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Abstract

We derive equilibrium incentives to use comparative advertising that pushes up own brand perception and pulls down the brand image of targeted rivals. Data on content and spending for all TV advertisements in OTC analgesics enable us to construct matrices of dollar rival targeting and estimate the structural model. Using brands. optimal choices, these attack matrices identify diversion ratios, from which we derive comparative advertising damage measures. We find that comparative advertising causes more damage to the targeted rival than benefit to the advertiser. We simulate banning comparative advertising to find industry profits rise.

JEL-Code: L130, M370, L650.

Keywords: comparative advertising, advertising targets, diversion ratios, attack matrix, push and pull effects, analgesics.

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1 Introduction

We investigate how brands strategically use comparative advertising. Comparative advertising both promotes positive perception of the advertiser's brand (the "push" effect) and detracts from the brand image of a targeted rival (the "pull" effect).[1] The distinctive characteristic of comparative advertising that sets it apart from purely self-promotional advertising is that specific rivals are targeted: advertising content matters. Our fundamental objectives are i) to develop a novel theoretical model that explains who uses comparative advertising against whom and to what extent, ii) to apply this model to the US OTC analgesics industry where comparative advertisements are extensively used, iii) to measure the damages inflicted, and iv) to find the consequences of a ban on comparative advertising in a simulated counterfactual.

We describe an equilibrium model, where brands simultaneously choose prices, self-promotion and comparative advertising expenditures, and derive the advertising first order conditions that predict oligopoly equilibrium relationships between advertising levels (for different types of advertising) and market shares. We use these first order conditions to rationalize the *attack matrix* of comparative advertising spending patterns against other brands. We show that the attack matrix identifies *diversion ratios* between brand pairs, where the diversion ratios measure the fraction of a target's lost consumers who are diverted to a rival brand following an attack. We employ the diversion ratios to estimate the damages inflicted by comparative attacks.

To estimate our model we use data constructed by Liaukonyte (2015), who watched over four thousand individual video files of all TV advertisements in the US OTC analgesics industry for 2001-2005 and recorded which brand(s) compared themselves to which other brand(s) or products. The US OTC analgesics industry is particularly suitable for our analysis. First, comparative advertising is prevalent and represents a large fraction of industry sales. Second, data on advertising expenditures per ad is available for all brands for a reasonable time period. Video files are available and their content is readily coded to determine targets.

In the empirical analysis we deal with left-censoring of advertising (in some periods

[1] The Pushmi-Pullyu is a fictitious two-headed llama befriended by Dr Doolittle. The heads are pointed in different directions. When one pushes forward, it pulls the other end back from its preferred direction.

some brands do not engage in some types of advertising - there are corner solutions) and endogeneity of market shares and advertising expenditures. We control for left-censoring by running Tobit regressions. We control for endogeneity by including brand fixed effects and the prices of generic products, which we use as instrumental variables.

Our empirical findings highlight how comparative advertising is inherently different from self-promotion. We find that outgoing attacks are about half as powerful as direct self-promotion ads in raising the brand's own perceived quality. But these attacks have a strong impact in terms of the damage that they cause to the target. This damage is heterogeneous across attacker-target pairs. For example, a marginal dollar of comparative advertising spent by Tylenol against Bayer reduces Bayer's profit by $1.3, but a marginal dollar spent by Advil against Tylenol reduces Tylenol's profit by $2. These losses are much larger than for pure self-promotion advertising. For instance, if Tylenol increased its self-promotion expenditure by $1, the decrease in its competitor's profit would range between 3 cents for Excedrin and 18 cents for Advil. Hence, much of the harm from comparative advertising comes from its negative impact on the target's perceived quality. We find that higher shares, ceteris paribus, are associated with higher self-promotion and comparative advertising. Each extra consumer raises self-promotion advertising by 55 cents.

Comparative advertising also has substantial positive spillovers to rivals that are not being attacked. For example, a marginal dollar's comparative attack by Tylenol on Aleve increases Advil's profit by 10 cents. This means that the benefit the third party gets from denigration of the target's quality is larger than the loss from an improved perception of the attacker. These results indicate substantial "free-riding" in attacking any given target.

Despite the positive spillovers, the total damage to the industry (i.e., harm to target minus the benefits to other industry members) remains substantial. Our measures of the damage to the target underscore the harm inflicted by comparative advertising: outgoing attacks cause much more damage to the target than benefit to the attacker. Spillovers are too small to make up for the difference. For example, the positive spillover to Advil of Aleve's marginal dollar attack on Tylenol is 33 cents, while the damage to Tylenol is $2. These large numbers concur with the widespread belief among industry executives that comparative advertising potentially damages all competitors in an industry and often results in excessive levels of advertising due to persistent attacks and counter-attacks (Beard, 2013). Analogous concerns have been voiced about negative political advertising in political campaigns (Johnson-Cartee and Copeland, 2013).

We conclude our analysis with a counterfactual exercise where firms are banned from running comparative ads. We use a linear demand system to solve for the new equilibrium values. We show that total advertising levels would show strong declines, while prices and shares would remain largely unchanged. We also find that the total profits would increase for all brands, indicating that comparative advertising hurts the industry as a whole.

There is a growing empirical literature on the role of advertising content on market outcomes. In a complementary paper, Liaukonyte (2015) shows that the elasticity of demand is larger with respect to comparative advertising than self-promotion advertising. Ching et al. (2015) study the impact of content of media coverage on anti-cholesterol drugs on consumer demand and show that the impact varies by media type. Bertrand et al. (2010) develop a field experiment to show that advertising content significantly affects demand for loans, and conclude that advertising content persuades by appealing "peripherally" to intuition rather than reason. All these papers focus on the demand side. By contrast, we develop a model of firm strategic behavior (the "supply side") and use it to rationalize the comparative advertising attack patterns and to measure the magnitude of the damages inflicted with these attacks.

We contribute to the literature on empirical equilibrium models of advertising in two ways. First, our advertising content data enables us to break down ad spending into comparative and self-promotion, and the comparative expenditures are further broken down into attacker-target pairs. Second, we use generic prices as sources of exogenous variation in the data. By contrast, Gasmi, Laffont, and Vuong (1992) use aggregate variables (e.g. the price of sugar) and Sovinsky Goeree (2008) uses entry and exit of products (Bresnahan, 1987), which is not feasible here because there is no entry of new brands.

Another branch of literature analyzes advertising bans (see Motta, 2013 for a good summary). Dubois et al. (2014) develop a structural model to analyze the effects of banning (persuasive) advertising in junk food markets. They find that such a ban leads to a direct reduction in demand but also toughens price competition. Doraszelski and Markovich

(2007) show that an advertising ban favors long-established brands (whose advertising stock is higher) to the detriment of recent entrants. Eckard (1991) and Sass and Saurman (1995) show that regulating or banning advertising has led to more concentration in beer and cigarettes markets, respectively. Our paper, on the other hand, is the first to consider a ban on only a single type of advertising – comparative advertising that explicitly mentions competitor brands.

Finally, our paper is related to the theoretical economics literature on comparative advertising. Anderson and Renault (2009) model it as directly informative revelation of horizontal match characteristics of products. Barigozzi, Garella, and Peitz (2009) and Emons and Fluet (2011) apply the signaling model of advertising (which goes back to insights in Nelson, 1974, and was formalized in Kihlstrom and Riordan, 1984, and Milgrom and Roberts, 1986). Our theory engages the complementary view of advertising (Stigler and Becker, 1977, and Becker and Murphy, 1993) with the added element of pulling down the rival. Thus, our approach is broadly consistent with advertising as a demand shifter (as in Dixit and Norman, 1978, and Johnson and Myatt, 2006).

2 The Model

2.1 Core Concepts

Using our coded advertising data we construct *attack matrices* of how much is spent by each advertiser against each rival target every month. These attack matrices allow us to identify *diversion ratios* that measure the substitutability between products. These diversion ratios are then used to find *damage measures* to a brand's profit from comparative advertising directed at that brand by different rivals. We now provide the intuition behind the use of diversion ratios, and link them to damage measures.

Let $\delta_j = Q_j - p_j$ be Brand j's attractiveness when it has quality Q_j and sets price p_j, and assume that market shares s_j for each firm j, depend on j's attractiveness relative to its competitors.[2] The *diversion ratio* from good j to k is the fraction of the market share

[2]This specification is consistent with a discrete choice model that allows for heterogeneous groups of consumers in terms of their choice probability functions, although it does assume that the δ_j is the same for all consumer groups. That is, they have the same quality function and marginal utility of income. The latter stipulation may not be too extreme for OTC pain-killers insofar as one might expect small income

lost by Brand j (due to a decrease in j's attractiveness) that is captured by Brand k.[3] It is defined as

$$d_{jk} = -\frac{ds_k/d\delta_j}{ds_j/d\delta_j} \in (0,1)\,, \tag{1}$$

where s_j is the market share of Brand j. One way to think of d_{jk} is in terms of consumers' second preferences: some consumers switch to their next preferred option when the first choice gets less attractive. For substitute differentiated products, d_{jk} is positive, and $\sum_k d_{jk} < 1$ because some customers no longer purchase at all when j gets less attractive.

It is useful to interpret the diversion ratio as the *neutralizing price change* that keeps j's market share the same after a drop of \$1 in k's attractiveness (e.g., following a rise in k's price by \$1). Such a lower rival attractiveness causes a $(-ds_j/d\delta_k)$ increase in j's market share. Now, this is exactly the market share picked up by k if j's attractiveness went down \$1, because the switching consumers are those broadly indifferent between j and k as first choice. This symmetry property implies that the increase in j's market share is equivalently $(-ds_k/d\delta_j)$.[4] On the other hand, a rise in j's price of Δp_j will cause j's market share to drop by $\Delta p_j\,(ds_j/d\delta_j)$. Equating these expressions gives the neutralizing price change as[5]

$$\Delta p_j = \frac{-ds_k/d\delta_j}{ds_j/d\delta_j} = d_{jk}. \tag{2}$$

The importance of the neutralizing price change is that we can measure the change in j's profit from a decrease in k's attractiveness as simply the price change applied to j's market, or $\Delta\pi_j = \Delta p_j M s_j = M s_j d_{jk}$, where M is the market base of potential consumers. This underscores why it is the outbound diversion ratio, d_{jk}, that matters in determining the worth of inbound customers. It also suggests that the diversion ratio should enter the marginal benefit for Brand j of targeting Brand k through comparative advertising, which adversely impacts Q_k. Indeed, let \$1 spent by j on comparative advertising against target k reduce Q_k by ΔQ_k (which is a positive number because it is defined as a reduction): this negative

effects due to small spending shares.

[3] The diversion ratio has been proposed as a useful statistic for analyzing the price effects of mergers (see for example Shapiro, 1996, and recent development by Jaffe and Weyl, 2013).

[4] See Anderson, de Palma, and Thisse (1992), Ch.3, p. 67.

[5] If a \$1 price rise by k allows j to pick up 10 of the customers shed by k, and a \$1 price rise by j loses it 50 consumers (10 of which would go to j, incidentally, by the symmetry property), then the neutralizing price hike for j is 20 cents. The diversion ratio from j to k is 1/5.

impact on k's attractiveness we call the "pull effect". The neutralizing price change argument above gives the marginal benefit for Brand j from the pull effect as $Ms_jd_{jk}\Delta Q_k$.

Because comparative advertising is also advertising for Brand j, there is also a "push" effect from an increase in Brand j's attractiveness. This is the amount of pure self-promotion spending that would result in the same change in j's attractiveness as a \$1 increase in comparative advertising, and is therefore the marginal rate of substitution between them. We assume it is constant at rate λ. Because the push effect of a comparative ad returns λ per dollar, optimal arrangement of the ad portfolio implies the pull effect must return $1-\lambda$ per dollar (whenever comparative advertising is used against a target). Hence the optimal comparative advertising strategy of Brand j is characterized by $Ms_jd_{jk}\Delta Q_k = 1-\lambda$ for any rival k it chooses to target. Diversion ratios may then be identified from the condition that comparative advertising expenditures should equate the marginal benefit to the marginal advertising cost (which is \$1).

The above condition also indicates that once we know the diversion ratios, we can write the drop in Brand k's attractiveness induced by one more dollar of comparative advertising by j targeted at k as $\Delta Q_k = \frac{1-\lambda}{Ms_jd_{jk}}$. This is therefore also the amount by which k must reduce its price to neutralize the hit to Q_k. Similarly, using the neutralizing price change interpretation of d_{kj}, it is readily shown that $\frac{d_{kj}}{Ms_j}$ is the drop in price that Brand k must incur in order to maintain its market share if Brand j were to raise Q_j by increasing its self-promotion by \$1 from its equilibrium level: a \$1 comparative ad only raises Q_j by a fraction λ of what \$1 self-promotion does. Pulling all this together, the harm to k's equilibrium profit of one more dollar of comparative advertising by j is:[6]

$$Ms_k\left(\frac{1-\lambda}{Ms_jd_{jk}} + \lambda\frac{d_{kj}}{Ms_j}\right), \tag{3}$$

where the first term in parentheses is the price drop that neutralizes the pull-down to Q_k and the second one is the price drop that neutralizes the push-up to Q_j.

2.2 Demand

Suppose that Brand $j = 1, ...n$ charges price p_j and has perceived quality $Q_j(.)$, $j = 1, ...n$. We retain the subscript j on $Q_j(.)$ because when we get to the estimation, exogenous vari-

[6] Our analysis below derives this using the envelope theorem.

ables and random variables summarizing the unobserved determinants of perceived quality will enter the errors in the equations to be estimated.

Brands can increase own perceived quality through both types of advertising, and degrade competitors' quality through comparative advertising. Comparative advertising, by its very nature of comparing, both raises own perceived quality and reduces the perceived quality of rival brands. The corresponding arguments of $Q_j(.)$ are advertising expenditure by Brand j which directly promotes its own product, denoted by A_{jj}; "outgoing" advertising by Brand j targeted against Brand k, A_{jk}, $k \neq j$, which has a direct positive effect; and "incoming" comparative advertising by Brand k targeting Brand j, A_{kj}, $k \neq j$, which has a negative (detraction) effect on Brand j's perceived quality. Thus, we write j's perceived quality as $Q_j(A_{jj}, \{A_{jk}\}_{k \neq j}, \{A_{kj}\}_{k \neq j})$, $j = 1, ..., n$, which is increasing in the first argument, increasing in each component of the second (outgoing) group, and decreasing in each component of the third (incoming) group, with $\frac{\partial^2 Q_j}{\partial A_{jj}^2} < 0$ and $\frac{\partial^2 Q_j}{\partial A_{kj}^2} > 0$ for $k \neq j$.[7]

The demand side is generated by a discrete choice model of individual behavior where each consumer buys one unit of her most preferred good. We will not estimate this demand model from (aggregate) choice data; we simply use it to frame the structure of the demand system. Preferences are described by a (conditional indirect) utility function:[8]

$$U_j = \delta_j + \varepsilon_j, \qquad j = 0, 1, ..., n, \tag{4}$$

in standard fashion, where ε_j is a brand-idiosyncratic match value and

$$\delta_j = Q_j(.) - p_j \tag{5}$$

is the "objective" utility, and where we let the "outside option" (of not buying an OTC pain remedy) be associated with an objective utility δ_0.

The distribution of the random terms determines the form of the market shares, s_j, $j = 0, ..., n$, and each s_j is increasing in its own objective utility, and decreasing in rivals' objective utilities.[9] Assume that there are M consumers in the market, so that the total demand for brand j is Ms_j, $j = 0, ..., n$.

[7] Throughout, we assume sufficient concavity that the relevant second order conditions hold.

[8] We could allow here for heterogeneity in the random utility distribution across different groups of consumers.

[9] For example, $s_j = \frac{\exp[\delta_j/\mu]}{\sum_{k=0}^{n} \exp[\delta_k/\mu]}$, $j = 0, ..., n$ in the standard multinomial logit model.

2.3 Equilibrium Relations

Assume that product j is produced by Brand j at constant marginal cost, c_j. Brand $j's$ profit-maximizing problem is:

$$\underset{\{p_j, A_j\}}{Max}\, \pi_j = M(p_j - c_j)s_j - A_{jj} - \sum_{k \neq j} A_{jk} \qquad j = 1, ...n. \tag{6}$$

where the advertising quantities (the A's) are dollar expenditures.

Prices and advertising levels are determined simultaneously in a Nash equilibrium.

The price condition is determined in the standard manner by:

$$\frac{d\pi_j}{dp_j} = Ms_j - M(p_j - c_j)\frac{ds_j}{d\delta_j} = 0, \qquad j = 1, ...n, \tag{7}$$

which yields a solution $p_j > c_j$: brands always select strictly positive mark-ups.

Self-promotion advertising expenditures are determined (for $j = 1, ..., n$) by:

$$\frac{d\pi_j}{dA_{jj}} = \frac{d\pi_j}{d\delta_j}.\frac{\partial Q_j}{\partial A_{jj}} - 1 = M(p_j - c_j)\frac{ds_j}{d\delta_j}\frac{\partial Q_j}{\partial A_{jj}} - 1 \leq 0, \text{ with equality if } A_{jj} > 0 \tag{8}$$

where the partial derivative function $\frac{\partial Q_j}{\partial A_{jj}}$ may depend on any or all of the arguments of Q_j. Substituting the pricing first-order condition (7) into the advertising one (8) gives

$$Ms_j\frac{\partial Q_j}{\partial A_{jj}} \leq 1, \quad \text{with equality if } A_{jj} > 0, \qquad j = 1, ..., n.^{10} \tag{9}$$

The interpretation is that raising A_{jj} by \$1 and raising price by $\$\frac{\partial Q_j}{\partial A_{jj}}$ too leaves δ_j unchanged. This change, therefore, increases revenue by $\$\frac{\partial Q_j}{\partial A_{jj}}$ on the existing consumer base (i.e., Ms_j consumers). This extra revenue is equated to the \$1 cost of the change, the RHS of (9). The relation in (9) implicitly determines self-promotion as a function of whatever advertising variables are in Q_j (these all involve brand j as either sender or target), along with j's share.

Recalling our assumption that $\frac{\partial^2 Q_j}{\partial A_{jj}^2} < 0$, from (9), brands with larger s_j will advertise more (choose a higher value of A_{jj}) than those with smaller market shares, ceteris paribus. The intuition is that the advertising cost per customer is lower for larger brands. The other relations in the following proposition follow similarly from the implicit function theorem through the dependence of perceived quality on self-promotion, and incoming and outgoing

[10] Below we (implicitly) invoke sufficient concavity of Q_j for interior solutions to (9): if $\frac{\partial Q_j}{\partial A_{jj}}$ were constant (if ads entered perceived quality linearly), then this is unlikely.

attacks. Through the next series of Propositions, we emphasize the various second derivatives of the Q function because these correspond to the parameters we estimate.

Proposition 1 ***(Self-promotion Advertising levels)*** *Brand j's choice of self-promotion advertising level is determined by* $Ms_j \frac{\partial Q_j}{\partial A_{jj}} \leq 1$, *with equality if* $A_{jj} > 0$. *For* $A_{jj} > 0$, A_{jj} *is an increasing function of* s_j; A_{jj} *is a decreasing function of* A_{jk} *iff* $\frac{\partial^2 Q_j}{\partial A_{jj} \partial A_{jk}} < 0$; A_{jj} *is an increasing function of* A_{kj} *iff* $\frac{\partial Q_j}{\partial A_{jj} \partial A_{kj}} > 0$.

The advertising relationships in the Proposition 1 hold for brands with large enough market shares.[11] They will be estimated below using a simple Q_j specification for which A_{jj} is written as a linear function of s_j and the other relevant advertising quantities.[12]

We now turn to comparative advertising levels. An attack raises own perceived quality and decreases that of the targeted rival. We can determine the advertising spending against rivals by differentiating (6) to get (for $k \neq j$):

$$\begin{aligned}\frac{d\pi_j}{dA_{jk}} &= \frac{d\pi_j}{d\delta_j}.\frac{\partial Q_j}{\partial A_{jk}} + \frac{d\pi_j}{d\delta_k}.\frac{\partial Q_k}{\partial A_{jk}} - 1 \\ &= \underbrace{M(p_j - c_j)\frac{ds_j}{d\delta_j}\frac{\partial Q_j}{\partial A_{jk}}}_{\text{own Q enhancement}} + \underbrace{M(p_j - c_j)(\frac{ds_j}{d\delta_k})\frac{\partial Q_k}{\partial A_{jk}}}_{\text{competitor's Q denigration}} - 1 \leq 0,\end{aligned}$$

with equality if $A_{jk} > 0$. We proceed by substituting the attacker pricing condition and its self-promotion condition to rewrite this comparative advertising condition in a form to be estimated. First, inserting the price first-order conditions (7) gives (for $k \neq j$):

$$\frac{d\pi_j}{dA_{jk}} = Ms_j \frac{\partial Q_j}{\partial A_{jk}} - Ms_j d_{jk} \frac{\partial Q_k}{\partial A_{jk}} \leq 1, \quad \text{with equality if } A_{jk} > 0, \tag{10}$$

where $d_{jk} > 0$ is the diversion ratio discussed in sub-section 2.1 above. Loosely, the diversion ratio measures how much of customer is picked up from a rival per customer it sheds. The restriction on the diversion ratios ($d_{jk} \in [0, 1]$) motivates restrictions below in the estimation.

The comparative advertising derivative, (10), provides a bound on the size of the marginal rate of substitution between *outgoing* comparative advertising and self-promotion

[11] Otherwise, from (7) the term $(p_j - c_j)\frac{ds_j}{d\delta_j}$ is small enough that the derivative $\frac{d\pi_j}{d\delta_j}$ in (8) is negative when $\frac{\partial Q_j}{\partial A_{jj}}$ is evaluated at $A_{jj} = 0$.

[12] This proposition and the next one provide equilibrium relations between endogenous variables rather than comparative statics results. In equilibrium, the differences in shares and ad levels are jointly determined by differences in marginal costs or perceived qualities across the different firms.

$(\frac{\partial Q_j}{\partial A_{jk}}/\frac{\partial Q_j}{\partial A_{jj}})$. Assume for the present argument that the solution for self-promotion spending (see (9)) is interior. Then, substituting the self-promotion condition ($Ms_j\frac{\partial Q_j}{\partial A_{jj}}=1$) into (10) implies

$$\frac{\partial Q_j}{\partial A_{jk}}/\frac{\partial Q_j}{\partial A_{jj}} \leq 1 + Ms_j d_{jk}\frac{\partial Q_k}{\partial A_{jk}} \tag{11}$$

where the LHS is less than one because $\frac{\partial Q_k}{\partial A_{jk}} < 0$ on the RHS. In summary:

Proposition 2 ***(Self-promotion and outgoing comparative advertising)*** *If Brand j uses a strictly positive amount of self-promotion, then the marginal rate of substitution between outgoing comparative advertising against Brand k and self-promotion $(\frac{\partial Q_j}{\partial A_{jk}}/\frac{\partial Q_j}{\partial A_{jj}})$ is strictly below 1.*

If this were not the case, then comparative advertising would drive out self-promotion since it would give a direct own-quality benefit per dollar greater than self-promotion, while additionally helping the attacker by denigrating a rival. We will assume in the estimation that the marginal rate of substitution between outgoing comparative advertising and self-promotion in (11) is constant, at rate λ, so that the testable implication of Proposition 2 is that $\lambda < 1$. Then we can write from (11):

$$(0 <) \quad -Ms_j d_{jk}\frac{\partial Q_k}{\partial A_{jk}} \leq 1-\lambda, \qquad \text{with equality if } A_{jk} > 0. \tag{12}$$

The intuition is as follows for $A_{jk} > 0$. The term $1-\lambda$ on the RHS of (12) is the marginal cost of the pull effect once we subtract the value of the push component of the comparative attack. Hence the LHS should be the marginal benefit of the pull effect. To see that this is so, first note that the pull effect of raising A_{jk} by \$1 is equivalent to brand k raising its price by $\$\frac{-\partial Q_k}{\partial A_{jk}}$ (since the same δ_k is attained). The neutralizing price change for j that just keeps s_j intact per dollar increment in p_k is given by (2) as d_{jk}, and this benefit is reaped on j's market base of Ms_j. The LHS of (12) then follows directly.

To determine predictions for how A_{jk} depends on the other relevant advertising levels, we apply the implicit function theorem to (12) and recall that $\frac{\partial^2 Q_k}{\partial A_{jk}^2} > 0$.

Proposition 3 ***(Comparative Advertising levels)*** *The choice of comparative advertising level by Brand j against Brand k is determined by $-Ms_j d_{jk}\frac{\partial Q_k}{\partial A_{jk}} \leq 1-\lambda$, with equality if*

$A_{jk} > 0$. For $A_{jk} > 0$, A_{jk} is: (i) an increasing function of d_{jk} and s_j; (ii) a decreasing function of A_{lk} iff $\frac{\partial^2 Q_k}{\partial A_{jk}\partial A_{lk}} > 0$; (iii) an increasing function of A_{kk} iff $\frac{\partial^2 Q_k}{\partial A_{kk}\partial A_{jk}} < 0$; (iv) an increasing function of A_{kl} iff $\frac{\partial^2 Q_k}{\partial A_{kl}\partial A_{jk}} < 0$; .

From Proposition 3(i), there are more attacks for given diversion ratio d_{jk} the higher the attacker market share. This is roughly borne out in the raw data insofar as Advil and Aleve are the largest attackers of Tylenol. Likewise, for a given attacker share, attacks are larger for a bigger diversion ratio.[13] We shall proceed for the estimation by estimating d_{jk} for each pair. Thus we are implicitly constraining the diversion ratios to be constant over time.

From Proposition 3(ii), attacks by j against k increase with attacks on k by others if and only if $\frac{\partial^2 Q_k}{\partial A_{jk}\partial A_{lk}} < 0$. This cross partial sign implies that more harm is inflicted with a marginal attack by j when others' attacks render k more susceptible.

The third property in Proposition 3 depends on the sign of the cross partial $\frac{\partial^2 Q_k}{\partial A_{kk}\partial A_{jk}}$; we now argue that the last one does too. Indeed, the cross-partial $\frac{\partial^2 Q_k}{\partial A_{kl}\partial A_{jk}}$ (used in the fourth property) has the same sign as does $\frac{\partial^2 Q_k}{\partial A_{kk}\partial A_{jk}}$ because we know $\frac{\partial Q_k}{\partial A_{kl}} = \lambda \frac{\partial Q_k}{\partial A_{kk}}$ with both derivatives positive by assumption, and λ therefore positive, so the assumption of λ constant implies the two cross partials have the same sign.

Hence, the last two properties in Proposition 3 are both determined by the sign of the cross partial $\frac{\partial^2 Q_k}{\partial A_{kk}\partial A_{jk}}$, which is estimated in the self-promotion equation. Hence, applying Proposition 1 to 3(iii) and 3(iv) yields the next result.

Corollary. If self-promotion is increasing with incoming comparative advertising then comparative advertising decreases with target self-promotion and with target outgoing comparative advertising.

These are implications of the model, and not imposed by functional form. The intuition is that a brand is attacked less when it advertises more if having more outgoing ads reduces the negative impact of attacks (i.e., $\frac{\partial^2 Q_k}{\partial A_{kk}\partial A_{jk}} > 0$), and this is also the condition for a brand to want to engage in more self-promotion when attacked more (its marginal benefit rises with incoming attacks).

[13] Alternatively, we can write $s_j d_{jk} = s_k D_{jk}$ where $D_{jk} = \frac{s_j}{s_k} d_{jk}$ is the ratio of cross elasticity of demand to own elasticity. In this case, for a given value of D_{jk}, a bigger target is attacked more. This roughly concurs with the data that the largest firm, Tylenol, is attacked most.

We now show how the damage to a rival from j's self-promotion depends on the diversion ratio. The effect on k's profits, $\pi_k^* = M(p_k^* - c_k) s_k^* - A_{kk}^* - \sum_{l \neq k} A_{kl}^*$ (where the stars denote equilibrium values) holding constant all other brands' actions (except the best-reply of k) is determined by the envelope theorem as

$$\begin{aligned} \frac{d\pi_k^*}{dA_{jj}} &= M(p_k^* - c_k) \frac{ds_k}{d\delta_j} \frac{\partial Q_j}{\partial A_{jj}} \\ &= -\frac{s_k}{s_j} d_{kj} \end{aligned} \tag{13}$$

where at the second step we have substituted in k's pricing condition (7) and the equality version of (9).

Similarly, the measure of the damage of an extra dollar of comparative advertising from Brand j against target k is a weighted average of push and pull effects, both of which can be written in terms of diversion ratios. Using the envelope theorem, the full effect of a marginal dollar of comparative advertising from j on $k's$ profits, with all other brands' actions fixed is

$$\frac{d\pi_k^*}{dA_{jk}} = M(p_k^* - c_k) \left(\frac{ds_k}{d\delta_k} \frac{\partial Q_k}{\partial A_{jk}} + \frac{ds_k}{d\delta_j} \frac{\partial Q_j}{\partial A_{jk}} \right).$$

Substituting in k's pricing condition (see (7)) implies

$$\begin{aligned} \frac{d\pi_k^*}{dA_{jk}} &= M s_k \left(\frac{\partial Q_k}{\partial A_{jk}} - d_{kj} \frac{\partial Q_j}{\partial A_{jk}} \right) \\ &= -\frac{s_k}{s_j} \left(\frac{1-\lambda}{d_{jk}} + \lambda d_{kj} \right) \end{aligned} \tag{14}$$

where we have substituted in the equality versions of conditions (12) and (9) at the second step.[14] The interpretation of (14) in terms of neutralizing prices was given in Section 2.1 (see (3)). Basically, the first term here is the amount of self-promotion required to restore Q_k and the second term is the harm inflicted by the rival's increased self-promotion component of the comparative advertising (hence the λ weight corresponding to the push effect). Note that the effect on profit here and below is measured in dollars: equivalently (by the target's optimality condition that the \$1 marginal cost of an extra dollar's advertising equals its marginal benefit), it is the amount of self-promotion advertising that would have to be spent to offset the harm. The empirical analysis will provide parameter estimates so the marginal harm can be estimated.

[14] Equivalently, we can write this as $\frac{d\pi_k^*}{dA_{jk}} = (1-\lambda) Pull_{jk} + \lambda Push_{jk} = \frac{(1-\lambda)}{D_{jk}} + \lambda D_{kj}$.

Proposition 4 *(**Damage Measure**) Assume that target k engages in self-promotion, and assume that outgoing comparative ads are perfectly substitutable with self-promotion at rate $\lambda \in (0,1)$. Then the profit lost by target k from an additional dollar of comparative advertising attack by Brand j is the sum of a pull damage, $\frac{1-\lambda}{d_{jk}}\frac{s_k}{s_j}$, and a push damage, $\lambda d_{kj}\frac{s_k}{s_j}$.*

In like manner we can determine the spillover benefit (related to free riding in comparative advertising) to l of an attack by j on k as

$$\frac{d\pi_l^*}{dA_{jk}} = \frac{s_l}{s_j}\left(d_{lk}\frac{(1-\lambda)}{d_{jk}} - \lambda d_{lj}\right). \tag{15}$$

The first term here is the direct benefit to l from the harm inflicted on k (pull); the second is (as above) the damage incurred by l from j improving its quality through the comparative advertising channel (push). This expression can readily be interpreted in terms of neutralizing price changes.

3 Description of Industry and Data

The OTC analgesics market is worth approximately $2 billion in retail sales per year (including generics) and covers pain-relief medications with four major active chemical ingredients. These are Aspirin (ASP), Acetaminophen (ACT), Ibuprofen (IB), and Naproxen Sodium (NS). The nationally advertised brands are such familiar brand names as Tylenol (ACT), Advil and Motrin (IB), Aleve (NS), Bayer (ASP or combination), and Excedrin (ACT or combination). Table 1 summarizes market shares, ownership, prices and advertising levels in this industry. Below we present major components of our dataset. We discuss the data construction process in great detail and provide more information about the industry in Appendix A.

The sales data, collected by AC Nielsen, consist of prices and dollar total revenues of all OTC oral analgesics products sold in the U.S. national market from March of 2001 through December of 2005 (58 monthly observations for each brand).

Our advertising dataset is from TNS-Media Intelligence. The data include video files of all TV advertisements for 2001-2005 for each brand advertised in the OTC analgesics category and monthly advertising expenditures on each ad (see Appendix A for details).

The unit of observation in the raw dataset is a single ad. There are 4,506 unique ads (346 of which are missing videos).

TABLE 1. Market Shares and Advertising Levels of OTC Analgesics Brands

Brand	Active Ing.	Price / serving	Inside Market Share	Max Pills	TA/ Revenue	CA/ Revenue	CA/ TA	Owner-ship
Tylenol	ACT	\$2.15	30.51%	7.2	17.4%	3.3%	19.3%	McNeil
Advil	IB	\$1.60	24.21%	5.9	20.0%	13.3%	66.4%	Wyeth
Aleve	NS	\$0.83	22.40%	3.0	26.0%	20.0%	75.7%	Bayer
Excedrin	ACT	\$2.40	8.28%	9.2	26.4%	3.4%	13.2%	Novartis
Bayer	ASP	\$1.85	6.98%	10.1	28.8%	6.4%	22.4%	Bayer
Motrin	IB	\$1.71	7.68%	5.9	20.4%	8.1%	39.6%	McNeil
Generic	ACT	\$1.17						
Generic	IB	\$0.66						
Generic	ASP	\$0.82						
Generic	NS	\$0.57						

Note: CA-Comparative Advertising; TA-Total Advertising.

Liaukonyte (2015) watched all the ads and coded their content. She recorded whether the product was explicitly compared to any other products. If a commercial was comparative, she recorded which brand (or class of drugs) it was compared to (e.g., to Advil or Aleve).

TABLE 2. Advertising and Comparative Advertising Target Pairs

Adver-tiser ⇓	TARGET: Advil	Aleve	Bayer	Excedrin	Motrin	Tylenol	Total CA	Total
Advil	92.1 [50]	17.8 [27]	-	4.3 [20]	-	160.2 [58]	182.2	274.3
Aleve	-	42.5 [45]	0.0 [3]	0.5 [7]	-	131.7 [58]	132.1	174.7
Bayer	13.8 [25]	-	104.9 [58]	-	-	15.7 [37]	29.5	131.8
Excedrin	-	1.9 [7]	2.2 [7]	158.4 [47]	-	19.9 [15]	24.1	182.5
Motrin	18.9 [27]	18.8 [27]	-	-	57.3 [54]	-	37.6	94.9
Tylenol	9.6 [16]	31.7 [31]	36.6 [27]	-	-	359.0 [58]	77.8	404.0
Total CA	42.6 [68]	70.2 [92]	38.7 [34]	4.7 [27]	-	327.5	483.4	

Notes: Row j indicates the advertiser brand and Column k indicates the target. The left part of cell jk is comparative ad expenditure in \$m.; the right part denotes how many time periods [out of 58] the attack pair jk happened. The diagonal entries are expenditures on self-promotional advertising.

Table 2 presents the complete picture of cross targeting and advertising expenditures on each of the rival brands targeted. This table shows that *every* nationally advertised brand used comparative advertising during the sample period. However, only four (of the six) brands were targeted: Tylenol, Advil, Aleve, and Excedrin.[15] These data provide some in-

[15] Motrin does not attack Tylenol because the parent company is the same; likewise, Bayer does not attack Aleve for the same reason.

formal support that larger brands both used more comparative advertising and were targeted more. Entries on the diagonal are self-promotion expenditures.

4 The Econometric Model

4.1 A Quality Function

We implement the following perceived quality function:[16]

$$Q_j\left(.\right) = \alpha \ln\left(A_{jj} + \lambda \sum\nolimits_{k\neq j} A_{jk} - \beta \sum\nolimits_{k\neq j} A_{kj} + \bar{A}_{jj}\right) - \phi \sum\nolimits_{k\neq j} \ln\left(\bar{A}_{kj} + A_{kj}\right) + \bar{Q}_j. \quad (16)$$

Variables other than advertising levels pertaining to j's perceived quality enter through $\bar{A}_{jj}$, $\bar{A}_{kj}$, and $\bar{Q}_j$. They include observed factors such as j's product characteristics as well as unobserved factors that determine the realization of random shocks. They enter the equations to be estimated only if they interact with advertising levels, that is only if they enter $\bar{A}_{jj}$ or $\bar{A}_{jk}$ for some k. Here, we interpret $\bar{Q}_j$ as the product differentiation from product characteristics and the remaining part of $Q_j\left(.\right)$ as the differentiation induced by advertising. This distinction is important when we discuss the identification strategy and we look into the nature of the structural unobservables because anything that enters into $\bar{Q}_j$ can be used as an instrumental variable in the advertising first order conditions.

The push effect is incorporated through the weighted sum of self-promotion and outgoing comparative ads $(A_{jj} + \lambda \sum_{k\neq j} A_{jk})$, where λ is the marginal rate of substitution between outgoing comparative and self-promotion ads, which is assumed to be constant. In order for self-promotion to favorably impact perceived quality, α should be positive. Recall from Proposition 2 that we should expect $\lambda < 1$. Whether there is a push effect for Brand j associated with its comparative advertising activity against rivals depends on whether λ is strictly positive or not.[17]

The pull effect from incoming comparative ads (A_{kj}) impacts the quality function in two ways. First, it enters the "net persuasion" term inside the first logarithm. The sign of β gives

[16]The use of logarithmic functions to ensure the concavity of the utility with respect to advertising is common in the literature. See, for example, Busse and Rysman (2005). See Bagwell (2007) for an extensive review of the literature on the economics of advertising.

[17]$\lambda < 0$ would mean that j's brand image is hurt by the use of comparative advertising, in line with conventional wisdom among marketers in continental Europe.

the sign of the cross effect between incoming attacks and outgoing ads. Second, incoming ads enter in a separable way with associated parameter ϕ. This additional term allows for disassociating the intensity of the overall pull effect from the intensity of the cross effect between incoming attacks and outgoing ads as measured by β.[18] Through this separable term, we also allow the A_{kj} to be imperfect substitutes with one another. Since attacks on target k constitute a public good for all the brands other than k, if expenditures attacking k were perfect substitutes, then there would be only one attacker in equilibrium in each period. The data show that this is not the case.

The equilibrium relations in Propositions 1 and 3 that link self-promotion and comparative advertising expenditures are determined by the signs of parameters α, β, and λ.[19]

4.2 The Equations To Be Estimated

The first order condition for self-promotion ads, corresponding to equation (9) above may be written as

$$\begin{cases} A^*_{jjt} = \alpha M s_{jt} - \lambda \sum_{k \neq j} A_{jkt} + \beta \sum_{k \neq j} A_{kjt} - \bar{A}_{jjt}, \\ \bar{A}_{jjt} \sim N\left(\mu_{jjt}, \sigma^2_{SP}\right), \ A_{jjt} = \max\left(A^*_{jjt}, 0\right), \qquad j = 1, ..., n. \end{cases} \tag{17}$$

A very attractive feature of our modeling strategy is that $\bar{A}_{jjt}$ incorporates the structural unobservable component of perceived quality that interacts with A_{jjt}. Subscripts j and t on the mean term reflect some possible brand fixed effect. The equation above is a Tobit regression that is linear in the parameters.

The first order condition for comparative ads follows from first writing (12) for the specification of quality (16) above. This gives

$$-M s_{jt} d_{jkt} \left(\frac{-\alpha\beta}{A_{kkt} + \lambda \sum_{l \neq k} A_{klt} - \beta \sum_{l \neq k} A_{lkt} + \bar{A}_{kkt}} - \frac{\phi}{\left(\bar{A}_{jkt} + A_{jkt}\right)} \right) \leq 1 - \lambda, \tag{18}$$

with equality if $A_{jkt} > 0$. Second, using the target k's self-promotion equation (9) when $A_{kkt} > 0$ (namely $A_{kkt} + \lambda \sum_{l \neq k} A_{klt} - \beta \sum_{l \neq k} A_{lkt} + \bar{A}_{kkt} = \alpha M s_{kt}$), we obtain the following

[18] With ϕ large enough, it also ensures that $\frac{\partial^2 Q_k}{\partial A^2_{jk}} > 0$ locally.

[19] This specification of Q imposes the sign of the cross effect between attacks by k on j and attacks by some other Brand l on j to have the sign of $-\alpha\beta^2$ so it is negative (provided that α is found to be positive). Then from Proposition 3, more attacks by other brands on j induce more comparative advertising by k against j.

econometric specification:

$$\begin{cases} A^*_{jkt} = \phi M s_{jt} \frac{s_{kt} d_{jk}}{(1-\lambda) s_{kt} - \beta s_{jt} d_{jk}} - \bar{A}_{jkt}, \\ \bar{A}_{jkt} \sim N\left(\mu_{jkt}, \sigma^2_{CA}\right), \ A_{jkt} = \max\left(A^*_{jkt}, 0\right), \qquad j = 1, ..., n. \end{cases} \tag{19}$$

as long as $A_{kkt} > 0$. Here again, the structural unobservable is in $\bar{A}_{jkt}$. In our estimation strategy, we assume that diversion ratios are constant over time, and given by $d_{jkt} = d_{jk}$. Equation (19) is a Tobit regression that is nonlinear in the parameters.

4.3 Identification Strategy

In both Tobit specifications above, the unobservables are correlated with the explanatory advertising and share variables because the brands take them into consideration when making their advertising and pricing decisions. The first, most straightforward, step to address the endogeneity of these variables is to exploit the panel structure of our data to account for time-constant differences across brands. Essentially, for the self-promotion equation, we set $\bar{A}_{jjt} = \bar{A}_{jj} + \Delta\bar{A}_{jjt}$, where $\bar{A}_{jj}$ is a brand fixed effect, while $\Delta\bar{A}_{jjt}$ are time-specific idiosyncratic shocks. We do not follow the same approach for the comparative ad equation since this would require estimating many pair specific dummy variables $\bar{A}_{jk}$, which cannot be achieved with much precision, given our limited number of observations. Hence the endogeneity of shares in the comparative ad equation (19) is only dealt with using instrumental variables, as described below. The dummy variables in the self-promotion equation (17) control for a brand's advertising base allure advantage, which picks up any persistent component of such an advantage. The remaining source of endogeneity in our regressions then comes from any potential correlation of temporary shocks, here picked up by $\Delta\bar{A}_{jjt}$ and $\bar{A}_{jkt}$, with advertising expenditures and shares[20].

To address the remaining endogeneity, we use generic prices and various functions of generic prices as instrumental variables. Following Anderson, Ciliberto and Liaukonyte (2013), generic prices are used as a proxy for marginal costs. If the marginal cost is constant and the generic prices are set at the marginal cost, then the generic prices are independent of

[20] The OTC analgesics market endured several medical news shocks over the analyzed time period. In the Appendix C.2 we introduce data on these shocks and investigate whether they help explain the variation in brand's base allure. We find that including these shocks as controls does not add much additional insight, thus we omit them in the further discussions in the paper.

the prices set by the national brands and can be appropriately used as instrumental variables. This argument was first proposed by Grabowski and Vernon (1992) and further discussed by Ching (2004, 2010) and Scott Morton (2004) in connection with the prescription drug market: Generic prices in markets with multiple generic entrants usually trend down (as happens in younger drug markets where a drug recently came off-patent, see Ching, 2004) and converge in mature markets.[21] We therefore checked for generic price downward trends and found no evidence. Instead, generic prices fluctuate (see Figure B2, Appendix B), which is consistent with the maturity of the OTC analgesics industry.[22] To summarize, within our sample, we justify using generic prices as instruments due to (i) a large competitive fringe, (ii) a long enough time since patent expiration; and (iii) no downward trend in generic price index during the sample period. See Appendix B.4 for more details.

To implement the estimation in our non-linear models, we use control functions (Heckman and Robb 1985, 1986). Our methodology follows Blundell and Smith (1986) and Rivers and Vuong (1988). Consider the self-promotion equation. Using control functions consists of rewriting the unobservable $\bar{A}_{jjt}$ as a linear function of v, the unobservable of the first stage reduced form regression, and of ϵ, a white noise term. For example, say that only shares are suspected to be endogenous. Then, v is the unobservable of a reduced form regression of the shares on all the exogenous variables, including the instrumental variables. We can then use the residuals from that reduced form regression, $\hat{v}$, and plug them in the regression (17) as follows: $A^*_{jjt} = \alpha M s_{jt} - \lambda \sum_{k \neq j} A_{jkt} + \beta \sum_{k \neq j} A_{kjt} + \theta \hat{v} + \epsilon$, where ϵ is now the unobservable that generates the Tobit model. The nice feature of this approach is that we can test the exogeneity of the shares by testing whether $\theta = 0$. With three endogenous variables, we have three control functions, but the problem is conceptually identical. The only econometric difficulty in the application of this methodology is created by the fact that two of the explanatory variables in the self-promotion equation, $\sum_{k \neq j} A_{jkt}$ and $\sum_{k \neq j} A_{kjt}$, are left-censored, and thus the estimated residuals that are required to construct the control functions would be biased whenever the variables are zero. To address this econometric

[21] Note, that in order for generic prices to be valid instruments we can also allow generic products to charge prices that are higher than marginal costs as long as this markup is explained by local conditions that national brands do not take into account when they set their prices.

[22] The patent for naproxen sodium was the last one to expire, in 1993.

problem, we derive the generalized residuals, as proposed by Gourieroux et al. (1987). We describe the econometric approach in detail in Appendix B.1. Because of the nonlinear nature of all these problems we estimate the system of the two equations (17) and (19) separately rather than with the generalized method of moments (as in Sovinsky Goeree, 2008).

5 Empirical Analysis

5.1 Self-Promotion

Each column in Table 3 presents the results for the parameters α, β, and λ for various specifications of Equation (17). Across all specifications, α, β, and λ are positive and statistically significant. The results in Proposition 1 that larger shares are associated with more self-promotion advertising is reflected in the positive sign of α. Outgoing attacks have a push-up self-promotion impact measured by $\lambda > 0$. However, because $\lambda < 1$, comparative advertising does not drive out self-promotion, as per Proposition 2. The direct own-quality benefit per dollar is smaller than the benefit from self-promotion. Finally, $\beta > 0$ means that self-promotion increases with incoming advertising. This reflects a positive cross effect, which, by Proposition 3, implies that comparative advertising decreases with target self-promotion. None of these empirical results reject the theoretical model. Next, we investigate the economic significance of the results in Table 3.

Column 1 of Table 3 shows the results from a straightforward Tobit regression, where self-promotion ad expenditures are regressed on sales, outgoing attacks and incoming attacks. We estimate $\alpha = 0.123$, which means that a brand would spend 12 cents a month more in self-promotion per additional customer. In our specification, a higher α means that more self-promotion has more impact on perceived quality. From Proposition 1, the positive correlation between market share and self-promotion is stronger.

The marginal rate of substitution between outgoing attacks and self-promotion ads is $\lambda = 0.768$, meaning that the self-promotion value of \$1 of outgoing comparative ads is the same as 77 cents of pure self-promotion. The value $\beta = 0.429$ provides a lower bound to how much additional self-promotion expenditures will offset one more dollar of attacks on the brand (43 cents).[23] We now investigate how the results change when we address the endogeneity of the explanatory variables.

TABLE 3. Self-Promotion Equation and Net Persuasion

Version	Baseline Model (1)	Brand Dummy (2)	IV (Generics) (3)
Alpha	0.123	0.432	0.551
	(0.027)	(0.076)	(0.045)
Lambda	0.768	0.660	0.616
	(0.072)	(0.074)	(0.087)
Beta	0.429	0.297	0.447
	(0.063)	(0.068)	(0.037)
Control: Out. Ads			-0.018
			(0.071)
Control: Inc. Ads			-0.164
			(0.035)
Control: Shares			-0.309
			(0.043)
Brand dummy		-0.353	-0.525
		(0.081)	(0.054)
/sigma	0.195	0.189	0.185
	(0.008)	(0.008)	(0.004)
Log likelihood	47.955	57.082	63.680
F-test: Outg. Ads			F(6,341) =6.27
F-test: Inc. Ads			F(6,341) =22.58
F-test: Shares			F(6,340) =40.09
Obs	348	348	348

Note: Bootstrapped s.e. are computed in column 3.

In Column 2 we run the Tobit regression including a dummy variable that is equal to 1 if the observation is for one of the top brands (Advil, Aleve, Tylenol), and zero otherwise.[24] Thus, we have $\mu_{jjt} = \mu^{TB}$ for a top brand and $\mu_{jjt} = \mu^{OB}$ otherwise. Using this specification, the coefficient estimate of λ drops from 0.768 to 0.660 and the coefficient estimate of β drops from 0.429 to 0.297. In contrast, the coefficient estimate of α increases from 0.123 to 0.432. The contrasting direction of the bias between the advertising explanatory variables and the

[23] It is not the full extent of the negative impact of attacks on the brand's perceived quality. This requires knowing ϕ, which is identified from estimating the comparative advertising equations (19).

[24] More discussion on the use of a top brand dummy variable is available in Appendix B.3.

shares reflects the relationship between the unobserved component of perceived quality and the explanatory variables. In particular, it is reasonable to think that products with a higher unobserved component of perceived quality will have a larger market share, *ceteris paribus*. Then, the downwards bias on α when the fixed effect is omitted means that brands with a stronger unobserved component of perceived quality do less self-promotion advertising, *ceteris paribus*. Similarly, the upwards bias on the estimates for λ and β means that brands with a higher perceived quality are attacked less and attack rivals less than brands with a lower perceived quality. These predictions are consistent with our specification of perceived quality, which assumes a negative cross partial between $\bar{A}_{jj}$ and outgoing ads and a positive cross partial between $\bar{A}_{jj}$ and incoming attacks. This discussion is mirrored by the result on the coefficient estimate of the Top Brand dummy. The Top Brand fixed effect, $\bar{A}_{jj}^{TB}$ is equal to -0.353. It has a negative sign, which means that the larger brands, Aleve, Tylenol, and Advil have inherently higher advertising base allure than the other brands.

To investigate whether we should still be concerned about any remaining endogeneity of s_j, $\sum_{k \neq j} A_{jkt}$, and $\sum_{k \neq j} A_{kjt}$, we run an instrumental variable regression. In Column 3 the instrumental variables are the generic prices of the product that shares the same active ingredient and the sum of the generic prices over all the competing active ingredients. We find that the instrumental variables do a fair job at explaining the first stage variation in outgoing comparative advertising and in incoming attacks. The first-stage F tests reject the null hypotheses that generic prices do not explain any of the first stage variation, and the F statistics are quite large. Instrumental variables are less important to control for the endogeneity of shares, since the brand dummies predict most of the variation in shares. Table B1 in Appendix B presents estimates and goodness-of-fit measures for all three first stage regressions.

Column 3 shows that $\alpha \approx 0.55$, which means that Brand j spends 55 cents per month in self-promotion advertising per additional consumer. We also find $\lambda \approx 0.6$ which means that each dollar spent in outgoing comparative advertising is worth approximately 60 cents in raising own perceived quality and the remaining 40 cents are gained from pulling down a competitor. $\beta \approx 0.44$ means that incoming attacks have at least a damage of 44 cents (and, as we calculate below, the full damage is much larger). The results in Column 3 shows that the variation in generic prices controls for the endogeneity of the variable $\sum_{k\neq j} A_{kjt}$ and of the variable s_j. The control function for $\sum_{k\neq j} A_{jkt}$ is not statistically significant, suggesting (from Blundell and Smith, 1986) that the endogeneity of $\sum_{k\neq j} A_{jkt}$ is not empirically significant.

5.2 Comparative Advertising and Diversion Ratios

Table 4 presents the estimation results for the parameter ϕ and for the diversion ratios d_{jk}. The diversion ratios are treated as parameters to be estimated from the data and are restricted to be between 0 and 1. Treating diversion ratios as parameters avoids imposing a functional form on demand. Rather, we are implicitly using a linear approximation. This approximation strategy may be vindicated by the stability of market shares over the period. Berry (1994) shows that, under fairly lenient regularity conditions on the joint distribution of random terms in (4), there is an invertible relation between market shares and mean utilities, δ_j. Since diversion ratios are determined by the vector of mean utilities, they should be essentially unchanged if market shares do not vary much.[25] It is worth noting that with more observations our general methodology would allow the diversion ratios to be a function of market shares or of any variables that the researcher believes might determine the degree of substitutability between products, on top of a pair specific component.

Recall that we use a two-step approach. We first estimate (17). Then, we plug the estimates of β and λ into (19) to estimate ϕ and the diversion ratios. Thus, each Column in Table 4 corresponds to one specification of (19) in Table 3. In particular: Column 1 uses the estimates of β and λ that we obtain from Column 2 in Table 4; Column 2 uses the estimates of β and λ from Column 3 in Table 3. All specifications use the same number of observations (601). Twelve diversion ratios are estimated. There are three reasons for a diversion ratio to be missing. First, there were too few or no attack months so the variable was omitted. For example, Aleve attacked Advil only three times (see Table 2). Second, there are no direct attacks on "sibling" brands. For example, Bayer does not attack Aleve (both are owned by the same parent company). Third, we do not estimate (19) whenever the attacker or the target did no self-promotion (see also equation (11)).

[25] The exception is Aleve, which suffered a loss of market share in 2005, but recovered in a few months.

TABLE 4. Comparative Advertising Eq. and Diversion Ratios

	No IV (β and λ from Column 2 of Table 3) (1)	IV: Generics (β and λ from Column 3 of Table 3) (2)
ALEVE ON:		
Tylenol, d_{AlT}	0.153 (0.028)	0.201 (0.031)
ADVIL ON:		
Tylenol, d_{AdT}	0.153 (0.028)	0.199 (0.032)
Aleve, d_{AdAl}	0.045 (0.019)	0.045 (0.022)
Excedrin, d_{AdE}	0.014 (0.017)	0.000 (0.019)
TYLENOL ON:		
Advil, d_{TAd}	0.026 (0.015)	0.024 (0.021)
Aleve, d_{TAl}	0.050 (0.015)	0.056 (0.021)
Bayer, d_{TB}	0.043 (0.011)	0.049 (0.014)
BAYER ON:		
Advil, d_{BAd}	0.152 (0.067)	0.165 (0.078)
Tylenol, d_{BT}	0.203 (0.063)	0.251 (0.077)
MOTRIN ON:		
Advil, d_{MAd}	0.167 (0.060)	0.191 (0.084)
Aleve, d_{MAl}	0.162 (0.060)	0.167 (0.081)
EXCEDRIN ON:		
Tylenol, d_{ET}	0.102 (0.068)	0.104 (0.089)
Control Function for s_j		-0.000 (0.098)
Control Function for s_k		-0.058 (0.058)
ϕ	0.595 (0.135)	0.411 (0.148)
Constant Term	-0.159 (0.039)	-0.131 (0.065)
Variance Unobservable	0.140 (0.008)	0.140 (0.008)
Log-Likelihood Function	11.323	11.290
Number of Observations	601	601

Note: Bootstrapped standard errors are shown.

The coefficient estimates of the control functions for the shares of the attacker (s_{jt}) and of the attacked (s_{kt}) are statistically insignificant and of small magnitude in Column 2, implying that the endogeneity of market shares is not empirically significant. This is not surprising in light of the fact that market shares are quite stable over time while advertising expenditures vary quite a bit. Column 1, which presents the main results for this section, does not include control functions. Henceforth we discuss the economic implications of the coefficient estimates in Column 1.

Consider the entry d_{AlT}, the diversion ratio from Aleve to Tylenol. In the second column we estimate d_{AlT} equal to 0.153, meaning that if Aleve sheds 100 consumers through a price rise (say), then 15.3 of them go to Tylenol. Now consider the entry d_{AdT}, the diversion ratio from Advil to Tylenol. We estimate d_{AdT} to be virtually the same number. This is fairly large, suggesting that Tylenol is a fairly large gainer from both Aleve and Advil. The two brands attack Tylenol in very similar fashion. Looking back at Table 2, we observe that Advil and Aleve both attack Tylenol every month. More striking is the fact that their overall expenditures are very close, with Advil spending a total of \$160 million and Aleve spending \$132 million attacking Tylenol.

The figure for d_{ET} is surprisingly low (at 10.2%) since Excedrin and Tylenol share acetaminophen as active ingredient in many of its variants, but it might indicate that Excedrin serves specialty niches of consumers (Excedrin markets itself as a migraine medicine) interested in its combinations with caffeine and with aspirin (which Tylenol does not have). Motrin equally loses to Advil and Aleve an approximate 16%, despite sharing the same active ingredient with Advil.

Next, Bayer loses even more (20.3%) to Tylenol, which suggests that consumers perceive Tylenol as the closest substitute to Bayer. This concurs with the findings of a number of medical studies (e.g. Hyllested et al., 2002), according to which Tylenol is the second safest branded OTC pain reliever, after Bayer (based on cardiovascular and gastrointestinal risk profiles). Yet, Tylenol loses more to Aleve than to Bayer, suggesting that substitution patterns are not symmetric.[26] Indeed, a price rise loses Tylenol just 11.9% to its 3 main attackers, but it picks up at least that amount following a price increase by either of them.

The diversion ratios for each of the six brands sum to less than 1, as the theory hopes for (we imposed them each to be below one, but we did not restrict the sum). For example, we see that if a consumer leaves Tylenol, then that consumer will go with probability 2.6% to Advil, 5.0% to Aleve, and 4.3% to Bayer. With the remaining 88.1% probability a consumer will switch to the outside good or some other OTC analgesics, branded or generic.

There are three pairs for which we estimate the diversion ratios in both directions: $(Bayer, Tylenol,)$, $(Advil, Tylenol)$, $(Aleve, Tylenol)$. Comparing them indicates relative

[26] It is also possible, but we cannot check it given the data we have, that as far as Bayer is concerned, consumers leaving Tylenol switch to the generic version of aspirin. Because generics do not use comparative advertising, we cannot estimate those diversion ratios.

own demand derivatives. In particular, $\frac{d_{jk}}{d_{kj}} = \frac{ds_k/d\delta_k}{ds_j/d\delta_j}$. Take for example $j = Tylenol$ and $k = Bayer$. Because we have $d_{TB} = 0.043$ and $d_{BT} = 0.203$ so $\frac{d_{TB}}{d_{BT}}$ is around $\frac{1}{5}$ (so $ds_T/d\delta_T \approx 5ds_B/d\delta_B$). This means the demand derivative is much more price sensitive for Tylenol. At first blush, this may seem to presage a poor prospect for the estimates, given that Tylenol has a much higher price than Bayer aspirin (suggesting a more inelastic demand). However, a rough calibration brings this into perspective. The price of a "serving" (here roughly 3 days of pain relief) of Tylenol is roughly \$2.15; taking the generic price of \$1.17 as representing marginal cost gives a mark-up of approximately \$1. A similar mark-up is found for Bayer, with a brand price of \$1.85 and a generic price of about \$0.8. The pricing equation (7) sets mark-up equal to demand over own demand derivative (in absolute value). Using the market shares of 0.3 for Tylenol and 0.07 for Bayer (these are rough inside market shares as a fraction of total market including generics, without outside good), the pricing formula predicts a demand derivative for Tylenol of 0.3 and for Bayer of 0.067, which gives us a 1-to-4.6 ratio that is very close to the one that we get from the ratio of diversion ratios.

Whenever we have both diversion ratios, the diversion from small to large is greater than vice versa. This property would hold with a logit demand (recall for logit $d_{jk} = \frac{s_k}{1-s_j}$). For logit, d_{jk} is increasing in s_k (as customers are shed, they go to other brands in proportion to those brands' shares). This works well: the only, important, violation is from Tylenol to Advil and Aleve. However, other properties of the logit do not hold. For logit, d_{jk} is increasing in s_j but we see no clear relation in the table of diversion ratios on this count.

5.3 Damage and Spillover Measures

We now derive measures of the damage that comparative advertising delivers to the attacked brand and the spillovers to other brands. We use the coefficient estimates of λ from Column 2 of Table 3 and of the diversion ratios and ϕ from Column 1 of Table 4[27].

As discussed when deriving the condition (14), the full damage can be decomposed into a push and a pull effect. Table 5 shows the damage measures that we can estimate given the pattern of attacks observed in the data. Targets are column entries, and attackers are on

[27] Measures of damages using estimates from other specifications were also calculated and they exhibited similar patterns to those reported in Table 5.

the rows. The entries are written as dollar damages to targets from a \$1 marginal increment in comparative advertising by the attacker. These are all positive numbers, so are all costs inflicted.[28]

The first entry is the impact on k of j's self-promotion push-up. From (13), the damage to k is given as $\frac{s_k}{s_j} d_{kj}$, and so this term is reported whenever d_{kj} is reported. If we multiply this by λ we get the impact of the push effect of outgoing comparative advertising by j, and hence the second term in (14). The second entry in the Table is the direct pull effect of an attack by j on k, which is given by the first term in (14) as $\frac{s_k}{s_j} \frac{(1-\lambda)}{d_{jk}}$, and so this is reported whenever d_{jk} is reported. When both effects are reported (i.e., when we have the diversion ratios in both directions), we can sum the pull effect with λ times the pure push effect to generate the third entry, which is the total damage on the target of a marginal dollar of comparative advertising. We report the bootstrapped 90% confidence intervals in square brackets underneath the point estimates. Several remarks follow from Table 5.

First, imprecision in the results of Table 4 feeds through to imprecise results in Table 5. This can lead to very large numbers via small diversion ratios that appear in the denominator of the damage expressions. Still, some of the damage estimates (e.g. Advil on Tylenol) are very precisely estimated, and show that the damage is between 1 and 2 dollars for a marginal dollar of comparative advertising.

Second, the pull effect is much larger than the push effect (of self-promotion). For example, when Advil attacks Tylenol, Tylenol suffers a \$1.91 loss, but (marginal) self-promotion by Advil only causes a 4.6 cent loss. The pull effect is large because the target must be pulled down a lot in order to induce a brand to use comparative advertising, since the fall-out is shared among all other rivals (the size of the spillover is investigated below). This effect is exacerbated by the fact that the push effect of the comparative ad is only around half of what it would be with self-promotion.

[28] The damage numbers can be interpreted as the amount of self-promotional advertising needed to compensate for the marginal attack dollar.

TABLE 5: Measures of Damages

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

Notes: A row-column entry denotes attacker-target \$ damage from a marginal \$1 comparative ad attack, split up from top down as: push-up effect damage from attacker's self-promotion component of comparison; pull-down effect damage; and total damage as sum of these two. Bootstrapped 90% confidence intervals appear in square brackets underneath the point estimates.

Third, the asymmetry between the Bayer-Tylenol numbers is striking. Tylenol needs \$4.99 to negate a marginal Bayer attack, but Bayer needs only \$1.31 to offset a marginal Tylenol attack. The difference between Aleve-Tylenol and Advil-Tylenol is striking for being in the opposite direction. For example, Aleve takes \$3.60 to negate a marginal Tylenol attack on it, whereas Tylenol needs \$2.11 to negate a marginal Aleve attack. These differences are explained by the fact that the main component of damage is the pull effect, given by (14) as $\frac{s_k}{s_j}\frac{(1-\lambda)}{d_{jk}}$. Differences in diversion ratios and market shares across pairs then explain the results. Because the diversion ratios from Tylenol to other brands are systematically smaller than in the opposite direction, the marginal effect of Tylenol attacks is larger on Advil and Aleve, whose shares are quite similar. However, the much smaller Bayer share reverses this.

TABLE 6. Spillover Effects

Attacker Brand:	Target Brand:	Spillovers to: Advil	Bayer	Motrin	Tylenol
Advil	Aleve			0.484 [0.243,0.773]	0.373 [0.167,0.561]
Advil	Tylenol		0.090 [0.031,0.118]		
Aleve	Tylenol	0.328 [0.240,0.361]			
Bayer	Advil				0.067 [−0.110,0.221]
Excedrin	Tylenol	1.856 [0.696,6.723]			
Tylenol	Advil		0.424 [0.200,1.030]		
Tylenol	Aleve	0.106 [−0.029,0.234]			

A row-column entry gives the dollar effect on the column brand of a $1 increment in comparative advertising on the row link. Bootstrapped 90% confidence intervals are in square brackets below the point estimates. Confidence intervals are based on 100 draws on the asymptotic distribution of the estimates from Column 6 of Table 4 and from Column 1 of Table 5.

Table 6 shows that other brands are affected when brand j attacks brand k. First, the push-up effect on brand j hurts all other brands $l \neq j$, and the pull-down effect on brand k benefits all other brands $l \neq k$. The net effect (see (15) above) can a priori be positive or negative. For all our specifications, we find non-negligible, positive and statistically significant spillovers for all but two cases (Bayer's attacks on Advil and Tylenol's attacks on Aleve). These range from 9 to 48 cents for each dollar spent on a marginal attack, except for the outlier case of Excedrin on Tylenol, where Excedrin does very little comparative advertising and the estimates are unreliable due to the small number of observations of this target pair. Notice that the imprecise estimates in Table 4 feed through into imprecision in Table 6 (for example, Bayer vs. Advil). However, except for the outlier case of Excedrin against Tylenol, the intervals are smaller than those in Table 5. This is because the expression for spillover damage, (15), is written in terms of ratios of diversion ratios, whereas the damage to the target, (14), encompasses the reciprocal of a diversion ratio: small estimates of diversion ratios therefore give large damages and large confidence intervals.

Even though the results of Table 5 indicate much stronger pull-down effects on the target than push-up effects, the pull-down effect only benefits rivals to the extent that demand shed by the target is diverted to them.[29] But rivals are also harmed by the attacker's push-up component of comparative advertising. Nonetheless, our results in Table 6 indicate that the net effect on other brands is positive. The positive spillovers on other brands are quite substantial. For example, a marginal comparative advertising dollar spent by Advil against Aleve benefits Motrin by 48 cents and Tylenol by 37 cents, while benefiting Advil by \$1, and hurting Aleve by \$5.24 (from Table 5). We are unable to estimate the spillovers on the other brands because we are unable to estimate the diversion ratios from those other brands to both target and attacker (Excedrin attacks neither, while Bayer does not attack Aleve). Indeed, estimating the spillover on l when j targets k requires estimates of the diversion ratios d_{jk}, d_{lk}, and d_{lj}. In turn, this requires there to be active attacks from j to k and l, and from l to k. Hence we cannot estimate any spillovers from Motrin attacks because no brand attacks Motrin in return.

The estimates of spillovers indicate significant free-rider effects in comparative advertising, insofar as other brands are shown to benefit from comparative advertising (the harm from the push effect is dominated by the gains from the pull effect on the target). Last, this suggests that comparative advertising is insufficient (which it is if we exclude the target!), bear in mind that the costs to the target far outweigh the sum of benefits to attacker and other rivals. For example, a marginal dollar spent by Advil attacking Tylenol causes a \$1.91 loss to Tylenol (Table 5) and a 9 cent gain to Bayer (Table 6), and a \$1 benefit to Advil. The practice of comparative advertising causes far more loss in profit to the target (at the margin) than it recoups to the attacker and spills over to other rivals.[30] This, quite likely, explains why there are so few industries (in so few countries) where comparative advertising is used. Recognizing the mutual harm, companies refrain from attacks.

[29] This dilution of pull-down is already reflected in the attacker's calculus: it only gets a fraction of the demand lost by its target.

[30] Other ways of conceptualizing comparative advertising might soften this conclusion.

6 Robustness Tests

Because our estimated model is static, we need to check whether we introduce a bias in estimating the relationships between the main variables of the model by omitting dynamic effects. Our static model might be missing goodwill effects and firms may engage in pulsing of advertising. We discuss these two robustness tests below and leave several other tests for Appendix C.

6.1 Goodwill

Firms may engage in advertising efforts to build brand equity and goodwill, which can be usually interpreted as a stock variable that depreciates over time but can be replenished with advertising (Nerlove and Arrow, 1962, Roberts and Samuelson, 1988, Doganoglu and Klapper, 2006). In our setting, $\bar{A}_{jj}$ and $\bar{A}_{jk}$ might depend on the goodwill of a brand, and that goodwill might depend on past advertising of the brand. Omitting dynamic goodwill effects can be particularly problematic when brands are relatively new, especially brands that are introduced during the sample period, as they might be in the process of a significant goodwill buildup. Fortunately, OTC-analgesics is a mature and concentrated market, with no new brand entry happening during the sample period. Additionally, we have data on major news coverage that could potentially shift goodwill stock (see Appendix C.2).

We can check the importance of including a goodwill component by explicitly writing the structural unobservable component of perceived quality (or "brand base allure"), $\bar{A}_{jj}$, as a function of the observed past advertising expenditures. Specifically, we can rewrite $\bar{A}_{jjt} = \varphi \bar{A}_{jjt-1} + \Delta \bar{A}_{jjt}$,where $\bar{A}_{jjt-1}$ is the advertising goodwill index based on past levels of advertising, and $\Delta \bar{A}_{jjt}$ represents remaining unobserved brand allure. We then proceed to estimate the modified self-promotion relation (17):

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

Table 7 presents the results, which should be compared to those in the first two columns in Table 3. Column 1 of Table 7 shows the results when we do not include the Top Brand dummy. Column 2 shows the results with the dummy. The signs of the key model parameters α, λ, β are the same as those reported in Table 3 and are consistent with the predictions of the theoretical model. We also find that these parameters, like in the original model are precisely estimated and the magnitudes are similar. We also note that adding past advertising expenditures into the model makes the estimate of the Top Brand dummy imprecise, suggesting that the Top Brand dummy picks up the majority of advertising goodwill.

TABLE 7: Robustness checks

	(a) Goodwill		(b) Pulsing	
	Coef. (s.e.)	Coef. (s.e.)	Coef. (s.e.)	Coef. (s.e.)
φ	0.614 (0.042)	0.602 (0.043)		
α	0.062 (0.021)	0.131 (0.064)	0.130 (0.041)	0.395 (0.117)
λ	0.407 (0.061)	0.390 (0.063)	0.838 (0.117)	0.726 (0.123)
β	0.148 (0.053)	0.126 (0.056)	0.426 (0.095)	0.302 (0.106)
Top Brand dummy		-0.078 (0.068)		-0.898 (0.373)
Constant	-0.049 (0.018)	0.021 (0.030)	0.436 (0.095)	0.081 (0.173)
/sigma	0.150 (0.006)	0.150 (0.006)	0.454 (0.030)	0.443 (0.030)
Log-likelihood	132.712	133.375	-72.547	-69.721

25 left-censored observations at PositAdver<=0 for specification (1), 2 for specification (2)
317 uncensored observations for specification (1), 112 for specification (2)

Further evidence that goodwill effects beyond brand fixed effects are not significant in this industry at a monthly level of aggregation is presented in Liaukonyte (2015). The results employing alternative specifications with and without goodwill effects suggest that the more parsimonious contemporaneous advertising model is preferable.

6.2 Pulsing

A static equilibrium model can also be problematic if the time interval between observations is short (e.g., weekly, daily, or hourly data). High frequency patterns in advertising activity in such data (see e.g., Doganoglu and Klapper, 2006) suggest that firms may be following more involved strategies, such as "pulsing," which entails high/low advertising levels over short periods of time. For example, an advertising campaign might have a specific start date, and a series of ads will be run at quite a high intensity in one week and low intensity during another week. In many industries, there is a considerable lag (or at least a lull) until the next campaign starts up (a new "media blitz"). Such a pulsing pattern might be more effective than running ads at a steady level if there are attention thresholds for individuals' perception and advertising goodwill depreciation (Dubé, Hitsch, and Manchanda, 2005). However, when viewed at a low frequency, such as a monthly or quarterly aggregation level, observed levels of contemporaneous advertising can smooth out short-term pulsing, especially for mature industries such as OTC analgesics.

To check whether monthly data might exhibit some pulsing patterns and therefore bias our results, we employ a simple test. We compare how the results change when we use quarterly instead of monthly data. Clearly, the more one aggregates the data over time, the smoother the intensity of advertising becomes. Therefore 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 self-promotion equation (17) using quarterly data. Table 7 presents the results, which should be compared to those in the first two columns in Table 3. Column 1 of Table 7 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 3. This test suggests that pulsing is not an empirical concern at all in our setting.

7 Counterfactual: Banning Comparative Advertising

Comparative advertising as a form of advertising that explicitly identifies a competitor has always been a controversial topic among advertisers and competition authorities. For example, comparative advertising was illegal in many European countries until the late 1990s. Despite the prevalent use of comparative advertising, especially in the US, there is a widespread belief that this tactic has a potential to damage all competitors in an industry (Beard, 2013). One might suggest that the levels of advertising are indeed excessive in the OTC analgesics industry[31]. Thus, the purpose of our counterfactual is to analyze what would happen to industry advertising levels and profits if it were illegal to engage in comparative advertising.

Before we discuss how we implement the counterfactual analysis, we want to stress our

[31] As reported in Table 1, the advertising to sales ratios range from 17.4% for Tylenol to 28.8% for Bayer, which are several orders of magnitude larger than ad-to sales ratios in similar industries. For example, advertising in manufacturing industries accounts for only 3.2% of sales revenues, and the "Pharmaceutical Preparations" sector, which encompasses OTC analgesic products (standard industrial classification code 2834), has a 4.8% advertising-to-sales ratio (Schonfeld and Associates, 2005).

methodological approach so far, which clarifies the nature of the assumptions we are going to make next. We have deliberately estimated only the supply side of the model and steered clear of distributional assumptions on the demand side.[32]

First, we have maintained that a supply-side analysis directly explains the supply-side question of who attacks whom by how much, and the strategic use of different types of advertising to maximize profits; whereas a demand-side analysis is the best tool to investigate demand-side questions, such as the effects of different advertising content on demand. One contribution that we have made so far is to show how to fully exploit the information on the supply side to estimate the parameters of the model without adding unnecessary assumptions on the demand side. Specifically, we used the unique feature of comparative advertising that it targets a specific rival, which enables us to find demand-side relations in the form of diversion ratios. This would not be possible in a market with purely self-promotional advertising or with standard equilibrium pricing relations that conflate all effects into a single variable (advertising or price).

Second, to estimate the supply side we needed to make the equilibrium behavior assumptions explicit, which is not required in demand estimation.[33] Thus, we cannot address the question of this paper (what explains the attack matrix) without equilibrium behavior assumptions (here, Nash equilibrium with firms simultaneously setting prices and different advertising types).

In order to run a counterfactual exercise we need to solve for the new equilibrium values of prices, quantities, and advertising decisions. Our empirical analysis above enables us to recover some diversion ratio estimates by using the supply side advertising first order conditions. Here we use these estimates to construct a linear demand system that can be used to perform a counterfactual analysis of the impact of a ban on comparative advertising. This enables us to explore how the results of our supply side structural analysis above

[32] For our counterfactual, we do need to make such assumptions.

[33] However, any demand estimation that uses instrumental variables implicitly invokes an equilibrium model (although its explicit structure may be obscured) because the first stage instrumental variable regression is a reduced form equation of the RHS endogenous variables (e.g. prices). Thus, any demand estimation implies an equilibrium behavior assumption, even though it is not spelled out. In addition, in order to run counterfactuals on the supply side (as in Bresnahan, 1987, e.g.), we would still need to make an equilibrium behavior assumption. This is the counterpart to our need to make a demand functional form assumption when we run our counterfactual.

can deliver predictions about the impact on the market outcome of a ban on comparative advertising.

The linear demand is the simplest demand system that exploits the information from our estimates. In order to better understand the changes induced by the ban, we show the results of our counterfactual when proportionally decreasing the level of comparative ads from what is seen in the data down to zero.

We first describe the theoretical setting using the notation from the model description in Section 2. We assume that the share of firm j, s_j, is now given by the linear formulation

$$s_j = \mathcal{A}_j + \mathcal{B}_j \delta_j - \sum_{k \neq j} \mathcal{C}_{jk} \delta_k,$$

where $\delta_k = Q_k - p_k$ for all k. Quality Q_j is given by specification (16):

$$Q_j = \alpha \ln \left(A_{jj} + \lambda \sum_{k \neq j} A_{jk} - \beta \sum_{k \neq j} A_{kj} + \bar{A}_{jj} \right) - \phi \sum_{k \neq j} \ln(A_{kj} + \bar{A}_{kj}) + \bar{Q}_j \equiv \tilde{Q}_j + \bar{Q}_j,$$

where $\bar{Q}_j$ is the part of the utility that does not interact with advertising decisions. Next, let $\hat{\mathcal{A}}_j = \mathcal{A}_j + \mathcal{B}_j \bar{Q}_j - \sum_{k \neq j} \mathcal{C}_{jk} \bar{Q}_k$, and notice that it does not need to be decomposed into its constituent parts. Thus, we can write demand as

$$s_j = \hat{\mathcal{A}}_j + \mathcal{B}_j(\tilde{Q}_j - p_j) - \sum_{k \neq j} \mathcal{C}_{jk}(\tilde{Q}_k - p_k), \tag{20}$$

We now describe how the parameters $\hat{\mathcal{A}}_j$, $\mathcal{B}_j$ and $\mathcal{C}_{jk}$ can be derived from price first order conditions and the estimated diversion ratios. The price first-order conditions (7) yield

$$\mathcal{B}_j = \frac{s_j}{p_j - c_j},$$

with all the terms on the right-hand side being observed data (assuming c_j equals the generic price).

Next, recalling the diversion ratio definition in equation (1) and flipping j and k we have

$$d_{kj} = -\frac{ds_j/d\delta_k}{ds_k/d\delta_k}.$$

Because $ds_k/d\delta_k = \mathcal{B}_k$ and $ds_j/d\delta_k = -\mathcal{C}_{jk}$, we have $\mathcal{C}_{jk} = d_{kj}\mathcal{B}_k$. Using these relations, our estimated parameters for the $\tilde{Q}_j$ function and the data, $\hat{\mathcal{A}}_j$ can be calculated.

Before we proceed to run our counterfactual exercise, we need to address one last issue. Table 4 shows the estimated diversion ratios for the pairs for which we observe a sufficiently large number of periods of comparative attacks. However, we need the diversion ratios for all the possible pairs to have a complete demand system in order to run the counterfactual. We therefore look for diversion ratio values that can be used to calibrate our model. We start by using the first-order condition for comparative ads expressed as in (18).[34] After we define

$$\Delta_{jkt} = \frac{\alpha\beta}{A_{jj} + \lambda \sum_{k \neq j} A_{jkt} - \beta \sum_{k \neq j} A_{kjt} + \bar{A}_{jjt}} + \frac{\phi}{A_{jkt} + \bar{A}_{jkt}},$$

equation (18) can be written as

$$d_{jk} \leq \frac{1-\lambda}{\Delta_{jkt}} \cdot \frac{1}{M s_{jt}} \equiv d_{jkt}^{UB}.$$

When $A_{jkt} > 0$ the diversion ratio must equal the bound whereas when $A_{jkt} = 0$, all we can say is that the diversion ratio cannot exceed the bound. Then we use the bound for calibration.

These bounds provide different numbers in different periods, whereas we need a unique value for the diversion ratio parameter. We therefore take the average of the upper bounds across time periods, $d_{ij}^{UB} = \frac{1}{T} \sum_t d_{ijt}^{UB}$. In Appendix D.2 we explore another calibration strategy using the symmetry in our theoretical model. The results obtained using this method are to a large extent similar to those obtained by using the bounds method.

7.1 Solving the Counterfactual

The counterfactual consists of solving the equilibrium model where the six demand functions are given by (20), the six price first order conditions are (7), and the six self-promotion advertising first order conditions are (8). There are thus 3×6 equations that we use to solve for the 18 endogenous variables. We do not solve for the equilibrium comparative advertising decisions. Our objective is to study how the shares, prices, and self-promotion advertising decisions change as we exogenously proportionally reduce the amount of comparative ad

[34] Appendix C shows that the results are robust to different approaches.

expenditures in the counterfactual equilibrium. We thus redefine $\tilde{Q}_j$ as

$$\tilde{Q}_j = \alpha \ln \left(A_{jj} + \lambda\gamma \sum_{k \neq j} A_{jk} - \beta\gamma \sum_{k \neq j} A_{kj} + \bar{A}_{jj} \right) - \phi \sum_{k \neq j} \ln(\gamma A_{kj} + \bar{A}_{kj})$$

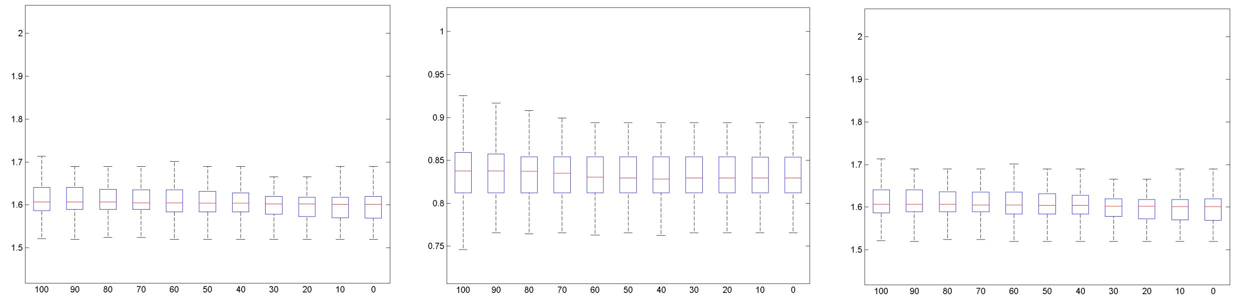
where $\gamma \in [0, 1]$ represents the proportional reduction in comparative ads. For example, if $\gamma = 0.3$, comparative ad levels are reduced to 30% of their original level. We show how the equilibrium changes as we exogenously draw down comparative advertising in 10% decrements from its observed level. Doing this enables us to verify that the counterfactual model with linear demand reacts smoothly and without discontinuities.

Figure 1 presents the results of our counterfactual exercise using box-and-whiskers plots. The line in the middle of the box is the median, and the box extends from the 25th to the 75th percentile. The whiskers extend from the 25th percentile to the 25th percentile minus 1.5 times the interquantile range at the bottom, and from the 75th percentile plus 1.5 times the interquantile range at the top. Thus, the plots provide a sense of the distribution of the counterfactual values of the variable of interest (total advertising, self-promotion advertising, prices, and profits) in our sample. We only report the results for the top three brands: Advil, Aleve, and Tylenol, and we refer the reader to Appendix D.1 for the results for the other brands.

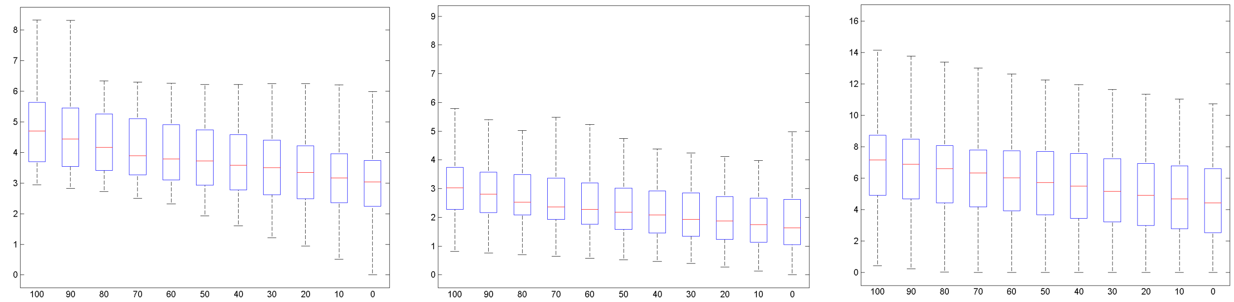
FIGURE 1.. Results of the Counterfactual of Banning Comparative Advertising

ADVIL ALEVE TYLENOL

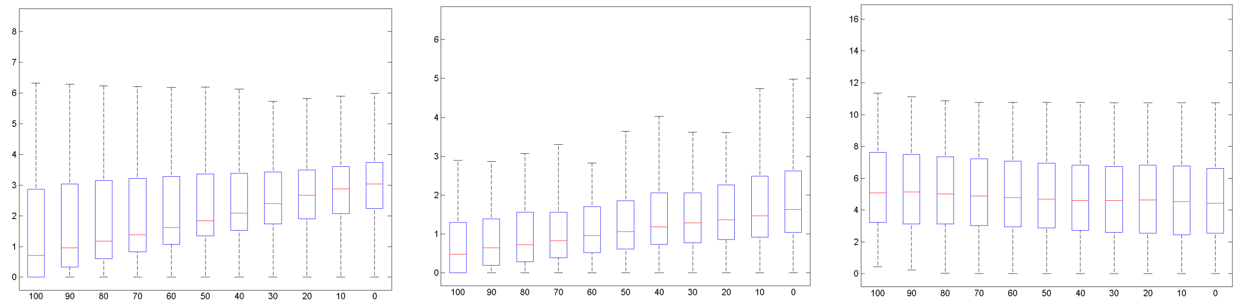
Prices ($)



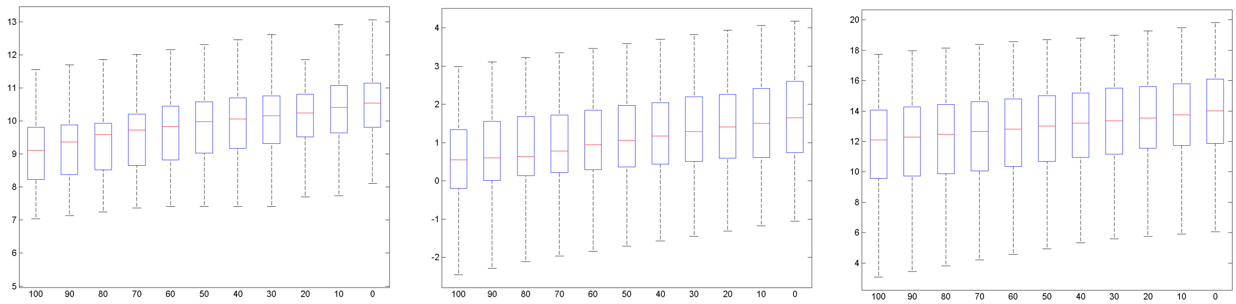
Total Advertising Expenditure (mln $)



Total Self-Promotion Advertising Expenditure (mln $)



Total Profits (mln $)



Notes: The center red line denotes the median; bottom and top of each box correspond to interquantile range (between 25th and 75th percentiles); whiskers extend to the most extreme data points falling within 1.5 times the width of the interquantile range.

First, we find that total advertising levels show fairly strong declines (with the exception of Excedrin, a minor player, see Appendix D.1 for a complete set and discussion of counterfactual results). Brands are therefore saving money on advertising expenses. The greatest saving is for Tylenol, although the percentage drop for Aleve is larger. The decomposition of the drop is interesting. Tylenol's self-promotion falls as comparative ads are progressively eliminated. This reflects the large reduction in attacks against Tylenol and so it has less use for self-promotion as a defensive measure. However, Advil and Aleve see marked rises in self-promotion. As comparative advertising is drawn down, they substitute the combined push-up and pull down impact of comparative advertising with the pure push-up impact of self promotion.

Both prices and equilibrium sales are roughly the same as we scale back comparative ads, reflecting the scaling back of ads as a whole but taking out the sting of the comparative part. The profit comparison illuminates the role of comparative advertising in the industry. For example, Tylenol's profits go up nearly \$2 million (per month) while its total advertising goes down over \$2 million. Thus its profit goes up less than its cost saving, its sales register a mild decrease as a result. Nevertheless, the similarity between the costs saved and the higher profit are suggestive of a "combative" view of comparative advertising in the sense that it mainly reshuffles profit among competitors[35] (if we take away the capability for all to do it, all are better off by the saved spending so that engaging in comparative advertising can be viewed as a form of prisoners' dilemma). However, for other brands the pattern is less pronounced, with advertising not being pure loss. For example, Advil spends nearly \$2 million less on ads, but its profits go up by less than only a quarter or so of that. Aleve's position (in absolute terms) is quite similar. So while banning the practice raises profits across the board, they do not go up by quite as much as ad spending falls (partly because the ad spending is refunnelled into self-promotion for Advil and Aleve), but the results indicate that the practice tends to hurt the industry as a whole.

At first blush, these counterfactual results seem different from our findings for the local effects of rebalancing comparative advertising, which indicate quite strong damage from a marginal comparative ad. However, the thought experiment in the counterfactual is quite

[35] In Marshall (1890, 1919) combative advertising reshuffles demand but does not increase the market size. See Renault (2015) and Bagwell (2007) for further discussion.

different from that in the damage analysis of Section 5.3, where we look at a local reduction of a dollar of comparative advertising against one target. Here we reduce comparative advertising across the board, so that gains from reducing incoming attacks are juxtaposed with increasing rival's perceived brand allure (qualities). To illustrate (loosely), suppose that all qualities rose by 1 because of reduced incoming attacks. Then the effect on brand j through own quality is to raise quantity by $\mathcal{B}_j$. But the effect through higher rivals' qualities is to reduce j's quantity by $\sum_{k \neq j} \mathcal{C}_{jk}$. As long as the latter term is similar in magnitude to the former (as is roughly confirmed in the data), then the overall impact is neutralized. This is to be contrasted with a reduction in a unilateral attack that raises j's quantity by $\mathcal{B}_j$ (and increases the erstwhile attacker k's quality by only $\mathcal{C}_{kj}$) without the countervailing demand reduction through higher rival qualities.

8 Conclusions

This paper models comparative advertising as having both a "push up" effect on own perceived quality, and a "pull-down" effect on a targeted rival's quality. The targeting of comparative advertising affords a unique opportunity for estimating diversion ratios between products solely from observed supply side comparative advertising expenditures. Diversion ratios are direct inputs into deriving estimates for the damage inflicted from comparative advertising and the spillover to other brands.

The empirical results for the OTC analgesics market indicate that the push-up effect from a marginal comparative ad is about half the push-up effect from a marginal self-promotion ad and that there is a significant pull-down effect on a targeted rival. The benefit from pull-down for an advertiser is much smaller than the damage inflicted on the target, while conferring significant net benefits on other rivals. In the aggregate, we find that comparative advertising causes more damage to the targeted rival than benefit to the advertiser.

We simulate a counterfactual in which comparative advertising explicitly mentioning a competitor's brand is banned. We find that such a ban leads to a decline in total advertising expenditures and an increase in profits. Our results are consistent with a widespread belief in the advertising world that comparative advertising has the potential to damage all competitors. The executives behind a number of comparative advertising campaigns (e.g., "Soup Wars" between Campbell's and Progresso, Unilever vs. Campbell "Spaghetti Sauce wars", "Burger Wars", "Cola Wars", "Baking Soda wars", etc.) have all acknowledged the unintended consequences of such advertising strategies – excessive levels of advertising due to persistent attacks and counter-attacks (Beard, 2013). Negative political advertising campaigns have also been the subject of similar worries.

Furthermore, our results are largely consistent with the idea that brands are using advertising as a defensive measure against comparative advertising targeting their brand and that advertising may play a "combative" role by reshuffling profit among competitors. Overall, we find that comparative advertising tends to hurt the OTC analgesics industry as a whole and that the advertising levels observed in this industry (which are serval orders of magnitude larger than advertising levels in similar industries that do not engage in comparative advertising) might indeed be excessive.

Our results might not be broadly applicable to all industries that engage in comparative advertising and we do not suggest that banning comparative advertising is always a preferable outcome. Our analyzed industry is mature and comprised of well established brands. Comparative advertising may be desirable in highly dynamic industries as a means to efficiently communicate product advantages of new products relative to the existing brands. In fact, the Federal Trade Commission (FTC) encourages the use of comparative advertising as long as it is truthful and substantiated because, such advertising may be a source of information to consumers and assist them in making purchase decisions. Our analysis highlights damage caused by comparative advertising, but future work should consider the informational role of such comparisons as well.[36] A first step in this direction is taken by Anderson, Ciliberto, and Liaukonyte (2013), who employ a much simpler, non-strategic, theoretical framework than the one developed here to explain the number of information cues in ads.

[36] When consumers have different tastes over different characteristics, then comparative advertising can convey information to consumers. However, it should then be expected that comparative advertising contains information that the target would choose not to include in its own ads. It would then incur a loss in profit that could outweigh the benefits to other parties. Anderson and Renault (2009) show that comparative advertising may induce the target to decrease its price and the losses thus inflicted may outweigh the benefits to the attacker and to consumers, so social surplus decreases. An informative advertising approach yields the same potential ambiguity as the push-pull set-up with regard to the desirability of comparative advertising for industry profit.

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