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Push-Me Pull-You: Comparative Advertising in the OTC Analgesics Industry

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Push-Me Pull-You: Comparative Advertising in the OTC Analgesics Industry*

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Abstract

We investigate how firms strategically use self-promoting and comparative advertising to push up own brand perception along with pulling down the brand images of targeted rivals. To this purpose, we first watch individual video files of all TV advertisements in the US OTC analgesics industry for the 2001-2005 time period to code the content of each ad and organize it into a unique and novel dataset. Then, we develop a simple model of targeting advertising, which we use to derive the advertising first order conditions that predict oligopoly equilibrium relations between advertising levels (for different types of advertising) and market shares.

We find: i) higher market shares are associated with higher self-promotion advertising; ii) outgoing attacks are half as powerful as direct self-promotion ads in raising own perceived quality; iii) every dollar spent by its competitors on incoming attacks has a statistically and economically strong effect on the perceived quality of the attacked brand.

Keywords: Comparative Advertising, persuasive advertising, targeted advertising, analgesics.

1 Introduction

This paper investigates how firms strategically use self-promoting and comparative advertising to push up own brand perception along with pulling down the brand images of targeted rivals.[1] While self-promotion advertising involves only positive promotion, a comparative advertisement, by comparing one's own product in favorable light relative to a rival, has both a positive promotion component (in common with self-promotion advertising) and an indirect effect through denigrating a rival. Denigration can be per se advantageous insofar

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[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.

as consumers who switch from the demeaned product are picked up by the denigrating firm. However, they may also be picked up by other rival firms. This logic indicates a possible free-rider situation in the provision of comparative advertising against any particular rival, but it also indicates an equilibrium at which each firm's positive promotion (through both comparative and self-promotion channels) is devalued by others' comparative advertising. In this paper we propose a simple model of targeting advertising to determine which firms engage in what kind of advertising against whom, and then use a novel dataset from the Over-The-Counter (OTC) analgesics industry in the US to look for whether those relationships are actually there and how large they are.

Our push-pull model is based on a discrete choice approach to demand, in which firms' perceived qualities are shifted by advertising. The way in which advertising enters the model is most simply thought of as persuasive advertising that shifts demand up.[2] Promoting one's own product increases demand directly, whether through self-promotion advertising or comparative advertising, while denigrating a rival helps a firm indirectly by decreasing perceived rival quality.[3] By hurting the rival product directly, some consumers are diverted, and the comparative advertiser succeeds in attracting some portion of those consumers.

We use our simple model to derive the advertising first order conditions that predict oligopoly equilibrium relations between advertising levels (for different types of advertising) and market shares. In particular, we use the equilibrium pricing (first-order) conditions to eliminate prices from the relation between advertising and sales.[4] ! 2

advertising. We must therefore look at each individual ad and determine whether or not it is comparative, and, if so, which is the target brand. This therefore requires a detailed coding of advertising content. Ideally, we should be able to analyze an industry for which comparative advertising is prevalent and represents a large fraction of industry sales, for which data on spending on ads is available for a full sample of firms and for a reasonably long period of time. Furthermore, video files (or audio files for radio ads or photographic files for newspaper/magazine ads) need to be available and their content readily coded for the desired information of comparison and targets. Fortunately, all these criteria are met with the US OTC industry.[6] We use data on national sales from AC Nielsen and advertising data on advertising expenditure (and movies) from TNS - Media Intelligence.

The crucial novelty of our approach is to code advertising content (focusing on comparative advertising) and organize it into a unique and original dataset.[7] We watched more than four thousands individual video files of all TV advertisements in the US OTC analgesics industry for the 2001-2005 time period and coded them according to their content. Specifically, we recorded whether the commercial had any comparative claims – whether the product was explicitly compared to any other products. If a commercial was comparative, we also recorded which brand (or class of drugs) it was compared to (e.g. to Advil or Aleve; or to Ibuprofen-based drugs).

There are two main methodological concerns that we need to address when estimating the advertising first order conditions: left-censoring of self-promotion and comparative advertising and endogeneity of market shares and advertising expenditures. Left-censoring occurs because in some periods some brands do not engage in self-promotion or comparative advertising (there are corner solutions). We control for the left-censoring by running Tobit regressions.

To control for the endogeneity of market shares and advertising expenditures, we use brand fixed effects and two sources of exogenous variation. First, we construct a dataset of news shock that hit the OTC analgesic markets in the time period of analysis.[8] These shocks might interact with the advertising decisions, and thus we cannot use them straight up as instrumental variables. However, adding these news shocks improves our empirical analysis dramatically.

Second, we use data on the prices of the generic products to construct measures of the marginal costs that

[6] Indeed, while explicit comparative advertising has flourished in the United States over the past 20 years (with the blessing of the FTC), its prevalence varies widely across industries. The US OTC analgesics industry (basically, medicine for minor pain relief, involving as major brands Advil, Aleve, Bayer Aspirin, and Tylenol) exhibits high advertising levels in general, and extraordinary levels of explicit comparative claims on relative performance of drugs.Most of the advertising expenditures are for television ads.

[7] See Liaukonyte (2009) for a paper that estimates demand-side parameters using this same dataset.

[8] As we discuss later on, we follow an approach similar to Chintagunta, Jiang and Jin (2007) when constructing our dataset of news shocks. In particular, between 2001 and 2005, the OTC analgesics market endured several major medical news related "shocks". The most notable, but by no means the only ones, of these were the following. The withdrawals of the Prescription NSAIDs Vioxx (October, 2004) and Bextra (April, 2005) affected the OTC NSAIDs market (which excludes Tylenol). Naproxen sodium, the active ingredient in Aleve was linked to increased cardiovascular risk, which led to a significant sales decrease for Aleve (December, 2004). The main idea here is that these shocks act as many natural experiments. The idea of using a natural experiment to study the effect of advertising (on prices) is the crucial insigth in Milyo and Waldfogel [1999].

firms face to produce the corresponding branded product. Here, the generic price of a pill of Acetaminophen is used as an instrumental variable of the share of Tylenol, whose main active ingredient is Acetaminophen. Thus, the prices of the generic products are the variables that are excluded from the utility function and that we use as instrumental variables in the estimation.[9] We show that adding the news shocks removes most of the endogeneity bias we could uncover, and the exclusion restriction on the generic prices provides, in practice, only a marginal contribution to the empirical analysis.

The main results are the following. With regard to self-promotion advertising we find: i) higher market shares are associated with higher self-promotion advertising, with an elasticity of self-promoting advertising expenditures to shares estimated to be between 1 and 1.5; ii) outgoing attacks are half as powerful as direct self-promotion ads in raising own perceived quality; iii) every dollar spent by its competitors on incoming attacks has a statistically and economically strong effect on the perceived quality of the attacked brand..

With regard to comparative advertising we find that firms have a greater incentive to attack larger firms, and this incentive is increasing in the share of the attacker, with the elasticities of comparative advertising expenditures to own market shares and to market shares of the attacked firm equal to 1. This result has a nice and simple interpretation: the return to attacking a large firm is higher than the return to attacking a smaller firms, since by attacking a larger firm, the attacker can hope that a larger pool of consumers switch away from the attacked to the attacker. Similarly, a large firm has a stronger incentive than a smaller firm to attack because the probability that consumers switch to the larger firm is higher than the probability that consumers switch to the smaller firm. We also find that firms carry attacks on their competitors jointly.

The paper is organized as follows. In the next section we review the literature. Section 3 presents the theoretical model. Data and industry background are discussed in Section 4. We present the empirical specification and discuss identification of the model in Sections 5 and 6. Section 7 discusses results and Section 8 provides the robustness analysis. Section 9 concludes.

2 Literature Review on Advertising

A lot of the economics literature on advertising has been concerned with the functions of advertising, and whether market provision is optimal. We here take more of a marketer's stance that advertising clearly improves demand (otherwise firms would not do it), and we take a rather agnostic view of how the advertising actually works on individuals, and bundle it all into a single "persuasive" dimension. Since we do not cover here the normative economics of the advertising, this is less controversial. The innovations we pursue are in advertising competition, and in the new strategic direction of comparative advertising.

[9] In addition we can interact these shocks with the price of the generic products and increase the number of instrumental variables that we use.

2.1 Theoretical Literature

Much of the economic theory of advertising has been concerned with the mechanism through which advertising affects choice, and the welfare economics of the market outcome.[10] Moreover, much work has considered very particular market structures, most often monopoly.[11]

Persuasive Advertising. Much of the early work linked advertising to market power, and reached a fairly negative assessment that advertising is a wasteful form of competition. Kaldor (1950) and Galbraith (1958) saw the differentiation achieved by advertising as spurious and artificially created by persuasion. Such persuasive advertising was thought to decrease social welfare by deterring potential competition and creating barriers for new entrants. Dixit and Norman (1978) propose viewing persuasive advertising as shifting demand curves out, but they then take an agnostic view as to the welfare effects of the shift (i.e., whether the demand curve before or after the advertising is a better representation of the true consumer benefit from consuming the good).[12] Regardless, they suggest that there is a tendency for too much advertising.

Informative Advertising. The persuasive view and the idea that advertising fosters monopoly was first challenged by Telser (1964) who argued that advertising can actually increase competition through improving consumer information about products (see also Demsetz, 1979).[13] Butters (1977) later formalized a monopolistically competitive model of informative advertising about prices, in which the level of advertising reach is socially optimal. These results were tempered somewhat by Grossman and Shapiro (1984), who extended the advertising content to include (horizontal) product differentiation.[14]

Another informative role, albeit indirect information, is at the heart of "money-burning" models of signaling product quality. Nelson (1970, 1974) claims that advertising serves as a signal of quality, especially in experience good markets, and reasons that consumers will rationally conclude that a firm doing a lot of advertising must be selling a product of high quality. These insights were later formalized and further developed, most frequently by using repeat purchases as the mechanism by which a high-quality firm recoups its advertising investment.[15] Kihlstrom and Riordan (1984) show a role for dissipative advertising in a perfectly competitive model. Milgrom and Roberts (1986) break out different roles for signaling quality through (low) price and through advertising by a monopoly, again using a repeat purchase mechanism.

[10] See Bagwell (2009) for a comprehensive survey.

[11] Almost all the signaling literature considers monopoly, with the notable exception of Fluet and Garella (2002) who consider a duopoly. The classic Butters (1977) model of informative advertising considers monopolistic competition and a homogenous good with zero profits sent on each message. Grossman and Shapiro (1984) allow for oligopoly and product differentiation (around a circle), but they use symmetry assumptions liberally.

[12] This analysis is not uncontroversial: see the subsequent issues of the RAND journal for comments, replies, and rejoinders. Dixit and Norman (1978) posited that advertising increases demand, and then perform the welfare analysis using consumer surplus measures from that starting point, according to which demand curve embodies "true" tastes.

[13] Indeed, informative advertising can reduce consumers' search costs to learn about the existence of products, their prices, qualities, and specifications.

[14] Cristou and Vettas (2008) analyse a non-localized discrete choice version of the Grossman-Shapiro model.

[15] Another mechanism is to suppose some consumers are informed already, so a low-quality firm has to distort its price so high to mimic the high-quality one that it does not wish to do so.

Fluet and Garella (2002) show that under duopoly there must always be dissipative advertising by the high quality firm if qualities are similar enough.

Advertising as a Complementary Good. Another foundational role for advertising is proposed by Stigler and Becker (1977) and Becker and Murphy (1993), who argue that advertising can be viewed as part of consumers' preferences in the same way as goods directly enter utility functions, and that there are complementarities between advertising levels and goods' consumption. Hence, ceteris paribus, willingness to pay is higher the more a good is advertised. The complementary goods approach affords one clean way for advertising to affect directly consumer well-being, and so gives a way of thinking about persuasive advertising.

The specification we use in our model is most directly interpreted in this vein of complementary goods, insofar as we can interpret that advertising expenditures as boosting demand. However, since we will not be doing a welfare analysis with the model, we are not constrained to this interpretation, but instead our approach is broadly consistent with advertising as a demand shifter (as in Dixit and Norman, 1978).

2.2 Modeling Comparative Advertising

The theoretical economics literature on comparative advertising is quite scarce. Modeling comparative advertising presents several alternative potential approaches. In common with much of the economics of advertising, these are perhaps complementary rather than substitute approaches, and elements of each are likely present (in different strengths) in different applications. Each though has drawbacks, and sometimes the predictions (e.g., comparative static properties) differ in direction.

One early contribution is Shy (1995), who argues that comparative advertising of differentiated products informs consumers about the difference between the brand they have purchased in the past and their ideal brand. The model explains only brand switching behavior, because according to that setting comparative advertising is meaningless for the inexperienced consumer as she would not be able to comprehend an ad involving a comparison of the brands' attributes that she never consumed. Aluf and Shy (2001) model comparative advertising using a Hotelling-type model of product differentiation as shifting the transport cost to the rival's product.

Horizontal Match. Anderson and Renault (2009) model advertising as purely and directly informative revelation of horizontal match characteristics of products.[16] Revelation of such information increases product differentiation, although this does not always increase firm profits. Comparative advertising in this context is modeled as revelation of characteristics (match information) of the rival product along with own charac-

[16] That paper builds on Anderson and Renault (2006), who show that a monopoly firm might limit information about its product attributes even if advertising has no cost. This result identifies situations where a firm is hurt by information disclosure about its own product, so there might be incentives for competitors to provide that information through comparative ads.

teristics. One key finding is that (under duopoly) comparative advertising is carried out by the smaller firm against its larger rival, and arises if firms are different enough.[17]

It is not immediately evident how these results extend to more firms, except insofar as an industry of roughly similar size firms would be expected to not deploy comparative advertising since individual incentives to broadcast own information should suffice. Otherwise, with firms of different sizes, there is a free-rider aspect to comparative advertising, that others (apart from the target) might benefit from it. A medium size firm might benefit from advertising relative to a large rival, but might lose relative to smaller ones. Small ones might have little to gain if indeed their small size stems from inherent disadvantages. However, it is not easy to introduce multiple firms in this context of asymmetric information divulging and hence asymmetric product differentiation.

The present model also relates the pattern of ads to market shares, but it treats the role of advertising differently. We do not model the informational content of the advertisement. Empirically we are unable to separate whether advertising was persuasive or informative, so we remain agnostic about the advertising effects and focus just on separation of comparative and self-promotion ads.

It is also important to note that the role of advertising in the Anderson-Renault (2009) model is only to divulge horizontal match information, which is two-edged sword – what characteristics one consumer likes, another dislikes. The analysis is phrased in terms of informing all consumers: it does not allow for advertising reach that tells only some. The same critique can be leveled at other models in the field, as well as (perhaps to a lesser degree) the model we actually propose here; and we return to this criticism in the conclusions.

Signaling. Another approach to modeling comparative advertising takes as staging point the signaling model of advertising, which goes back to insights in Nelson and was formalized in Milgrom and Roberts (1986). The original theory views advertising as "money-burning" expenditure which separates out low-quality from high quality producers. Equilibrium advertising spending, in this adverse-selection context, smokes out the low type because a low-type would never recuperate in repeat purchases the high level of spending indicated in equilibrium. The comparative advertising version of this theory expounded in Barigozzi, Garella, and Peitz (2006) relies on the possibility of a law-suit to punish an untrue claim. Recently, Emons and Fluet (2008) also took a signaling approach to comparative advertising, although their analysis relies on advertising being more costly the more extreme are the claims it makes, instead of a law-suit.

Persuasion Games. In parallel work, we are developing another approach along the lines of the Persuasion

[17] To understand the incentives to advertise requires understanding the benefits of more information on each firm's profits. With no information at all, firms are homogenous apart from the quality advantage, and the large firm can price out its advantage and still serve the whole market. It has no incentive to advertise because, while such advertising will raise the willingness to pay of consumers who discover they appreciate its product, it will also decrease the valuations of those who discover they like the product less than average, and so the firm will lose customers to its rival as well as having to price lower to staunch the loss of consumer base. This means that the large firm does not want to advertise, while the smaller rival does. These incentives extend to comparative advertising, which further enhances differentiation and further erodes the customer base (and price) of the larger firm to the advantage of the smaller one.

Game of Milgrom (1981) and Grossman (1981). In this work the firms must (truthfully) announce levels of product characteristics their products embody. Comparative advertising, through this lens, involves announcing characteristics levels of rivals that those rivals would prefer to keep silent. However, the actual ads are quite vague for the most part in specifics of actual claims (e.g., a product may act "faster" than another, but it is not usually specified how much faster, or indeed what the response time in minutes is for the two products or the statistical significance of the difference across different individuals, etc.)

2.3 Empirical Literature

In this Section we discuss the papers that are most closely related to ours and discuss the original contributions of our paper.[18] To do this, we identify four modeling choices that have to be made when empirically studying advertising: how to measure advertising; whether to use a static or a dynamic model of advertising; whether to have a partial or a full equilibrium model, where both consumer and firm sides of the market are explicitly modeled; and whether to model advertising as having only a persuasive or informative effect, or both. Next, we discuss how the literature has dealt with these choices.

Advertising Content. Ours is the first paper to code the content of advertising into self-promotion and comparative ads and use the information to address the incentives to use the different types of advertising.[19] Previous papers have used total ad expenditures as the sole advertising explanatory variable (notable examples are Nevo, 2000 and 2001, and Goeree, 2008). Here, because we have data on content, we break down the ad expenditures into comparative and self-promotion expenditures, and the comparative expenditures are further broken down into attacker-target pairs. We then look at the first order conditions of the advertising decisions, and so estimate the choice of advertising of the different types from the supply side. In related work with the same data, Liaukonyte (2009) estimates a model of demand where self-promotion and comparative advertising are found to have different quantitative effects on consumer choices.

Dynamic vs. Static and Partial vs. Full Equilibrium Models. We estimate a static model of firm behavior, where firms jointly choose product prices and advertising levels. We consider a full equilibrium static model of the advertising and product markets, where advertising is determined endogenously within the model. We use the first order conditions and demand equations for the product (analgesics) to solve the prices out of the first order conditions for advertising. This procedure yields simple relations between ad levels and market shares, which we term "quasi-reaction functions" (they are not the full reaction functions

[18] For more detail on the broader findings of the literature, see Bagwell's (2007) superb review of the empirical literature on advertising.

[19] Contemporaneous and independent work by Crawford and Molnar (2009) looks at advertising content of TV ads for Hungarian mobile telephony. They estimate a demand model, in the same fashion as Liaukonyte (2009). Anderson and Renault (2008) study newspaper ads for airlines, and they code their content. In the former case, only 5% of ads are comparative, and even fewer in the latter case. For Hungarian telephones, much of the advertising concerns prices; in analgesics, virtually none. For airlines, mainly the low-cost carriers emphasize prices.

because they still include market shares, which in turn depend on all prices and all advertising). We estimate the structural parameters of the model from these advertising first order conditions.

Because advertising is likely to have long-run effects on demand, the decision to use a static model to study advertising needs to be carefully justified. This modeling decision is tightly linked to another one: whether or not to have a full equilibrium model of the advertising and product markets. In short, estimating a fully dynamic equilibrium model even of just the product market is beyond what is feasible at this stage of the literature.[20] Previous work in advertising has either estimated a dynamic model of demand (Hendel and Nevo, 2006, and Gowrisankaran and Rysman, 2009) or has looked at a static model of demand and a dynamic model of supply (Roberts and Samuelson, 1988, and Dube, Hitsch, Manchanda, 2005).

Thus, a practical choice must be made. Either one models only one side of the market in a dynamic setting and must relinquish analyzing a full equilibrium model. Or else one can analyze a full equilibrium static model. In this paper we follow the second route. Clearly, these two approaches are complementary and provide different insights into the role of advertising. Most importantly, a static model simplifies the treatment of advertising as an endogenous variable. To our knowledge, all papers that study advertising in a dynamic context treat it as an exogenous variable (notable examples are Erdem and Keane, 1996, Ackerberg, 2001 and 2003, and Dube, Hitsch, Manchanda, 2005).[21]

Persuasive vs. Informative Advertising. The last modeling choice is about the way that advertising affects consumer choice. Ideally, one would like advertising to have both an informative and persuasive effect. The informative effect has been modeled using a Bayesian learning model (Erdem and Keane, 1996, Ackerberg, 2003), a limited consumer information model based on information sets (Goeree, 2008), or horizontal match information models (Anderson and Renault, 2008, and Anand and Shachar, 2004). The persuasive effect is easier to model, as advertising is simply introduced into the utility function (e.g. Nevo, 2001, Shum, 2004).[22] There are only two papers that allow for both effects to be present, both by Ackerberg (2001, 2003).

In order to identify the persuasive from the informative role, Ackerberg (2001, 2003) analyzes consumer reactions to the advertising of a new product (the yogurt Yoplait 150). Essentially, advertising is only informative for first buyers, while it is both informative and persuasive for repeat buyers.[23] This is a clever

[20] The problem is both computational complexity and multiplicity of solutions. One would have to solve for rational and consistent expectations that consumers and producers have on the future values of the state variables, which means solving for a fixed point. There might be multiple future values of the state values for which such consistency requirements hold (that is, there might be multiple equilibria).

[21] Although the latter paper presents a dynamic theoretical model of advertising, the econometric study estimates only the demand side parameters. These estimates are then used to calibrate the theoretical dynamic model.

[22] Gasmi, Laffont, and Vuong [1992], Kadiyali [1996], and Slade [1995] postulate a set of residual demand functions, which include advertising. Thus, the interpretation of the role of advertising as persuasive or informative is not transparent.

[23] Ackerberg (2001, 2003) argues that the observed facts that "experienced" consumers (those who have previously bought Yoplait 150) are much less sensitive to advertising than inexperienced ones is strong evidence in favor of advertising fulfilling an informative role rather than a "prestige" one. However, he does not control for the content of the particular ads in his sample; nor does he allow for the possibility (in his interpretation) that advertising 'prestige' could exhibit strong threshold effects, which could also account for the observed behavior.

identification device, but we cannot use it here because we have aggregate and not individual data (that is, we cannot identify first buyers).[24]

Our Push-Pull perspective on advertising is coherent with the persuasive view. In addition to positive persuasion on own quality, comparative advertising also gives negative persuasion on rivals.

Review of Similar Models of Advertising. We conclude this Section with a review of the three papers which deploy models of price and advertising competition that are close to ours.[25]

Gasmi, Laffont, and Vuong (1992) propose an empirical methodology for studying various types of collusive behavior in pricing and advertising. They derive two first order conditions (for prices and advertising) and one demand equation (for the product market, cola) for each firm and estimate them all jointly.[26]

Roberts and Samuelson (1988) estimate a model where demand is modeled statically, while supply is modeled dynamically. By assuming that firms have perfect foresight of future input prices, Roberts and Samuelson end up estimating a set of first order conditions for prices and advertising, as well as demand equations. Thus, even if they start from a dynamic supply model, in practice the system of equations they estimate is quite similar to the one considered by Gasmi, Laffont, and Vuong (1992).

Goeree (2008) considers a discrete choice consumer model under limited information, where advertising influences the set of products from which consumers choose to purchase, but does not enter into the utility function. She derives first order conditions for advertising and prices, as well demand functions for the products (computers).

In many ways our approach is similar to the ones used in these three papers. We also use a theoretical model to derive the first order conditions for prices and advertising. There are, however, important differences between our work and theirs. The main methodological differences are related to how we code advertising content, how we model demand, the nature of the exogenous variation that we use to identify the model, and how we estimate the parameters of the model.

First, all three look at the total advertising expenditure, while we distinguish between comparative and self-promotion advertising expenditures.

Second, our demand (as well as Goeree's, 2008) is derived from a discrete choice model, while Gasmi, Laffont, and Vuong (1992) and Roberts and Samuelson (1988) postulate a set of residual demand functions. We have in common with Roberts and Samuelson (1988) a market expansion effect and a share effect, although we do not have the possibility that rivals' demands can rise with own advertising.

[24] This identification assumption excludes the possibility that a first buyer of a new product might have consumed other products of the same brand in the past, otherwise it is unclear that there is no persuasion effect for that type of buyer. Thus, while very clever, this assumption might not hold in practice.

[25] Other papers (e.g. Shum [2004] or Nevo [2000,2001]) that use static models assume that advertising is exogenous, though they justify that assumption in their contexts. Clearly, these papers do not include first order conditions for advertising.

[26] Kadiyali [1996] proposes an empirical methodology to investigate strategic entry and deterrence, where firms compete in prices and advertising. Since she closely follows Gasmi, Laffont, and Vuong [1992], the methodological differences between her paper and ours are the same as those between our paper and Gasmi, Laffont, and Vuong [1992].

Third, we use a combination of exogenous shocks and firm-specific generic prices to construct sources of exogenous variation in the data. By contrast, Gasmi, Laffont, and Vuong (1992) use aggregate variables (e.g. the price of sugar). Roberts and Samuelson (1988) use aggregate variables (e.g. cost of capital) and the number of own and rival brands.[27] Goeree (2008) uses the type of instrumental variables introduced by Bresnahan (1987): the characteristics of the products produced by competitors. Because we look at brands and not products, such instrumental variables cannot be used in an obvious way (brands have many differentiated products).

Finally, our estimation methodology is different from those in the other papers. While they estimate a full set of simultaneous equations, we use the first order conditions for prices to solve prices out of the advertising first order conditions. Thus, we fully exploit the theoretical model in the same way that they do, but we reduce the number of equations to be estimated. If the model is correctly specified (which is the maintained assumption in their studies, as in ours), then the estimation results should be the same under the two approaches.[28]

3 The Model

The theoretical model suggests certain regularities between market shares and both self-promotion and comparative advertising. We first describe the demand side assumptions and then we derive the equilibrium relations from the model. These take the form of advertising intensities as a function of market shares, and they form the basis of the estimation which follows. As we will see, several key predictions are supported by the data.

We assume that each product is associated to a quality index and demand depends on the quality indices of all firms, in a manner familiar from, and standard in discrete choice analysis. These quality indices are influenced positively by own advertising (both self-promotion and comparative) and negatively by competitors' comparative advertising. They are also influenced by medical news shocks which unexpectedly indicate good news or bad news about the health effects of the product(s).

3.1 Demand

Suppose that Firm $j = 1, ...n$ charges price p_j and has perceived quality $Q_j\left(.\right)$, $j = 1, ...n$. We retain the subscript j on $Q_j\left(.\right)$ because when we get to the econometrics, exogenous variables such as medical news shocks and random variables summarizing the unobserved determinants of perceived quality will enter the errors in the equations to be estimated.

[27] The numbers of own and rival brands are valid instruments as long as these numbers are determined prior to price and advertising choices. This type of instrument was first proposed by Bresnahan [1987] and has been widely used since. We cannot use such brand numbers, since these are constant over the time period.

[28] In our small sample, estimating the full model would likely to lead to more precise estimates. We leave the estimation of the full model to future work.

Firms 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 products. The corresponding arguments of $Q_j(.)$ are advertising expenditure by Firm j which directly promotes its own product, denoted by A_{jj}; "outgoing" advertising by Firm j targeted against Firm k, A_{jk}, $k \neq j$, which has a direct positive effect; and "incoming" comparative advertising by Firm k targeting Firm j, A_{kj}, $k \neq j$, which has a negative (detraction) effect on Firm 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.[29]

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:

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

in standard fashion, where

$$\delta_j = Q_j(.) - p_j \tag{2}$$

is the "objective" utility, and where we let the "outside option" (of not buying a painkiller) be associated to an objective utility $\delta_0 = V_0$. The parameter μ expresses the degree of horizontal consumer/product heterogeneity.[30]

The structure of the random term determines the form of the corresponding demand function. The corresponding market shares are denoted s_j, $j = 0, ..., n$, and each s_j is increasing in its own objective utility, and decreasing in rivals' objective utilities.[31] Assume that there are M consumers in the market, so that the total demand for product j will be Ms_j, $j = 0, ..., n$.

3.2 Profits

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

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

[30] As in Anderson, de Palma, and Thisse (1992). Note that econometric specifications often set a marginal utility of money parameter (often α) before the price term, and they normalize $\mu = 1$. This is therefore effectively setting $\alpha = 1/\mu$: we do not do this here because we shall shortly substitute out price term anyway, and the intuitions are cleaner without carrying around this α.

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

$$\underset{\{p_j,A_j\}}{Max}\,\pi_j = M(p_j - c_j)s_j - A_{jj} - \gamma \sum_{k\neq j} A_{jk} \qquad\qquad j = 1, ...n. \tag{3}$$

Here $\gamma > 1$ reflects that comparative advertising may be intrinsically more costly because of the risk involved that a competitor might challenge the ad and it will have to be withdrawn and replaced with a less suitable one.[32]

The advertising quantities (the A's) are dollar expenditures.[33] The idea is that advertising expenditures will be optimally allocated across media (and times of day in the case of radio/TV). Then market prices for access to eyeballs (and eyeballs of different value to advertisers) should embody the condition that there should be no systematically better/cheaper way to reach viewers. The strong form of this (efficient markets) hypothesis implicitly assumes that there are enough advertiser types, and there is no great difference in the values of consumers to OTC analgesics advertising compared to other sectors.[34]

We assume in what follows that pricing and advertising levels are determined simultaneously in a Nash equilibrium.

3.3 Firms' Optimal Choices

Pricing. Recalling that shares, s_j, depend on all the δ's, the price condition is determined in the standard manner by:

$$\frac{d\pi_j}{dp_j} = Ms_j - M(p_j - c_j)\frac{ds_j}{d\delta_j} = 0, \qquad j = 1, ...n, \tag{4}$$

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

Self-promotion. Self-promotion refers to advertising expenditures which increase own perceived quality without directly affecting the perceived qualities of rivals. The following analysis covers persuasive advertising generally, insofar as it does not involve comparisons with rivals.

[32] Hosp (2007) from Goodwin Procter LLP notes that "Comparative advertising is a useful tool to promote an advertiser's goods and to tout the superior quality of the advertiser's goods over those of its competitors. Comparative advertising, however, is also the form of advertising that is most likely to lead to disputes. In undertaking comparative advertising a company should be cognizant of the potential risks and pitfalls that can lead to costly disputes and litigation. The competitor will scrutinize the advertising, and is more likely to be willing to bear the expense of litigation or dispute resolution in an instance where the competitor itself has been targeted."

More formally, suppose that a comparative ad is successfully challenged with probability $\mathbb{P}$, and that when withdrawn it must be replaced with an ad of lower effectiveness, and the effectiveness is a fraction β of that of the preferred ad. Let p^A per denote the cost of airing a self-promotion (on a particular channel at a particular time). Then the cost of airing the comparative ad is $p^A\left((1 - s_j) + s_j/\beta\right)$. If we normalize the cost of the self-promotion advertising by setting $p^A = 1$, then we have the effective comparative ad cost as $\gamma = ((1 - s_j) + s_j/\beta) > 1$.

[33] They therefore need to be deflated by an advertising price index: as long as the price per viewer reached has not changed in a manner systematically different from the general inflation rate, the CPI is a decent proxy, and will be used below.

[34] For example, suppose that each ad aired at a particular time on a particular channel cost $\hat{p}$ and delivered H "hits" (where the hit is measured in dollars). Then the equilibrium price of an ad delivering $H/2$ hits should be $\hat{p}/2$, etc.: the price per hit ought to be the same. Factoring in hits of different worth (the audience composition factor) follows similar lines. Notice though that such arbitrage arguments require sufficient homogeneity in valuations of at least some sub-set of advertising agents. The second caveat is that the arbitrage argument most directly applies to numbers of viewers hit, whereas here we deploy a demand form where ads enter a representative utility. It remains to be seen how consistent this is with an approach where heterogenous individuals (who see different numbers of ads) are aggregated up to give a market demand function (see for example Goeree (2008) for an empirical application, albeit in the context of informative ads / consideration sets).

Self-promotion advertising expenditures are determined by:[35]

$$\frac{d\pi_j}{dA_{jj}} = \frac{d\pi_j}{d\delta_j} . \frac{\partial Q_j}{\partial A_{jj}} - 1 = M(p_j - c_j)\frac{ds_j}{d\delta_j}\frac{\partial Q_j}{\partial A_{jj}} - 1 \leq 0, \quad \text{with equality if } A_{jj} > 0 \quad j = 1, ..., n, \tag{5}$$

where the partial derivative function $\frac{\partial Q_j}{\partial A_{jj}}$ may depend on any or all of the arguments of $Q_j(.)$. The pricing first-order condition (4) can be substituted into the advertising one (5) to give the equilibrium conditions:[36]

$$Ms_j \frac{\partial Q_j}{\partial A_{jj}} \leq 1, \quad \text{with equality if } A_{jj} > 0, \qquad j = 1, ..., n. \tag{6}$$

This equation is consistent with discrete choice models with an objective utility $u_j = Q_j - p_j + \mu\varepsilon_j$ as per (1) and (2) and is general up to the assumption of quality not interacting with consumer type.[37]

The interpretation is the following. 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 the 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 marginal cost of the change, the RHS of (6). We term the relation in (6) the self-promotion quasi-reaction function. It is a function of whatever advertising variables are in Q_j (note that these all involve firm j as either sender or target), along with j's share. This differs from a full reaction function because it still may include j's other advertising choices, and because it includes the market share, which in turn includes all prices and advertising.

The relationship in (6) already gives a strong prediction for markets where there is no comparative advertising (e.g., when comparative advertising is barred). To see this, suppose that the perceived quality changes with advertising in the same (concave) manner for all firms. Then the firms with larger market shares will advertise more.[38] The intuition is that the advertising cost per customer is lower for larger firms. This is a useful characterization result for advertising in general: note (as per the discussion in the introduction) that it is not a causal relationship. The fundamental parameters of the model determine which firms will be large and advertise more. For example, if firms differ by intrinsic "quality" which is independent of the marginal benefit from advertising (this is the case for our parameter $\bar{W}_j$ in the econometric specification below in Section 5), then one might expect that firms with higher such quality will be those advertising more.[39] The same relation holds in the presence of comparative advertising, given those other advertising levels. Indeed, assuming that $\frac{\partial Q_j}{\partial A_{jj}}$ is decreasing in A_{jj}, from (6) firms for which s_j is larger will advertise

[35] These conditions can be written in the form of elasticities. This yields Dorfman-Steiner conditions for differentiated products oligopoly; the comparative advertising conditions below can also be written in such a form.

[36] If $\frac{\partial Q_j}{\partial A_{jj}}$ were constant (which would arise if ads entered perceived quality linearly), then it is unlikely that the system of equations given by (6) has interior solutions. Below we (implicitly) invoke sufficient concavity of Q_j for interior solutions.

[37] This would happen in a vertical differentiation model, for example. The advertising-size relation is also consistent with a representative consumer model with $\delta_j = Q_j - p_j$ replacing $-p_j$ in the corresponding indirect utility function.

[38] In this case, $Ms_jQ'(A_{jj}) = 1$, is the first order condition, with (temporarily) $Q(.)$ the production of quality from advertising. Clearly, the larger is the share, the smaller must be Q', and hence the higher must be ads. Note we did not use any symmetry property of the share formula: what did all the work was the same Q' function.

[39] This indeed can be shown to be the case in some specifications of the model.

more (choose a higher value of A_{jj}) than those with smaller market shares. The other relations in the following proposition then follow from recalling that the perceived quality is $Q_j(A_{jj}, \{A_{jk}\}_{k\neq j}, \{A_{kj}\}_{k\neq j})$, $j = 1, ..., n$.

Proposition 1 ***(Self-promotion Advertising levels)*** *The choice of self-promotion advertising level is determined implicitly for all $j = 1, ..., n$ by $Ms_j \frac{\partial Q_j}{\partial A_{jj}} \leq 1$, with equality if $A_{jj} > 0$. This relationship determines A_{jj} as a function of own market share, s_j; j's outgoing attacks, $\{A_{jk}\}_{k\neq j}$; and the incoming attacks on j, $\{A_{kj}\}_{k\neq j}$. Assume $\frac{\partial Q_j}{\partial A_{jj}}$ is decreasing in A_{jj} then A_{jj} is an increasing function of s_j (loosely, firms with larger market shares will use more self-promotion advertising). If $\frac{\partial Q_j}{\partial A_{jj}}$ is decreasing in A_{jk} (A_{jk} and A_{jj} are substitutes in the production of Q_j) then A_{jj} is a decreasing function of A_{jk}. If $\frac{\partial Q_j}{\partial A_{jj}}$ is increasing in A_{kj}, then A_{jj} is an increasing function of A_{jk}.*

The advertising relationships in the Proposition hold for firms with positive market shares, and we have written them consistent with the coefficients we find in the estimation of the self-promotion equation. For firms with low enough market shares, from (4) 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 (5) is negative when $\frac{\partial Q_j}{\partial A_{jj}}$ is evaluated at $A_{jj} = 0$.

We now turn to comparative advertising levels.

Comparative Advertising. Since the perceived quality is $Q_j(A_{jj}, \{A_{jk}\}_{k\neq j}, \{A_{kj}\}_{k\neq j})$, $j = 1, ..., n$, we can determine the advertising spending against rivals by differentiating (3) to get (for $k = 1, ..., n$, $\;j = 1, ...n$, $k \neq j$):

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

with equality if $A_{jk} > 0$. We proceed by using a sequence of three substitutions – of the attackers' pricing condition, its self-promotion condition, and the target's self-promotion condition – to rewrite this comparative advertising condition in a form to be estimated. The final form takes a simple structure written as the product of the ratio of attacker to target market shares ($\frac{s_j}{s_k}$), the diversion ratio of demand from the attacker to the target ($d_{jk} \in (0, 1)$), and the marginal rate of substitution between target self-promotion and incoming attacks in the target's perceived quality function ($MRS_{k,j} > 0$).

Inserting the price first-order conditions (4) gives (for $k = 1, ..., n$, $\;j = 1, ...n$, $\;k \neq j$):

$$\frac{d\pi_j}{dA_{jk}} = Ms_j\frac{\partial Q_j}{\partial A_{jk}} - Ms_j d_{jk}\frac{\partial Q_k}{\partial A_{jk}} \leq \gamma, \tag{7}$$

where $d_{jk} = -\frac{ds_j}{d\delta_k}/\frac{ds_j}{d\delta_j} > 0$ is the diversion ratio, discussed further below, and obeying the property $\Sigma_k d_{jk} < 1$. Loosely, the diversion ratio measures how much custom is picked up from a rival per customer it sheds.

The comparative advertising derivative, (7), can be used to derive a bound on the size of the marginal rate of substitution between outgoing comparative advertising and self-promotion ($\frac{\partial Q_j}{\partial A_{jk}}/\frac{\partial Q_j}{\partial A_{jj}}$). Assume for the present argument that the solution for self-promotion spending (see (6)) is interior. Then, substituting the self-promotion condition ($Ms_j \frac{\partial Q_j}{\partial A_{jj}} = 1$) into (7) implies that

$$\frac{\frac{\partial Q_j}{\partial A_{jk}}}{\frac{\partial Q_j}{\partial A_{jj}}} \leq \gamma + Md_{jk}\frac{\partial Q_k}{\partial A_{jk}} < \gamma \tag{8}$$

where the last inequality follows because $\frac{\partial Q_k}{\partial A_{jk}} < 0$. In summary:

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

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.

If the marginal rate of substitution between outgoing comparative advertising and self-promotion in (8) is constant, at rate λ, then we can write:[40]

$$(0 <) \quad -Ms_j d_{jk}\frac{\partial Q_k}{\partial A_{jk}} \leq \gamma - \lambda. \tag{9}$$

The intuition is as follows. 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). Such a rival price change (which j thus effectuates through comparative advertising) causes j's market share to rise by $-\frac{ds_j}{d\delta_k}$. This increment is valued at $M(p_j - c_j)$. By the price first-order condition, $p_j - c_j = \frac{s_j}{\frac{ds_j}{d\delta_j}}$, and (9) follows.

Condition (9) may be further rewritten as a function of the marginal rate of substitution between attacks on Firm k and self promotion by firm k. If firm k undertakes some strictly positive amount of self-promotion (so that its first-order condition holds with equality), then the corresponding first order condition, $Ms_k\frac{\partial Q_k}{\partial A_{kk}} = 1$, may be substituted in to yield:

$$(0 <)\frac{s_j}{s_k}d_{jk}MRS_{k,j} \leq \gamma - \lambda, \tag{10}$$

where $MRS_{k,j} = -\frac{\partial Q_k}{\partial A_{jk}}/\frac{\partial Q_k}{\partial A_{kk}}$ is the desired marginal rate of substitution in k's perceived quality function between k's self-promotion and j's attacks, and d_{jk} is the diversion ratio between goods j and k.[41] We discuss these terms in turn after the following summary Proposition.

[40] This formulation includes the Net Persuasion form used below in the estimation. Suppose therefore that the quality function can be written as $Q_j(A_{jj}, \{A_{jk}\}_{k\neq j}, \{A_{kj}\}_{k\neq j}) = Q_j(A_{jj} + \lambda\Sigma_{k\neq j}A_{jk}, \{A_{kj}\}_{k\neq j})$, $j = 1, ..., n$, where $0 < \lambda < 1$ reflects the idea that comparative advertising should not have a stronger *direct* effect than self-promotion. The precise Net Persuasion form used below has $Q_j(A_{jj} + \lambda\Sigma_{k\neq j}A_{jk}, \{A_{kj}\}_{k\neq j}) = Q_j(A_{jj} + \lambda\Sigma_{k\neq j}A_{jk} - \beta\Sigma_{k\neq j}\ln A_{jk})$, and $Q_j(.)$ is a logarithmic function.

[41] Alternatively, we can write the comparative advertising condition as $D_{jk}MRS_k \leq \gamma - \lambda$, where $D_{jk} = -\frac{s_j}{s_k}\left(\frac{ds_j}{d\delta_k}/\frac{ds_j}{d\delta_j}\right)$ is a diversion measure between goods j and k, which can also be seen as the ratio of cross elasticity to own demand elasticity.

Proposition 3 ***(Comparative Advertising)*** *Assume that the target, k, engages in a strictly positive level of self-promotion, and assume that outgoing comparative ads are perfectly substitutable with self-promotion at rate λ. The choice of comparative advertising by Firm k against j is determined implicitly for all $j = 1, ..., n$ by $\frac{s_j}{s_k} d_{jk} MRS_{k,j} \leq \gamma - \lambda$, with equality if $A_{jk} > 0$. Here $MRS_{k,j} > 0$, and $d_{jk} > 0$ with $\Sigma_k d_{jk} < 1$.*

The restriction on the diversion ratios motivates restrictions below in the estimation. Notice that patterns in the data between advertising levels and shares can potentially have explanations via the MRS or via the diversion ratio, or through the interaction of the two.

Marginal Rate of Substitution. The marginal rate of substitution tells us how much self-promotion by k will compensate in k's quality function for an extra dollar's worth of incoming comparative advertising from Firm j targeting Firm k. This is a measure of the direct damage caused by j, although it understates the profit loss because the comparative advertising also has an effect through Q_j in raising the quality of rival j. Notice that (as argued below) $d_{jk} \in (0, 1)$ so that when there is a positive amount of comparative advertising from j targeting k then the comparative advertising first order condition holds with equality and so

$$MRS_{k,j} = \frac{\gamma - \lambda}{d_{jk}} \frac{s_k}{s_j} > (\gamma - \lambda) \frac{s_k}{s_j}.$$

Thus:

Proposition 4 ***(MRS bounds)*** *Assume that the target, k, engages in a strictly positive level of self-promotion, and assume that outgoing comparative ads are perfectly substitutable with self-promotion at rate λ. Then the marginal rate of substitution between self-promotion and incoming attacks is $MRS_{k,j} = \frac{\gamma - \lambda}{d_{jk}} \frac{s_k}{s_j} > (\gamma - \lambda) \frac{s_k}{s_j}$.*

Hence, if two firms of equal size are observed to target each other ($s_j = s_k$), their marginal rates of substitution through their quality functions must both exceed $(\gamma - \lambda)$. If they are of different sizes and one MRS is below $(\gamma - \lambda)$, the other must be above $(\gamma - \lambda)$.

Further insight into the role of the Marginal Rate of Substitution is afforded by considering special cases. Suppose that we write the perceived quality function in the following form: $Q_j(A_{jj} + \lambda \Sigma_{k \neq j} A_{jk} + \Sigma_{k \neq j} g(A_{kj}))$, $j = 1, ..., n$, with Q_j increasing and concave in its argument. This formulation embodies the assumption that quality depends on net persuasion, and that outgoing ads are perfectly substitutable with parameter $\lambda \in (0, 1)$ with self promotion. Further assume that the function $g(.)$ is decreasing and convex, so that incoming comparative ads with target j are harmful, with diminishing marginal impact. The additive form of net persuasion under the function Q_j has the implication that $MRS_{k,j}$ is independent of the level of all advertising other than the particular attacker: $MRS_{k,j} = -g'(A_{jk})$. In this case any size relation must be picked up solely through the diversion ratios.

Diversion Ratio. The diversion ratio was defined above as $d_{jk} = -\frac{ds_j}{d\delta_k}/\frac{ds_j}{d\delta_j}$. For interpretation, note that for discrete choice models we have $\frac{ds_j}{d\delta_k} = \frac{ds_k}{d\delta_j}$ (see Anderson, de Palma, and Thisse, 1992, Ch. 3, p. 67), and hence

$$d_{jk} = -\frac{ds_k}{d\delta_j}/\frac{ds_j}{d\delta_j}.$$

This *diversion ratio* between goods j and k has been proposed as a useful statistic for analyzing the price effects of mergers (see for example Shapiro) insofar as it tells us what fraction of the demand lost by product j due to a price increase is picked up by product k. One useful way to think of it is in terms of consumers' second preferences because consumers switch to their next preferred option when the price of the erstwhile first choice rises. For substitute differentiated products, d_{jk} is positive, and must be less than one in a discrete choice context because lost consumers switch to other products too. We will discuss some special cases in the empirical section.

Consider two special cases. If the differentiated product demands are linear, as is the case if they are generated from a quadratic representative consumer's utility function (as per Ottaviano and Thisse, 2002), with qualities introduced in the place of prices,[42] then the diversion ratios are constants for any pair of products. This implies that, holding constant the effect of the MRS in determining the levels of comparative ads, an attacker with a larger market share will attack any given target more, but larger targets will be attacked less than smaller ones (by any given attacker).[43] This is clearly not consistent with the attack matrix, and so we will not consider this case.

If the differentiated product demands are logit functions,[44] then $d_{jk} = \frac{s_k}{(1-s_i)}$, reflecting the IIA property that lost demand from product j will be attracted to other products proportionately to their market shares. However, then, since the the D_{jk}'s in the relation $D_{jk}MRS_{k,j} = \gamma - \lambda$ (where $D_{jk} = \frac{s_j}{s_k}d_{jk}$) will be independent of the target size, any dependent relation between comparative ad levels and target size if a logit (or nested logit) were assumed for demand would have to come through the MRS.

The relation $D_{jk}MRS_{k,j} = \gamma - \lambda$ defines A_{jk} as an implicit function of the other arguments in this relation. This observation gives us the next Proposition.

Proposition 5 ***(Diversion factor comparative statics)*** *Assume that the target, k, engages in a strictly positive level of self-promotion, and assume that outgoing comparative ads are perfectly substitutable with self-promotion at rate λ. Assume that the marginal rate of substitution between self-promotion and incoming attacks $MRS_{k,j}$ is decreasing in A_{jk}. Then A_{jk} is increasing in $D_{jk} = \frac{s_j}{s_k}d_{jk}$.*

[42] More correctly, replace $-p_k$ by $\delta_k - p_k$ in the resulting demand functions to give linear demands as functions of net qualities, $\delta_k - p_k$.

[43] To see the implications more fully, write the comparative advertising condition when there are positive ad levels as $D_{jk}MRS_{k,j} = \gamma - \lambda$ where $D_{jk} = \frac{s_j}{s_k}d_{jk}$. With the linear demand system, the D_{jk}'s depend only on the ratio of attacker to target market shares.

[44] Similar results hold for nested logit specifications.

Hence, if we track how D_{jk} varies with its arguments (the market shares), then we can determine how attacks vary with these arguments.

4 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, Acetaminophen, Ibuprofen, and Naproxen Sodium. The nationally advertised brands are such familiar brand names as Tylenol (acetaminophen), Advil and Motrin (ibuprofen), Aleve (naproxen sodium), Bayer (aspirin or combination), and Excedrin (acetaminophen or combination). **Table 1** summarizes market shares, ownership, prices and advertising levels in this industry.[45]

We use three different data-sets: (1) sales (2) advertising, and (3) medical news data. Sales and advertising data were collected by AC Nielsen and TNS - Media Intelligence respectively, and we coded the advertising content. We constructed the medical news data-set from publicly available news archives.

4.1 Sales Data

The product level data consist of average prices, dollar sales, and dollar market shares (excluding Wal-Mart sales) of all OTC oral analgesics products sold in the U.S. national market during the 5 years from March of 2001 through December of 2005 (a total of 58 monthly observations).[46] Products vary in package size (the number of pills) and the strength of the active ingredient in milligrams.

Episode of Pain. We construct a measure of a *serving* of pain medication, or an *episode of pain*, so that we can aggregate across different package sizes and across different medication strengths.

First, we assign to each analgesic product in the sales dataset the strength of its active ingredient in milligrams. To do so, we combined the descriptive data in the Nielsen dataset with the data of milligrams of a specific active ingredient in a specific formula.[47] Since the strength information was given, we were able to match the milligrams of active ingredients of the products in our dataset with the products found on the brands' websites. From the amount of milligrams of the active ingredient we derived the maximum number of pills that a consumer can take of each particular product in 24 hours.[48]

[45] We exclude Midol and Pamprin from the sample because they are both aimed more narrowly at the menstrual pain-relief market and they both have small market shares.

[46] We have data on essential product attributes noted on the packages and the fraction of products sold of each such type: active ingredient, strength (regular, extra strength, etc. - as regulated by the FDA), pill type (caplet, tablet, gelcap, etc.), number of pills contained in the product, and purpose (menstrual, migraine, arthritis, general, children, etc.), although in the end we did not use these data. In this paper we look at the strategic interaction among brands, rather than products.

[47] In the case of Ibuprofen- and Naproxen Sodium- based pain relievers, the assignment was straightforward, since these OTC products can come only in 200mg (for Ibuprofen) and 220mg (for Naproxen Sodium). In the case with Aspirin and Acetaminophen, the situation is more delicate, since these products can come in varying strengths and as a combination with other analgesic agents.

[48] For a certain analgesic drug to be sold as an OTC drug, FDA requires that the daily (24 hours) dosage does not exceed a certain threshold (the thresholds are different for different active ingredients. For example, for acetaminophen the daily dosage

We define the unit of consumption as an episode of pain. An episode of pain is given by the maximum number of pills (for OTC consumption) an individual can take over 24 hours, as defined and required by the FDA (e.g. 3 in the case of Aleve, and from 6 to 12 for Tylenol, depending on the acetaminophen formula) times the average number of pain days per month in the population. The average monthly number of pain days is three.[49]

Market Size, Brand Market Shares and Prices. The definition of market size follows immediately from this: we define the *market size* for OTC analgesic products as the US population 18 years or older. Then, we can compute each brand's market share as the fraction of total number of episodes of pain sold over the market size. The average price of an episode of pain is computed as the ratio of the total sales by a brand divided by the total number of episodes of pain sold in a month.

Generic Prices. Next, we construct the generic product price information which we use as the exogenous variation in our instrumental variable approach. For each month we calculate the average price of the unit of episode of pain relief for the generic brands. The resulting output is the time series of average prices of episodes of pain relief for each of the four active ingredients for the generic products. We interpret the generic prices as proxies of the marginal cost of providing care to an episode of pain.

4.2 Advertising Data

Our advertising dataset is from TNS-Media Intelligence and data is reported on monthly basis. The advertising data contain monthly advertising expenditures on each ad, and video files of all TV advertisements for the 2001-2005 time period for each brand advertised in the OTC analgesics category. The unit of observation in the raw dataset is a single ad. There are more than four thousands different ads. For each ad, we know the amount spent in each month and the number of times that creative was shown during the specific month. Each ad is also associated with a video file

Advertising Content. As discussed in the Introduction, we watched all the ads and coded according to their content. Specifically, we recorded whether the commercial had any comparative claims – whether the product was explicitly compared to any other products. If a commercial was comparative, we also recorded which brand (or class of drugs) it was compared to (e.g. to Advil or Aleve; or to Ibuprofen-based drugs). If an ad had no comparative claims, it was classified as a self-promotion ad. We are then able to gather information on the advertising relationships between all potential pairs of brands.[50] The unit of observation is a year-month-brand-attacked brand combination. For example, a line in this dataset tells how much Advil

is 4000 mg of this active ingredient). Recall, that the maximum number of pills that one is allowed to take in a day (according to FDA standards) is a crucial variable in defining the market share of a product.

[49] This information is from the Morbidity and Mortality Weekly Report, Centers for Disease Control and Prevention, Feb 27, 1998/47(07);134-140.

[50] We also include combinations that never see any attack. For example, Advil never attacks Motrin.

spent on comparative advertising against Tylenol in March 2004. Each month has thirty pair combinations.

Indirect Attacks. One delicate issue is how to deal with indirect attacks. An indirect attack occurs when one brand, say Tylenol, makes a claim against "all other regular" brands.[51] Because it is not clear how to deal with this type of ads, we consider two solutions. First, we consider the case where indirect attacks are equivalent to direct attacks (e.g. Tylenol on Advil), but are divided among all the brands falling within the attacked category. So, for example, when Tylenol makes a claim against "all other regular" brands, each one of the other five brands is being attacked the amount of dollars spent on that advertisement divided by five.[52] Second, we consider the case where indirect attacks should simply be interpreted as self-promotion ads. We look at this second case in the Robustness section.

The Attack Matrix. **Table 2** presents the complete picture of cross targeting and the advertising expenditure on each of the rival brand targeting. This table shows *every* nationally advertised brand used comparative advertising during the sample period. However, the brands against which comparisons were made are only a subset of the nationally advertised brands. The targets are the "big Three": Tylenol, Advil, Aleve, plus Excedrin.[53] Notice that these data provide some informal support for the larger firms both using more comparative advertising and being targeted more. The entries on the diagonal are zeroes through not attacking oneself.

4.3 News Shocks

Between 2001 and 2005, the OTC analgesics market endured several major medical news related shocks. We follow an approach similar to Chintagunta, Jiang and Jin (2007) to collect the data on these shocks. We used Lexis-Nexis to search over all articles published between 2001 and 2005 on topics related to the OTC analgesics industry.[54]

Definition of a News Shock. We recorded the article name, source and date. From a data-set of articles we then constructed a data-set of news shocks. First, multiple articles reporting the same news were assigned to a unique shock ID. Second, we checked whether a news shock was associated with any new medical findings that were published in major scientific journals. As a result of this data cleaning, our news shock data-set

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

[52] Because McNeil owns both Motrin and Tylenol and Bayer also owns Aleve, we consider both the case of "independent" brands and "multi-brands" firms (stablemates). In the case of multi-brands firms, we assume that indirect attacks carried out by a firm do not negatively affect its other stablemate brands. Thus, for example, we maintain that an indirect attack by Tylenol on all the NSAIDs is not perceived by the consumer as an attack on Motrin. Section () deals with the multi-brand specification.

[53] Motrin does not attack Tylenol because the parent company is the same; likewise, Bayer does not attack Aleve for the same reason. However, we have effectively ignored these multi-product firm relations in the data.

[54] The keywords that we used consisted of brand names, such a "Aleve," "Tylenol," "Advil," "Vioxx," and the names of their active ingredients, such as "Naproxen," or "Acetaminophen." Then we made searches using generic terms such as "pain killers" or "analgesics."

includes 16 news shocks between March of 2001 and December of 2005.

Major vs. Minor Shocks. We classified the shocks by their impact. If a news shock was reported in a major national newspaper (USA Today, Washington Post, Wall Street Journal, New York Times), then we classified it as a major shock. Otherwise we classified it as a minor shock. This classification is useful to verify whether our identification strategy is robust to changes in the way we define news shocks. **Table 3** reports the news shocks, by their title, date, scientific publication, and impact (Major or Minor).

Measuring the Effect of the News Shocks. For each shock that happened during period t we construct a dummy variable which is equal to 1 in all the periods after and including t: (i.e., t through T).[55] In the empirical analysis below, we interact each of the major shocks listed in **Table 3** with brand dummies. This approach enables us to let the data determine whether a medical news shock affected the demand (instead of us arbitrarily assigning which shock affected which brand in which way), and, if it did, whether a shock had a positive or negative effect on that brand. **Figure 1** presents the occurrence of the *eight* major shocks, highlighting the reaction of sales and advertising to those medical shocks.

5 Econometric Analysis

Here we first discuss the quality function upon which we base the empirical analysis. Then we illustrate the equations that we want to estimate. Finally, we deal with the sources of exogenous variation in the data that identify the parameters of the model.

5.1 A Quality Function

Quality Function. We separate out the advertising contribution to perceived quality from the intrinsic, or "base quality." That is, we write

$$Q_j\left(.\right) = \bar{Q}_j\left(.\right) + \bar{W}_j,$$

where only $\bar{Q}_j\left(.\right)$ depends on advertising levels, and $\bar{W}_j$ is a variable specific to firm j which affects quality with no interaction with j's advertising.

Equations (6) and (11) implicitly define A_{jj} and A_{jk}, when holding with equality, as functions of market shares and other advertising levels.

After *extensive* experimentation, we chose the following functional form for the base quality, which combines the push and pull effects of advertising.:

$$Q_j = \alpha \ln \Big(A_{jj} + \lambda \sum\nolimits_{k \neq j} A_{jk} - \beta \sum\nolimits_{k \neq j} \ln \left(\bar{A}_{kj} + A_{kj} \right) + \bar{A}_{jj} \Big) \tag{11}$$

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

The push effect is given by the weighted sum of the self-promotion advertising and the outgoing comparative advertising ($A_{jj} + \lambda \sum_{k \neq j} A_{jk}$). Here, λ is a substitutability parameter of outgoing comparative ad with self-promotion ads. In other words, λ measures how much must be spent on self-promotion advertising to replace \$1 spent on comparative advertising to generate the same "push" in (own) perceived. For example, $\lambda = 0.75$ means that the firm can raise its perceived quality by the same amount if it spends 1.33 dollars in comparative advertising or 1 dollar in self-promotion advertising. This parameter does not represent the full effect of comparative advertising relative to self-promotion advertising, as there is also the Pull effect which is directly denigrating the perceived quality of targeted competitors' brands. Were we to find $\lambda = 1$ then comparative and self-promotion advertising would have the same effect on the perceived quality of a brand. If $\lambda \neq 1$, then we should conclude that comparative and self-promotion advertising have different effects and should be coded separately. We expect $\lambda \in (0, 1)$ so that outgoing attacks increases the perception of own quality, although less effectively than self-promotion ads.

The pull effect is given by incoming advertising comparative ads (A_{kj}). We write A_{kj} inside a negative logarithmic function, which is decreasing and convex and, as previously discussed, this ensures that incoming comparative ads with target j are harmful, with diminishing marginal impact. A crucial advantage of using the logarithmic function is that it leads to closed form first order conditions.

Advertising Allure and Base Quality Variables. By contrast to the $\bar{W}_j$, the A variables with overbars interact with their corresponding advertising levels, and determine the marginal efficiency of self-promotion and comparative advertising. For example, the higher is $\bar{A}_{jj}$, the lower is the marginal efficiency of self-promotion advertising; while the higher is $\bar{A}_{kj}$, the lower the marginal efficiency of attacks by k against j, in the sense of less incremental pull-down. In the econometric specification, both types of variables will depend on some of the observed variables (for example news shocks) as well as some of the random shocks. Here, we refer to the $\bar{W}$ variables as base quality, while the $\bar{A}$ variables are called advertising base allure.

5.2 The Equations to Be Estimated

Self-Promotion. After taking the derivative with respect to A_{jj} of equation (11) we find the self-promotion ad equations:

$$A_{jj} = \max \left\{ -\bar{A}_{jj} - \alpha M s_j - \lambda \sum_{k \neq j} A_{jk} + \beta \sum\nolimits_{k \neq j} \ln \left(\bar{A}_{kj} + A_{kj} \right), 0 \right\}, \quad j = 1, ..., n. \tag{12}$$

Thus, self-promoting advertising is a linear function of the shares of the brand; its outgoing comparative advertising and its incoming comparative advertising. Notice that $\bar{A}_{kj}$ is not observed. As we will discuss later on, we either have to normalize this to 1, or we have to estimate it from the next equation.

Comparative Advertising. For the maintained quality function we have:

$$MRS_{k,j} = -\frac{\partial Q_k}{\partial A_{jk}} / \frac{\partial Q_k}{\partial A_{kk}} = \frac{\beta}{\bar{A}_{kj} + A_{kj}}.$$

Then, the first order conditions for comparative advertising can be written as:

$$A_{jk} = \max\left\{ -\bar{A}_{kj} + \frac{s_j}{s_k} d_{jk} \frac{\beta}{(\gamma - \lambda)}, 0 \right\}, \quad j = 1, ..., n.. \tag{13}$$

Specifying Diversion Ratios. Up to this point we have not assumed any distribution on the individual specific unobservables ε_i that enter into the utility function (1). Clearly, d_{jk} depends on the distribution of such unobservables. As previously discussed, if the differentiated product demands are logit functions, then $d_{jk} = \frac{s_k}{(1-s_i)}$ and we can rewrite the comparative advertising equation as follows:

$$A_{jk} = \max\left\{ -\bar{A}_{kj} + \frac{s_j}{(1 - s_i)} \frac{\beta}{(\gamma - \lambda)}, 0 \right\}, \quad j = 1, ..., n.$$

This leads to a simple way to estimate all the parameters of the model. First we run the comparative advertising equation. From this equation we derive estimates of $\bar{A}_{kj}$. We plug those estimates in the self-promotion equation, and estimate the remaining parameters. Notice that all parameters are identified if we assume that demands are logit functions.

More generally, we also allow for flexibility in the diversion ratio by not imposing a particular demand structure. Instead, we will estimate an approximation to the diversion ratio. Note first that the diversion ratio, $d_{jk} = -\frac{ds_j}{d\delta_k} / \frac{ds_j}{d\delta_j}$, is naturally a function of the equilibrium δ's. However, following Berry (1994) we can write these δ's as implicit functions of the shares, s_j, and therefore we will approximate the equilibrium d's as functions of shares.

The approximation that we will consider is the following:

$$d_{jk} = \frac{\exp\left(f\left(s_k, s_j\right)\right)}{1 + \exp\left(f\left(s_k, s_j\right)\right)},$$

where $f\left(s_k, s_j\right)$ is a third degree polynomial in s_j and s_k.

6 Identification

We estimate the equations (12) and (13). As mentioned in the Introduction, there are two main concerns that we need to address: left-censoring of self-promotion and comparative advertising and endogeneity of market shares and advertising expenditures. Left-censoring occurs because in some periods some brands do not engage in self-promotion or comparative advertising (there are corner solutions). Hence the variables A_{jjt}, A_{jkt}, $j, k = 1, ..., n$, are left-censored.[56] We control for the left-censoring by running Tobit regressions.

[56] As noted above, there are two brands, Pamprin and Midol, which are primarily menstrual formulations, and that we exclude them from the empirical analysis because of their negligible market shares. Interestingly, they never engage in self-promotion advertising, only in comparative advertising. Generic brands never engage in any type of advertising.

The Nature of Endogeneity. The endogenous variables are A_{jjt}, A_{jkt}, A_{kjt}, s_{jt}, $j,k = 1,...,n$.[57] To clarify the nature of the endogeneity in our analysis, we start from equation (12). To further simplify the discussion we assume, just for the sake of exposition, that $\lambda = 0$ and $\phi^* = 0$. We will drop these two assumptions at the end of this section. Then (12) becomes, with the appropriate time subscripts:

$$A_{jjt} = \max\left\{-\bar{A}_{jjt} - \alpha M s_j, 0\right\}.$$

The term $\bar{A}_{jjt}$ captures the advertising base allure of a brand, which we write as follows:

$$\bar{A}_{jjt} = Z_{jt}^{'}\Phi + \xi_{jt},$$

where Z_{jt} are observable determinants of the advertising base allure. In this paper, these are the news shocks. The ξ_{jt} are unobservable shocks to the base allure, so ξ_{jt} is a structural error. Notice that ξ_{jt} is here assumed to be observed by firms, but not by the econometrician.

Next, if demands are logit functions then the market share for brand j is written as:[58]

$$s_{jt} = \frac{\exp[\delta_{jt}/\mu]}{\sum\limits_{k=0}^{n}\exp[\delta_{kt}/\mu]}, \qquad j = 0, 1, ..., n$$

where

$$\delta_{jt} = \bar{Q}_{jt}\left(.\right) - p_{jt} + \bar{W}_{jt}. \tag{14}$$

Because firms observe ξ_{jt} when they choose advertising and because shares are a function of advertising (through Q, the perceived quality), then shares are a function of ξ_{jt}, and thus we will get inconsistent estimates of α^* and Φ if we run the following simple Tobit regression:

$$\left\{\begin{array}{c} A_{jjt}^{*} = -Z_{jt}'\Phi - \alpha M s_j - \xi_{jt}, \qquad \xi_{jt} \sim N\left(0,\sigma^2\right) \\ A_{jjt} = \max\left(A_{jjt}^{*}, 0\right). \end{array}\right. \tag{15}$$

Top Brands vs. Other Brands. The first step to address the endogeneity of the market shares is to exploit the panel structure of our data to account for time-constant differences across brands. Essentially, we model the unobservable ξ_{jt} as follows:

$$\xi_{jt} = \bar{\xi}_j + \Delta\xi_{jt},$$

where $\bar{\xi}_j$ is a brand fixed effect, while $\Delta\xi_{jt}$ are time specific idiosyncratic shocks. We have investigated various specifications for the fixed effects, and concluded that a specification where there are two fixed effects, one for the top brands (Advil, Aleve, Tylenol), and one for the other brands (Excedrin, Motrin,

[57] Notice that prices, which are also endogenous, have been substituted out in the equations to be estimated.

[58] Notice that the generics are included here: abusing notation, generic drugs can be funneled into multiple options 0. However, as we will show later, we do not need to estimate the demand functions to estimate the relevant structural parameters.

Bayer) fits our data best.[59] We provide in **Figure 2** a graphical description of the relationship between self-promotion advertising and market sales (Ms_j) for all brands and months.

Figure 2 shows that there are two types of brands in the market. Aleve, Advil, and Tylenol (the 'Top Brands') control large market shares compared to Excedrin, Bayer, and Motrin. This is consistent with the reported weighted market share descriptive statistics in **Table 1** . This observation parallels the economic intuition that 'Top Brands' have a larger advertising base allure which translates into larger inherent quality, $\bar{A}_{jj}$. Additionally, the linear fit between shares and self-promotion advertising has the same slope for the 'Top Brands' and the rest of the brands. We use the evidence from this figure to justify the construction and use of a dummy variable 'Top Brand'.

One route is then simply to specify conditions under which there is no remaining correlation, and proceed directly to the estimates. This is the essence of Assumption 1. If this is untenable, various exclusion restrictions can remove residual endogeneity. These are described in Assumptions 2. In our regressions, we will start with estimates under the simple Assumption 1, and then proceed to deploy the other Assumption. (Note that Assumption 1, if correct, obviates the other).

Using Timing to Identify the Parameters. The parameters of the regression (15) can be identified when $\Delta\xi_{jt}$ and $\frac{1}{s_{jt}}$ are uncorrelated by estimating a variant of (15) where the ξ_{jt} are allowed to have different means corresponding to the brand-group fixed effects. The (non-)correlation condition can be given a justification, paralleling a standard assumption in a large part of the literature estimating production functions with a particular assumption on the timing of the realizations of the errors.[60] More specifically, a sufficient condition is the following:

Assumption 1 *After controlling for the news shocks, which we assume to enter directly through Z_{jt}, and after including brand fixed e!ects, the time specific idiosyncratic error $\Delta\xi_{jt}$ is uncorrelated with s_j, that is $E\left(\Delta\xi_{jt}|s_{jt}, Z_{jt}\right) = 0$.*

Clearly, the news shocks are exogenous since they require new medical discoveries, which 'surprise' both the consumers and the firms. Here, variation in the knowledge of the health properties of the products is captured by the news shocks. One standard interpretation for this maintained assumption is that we are basically able to observe all the variables that the firms take into account when taking their decisions, including the news shocks (e.g. the information that consumers and firms have at any point in time). This means that neither the econometrician nor the firms observe $\Delta\xi_{jt}$ before taking their advertising and pricing decisions. When this assumption is untenable, identification can be achieved using exclusion restrictions.

[59] One important reason, to which we will return later on, is that brand shares change little over time (except for Aleve, which suffered large losses after the negative news shock at the end of 2004). The identification of the share effect is mostly from cross section variation.

[60] See Griliches and Mairess [1999] for an illuminating review of the literature on the estimation of production functions.

We now discuss the identification assumption of this paper.[61]

[THE USE OF INSTRUMENTAL VARIABLES IS DISCUSSED BUT NOT IMPLEMENTED IN THIS VERSION].

Exclusion Restrictions.

To implement our estimation in our non-linear models, we use control functions (Heckman and Robb [1985,1986]).[66] Our methodology follows Blundell and Smith (1986) and Rivers and Vuong (1988).

Generalizing the Identification Strategy. In the above discussion we have focused on the first order condition (12) under the assumptions that $\lambda = 0$ and $\phi^* = 0$. It is quite clear that even if we let that λ and ϕ^* to be different from zero, we can use the same instrumental variables. This is exactly what we do. Essentially, we use variation in the generic prices (i.e. production costs) and their interactions with the news shocks to identify the effect of all of our endogenous variables.[67]

7 Results [very preliminary]

7.1 Self-Promotion Advertising

Clearly, one of the great advantages of using the functional form (11) is the transparency and simplicity of the first order condition above. We have a simple and clean relationship between expenditures on self-promotion advertising (A_{jjt}) and shares ($\frac{1}{Ms_{jt}}$), outgoing comparative advertising ($\sum_{k\neq j} A_{jk}$), and incoming comparative ad attacks ($\sum_{k\neq j} \ln\left(\bar{A}_{kj} + A_{kj}\right)$). The main difficulty when running the self-promotion advertising regression is that we do not observe $\bar{A}_{kj}$. There are two solutions. We can normalize $\bar{A}_{kj}$ to 1, and we do this in Columns 1-3 of Table 4. Otherwise we can estimate $\bar{A}_{kj}$ from the comparative advertising equation and then plug it in the self-promotion regression equation.

Baseline Regression. **Column 2** of **Table 4** provides the estimates of α, β, and λ when we run the following simple Tobit regression:

$$\left\{ \begin{array}{c} A^*_{jjt} = -\alpha M s_j - \lambda \sum_{k\neq j} A_{jk} + \beta \sum_{k\neq j} \ln\left(1 + A_{kj}\right) - Z'_{jt}\Phi - \xi_{jt}, \quad \xi_{jt} \sim N\left(0, \sigma^2\right), \\ A_{jjt} = \max\left(A^*_{jjt}, 0\right). \end{array} \right. \tag{16}$$

The substitutability parameter, λ, is estimated to be 0.733. This means that each dollar spent on comparative ad increases the perceived quality of the attacking brand by the same amount as 73 cents spent

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

[67] Thus, there are no exogenous variables that identify shares but not the other advertising variables. We know that advertisers must meet the Federal Trade Commission (FTC) standard of truthful and not misleading advertising claims. All material claims must be substantiated by a reasonable basis of support and firms need to evaluate whether their promotional message is likely to be challenged by a competitor or ad monitoring institution. Failure to have robust substantiation for a commercial may result in serious and costly consequences among which are failure to gain network approval and high litigation costs. The most common serious consequence is the publicized disruption of the ad campaign, sunk costs invested in the ad campaign and negative press related to the brand name. Over the five year period, we observe 15 OTC analgesics advertising claims challenged by the FTC, National Advertising Division (NAD), a competitor or a consumer. The problem with using these data is that the challenges are a function of the amount of advertising expenditures. So they cannot be considered exogenous in our regressions. This problem is not different from the one that it is encountered when we estimate market power and we do not have information on the marginal cost. Adding more equations (the first order condition for price and the demand equation) would let us identify α_I, γ, and β.

on self-promotion ad. Notice that comparative advertising also pulls down the rivals, which is what we discuss next.

The parameter, β is estimated to be 0.587. This suggests that incoming attacks do have a sizeable negative effect on the perceived quality of the attacked firm. In particular, recall $MRS_{k,j} = \frac{\beta}{1+A_{kj}}$ in this specification. The average value of A_{kj} is 0.097, which corresponds to 9.7 million dollars. So, here we can say that an increase in the attacks of 1 dollar would require approximately 58.7 cents ($\frac{58.7}{1+0.01}$ cents) to mitigate.

The coefficient α is small. [*Here needs to add discussion of the elasticity*].

Top Brand Dummy. As discussed in Section (**??**), one simple way to control for the endogeneity of shares and advertising expenditures is by adding the Top Brand dummy. Formally, we then have $\bar{\xi}_j = \bar{\xi}_{TB}$ for $j \in \{Advil,\, Aleve,\, Tylenol\}$ and $\bar{\xi}_j = \bar{\xi}_{OB}$ for $\{Motrin,\, Excedrin,\, Bayer\}$ (for obvious collinearity reasons, only the fixed effect for Top Brand will be reported). Given our relatively small sample, it helps to reduce the number of brand fixed effects. Another useful advantage of having such group-type fixed effects is that we avoid the incidental parameter problem that would have been there with the nonlinear Tobit regression and individual brand-specific fixed effects.[68]

This dummy controls for the Top Brands' advertising base allure advantage, so that it picks up any persistent component of such advantage. The remaining source of endogeneity in our regressions then comes from any potential correlation between $\Delta\xi_{jt}$ and s_{jt}.

In **Column 3** of **Table 4** the Top Brand fixed effect, $\bar{\xi}_{TB}$, has a negative sign, which means that the larger firms, Aleve, Tylenol and Advil have inherently higher advertising base allure than the other brands. This result is very robust across specifications.

Confirming that the endogeneity concern is relevant in our context, **Column 3** shows that the coefficient α, equal to 0.056, is nine times larger than in **Column 2** and is estimated very precisely.

λ is also changed, down to 0.571 from 0.733. β is also down to 0.344 from 0.587. This is consistent with the notion that the measures of advertising on the right hand side are endogenous.

Major News Shocks. Column 4 adds on the *major* news shocks vector Z.[69] Thus, we estimate their effects on the amount spent on self-promotion advertising by getting estimates for Φ. Under Assumption 1, we get consistent estimates of the parameters of the model. The idea is that any component of the unobservable that remains, after controlling for persistent advertising base allure advantages (picked up by the Top Brand dummy) and news shocks, is not observed by the firms before making their advertising and

[68] Notice, however, that even with individual brand specific fixed effects that incidental parameter problem would be marginal for two reasons. First, the time dimension grows over time, while the number of brands remains equal to six. Second, the incidental parameter problem is less important with a Tobit than with a Probit .

[69] The results do not change if we interact each news shock with brand dummies for all brands. This leads to six (brands) times eight (shocks) variables to include in the regression. This way to deal with the shocks lets the data pick up which shocks had an impact on the firms' decisions and, also, it allows the shocks to have different effects on different brands. Because of the large number of variables, we do not report the results for the shocks.

pricing decisions. Formally, we estimate the regression (16), where A^*_{jjt} is now written as follows:

$$A^*_{jjt} = -\alpha M s_j - \lambda \sum_{k \neq j} A_{jk} + \beta \sum\nolimits_{k \neq j} \ln\left(1 + A_{kj}\right) - Z^{'}_{jt}\Phi - \bar{\xi}_{TB} - \Delta\xi_{jt}, \quad \Delta\xi_{jt} \sim N\left(0, \sigma^2\right)$$

The dummy variable *TopBrand* is now equal to -0.624, and is statistically significant.

The estimate of λ is 0.569, and thus pretty much the same as in Column 3. The estimate of β is now down to 0.277 from 0.344.

Fully Structural Model. Column 5 considers the most interesting case, when we do not normalize $\bar{A}_{kj}$ to 1. Now we estimate $\bar{A}_{kj}$ from the comparative ads regression, which we discuss in the next section. To get estimates of $\bar{A}_{kj}$ we use the methodology proposed by Gourieroux et al.[1987]. More on this in the next section. For now, let us assume that we have an estimate of $\bar{A}_{kj}$. Then, A^*_{jjt} is now written as follows:

$$A^*_{jjt} = -\alpha M s_j - \lambda \sum_{k \neq j} A_{jk} + \beta \sum\nolimits_{k \neq j} \ln\left(\bar{A}_{kj} + A_{kj}\right) - Z^{'}_{jt}\Phi - \bar{\xi}_{TB} - \Delta\xi_{jt}, \quad \Delta\xi_{jt} \sim N\left(0, \sigma^2\right)$$

The estimate of λ, 0.538, not surprisingly, is essentially the same as in Column 3. The estimate of β is instead quite different. β is now equal to 0.135. The interesting issue here is that the average of $\bar{A}_{kj}$ is 0.6638. This means that an increase in the attacks of 1 million dollar would require approximately 20 cents $\left(\frac{13.5}{0.664+0.01}\right)$ cents to mitigate. This number is not much different from the 27.7 cents that we estimate in Column 4.

Summary. We summarize our empirical analysis of the first order condition 12) as follows. First, Proposition 1's suggestion that higher shares, ceteris paribus, are associated with higher self-promotion advertising is confirmed.

Second, as we expected, we find evidence of a clear endogeneity of market shares (and other advertising variables) in the advertising first order conditions, which creates a substantial downward bias on the coefficient of market shares and upward bias on the coefficients of outgoing and incoming comparative advertising. We find that the inclusion of a Top Brand fixed effect and of brand-specific news shocks controls for the endogeneity in the variables. The Top Brand fixed effect, $\bar{\xi}_{TB}$, has a negative sign, which means that the larger firms, Aleve, Tylenol and Advil have inherently higher advertising base allure than the other brands.

Finally, the estimates of the components of the Net Persuasion function lie within the expected ranges. Outgoing attacks are half as powerful as direct self-promotion ads in raising perceived quality. For given shares, incoming attacks draw down a brand by around 20 cents at the mean, in terms of the self-promotion ads that restore Net Persuasion.

7.2 Comparative Advertising

The second relation that we test is the comparative ad relation (13). The unit of observation now is a *pair of brands*, as we study attacks of one brand, j, on another brand, k.

We start by considering the case when the differentiated product demands are logit functions, and $d_{jk} = \frac{s_k}{(1-s_i)}$. Then, we will consider the more general case when $d_{jk} = \frac{\exp(f(s_i,s_j))}{1+\exp(f(s_i,s_j))}$, where $f(s_i, s_j)$ is a third degree Taylor expansion in s_j and s_k.

Baseline Regression. Column 2 of **Table 5** provides the estimates of $\frac{\beta}{(\gamma-\lambda)}$ when we run the following simple Tobit regression:

$$\left\{ \begin{array}{c} A^*_{jkt} = \frac{s_j}{(1-s_i)} \frac{\beta}{(\gamma-\lambda)} - Z'_{jt}\Phi - \xi_{jkt},\, \xi_{jkt} \sim N\left(0, \sigma^2\right) \\ A_{jkt} = \max\left(A^*_{jkt}, 0\right) \end{array} \right\} \tag{17}$$

We estimate $\frac{\beta}{(\gamma-\lambda)}$ precisely and equal to 3.144. This implies that $\gamma > \lambda$.

Brand Dummies. In **Column 3** we add two brand dummies. One brand dummy is $\bar{\xi}_{TB}$, the same as in the previous section. The second is $\bar{\xi}_{ATB}$, which is equal to 1 if the attacked brand is one of the Top Brands We find that the estimate of $\frac{\beta}{(\gamma-\lambda)}$ changes dramatically, which is consistent again with the hypothesis that market shares are endogenous variables.

Pair-Specific Brand Dummies. In **Column 4** we add pair specific brand dummies. In particular, we run the tobit regression (17), where ξ_{jkt} is replaced by $\bar{\xi}_{TB,TB}+\bar{\xi}_{TB,OB}+\bar{\xi}_{OB,OB}+\Delta\xi_{jkt}$, with $\Delta\xi_{jkt} \sim N\left(0, \sigma^2\right)$. Here, $\bar{\xi}_{jk} = \bar{\xi}_{TB,TB}$ if j and k are both Top Brands, $\bar{\xi}_{jk} = \bar{\xi}_{TB,OB}$ if j is a Top Brand (i.e., Advil, Aleve, Tylenol) and k is an Other Brand, and likewise for $\bar{\xi}_{OB,TB}$ and $\bar{\xi}_{OB,OB}$ (one is omitted because we include a constant term in the regression). For example, $\bar{\xi}_{TB,TB}$ is the pairwise group-fixed effect (to be estimated) if both the 'attacker', j, and the 'attacked', k, are top brands.

We do not find much difference between Column 3 and 4, suggesting that controlling for pair-specific heterogeneity is not necessary.

Tylenol Dummy. A look at the Attack Matrix tells us that most brands attack Tylenol. Then, it is natural to ask how the results change if we include a dummy variable that is equal to 1 when the attacked brand is Tylenol. **Column 5** shows that the results change quite dramatically, with the estimate of $\frac{\beta}{(\gamma-\lambda)}$ back up to 2.747.

News Shocks. Column 6 add major shocks in the tobit regression. Now $\frac{\beta}{(\gamma-\lambda)}$ is up to 3.301.

We can now use this estimate to get an estimate of γ. We know that λ is approximately 0.569; β is approximately 0.277. Then $\gamma = \frac{0.277}{3.301} + 0.569$, or $\gamma \approx 0.65$. This number is quite surprising, since it tells us that comparative ads have a lower marginal cost than self-promotion ads. We should have expected γ to be

above 1. Most likely this is because we underestimate β in the self-promotion regression. There incoming attacks are endogenous but at this point in time we are treating them as exogenous (conditional on including fixed effects).

Relaxing the Nonseparability Assumption inside the Quality Function. Column 7 estimates the comparative advertising equation when we include additional terms. The additional terms are the attacked's self-promoting advertising, A_{kkt}, its outgoing comparative ads, $\sum_{l \neq k} A_{klt}$, and the targeted's incoming attacks, $\sum_{l \neq k} \ln\left(\bar{A}_{lk} + A_{lk}\right)$. Of those, only the last ones show up as playing an important role. Otherwise, there is no evidence that the separability assumption in the quality function is rejected by the data. The finding on $\sum_{l \neq k} \ln\left(\bar{A}_{lk} + A_{lk}\right)$ will be explored in the next future.

Relaxing the Logit Assumption. Finally, Columns 8 relaxes the assumption that the differentiated product demands are logit functions. Now we consider the more general case when $d_{jk} = \frac{\exp(f(s_i,s_j))}{1+\exp(f(s_i,s_j))}$, where $f\left(s_i, s_j\right)$ is a third degree Taylor expansion in s_j and s_k.

We estimate $\frac{\beta}{(\gamma-\lambda)}$, the coefficient of $\frac{s_j}{s_k}\frac{\exp(f(s_i,s_j))}{1+\exp(f(s_i,s_j))}$ equal to 1.244. This is pretty much the same as the estimate in Column 3, where we estimated $\frac{\beta}{(\gamma-\lambda)}$ to be equal to 1.444. From this regression, we construct the values of $\bar{A}_{kj}$ that are used in the last Column of Table 4. In particular we apply the methodology proposed by Gourieroux, Monfort, Renault, and Trognon [1987]. They propose to estimate the generalized residuals, which are equal to the observed residuals for the uncensored observations, and are equal to the expected value of the residual for the censored observations. Clearly the standard errors need to be corrected. We use a bootstrap procedure.

8 Robustness [TO BE DONE]

- Goodwill
- Pulsing
- Multi-brand Firms

9 Conclusions [TO BE DONE]

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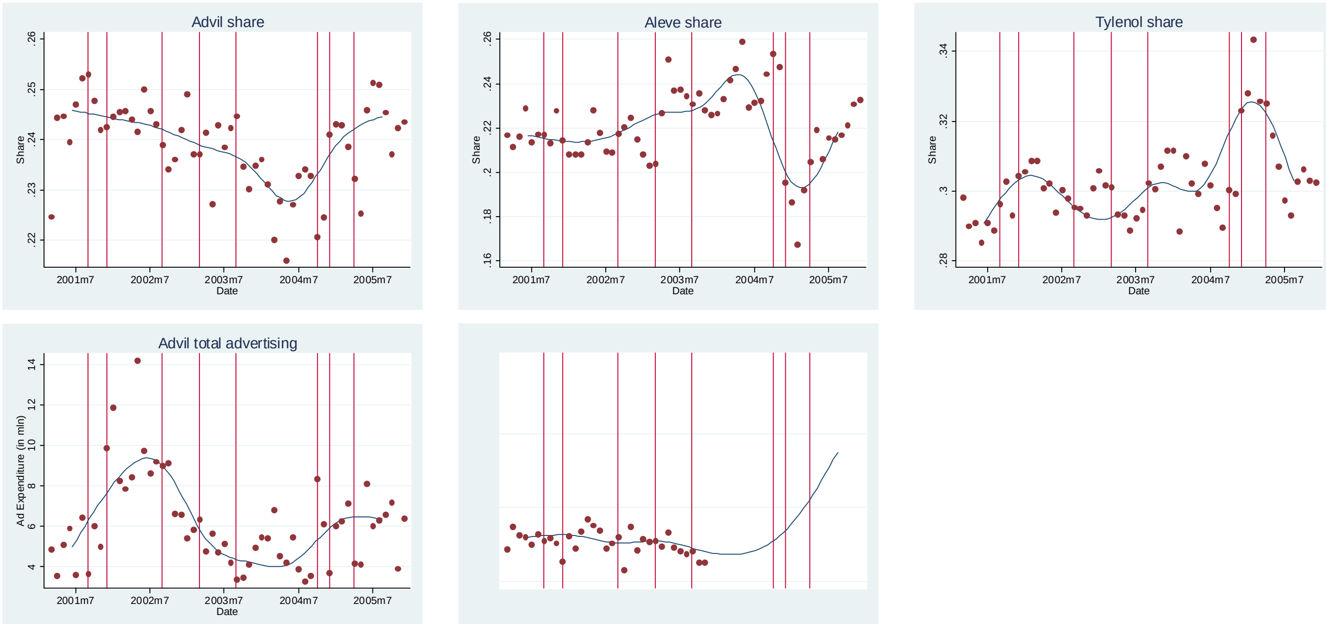
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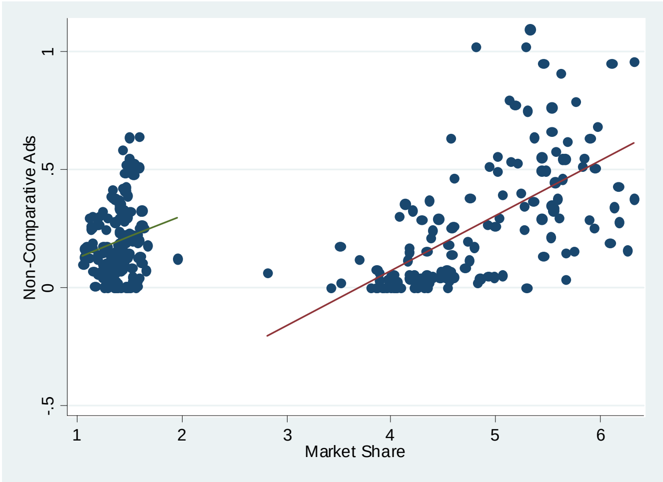

Figure 2. Relationship between Non-Comparative Ads and Market Shares

Table 1: Brands, market share and advertising levels of OTC analgesics market

Brand	Active Ing.	Price per serving	Sales Share	Brand Vol. Share	Weighted Share	Max Pills	TA/ Sales	CA/ Sales	CA/ TA	Owner-ship
Tylenol	ACT	$2.15	29.16%	38.90%	30.51%	7.22	17.34%	4.98%	28.71%	McNeil
Advil	IB	$1.61	17.15%	22.87%	24.21%	5.90	20.00%	14.60%	72.99%	Wyeth
Aleve	NS	$.84	8.25%	11.00%	22.40%	3	26.56%	23.82%	89.71%	Bayer
Excedrin	ACT	$2.41	8.80%	11.74%	8.28%	9.22	26.42%	4.02%	15.22%	Novartis
Bayer	ASP	$1.85	5.73%	7.65%	6.98%	10.07	28.82%	8.80%	30.53%	Bayer
Motrin	IB	$1.73	5.83%	7.78%	7.68%	5.86	20.39%	8.07%	39.58%	McNeil
Generic	ACT	$1.17	8.00%							
Generic	IB	$.66	9.25%							
Generic	ASP	$.82	6.08%							
Generic	NS	$.57	1.66%							

Table 2: Comparative advertising and target pairs

Adv-ertiser ⇓	TARGET: Advil	Aleve	Bayer	Excedrin	Motrin	Tylenol	Total
Advil	-	17.80 [26]	-	4.26 [20]	-	160.20 [56]	182.26 [102]
Aleve	2.64 [9]	-	2.64 [9]	3.12 [16]	2.64 [9]	134.31 [58]	145.36 [101]
Bayer	13.17 [25]	2.05 [8]	-	-	2.05 [8]	15.69 [37]	32.95 [78]
Excedrin	-	1.96 [6]	2.15 [7]	-	-	19.96 [14]	24.08 [28]
Motrin	18.84 [25]	18.79 [25]	-	-	-	-	37.63 [50]
Tylenol	23.07 [43]	45.11 [51]	28.10 [40]	4.27 [21]	15.64 [39]	-	116.18 [194]
Total	57.72 [102]	85.71 [116]	32.89 [56]	11.66 [57]	20.33 [56]	330.15 [165]	538.47 [552]

Table 3: Medical News Shocks

No.	News Shock Description	Date	Source
	Major		
1	Risk of Cardiovascular Events Associated With Selective COX-2 Inhibitors	8/21/2001	Journal of the American Medical Association (JAMA)
2	Ibuprofen Interferes with Aspirin	12/20/2001	New England Journal of Medicine
3	FDA Panel Calls for Stronger Warnings on Aspirin and Related Painkillers	9/21/2002	FDA Public Health Advisory
4	Aspirin Could Reduce Breast Cancer Risk/ NSAIDs Protect Against Alzheimer's	4/8/2003/ 4/2/2003	JAMA American Academy Of Neurology
5	Anti-Inflammatory Pain Relievers Inhibit Cardioprotective Benefits of Aspirin	9/9/2003	Circulation
6	Vioxx Withdrawn From the Market	9/30/2004	
7	Long Term Use of Naproxen Associated with Increased Cardiovascular Risk	12/23/2004	FDA Public Health Advisory
8	Bextra Withdrawn	4/7/2005	
	Minor		
9	Ibuprofen May Prevent Alzheimer's	11/8/2001	Nature
10	Aspirin May Prevent Prostate Cancer	3/12/2002	Mayo Clinic Proceedings
11	Aspirin May Prevent Pancreatic Cancer	8/6/2002	J. of the National Cancer Institute
12	Aspirin Prevents Colorectal Adenomas	3/6/2003	New England Journal of Medicine
13	Misusing acetaminophen, can be deadly	1/23/2004	FDA Public Health Advisory
14	Myocardial infarction associated with Vioxx	4/19/2004	Circulation
15	Celebrex and Vioxx increases risk of acute myocardial infarction or cardiac death	8/25/2004	Annual meeting of the International Society for Pharmacoepidemiology
16	Acetaminophen, NSAIDs Increase Women's Hypertension Risk	8/15/2005	Hypertension

Table 4: Self Promotion, No IV

	Baseline	Brand Dummy	Major News Shocks	Fully Structural
Ms_{jt}	0.008***	0.056 ***	0.064***	0.084***
	(0.003)	(0.008)	(0.008)	(0.002)
$\sum_{k \neq j} A_{jk}$	-0.733***	-0.571***	-0.569***	-0.538***
Outgoing Comp Ads	(0.073)	(0.073)	(0.070)	(0.033)
$\sum_{k \neq j} Log(1 + A_{kj})$	0.587***	0.344***	0.277***	
Incoming Comp Ads	(0.081)	(0.084)	(0.08)	
$\sum_{k \neq j} Log(\bar{A}_{kj} + A_{kj})$				0.135***
Incoming Comp Ads				(0.013)
$\bar{\xi}_T$		-0.546***	-0.624***	-0.138*
Top Brand FE		(0.082)	(0.082)	(0.060)
Constant	0.125***	-0.077**	-0.092**	-0.500***
	(0.023)	(0.038)	(0.038)	(0.035)
Variance Residuals	0.205	0.192	0.183	0.197
	(0.008)	(0.008)	(0.007)	(0.002)
Observations	348	348	348	
Log Likelihood	10.388	38.953	47.978	
GMM	10.388	38.953	47.978	
Major News Shocks	No	No	Yes	No
Fully Structural	No	No	No	Yes

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in Column 5

Table 5: Comparative Advertising, No IV

	Baseline	Brand Dummies	Pair Brand Dummies	Tylenol Dummy	Major News Shocks	Testing Specific	Taylor Expansion
$\frac{s_j}{1-s_j}$	3.144***	1.444**	1.450**	2.747***	3.301***	3.246***	
	(0.256)	(0.596)	(0.593)	(0.550)	(0.571)	(0.534)	
$\frac{s_j}{s_k} \frac{\exp Taylor(s_j, s_k)}{1+\exp Taylor(s_j, s_k)}$							1.2443***
Taylor Expansion		(0.026)					(0.1633)
$\bar{\xi}_{TB}$		0.118***		0.054**	0.030	-0.000	-0.229***
Top Brand		(0.026)		(0.024)	(0.025)	(0.024)	(0.053)
$\bar{\xi}_{ATB}$		0.181***		0.116***	0.116***	0.117***	0.903***
Top Attacked Brand		(0.011)		(0.010)	(0.010)	(0.011)	(0.067)
$\bar{\xi}_{TB,ATB}$			0.281***				
Top Brand-Top Brand FE			(0.031)				
$\bar{\xi}_{TB,AOB}$			0.092***				
Top Brand-Other Brand FE			(0.031)				
$\bar{\xi}_{OB,AOB}$			0.156***				
Other Brand-Other Brand FE			(0.020)				
$\bar{\xi}_{ATyl}$				0.151***	0.154***	0.276***	
Tylenol Attacked FE				(0.011)	(0.011)	(0.018)	
A_{kk}						-0.007	
Targeted Self-Promotion						(0.022)	
$\sum_{k \neq l} A_{kl}$						0.042	
Targeted Outgoing Comp Ads						(0.027)	
$\sum_{l \neq k,j} Log(1 + A_{lk})$						-0.403***	
Targeted Incoming Comp Ads						(0.040)	
Constant	-0.218***	-0.304***	-0.283	-0.302***	-0.300***	-0.252***	-1.368***
	(0.014)	(0.018)	(0.022)	(0.016)	(0.017)	(0.016)	(0.085)
Variance Residuals	0.176	0.150	0.149	0.133	0.131	0.121	0.153
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	1740	1740	1740	1740	1740	1740	
Log Likelihood	-340.391	-178.450	-177.428	-94.917	-76.301	-026.955	
GMM							
Major News Shocks	No	No	No	No	Yes	Yes	No
Fully Structural	No	No	No	No	Yes	Yes	Yes

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.