Information content of advertising: empirical evidence from the OTC analgesic industry

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Information Content of Advertising: Empirical Evidence from the OTC Analgesic Industry

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Abstract

We use data from video files of all advertisements in the OTC analgesics industry from 2001 to 2005 to measure the information content in ads. We propose a simple theoretical framework to motivate an ordered probit model of information content. We find that stronger vertical differentiation is positively associated with the delivery of more product information in a brand's advertisements: brands with higher levels of quality include more information cues. Comparative advertisements contain significantly more product information than noncomparative advertisements. Brands with higher market shares and brands competing against generic substitutes with higher market shares have less information content.

Keywords: Information Content, Advertising, Information-persuasion tradeoff, Content analysis.

JEL Codes: L13, M37, L65.

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How much information brands choose to disclose in advertisements is a question of considerable 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 (Anderson and Renault 2009; Guo and Zhao 2009; Sun 2010). The empirical work on advertising content is split into two camps, with essentially no overlap. The first camp uses Resnik and Stern's (1977) methodology to analyze content (for a summary, see Abernethy and Franke 1996). The second camp treats advertising content as a choice variable (Anderson et al. 2012 (ACLR); Bertrand et al. 2010; Liaukonyte 2011). We develop the first empirical study of the *information-persuasion trade-off* that use data on the *information content* of ads. In our approach the "persuasive" content of an ad is interpreted here as the content that is not objective information.

The key idea of this paper is that there exists an optimal amount of information to be included in an advertisement. Advertisements that provide too little objective information about the brand arguably waste the opportunity to sufficiently convince prospective consumers to buy it (Jacoby 1977). Conversely, those that provide too much information may crowd the ad message and lead to information overload for the consumer (Chervany and Dickson 1974; Peters, Wedel and Zhang 2007). Factors such as motivation and the ability to process information mediate individual responses to advertising (Cacioppo and Petty 1985; MacInnis and Jaworski 1989). Therefore, the complexity of advertising, including too many information cues, can create attention wear-out (Pieters, Warlop and Wedel 2002), which suggests that an optimal degree of information content exists. The optimal amount of information content may vary systematically across brands and may be partially explained by observable factors such as brand type, brand size, suitability of various combinations of information, and recent news about the product.

Our empirical analysis examines the relationship between market variables and the information content of advertising. First, we classify and fully measure different types of advertising content, as well as the distribution of information cues, within an entire industry. Second, we use an ordered probit model of the number of information cues in advertisements as a function of the market share of a brand, its core vertical characteristics, and the share of the generic substitute. To motivate the selection of an ordered probit we develop a simple and intuitive framework in which firms decide how much objective information to include in an advertisement. The underlying idea behind our empirical analysis is that there exists a trade-off between objective information and other persuasion, subject to random factors intrinsic to specific ads. The amount of time spent on information—as approximated by the number of information cues—has systematic and random components.

We find that stronger vertical differentiation is positively associated with more information. We also find that comparative advertisements contain significantly more information than non-comparative advertisements, and that larger brands and a higher market share of the generic version of a brand are both associated with less informative ads. Significant estimation bias results from not controlling for the endogeneity of the decision to use comparative advertising and from the endogeneity of market share.

Our analysis contributes to the sparse empirical literature on the persuasive vs. informative content of advertising (see Bagwell, 2007, for a comprehensive survey). To our knowledge, the only papers that have tried to disentangle the informative from the persuasive effect of advertising are 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, Ackerberg uses a clever identification assumption that advertising is only informative for first buyers, while it is both informative and persuasive for repeat buyers.

Our approach is fundamentally different because we explicitly code the information content. This enables us to distinguish between the informative and the persuasive role of advertising directly from the content data.

The present paper is related to ACLR (2012) because it analyzes the same industry. The analysis in ACLR (2012), however, is very different. It deploys a structural empirical oligopoly model of how much each brand spends "attacking" each other brand through comparative advertising, where an attack both pulls down the target's perceived quality and pushes up the sender's. The attack matrix of how much is spent attacking each rival is used to derive the matrix of diversion ratios between brand pairs. However, the attack spending is not broken down by characteristic. In this paper, on the other hand, we focus explicitly on the advertising content by analyzing product attributes promoted in the ads.

Advertising Content and the Information-Persuasion Trade-off in an Ordered Probit Model

In general, information in advertisements can be (1) about the brand, brand attributes, benefits, users, or usage situation; (2) cognitive, emotional or subconscious; or (3) contextual information, including consumers' past experiences (MacInnis, Moorman, and Jaworski 2001; Vakratsas and Ambler 1999). We focus on the first aspect of brand information (tractable, objective information cues) and treat cognitive, emotional, and contextual information as the intractable, subjective element of an ad. We define this subjective element as the *persuasive component*.[4]

Contrary to the classic content analysis, which determines the fraction of advertisements that fall into each category given a number of cues and uses univariate analysis to compare scenarios,

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[4] The persuasive component can also be tractable in well-defined studies (e.g., Maheswaran and Joan Meyers-Levy 1990), but it is outside of the scope of this paper.

we use an ordered probit model to study the *determinants* of the distribution of cues. We now present a simple way to motivate the use of an ordered probit in this context.

We maintain that firms face a trade-off: given the limited amount of time available in an ad, the firm must decide how much of that time to allocate to providing information and how much of it to allocate to persuading consumers to buy the brand through the use of channels other than objective information. We assume that the persuasive power of an advertisement depends on the number of seconds devoted to the persuasive component, and a random term, which reflects the idiosyncratic features of a particular advertisement. Let the persuasive power of the ad be
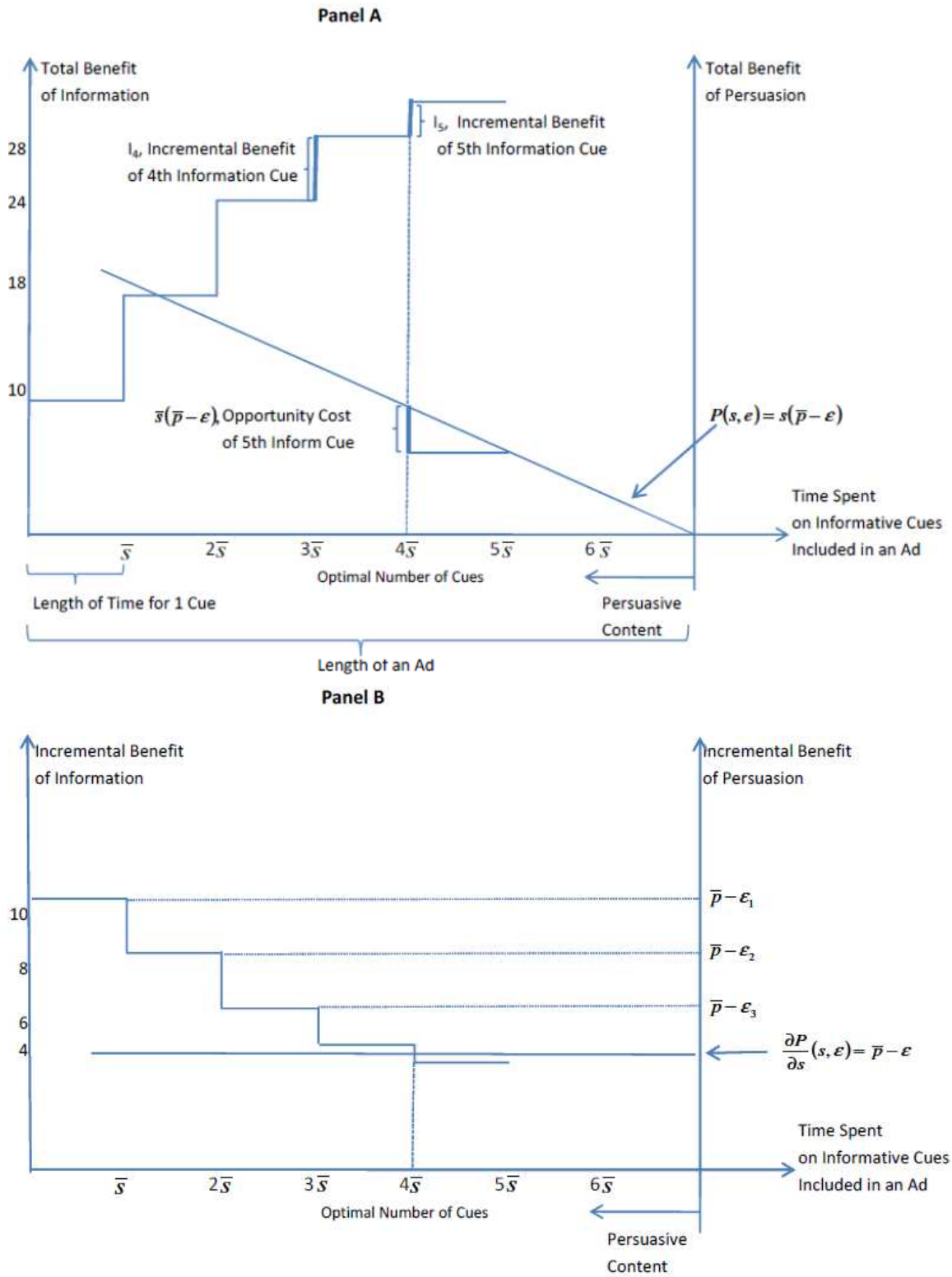
$$P(s, \varepsilon) = (\bar{p} - \varepsilon)s$$

where *s* is the number of seconds spent on persuasion, $\bar{p}$ is a constant and ε is a random term.[5] Panel A of Figure 1 illustrates the function *P(s,ε)*. The x-axis indicates the number of seconds used for persuasion. As more time is allocated to persuasion, the function *P(s,ε)* increases from right to left. The y-axis shows the total benefit from persuasion. The more time spent on persuasion, the larger the total benefit.

The marginal persuasion for an advertisement with *s* seconds of persuasion and a given draw of the random term ε is therefore $\bar{p} - \varepsilon$. The persuasion function is linear, and therefore the marginal persuasion does not change with the share of the advertisement that is allocated to it. Panel B of Figure 1 illustrates the function $\bar{p} - \varepsilon$. The x-axis again indicates the number of seconds used for persuasion. Because $\bar{p} - \varepsilon$ does not change with *s*, the function $\bar{p} - \varepsilon$ is parallel to the x-axis. The y-axis depicts the marginal benefit of persuasion. In the empirical implementation of the econometric model that we are developing here, $\bar{p}$ will vary according to the observable features of the advertised brand (e.g., market share, observable quality, generic competition, etc.) and of the advertisement itself, such as whether it is a comparative or non-comparative advertisement.

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[5] *P(s,ε)* does not have to be linear in s. It should be an increasing and concave function of s. The linear specification simplifies the exposition significantly.

Figure 1. Trade-off Between Informative and Persuasive Content

Panel A

Total Benefit of Information

Total Benefit of Persuasion

28

24

18

10

I_4, Incremental Benefit of 4th Information Cue

I_5, Incremental Benefit of 5th Information Cue

$\bar{s}(\bar{p}-\varepsilon)$, Opportunity Cost of 5th Inform Cue

$P(s,e)=s(\bar{p}-\varepsilon)$

Time Spent on Informative Cues Included in an Ad

$\bar{s}$ $2\bar{s}$ $3\bar{s}$ $4\bar{s}$ $5\bar{s}$ $6\bar{s}$

Optimal Number of Cues

Length of Time for 1 Cue

Persuasive Content

Length of an Ad

Panel B

Incremental Benefit of Information

Incremental Benefit of Persuasion

10

8

6

4

$\bar{p}-\varepsilon_1$

$\bar{p}-\varepsilon_2$

$\bar{p}-\varepsilon_3$

$\frac{\partial P}{\partial s}(s,\varepsilon)=\bar{p}-\varepsilon$

Time Spent on Informative Cues Included in an Ad

$\bar{s}$ $2\bar{s}$ $3\bar{s}$ $4\bar{s}$ $5\bar{s}$ $6\bar{s}$

Optimal Number of Cues

Persuasive Content

Let each information cue take $\bar{s}$ seconds to convey, so that if there are S seconds in the ad (i.e. n information cues are conveyed), there are $s=S-n\bar{s}$ seconds of persuasion. Let I_i be the benefit of the ith information cue i, with $i=1,...,n$. We rank the cues from the highest to the lowest information benefit for each given advertisement (and the ranking may differ across advertisements according to the particular theme of the ad). Clearly, the brand will choose to include the cues delivering the highest information benefit, i.e., those cues for which the values of I_i are the highest.

Because a given advertisement only has a limited amount of available time, S, the brand must decide how much of that time to allocate to providing information vs. for persuasion. This trade-off and the total benefit of information are depicted in Panel A of Figure 1. Panel B of Figure 1 shows the marginal benefit of information, which is decreasing in the amount of information already provided. The marginal benefit of information is also a step function. The firm chooses s (or, alternatively, n) to maximize the sum of the total benefit of persuasion and the total benefit of information. Formally, the firm solves:

$$\begin{cases} \max_{s} D\left(\sum_{i=1}^{n} I_i + P(s, \varepsilon)\right) \\ s.t. \quad n = \dfrac{S-s}{\bar{s}}. \end{cases}$$

Here $D(.)$ is an increasing function representing the firm's demand as a function of an advertisement's information and persuasion content. The solution to this optimization problem can be described by comparing the incremental benefit from adding a cue to the advertisement to the opportunity cost of reducing the time spent on persuasion. If the advertisement contains $n-1$ cues, then the extra benefit from the nth cue is I_n. We can see this graphically in Panel A of Figure 1. There we see that I_4, the marginal benefit of the fourth information cue, is larger than I_5, the marginal benefit of the fifth information cue. The slope of the persuasion function, $\bar{p} - \varepsilon$, is such that:

$$I_5 < \bar{s}(\bar{p} - \varepsilon) < I_4.$$

This implies that the optimal number of cues depicted in Panel A of Figure 1 is four.

Panel B of Figure 1 shows this solution in a way that allows us to introduce our ordered probit in a straightforward way. Define for all I_i the value ε_i such that

$$I_i = (\bar{p} - \varepsilon_i)\,\bar{s},$$

so that ε_i is the threshold value of the random error such that the firm chooses to include at least i information cues in the advertisement if $\varepsilon > \varepsilon_i$. In Figure 1, Panel A depicts $\varepsilon_4 < \varepsilon < \varepsilon_5$. Hence, in this particular illustration, the brand chooses to include four information cues in the advertisement.

Accounting for the fact that there can be no fewer than zero cues and no more than $C = S/\bar{s}$, we have the following mapping from the value of ε to the number of cues, here denoted by y:

$$\begin{cases} y = 0, \text{ for } \varepsilon \leq \varepsilon_1 \\ \quad ... \\ y = i, \text{ for } \varepsilon_i < \varepsilon \leq \varepsilon_{i+1} \\ \quad ... \\ y = n, \text{ for } \varepsilon > \varepsilon_n. \end{cases}$$

The basic intuition of this statistical model is the following: when the (negative) random shock is very small ($\varepsilon < \varepsilon_1$) — which implies that an advertisement has ability to have very strong persuasive power (relative to the benefit of information in that particular advertisement) — then the firm has no incentive to include information cues. As the persuasive power of an advertisement decreases, the firm chooses to include more information cues.

From the specification above we can construct a probability distribution of observing the corresponding number of cues, where $F(\,.\,)$ denotes the cumulative distribution of ε:

$$\begin{cases} y = 0, \text{ with probability } F(\varepsilon_1) \\ \quad ... \\ y = i, \text{ with probability } F(\varepsilon_{i+1}) - F(\varepsilon_i) \\ \quad ... \\ y = n, \text{ with probability } 1 - F(\varepsilon_n). \end{cases}$$

If *F(.)* is normally distributed, the formulation corresponds to an ordered probit model.[6] In particular, we show how the probability function in the model above can be written as the textbook version of the ordered probit, where $\varepsilon_i = \alpha_i - X\beta$ and therefore $F(\varepsilon_i) = \Phi(\alpha_i - X\beta)$. In this ordered probit specification the unobserved components, i.e. *ε,* are drawn from a normal distribution, and the cutoff values (α_i) are such that the realization of a latent variable (explained component plus noise) lies within a range that corresponds to each specific number of cues.[7] β is a $K \times 1$ vector of parameters, and *X* is a $K \times 1$ vector of observable features of the brand, which does not include a constant. For $\beta > 0$, an increase in *X* will lower the threshold ε_i which will in turn make it more desirable to add additional information cues. Therefore, for $\beta > 0,$ larger *Xs* are associated with more information content in an advertisement.

We can rewrite $F(\varepsilon_i) = \Phi(\alpha_i - X\beta)$. First, recall that $\varepsilon_i = \bar{p} - \frac{I_i}{\bar{s}}$. Here $\bar{p}$ is a variable, the value of which determines the benefit of persuasion content. Hence, we set $\alpha_i - X\beta = \bar{p} - \frac{I_i}{\bar{s}}$. It is useful to extract a constant from $-\frac{I_i}{\bar{s}}$ and to rewrite the equality as $\alpha_i - X\beta = \bar{p} - \bar{I} - \frac{I_i}{\bar{s}}$. Then $X\beta = \bar{I} - \bar{p}$ so that, consistent with the discussion in the preceding paragraph, the *X* variables increase the benefit of information or, equivalently, decrease the benefit of persuasion. Second, we can define the cutoff value $\alpha_i = -\frac{\bar{I}_i}{\bar{s}}$, which determines whether the firm is including *i* or *i+1* information cues. The econometric model does not identify the constant term $\bar{I}$ separately from the cutoffs α_i, which we need to keep in mind when we interpret the cutoffs.

In our framework, the cutoffs have a clear structural interpretation. In particular:

$$\alpha_{i+1} - \alpha_i = \frac{I_i - I_{i+1}}{\bar{s}}.$$

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[6] For a comprehensive review of ordered models, see Greene (1997) and Woolridge (2001).

[7] For concreteness, we describe the random term as entering the persuasion power, but it could just as well enter the marginal information benefit described below. Or, indeed, the random term could enter on both sides and the analysis would then capture the net effect.

Thus, conditional on $\bar{s}$ (which is unobserved), differences in the cutoffs provide information on differences in the information benefits of an additional cue.

We estimate this ordered probit model and use the results to examine the relationships between the fundamental variables (e.g., a market share of a firm) and the number of information cues that a firm includes in an advertisement. Before discussing the relationships of interest, we state and prove a helpful result.

Lemma 1. An increase in I_i stochastically increases the number of information cues.

Proof. From the analysis above, i cues will be advertised if $\varepsilon \in (\varepsilon_i, \varepsilon_{i+1})$, where, as above, $\varepsilon_i = \bar{p} - \frac{I_i}{\bar{s}}$. The corresponding probability of observing i cues is $P_i = F(\varepsilon_{i+1}) - F(\varepsilon_i)$, or

$P_i = F(p - \frac{I_{i+1}}{s}) - F\left(p - \frac{I_i}{s}\right)$. Suppose now that I_i increases while retaining its position as the ith largest information benefit. Then P_i increases at the expense of P_{i-1}, while all other probabilities remain unchanged. Hence, the number of cues increases stochastically. Now suppose that the increase in I_i raises it to the jth highest cue, with $j < i$. Then each intervening cue is promoted so that the probability of observing at least that number of cues rises. The probability of observing $i+1$ cues or more stays the same, as does the probability of observing each number less than j. Again, the number of cues stochastically increases. QED

Explanatory Variables in the Ordered Probit Model

First, we consider intrinsic characteristics of a product, which include: strength of pain relief, relative efficiency, and safety. In the industry analyzed in this paper, these variables are naturally exogenous to the information decision. This is because they depend on the medical properties of the active ingredients in analgesic pain relievers, which in turn are inflexibly regulated

by the Federal Drug Administration (FDA). Therefore, the direction of causality can be clearly identified, and we can investigate how different locations in the product characteristics space are associated with information disclosure.

The driving idea here is that the information benefit to the brand from communicating a characteristic is increasing in the strength of the performance of the brand in that characteristic. Communicating a weak characteristic does not give as much incremental benefit as communicating a strong one. Characteristics that are important to consumers are more likely to be communicated, and additional strength in any particular cue will raise its relative information benefit and also make it more likely to be included in the advertisement. Thus, using the result from **Lemma 1** we would expect that brands with higher levels of quality (on each of the quality dimensions for which we have data) will include more information cues in their advertisements.

The second relationship that we study is that of information disclosure and the market share of a brand. We investigate whether larger brands benefit less than smaller brands from providing information, because larger brands are already well known and have higher advertising goodwill and brand equity (Simon and Sullivan 1993, Dekimpe and Hanssens 1995). In other words, the incremental benefit is smaller because consumers are already more aware of the features of commonly used products. The simple framework that we have presented above does not provide any insight on the effect of market share on information content, and so we will learn from the empirical analysis the nature of the relationship between market share and information content in an ad.

Next, we investigate the relationship between information disclosure and the size of the generic counterpart market. An important characteristic of our analyzed market and of many other consumer product categories is the presence of generic substitutes. The simple framework presented above does not provide any prediction on the presence of generic substitutes on information content.

However, we can impose some restrictions to our theoretical framework that would lead to tighter predictions about this relationship. Consider the following simple specification for the objective function of a non-generic firm:

$$D\left(\sum_{i=1}^{n} I_i + P(s, \varepsilon)\right) - L\left(s_g, \sum_{i=1}^{n} I_i\right),$$

where $D(\sum_{i=1}^{n} I_i + P(s, \varepsilon))$ denotes the increase in demand for both the branded product and its generic counterpart, and $L\left(s_g, \sum_{i=1}^{n} I_i\right)$ denotes the leakage to the generic. The leakage is assumed to be increasing in the generic market share, s_g, and in the information content, $\sum_{i=1}^{n} I_i$. Note that n information cues will be preferred to n+1 if

$$D(\sum_{i=1}^{n} I_i + P(s, \varepsilon)) - L\left(s_g, \sum_{i=1}^{n} I_i\right) > D(\sum_{i=1}^{n+1} I_i + P(s, \varepsilon)) - L\left(s_g, \sum_{i=1}^{n+1} I_i\right)$$

where we have let the argument n denote the use of the first n information cues. Rewriting this condition as $L\left(s_g, \sum_{i=1}^{n+1} I_i\right) - L\left(s_g, \sum_{i=1}^{n} I_i\right) > D(\sum_{i=1}^{n+1} I_i + P(s, \varepsilon)) - D(\sum_{i=1}^{n} I_i + P(s, \varepsilon))$ and noting that the right hand side of the inequality does not depend upon s_g, then including the lower number of cues, n, is more likely to be preferred as the left hand side of the equation increases. That holds if the incremental leakage is increasing in s_g. This is a natural condition given that the leakage itself is increasing in s_g (for example, if leakage were proportional to generic market size times an increasing and concave function of information cues). This is consistent with the rationale that brands that emphasize product quality also provide free advertising for generic counterparts of their products[8], and therefore this would decrease the incentive to include information in the ads. On the other hand, consumers of brands might not be inclined to consume generics, and, in that case, brands might include information in their ads, independently of the size of the generic counterpart. While this is an intuitive and interesting exercise, our empirical analysis will not impose any (sign)

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[8] Unlike other generic substitutes of consumer products, the generic versions of OTC analgesics are (and, by regulation, have to be) identical in quality to branded products with the same active ingredient, since the quality of these OTC drugs is overseen by the FDA.

restriction on the relationship between the share of the generic counterpart and the amount of information included in an ad.

Finally, the last relationship that we study is the one between the decision to make a comparative claim and amount of information provided. There is no existing theory that tells us whether comparative advertisements should include more or less information than non-comparative advertisements.[9] More information is conveyed by comparing two brands than just promoting a brand, and comparing relative performance provides a more precise and concrete reference point. On the other hand, an advertisement with comparative content is likely to have a weaker persuasion effect, even if the amount of time devoted to persuasion is the same. This might happen because mentioning the other brand dilutes the persuasion because it reiterates the existence of the rival brand. Previous research (Chou, Franke, and Wilcox 1987; Harmon, Razzouk, and Stern 1983) has found that comparative advertisements have more information, and we expect to find similar patterns. In particular, we might expect a comparative advertisement to both increase the marginal information and decrease the marginal persuasion benefit of an advertisement. Both effects cause the number of cues to rise stochastically (see Figure 1).

Data and Content Analysis

We use sales and advertising data from the OTC analgesics industry in the United States. The OTC analgesics market covers pain relief medications with four major active chemical ingredients: aspirin, acetaminophen, ibuprofen, and naproxen sodium. The nationally advertised brands include Tylenol (acetaminophen), Advil (ibuprofen), Motrin (ibuprofen), Aleve (naproxen sodium), Bayer (aspirin or combination), and Excedrin (acetaminophen or combination).

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[9] Each comparative advertisement must include at least one cue, because the comparison is made for at least one characteristic. We compare all non-comparative advertisements to all comparative advertisements, conditional on an advertisement having at least one cue.

We focus on the OTC analgesics industry for several reasons. First, television advertising constitutes a large fraction of total advertising and of total sales, implying that it is the most important marketing strategy used by the industry to communicate to its consumers. Second, the products sold by firms differ significantly in their characteristics, so that there is a range of meaningful information to potentially communicate (Lancaster 1971, Christou and Vettas 2008). Third, the information is concentrated in experience- and credence-based characteristics, which tend to be advertised, rather than search characteristics that consumers can learn in the store before purchase (Erdem, Keane and Sun 2008). Fourth, product differentiation—both real and spurious—is important because we emphasize the trade-off between persuasion and information, with the optimal mix depending upon a product's characteristics (see Soberman 2002). Finally, the type of cues mentioned (e.g., "strong") are clearly identifiable, which enables us to avoid making any subjective judgments while coding the information cues.

The advertising data come from TNS Media Intelligence and cover the entire U.S. OTC analgesics product category. The dataset contains video files of all advertisements, as well as monthly advertising expenditures, for each product advertised in the OTC analgesics category from 2001 to 2005. The advertising numbers also include expenditures on other media, but almost all the advertising budgets (approximately 90%) were spent on television advertising, including network and cable networks. In our analysis, we examine only the television advertising data. We watched 4503 individual commercials that were broadcast during the 2001–2005 period, 346 of which had missing video files. Each individual advertisement was usually shown multiple times.

The widely used Resnik and Stern (1977) method for measuring advertising information categorizes the information provided in advertisements into 14 distinct "information cues," including price, quality, performance, components, availability, special offers, taste, nutrition, packaging, warranties, safety, independent research, company research, and new ideas. More than

60 studies have applied the Resnik and Stern's approach 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 (Hong, Muderrisoglu, and Zinkhan 1987; Madden, Caballero, and Matsukubo 1986), and product categories (Stern, Krugman, and Resnik 1981). The results have varied markedly, even within the same medium, because of the lack of a multivariate statistical analysis, redundant or too broad definitions of information cues, and small sample size (Abernethy and Franke 1996). The main advantage of the Resnik and Stern's classification system is the general nature of the information cue categories, which allow for comparison of products from multiple industries. However, this advantage is also a disadvantage. Categorizing advertising information content into coarse categories inevitably omits some information that consumers might find important. For example, in the OTC analgesics industry, two distinct information cues (e.g., fast and strong) would be coded as one "performance" cue in the Resnik and Stern's classification system.

Our attribute coding approach documents every attribute mentioned. For each advertisement, we recorded whether the commercial had any comparative claims and, if so, the specific claim (e.g., faster, stronger). We also noted all information cues mentioned, including the purpose of the drug (e.g., arthritis, headache), drug efficiency (e.g., strength, speed), safety, and other characteristics. The type of information cues that were mentioned (e.g., "strong") are clearly identifiable, which enables us to avoid making any subjective judgments while coding the information content. The disadvantage of this approach is that it is industry-specific.

Our analysis also incorporates data on the strength of pain relief, relative efficiency, and safety for each brand. We collected this information from peer-reviewed medical journals. Clinically, all four main active ingredients have varying degrees of side effects. Because individuals react to each ingredient differently, clinical pain researchers hesitate to assign superiority to any

single drug. Each active ingredient has a comparative advantage. A sample of these comparative advantages and disadvantages is the following: Aspirin (brand name - Bayer) is weak in pain relief but has low, almost nonexistent cardiovascular risk. Naproxen sodium (Aleve) is the most potent drug but is associated with very high gastrointestinal risk. Acetaminophen (Tylenol and Excedrin) has low gastrointestinal risk but is weak in pain relief and has medium cardiovascular risk. Ibuprofen (Advil and Motrin) and naproxen sodium–based brands (Aleve) have the highest cardiovascular risk but are also the fastest in pain relief.

Table 1. Descriptive Statistics of Information Disclosure, Vertical Attributes, Ad Spending and Sales

Brand	Information Disclosure		Vertical Characteristics[1]				Advertising and Sales				
	Number of Cues	Compa-rative?	NNT	GI Risk	CV Risk	Relative Speed	Avg Monthly Spending per Ad	Average Monthly Sales	Total Ad Spending	Total Sales	Ad to Sales Ratio
Advil	3.6 (1.004)	0.74 (0.441)	2.40	2.00	1.44	1	$0.14 (0.241)	$23.92 (1.693)	$293.10	$1,374	21.30%
Aleve	3.77 (1.156)	0.9 (0.298)	2.30	9.10	1.44	3	$0.12 (0.293)	$11.41 (1.123)	$174.80	$659	26.50%
Bayer	3.19 (1.320)	0.31 (0.461)	4.00	3.10	1.07	4	$0.10 (0.222)	$7.95 (0.964)	$131.20	$458	28.80%
Excedrin	2.4 (0.695)	0.15 (0.359)	3.86	1.67	1.26	2	$0.26 (0.456)	$12.39 (1.172)	$182.40	$689	26.50%
Motrin	2.61 (0.937)	0.37 (0.484)	2.40	2.00	1.44	1	$0.10 (0.240)	$8.03 (0.762)	$102.00	$466	21.90%
Tylenol	2.54 (0.957)	0.28 (0.449)	3.80	1.00	1.35	2	$0.13 (0.346)	$40.59 (3.195)	$414.90	$2,328	17.80%

Notes: [1] Larger number implies weaker performance. These are relative risk and performance measures taken from peer-reviewed medical literature. See Appendix for more details.

We quantify or rank all of 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 perceptible or meaningful pain relief (medical literature calls this "onset to perceptible pain relief"). Second, we interpret claims about strength (e.g., "strong," "stronger," "tougher on pain") as the maximum level of pain relief achieved; we use the number-needed-to-treat (NNT) measure to approximate analgesic efficiency claims. Finally, we collect reported data on gastrointestinal and cardiovascular risks (GI Risk and CV Risk, respectively) for each of the active ingredients.

Appendix describes these measures in greater detail and presents a list of peer-reviewed medical articles that quantify these performance attributes. The first two columns of Table 1 also present each brand's (expenditure-weighted) average number of information cues mentioned in ads as well as the incidence of comparative ads. We also add advertising spending and sales descriptive statistics to Table 1.

Figure 2. Advertised Attributes and Expenditures
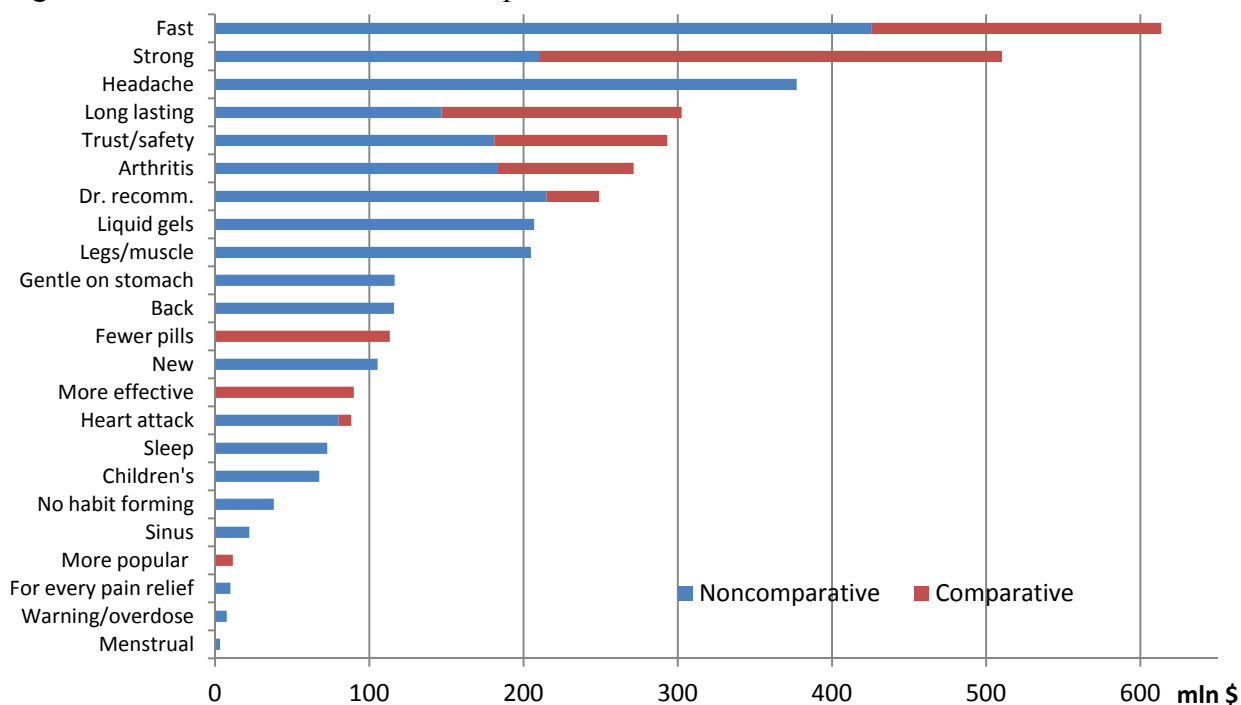
During our analyzed period, 30 different product attributes were mentioned. Figure 2 represents the top 23 attributes and shows the advertising expenditures (in millions of dollars) spent on advertising those attributes during the sample period.[10] We separate advertising expenditures by type of advertisement (comparative versus non-comparative). The attributes "fast," "strong," "long lasting," and "trust and/or safety" are among the top five most heavily advertised attributes. These

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[10] The remaining 7 attributes (not reported) had negligible advertising expenditures. The sum of the expenditures in Figure 2 exceeds total ad spending because many advertisements promote multiple characteristics and, for the purpose of this Figure only, we attributed total ad spending to each characteristic mentioned.

attributes are directly related to the inherent (exogenous) chemical characteristics of each active ingredient in each analyzed brand.

Table 2. 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%		

We examine the attribute usage correlations to investigate whether the coded cues represent distinct information. For example, although we code "strong" and "fast" as separate information categories, we also ensure that the coded information categories are indeed distinct information cues. Table 2 portrays the correlation matrix of cue usage and shows that the cue descriptors that we use are distinctive. For example, both "fast" and "strong" are often used together, but they are also

used separately in more than half of the occurrences (in dollar terms).[11] Thus, two cues may be used together frequently, but each still provides consumers with important information. "Strong" denotes how powerful the medicine is, and "fast" denotes the speed of the onset of pain relief.

Identification Strategy

A brand's decision about how much information to include in an advertisement is likely to be made simultaneously with the decision about the type of advertisement (comparative or non-comparative). Therefore, these two decisions are interdependent, in much the same way as equilibrium price and quantity are determined at the same time in a simple demand–supply model. In other words, there is some unobservable exogenous variable that explains both the information content and whether that content is a non-comparative or comparative advertisement. For example, a higher-quality brand might provide less information and have more comparative advertisements than a lower-quality brand.

The other two potentially endogenous explanatory variables that we consider are the size of the brand and the size of a brand's generic counterpart. To see why endogeneity might be an issue, note that market size and information content are outcomes of brands' strategic interactions, and a fully structural equilibrium model would specify three equations, one for each of the three variables (information content, market size, and the generic counterpart's market size). Here, we estimate only one of the three equations—the one that explains information content as a function of the other two endogenous variables—but we control for the endogeneity of the other two variables. Equivalently, we could consider an unobservable variable (e.g., quality) that is correlated with the

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[11] There are two instances of high correlation that merit comment. First, whenever "liquid gels" are mentioned, "fast" is almost always mentioned. Second, "long lasting" and "fewer pills" are used together 33% of the time. Conversely, when "fewer pills" are mentioned, long lasting was mentioned 88% of the time. We experimented with providing an umbrella classification that encompasses both, but the differences in the results were minor.

brand's market size and information content. By omitting that variable from our regressions, we would introduce a bias into the estimation of the parameters of the model.

We use an instrumental variable approach to determine whether our concerns about the endogenous variables are empirically relevant (Villas-Boas and Winer 1999). Instruments that correlate with sales and advertising but not with unobserved quality provide information on how important the endogeneity problem is likely to be. Our main identification strategy is to use variation in generic prices as the exogenous source of variation in the industry.

The crucial observation for our identification strategy is that all of the patents for the OTC analgesics have expired. The patent for Naproxen was the last one to expire in 1993. After patents expire, generic counterparts are produced at prices that are substantially lower than the brand name product (here, Aleve). As time passes by, new entry of generic competitors brings the price of the generic counterpart down to marginal cost, as shown by Grabowski and Vernon (1992). If the marginal cost is constant and the generic prices are set at the marginal cost, then the generic prices are independent of the prices set by the national brands. Then, the generic prices are exogenous and can be appropriately used as instrumental variables.[12] More specifically, we include constructed means, squared and cubed terms of the brand's active ingredient generic counterpart prices and generic prices of brand's competitors. We also construct interactions between generic prices (own and competitors') and a multi-brand parent company. Finally, we interact the characteristics with the 2005 year dummy to capture advertising content changes—2005 was considered one of the most turbulent years in the analgesics industry.[13]

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[12] Notice that we can allow generic brands to charge prices that are higher than marginal costs as long as this is explained by local conditions that national brands do not take into account when they set their prices.

[13] The growth of information content during 2005 is most likely due to the FDA's announcement of the results of a clinical study, at the end of 2004, which indicated that patients taking naproxen sodium (Aleve) may be at an increased risk 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 more than 50%, suffering the largest decline in brand history.

To deal with the endogenous variables in our nonlinear ordered probit model, we follow Rivers and Vuong's (1988) proposed approach. First, we rewrite the information content as $\alpha_i - X\beta - w\gamma = \bar{p} - \bar{I} - \frac{\bar{I}_i}{\bar{s}}$, where w is a vector of the three endogenous variables. The main identification assumption is that instruments are not correlated with the error term (i.e., $(Z'\epsilon) = 0$). Here, Z includes all of the exogenous variables, such as brand characteristics (X) and functions (here, the average) of the characteristics of the brand's competitors. We use a two-step procedure described in Rivers and Vuong (1988). First, we run an ordinary least squares regression, $w = Z\delta + v$, where v is not observed and is the omitted variable that generates the endogeneity problem. This first stage regression yields residuals $\hat{v}$, which we include in the ordered probit in the second stage of the estimation.[14] The estimation of this ordered probit provides consistent estimates of all of the parameters. Here, we are not interested in the magnitude of the parameters of the information content relationship (i.e., β) but rather in the marginal effects of a change in the endogenous variables, which we can consistently estimate using Blundell and Powell's (2003) approach.

Empirical Findings

Table 3 reports the findings of the various specifications estimated with our data. We investigate whether brands with higher vertical quality transmit more information, by associating the number of information cues (our dependent variable) with the values of the exogenous medical characteristics of the active ingredients. The first column of Table 3 includes NNT, relative speed, and measures of cardiovascular and gastrointestinal risk as such explanatory variables.

Keeping all else constant, we find that brands with inherently stronger pain relief have advertisements with more information content. As explained in the Appendix, for NNT (as well as for Relative Speed, CV Risk and GI Risk), a higher number implies worse performance and a less

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[14] The variable Comparative is a dummy variable. Here we run a linear probability model.

effective drug. Thus, the negative coefficient on NNT is consistent with strong and efficient drugs having more information in their advertisements. We find a similar pattern for brands that have lower gastrointestinal and cardiovascular risks: their advertisements also tend to be more informative. Finally, consistent with our theoretical framework, brands that offer faster relief also have more information content.

Overall, the first column of Table 3 suggests that there is a positive relationship between the amount of information provided and the strength of a painkiller along one of the four dimensions identified by the exogenous medical characteristics of the active ingredient.

Figure 3. Estimated Decreasing Marginal Returns of Informative Content
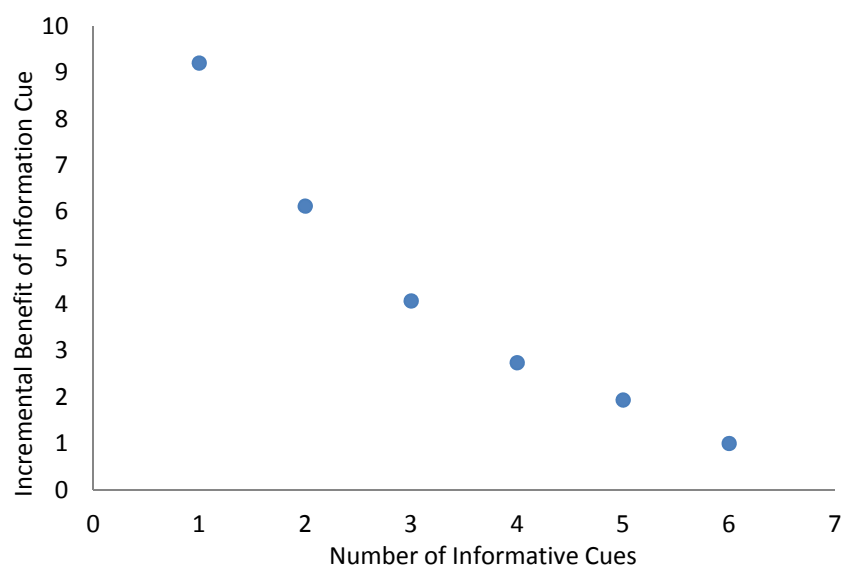
The cutoffs estimated in these regressions have a clear interpretation. In particular, we showed that $\alpha_{i+1} - \alpha_i = \frac{I_i - I_{i+1}}{\bar{s}}$. In our analysis $\bar{s}$ is unknown, so assume for the sake of interpretation that $\bar{s} = 1$.[15] Then, for each i we can compute the difference I_i - I_{i+1}, which is the incremental benefit of the ith information cue i. Consider the case of $i=5$. Then, $I_5 - I_6 = 1.002$.

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[15] Instead of normalizing $\bar{s} = 1$, one could also report $\frac{\alpha_{i+1} - \alpha_i}{\alpha_6 - \alpha_1}$, but that would only rescale Figure 2. The normalization $\bar{s} = 1$ gives a more intuitive interpretation for Figure 2.

We can then find the point (6, 1.002) in Figure 3 to represent the empirical analogue of the theoretical incremental benefit corresponding to six information cues that we had derived in Panel B of Figure 2. We can replicate this exercise for the case of $i=4$, for which the scatter point will correspond to (5, 1.939), which is equal to $1.002 + 0.937$. By repeating this exercise for all $i = 1,…,6$, we derive the scatter plot in Figure 3. What we see in Figure 3 is remarkably similar to what we derive theoretically in Panel B of Figure 1: there is a fundamental trade-off between information and persuasion content that firms face when preparing an advertisement. This relationship, depicting the diminishing marginal returns to information, holds in every specification that we estimate and looks very similar to the one illustrated in Figure 3.

Next, we want to investigate whether brands include more information in comparative advertisements than in non-comparative advertisements. Note that comparative advertisements will always have at least one cue because a brand must compare itself with another brand along at least one dimension. Therefore, the analysis examines whether comparative and non-comparative ad information content is different, conditional on having at least one information cue. The results are presented in column 2 in Table 3. Here, we treat the choice of comparative advertisement as an exogenous variable. We find that the comparative advertising dummy is highly statistically significant and positive. This result indicates that comparative advertisements have more informational cues and that the likelihood that an advertisement is comparative increases with the number of cues.

In Column 3 we include the variables that measure brand size, brand size squared (to capture a possible nonlinear relationship), and the size of the brand's generic counterpart. We find that the largest brands transmit less information than the rest of the brands.

The evidence is also consistent with a relatively large spillover effect from informative advertising. We find that branded firms include less information content when the size of their generic competitors is large because the parameter of standardized generic sales is negative.

Table 3. Determinants of Information Disclosure

	(1)	(2)	(3)	(4)
Comparative?		0.559***	0.476***	0.968***
		(0.025)	(0.026)	(0.077)
Standardized Sales			0.445***	0.309***
			(0.027)	(0.036)
Standardized Sales Squared			-0.204***	-0.130***
			(0.017)	(0.021)
Standardized Generic Sales			-0.136***	-0.140***
			(0.043)	(0.045)
Standardized NNT	-0.724***	-0.602***	-0.785***	-0.670***
	(0.029)	(0.029)	(0.047)	(0.050)
Relative Speed	0.336***	0.281***	0.260***	0.198***
	(0.041)	(0.041)	(0.047)	(0.048)
Standardized GI Risk	-0.133***	-0.132***	-0.151***	-0.189***
	(0.035)	(0.035)	(0.056)	(0.059)
Standardized CV Risk	-0.151***	-0.185***	-0.478***	-0.465***
	(0.029)	(0.029)	(0.053)	(0.054)
Residuals-Comparative				-0.557***
				(0.082)
Residuals-Sales				-0.175**
				(0.068)
Residuals-Generic Sales				-0.167***
				(0.041)
Cutoff (0->1 Cues)	-3.085***			
	(0.194)			
Cutoff (1->2 Cues)	-1.041***	-0.941***	-1.199***	-1.042***
	(0.090)	(0.091)	(0.100)	(0.104)
Cutoff (2->3 Cues)	0.291***	0.436***	0.196**	0.360***
	(0.089)	(0.090)	(0.098)	(0.103)
Cutoff (3->4 Cues)	1.095***	1.271***	1.054***	1.218***
	(0.090)	(0.090)	(0.099)	(0.103)
Cutoff (4->5 Cues)	2.032***	2.228***	2.029***	2.196***
	(0.091)	(0.092)	(0.100)	(0.105)
Cutoff (5->6 Cues)	3.034***	3.234***	3.035***	3.213***
	(0.097)	(0.097)	(0.105)	(0.109)
# of Obs.	9739	9708	9708	9708
Log-Likelihood	-13847.5	-13527.6	-13378.8	-13351.8

note: *** p<0.01, ** p<0.05, * p<0.1; Bootstrapped standard errors reported in Column 4. Endogenous variables: Comparative?, Standardized Sales, Standardized Generic Sales. Instrumental Variables: Functions of Generic Prices. The first stage R^2 for endogenous variables is the following: Comparative? - R^2 =.35, Standardized Sales - R^2= 0.96, Standardized Generic Sales - R^2=0.77)

We also find that the coefficient estimate for the comparative advertisement dummy is close to the one in the second column of Table 3. Therefore, we conclude that comparative advertising decisions are not collinear with brand sales and generic sales. This result is noteworthy because it suggests that the comparative advertisement decision might not depend significantly on the market share of the attacking brand but rather on the market share of the target brand (i.e., attack larger brands). ACLR (2012) investigate the relationship among the attacker's market share, the attacked brand's market share, and the amount of their comparative advertising. They show that the decision to use comparative advertising is due to the market share of the attacked brand and the interaction between the shares of the attacked brand and those of the attacking brand.

In Column 4 we follow an instrumental variable approach to estimate the effect of comparative advertisements, sales, and generic sales on information content. Column 4 uses the generic prices as instrumental variables. The results in Column 4 are those that we will use to discuss the main implications of our analysis. We find that the estimated coefficient of comparative advertisements is larger than in Column 3, implying that comparative advertisements have more information content than non-comparative advertisements and that such information content is significantly higher than under the exogenous treatment. The strong endogeneity of this dummy variable is confirmed by the estimated coefficient of the control function, which is statistically significant at the 1% confidence level. Thus, we cannot reject the hypothesis that the variable "Comparative" is endogenous (Smith and Blundell 1986). Therefore, our omitted variable concern in this setting is valid, and such unobserved quality is associated with the attractiveness of having comparative advertisements.

Both the coefficient on standardized sales and the on the squared standardized sales are smaller in absolute value than in Column 3, suggesting a flatter, but still negative, relationship

between brand shares and information content. The coefficient estimate of the control function is statistically significant, confirming the endogeneity of shares.

Finally, the marginal impact of the generic counterpart's market share is the same in Column 3 and 4, suggesting that its endogeneity is not empirically significant. The coefficient is negative, implying the negative relationship between the generic counterpart and information disclosure, as suggested by our extended theoretical framework.

To understand the economic importance of the results regarding brand and its generic counterpart market sizes, we constructed figures that associate a brand's probability of choosing a given amount of information (e.g., one cue) with the distribution of brand's size and the size of the market for generic substitute (at the 10th, 25th, 50th, 75th, and 90th percentiles of market size distribution). For example, Figure 4 shows that the likelihood of an advertisement including only one cue increases sharply with size. In contrast, the probability of observing an advertisement with four or more cues decreases with size. Specifically, a move from the 10th percentile in the size distribution to the 90th percentile increases the probability of providing only one cue by approximately 16%. Similarly, Figure 5 represents the changes in the likelihood that an advertisement includes a certain number of information cues depending on the size of the generic counterpart market share. For example, the likelihood that a product with a large generic counterpart will include one information cue is approximately 10% higher than the likelihood that a product with a small generic counterpart will include one information cue. The converse is true for three or more information cues: brands with smaller generic counterparts are significantly more likely to include more information in their advertisements.

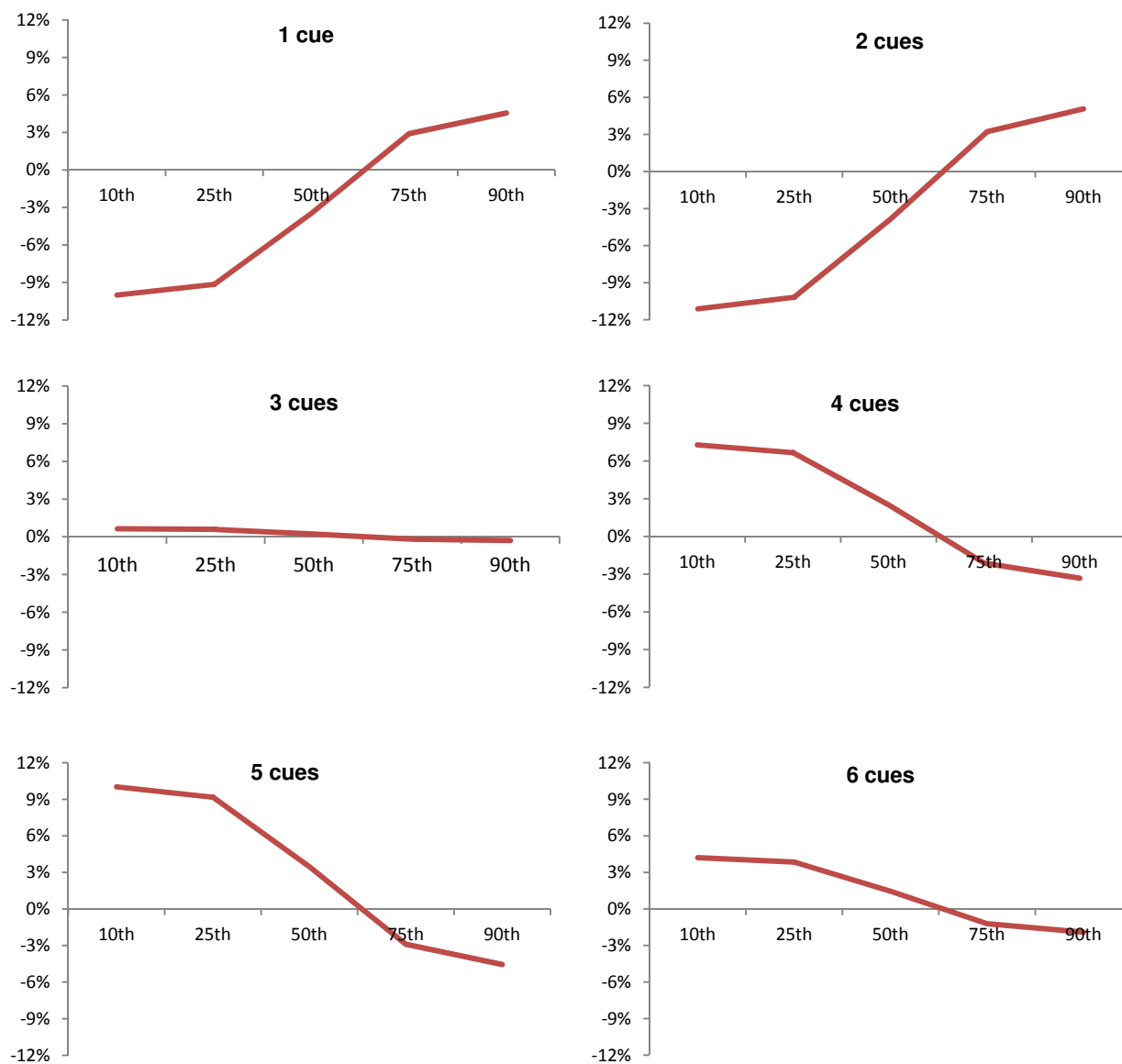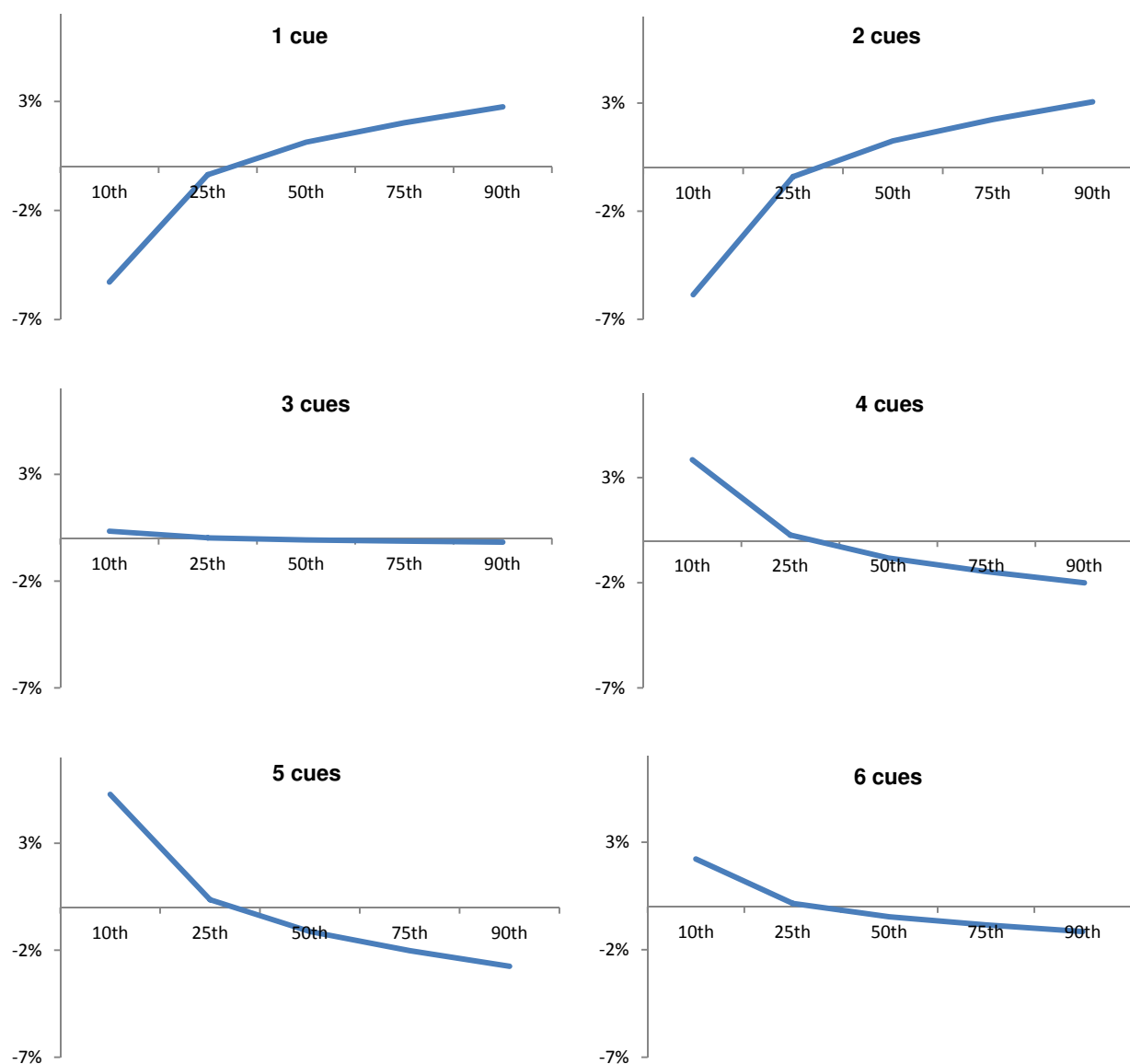Figure 4. Marginal effects on Information Disclosure by Brand Size

Figure 5. Marginal effects on Information Disclosure by Generic Counterpart Size

Conclusions

We find that brands with higher vertical quality disclose more information, and advertisements for brands with a high market share provide less information. These two results are not contradictory. The endogeneity of brand size underscores the importance of correcting for it. Otherwise, it might be assumed that larger brands are fundamentally of higher quality than smaller brands and, therefore, their advertisements should have more information content. Correcting for

endogeneity, we also show 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 spillovers to informative advertising. Finally, we quantify the extent to which comparative advertisements have significantly more information content than noncomparative ones, and find that this effect is much larger than would be predicted without correcting for endogeneity.

From a methodological standpoint, we describe a method that is appropriate for dealing with information content with multiple explanatory variables, and show how the analysis can be corrected for endogeneity and how this alters the results. Our empirical analysis is restrictive in several aspects, and therefore suggests extensions that constitute themes for further research into information content. First, further research could use a sub-classification of cues (e.g., into vertical cues such as "fast" that all consumers would appreciate, or horizontal cues such as "headache" or "menstrual pain" that only some consumers desire) to explore the differential content of various cue types. Second, an information cue can be deployed only if a product has the attribute communicated in the cue, and can be used comparatively only if a product has an advantage over another product. Thus, further research might examine the amount of information advertised as a function of the total number of cues that could feasibly be advertised. Likewise, investigating whether products use comparative advertisements more often against similar or dissimilar products would be an interesting extension. Third, we do not examine product advertising campaigns in which advertisements address a subset of themes over a limited horizon. Fourth, we code only the objective content of advertisements as quantified by their reference of specific characteristics and competitors. We recognize that advertising may persuade through channels other than pure information, thereby leading consumers to act on emotional factors. While our paper recognizes that the trade-off between persuasive and informative content of an ad exists, we have not attempted to code persuasive effects. The primary purpose of the empirical component of this paper was to

measure the objective content of advertising along the lines of traditional content analysis and incorporating the subjective side would be an important aspect to explore in future research. Finally, we do not address whether the market provision of information is optimal, how valuable the information is to consumers (Ippolito and Pappalardo 2002; Pappalardo and Ringold 2000) or how government policy towards advertising content might affect promotion effectiveness (Goldfarb and Tucker 2011). Instead, the purpose of this paper was to document empirical regularities present in the data, rationalized via our *information-persuasion trade-off* theoretical framework, and to provide measures of the fundamental variables that can be used to answer such questions

Our content analysis methodology can readily be applied to other product categories and industries. Extensions of the proposed methodology could be applied to answer questions such as: How does advertising information content differ for experience, search, and credence products? Does the relationship between brand size and information hold in more broad contexts? Do new products provide more information? These questions should hold both empirical and theoretical interest.

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APPENDIX. **Vertical Product Performance and Medical Measures**

We reviewed 10 peer-reviewed medical journal articles to collect efficiency measures for:

1. Strength (Numbers Needed To Treat (**NNT**));

2. Speed (Onset to perceptible pain relief (**Relative Speed**));

3. Gastrointestinal side effects (Gastrointestinal risk (**GI risk**));

4. Cardiovascular side effects (Cardiovascular risk (**CV risk**).

These 4 efficacy measures for each brand are reported in Table 1.

The peer-reviewed medical literature provides objective risk and efficiency measures for each product, based on its active ingredient (or combination of ingredients), strength, and recommended dosage. Each active ingredient has definitive maximum doses and durations of therapy. Differences exist across active ingredients in terms of the important safety issue of the potential for gastrointestinal toxicity and cardiovascular risk as well as relative strength and onset to perceptible pain relief. We collected the measurable characteristics for maximum OTC recommended dosage (single dose): Ibuprofen: 400 mg; naproxen sodium: 440 mg; aspirin: 1000 mg; and acetaminophen: – 1000 mg.

Relative risk 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 (nonexposed) group:

$$RR = \frac{\Pr\left(E|treatment\right)}{\Pr\left(R|control\right)}$$

Relative risk is used frequently in clinical trial data to compare the risk of developing a disease in people not receiving the new medical treatment (or receiving a placebo) versus people receiving an established (standard of care) treatment. In the case of the gastrointestinal (**GI Risk**) and cardiovascular relative risk (**CV Risk**) numbers used herein, we use them to compare the risk of developing a side effect in people receiving a drug with people who do not receive the treatment (or receive a placebo). Thus, a cardiovascular relative risk of 1.44 means that cardiovascular problems arise with 44% higher likelihood using the drug (versus placebo).

The number needed to treat (**NNT**) is an epidemiological measure used in assessing the effectiveness of a health-care intervention, typically a treatment with medication. The NNT is the average number of patients who need to be treated to prevent one additional bad outcome (i.e. the number of patients that need to be treated for one to benefit compared with a control in a clinical trial). It is defined as the inverse of the absolute risk reduction. The ideal NNT is 1, where everyone improves with treatment and no one improves with control. The higher the NNT, the less effective is the treatment. More specifically, NNT is used with respect to two treatments, A and B, with A typically a drug and B a placebo. If the probabilities P_A and P_B under treatments A and B, respectively, are known, we can compute NNT as follows:

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

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 a hypothetical migraine study, if risk decreased from P_B= .30 without treatment with drug M to P_A = .05 with treatment with drug M, for a relative risk of .17 (.05/.3), a relative risk reduction of .83 ([.3 − .05]/.3), and an absolute risk reduction of .25 (.3 − .05), the NNT would be 1/.25, or 4. In clinical terms, an NNT of 4 means that four patients need to

be treated 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.

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