0002	0.0003	0.0003	-1 6326	0.0004	0.0001
Generic $(50)$	0.0007	0.0020	0.0017	0.0005	0.0008	0.0002	0.0003	0.0003	0.0002	-0.6947	0.0001
Generic $(100)$	0.0007	0.0020	0.0017	0.0005	0.0008	0.0002	0.0003	0.0003	0.0002	0.0004	-1 8466
Generic (100)	0.0001	0.0020	0.0017	0.0000	0.0000	0.0002	0.0000	0.0000	0.0002	0.0004	-1.0400

Looking at the elasticities of substitution shows the full advantage of the more flexible random coefficients model. The random coefficients model allows for much larger substitution effects because it allows for the fact that price sensitive consumers will substitute more to lower priced goods whereas brand sensitive consumers will substitute more to branded goods.

The random coefficients model also allows for substitution effects to vary across alternatives as the price of a single product changes, instead of being driven by market share alone as in the logit model.

Finally, it is worth noting that because the outside good has such a large market share, substitution to the outside good keeps substitution among inside goods perhaps artificially small. A way to relax this and allow for the fact that perhaps people who are at the store to buy pain medicine are more likely to substitute between the inside goods would be to introduce a random coefficient for the inside goods.

## 2.3 Marginal Costs

With a behavioral assumption on firms (we use a NE in prices) we can back out the marginal costs from the firms' first-order conditions. We assume that prices are set at the brand (firm) level, where each brand (Tylenol, Advil, Bayer, Store) sets price to maximize its total profits. The FOC in this case are a vector  $\frac{\partial \pi_f}{\partial p_f}$  with the element corresponding to product j in the set  $F_f$ of products sold by firm f being (again dropping the t subscript, assuming prices are set at the individual market level)

$$0 = \frac{\partial \pi_f}{\partial p_j} = \frac{\partial}{\partial p_j} \sum_{n \in F_f} s_n(p_n - mc_n) = s_j + \sum_{n \in F_f} \frac{\partial s_n}{\partial p_j}(p_n - mc_n)$$

which can be rewritten in vector form (as in BLP p.853) as

$$0 = s + \Delta(p - mc)$$

where  $\Delta$  is a  $J \times J$  matrix with  $\Delta_{n,j}$  equal to  $\left(\frac{\partial s_n}{\partial p_j}\right)$  if both n and j owned by the same firm, and equal to zero otherwise.

Thus the vector of marginal costs for all products is

$$mc = \Delta^{-1}s + p \tag{4}$$

giving us the estimates in Table 5.

Table 9.			
	Marginal Cost		Wholesale Cost
	Logit	BLP	
Tylenol $(25)$	0.85	0.93	2.10
Tylenol $(50)$	2.43	2.47	3.29
Tylenol $(100)$	3.94	3.93	5.66
Advil $(25)$	0.40	0.49	2.10
Advil $(50)$	2.86	2.88	3.46
Advil $(100)$	5.96	5.89	5.76
Bayer $(25)$	0.28	0.38	1.79
Bayer $(50)$	0.91	0.99	2.08
Bayer $(100)$	1.54	1.60	3.71
Generic $(50)$	-0.74	-0.62	0.94
Generic $(100)$	2.06	2.11	1.92

 Table 5. Costs for Store 9 in Week 10

Pursuant to our discussion in problem 1, interpreting these results requires that we specify whose marginal costs we think we are explaining with our behavioral model. I assume we are estimating the manufacturers' marginal costs, in which case we get some very unrealistic results, like the fact that the generic 50 tablet bottles having a negative marginal cost and the Advil and generic 100 tablet bottles being sold at a wholesale price that is less than the marginal cost of producing them. This is a red flag that our markup estimates are wrong. That could be for two reasons: 1) the price-setting model is wrong; 2) the partial derivatives matrix is wrong. We might think there are problems with both in this model. As we discussed when looking at the elasticities, our model is still not fully flexible and might be underestimating substitution effects among the inside goods, which might implies "softer" competition and thus might lead to markups that are too large. Further, as we discussed in problem 1 when we were considering instruments, retail goods go through two sets of markups by different entities (the manufacturer and the retailer) with different environments, thus it is not clear how our equilibrium assumption matches the market mechanism at work here.

# 3 Merger Analysis

Now that we have marginal costs and a model of demand, we can predict the impact of changes<sup>1</sup> such as mergers, where we assume these changes do not affect marginal costs or demand parameters (again making a behavioral assumption on the price setting mechanism). A Nash Equilibrium is a vector of prices  $\hat{p}$  that satisfy the FOC

$$0 = \mathfrak{s}(\hat{p}) + \Delta(\hat{p})(\hat{p} - mc)$$

which we can solve numerically (e.g. choose  $\hat{p} = \arg \min_p \|\mathfrak{s}(p) + \Delta(p)(p - mc)\|$  where  $\|\cdot\|$  is some norm).

## 3.1 Logit predictions

For consistency (so we will get the exact same prices when we don't have a merger), we want to use the marginal costs implied by the Logit model, which involves changing  $\Delta$  to contain the Logit partials and again using equation (4).

With marginal costs and our parameter values, the only thing we need to compute the FOC at a new price is a model for the shares at a given price. For the Logit model, the formula for  $\mathfrak{s}(p)$ , given our data X and parameters estimates from earlier analysis  $\beta, \alpha, \xi$  is then

$$\mathfrak{s}_j(p) = \frac{\exp(x_j\beta + \alpha p_j + \xi_j)}{\sum_{m=0}^J \exp(x_m\beta + \alpha p_m + \xi_m)}$$

which gives us all the components we need to compute the new equilibrium price vector, reported with the predictions of the random coefficients model in the next section.

## **3.2** BLP predictions

Prediction with the BLP random coefficients model proceeds in much the same way, with the difference being that computing the shares implied by the model for a given price requires the computational machinery for aggregating

 $<sup>^{1}</sup>$ Note such out of sample predictions is one of the fundamental reason we take the time to estimate "structural" models, where we believe the parameters we estimate may not change with the environment.

over "individual" choice probabilities that we employed in estimation when we were computing the shares for new parameter vectors.

	0		
	Pre-merger Price	Logit Prediction	<b>BLP</b> Prediction
Tylenol (25)	3.29	3.28	3.30
Tylenol $(50)$	4.87	4.86	4.88
Tylenol $(100)$	6.38	6.37	6.39
Advil $(25)$	2.83	2.82	2.84
Advil $(50)$	5.29	5.28	5.30
Advil $(100)$	8.39	8.37	8.40
Bayer $(25)$	2.71	2.70	2.72
Bayer $(50)$	3.34	3.33	3.35
Bayer $(100)$	3.97	3.96	3.98
Generic $(50)$	1.69	1.69	1.69
Generic $(100)$	4.49	4.49	4.49
	$\sup(FOC)$	1.10E-07	4.85E-08

Table 6. Pre and Post-Merger Prices for Store 9 in Week 10

Here we see no discernable effect of the merger. This is because the substitution effects are so small between the products that there that the "gains from collusion" are not very high. We do see a very small increase in prices of the branded products under the random coefficients prediction, which makes sense since substitution effects are larger in that model.