Supplement to Push-Me Pull-You: Comparative Advertising in the OTC Analgesics Industry. **For Online Publication**

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Appendix A: Dataset Construction in Detail

A.1 Sales Dataset

We take the original dataset and we follow these steps:

1. We drop all the products that are analgesics but do not come in the form of pills or are unconventional analgesics (e.g., pain relief patches).

2. We drop Pamprin and Midol, which have less than 1% of the inside market - much less than other brands; in addition, they specialize only in menstrual pain.

3. We determine the active ingredient for each product: acetaminophen, ibuprofen, naproxen, or aspirin.

4. We assign a number of milligrams to each product, according to the strength of its primary active ingredient. To do so, we combine the descriptive data in the Nielsen dataset with the data of milligrams of a specific active ingredient in a specific formula. In the case of Ibuprofen- and Naproxen Sodium- based pain relievers, the assignment was straightforward, since these OTC products can come only in 200mg (for Ibuprofen) and 220mg (for Naproxen Sodium). In the case of Aspirin and Acetaminophen, the situation is more delicate, since these products can come in varying strengths and as a combination with other analgesic agents. Therefore, we consider whether the product

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is of regular strength, extra strength, body and back pain (which includes caffeine), and rapid headache; whether the product is for rapid release; whether the product is for children; whether the product has a sleepaid; whether it is for arthritis; for migraine, for menstrual purposes; or for sinus headache.

5. For a certain analgesic drug to be sold as an OTC drug, the FDA requires that the daily (24 hours) dosage does not exceed a certain threshold (the thresholds are different for different active ingredients. For example, for acetaminophen the daily dosage is 4000 mg. of this active ingredient). Thus, we create a variable that indicates the maximum amount of pills allowed in 24 hours by the FDA regulation.

6. We deflate the prices of the pills by the CPI (January 2000=100).

7. As explained in the main text, the *market size* for OTC analgesic products is the US population 18 years or older minus the number of people who buy pain medication at Wal-Mart, a store that does not provide information on the sales of products.

8. We take the number of pills in a pack and multiply by the number of packs sold. We divide this number by 3 (the average number of sick days per month) and we divide the result by the maximum number of pills allowed by the FDA to obtain the number of servings sold for each type of pill in a month. This is how we compute the market share for each product.

9. As discussed in the text, we do the same exercise for the generic products, which are differentiated only by their active ingredient. Thus, we assume the generic products are provided by a competitive fringe.

A.2 Advertising Dataset

1. When coding the ads, a few things need to be kept in mind: the same ads are named with different names, sometimes the names are the same, but ad content is slightly different, the same ad might be broadcast in different media, and it might have a different name. We watched every single ad and sorted out which ad is which. Then, we aggregated by ad id the expenditures over a month, if the same ad was listed under two different lines.

2. We deflate the ad expenditures by the CPI (January 2000=100)

3. In reporting ad spending, the lowest amount that we can report is $100. Note that we obtain rate card information from media sellers (i.e. TV stations/networks, websites, publications, etc.). Estimated advertising expenditures are assigned to every commercial based on the average 30-second rate for the program. When the commercial is longer or shorter than 30 seconds, the reported dollars are automatically converted in proportion to the number of seconds in the spot. Depending on the length, the reported dollars are adjusted accordingly. Please note that we do not make adjustments

for purchased ratings, as we monitor the occurrence level information. Ratings will not affect reported spending. Low prices could be explained by the time of the day (night) or by type of television program (e.g. with low viewership).

4. If a brand is attacking more than one brand with an ad, then we divide the expenditure on that ad by the number of brands attacked to construct how much the brand attacked each one of its competitors.

5. If a brand is attacking prescription drugs, such as Vioxx or non brand specific prescription drugs, then we code it as self-promotion advertising.

6. If a brand is attacking other competitors by mentioning non-brand specific NSAID drug, generic ibuprofen, or other regular OTC pain relief medication, then we code the ad as self-promotion ad.

7. If there was never an attack from one brand to another brand, then we exclude this combination of attacks as a possible attack pair. However, if there ever was at least one attack, then we filled each month of the pair with zero expenditures.

A.3 News Dataset

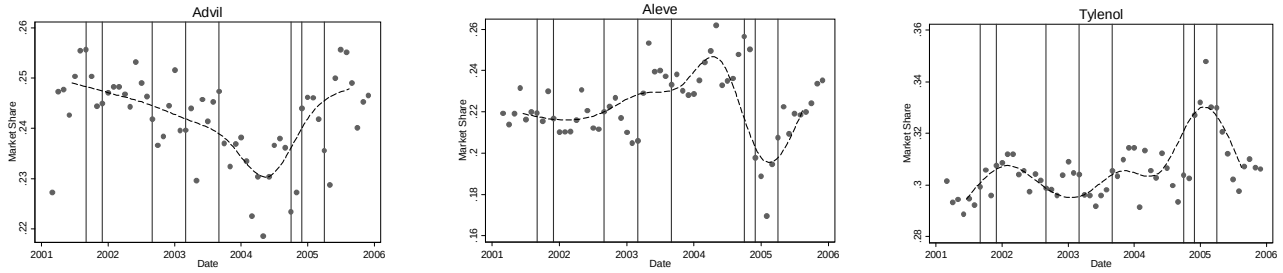
1. The keywords that we used in our news search consisted of brand names, such as "Aleve," "Tylenol," "Advil," "Vioxx," and the names of their active ingredients, such as "Naproxen" or "Acetaminophen." Then we made searches using generic terms such as "pain killers" or "analgesics."

2. We experimented with allowing shocks to depreciate over time at varying rates, but found that the version without depreciation had a better explanatory power. Also, allowing shocks to affect brands only in the short term (varying number of periods after the shock happened) did not prove to be an effective strategy either.

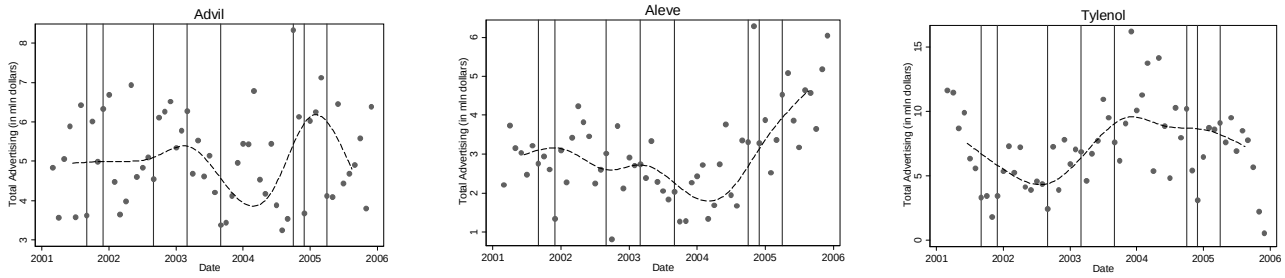
3. **Figure A1** presents the occurrence of the *eight* major shocks, highlighting the reaction of sales and advertising to those medical news.

FIGURE A1. Timelines of Market Shares, Advertising Expenditures and Medical New Shocks

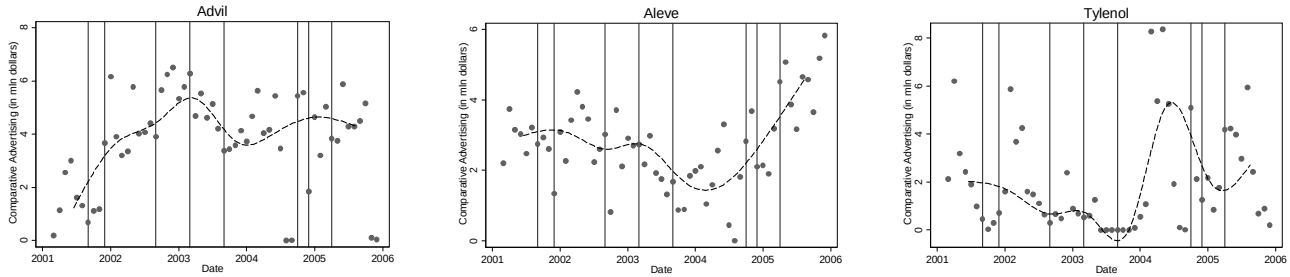
Market Share:



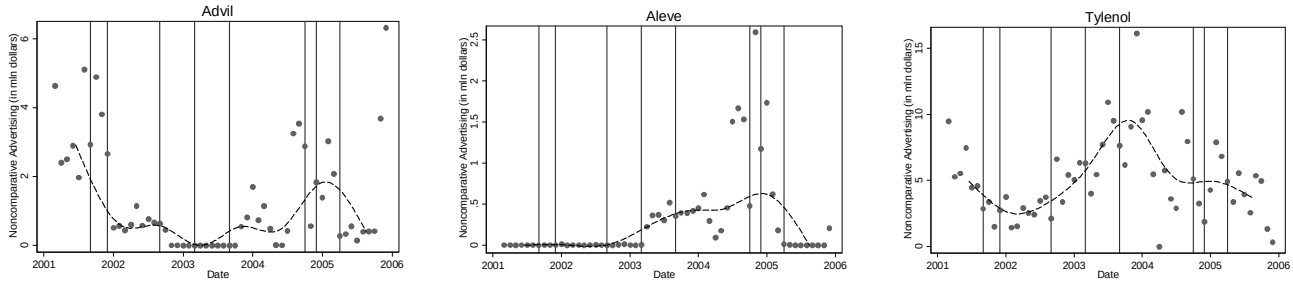
Total Advertising:



Comparative Advertising:



Noncomparative Advertising:



Exogenous Medical Shocks:

Month	Description	Month	Description
09/2001	Early Vioxx/Celebrex safety concerns	09/2003	NSAIDs inhibit cardioprotective benefits of Aspirin
12/2001	Ibuprofen counteracts Aspirin	10/2004	Vioxx withdrawal
09/2002	FDA calls for stronger warnings on NSAIDs	12/2004	Aleve is associated with increased cardio risk
03/2003	Aspririn prevents colorectal adenomas	04/2005	Bextra withdrawal

Appendix B: Econometric Model in Detail

B.1 Control Function and Generalized Residuals

The quality function is written as:

$$Q_j = \alpha \ln\left(A_{jj} + \lambda \sum\nolimits_{k \neq j} A_{jk} - \beta \sum\nolimits_{k \neq j} A_{kj} + \bar{A}_{jj}\right) - \varphi \sum\nolimits_{k \neq j} \ln\left(\bar{A}_{kj} + A_{kj}\right)$$

We now want to show how we can apply the Rivers and Vuong (1988) and the Blundell and Smith (1986) approach when some of the endogenous explanatory variables are left-censored.

We postulate that there exists a vector of instrumental variables Z, and we write:

$$\begin{aligned} s_j &= Z\lambda_1 + u_{1j} \\ \tilde{A}_{jk} &= Z\lambda_2 + u_{2j} \\ \tilde{A}_{kj} &= Z\lambda_3 + u_{3j} \end{aligned}$$

where $\tilde{A}^*_{jk} = \sum_{k \neq j} A^*_{jk}$, $\tilde{A}^*_{kj} = \sum_{k \neq j} A^*_{kj}$ and A^*_{jk} and A^*_{kj} are the advertising expenditures incurred by the brands. Notice that A^*_{jk} and A^*_{kj} are both left-censored, so that we only observe $A_{jk} = \max\left(A^*_{jk}, 0\right)$ and $A_{kj} = \max\left(A^*_{kj}, 0\right)$. As a result, $\tilde{A}^*_{jk}$ and $\tilde{A}^*_{kj}$ can be (and are in our data) left-censored.

B.1.1 Self-Promotion Equation

Now, write:

$$\xi_j = \rho_1 u_{1j} + \rho_2 u_{2j} + \rho_3 u_{3j} + \upsilon_j$$

So, then:

$$\begin{cases} A^*_{jjt} = -\alpha M s_j - \lambda \sum\nolimits_{k \neq j} A_{jk} + \beta \sum\nolimits_{k \neq j} A_{kj} - const \\ -\rho_1 u_{1j} - \rho_2 u_{2j} - \rho_3 u_{3j} - \upsilon_j, \upsilon_j \sim N\left(0, \sigma^2\right) \\ A_{jj} = \max\left(A^*_{jj}, 0\right). \end{cases}$$

And so the issue is how to get u_{1j}, u_{2j}, and u_{3j}. For u_{1j} we just run a simple OLS regression of shares on the IVs, then take the predicted residuals $\hat{u}_{1j}$ and plug them in the regression above.

For u_{2j} and u_{3j} the analysis is more complex, because $\tilde{A}_{jk}$ and $\tilde{A}_{kj}$ are left-censored. We use the notion of generalized residuals as introduced by Gourieroux et al. (1987). Here, the generalized residual $\tilde{u}_{2j}$ is defined as:

$$\tilde{u}_{2j} = E\left[u_{2j} | \tilde{A}_{jk}\right] = \left(\tilde{A}_{jk} - Z_2\lambda_2\right) 1\left[\tilde{A}_{jk} > 0\right] - \sigma_2 \frac{\phi\left(Z_2\lambda_2/\sigma_2\right)}{\Phi\left(-Z_2\lambda_2/\sigma_2\right)} 1\left[\tilde{A}_{jk} = 0\right],$$

where ϕ denotes the normal pdf, Φ denotes the normal cdf, and σ_2 is the standard deviation of u_{2j} that is estimated. The generalized residual $\tilde{u}_{3j}$ is defined in a similar fashion.

In practice, we start by running the Tobit regression

$$\begin{cases} \tilde{A}^*_{jk} = Z_2\lambda_2 + u_{2j}, u_{2j} \sim N\left(0, \sigma_2^2\right) \\ \tilde{A}_{jk} = \max\left(\tilde{A}^*_{jk}, 0\right). \end{cases}$$

We then use the parameter estimates $\hat{\lambda}_2$ and $\hat{\sigma}_2$ to compute the estimated generalized residuals $\widehat{\tilde{u}}_{2j}$. We proceed similarly to determine $\widehat{\tilde{u}}_{3j}$. To estimate α, λ, β, σ, and the constant we run the following Tobit regression:

$$\begin{cases} A^*_{jjt} = -\alpha Ms_j - \lambda \sum_{k \neq j} A_{jk} + \beta \sum_{k \neq j} A_{kj} - const \\ \quad -\rho_1 \hat{u}_{1j} - \rho_2 \widehat{\tilde{u}}_{2j} - \rho_3 \widehat{\tilde{u}}_{3j} - \upsilon_j, \upsilon_j \sim N\left(0, \sigma^2\right) \\ A_{jj} = \max\left(A^*_{jj}, 0\right). \end{cases}$$

Because we are running a regression with generated regressors, we compute the adjusted standard errors with a bootstrap procedure.

B.1.2 Comparative Advertising Equation

As regards endogeneity concerns, the analysis is simpler when we look at the comparative ads first order condition since the only endogenous variables in that equation are the shares of the attacker and of the attacked. So, we can simply use $\hat{u}_{1j}$ and $\hat{u}_{1k}$ and apply the Rivers and Vuong (1988) and the Blundell and Smith (1986) approach again.

In practice, the estimation is made in two steps. First, we run the LHS endogenous variables (here market shares) on all exogenous variables, including those excluded from the second stage relationship. Then, we run the second stage regression (advertising levels here) including the residuals from the first regression as an additional explanatory variable (the "Control Function") to all the second stage explanatory variables. For example, if we want to estimate the parameters of the self-promotion advertising first order condition (ads on sales), we first run shares on generic prices and news shocks, and compute the residuals. Then we run a Tobit where ads are explained by market share, news shocks (if not excluded) and the residuals.

B.2 Standard Errors

For the estimates in **Table 4** and **5** we bootstrap the standard errors as follows. We draw 100 independent samples out of the original dataset. On each one of these 100 datasets we rerun the self-promotion and comparative advertising regressions. We store the results and then we take the standard deviation of each coefficient.

For the estimates in **Table 6** and **7** we take the 100 samples and use them to compute the damages. Then, for each parameter, we sort them from the largest to the smallest, and we construct the confidence interval using the one at the 5th position and the one at the 95th position.

Appendix C: Top Brand Dummy

We have investigated various specifications for the fixed effects, and concluded that a specification where there are two fixed effects, one for the top brands (Advil, Aleve, Tylenol), and one for the other brands (Excedrin, Motrin, Bayer) fits our data best. We provide in **Figure C1** a graphical description of the relationship between non-comparative advertising and market shares for all brands and months.

FIGURE C1. Relationship between Noncomparative Ads and Market Shares

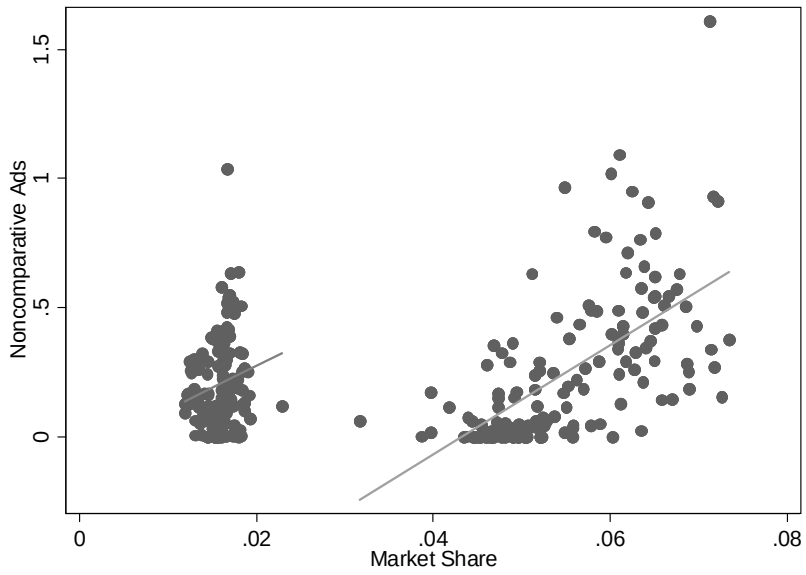


Figure C1 shows that there are two types of brands in the market. Aleve, Advil, and Tylenol (the 'Top Brands') control large market shares compared to Excedrin, Bayer, and Motrin. This is consistent with the reported weighted market share descriptive statistics in **Table 1** in the main body of the paper. This observation parallels the economic intuition that 'Top Brands' have a larger advertising base allure which translates into larger inherent quality, $\bar{A}_{jj}$. Additionally, the linear fit between shares and non-comparative advertising has the same slope for the 'Top Brands' and the rest of the brands. We use the evidence from this figure to justify the construction and use of a dummy variable 'Top Brand'.

Appendix D: Pulsing and Goodwill

In our view, the main issue that we have to deal with is whether by omitting dynamic effects, we introduce a bias in the estimation of the relationships between the main variables of the model. There are two related dynamic features that our static model might be missing. First, $\bar{A}_{jj}$ and $\bar{A}_{jk}$ might be related to the goodwill of a brand, and that goodwill might depend on past advertising decision of the brand. We can check the importance of this aspect by adding lags in our regressions. Second, as Dube, Hitsch, Manchanda (2005) show in their descriptive analysis, pulsing might play an important role in advertising decisions depending on the industry that we look at. In this section, we look at these two features and indirectly check whether omitting them from the analysis might bias our results. Because we are just checking for the robustness of the results, we only look at the non-comparative advertising first order condition.

D.1 Goodwill

Advertising goodwill represents the idea that past advertising is like an investment over time and that at any given time there exists a stock of goodwill dependent on past advertising. This stock, in turn, without further investment is subject to depreciation as the consumer "forgets" past ads. If there are strong stock effects (depreciation is not quick), then brands are engaged in a dynamic game. Solving such a game and writing the appropriate structural model would be substantially more involved than the simple static model.

Here we essentially estimate the self-promotion equation after including the one month lagged value of A_{jjt}.

That is, we estimate the following:

$$\begin{cases} A^*_{jjt} = \varphi A_{ij,t-1} + \alpha M s_{jt} - \lambda \sum_{k \neq j} A_{jkt} + \beta \sum_{k \neq j} A_{kjt} - \bar{A}_{jjt}, \\ \bar{A}_{jjt} \sim N\left(0, \sigma^2_{SP}\right), \ A_{jjt} = \max\left(A^*_{jjt}, 0\right), \qquad j = 1, ..., n. \end{cases}$$

One way to read this equation is to notice that past expenditures in non-comparative advertising enter into the term $\bar{A}_{jjt}$, brand j's time t advertising base allure.

Table D1 presents the results, which should be compared to those in the first two columns in **Table 4**. **Column 1** of **Table D1** shows the results when we do not include the Top Brand dummy. Column 2 shows the results with the dummy.

The key observations are the following:

- The signs of the coefficients are the same as in Table 4.
- Adding $A_{ij,t-1}$ does not change the precision of the estimates of α, λ, and β: these parameters are all precisely estimated.
- However, adding $A_{ij,t-1}$ makes the estimate of the Top Brand dummy not precise, suggesting that the Top Brand dummy picks up the goodwill, or brand image.

TABLE D1: Goodwill

	Coef. (s.e.)	Coef. (s.e.)
φ	0.614 (0.042)	0.602 (0.043)
α	0.062 (0.021)	0.131 (0.064)
λ	0.407 (0.061)	0.390 (0.063)
β	0.148 (0.053)	0.126 (0.056)
Top Brand dummy		-0.078 (0.068)
Constant	-0.049 (0.018)	0.021 (0.030)
/sigma	0.150 (0.006)	0.150 (0.006)
Log-likelihood	132.712	133.375

25 left-censored observations at PositAdver<=0

317 uncensored observations

D.2 Pulsing

Pulsing is the phenomenon of uneven advertising levels over time. A campaign will have a specific start date, and a series of ads will be run at quite a high intensity. In many industries, there is a considerable lag (or at least a lull) until the next campaign starts up (a new "media blitz"). This pattern is thought to be more effective than running ads at a steady level, in part because of attention thresholds for individuals' perceptions, ad depreciation levels, etc.

Usually pulsing might be a concern when using high frequency data (e.g. weekly). However, monthly data, might still exhibit some pulsing patterns and we need to check whether that is the case with our data. One very simple way to test whether pulsing occurs in this industry with monthly data is the following: We compare how the results change if we use quarterly instead of monthly data. Dube, Hitsch, Manchanda [2005] show very irregular episodes of advertising to test their theory of pulsing. Clearly, the more one aggregates the data over time, the smoother the intensity of advertising becomes. So our idea is that if there is pulsing in our monthly data, and if accounting for pulsing would affect our results radically, then we should see sizeable differences in the estimates that we get by using quarterly instead of monthly data.

Hence we estimate the following regression using quarterly data:

$$\begin{cases} A^*_{jjt} = \alpha M s_{jt} - \lambda \sum_{k \neq j} A_{jkt} + \beta \sum_{k \neq j} A_{kjt} - \bar{A}_{jjt}, \\ \bar{A}_{jjt} \sim N\left(0, \sigma^2_{SP}\right), \ A_{jjt} = \max\left(A^*_{jjt}, 0\right), \qquad j = 1, ..., n. \end{cases}$$

Table D2 presents the results, which should be compared to those in the first two columns in **Table 4**. **Column 1** of **Table D2** shows the results when we do not include the Top Brand dummy. **Column 2** shows the results when we include that dummy.

The key observation is that the estimates are basically the same as in the first two columns in **Table 4**. Thus, pulsing is not an empirical concern at all in our empirical study.

TABLE D2. Pulsing

	Coef. (s.e.)	Coef. (s.e.)
α	0.130 (0.041)	0.395 (0.117)
λ	0.838 (0.117)	0.726 (0.123)
β	0.426 (0.095)	0.302 (0.106)
Top Brand dummy		-0.898 (0.373)
Constant	0.436 (0.095)	0.081 (0.173)
/sigma	0.454 (0.030)	0.443 (0.030)
Log-likelihood	-72.547	-69.721

2 left-censored observations at PositAdver<=0

112 uncensored observations

Appendix E: Indirect Attacks

One delicate issue is how to deal with indirect attacks. An indirect attack occurs when one brand, say Tylenol, makes a claim against "all other regular" brands.[1] Because it is not clear how to deal with this type of ad, we consider two solutions. In the main paper we consider the case where indirect attacks should simply be interpreted as self-promotion ads.

Here, we consider the case where indirect attacks are equivalent to direct attacks (e.g. Tylenol on Advil), but are divided among all the brands falling within the attacked category. So, for example, when Tylenol makes a claim against "all other regular" brands, each one of the other five brands is being attacked the amount of dollars spent on that advertisement divided by five.

Table E1 presents the results, which should be compared to those in the first two columns in **Table 4**. **Column 1** of **Table E1** shows the results when we do not include the Top Brand dummy. **Column 2** shows the results when we include that dummy.

The key observation is that the estimates are basically the same as in the first two columns of **Table 4**. Thus, the coding of indirect attacks is not an empirical concern at all in our empirical study.

TABLE E1. Indirect Attacks

	Coef. (s.e.)	Coef. (s.e.)
α	0.122 (0.027)	0.478 (0.074)
λ	0.804 (0.071)	0.673 (0.073)
β	0.381 (0.065)	0.229 (0.069)
Top Brand dummy		-0.410 (0.080)
Constant	0.132 (0.022)	-0.021 (0.037)
/sigma	0.193 (0.008)	0.186 (0.037)
Log-likelihood	45.302	58.018
31 left-censored observations at PositAdver<=0		
317 uncensored observations		

[1] Or it could be an attack against NSAIDs (Non Steroidal Anti-Inflammatory drugs), which are all drugs in our sample except those with acetaminophen as an active ingredient.

Appendix F: Robustness Analysis of the Measures of Damage

- In this Section we check on the robustness of the results of **Table 6** in the paper. We derive measures of the damage that comparative advertising delivers to the attacked brand and the spillovers to other brands using different combinations of the estimates of α, β and λ from **Table 4** and of the diversion ratios and of φ from **Table 5**.

- We start by using the estimates of α, β and λ from **Column 2** of **Table 4** and of the diversion ratios and of φ from **Column 1** of **Table 5**. Thus, we use the same estimates of the diversion ratios that we used to construct the measures in **Table 6** but we use different estimates of α, β and λ. **Table F1** presents the estimation results of the damages. We notice the following: the damages are smaller than those in **Table 6** of the paper, but the main result that all the damages are larger than 1 is confirmed; the pull effect is still very much larger than the push effect for all the pairs; there is still asymmetry in the damages. Thus, overall, the key results concerning the damages inflicted by comparative advertising are the same as in **Table 6** of the paper.

- Next, we derive the damages measures using the estimates of α, β and λ from **Column 6** of **Table 4** and of the diversion ratios and of φ from **Column 2** of **Table 5**. Now we are using the estimates of α, β and λ that we used to construct the measures of damage in **Table 6**, but we use different diversion ratios. **Table F2** presents the estimated damages. We immediately notice the following: whenever the estimates of the diversion are precise the estimated damages are not very different in **Table 6** and **Table F2**. For example, we estimate the damage inflicted by Advil on Tylenol equal to 3.197 in Table 6 and equal to 3.401 in **Table F2**. On the other hand, when the estimates of the diversion ratios are not precise, the corresponding estimated damages are very different in **Table 6** and **Table F2**. We conclude that the precise estimation of the diversion ratios is critical to derive reliable measures of damages.

- Finally, in **Table F3** we derive the measures of damages using the estimates of α, β and λ from **Column 7** of **Table 4** and of the diversion ratios and of φ from **Column 3** of **Table 5.** The conclusions are exactly as the ones we just derived in the preceding bullet point: when the estimates of the diversion ratios are precise, the damage estimates are again between 2 and 4 dollars; but when the estimates of the diversion ratios are imprecise, the damage estimates can be way off.

TABLE F1. Robustness of Damage Estimates, Version I

	Advil	Aleve	Bayer	Excedrin	Motrin	Tylenol
Advil		5.241 [2.294,7.339] N/A N/A	0.064 [0.017,0.070] N/A N/A	7.349 [2.153,50.077] N/A N/A	0.073 [0.024,0.080] N/A N/A	1.879 [1.098,2.329] 0.046 [0.016.067] 1.909 [1.330,2.349]
Aleve	0.066 [0.023,0.074] N/A N/A				0.081 [0.023,0.073] N/A N/A	2.044 [1.221,2.387] 0.098 [0.016,0.113] 2.109 [1.330,2.447]
Bayer	5.338 [2.835,7.208] N/A N/A					4.814 [2.916,6.414] 0.272 [0.159,0.303] 4.994 [3.173,6.577]
Excedrin	0.046 [0.000,0.131] N/A N/A					10.493 [3.665,51.906] N/A N/A
Motrin	4.653 [2.382,6.066] N/A N/A	4.267 [2.382,5.403] N/A N/A				
Tylenol	7.349 [3.532,14.493] 0.181 [0.098,0.201] 7.468 [3.694,14.634]	3.489 [1.979,4.386] 0.168 [0.094,0.188] 3.599 [2.156,4.484]	1.259 [0.726,1.492] 0.071 [0.036,0.079] 1.307 [0.805,1.540]	0.032 [0.002,0.061] N/A N/A		

Note: and MRS_{jk} (2) dropped out; Possible Mirrors:
d_{jk} (1) and dQ_k/dA_{jk} (3), and dQ_j/dA_{jk} (4), and dP_i (5)

TABLE F2. Robustness of Damage Estimates, Version II

	Advil	Aleve	Bayer	Excedrin	Motrin	Tylenol
Advil		13.568 [4.160,20.546] N/A N/A	0.023 [0.017,0.062] N/A N/A	166.038 [2.935,5.578e3] N/A N/A	0.032 [0.019,0.067] N/A N/A	4.073 [2.326,5.0684] 0.015 [0.001,0.042] 4.082 [2.340,5.076]
Aleve	0.029 [0192,0.073] N/A N/A				0.031 [0.015,0.078] N/A N/A	4.412 [2.472,5.612] 0.041 [0.017,0.061] 4.437 [2.504,5.631]
Bayer	16.476 [5.019,25.139] N/A N/A					12.486 [5.498,16.917] 0.127 [0.041,0.182] 12.565 [5.267,16.964]
Excedrin	0.002 [0.001,0.095] N/A N/A					24.669 [6.384,401.657] N/A N/A
Motrin	12.077 [4.716,19.063] N/A N/A	12.635 [3.916,25.380] N/A N/A				
Tylenol	25.462 [6.097,171.067] 0.095 [0.049,0.087] 25.520 [6.176,171.126]	9.416 [3.755,13.976] 0.088 [0.045,0.084] 9.470 [3.833,14.025]	3.033 [1.254,6.661] 0.031 [0.014,0.042] 3.052 1.296,6.675]	0.016 [0.001,0.484] N/A N/A		

Note: and MRS_{jk} (2) dropped out; Possible Mirrors:
d_{jk} (1) and dQ_k/dA_{jk} (3), and dQ_j/dA_{jk} (4), and dP_i (5)

TABLE F3. Robustness of Damage Estimates, Version III

	Advil	Aleve	Bayer	Excedrin	Motrin	Tylenol
Advil		9.240 [4.559,18.904] N/A N/A	0.035 [0.018,0.074] N/A N/A	12.078 [2.908,4.52e3] N/A N/A	0.044 [0.022,0.074] N/A N/A	3.401 [2.027,4.979] 0.027 [0.002,0.034] 3.418 [2.140,4.979]
Aleve	0.041 [0.020,0.067] N/A N/A				0.044 [0.018,0.083] N/A N/A	3.688 [2.140,5.540] 0.056 [0.019,0.064] 3.724 [2.187,5.573]
Bayer	10.722 [5.947,23.284] N/A N/A					8.916 [5.012,13.387] 0.166 [0.053,0.168] 9.020 [5.145,13.450]
Excedrin	0.031 [0.000,0.116] N/A N/A					15.024 [5.947,1.55e3] N/A N/A
Motrin	8.396 [4.203,18.249] N/A N/A	8.547 [3.771,16.763] N/A N/A				
Tylenol	13.585 [6.280,99.419] 0.109 [0.049,0.105] 13.654 [6.372,99.481]	6.623 [3.319,13.140] 0.102 [0.045,0.099] 6.687 [0.019,0.047]	2.253 [1.221,4.826] 0.042 [0.019,0.047] 2.279 [1.266,4.839]	0.025 [0.000,0.067] N/A N/A		

Note: and MRS_{jk} (2) dropped out; Possible Mirrors:
d_{jk} (1) and dQ_k/dA_{jk} (3), and dQ_j/dA_{jk} (4), and dP_i (5)