Pharmaceutical Advertising in Dynamic Equilibrium.

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Background

• U.S. is the largest pharmaceutical market in the world in terms of both revenue ($\approx$ \$500 billion per annum) and promotional spending.

• Two types of promotional spending (data is from 2005-14).

- detailing (representatives of pharma visiting providers,...)
  \$11.3 to \$13 billion per annum.
- direct to consumer advertising (DTC; largely TV)
  \$3.7 to \$4.9 billion per annum .

• Only two developed countries allow DTC of prescription drugs (U.S. & New Zealand), and detailing most often restricted in ways that the U.S. does not do.

• Markets Analyzed: treatments for Asthma, Cholesterol, Depression, & Ulcer. Constitute about 25% of all DTC, and about 22% of all detailing.

- In all of these markets not all drugs are advertised.
  - More of the products do detailing than DTC. About 50% of our observations have positive detailing but only 10% have positive DTC. Firms that do DTC almost always do detailing.
  - However the average DTC expenditures given that a firm does DTC are as large (or larger) than the average detailing expenditures among firms that do detailing.

- The argument for and against advertising.
  - *Against*; incentives for miss-information & returns largely a result of business stealing and so do not generate benefits to society.
  - *For*; make consumers aware that they can treat a condition before it becomes serious (particularly those that do not regularly see doctors), and providers aware of treatment alternatives.

- Question: How useful is the advertising, and is there a more socially efficient way to organize it?

Framework for the Analysis.

- Complicated markets with 30 to 50 competitors. Cognitive constraints: can we obtain a better approximation than full information MPE?

- Use *Experience Based Equilibrium:*
  1. firms chose policies to maximize their perceptions of their EDVs conditional on the variables they use to determine their expenditures,
  2. perceptions are consistent with outcomes at states that are visited repeatedly by the Markov process generated by the policies.

- Implementation in empirical work.
  - Use data to determine *observables* that firms' advertising responds to.
  - Allow for serially correlated unobserved state variables (one for each of DTC & detailing) to account for impact of variables that the firm knows but we do not observe.

- *Properties of Equilibrium.*
  - Asymmetric information (firms differ in the information they use.)
  - Rationale for consistent perceptions at states visited repeatedly; can use the empirical distributions at those states.

• Empirical work generates the parameters that are invariant to equilibrium calculations: fixed and marginal costs (net of rebates), & the parameters of the stochastic process generating the unobserved states.

• Computational algorithm computes continuous policy function on a continuous state space that are consistent with the results from the empirical analysis and the equilibrium notion.

• Compare equilibrium policies both to the data, and to the policy functions that we compute under different rules governing advertising: i) no DTC, ii) no advertising, (iii) tax advertising and use the proceeds to advertise without identifying actual drugs.

Steps in the analysis

Begin with

- Estimate of a BLP demand system, and recover the "quality" (ξ) terms for each drug in each period (quarter).
- Estimate a "controlled" Markov process for how quality evolves over time, where the controls are the two types of advertising.

• This is enough to compute business stealing incentives: i.e. the profit loss were the firm to stop advertising when its competitors did not.

• To go further we need a model for advertising, so we outline: theory, estimation, & computational algorithm.

• Ready for today: compare expenditures and profits; from data, to equilibrium generated by current institutions, & to no-DTC counterfactual equilibrium.

Demand.

• An individual with the given health condition maximizes utility among $j \in \{0, 1, \ldots, J\}$ where $j = 0$ is the choice not to be medicated

$$U_{ijt} = \beta^i_p p_{jt} + \beta_g g_{jt} + \beta_{m(j)} + \beta_x X_{jt} + \xi_{jt} + \varepsilon_{ijt}$$

- p_{jt} is the price of drug j at time t, & $\beta^i_p \sim N(\beta_p, \sigma^2_p)$,
- β_m is a molecule fixed effect,
- g_{jt} is a dummy variable indicating patent expiration
- X_{jt} are controls which vary by market,
- $\xi_{j,t}$ is the quality term
- ε_{ijt} is an i.i.d. extreme value error.

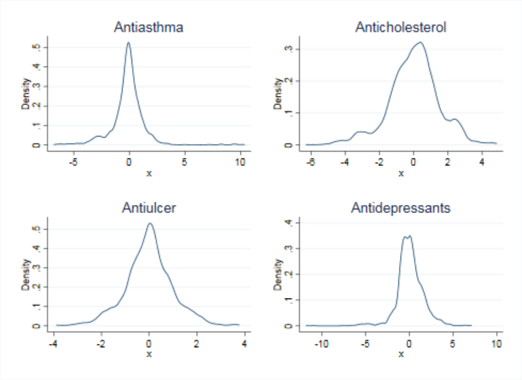
Table: BLP demand models

	Anticholesterol	Antiasthma	Antidepressants	Antiulcer
Mean Price Coefficient				
Price	-2.167***	-4.292***	-1.547***	-1.860***
	(0.2440)	(0.7405)	(0.4419)	(0.2105)
Price × Generic	-0.740**	-7.477*	-4.287	
	(0.2418)	(3.2038)	(2.6022)	
Price × OTC				-7.231***
				(0.8210)
Standard Deviation Price Coefficient				
Price	1.015***	1.625***	0.550***	0.671***
	(0.1457)	(0.2790)	(0.1624)	(0.1120)
Price × Generic		4.018***	3.021*	
		(0.9874)	(1.5108)	
Controls				
Generic		1.611	0.415	2.115***
		(2.6141)	(1.0504)	(0.2590)
OTC				-0.461*
				(0.2254)
Drug fixed effects	Molecule	Molecule ×Patent status	Molecule	Product
Year dummies	✓		✓	
ATC4×Year dummies		✓		✓
N	1088	1733	1592	1602
Parameters	20	44	231	100
Nb products	31	51	44	29

* for $p < .05$, ** for $p < .01$, and *** for $p < .001$. Molecules: ATC5 level. For each market all combinations of drug fixed effects and (β_p, σ_p^2) are tested. Table: preferred specification. Product fixed effect = brand-molecule combo, a molecule and patent status fixed effect = combo of molecule fixed effect & dummy for patent expiration.

- Fixed Effects: molecule, time, Generic, OTC (latter two also $\times p$).
- Both μ & σ of price coefficient highly significant in each market.
- The distribution of ξ seems approximately normal. We are using the normal approximation in the equilibrium calculations, but we probably should be using the actual values, which would also improve performance.

Figure: Density distribution of ξ_{jt}



Advertising and the Evolution of Quality.

$$\xi_{j,t} = \rho_\xi \xi_{j,t-1} + f(a_{Dj,t}, a_{dj,t}) + z_{j,t}\beta_z + d_t\beta_{dt} + \mu_{j,t}, \qquad (1)$$

so the impact of advertising is stochastic. d_t are time dummies, $z_{j,t}$ are other observable determinants, and

$$f(a_{dj,t}, a_{Dj,t}) = \beta_{a_d} log(1+a_{dj,t}) + \beta_{a_D} log(1+a_{Dj,t}) + \beta_{a_{d,D}} log(1+a_{dj,t}+a_{Dj,t}),$$

- Tested for
  - separate ρ for generics and patented alternatives (not needed).
  - $d_t \equiv 0$: accepted: we have time dummies in demand so this accepts that the impact of advertising does not change over time.
  - $\beta_{a_{d,D}} = 0$: always accepted.
  - $\beta_{a_d} = \beta_{a_D}$. Always accepted, but cholesterol had precise and slightly different coefficients. In two markets, the DTC coefficient though positive was not individually significant.

Table: Regression of ξ for all markets

	Anticholesterol	Antiasthma	Antidepressants	Antiulcer
	Xsi	Xsi	Xsi	Xsi
TLxsi2	0.895***	1.006***	0.965***	0.969***
	(0.012)	(0.006)	(0.011)	(0.008)
TLxsi2_nongen				
TLxsi2_gen				
TlaglogDetailing	0.048***			
	(0.008)			
TlaglogDTC	0.034***			
	(0.007)			
Tlog_ad		0.022***	0.019**	0.035***
		(0.005)	(0.007)	(0.008)
Tgeneric_dummy	0.318***	-0.023	0.000	0.100**
	(0.057)	(0.049)	(0.045)	(0.035)
Totc		0.145		-0.035
		(0.087)		(0.030)
Constant	-1.237***	0.114**	0.081	0.164***
	(0.163)	(0.037)	(0.050)	(0.040)
R-Square	0.9474	0.9705	0.9191	0.9783
Adj. R-Square	0.9472	0.9704	0.9189	0.9782
N	838	1252	1217	1214

* for $p < .05$, ** for $p < .01$, and *** for $p < .001$

Data and Business Stealing Incentives.

• The average DTC expenditures given that a firm does DTC are larger than detailing expenditures in 2 industries and lower in the other two.

• Business stealing effects are huge: if a firm stopped its DTC when its competitors did not it would lose, on average, between 27% to 50% of its revenue; & if it stopped all advertising it would lose between 30% to 72%.

• This translate into revenue losses per dollar advertising expenditure in the thousands of dollars (largely returns to infra-marginal expenditures).

•. The loss per dollar for DTC is larger than for detailing.

• *One Goal*: compare this to the losses that would be incurred if we banned DTC (or all of advertising) for all participants.

• For this we need an advertising model.

Business Stealing Incentives.

Table: Rev/Adv are ratio of averages, and not averages of ratios. Redo.

	Cholesterol	Asthma	Depressants	Ulcer
No DTC				
Advertising				
Average	175	199	211	86
Sum	2,100	2,591	1898	88
In Sample Loss: Revenue				
Average	4,525,828	4,320,994	1,688,996	5,554,300
Sum	54,309, 940	56,172, 924	15,200,962	44, 434, 398
In Sample Loss: Statistics				
Ave Rev share	.39	.5	.34	.27
Ave $ Rev/ $ DTC	25,861	21,173	8,005	64,584
No Advertising				
Advertising				
Average	227	197	164	88
Sum	6,813	8,678	6,884	3522
In Sample Loss: Statistics				
Ave Rev share	.48	.72	.30	.44
Ave $ Rev/ $ DTC	11,723	10,447	4,764	15,402

A Model of Advertising.

- $W(a|\xi_{i,t}, J_{i,t})$ is the decision maker's perception of the EDV of returns conditional on $a = (a_D, a_d)$, or

$$W(a|\xi_{i,t}, J_{i,t}) \equiv \mathcal{E}\left[\sum_{\tau=1}^{\infty} \beta^{\tau} \pi(\cdot)_{t+\tau} \Big| \xi_{i,t}, J_{i,t}\right],$$

  - $\mathcal{E}(\cdot|\cdot)$ is the agent's expectations operator,
  - $(J_{i,t}, \xi_{i,t})$ are the set of variables the firm conditions on when making its advertising decisions.

- The other variables include:
  - those in our data, say $w_{h,t}$, determined empirically.
  - those we do not observe; their impacts are denoted by $\{\omega_{h,t}\}_{h\in\{d,D\}}$ and can be serially correlated.

• Management maximizes. So the marginal return to advertising is

$$\mathcal{E}\Big[\sum_{\tau=1}^{\infty}(\beta\rho)^{\tau}\frac{\partial\pi(\cdot)_{t+\tau}}{\partial a_{h,t}}|J_{i,t},\xi_t\Big]$$

and we approximate with

$$\approx \theta_{0,h}\left(\left[\frac{\partial\pi(\cdot)_{t-1}}{\partial\xi_{t-1}}\right]\frac{\beta_{a,h}}{a_h}\right)^{\theta_{1,h}} exp[w_{h,t-1}\beta_{w,h}+\omega_{h,t}],$$

where $\omega_{h,t}\in J_t$ gives the impact of variables not in our data and

$$\omega_{h,t}=\rho_{\omega,h}\omega_{h,t-1}+\nu_{h,t}, \text{ for } h\in\{d,D\}$$

$$E[(\nu_{d,t},\nu_{D,t})'|J_t,\xi_t]=0 \text{ and } Var[\nu_{d,t},\nu_{D,t}]'=\Sigma_{\nu}.$$

• Notice that though the impact of competitors' advertising policy is partly captured by $\pi(\cdot)$, it may also directly enter the variables in w.

Accounting for Two Properties of the Data.

• Assume the firm knows the demand system, production costs, and the process generating ξ. Still two problems.

1. We need estimates of

$$\frac{\partial \pi(\cdot)_{t-1}}{\partial \xi_{t-1}} = \frac{\partial D(\cdot)_{t-1}}{\partial \xi_{t-1}}(p_{t-1} - c)$$

where

- p is list prices which are known to us, and
- c is *marginal cost minus rebates* & is not known.

• We estimate c from the advertising equation & compare the estimate to those from the f.o.c. from a static Nash pricing assumption.

2 Drugs often advertised in some periods but not others (Dube et. al 2022, advertising "pulsates").

Market	N	$a_{dt} > 0$	$a_{Dt} > 0$	$a_{Dt} > 0$ $\& a_{Dt-1} > 0$	$a_{dt} > 0$ $\& a_{dt-1} > 0$	$a_{Dt} > 0$ $\& a_{Dt-1} > 0$ $\& a_{dt-1} > 0$	$a_{dt} > 0$ $\& a_{dt-1} > 0$ $\& a_{Dt-1} > 0$
Antiasthma	1733	0.552	0.095	0.089	0.516	0.089	0.096
Antiulcer	1602	0.448	0.052	0.045	0.392	0.045	0.052
Anticholesterol	1088	0.492	0.142	0.125	0.449	0.117	0.131
Antidepressants	1592	0.417	0.072	0.067	0.367	0.062	0.065

• Introduce a fixed cost, $\{u_h \sim Exp(f_h)\}_{h\in\{d,D}$. If the increment in the expected returns from advertising is less than u_h, $a_h = 0$.

• Parameter heterogeneity

- the parameters $\{\rho_{\omega,h}, \theta_{0,h}, \theta_{1,h}, \beta_{w,h}\}_{h\in\{d,D\}}$ differ across markets.
- $\{c_j\}_j$ differs both across drugs in a given market, and since it includes rebates, between the branded and generic versions of the drug.

Summary of Empirical Results.

- Cost Estimates (from advertising equation vs from static Nash pricing).
  - Costs from the static analysis are noticeably higher.
  - Advertising Equation: branded markups between 86 and 100%. Highest branded markup from static f.o.c. was 42%.
  - Advertising Equation: markups that are higher for branded drugs. Static f.o.c: markups are higher for generic drugs.
- *Variables needed for policy function*
  - Observables: derivative of profits w.r.t. advertising; advertising of competitors, time to loss of exclusivity.
  - Highly significant positive serial correlation in seven of the eight equations. Need serial correlated unobserved state variable.
  - Parameters differ quite a bit across markets.

• Variances: higher for DTC than d (in both ν and u), and u then (ν), but same oder of magnitude and this does not vary across industries.

This implies

$$(i) \quad a_{h,t} = 0 \quad \Rightarrow \quad Pr\left\{ u_{h,t} \geq \theta_{0,h} + \theta_{1,h} log[\frac{\partial \pi(\cdot)_{t-1}}{\partial \xi_{t-1}}] + w_{t-1}\beta_{w,h} + \omega_{h,t} \right\},$$

$$(ii) \quad a_{h,t} > 0 \quad \Rightarrow \quad log[a_{h,t}] = \theta_{0,h} + \theta_{1,h} log[\frac{\partial \pi(\cdot)_{t-1}}{\partial \xi_{t-1}}] + w_{t-1}\beta_{w,h} + \omega_{h,t}$$

If

$$\underline{\nu}_{h,t} \equiv \theta_{0,h} + \theta_{1,h} log[\frac{\partial \pi(\cdot)_{t-1}}{\partial \xi_{t-1}}] + w_{t-1}\beta_{w,h} + \rho_{\omega,h}\omega_{h,t-1},$$

the rhs of these two equations is $\underline{\nu}_{h,t} + \nu_{h,t}$, so we have

$$E[\{a_{h,t} = 0\}|J_t] = Pr\left\{u_h \geq \nu_{h,t} + \underline{\nu}_{h,t}\right\} = \int_{u_h} F_{\nu_h}(u_h - \underline{\nu}_{h,t}) dF_{u_h} \equiv P_h(\underline{\nu}_{h,t})$$

where $(F_{\nu_h}(\cdot), F_{u_h}(\cdot))$ are distributions for (ν_h, u_h). Initially put everything we try in (ii) in w, and estimate $P(\cdot)$ nonparametrically.

Compute $E[a_{h,t}|a_{h,t} > 0, J_{i,t}, \xi_{i,t}]$.

- Non-parametric $(F_\nu(\cdot), F_u(\cdot))$, $\underline{\nu}_{h,t} = P_h^{-1}(P_{h,t})$. Quasi first-differencing

$$log[a_{h,j,t}] - \rho_h log[a_{h,j,t-1}] = \theta_{0,h}(1-\rho_h)$$

$$+\theta_{1,h}\left[log\left(\frac{\partial D(\cdot)_{t-1}}{\partial \xi_{t-1}}(p_{t-1,j} - c_j)\right) - \rho_{\omega,h} log\left(\frac{\partial D(\cdot)_{t-2}}{\partial \xi_{t-2}}(p_{t-2,j} - c_j)\right)\right]$$

$$+\beta_{w,h}\left(w_{j,t-1} - \rho_{\omega,h} w_{j,t-2}\right) + M(P_{h,t,j}) + e_{h,j,t},$$

where $e_{h,t} = \nu_{h,t} - E[\nu_{h,t}|a_{h,t} > 0, J_t, \xi_t]$.

Estimation: determine variables in w_h, & parameters of costs & ω_h process (needed for equilibrium computation).

• Nested algorithm: for each value of $\{(\rho_{\omega,h}, \theta_{0,h}, \theta_{1,h}, \beta_{w,h})\}_{h\in\{d,D\}}$ and $M(\cdot)$, we concentrate out the $\{c_j\}_{j\in J}$ by finding the value that solves

$$0 = \sum_t \left(log[a_{h,t}] - \rho_{\omega,h} log[a_{h,t-1}] - [\theta_{0,h}(1-\rho_{\omega,h}) \right)$$

$$-\sum_t \left[\theta_{1,h} log\left(\frac{\partial D(\cdot)_t}{\partial \xi_t}(p_t - c)\right) - \rho_{\omega,h}\theta_{1,h} log\left(\frac{\partial D(\cdot)_{t-1}}{\partial \xi_{t-1}}(p_{t-1} - c)\right) + \beta_{w,h}\left(w_t - \rho_{\omega,h} w_{t-1}\right) + M(P_{h,t}) \right].$$

• Since $e_{h,t}$ may be correlated with the right hand side variables, the outer loop estimated with and without instruments (prior period observables), and we needed the instruments.

• Tried several functional forms for $M(\cdot)$. A linear function of the log odds ratio (i.e. $P/(1-P)$) performed best[1].

[1] We We also tried to estimate the discount factor but the objective was flat about the 95% annual value we are using.

Estimates of Variances of ν and u.

- Recall that for $a_h = 0$ we require $u_h > \nu_h - \underline{\nu}_h$ where

$$\underline{\nu}_{h,t} \equiv \theta_{0,h} + \theta_{1,h} log[\frac{\partial \pi(\cdot)_{t-1}}{\partial \xi_{t-1}}] + w_{t-1}\beta_{w,h} + \rho_{\omega,h}\omega_{h,t-1}.$$

Assume $\nu_h \sim \mathcal{N}(0, \sigma^2_{\nu,h})$ and $u_h \sim exp[f]$, so $Var(u) = 1/f^2$. Then

$$P_h(\hat{\underline{\nu}}_{h,t}) = \int_\nu exp[-f_h \nu_{h,t} - f_h \hat{\underline{v}}_{h,t}] d\mathcal{N}_{\nu,h} = exp[-f_h \hat{\underline{v}}_{h,t} + f_h^2 \sigma^2_{\nu,h}/2],$$

where we have substituted $\hat{\underline{\nu}}_{h,t}$ for $\underline{\nu}_{h,t}$. Use a minimum χ^2 estimator.

- *Results.* Variances similar across markets and types of expenditures. Quite precise (DTC less), but need to add first stage parameter variance.

- Larger in magnitude than the variance of $\mu \approx .55$ $(= \xi_t - f(a) - \rho_\xi \xi_{t-1})$.

Marginal Costs.

Table: Statistics on Prices and Marginal Costs Estimates from Detailing First Order Condition

marketgeneric			Mean		
	Price	Marginal cost	Margin	Marginal cost	Margin
Antiasthma: Branded	2.01	0.22	0.86	1.49	0.36
Antiasthma: Generic	0.29	0.12	0.56	0.13	0.60
Anticholesterol: Branded	2.70	0.19	0.92	1.62	0.42
Anticholesterol: Generic	1.17	0.12	0.90	0.78	0.48
Antidepressants: Branded	5.01	0.35	0.92	3.52	0.34
Antidepressants: Generic	0.43	0.12	0.74	0.12	0.75
Antiulcer: Branded	2.99	0.00	1.00	2.17	0.33
Antiulcer: Generic	1.18	0.00	1.00	0.72	0.54

Mean prices, marginal costs and margins relative to price using cost estimates from advertising equation (columns 2 and 3) and from static FOC (4 and 5). Margins are (p-c)/p. Costs to zero when estimates were negative (21%).

GMM estimates of Detailing and DTC equation

	Antiasthma	Anticholesterol	Antiulcer	Antidepressants
rho				
Constant	0.842***	0.597***	1.000***	0.625***
	(0.019)	(0.035)	(0.122)	(0.040)
theta1d				
Constant	1.158***	0.791***	0.355	1.258***
	(0.104)	(0.054)	(1.527)	(0.144)
betad				
Constant	-0.217	-0.485***	-0.555**	-0.508***
	(0.115)	(0.098)	(0.191)	(0.139)
betad2				
Constant	0.036***	0.041***	0.037	0.076***
	(0.010)	(0.009)	(0.145)	(0.009)
Md				
Constant	1.256***	0.273***	0.666**	0.542***
	(0.132)	(0.052)	(0.207)	(0.061)
rhoDTC				
Constant	0.015	0.157**	0.641***	1.000***
	(0.066)	(0.057)	(0.103)	(0.015)
theta1DTC				
Constant	0.147	0.453***	1.306	2.651
	(0.081)	(0.090)	(1.340)	(2.545)
betaD				
Constant	-0.140	-0.240	-1.802*	-0.574*
	(0.205)	(0.134)	(0.734)	(0.292)
betaD2				
Constant	-0.042***	0.054***	0.167	-1.020
	(0.006)	(0.013)	(0.104)	(0.919)
MD				
Constant	0.017***	-0.499***	-0.002*	0.729***
	(0.003)	(0.107)	(0.001)	(0.167)
constantd				
Constant	14.328***	13.586***	-113.669	14.721***
	(0.592)	(0.440)	(254829.395)	(0.803)
constantD				
Constant	10.449***	10.547***	12.011**	-2545.971
	(0.430)	(0.371)	(3.894)	(101144.757)
N	898	507	683	626

Table: Min $\sum_{j,t} \frac{\left(\hat{P}_{j,t}(\cdot) - exp[-f\underline{v} + f^2\sigma_\nu^2/2]\right)^2}{\hat{P}_{j,t}(\cdot)[1-\hat{P}_{j,t}(\cdot)] + var(\hat{P}_{j,t})}$ - Detailing

Market	f	(Std. Err.)	$1/f^2$	(Std. Err.)	σ_ν^2	(Std. Err.)
Antiasthma	.547	(.0082)	3.333	(.0998)	2.893	(.0177)
Antiulcer	.659	(.0138)	2.297	(.0964)	3.381	(.0217)
Anticholesterol	.866	(.0233)	1.332	(.0717)	3.849	(.0411)
Antidepressants	.43	(.0133)	5.399	(.3358)	2.589	(.0763)

Note: * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Table: Min $\sum_{j,t} \frac{\left(\hat{P}_{j,t}(\cdot) - exp[-f\underline{v} + f^2\sigma_\nu^2/2]\right)^2}{\hat{P}_{j,t}(\cdot)[1-\hat{P}_{j,t}(\cdot)] + var(\hat{P}_{j,t})}$ - DTC

Market	f	(Std. Err.)	$1/f^2$	(Std. Err.)	σ_ν^2	(Std. Err.)
Antiasthma	.385	(.0083)	6.728	(.292)	3.903	(.0461)
Antiulcer	.625	(.208)	2.558	(1.7022)	1.238	(1.1409)
Anticholesterol	.644	(.0204)	2.409	(.1531)	4.186	(.0619)
Antidepressants	.37	(.0209)	7.291	(.823)	6.086	(.15)

Note: * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Algorithm for Computing Equilibria.

- Take demand, costs, the processes generating ξ, $\{u_h \ \& \ \omega_h\}_{h\in\{d.D\}}$, and the observable variables the firms condition on, from above.
- Use these in an iterative algorithm to compute policy functions that satisfy the conditions of an experience based equilibrium for the current institutions, and then for counterfactual institutions.
- Both the states and the policy functions are continuous. Convergence: the policies from adjacent iterations coincide for each period & drug.

Experience Based Equilibrium:

1. firm choses policies that maximize their perceptions of the EDV of future net cash flows conditional on the variables they use to determine their advertising expenditures, and
2. perceptions are consistent with outcomes at states that are visited repeatedly by the Markov process generated by the policies.

Algorithm

• Iterations are indexed by l (associated with policy functions), and we use estimated parameters to evaluate profits in $W^l_{j,t} \equiv \sum_{\tau=1}^{\infty} \beta^\tau \pi(\cdot)_{j,t+\tau}$.

• Initial estimate of the policy function is the function estimated above and we drop the firm index where it is not necessary.

• Iteration l. Simulate K sample paths for $\pi(\cdot)$ and $\{\omega_h\}$ for each firm. Keep the underlying random draws on (μ, u, ν) the same over iterations (otherwise it will not converge).

• Then compute their averages, $\{\pi^l(\cdot)_t\}_t$ and $\{\omega^l_{h,t}\}_{h,t}$.

• Use these averages to estimate the marginal returns to a_h as

$$\sum_{\tau=t}^{\infty}(\beta\rho)^\tau \frac{\partial \pi^l(\cdot)_{t+\tau}}{\partial \xi_{t+1}} \frac{\beta_{a,h}}{a_{h,t}} \approx \mathcal{E}\Big[\sum_{\tau=t}^{\infty}(\beta\rho)^\tau \frac{\partial \pi(\cdot)_{t+\tau}}{\partial \xi_{t+1}} \frac{\beta_{a,h}}{a_{h,t}}\Big) | J_t, \xi_t\Big].$$

- Our iteration l estimate of $a^l_{h,t}$ is obtained as

$$a^l_{h,t} = \mathbb{P}[a^l_{h,t} = 0] + [1 - \mathbb{P}(a^l_{h,t} = 0)]a^{*,l}_{t,h},$$

where

$$\mathbb{P}[a^l_{h,t} = 0] = \exp(-f \cdot (\theta^l_{0,h} + \theta^l_{1,h} \log(\frac{\partial \pi \widehat{(\xi', J')}}{\partial \xi'}|_{\xi^{lk}_t}) + w_t \beta^l_{w,h} + \omega^l_{h,t}))$$

and

$$a^{*,l}_{t,h} = \sum_{\tau=t}^{\infty} (\beta\rho)^\tau \frac{\partial \pi^l(\cdot)_{t+\tau}}{\partial \xi_{t+1}} \beta_{a,h}.$$

- Update the policy function. Regress the dependent variable

$$log\left[\sum_{\tau=t}^{\infty}(\beta\rho)^{\tau}\frac{\partial\pi^{l=1}(\cdot)_{t+\tau}}{\partial\xi_{t+1}}\beta_{a,h}\right]-\omega^{l}_{h,t}\ \ (\equiv \log(a^{l*}_{h,t})-\omega^{l}_{h,j,t})$$

on

$$\approx \theta^{l+1}_{0,h}+\theta^{l+1}_{1,h}log\left(\frac{\partial\pi^{l}(\xi',J')}{\partial\xi'}\right)+w_t\beta^{l+1}_{w,h}$$

- Finally compute

$$Y^{l}\equiv\frac{1}{\sum_{j,t}1}\sum_{j,t}(\frac{W^{l}_{j,t}-W^{l-1}_{j,t}}{W^{l-1}_{j,t}})^{2}.$$

- If $Y^l < 10^{-5}$ stop. If $Y^l > 10^{-5}$ proceed to iteration $l+1$.

- Two possibilities for terminal period's contribution:
  - Simulate model out a hundred periods. This does not account for perceptions of any differences between the future and the past.
  - Use the last observed advertising, say T_j, to approximate for $\sum_{\tau=T_j}^{\infty}(\beta\rho)^{\tau}\frac{\partial\pi(\cdot)_{t+\tau}}{\partial\xi_{t+1}}\beta_{a,h}$. (eliminates the need to assume something for the firm's perceptions about $\pi(\cdot)$ after the sample ends)[2].

Table of Results

- All three variables matter (though incorrect standard errors).
- Profit derivative and time to loe always positive. Advertising goes down as we approach the end to the patent life.
- Other advertising differs in sign in the two markets

[2] This does induce an expectational error, but it is mean zero. Because the error is in the argument of a log, it must be analyzed through an expansion.

Estimates for Cholesterol and Ulcer.

Table: Dynamic Policy Equations

	Anticholesterol		Antiulcer	
	detailing	DTC	detailing	DTC
θ_h (*profit deriv*)	.99	.88	1.03	1.04
	(.0003)	(.0002)	(.0003)	(.0001)
$\beta_{w,h}(\textit{others adv}) \times 10^{-4}$	-.49	- 7.0	.17	.32
	(.0014)	(.0002)	(.0001)	(.00001)
$\beta_{w,h}(\textit{time to loe}) \times 10^{-2}$	1.4	1.1	2.48	1.09
	(.0064)	(.0006)	(.0016)	(.0005)
$\theta_{0,h}$	-2.85	-3.5	-2.29	-3.66
	(.062)	(.043)	(.029)	(.010)

Standard error in parenthesis (not corrected for first stage variance).

Fit Comparisons for Cholesterol

- We have yet to do this correctly.
  - We are using ξ_0 and simulating $\{\xi_t\}_{t=1}$. This is because we want to compare to an equilibrium without DTC and use the same procedure for both. For fit we would use the data's $\{\xi_t\}_t$ and compare estimated perceptions to those implied by the data
  - Now we are assuming initial $\omega = 0$. For fit to actual data could first period of advertising to initiate the $\{\omega_h\}$ processes.

Also

- The data is a random draw and we predict averages.
- The graphs compare for the non-zero actual data values, against the simulated averages. Simulations will average over zeros, so we expect the simulations to be a bit lower (more so for DTC).

Fit Results.

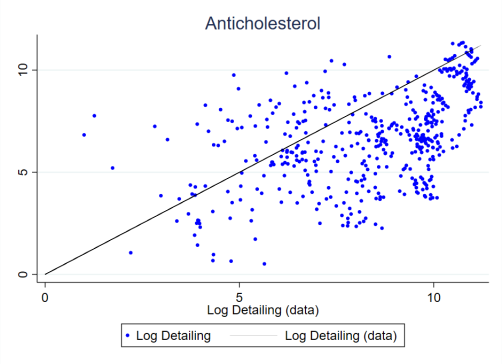
• Hard to evaluate given how we are doing this.

• Better for detailing than DTC.

• This was expected since both the variances in the u and in ν are higher for DTC than detailing (2.4 vs 1.3; and 4.2 vs 3.8).

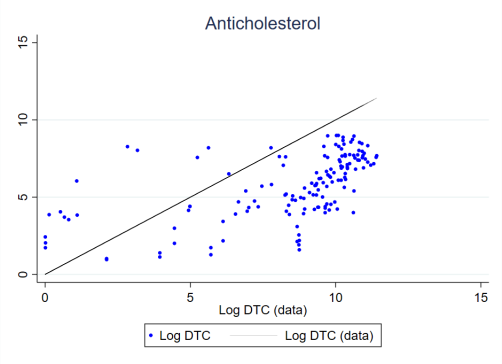
• The estimates that use the OOS simulation and those that do not only differ in the final few quarters where the one's that use the advertising approximation for OOS do a bit better.

Figure: Simulated against observed values (without zeros): Anticholesterol



Note: Simulated log Detailing against observed log Detailing on horizontal axis.

Figure: Simulated against observed values (without zeros): Anticholesterol



Note: Simulated log DTC against observed log DTC on horizontal axis.

Time Series for Three Drugs with the Largest Share.

- Detailing is exceptional good, noticeable under-predictions for DTC.
- Use of data for end of sample value generates a bit of an advantage at the end of the data period (the red).
- Notice that detailing goes down as these drugs are approaching the end of their patent life.

Figure: LIPITOR

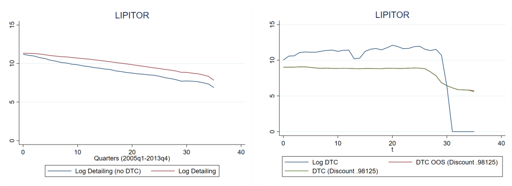
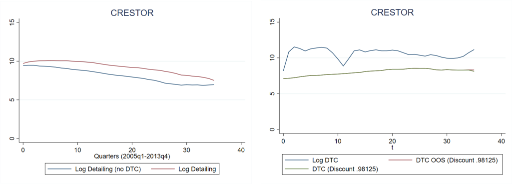
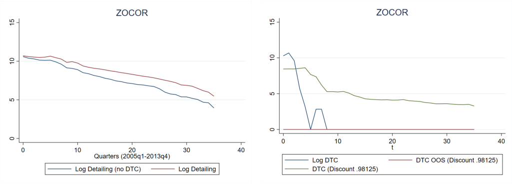


Figure: CRESTOR



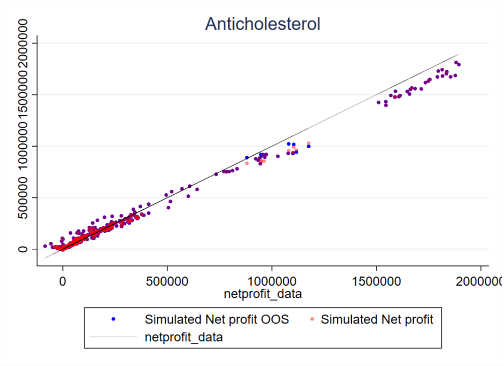
Note: Simulated values with and without OOS. Quarters on horizontal axis (starting 2005q1).

Figure: Simulated Detailing and DTC against observed values: ZOCOR



Note: Simulated values with and without OOS. Quarters on horizontal axis (starting 2005q1).

Figure: Simulated Net Profit against observed: Anticholesterol



- Profits are larger in magnitude than advertising, and they change only to the extent that the advertising changes quantity sold.
- From the table with business stealing effects, we know that large changes in advertising can lead to huge changes in revenue, but with good fits we expect small differences in profits.

Eliminating DTC: Two Comparisons.

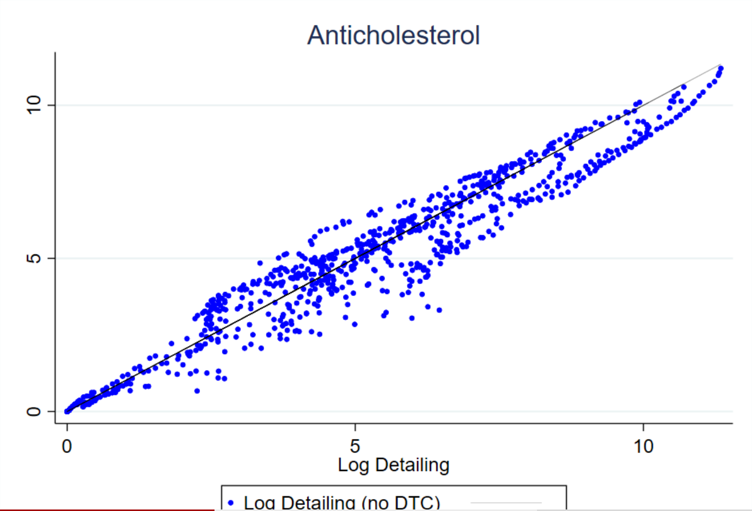
1. Compare equilibrium outcomes when DTC is allowed to equilibrium outcomes when it is not allowed.
2. Compare outcomes to the outcomes when only the given firm stops DTC and the rest of its competitors continue with DTC to examine the relative importance of business stealing.

- In both cases we compare:
  - detailing policies,
  - net profit, and
  - we will compare consumer surplus (not done yet).

- Will compare this to a revenue tax with proceeds going to advertising the ability of drugs to resolve conditions, but does not use brand names.

Detailing With and Without DTC

Figure: Simulated Detailing with (horizontal axis) and without DTC :



Quantiles of log detailing with and without DTC Anticholesterol market (in millions per quarter).

	5%	10%	25%	50%	75%	90%	95%
Log detailing	0.0	.20	2.7	5.0	7.1	8.9	9.9
Log detailing (no DTC)	0.0	.23	3.0	4.9	6.9	8.4	9.2

- Detailing Comparisons:
  - firms that do no or only a moderate amount when DTC is allowed, do more detailing when DTC is not allowed, while
  - firms that do a lot of detailing when DTC is allowed do less detailing when DTC is not allowed.

- Comparing distributions: a single crossing between quantiles just under median.

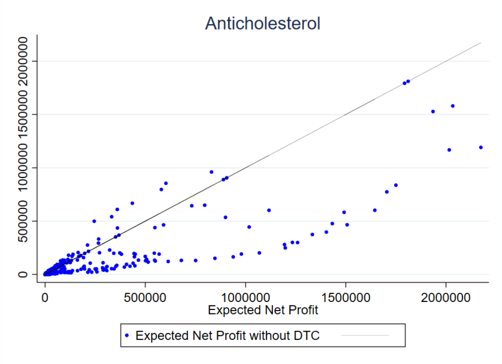
Net Profits With and Without DTC.

Table: With and without DTC for Anticholesterol market (in millions per quarter)

	5%	10%	25%	50%	75%	90%	95%
Net profit	.004	.23	.34	3.3	25	240	497
Net profit (no DTC)	.004	.23	.40	2.9	24	112	206

- Revenue changes mimic detailing changes but the magnitude of the revenue change is more than that of detailing changes, so
  - firms that did little detailing increase their detailing and their net profits, while
  - firms that do a lot of detailing, would decrease their detailing and their net profits
- The highest 10% of firms loose more than half of their profits.

Figure: Simulated Net Profit without DTC against with DTC.



Note: Simulated Net Profit with DTC on horizontal axis against without DTC.

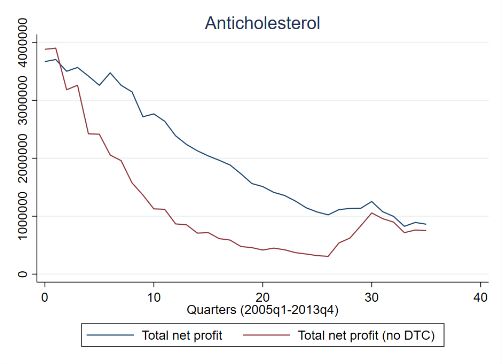
Possible Explanation.

• DTC and detailing are highly positively correlated. The effect of eliminating DTC on detailing depends on the amount of detailing a firm does when DTC is allowed.

• *Possible Explanation.* DTC influences what the patient asks the doctor for.

- Firms with a lot of DTC have an incentive to convince doctors that their drug is suitable.
- When there is no DTC the doctor is less subject to patient priors, and hence more open to all drugs. This increases the incentives for detailing of less well known drugs.

Figure: Simulated Total Net Profits: Anticholesterol



Note: Simulated Total Net Profits.

• Initially the impact grows but as patents moved toward the end of their patent lives they reduce DTC and the impact of earlier DTC dissipates.

Table: Mean and Standard Deviation of simulated log detailing and net profit with and without DTC for Anticholesterol market

	Mean	Standard Deviation
Log detailing	4.931	2.957
Log detailing (no DTC)	4.767	2.806
Net profit	85,953.352	262,246.781
Net profit (no DTC)	50,908.809	170,374.922
Subsample doing DTC in data		
Log detailing	7.993	2.160
Log detailing (no DTC)	7.353	1.984
Net profit	361,504.188	515,366.188
Net profit (no DTC)	171,704.859	335,847.281
Unilateral deviation to no DTC for drugs doing DTC		
Net profit	308,933.63	1,479,590.00
Net profit (no DTC)	54,540.87	280,365.94

Note: In 1,000 US$ per quarter .

Losses from cancelling DTC for firms who do DTC.

- They would save \$235 million per quarter in detailing expenditures.
- However there is still a net profit loss of about \$190 million per quarter.
- This implies that they would lose about 53% of their profits.

• The profit loss from unilaterally cancelling detailing would be even higher, about 82% (this is calculated from the actual advertising expenditures rather than the computed equilibrium expenditures).

- Caveats
  - A loss in profits might translate into a loss in R&D, hampering the development of new drugs to treat diseases.
  - We know the consumer surplus went down but we don't have a comparison ito R&D saving in terms of costs.

- Thats all we have now. Thanks for inviting me and for your time. ♠