Getting into Your Head(Ache): The Information Content of Advertising in the Over-the-Counter Analgesics Industry

Anderson, Simon and Ciliberto, Federico and Liaukonyte, Jura

University of Virginia, University of Virginia, Cornell University

10 August 2010

Getting into your Head(ache): the Information Content of Advertising in the over-the-counter analgesics industry*

Simon P. Anderson† University of Virginia

Federico Ciliberto‡ University of Virginia

Jura Liaukonyte§ Cornell University

July 2010

Abstract

We study how much information firms include in their advertisements and what determines their choices. We use data from advertisement videos from the US OTC analgesics industry between 2001 and 2005 to measure information content in ads. For each video we code the number of cues it contains. The correlation between any two cues is rarely large, suggesting that each cue provides different information. We find: i) brands with inherently better characteristics (e.g. faster relief) transmit more information; ii) comparative advertisements contain significantly more information than self-promotion ads; iii) market share is negatively associated with the amount of information content; iv) a higher market share of the generic version of a brand is also associated with less information by the brand. Not controlling for endogeneity of market share and the decision to use comparative advertising would lead to significant estimation bias. Result (iii) is consistent with recent theoretical work that larger firms disclose less information, while result (iv) indicates the likely presence of information spillovers from brands to their generic counterparts.

Keywords: Information Content, Advertising, Comparative Advertising, Content Analysis.

JEL Codes: D83, L15, M37.

*We thank Michaela Draganska, Bart Bronnenberg, Kenneth Wilbur, Jill Klein, Brian Wansink, Carrie Heilman, Ross Rizley and participants of the III Conference on the Economics of Advertising and Marketing in Barcelona for comments and suggestions. We sincerely thank the Marketing Science Institute (MSI) for funding the aquisition of the data used in this paper. All remaining errors are our own.

†Department of Economics, University of Virginia, sa9w@virginia.edu, ph: (434) 924-3861.

‡Department of Economics, University of Virginia, ciliberto@virginia.edu, ph: (434) 924-6755.

§Charles H. Dyson School of Applied Economics and Management, Cornell University, Jurate@cornell.edu, ph: (607) 255-6328.

1 Introduction

How much information firms choose to disclose in advertisements is a question of substantial theoretical and empirical debate. Recent research in marketing and economics provides some theoretical predictions on the relationship between market structure or firm size and the amount of information transmitted (Sun 2010; Guo and Zhao 2009; Anderson and Renault 2009). The empirical work on the content of advertising is split into two camps with essentially no overlap - vast numbers of content analysis articles in marketing (see Abernethy and Franke 1996 for a fine summary) and a nascent literature in marketing and economics where advertising content is treated as a choice variable (Bertrand et al. 2010; Anderson et al. 2010; Liaukonyte 2010). This paper provides some relevant evidence for the theory and bridges the gap between the two empirical camps by improving the methodology of the content analysis literature, which enables us to study the determinants of advertising content.

We use data from the Over the Counter (OTC) Analgesics industry in the US. This industry is noteworthy for several reasons. First, firms spend large amount of money on advertising relative to other industries. Advertising-to-sales ratios for OTC analgesics typically range from 20 to 30 percent of sales, making them one of the most heavily promoted manufactured goods. Second, firms do both self-promotion and comparative advertising, so we can investigate whether more or less information is included in each of these two types of ads. Finally, the type of cues that are mentioned (e.g. "strong") are clearly identifiable, so the coding of the actual ads is only marginally subjective.

We classify and fully measure different types of advertising content (within this industry) by analyzing each television commercial that was broadcast between 2001 and 2005. We code each product characteristic mentioned in the advertisements. These data are then integrated with data on the total amount spent to air each advertisement. The richness of the data allows us to

propose a novel methodological technique to analyze the informational content of advertising – to weigh the distribution of information by the advertising expenditure, which is a close approximation of consumer reach. We then merge this dataset with brand sales data in order to determine the effect of brand size on ad content. Further variables are constructed by collecting information on the exogenous product characteristics, determined by their active ingredient and assembled from medical research published in peer-reviewed medical journals.

Our analysis consists of three broad steps. First, we show some stylized patterns in the data such as the distribution of cues across different types of ads (comparative and self-promotion). We also analyze in detail the extent to which different cues are mentioned together. For example, if product attribute "strong" is always mentioned together with "long-lasting," then we should not necessarily think of these two cues as providing different information. However, we show that the correlation between cues is rarely large, which supports the claim that our classification of cues is consistent with the idea that each cue provides different information.

Second, we relate the number of cues to exogenous explanatory variables. We run ordered probit models where the dependent variable is the number of cues and the explanatory variables are the quantifiable medical characteristics of the active ingredient of a brand, standardized so as to indicate the strength of each brand in each characteristic relative to the other brands. Brands with inherently higher strength of pain relief, those with faster relief, and those with a lower potential for gastrointestinal (GI) toxicity or cardiovascular (CV) risk include more information in their ads.

Third, various effects of interest involve endogenous variables, such as the relative content of comparative ads, the relationship between content and firm market share or generic counterpart size. Comparative advertisements contain more information than self-promotion ads. In particular, after accounting for the endogeneity of the decision to use comparative claims, we

show that the probability of observing at least three cues is 73.3 percent higher in comparative ads than in self-promotion ads. Next, we show that market share is negatively associated with the amount of information content as larger firms put out less informative ads. This finding is particularly interesting because, a priori, the effect of firm size on information content is ambiguous. On the one hand, firms with stronger market positions might have better quality products, providing a lot of possible topics for advertising content. On the other hand, imparting a lot of information can be a two-edged sword as some consumers may be turned off buying if they infer or realize that a product does not deliver their preferred characteristics. Smaller brands may want to communicate characteristics in order to compare themselves in a favorable light to larger and more popular brands, and they may also want to stress differences. The latter theme, in essence, is at the heart of the Anderson and Renault (2009) result that sufficiently small firms want to provide information while large ones do not. But it could instead be the case that small brands wish to deploy narrow advertising themes to target specific audiences (Iyer, Soberman and Villas-Boas 2005; Anand and Shachar 2009), and they may not possess many favorable advantages to highlight in their marketing activity. Finally, similarly to work by Rutz and Bucklin (2010), which finds evidence that generic internet search activity positively affects branded search activity via increased awareness, we also find evidence of similar spillover effect. We find that a higher market share of the generic version (e.g. ibuprofen) of a brand (e.g. Advil) is also associated with less information by the brand (Advil). This finding constitutes evidence that brands are concerned about spillover effects that would benefit their generic competitors, and that these spillovers are larger for more informative ads. Instead, the branded firm might concentrate its advertising strategy less on drug performance and more on promoting the brand per se.

Our paper is related to the literature on content analysis, which also counts the number of cues (pieces of information) included in advertisements and argues that more information is

provided by ads with more cues. This approach, initially advocated by Resnik and Stern (1977) has been applied in more than 60 studies to measure the information content of advertising in different media (Chou, Franke, and Wilcox 1987; Harmon, Razzouk, and Stern 1983; Stern and Resnik 1991), countries (Madden, Caballero, and Matsukubo 1986; Hong, Muderrisoglu, and Zinkhan 1987), and product categories (Stern, Krugman, and Resnik 1981).[1] While the Resnik-Stern approach has been used extensively, results have varied markedly, even within the same medium, because of lack of a multivariate statistical analysis, redundant definitions of information cues, and small sample size (Abernethy and Franke 1996). We analyze a single industry, which enables us to deal with most of these criticisms. First, we can consistently set product attribute categories that are specific to the industry. Second, our sample size is relatively large and fully inclusive. Finally, to avoid the bias that is caused by analyzing only each distinct advertisement or a sample subset, we weight our results by the advertising expenditures on each ad and use all ads produced.

The paper is organized as follows. Section 2 describes the data. Section 3 presents the classical content analysis. Section 4 introduces the ordinal statistical models that we use for our multivariate analysis. Section 5 investigates the relationship between information content and the decision to make a comparative ad. In this Section we also relate market share of the brand and of its generic competitor to information content. Section 6 summarizes, notes limitations of our approach, and discusses future research opportunities in advertising content.

2 Data Description

We use two main datasets. We present the advertising dataset first to give a sense of what information brands choose to communicate to their consumers about their products. Then we present a dataset on the characteristics of the active ingredient of the brands. The characteristics

are exogenous and in our empirical analysis we will use them as explanatory variables of the amount of information released by the firms. We will also use these characteristics to construct instrumental variables.

2.1 Advertising Dataset

The OTC analgesics market covers pain-relief medications with four major active chemical ingredients. These are aspirin, acetaminophen, ibuprofen, and naproxen sodium. The nationally advertised brands are familiar names: Tylenol (acetaminophen), Advil and Motrin (ibuprofen), Aleve (naproxen sodium), Bayer (aspirin or combination), and Excedrin (acetaminophen or combination).

The advertising data come from TNS-Media Intelligence and cover the entire OTC analgesics product category in the U.S. The data set contains video files of all advertisements, as well as monthly advertising expenditures by ad, for 2001-2005 for each product advertised in the OTC analgesics category. While the advertising numbers also include expenditures on other media, almost all (around 90%) of the advertising budgets were spent on broadcast television advertising, including network and cable TV. In the analysis below, we only look at the TV ad data.

We watched 4503 individual commercials broadcast during 2001-2005, 346 of which had missing video files. Each individual ad was usually shown multiple times. The total number of times these commercials were shown over the 5-year period in all types of media was a staggering 466,413 times. For each ad we recorded whether the commercial had any comparative claims, and if a commercial was comparative, what was the comparative claim (e.g. faster, stronger, etc.). If the advertisement was not comparative, then we recorded any claim (e.g. safety, strength, speed, etc.) that was made. In a related paper, Anderson, Ciliberto, Liaukonyte and Renault (2010) construct and estimate a structural model of comparative advertising and target brand choice.

We do not use the information on which brand was targeted here because this is not the focus of this paper.

We coded claims into characteristics, according to the purpose of the drug (menstrual, arthritis, headache, etc.), efficiency and/or safety (safety, strength, speed, etc.) of the drug, and other characteristics (non-habit forming, overdose warning, etc.).

In total there are thirty product attributes, but, for the sake of clarity, **Figure 1** includes only the top 23 attributes and shows how many millions of dollars brands spent advertising the top product attributes over five years, ranked by dollars spent. The dollar expenditures given are for the full sample. If an ad mentioned a characteristic, we count the spending on that ad as spending on that characteristic. This means that the sum of the expenditures in **Figure 1** exceeds the total ad spending because many ads promote multiple characteristics. The ad spending is broken down into whether the ad was categorized as comparative or not. The remaining 7 attributes had negligible advertising expenditures.

The attributes "Fast", "Strong", "Long Lasting" and "Safe and/or Trusted" are among the top five most heavily advertised attributes. These attributes are directly related to the inherent (exogenous) chemical characteristics of each active ingredient in each analyzed brand, which we discuss in great detail in the next section.

Table 1 portrays the correlation matrix of cue usage. We look at the correlations to investigate whether the cues chosen represent distinct information or not. For example, we have coded "strong" and "fast" as separate categories, but we need to make sure that the information categories we have coded are indeed distinct information cues. **Table 1** shows that the cue descriptors we use are indeed quite distinctive. For example, even though "Fast" and "Strong" are often used together, in over half the occurrences (in dollar terms) they are also used separately.[2] Thus, two cues may be used together frequently, but each still gives extra

information. Strong denotes how powerful is the medicine when it is in effect, Fast denotes speed of the onset of pain relief. Of course, the active ingredient present in each drug may have both of these properties. Our take-away from **Table 1** is that the classification we use does describe independent information cues.

Table 2 compiles spending and cue information by brand and by year.[3] The first two columns reflect the (expenditure weighted) average number of attributes and likelihood of any observation to be a comparative ad, reported by brand. Aleve and Advil ads mention on average one more attribute than Tylenol, Motrin, and Excedrin ads, and approximately half an attribute more than Bayer ads. Furthermore, almost half the ad spending was on comparative ads: we will pay special attention to the difference in advertising content according to whether or not an ad was comparative. The breakdown is striking across brands: almost all of Aleve's ads are comparative ads; two thirds of Advil's ads are comparative. The others have around one third of their ads comparative, with the exception of Excedrin which has just one sixth. **Column 3** in **Table 2** gives the average dollars spent per ad creative, averaged over the ads aired in a month. Excedrin spent the most per ad per month, with an average of $255,000. Other brands spent between $100,000 and $140,000. These numbers reflect Excedrin's reliance on a relatively small number of ads in their portfolio at any one time. Even though Excedrin spends more per ad in any month, it ranks only third in overall advertising spending. During the 5 year period analyzed, Tylenol spent by far the most on advertising, $414 million, constituting some 32% of the (dollar weighted) observations. Advil spent around a third less, and the other four spent each roughly half of that amount. The average monthly sales (averaged across firms) are around 23 million dollars.

The advertising to sales ratios are very high in this industry: we can see from the last Column of **Table 2** that they range from 17.8% for Tylenol to 28.8% for Bayer. **Table 2** also

indicates that advertising-to-sales-ratios across the industry increased slightly to its peak in 2004 when both OTC and prescription analgesics were faced with several adverse effects, such as the Vioxx withdrawal and Aleve's association with elevated cardiovascular risk.

2.2 Characteristics Dataset

Our analysis also incorporates data on strength pain relief, relative efficiency and safety for each brand. This information was collected from peer-reviewed medical journals. Although each of the drugs generally treat pain, fevers and headaches (hence implying that they are close substitutes), there are some differences between analgesic types. While aspirin, naproxen sodium and ibuprofen are non-steroidal anti-inflammatory drugs (NSAIDs), Acetaminophen is not. In general, ibuprofen and naproxen are more potent pain relievers, i.e., they reduce more pain than the corresponding dose of Acetaminophen or Aspirin. On the other hand, Acetaminophen is considered to be the safest pain reliever because it does not block prostaglandins, and therefore does not cause any gastrointestinal (GI) bleeding. However, even though Acetaminophen reduces pain and fever, it does nothing for inflammation. Additionally, high doses of Acetaminothen may damage the liver. Aspirin is the only pain reliever shown to reduce the risk of heart attack (albeit in low doses).

We can quantify or rank all the true characteristics that were used in advertising associated with each active ingredient as follows. First, we interpret "fast" as the time taken to achieve a perceptible or meaningful pain relief (in medical literature terminology: onset to perceptible pain relief). Second, such claims as "long lasting" are interpreted as a duration of meaningful pain relief. Third, we interpret claims concerning strength (e.g. "strong", "stronger", "tougher on pain") as the maximum level of pain relief achieved and we use NNT (Number Needed to Treat) measure to approximate analgesic efficiency claims. NNT is a standard efficiency measure used in the pain relief evaluation literature. See Appendix B for an explanation of how NNT, CV and GI risks are calculated.

The medical literature provides objective risk and efficiency measures for each product, based on its active ingredient (or combination of ingredients), strength and recommended dosage. There are definitive maximum doses and durations of therapy for each active ingredient. Differences exist across different active ingredients in terms of the important safety issue of the potential for gastrointestinal (GI) toxicity and cardiovascular (CV) risk. The measurable characteristics were collected for maximum OTC recommended dosage (single dose): Ibuprofen – 400mg; Naproxen Sodium - 440 mg.; Aspirin – 1000mg; ACT – 1000mg. These measurements enable us to identify the locations of all the products in the characteristics space.

Now we turn to discussing in greater detail the measurable product characteristics and characteristics that can be unambiguously ranked. The measurable characteristics are the Numbers Needed to Treat, Cardiovascular Risk and Gastrointestinal Risk. **Figure 4** depicts quantifiable active ingredient attribute positions in characteristics space.

In addition to using absolute risk and efficacy measures, we supplement our data with relative performance metric for speed of pain relief.[4] Each active ingredient can be unambiguously ranked by the onset of pain relief (i.e. "Fast") using the results in published medical studies.[5]

Figure 2 clearly exhibits the fact that no active ingredient is superior in all characteristics. Clinically, all four main active ingredients have varying degrees of side effects. Because people react to each ingredient differently, clinical pain researchers are hesitant to assign superiority to any single drug. Each active ingredient has a comparative advantage. Aspirin (brand name: Bayer) is weak (high NNT) but it has low, almost non-existent cardiovascular risk. Naproxen sodium (Aleve) has lowest NNT (which implies that it is the most potent drug) but is associated with very high GI risk. Acetaminophen (Tylenol and Excedrin) has low GI risk, but is weak in pain relief and has a medium cardiovascular risk. Ibuprofen (Advil and Motrin) and Naproxen Sodium (Aleve) based brands have highest CV risk but are also the fastest in pain relief. The

longevity measure is inversely related to the maximum number of regular strength pills allowed to be taken within 24 hours. Naproxen Sodium (Aleve) tops the list in this regard, whereas Acetaminophen (Excedrin and Tylenol) have the lowest duration of pain relief. Therefore the informational content of advertising is very important as it helps consumers to be better matched to a particular drug with a particular active ingredient.

3 Content Analysis

3.1 Univariate Histograms

The classic Content Analysis compiles the distribution of numbers of information cues. With our elaborate data set, which includes how many times an ad was aired, and how much was spent on doing so, we can compare different ways of counting observations. These are compared in **Figure 3a**.

The numbers on the horizontal axis are the number of information cues in an ad, and the vertical axis is the relative frequency in the sample. The third columns in **Figure 3a** treat each unique ad as a different observation. The middle, lightest color columns, weigh each occurrence of each ad. Finally, the darkest color columns weight each occurrence by how much was spent airing it. Arguably, the latter is the best measure of the economic importance of each information category and the extent of information content. However, the similarity across the different measures is striking. This issue is discussed further in Section 4.

3.2 Comparative Advertising

Figure 3b shows the cue distribution and descriptive statistics for comparative and noncomparative ads. These findings are broadly consistent with the findings of Harmon, Razzouk, and Stern (1983) and Chou, Franke and Wilcox (1987) for magazine advertisements. Harmon, Razzouk, and Stern (1983) find that comparative ads on average have 1.84 cues and

non-comparative ads have only 0.86 cues. However, we find that, on average, each ad contains more information than found by Harmon et al. and that the difference between the number of cues for comparative and non-comparative ads, even though statistically significant, is much smaller. One might expect a comparison of comparative and non-comparative ads on broadcast TV to yield similar patterns, although perhaps at a lower level of information, since meta analysis evidence in Abernethy and Franke (1996) suggests that television advertisements have significantly fewer informational cues than print media advertisements. Overall, though, we would expect more informational cues in comparative advertisements simply because some objective criteria should be presented to the consumer as required to comply with Federal Trade Commission (FTC) guidelines on comparative advertising. Additionally, the prior analysis of quantifying information content in comparative vs. noncomparative ads might be misleading due to endogeneity problem, which we explain in Section 5.2.

4 Multivariate Analysis with Ordered Probits

The classic content analysis determines the fraction of ads for each given number of cues and uses univariate histograms to compare scenarios. In this paper, we use an ordered probit model to study the *determinants* of the distribution of cues.[6]

Providing too little information arguably wastes the opportunity of convincing prospective consumers sufficiently. Providing too much may cause crowding of the messages of the ad and may cause information overload for the consumer. This suggests an optimal degree of information content. The optimal degree may vary systematically across firms and may be partially explained by observable factors, such as firm size. It may also vary across messages from the same firm according to the suitability of various combinations of information, recent news about the product, and the medium (or TV show) in which the ad is placed – these are the factors affecting

choice which are unobservable (to the econometrician).

We use a discrete measure of content (number of cues) and describe outcomes as integer values. Loosely, think of an optimal number of cues as a random variable with a systematic component which differs across firms and can be in turn explained by observable features. The ordered probit model assumes that unobserved components are drawn from a normal distribution and determines cut-off values such that the realization of a latent variable (explained component plus noise) lies within a range corresponding to each specific number of cues.

4.1 Information Content in an Ordered Probit Model

Let y denote the number of cues included in an ad where y takes the values $\{0, 1, 2, ..., J\}$. In our sample $J = 6$ is the maximum number of characteristics observed in any ad. The ordered probit model can be derived from a latent variable model. The latent variable, y^*, here *the information content*, is determined by:

$$y^* = X\beta + e,$$

where e has a normal distribution, β is a $K \times 1$ vector of parameters, and X is a $1 \times K$ vector of observable features of the brand, which does not include a constant. Here $y^* = X\beta + e$ can be interpreted as describing the equilibrium choice of information content as a function of the exogenous variables. Then more information content is associated with a larger number of cues. This simple interpretation makes the use of ordered models an attractive framework to study information content.

Define $\alpha_1 < \alpha_2 < ... < \alpha_J$ as unknown thresholds or cutoff points. The relationship between the latent variable y^* and the observed variable y is as follows:

$$\begin{aligned} y &= 0 \text{ if } y^* \leq \alpha_1 \\ y &= 1 \text{ if } \alpha_1 \leq y^* \leq \alpha_2 \\ &... \\ y &= J \text{ if } y^* > \alpha_J. \end{aligned}$$

Assume that e is distributed according to a standard normal distribution $e \sim N(0,1)$. Then, the probability of each outcome is:

$$\begin{aligned} \Pr(y=0|X) &= \Phi(\alpha_1 - X\beta) \\ \Pr(y=1|X) &= \Phi(\alpha_2 - X\beta) - \Phi(\alpha_1 - X\beta) \\ &... \\ \Pr(y=J|X) &= 1 - \Phi(\alpha_J - X\beta). \end{aligned}$$

The parameters $\alpha_1, ..., \alpha_J$ and β can be estimated using maximum likelihood. The marginal effect for a change in w is given as follows:

$$\frac{\partial \Pr(y=j)}{\partial w} = \left[\phi\left(\alpha_j - X\beta - w\gamma - \frac{\rho_{v\epsilon}}{\sigma_v}v\right) - \phi\left(\alpha_{j-1} - X\beta - w\gamma - \frac{\rho_{v\epsilon}}{\sigma_v}v\right)\right](-\gamma).$$

Notice that there are as many marginal effects as outcomes. Moreover, the marginal effects do not have the same sign across outcomes. If γ is positive, then a higher w means that the first outcome ($j=0$) is less likely to occur while the last outcome, (e.g. $j=6$) is more likely to occur. The sign of the effect for the intermediate outcomes is ambiguous.

4.2 Heterogeneity in Information Cues

We start our analysis of explaining the pattern of information cues by first by breaking down the ads by identity of the advertiser and by year. Then we look at how information content is related

to the exogenous characteristics of the active ingredients of each brand. Essentially we take the view that medical properties of the underlying Active Ingredient molecules influence the information content of an advertiser's series of ads, and we break down the information with this explanatory variable. Our first step consists of showing how using an ordered probit without any additional control variables can improve on the classic univariate content analysis.

Columns 1 and **2** of **Table 3** report the results when we do not include any control variables in the estimation. Thus, we only estimate the cutoffs. In **Column 2** we weight each ad by the advertising expenditure in that ad whereas in **Column 1** we report the results from the unweighted regression. Recall that the classic content analysis does not weigh ad observations by advertising expenditure.[7] As discussed in Section 2, two appealing features of our data are that we have the complete set of ads run over the sample period, and we have the expenditure data on each ad. Many traditional studies do not have the data on what was paid to screen, air, or publish ads, so they are constrained to just report information cues per ad analyzed.

The standard errors of the cutoffs in **Columns 1** and **2** are small because of the large sample size: all the cutoffs are precisely estimated. The first cutoff is very small, reflecting that very few ads have no information content. The cutoffs in **Columns 1** and **2** are not much different, but they are statistically different.[8] The cut-points are all slightly larger when the ads are not expenditure-weighted. This means that the probability of seeing a number of cues below any particular number is higher when the data are unweighted.

One way to visualize this is to think of the given normal distribution and the cut-points being to the right for the unweighted case. An alternative visualization is in terms of the cumulative number of cues, which is larger for the unweighted case. We can therefore say that the distribution of cues for the unweighted data stochastically first-order dominates the distribution for the weighted data – there is a greater fraction of ads with zero cues, a greater fraction with

one or fewer, etc. This implies that more money tends to be spent on running ads with more cues in them. As a benchmark, if all ads cost the same amount to screen, then ads with more cues are being screened more often. Alternatively, if they were all aired the same number of times, those with more cues are being aired to more expensive (i.e., typically larger) audiences.

However, as we mentioned above, the difference in the cutoffs estimated in **Columns 1** and **2**, while statistically significant, is small. This indicates that a lack of data on the amount spent on airing the ads does not distort the results much for our particular sample. For example, in an industry with a lot of seasonality within a month, the results might be quite different.

In the sequel, we only provide the results for the expenditure-weighted case.

4.3 Brand and Time Fixed Effects

We add brand fixed effects to see which brands choose to provide more information cues, and we add year fixed effects to see whether the information pattern across the analyzed years is different. The results are reported in **Columns 3-5** of **Table 3**, . Notice that the number of brands (six) does not change over time, while the number of observations for each brand increases each year-month. This explains why we are not concerned about the incidental parameters problem (Heckman 1981).

The brand "Tylenol" and year "2001" fixed effects are used as a base and therefore omitted. The results reported in **Column 3** of **Table 3** suggest that only Excedrin advertises fewer cues than Tylenol (the negative entry in the Column), but not significantly less. Below we further explore the relation between the fundamental active ingredients and cues, using performance measures for the Active Ingredients. Motrin provides only slightly more cues than Tylenol. Aleve ranks the highest in terms of average number of cues used in ads, Advil is a close second. Both of these brands engage in a lot of comparative advertising, which is the focus of analysis in Section (5.3) where we trace how much incremental information is driven by comparative advertising.

Columns 4 and **5** add year fixed effects. Comparing to 2001 (which is the omitted fixed effect), the information patterns in 2002 and 2003 are not noticeably different. However, ads aired during 2004 have slightly fewer cues, whereas ads aired in 2005 have significantly more. The rise of information content during the year 2005 is most likely related to the FDA's announcement at the end of 2004 of the results of a clinical study, which indicated that patients taking naproxen sodium (Aleve) may be at an increased risk of suffering heart attack or stroke (the withdrawal of Vioxx was also associated with this clinical study). By the end of January 2005, sales of Aleve plummeted by over 50% suffering the largest decline in brand history (for more details, see Aleve Case History, Real People Campaign (2006)).

The source of increased information content in 2005 most likely comes either from Aleve trying to re-establish its position by providing more information that its risk was exaggerated, or by competitors trying to compare themselves directly or indirectly to Aleve, and reminding consumers that the risk of their brand is lower. [9] We explore the heterogeneity of information changes across brands in 2005 by constructing a variable that interacts the fixed effect of 2005 with brand fixed effect ($Tylenol * 2005$ is omitted). The results of this estimation are reported in **Column 5**. Even after controlling for the mean information content in 2005, we see that Aleve changed its advertising strategy the most, which resulted in the highest increase of informational content. Tylenol, Excedrin and Motrin also exhibited the increased pattern in advertising content, whereas Advil's reaction was in the opposite direction.

To summarize the results of **Table 3**, there is substantial heterogeneity in the degree of ad informativeness across brands. However the variation across time is not significant, with the exception of year 2005, which was a turbulent year for the entire analgesics category.

4.4 Exogenous Determinants of Information Cues

Finally, we look at how information content is associated with the exogenous medical characteristics of the active ingredients. **Column 6** of **Table 3** includes NNT, Relative Speed, CV and GI Risk measures.

We find that brands with inherently higher strength of pain relief (lower NNT) have ads with higher information content. Recall first that for Numbers Needed to Treat (NNT), a higher number means worse performance and a less effective drug. So the negative coefficient on NNT is consistent with strong and efficient drugs putting more information in their ads. A similar pattern holds for brands that have lower GI and CV risks: their ads also tend to be more informative. Finally, brands that offer faster relief also have higher information content.

Overall, **Column 3** of **Table 5** suggests that more information is transmitted the stronger is a brand along one of the four dimensions identified by the exogenous medical characteristics of the active ingredient.

5 Comparative Advertising, Sales, and Information Disclosure

In this Section we look at the relationship between endogenous explanatory variables and information content. We consider three endogenous variables. First, we investigate whether comparative ads contain more information content than self-promotion ads. Next, we study how brand size is associated with information content. Finally, we study whether spillover effects, whereby a brand is concerned about ads that might benefit its generic competitor, play an important role in determining the information content of an ad. We first explain the instrumental variable approach in the current context.

5.1 Identification

In Sections (4.2), (4.3), and (4.4) we studied how exogenous variables are associated with the amount of information content in advertisements. Since all the regressors are exogenous, we could run a standard ordered probit. Below we study whether comparative ads contain more information and whether the amount of information released is a function of the market share of a brand (e.g. Tylenol) and of the market share of its generic competitors (e.g. analgesics whose active ingredient is ACT). Because the decision to include a comparative statement is made by the firm at the same time that the firm decides how much information to release in an ad, this raises serious endogeneity concerns. Similarly, a brand's market share is likely determined, at least in part, by its location in the characteristics space. We show that the amount of information released is a function of a brand's characteristics. This also raises serious endogeneity concerns. If endogeneity is important and is not controlled for then we can end up with biased estimates of the relationship between the endogenous variables (comparative ads and sales) and the outcome (information content).

We use an instrumental variable approach to see whether our endogeneity concerns are empirically relevant. Instruments that are correlated with sales and advertising, but not correlated with an unobserved quality, provide information on how important the endogeneity problem is.

Following the literature on the estimation of demand in differentiated product markets (e.g. Bresnahan 1987), we assume that the product characteristics space is exogenous. This is a very reasonable assumption in this industry, since the "true" characteristics of pain relievers are essentially fixed, determined by the chemical properties of the particular active ingredient that constitutes the drug. Recall that the exogenous product characteristics (described in Section 2.2) are the NNT value, relative speed, CV risk and GI risk.

Then, we consider the case when a brand's own characteristics enter directly in the ordered

probit regression and the instrumental variables are constructed using functions (here, the average) of the characteristics of the brand's competitors. This follows the standard approach in the empirical industrial organization literature. More specifically, we construct the means of the characteristics of the brand's competitors as well as the minimum values of them. We also interact these characteristics with a dummy that is equal to 1 a brand has the parent company shared by other brand, which is the case for Tylenol and Motrin (parent company McNeil), as well as for Aleve and Bayer (parent company Bayer). Finally, we interact the characteristics with the 2005 year dummy to capture advertising content changes during the turbulent year.

5.2 The Econometric Approach

To deal with endogenous variables in our nonlinear ordered probit model we follow the approach proposed by Rivers and Vuong (1988). First, rewrite the information content y^* as:

$$y^* = X\beta + w\gamma + \epsilon,$$

where w (e.g. market share) is an endogenous variables: $E(w'\epsilon) \neq 0$. For now we consider the case where w consists of only one endogenous variable. Later, we consider the case where there are up to three endogenous variables on the right hand side.

The main identification assumption is that there exists a matrix of variables Z (which contains X) such that $E(Z'\epsilon) = 0$. Here Z includes all the exogenous variables, such as X and functions (here, the average) of the characteristics of the brand's competitors. Let

$$w = Z\delta + v,$$

which tells us how the variation in the endogenous variable w is explained by the variation in the exogenous variables Z (e.g., appropriate summary statistics of the characteristics of a brand's competitors). We assume that (v, ϵ, Z) are i.i.d., and v and ϵ have, conditional on Z, a joint

normal distribution:

$$\begin{pmatrix} \epsilon \\ v \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{v\epsilon}\sigma_\epsilon\sigma_v \\ \rho_{v\epsilon}\sigma_\epsilon\sigma_v & \sigma_v^2 \end{pmatrix}\right)$$

We can then use a basic property of jointly normal random variables and write:

$$E\left(\epsilon|v\right) = \rho_{v\epsilon}\frac{\sigma_\epsilon}{\sigma_v}v = \frac{\rho_{v\epsilon}}{\sigma_v}v.$$

Let the error e be defined as:

$$e = \epsilon - E\left(\epsilon|v\right) = \epsilon - \frac{\rho_{v\epsilon}}{\sigma_v}v.$$

Then, $e \sim N\left(0, 1-\rho_{v\epsilon}^2\right)$, and

$$y^* = X\beta + w\gamma + \frac{\rho_{v\epsilon}}{\sigma_v}v + e.$$

If we observed v, then we could run again a standard ordered probit model because the inclusion of v controls for the endogeneity of w. We would only have to pay extra attention to how to interpret the estimated parameters. Then, we would have:

$$\Pr\left(y = j|X\right) = \Phi\left(\alpha_{j\rho} - X\beta_\rho - w\gamma_\rho - \theta_\rho v\right) - \Phi\left(\alpha_{j-1,\rho} - X\beta_\rho - w\gamma_\rho - \theta_\rho v\right),$$

where each parameter has been rescaled: $\alpha_{j\rho} = \alpha_j/\sqrt{1-\rho_{v\epsilon}^2}$, $\beta_\rho = \beta/\sqrt{1-\rho_{v\epsilon}^2}$, $\gamma_\rho = \gamma/\sqrt{1-\rho_{v\epsilon}^2}$ and $\theta_\rho = \left(\frac{\rho_{v\epsilon}}{\sigma_v}\right)/\sqrt{1-\rho_{v\epsilon}^2}$.

Yet, v is not observed: it is the omitted variable that generates the endogeneity problem. The idea of Rivers and Vuong (1988) is to follow a two-step procedure. First run the OLS regression $w = Z\delta + v$. This yields residuals $\hat{v}$, which are plugged into the ordered probit above. The estimation of this ordered probit has been shows to provide consistent estimates of all the parameters.[10]

This approach is straightforward when there is only one endogenous regressor on the right hand side. When there is more than one, then the analysis becomes much more cumbersome and

to recover the original parameters of the information content relationship (e.g. β) is very difficult. Appendix C illustrates the difficulty with an example.

The crucial observation here is that we are not interested as much in the parameters of the information content relationship (e.g. β), but rather in the marginal effects of a change in the endogenous variables. Then, following Blundell and Powell (2003), we can consistently estimate the average structural function,

$$\widehat{ASF}\left(X,w\right)=N^{-1}\sum_{i=1}^{N}\phi\left(\hat{\alpha}_{j\rho}-X_i\hat{\beta}_{\rho}-w_i\hat{\gamma}_{\rho}-\hat{\theta}_{\rho}\hat{v}_i\right)-\phi\left(\hat{\alpha}_{j\rho}-X_i\hat{\beta}_{\rho}-w_i\hat{\gamma}_{\rho}-\hat{\theta}_{\rho}\hat{v}_i\right),$$

which then can be used to rescale the coefficient of the variable whose marginal effect we are interested in. For example, to get the marginal effect of a change in w, we multiply $\widehat{ASF}\left(X,w\right)$ by $\hat{\gamma}_{\rho}$.

5.3 Comparative Advertising

As illustrated in Section (3.2), brands use comparative ads extensively. The question we want to address now is whether more information is contained in comparative ads than in self-promotion ads. This seems to be suggested by the frequency distribution in **Figure 3b**. Notice that comparative ads will always have at least one cue, since a brand must be comparing itself to another brand along at least one dimension. So, the analysis will look at whether comparative and self-promotion ads are different, conditional on having at least one information cue.

Table 4 presents ordered probit results of advertising content as a function of whether an ad was comparative or not. **Columns 1-3** treat the choice of comparative ad as an exogenous variable. **Columns 4-6** treat the choice as an endogenous variable.

Column 1 shows that the comparative ad dummy is highly statistically significant, and its positive value (0.843) indicates that cut-points are lower for comparative ads: 0.843 is to be subtracted from the cut-off values for comparative ads. One can visualize this in two ways. First,

given the distribution function and the set of cut-offs for the non-comparative ads, the cut-offs for comparative ads are shifted uniformly lower. Alternatively, we can visualize leaving the cut-offs the same, and shifting the distribution right for comparative ads. The latter thought experiment makes it clear that the non-comparative ad distribution first-order stochastically dominates the comparative ad one. It always lies above, meaning that there is stochastically more information – and a significant amount – in the comparative ads. The simple summary is that comparative ads have more informational cues. Put from the opposite perspective, the likelihood that the ad is comparative increases with the number of cues.

We compute the marginal effects for comparative ads using the result in **Column 1**. The marginal effects are reported in **Table 5**. In particular, the first row shows that when an ad has comparative content, then it is 14.4 percent less likely to include only one cue and 4.7 percent more likely to include six cues. The other numbers are interpreted in the same fashion. For example, if an ad has comparative content, then it is 13.9 percent more likely to include five cues. Overall, we find evidence that comparative ads do include more content and the magnitude of the difference is economically significant.

Column 2 includes the exogenous medical characteristics, in addition to the comparative ad dummy. To illustrate why we do this, suppose that Aleve was intrinsically both more likely to use more cues, and more likely to use comparative advertising (we treat the comparative advertising decision here as exogenous – later we consider endogeneity of this choice). Then we might be attributing to comparative advertising what might more strictly be properly attributed to an Aleve effect. Indeed, we find that the parameter on the comparative ad dummy is down to 0.559 from 0.843. Thus, after controlling for the exogenous characteristics, the difference in information content is smaller. In particular, if we take the marginal effects, we observe that now comparative ads are 10.3 percent less likely than self-promotion ads are to include only one cue,

while we had found this difference to be 14.4 less likely when not including the exogenous characteristics. Comparative ads are 10.7 more likely to have five cues while without exogenous characteristics they were 13.9 percent more likely. Overall, adding exogenous characteristics make a considerable difference and provides a first piece of evidence that omitting them could lead to biased estimates of how much more information comparative ads really contain.

Column 3 includes brand dummies, and the results are pretty much the same as in **Column 2**. This is not surprising, since the exogenous characteristics do not change over time, and are largely explained by the brand dummies. More generally, including brand dummies is as effective as including the (time constant) exogenous characteristics that differentiate brands.

The next three columns allow for the comparative ad dummy to be endogenous. Following a suggestion made by Angrist (2001), we run a linear probability model in the first stage, and then treat the case of this discrete variable as we illustrated in Section (5.1). It is a very difficult problem to allow for endogenous discrete variables (i.e., the comparative ad decision) in a nonlinear model (i.e., the ordered probit). As explained by Imbens and Woolridge (2007), the Rivers and Vuong (1988) approach illustrated above does not produce consistent estimates of the parameters for discrete endogenous explanatory variables.

Column 4 shows the results when we instrument for the comparative ad dummy and we do not include any control variable. The results are truly striking. We find that comparative ads have much more information content than self-promotion ads. **Table 5** shows the marginal effects for this specification. The probability of containing only one cue is now 33.7 percent less likely in comparative ads than in self-promotion ads. Recall that we estimated the difference to be equal to 14.4 percent in **Column 1**, suggesting that the bias introduced by the endogeneity of the comparative advertising choice is very large. Similarly, we find that the probability of observing two cues is 43.4 less likely in comparative ads than in self-promotion ads. Overall, the probability

of observing at least three cues is 73.3 percent higher in comparative ads than in self-promotion ads.

The strong endogeneity of the dummy variable "Comparative?" is confirmed by the estimated coefficient of the control function, here equal to -1.450. The coefficient is statistically very significant, which means that we cannot reject the hypothesis that the variable "Comparative?" is endogenous (Smith and Blundell 1986).

In **Column 5** we add the brand's exogenous medical characteristics as regressors. Now the parameter estimate for the comparative dummy is even higher, at 2.115.

Overall, the key finding in **Table 4** is that comparative ads contain much more information than self-promotion ads. Moreover, we find evidence of a strong endogeneity bias in the parameter estimate of the comparative ad dummy if we do not use an instrumental variable approach.

5.4 Sales and Comparative Advertising

In this Section we study how brand market size affects the amount of information in ads. There is little theoretical literature relating the information content of advertising to firm size. The theoretical result of most interest here is the one in Anderson and Renault 2009, who suggest that small firms should provide more informative content relative to large firms.

In our analysis, we also include a measure of the size of the generic counterpart of the brand for which we observe the ad. For example, we look at the generic sales of acetaminophen-based pills when we look at the ads of Tylenol. We might suspect that there are significant spillovers from branded drug advertising to generic counterparts (Tylenol might worry about increasing the demand for the generic producer acetaminophen analgesics). These spillovers will be presumably more important the larger the market share of the generic counterpart and the larger the informative content about the performance of the molecule. We would thus anticipate that the information content of a brand's ads would be smaller the larger the generic's sales. Although we

do not formalize this idea here, our results do uncover such a relationship in the data.

Column 1 of **Table 6** presents the results for the ordered probit with just the simple cut-offs, standardized sales, squared sales, and generic sales. We find that there is a hump-shaped relationship between brand size and information content as the linear term of sales is equal to 0.357 and the quadratic term is equal to -0.356. Thus, these results indicate that small and large firms include less content than medium-sized firms. We do find that branded firms include less information content the larger is the size of their same-active-ingredient generic competitors, as the parameter of standardized generic sales is estimated equal to -0.220. The evidence is consistent with a relatively larger spillover effect from informative advertising.

Column 2 adds the comparative ads. The results for the standardized sales and generic sales are quite similar to those in **Column 1** of this table. Moreover, the coefficient estimate for the comparative ad dummy is very close to the one in **Column 1** of **Table 4**. We therefore conclude that the decisions to do comparative advertising is not collinear with brand sales and generic sales, otherwise we would have seen different coefficient estimates in **Columns 1** and **2**. This result is quite interesting because it suggests that the decision of doing comparative ads might not depend in a significant way on the market share of the attacking brand. In a related paper (Anderson et al. 2010) we investigate the relationship between the attacker's market share, the attacked brand's market share, and how much comparative advertising to do. In preliminary findings we show that what drives the decision to do comparative advertsements is the market share of the attacked brand and the interaction of the shares of the attacked and of the attacking brands.

Column 3 adds the exogenous medical characteristics. The coefficient of the comparative ad dummy is almost equal to the one in **Column 3** of **Table 4**. The linear term of the standardized sales is doubled, a first indication that sales are endogenous.

In **Column 4** we follow an instrumental variable approach to estimate the effect of comparative ads, sales and generic sales on information content. The estimated coefficient of comparative ads is large, although not as much as in **Column 4** of **Table 4**. Now there is no evidence of a hump-shaped relationship between size and information content. The linear term is estimated equal to 0.096 and the quadratic term is estimated equal to −0.147. Thus, size is negatively related to information content. We also observe that the coefficient estimate of the control functions for the generic sales (0.342) and for the decision to do comparative advertising (−1.042) are both statistically significant, clearly proving that both variables (generic sales and comparative ads) are endogenous. The estimated coefficient of the control function for the brand sales (0.305) is only statistically significant at approximately a 15 percent level. This is probably because our instrumental variables only have just enough identification power to precisely identify three endogenous variables. Generic sales continue to be negatively related to information content, but the parameter estimate is down to −0.082 from the value of −0.146 that we found in **Column 3**. Overall, we interpret this as evidence that sales are endogenous explanatory variables. This is confirmed by the results for the coefficient of two of the three control functions. The control function for the comparative ads is equal to −1.042; the control function for generic sales is equal to 0.342. Both of these estimates are statistically very significant. In contrast, the control function for sales is equal to 0.305 and is imprecisely estimated. Notice that the control function for the standardized sales also controls for the endogeneity of the squared standardized sales.

Column 5 shows the results when we include the exogenous medical characteristics. The results are very similar to those in **Column 4**.

To get a sense of the economic meaning of the results concerning size, we constructed figures that associate the probability of choosing a given amount of information (e.g. one cue) with the distribution of size. For example, the graph in the top left corner of **Figure 5** shows that the

likelihood of an ad including just one cue increases sharply with size. In contrast, the probability of observing an ad with four or more cues drops with size. The marginal effects in changes in size are implicitly shown in the figure. For example, a move from the 25th percentile in the size distribution to the 75th percentile increases the probability of seeing only one cue by 20 percent.

The marginal effects for the decision to do comparative advertising are fairly close to the ones that we derived in the previous section. For example, we now find that the probability of observing two cues is 32.1 less likely in comparative ads than in self-promotion ads while it was equal to 43.2 percent when using the estimated coefficients from **Table 4**.

6 Conclusions

The paper delivers several contributions. The first is a deeper and wider description of information content which combines content knowledge with industry structure and advertising spending data. Second, we describe a methodology appropriate for dealing with information content with multiple explanatory variables; we show how the analysis can be corrected for endogeneity and how this alters the results. Third, we evaluate several theoretical propositions, giving some strong takeaways: more information is disclosed by firms with higher characteristics quality; less information is contained in popular brand advertisements. These two results are not contradictory: the endogeneity of firm size here underscores the importance of correcting for it, otherwise, one might expect that larger firms are also fundamentally stronger and therefore their ads should have more information content. Correcting for endogeneity also indicates that more competition from generics gives rise to less information transmission by branded products, which is in line with the view that there are significant spill-overs to informative advertising. Finally, comparative advertisements have significantly more information content than non-comparative ones, and the effect is much larger than is predicted without correcting for endogeneity.

Our analysis is restrictive in a number of aspects and suggests numerous extensions, which constitute themes for future research and for our own ongoing investigations on the theme of information content. First, we might use sub-classification of cues (for example, into vertical cues like "Fast" which are presumably appreciated by all consumers, and horizontal cues like "Headache" or "Menstrual" which are desired by some, and not desired by others) and look at the differential content of the different types of cue. Second, a cue can only be deployed if product has it, and can only be used comparatively if a product has an advantage over another product. It would be interesting to study the amount of information advertised as a function of the total number of cues that could feasibly advertised. Likewise, we might want to determine whether products use comparative ads more against similar products or dissimilar ones. Third, we have not looked at product advertising campaigns, whereby ads address a subset of themes over a limited horizon. Fourth, we only code the objective content of advertisements as quantified through their referencing of specific characteristics and competitors. We recognize that advertising may persuade through channels other than pure information, and lead consumers to act on emotional factors. However, we have not attempted to code such effects. The primary purpose of this study is to measure objective content of advertising along the lines of traditional content analysis. Incorporating the subjective side would be an interesting aspect to explore in further extensions. Finally, we do not address whether market provision of information is optimal or how valuable the information is to consumers (Ippolito and Pappalardo 2002 and Pappalardo and Ringold 2000). Our purpose here is to document and to rationalize empirical regularities present in the data and provide measures of the fundamental key variables that can be used in future research to answer such questions.

The current methodology can readily be applied to other product categories and industries. It would be interesting to compare results. For example, how does advertising information

content differ for experience, search, and credence products? Does the inverse relation between firm size and information hold more broadly? Do new products provide more information? These are questions which hold both empirical and theoretical interest.

References

Abernethy, Avery M. and George R. Franke (1996), "The information content of advertising: a meta-analysis," *Journal of Advertising*, 25, 1-17.

"Aleve case history - real people campaign" (2006), ARF Ogilvy Awards.

Anand, Bharat and Ron Shachar (2009), "Targeted advertising as a signal," *Quantitative Marketing and Economics*, 7(3), 237-66.

Anderson, Federico Ciliberto, Jura Liaukonyte and Régis Renault (2010), "Push-me, Pull-you: Comparative Advertising in OTC Analgesics Industry," Mimeo, University of Virginia.

Anderson, Simon P. and Régis Renault (2009), "Comparative Advertising: disclosing horizontal match information," *RAND Journal of Economics*, 40(3), 558-81.

Angrist, Joshua D. (2001), "Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice," *Journal of Business Economic Statistics*, 19(1), 2-16.

Bertrand, Marianne, Dean Karlan, Sendhil Mullainathan, Eldar Shafir and Jonathan Zinman (2010), "What's Advertising Content Worth? Evidence from a Consumer Credit Marketing Field Experiment," *Quarterly Journal of Economics*, 125(1), 263–305.

Blundell, Richard. and James L. Powell (2003), "Endogeneity in Nonparametric and Semiparametric Regression Models," in Advances in Economics and Econometrics, Theory and Applications, Eighth World Congress, Volume II, edited by M. Dewatripont, L.P. Hansen, and S.J.Turnovsky, Cambridge University Press, Cambridge, U.K.

Bresnahan, Timothy F. (1987), "Competition and Collusion in the American Automobile Industry: The 1955 Price War," *The Journal of Industrial Economics*, 35(4), 457-82.

Chou, Linly, George R.Franke and Gary B. Wilcox (1987), "The Information Content of Comparative Magazine Ads: A Longitudinal Analysis," *Journalism Quarterly*, 64 (1),119-24.

Franke, George.R., Bruce A. Huhmann and David L. Mothersbaugh (2004), "Information content and consumer readership of print ads: A comparison of search and experience products," *Journal of the Academy of Marketing Science,* 32(1), 20-31.

Greene, William H. (1997), Econometric Analysis, 3rd edition, London, Prentice Hall.

Guo, Liang and Ying Zhao (2009), "Voluntary Quality Disclosure and Market Interaction," *Marketing Science*, 28 (3), 488-501

Harmon, Robert, Nabil Razzouk, and Bruce L. Stern (1983), "The Information Content of Comparative Magazine Advertisements," *Journal of Advertising*, 12 (4), 10-19.

Heckman, James, J. (1981), "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process," in Manski, C. and D.McFadden, eds., Structural Analysis of Discrete Data with Econometric Applications, MIT Press, Cambridge, pp. 114-78.

Hong Jae W., Aydin Muderrisoglu, George M. Zinkhan (1987), "Cultural Differences and Advertising Expression: A Comparative Content Analysis of Japanese and U.S. Magazine Advertising," *Journal of Advertising*, 16 (1), 55-68.

Imbens, Guido and Jeffrey Wooldridge (2007), "What's New in Econometrics?", National Bureau of Economic Research, Summer Institute.

Ippolito Pauline M. and Janis K.Pappalardo (2002), "Advertising Nutrition and Health: Evidence from Food Advertising," Bureau of Economics, Federal Trade Commission.

Iyer Ganesh, David Soberman, and J. Miguel Villas-Boas (2005), "The Targeting of Advertising", *Marketing Science,* 24(3), 461 - 76.

Jeffrey Woolridge (2001), Econometric Analysis of Cross Section and Panel Data, The MIT Press, 1st edition.

Liaukonyte, Jura (2010), "Is Comparative Advertising an Active Ingredient in the Market for Pain Relief? Structural Model of Advertising Content," Mimeo, Cornell University.

Madden, Charles S., Marjorie J. Caballero and Shinya Matsukubo (1986), "Analysis of information content in U.S. and Japanese magazine advertising," *Journal of Advertising.* 38-45.

Pappalardo, Janis K. and Debra J. Ringold (2000), "Regulating Commercial Speech in a Dynamic Environment: Forty Years of Margarine and Oil Advertising Before the NLEA," *Journal of Public Policy and Marketing*, 19(1), 74-92.

Resnik, Alan J. and Bruce L. Stern (1977), "An analysis of information content in television advertising," *Journal of Marketing*, 41, 50-53.

Rivers, Douglas and Quang H. Vuong (1988), "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models," *Journal of Econometrics*, 39, 347-366.

Rutz, Oliver and Randolph E. Bucklin (2010), "From Generic to Branded: A Model of Spillover in Paid Search Advertising," *Journal of Marketing Research*, forthcoming.

Smith, Richard J. and Richard W. Blundell (1986), "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply," *Econometrica*, 54 (3), 679-685.

Stern, Bruce. L. and Alan J. Resnik, (1991), "Magazine Advertising: an analysis of its information content," *Journal of Advertising Research*, 21, 39-44.

Stern, Bruce L., Dean M. Krugman, and Alan Resnik (1981), "Magazine Advertising: An Analysis of Its Information Content," *Journal of Advertising Research*, 21 (2), 3944.

Stewart, David W. and David H. Furse (1986), "Effective TV Advertising: A Study of 1000 Commercials," Lexington, MA: Lexington Books.

Sun, Monic (2010), "Disclosing Multiple Product Attributes," forthcoming, *Journal of Economics & Management Strategy.*

Notes

[1]Resnik and Stern (1977) proposed to categorize the information provided in the advertisement into 14 distinct "information cues" which included price, quality, performance, components, availability, special offers, taste, nutrition, packaging, warranties, safety, independent research, company research and new ideas.

[2]There are, though, two instances of high correlation that merit comment. First, whenever "Liquid Gels" are mentioned, "Fast" is almost always mentioned (although the converse is not true - a pill does not need to be in Liquid Gel form to be fast). Second, "Long-lasting" and "Fewer Pills" are often used together. When the ad mentioned "Long-lasting", it mentioned "Fewer Pills" 33% of the time (for a total around $100m.). Conversely, when "Fewer Pills" was mentioned, long-lasting was mentioned 88% of the time. In this instance, we could provide an umbrella classification encompassing the union of both, but the difference in results would be minor.

[3]The 2001 figures include only 10 months of observations, since we do not have the corresponding sales data for January and February of 2001. The low total ad expenditures can be partially explained by this, but the average monthly expenditures should not be affected much. Even adjusted for inflation, ad expenditures have tended to increase over time.

[4]See Appendix A for the method used to obtain the relative ranking of selected attributes.

[5]We have also found information on the relative performance on the duration of pain relief (i.e. "Long Lasting"; see appendix A for the ranking), however we exclude this metric from further multivariate analysis because it is highly correlated with the NNT measure (corr coef = 0.94).

[6]See Greene (1997) and Woolridge (2001) for an introduction to ordered models.

[7]The “unweighted” data in Figure 2 use each separate ad within any given month as an observation: in this case the multiple airing of the same ad within the same month and total ad expenditures are ignored. This is in line with most of the traditional Content Analysis studies: multiple copies of the same ad were typically not counted as different observations.

[8]We rejected the hypothesis at the 1% confidence level that the cutoff pairs in weighted and unweighted cases are the same. The cutoffs in the unweighted case are higher than in the weighted case, and the difference is statistically significant. This suggests that more money is being spent on ads with more informational cues.

[9]The aggressive “Good News” and personal testimonials advertising campaigns were designed to demonstrate Aleve’s safety and efficacy in a way that would restore confidence in the brand.

[10]Because v is a generated regressor, we need to correct the standard errors. We use a bootstraps procedure to do that. We run 100 times the two steps using 100 different samples of the original dataset.

Appendix A: Explanation of Medical Measures

Relative risk (RR) is the risk of an event (e.g., developing a disease) relative to exposure. Relative risk is the ratio of the probability of the event E occurring in the exposed group versus the control (non-exposed) group:

$$RR = \frac{\Pr(E \mid treatment)}{\Pr(R \mid control)}$$

Relative risk is used frequently in clinical trial data, where it is used to compare the risk of developing a disease, in people not receiving the new medical treatment (or receiving a placebo) versus people who are receiving an established (standard of care) treatment. In the case of GI and CV relative risk numbers used in this paper, it is used to compare the risk of developing a side effect in people receiving a drug as compared to the people who do not receive the treatment (or receiving a placebo). Thus, a CV RR of 1.44 means that CV problems arise with 44% higher likelihood using the drug (vs. placebo).

Number-Needed-to-Treat (NNT) is computed with respect to two treatments A and B, with A typically a drug and B a placebo. If the probabilities PA and PB under treatments A and B, respectively, are known, then the NNT is computed as:

$$NNT = \frac{1}{P_B - P_A}$$

The NNT for a given therapy is simply the reciprocal of the absolute risk reduction (ARR= P_B -P_A)for that treatment. For example, in hypothetical migraine study, risk decreased from P_B =0.30 without treatment with drug M to P_A =0.05 with treatment with drug M, for a relative risk of 0.17 (0.05/0.3), a relative risk reduction of 0.83 ((0.3-0.05)/0.3), and an absolute risk reduction of 0.25 (0.3-0.05), the NNT would be 1/0.25, or 4. In concrete clinical terms, an NNT of 4 means that you would need to treat four patients with drug M to prevent migraine from recurring in one patient. Typically, the lower the NNT number, the more potent and efficient the treatment is.

Appendix B: Explanation of Medical Measures

We reviewed a number of medical journal articles in order to rank the three efficiency measures (maximum level of pain relief achieved, onset to perceptible pain relief and duration of meaningful pain relief) of the analyzed active ingredients. Most medical articles compare only two or three active ingredients. If article X said that drug A is more efficient than drug B ($A \succ B$) and article Y said that drug B is more efficient than C ($B \succ C$), then we conclude by transitivity that A is more efficient than B and C ($A \succ B \succ C$). Below we also present the numbered list of references that were used to infer relative rankings. **Table 7** lists all those relative relationships, references of medical articles (in parentheses), and gives the resulting ranking presented in **Figure 2**.

References:

(1) Packman, B., Packman, E. Doyle, G., Cooper, S., Ashraf, E., Koronkiewicz, K. and Jayawardena, S. (2000), "Solubilized Ibuprofen: Evaluation of Onset, Relief, and Safety of a Novel Formulation in the Treatment of Episodic Tension-type Headache," *Headache: The Journal of Head and Face Pain*, 40(7), 561-567.

(2) Hyllested, M., Jones, S., Pedersen, J. L., Kehlet, H. (2002), "Comparative effect of paracetamol, NSAIDs or their combination in postoperative pain management: a qualitative review," *British Journal of Anaesthesia.* 88, 199–214.

(3) Forbes, J. A., Keller, C. K., Smith, J. W., Zeleznock, J. R., Sevelius, H., Beaver, W. T. (1986), "Analgesic effect of naproxen sodium, codeine, a naproxen-codeine combination and aspirin on the postoperative pain of oral surgery," *Pharmacotherapy*, 6(5), 211-218.

(4) Milsom, I., Minic, M., Dawood, Y., Akin, M., Spann, J., Niland, N. and R. Squire, A. (2002), "Comparison of the efficacy and safety of nonprescription doses of naproxen and naproxen sodium with ibuprofen, acetaminophen, and placebo in the treatment of primary dysmenorrhea: a pooled analysis of five studies," *Clinical Therapeutics*, 24(9), 1384-1400.

(5) Cooper, S. A., Schachtel, B. P., Goldman, E., Gelb, S., and Cohn, P. (1989), "Ibuprofen and acetaminophen in the relief of acute pain: a randomized, double-blind, placebo-controlled study," *Journal of Clinical Pharmacology*, 29, 1026-1030.

(6) Olson, N. Z., Otero, A.M., Marrero, I., Tirado, S., Cooper, S., Doyle, G., Jayawardena, S., and Sunshine, A. (2001), "Onset of analgesia for liquigel ibuprofen 400 mg., acetaminophen 1000 mg., ketoprofen 25 mg., and placebo in the treatment of postoperative dental pain," *Journal of Clinical Pharmacology*, 41(11), 1238-1247.

(7) Ong, C. K. S., Lirk, P., Tan, C. H. and Seymour, R. A. (2006), "An Evidence-Based Update on Nonsteroidal Anti-Inflammatory Drugs," *Clinical Medicine & Research*, 5(1), 19-34.

(8) Miller, D., Talbot, C., Simpson, W., Korey, A. (1987), "A Comparison of Naproxen Sodium, Acetaminophen and Placebo in the Treatment of Muscle Contraction Headache," *Headache: The Journal of Head and Face Pain*, 27(7), 392-396.

(9) Lee, C., Straus, W. L., Balshaw, R., Barlas, S., Vogel, S., Schnitzer, T. J. (2004), "A comparison of the efficacy and safety of nonsteroidal antiinflammatory agents versus acetaminophen in the treatment of osteoarthritis: a meta-analysis," *Arthritis Rheum*, 51, 746-754.

(10) Hersh, Elliot, Moore, Paul A. and Ross, Gilbert L. (2000), "Over-the Counter Analgesics and Antipyretics: A Critical Assessment," *Clinical Therapeutics*, 22(5).

Appendix C: Illustration of Probit with two Endogenous Regressors

Suppose that there are two endogenous regressors:

$$y^* = X\beta + w\gamma + \epsilon,$$

with

$$\begin{aligned} w_1 &= \delta_1 Z_1 + v_1, \\ w_2 &= \delta_2 Z_2 + v_2. \end{aligned}$$

Assume:

$$(\epsilon, v_1, v_2) \sim N\left(0, \begin{pmatrix} \sigma_\epsilon^2 & \rho_{1\epsilon}\sigma_\epsilon\sigma_1 & \rho_{2\epsilon}\sigma_\epsilon\sigma_2 \\ \rho_{1\epsilon}\sigma_\epsilon\sigma_1 & \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 \\ \rho_{2\epsilon}\sigma_\epsilon\sigma_2 & \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}\right).$$

Then, after some tedious algebra, we can show that:

$$\begin{aligned} var(\epsilon) &= \sigma_u^2 + \left[\frac{(\rho_{1u} - \rho_{12}\rho_{2u})}{(1-\rho_{12}^2)}\sigma_u\right]^2 + \left[\frac{(\rho_{2u} - \rho_{12}\rho_{1u})}{(1-\rho_{12}^2)}\sigma_u\right]^2 - 2\frac{(\rho_{1u} - \rho_{12}\rho_{2u})}{(1-\rho_{12}^2)}\sigma_u^2\rho_{1u} \\ &\quad -2\frac{(\rho_{2u} - \rho_{12}\rho_{1u})}{(1-\rho_{12}^2)}\sigma_u^2\rho_{2u} + 2\frac{(\rho_{1u} - \rho_{12}\rho_{2u})}{(1-\rho_{12}^2)}\frac{(\rho_{2u} - \rho_{12}\rho_{1u})}{(1-\rho_{12}^2)}\sigma_u^2\rho_{12}. \end{aligned}$$

Clearly it would be very hard to recover the original parameters.

Figures and Tables

FIGURE 1. Advertised Attributes and Expenditures.

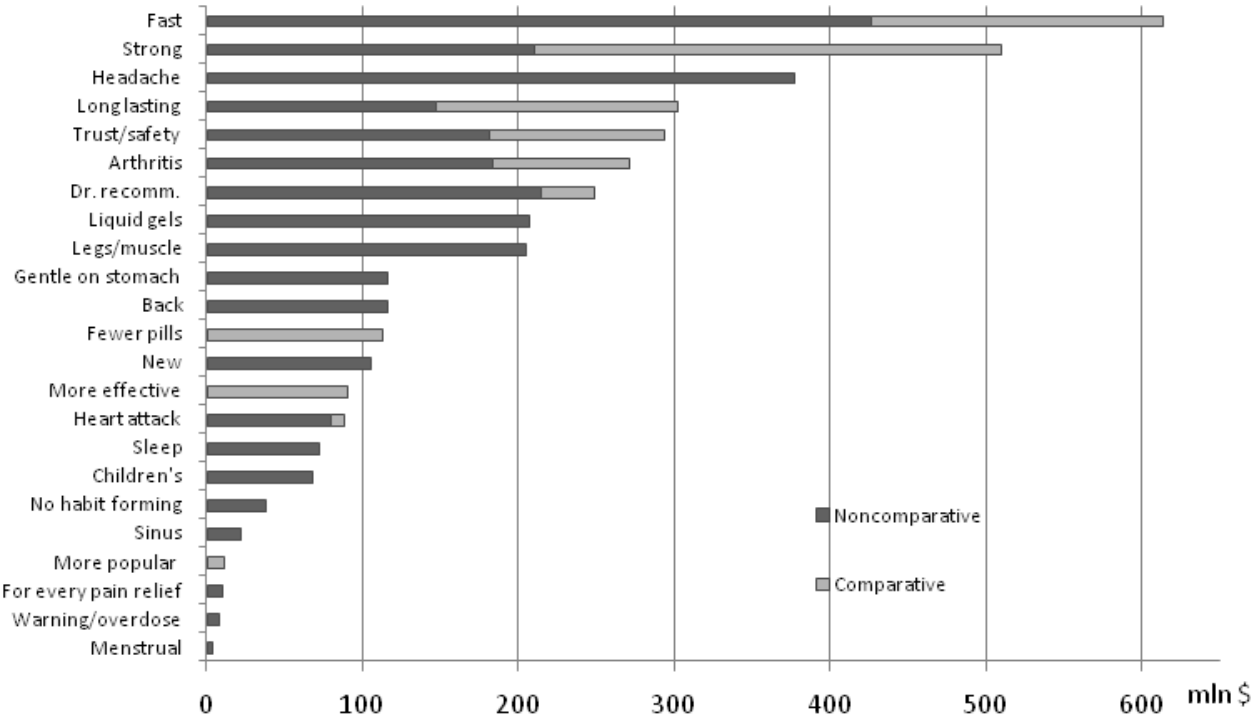


FIGURE 2. Location of Active Ingredients in the Characteristics Space

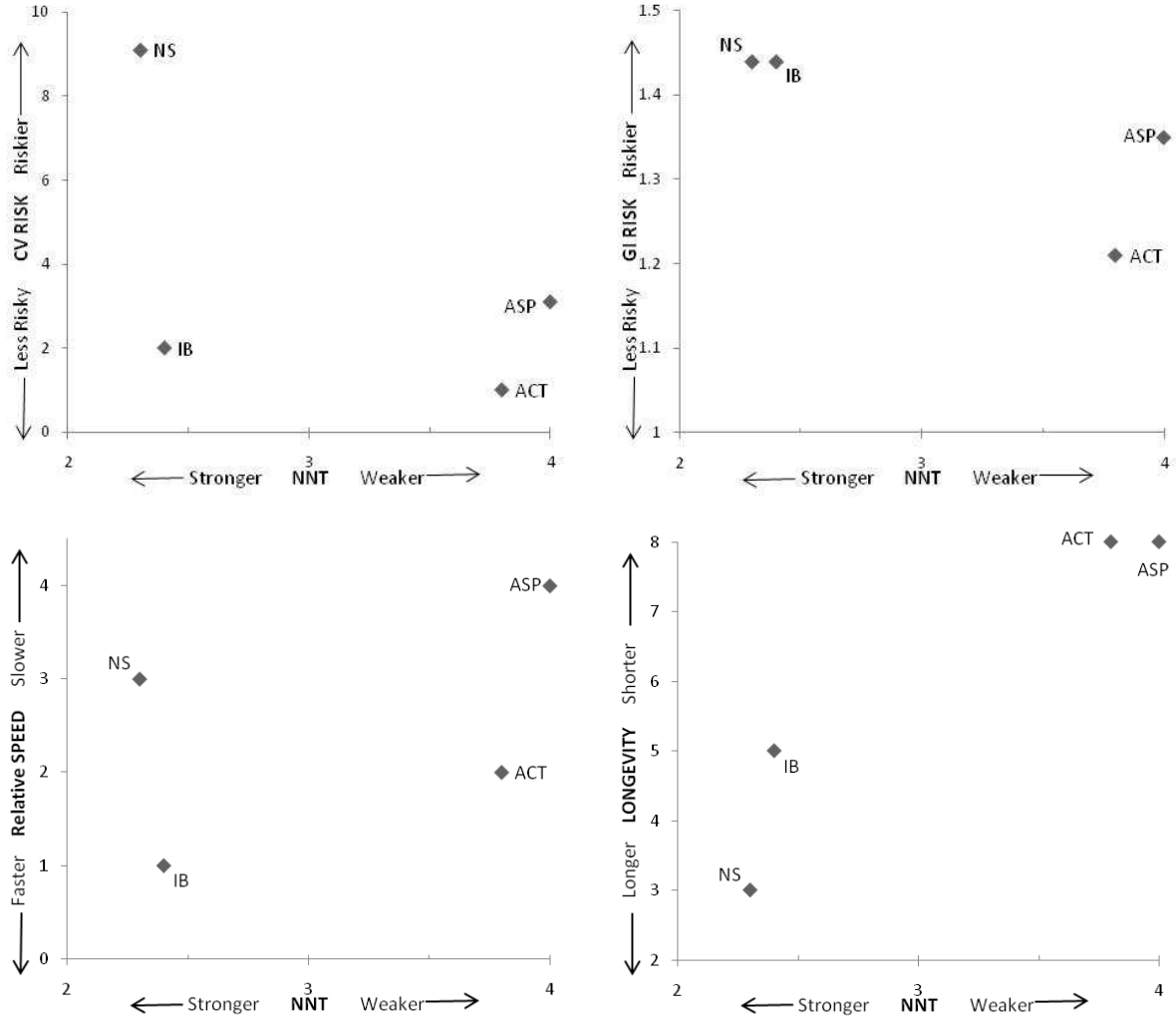
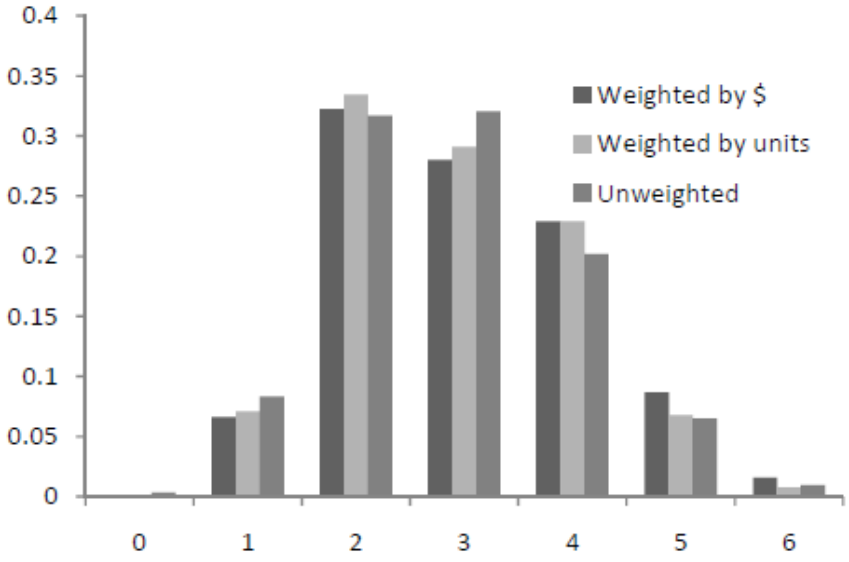


FIGURE 3. Distribution of Number of Cues

(a) Within an Ad



(b) By Ad Type

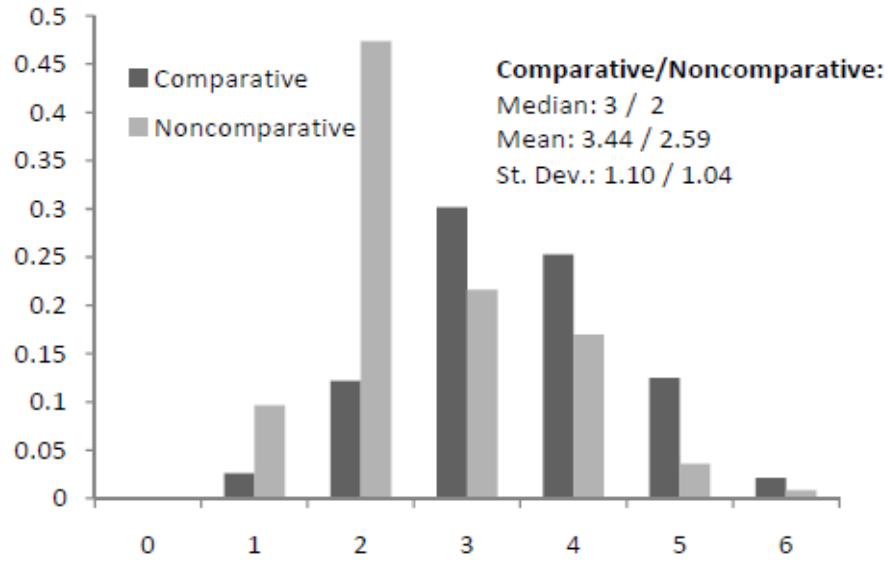


FIGURE 4: Marginal efects on Information disclosure by firm size

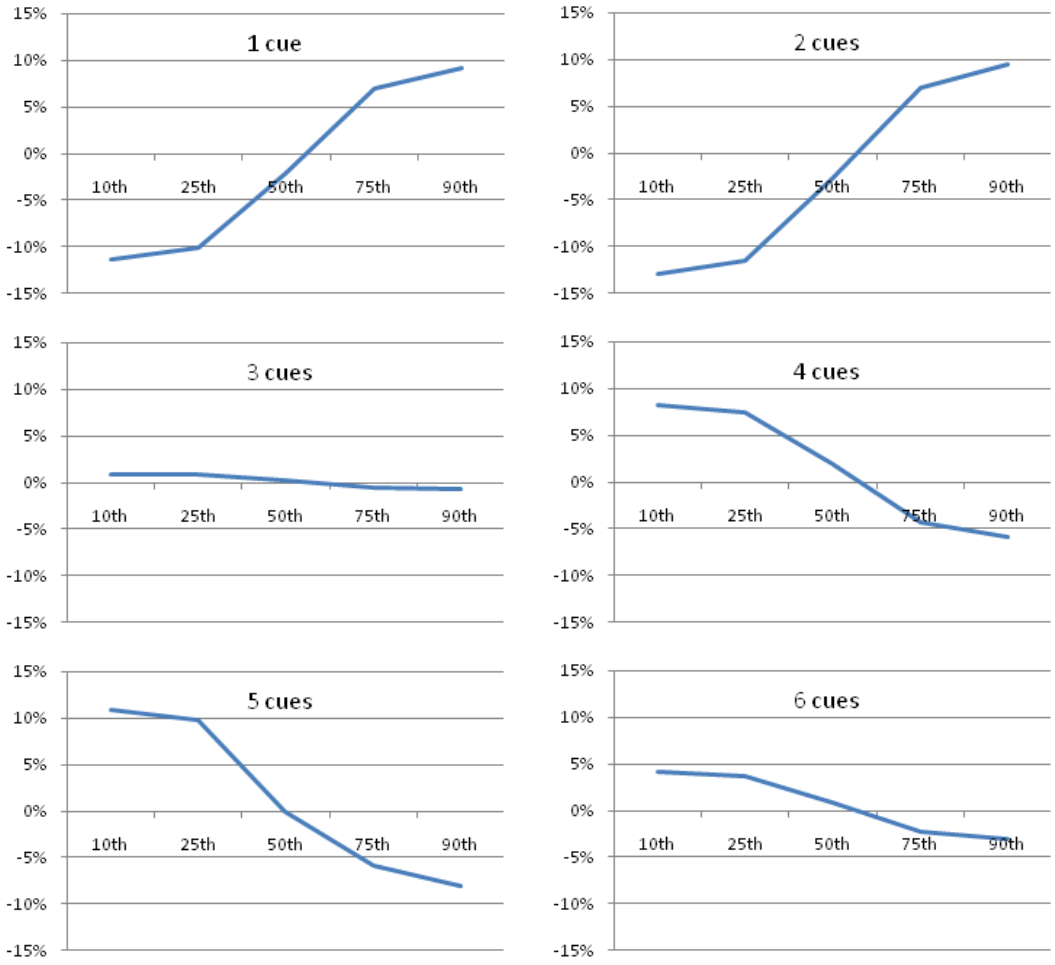


TABLE 1. Matrix of Frequency of Attributes that are Mentioned Together

	Fast	Strong	Head-ache	Long lasting	Safe	Arthritis	Dr. recomm	Liquid gels	Legs/ muscle	Gentle on stomach	Back	Fewer pills	**Total**
Fast		$251.61	$296.52	$70.25	$32.76	$23.80	$16.69	$204.55	$101.42	$66.32	$25.65	0	**$613.52**
		49.32%	78.63%	23.22%	11.17%	8.77%	6.70%	98.90%	49.52%	56.98%	22.11%	0	
Strong	$251.61		$126.43	$103.37	$93.88	$123.06	$97.80	$140.66	$133.31	$45.46	$51.94	$53.01	**$510.20**
	41.01%		33.53%	34.16%	32.02%	45.34%	39.28%	68.01%	65.10%	39.05%	44.78%	46.81%	
Headache	$296.52	$126.43		$6.22	$28.85	$11.95	$25.42	$84.88	$17.53	$24.40	$15.88	$6.22	**$377.09**
	48.33%	24.78%		2.06%	9.84%	4.40%	10.21%	41.04%	8.56%	20.96%	13.69%	5.49%	
Long lasting	$70.25	$103.37	$6.22		$68.50	$153.97	$83.96	$14.43	$64.17	$23.18	$44.99	$100.06	**$302.56**
	11.45%	20.26%	1.65%		23.36%	56.73%	33.72%	6.98%	31.34%	19.91%	38.79%	88.35%	
Safe	$32.76	$93.88	$28.85	$68.50		$115.84	$77.64	$5.51	$29.96	$55.50	$39.29	$30.46	**$293.20**
	5.34%	18.40%	7.65%	22.64%		42.68%	31.18%	2.67%	14.63%	47.68%	33.87%	26.90%	
Arthritis	$23.80	$123.06	$11.95	$153.97	$115.84		$125.59	$21.58	$18.38	$55.21	$19.22	$80.12	**$271.42**
	3.88%	24.12%	3.17%	50.89%	39.51%		50.43%	10.43%	8.97%	47.43%	16.57%	70.75%	
Dr. recomm.	$16.69	$97.80	$25.42	$83.96	$77.64	$125.59		0	$23.88	$38.35	$4.71	$50.65	**$249.02**
	2.72%	19.17%	6.74%	27.75%	26.48%	46.27%		0	11.66%	32.95%	4.06%	44.73%	
Liquid gels	$204.55	$140.66	$84.88	$14.43	$5.51	$21.58	0		$23.06	$44.74	0	0	**$206.82**
	33.34%	27.57%	22.51%	4.77%	1.88%	7.95%	0		11.26%	38.43%	0	0	
Legs/ muscle	$101.42	$133.31	$17.53	$64.17	$29.96	$18.38	$23.88	$23.06		$23.06	$56.44	$7.54	**$204.79**
	16.53%	26.13%	4.65%	21.21%	10.22%	6.77%	9.59%	11.15%		19.81%	48.66%	6.65%	
Gentle on stomach	$66.32	$45.46	$24.40	$23.18	$55.50	$55.21	$38.35	$44.74	$23.06		$0.88	0	**$116.40**
	10.81%	8.91%	6.47%	7.66%	18.93%	20.34%	15.40%	21.63%	11.26%		0.76%	0	
Back	$25.65	$51.94	$15.88	$44.99	$39.29	$19.22	$4.71	0	$56.44	$0.88		$14.83	**$115.98**
	4.18%	10.18%	4.21%	14.87%	13.40%	7.08%	1.89%	0	27.56%	0.76%		13.10%	
Fewer pills	0	$53.01	$6.22	$100.06	$30.46	$80.12	$50.65	0	$7.54	0	$14.83		**$113.25**
	0	10.39%	1.65%	33.07%	10.39%	29.52%	20.34%	0	3.68%	0	12.79%		

TABLE 2. Descriptive Statistics of Information Attributes and Ad Spending

By Brand							
Brand	Number of Cues	Comparative?	Avg Monthly Spending per Ad Aired	Average Monthly Sales	Total Ad Spending	Total Sales	Ad to Sales Ratio
Advil	3.600	0.740	$0.14	$23.92	$293.1	$1,374	21.3%
	(1.004)	(0.441)	(0.241)	(1.693)			
Aleve	3.770	0.900	$0.12	$11.41	$174.8	$659	26.5%
	(1.156)	(0.298)	(0.293)	(1.123)			
Bayer	3.190	0.310	$0.10	$7.95	$131.2	$458	28.8%
	(1.320)	(0.461)	(0.222)	(0.964)			
Excedrin	2.400	0.150	$0.26	$12.39	$182.4	$689	26.5%
	(0.695)	(0.359)	(0.456)	(1.172)			
Motrin	2.610	0.370	$0.10	$8.03	$102.0	$466	21.9%
	(0.937)	(0.484)	(0.240)	(0.762)			
Tylenol	2.540	0.280	$0.13	$40.59	$414.9	$2,328	17.8%
	(0.957)	(0.449)	(0.346)	(3.195)			
Overall	2.990	0.460	$0.13	$22.86	$1,299.2	$5,975	21.7%
	(1.143)	(0.498)	(0.305)	(13.677)			
By Year							
Year	Number of Cues	Comparative?	Avg Monthly Spending per Ad Aired	Average Monthly Sales	Total Ad Spending	Total Sales	Advertising to Sales Ratio
2001	2.954	0.426	$0.10	$24.71	$213.8	$1,114.75	19.2%
	(0.899)	(0.495)	(0.248)	(14.012)			
2002	2.958	0.583	$0.12	$25.27	$235.7	$1,282.60	18.3%
	(1.140)	(0.493)	(0.261)	(14.246)			
2003	2.924	0.350	$0.13	$23.24	$268.6	$1,256.95	21.4%
	(1.262)	(0.477)	(0.269)	(13.538)			
2004	2.654	0.445	$0.16	$20.25	$298.5	$1,184.68	25.2%
	(0.962)	(0.497)	(0.402)	(12.623)			
2005	3.482	0.498	$0.16	$20.10	$283.0	$1,136.19	24.9%
	(1.207)	(0.500)	(0.332)	(12.879)			
Overall	2.995	0.459	$2.99	$22.86	$1,299.1	$5,975.17	21.7%
	(1.143)	(0.498)	(1.150)	(13.677)			

TABLE 3. Results after controlling for brand-, time- and AI fixed effects

	Unweighted	Weighted				
	(1)	(2)	(3)	(4)	(5)	(6)
Advil			1.080***	1.098***	1.292***	
			(0.030)	(0.031)	(0.035)	
Aleve			1.264***	1.257***	1.145***	
			(0.036)	(0.036)	(0.041)	
Bayer			0.672***	0.674***	0.717***	
			(0.039)	(0.039)	(0.044)	
Excedrin			-0.109***	-0.125***	-0.201***	
			(0.035)	(0.035)	(0.039)	
Motrin			0.101**	0.130***	0.078	
			(0.043)	(0.043)	(0.047)	
2002				-0.082**	-0.086**	
				(0.036)	(0.036)	
2003				0.030	0.037	
				(0.036)	(0.036)	
2004				-0.242***	-0.235***	
				(0.035)	(0.035)	
2005				0.511***	0.583***	
				(0.035)	(0.053)	
Advil*2005					-0.802***	
					(0.072)	
Aleve*2005					0.463***	
					(0.082)	
Bayer*2005					-0.135	
					(0.093)	
Excedrin*2005					0.329***	
					(0.085)	
Motrin*2005					0.319***	
					(0.111)	
Standardized NNT						-0.724***
						(0.029)
Relative Speed						0.336***
						(0.041)
Standardized GI Risk						-0.133***
						(0.035)
Standardized CV Risk						-0.151***
						(0.029)
Cutoff (0->1 cues)	-2.728***	-3.523***	-3.258***	-3.255***	-3.241***	-3.085***
	(0.059)	(0.184)	(0.170)	(0.168)	(0.164)	(0.194)
Cutoff (1->2 cues)	-1.363***	-1.504***	-1.223***	-1.226***	-1.225***	-1.041***
	(0.018)	(0.020)	(0.025)	(0.035)	(0.036)	(0.090)
Cutoff (2->3 cues)	-0.244***	-0.283***	0.132***	0.169***	0.185***	0.291***
	(0.013)	(0.013)	(0.020)	(0.032)	(0.033)	(0.089)
Cutoff (3->4 cues)	0.594***	0.436***	0.969***	1.036***	1.064***	1.095***
	(0.014)	(0.013)	(0.022)	(0.032)	(0.034)	(0.090)
Cutoff (4->5 cues)	1.444***	1.266***	1.938***	2.032***	2.086***	2.032***
	(0.019)	(0.017)	(0.027)	(0.037)	(0.038)	(0.091)
Cutoff (5->6 cues)	2.352***	2.149***	2.954***	3.122***	3.217***	3.034***
	(0.039)	(0.032)	(0.041)	(0.051)	(0.053)	(0.097)
Log-Likelihood:	-14594.2	-14782.5	-13601.4	-13157.2	-13157.2	-13848
N of Observations	9,739	9,739	9,739	9,739	9,739	9,739

note: *** p<0.01, ** p<0.05, * p<0.1, Brand "Tylenol" and Year "2001" fixed effects are used as a base and therefore omitted.

TABLE 4. Results after Controlling for Comparative Advertising

	(1)	(2)	(3)	(4)	(5)
Comparative?	0.843***	0.559***	0.473***	1.906***	2.115***
	(0.022)	(0.025)	(0.026)	(0.130)	(0.367)
Advil			0.887***		
			(0.032)		
Aleve			1.004***		
			(0.039)		
Bayer			0.673***		
			(0.039)		
Excedrin			-0.050		
			(0.035)		
Motrin			0.052		
			(0.043)		
Standardized NNT		-0.602***			-0.220*
		(0.029)			(0.128)
Relative Speed		0.281***			0.111
		(0.041)			(0.121)
Standardized GI Risk		-0.132***			-0.134
		(0.035)			(0.095)
Standardized CV Risk		-0.185***			-0.274***
		(0.029)			(0.084)
Residuals-Comparative				-1.450***	-1.652***
				(0.146)	(0.364)
Cutoff (1->2 cues)	-1.251***	-0.941***	-1.121***	-0.837***	-0.569**
	(0.021)	(0.091)	(0.025)	(0.075)	(0.237)
Cutoff (2->3 cues)	0.078***	0.436***	0.270***	0.538***	0.823***
	(0.016)	(0.090)	(0.022)	(0.064)	(0.243)
Cutoff (3->4 cues)	0.871***	1.271***	1.128***	1.382***	1.677***
	(0.018)	(0.090)	(0.023)	(0.072)	(0.251)
Cutoff (4->5 cues)	1.762***	2.228***	2.110***	2.324***	2.647***
	(0.022)	(0.092)	(0.029)	(0.079)	(0.257)
Cutoff (5->6 cues)	2.694***	3.234***	3.129***	3.334***	3.670***
	(0.036)	(0.097)	(0.042)	(0.118)	(0.274)
Log-Likelihood:	-13990.3	-13527.6	-13359.9	-13670.0	-13525.0
N of Observations	9,708	9,708	9,708	9,708	9,708

note: *** p<0.01, ** p<0.05, * p<0.1, Brand "Tylenol" fixed effect is used as a base and therefore omitted. Columns (4) and (5) treat "Comparative?" as an endogenous variable and instruments it with the following exogenous variables: Mean Std NNT, Mean Std GI Risk, Mean Relative Speed, Mean Std CV Risk, Min Std. CV Risk, Min Std. GI Risk,attribute interactions with year 2005 dummy and with the dummy indicating whether a brand has the parent company shared by other brand.

TABLE 5. Results of **Table 4** Marginal Effects

Marginal effects (by number of cues)						
Variable:	**1**	**2**	**3**	**4**	**5**	**6**
Exogenous Treatment (Table 4 Column 1)						
Comparative?	-0.144***	-0.188***	0.007	0.134***	0.139***	0.047**
	(0.032)	(0.013)	(0.095)	(0.021)	(0.040)	(0.023)
Exogenous Treatment (Table 4 Column 2)						
Comparative?	-0.103***	-0.126***	0.000	0.085***	0.107***	0.045**
	(0.037)	(0.035)	(0.076)	(0.031)	(0.021)	(0.020)
Endogenous Treatment (Table 4 Column 4)						
Comparative?	-0.337***	-0.434***	0.024	0.256**	0.312**	0.165**
	(0.070)	(0.085)	(0.243)	(0.121)	(0.132)	(0.082)
Endogenous Treatment (Table 4 Column 5)						
Comparative?	-0.375***	-0.463***	0.008	0.266*	0.377***	0.176*
	(0.110)	(0.138)	(0.269)	(0.144)	(0.100)	(0.097)

TABLE 6. Results after Controlling for Comparative Content, and Sales

	(1)	(2)	(3)	(4)	(5)
Comparative?		0.662***	0.476***	1.499***	1.576**
		(0.024)	(0.026)	(0.174)	(0.624)
Standardized sales	0.357***	0.215***	0.445***	0.096	0.268*
	(0.021)	(0.021)	(0.027)	(0.073)	(0.149)
Standardized sales squared	-0.356***	-0.243***	-0.204***	-0.147***	-0.160**
	(0.013)	(0.014)	(0.017)	(0.052)	(0.076)
Standardized generic sales	-0.220***	-0.146***	-0.136***	-0.082**	-1.571***
	(0.013)	(0.013)	(0.043)	(0.038)	(0.227)
Standardized NNT			-0.785***		-1.408***
			(0.047)		(0.239)
Relative Speed			0.260***		0.024
			(0.047)		(0.142)
Standardized GI Risk			-0.151***		-1.741***
			(0.056)		(0.241)
Standardized CV Risk			-0.478***		-0.996***
			(0.053)		(0.173)
Residuals-Comparative				-1.042***	-1.103*
				(0.187)	(0.624)
Residuals-Sales				0.305	0.174
				(0.254)	(0.288)
Residuals-Generic Sales				0.342***	1.844***
				(0.127)	(0.258)
Cutoff (0->1 cues)	-4.103***				
	(0.178)				
Cutoff (1->2 cues)	-1.986***	-1.654***	-1.199***	-1.222***	-1.187***
	(0.025)	(0.028)	(0.100)	(0.114)	(0.277)
Cutoff (2->3 cues)	-0.680***	-0.285***	0.196**	0.172	0.247
	(0.018)	(0.023)	(0.098)	(0.121)	(0.276)
Cutoff (3->4 cues)	0.091***	0.530***	1.054***	1.020***	1.134***
	(0.017)	(0.024)	(0.099)	(0.124)	(0.276)
Cutoff (4->5 cues)	0.983***	1.457***	2.029***	1.975***	2.125***
	(0.020)	(0.027)	(0.100)	(0.126)	(0.279)
Cutoff (5->6 cues)	1.926***	2.424***	3.035***	2.992***	3.150***
	(0.035)	(0.039)	(0.105)	(0.148)	(0.294)
Log-Likelihood:	9,739	9,708	9,708	9,708	9,708
N of Observations	-14165.7	-13704.1	-13378.8	-13372.3	-13138.6

note:*** p<0.01,** p<0.05,* p<0.1. Column (4) and (5) treat "Comparative?", "Sales". and "Generic Sales" as endogenous variables. Instruments are the same as in Table 4

TABLE 7. Relative Rankings of Speed and Duration of Pain Relief

Time to Perceptible Pain Reliefj	**Duration of Meaningful Time Relief (Longevity)**
Sol Ibuprofen>Ibuprofen (1, 6) Ibuprofen> Acetaminophen (1, 5, 6) Acetaminophen> Naproxen (10) Naproxen>Aspirin (3)	Naproxen>Aspririn (3) Ibuprofen>Acetaminophen (2, 4, 5, 9, 10) Ibuprofen/Sol Ib>Acetaminophen (6) Naproxen>Acetaminophen (2, 4, 8, 9) Acetaminophen>Aspirin (10)
Resulting Ranking (Highest to Lowest):	
1. Soluble Ibuprofen 2. Ibuprofen 3. Acetaminophen 4. Naproxen Sodium 5. Aspirin	1. Naproxen Sodium 2. Ibuprofen/Soluble Ibuprofen 3. Acetaminophen 4. Aspirin