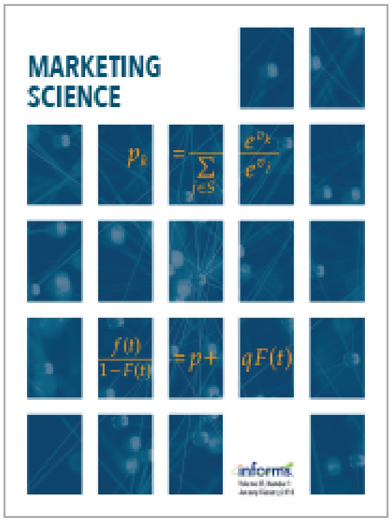

Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MARKETING SCIENCE
CELEBRATING 30 YEARS
Vol. 30, No. 3, May–June 2011, pp. 430–446
ISSN 0732-2399 | EISSN 1526-548X | 11 | 3003 | 0430

informs
DOI 10.1287/mksc.1110.0638

The Seeds of Negativity: Knowledge and Money

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This paper studies the tendency to use negative ads. For this purpose, we focus on an interesting industry (political campaigns) and an intriguing empirical regularity (the tendency to "go negative" is higher in close races). We present a model of electoral competition in which ads inform voters either of the good traits of the candidate or of the bad traits of his opponent. We find that in equilibrium, the proportion of negative ads depends on both voters' knowledge and the candidate's budget. Furthermore, for an interesting subset of the parameter space, negativity increases in both knowledge and budget. Using data on the elections for the U.S. House of Representative in 2000, 2002, and 2004, we examine the model and its implications. Using nonstructural estimation, we find that negativity indeed increases in both voters' knowledge and the candidate's budget. Furthermore, we also find that knowledge and budget mediate the effect of closeness on negativity. Using structural estimation, we reinforce these findings. Specifically, we find that the model's parameters are within the subset of the parameter space discussed above. Thus, the evidence implies that the model is not only helpful in identifying variables that were ignored by previous studies (i.e., knowledge and budget) but also in explaining an intriguing empirical regularity.

Key words: political marketing; advertising; analytical models; Bayesian estimation; cross-sectional analysis
History: Received: December 22, 2008; accepted: December 11, 2010; Eric Bradlow served as the editor-in-chief and Yuxin Chen served as associate editor for this article.

1. Introduction

This study presents a model of negative advertising and examines it empirically. By *negative advertising*, we refer to cases in which the ad discusses the competitor explicitly or implicitly. The empirical context of the research is political advertising, where negative advertising is frequent and variation in negativity is high. The aim of this study is not only to shed light on the tendency to "go negative" but also to explain an interesting empirical regularity—the closer the political race, the higher the proportion of negative ads (Goldstein and Freedman 2002b). We present a model of electoral competition in which ads inform voters either of the good traits of the candidate or of the bad traits of her opponent. We find that in equilibrium, the proportion of negative ads depends on both voters' knowledge and candidates' budgets. Furthermore, for a subset of the parameter space, negativity increases in both knowledge and budget. We find this subset of the parameter space interesting, because close races are not only characterized by high negativity but also by (a) high media coverage (West 1994), which can lead to high levels of knowledge; and (b) large marketing spending (i.e., large budgets) by both candidates (Goldstein and Freedman 2002b). In this sense, for that subset of the parameter space, our model can tie together these three empirical regularities.

We examine the model and its implications using both nonstructural and structural estimation and data on the elections for the U.S. House of Representative in 2000, 2002, and 2004. The nonstructural estimation demonstrates that negativity indeed increases in both voters' knowledge and the candidate's budget. Interestingly, these variables were ignored by previous studies of negative advertising. Furthermore, we also find that knowledge and budget mediate the effect of closeness on negativity. The structural estimation results reinforce these findings. Specifically, we find that the model's parameters are within the subset of the parameter space discussed above.

In commercial environments, firms can improve their standing (profits, stock value, etc.) either by becoming more attractive to their audience (i.e., positive appeals) or by making their competitors less appealing (i.e., negative appeals). Although some combative acts, such as sabotaging competitors' products, are forbidden by law, comparative (which implicitly includes negative appeals) advertising is not only allowed but even encouraged by the Federal

Trade Commission.[1] Furthermore, the portion of comparative advertisements out of all advertisements has been approximated as close to one out of three (Niemann 1987), representing a substantial advertising volume. Indeed, arguably some of the most memorable recent ads and advertising campaigns were negative—for example, the "Mac versus PC" campaign of Apple, the wireless carrier campaigns of Verizon and AT&T, and the "1984" ad by supporters of Obama in the previous primary campaign.[2]

However, research on negative advertisements is relatively thin.[3] Almost all the scholars that studied negative (versus positive) advertising examined consumers' (and voters') reactions to them, not firms' motivation to use them. We present a theoretical foundation for the strategic use of negative advertising (i.e., in equilibrium) and examine our theory empirically.

To learn the most about negative advertising, we focus on political campaigns, which exhibit frequent and high variation in negativity. We aim to explain one of the most interesting empirical regularities about negativity in political campaigns—the greater tendency to go negative in competitive elections. For example, in the 2000 Senate elections, the portion of all ads that were negative was 33% in the less competitive races but 65% in the more competitive races (Goldstein and Freedman 2002b).[4] This empirical regularity is important both because it is a central feature of the application studied here (i.e., political campaigns), and because, more generally, it is an intriguing relationship between competition and advertising tone. We believe that a model that can explain this regularity is likely to be insightful about the strategic forces behind negative advertising.

To shed light on the empirical regularity and incentives to go negative, we present a model. In the model there are two candidates, a Republican and a Democrat, and each one of them has good traits (e.g., effective manager) and bad traits (e.g., performs badly under pressure). Of course, voters' utility increases in the candidate's good traits and decreases in the bad traits, but not all of the traits are known to the public. The model has two decision stages. In the first, the candidates raise funds and decide on their budgets. In the second, they decide how to divide their budgets between ads that present their good traits (i.e., positive advertising) and ads that present their opponent's bad traits (i.e., negative advertising).

We find that there is a unique equilibrium in the first stage and that (in the second stage) the portion of negative ads in a campaign is a function of both the size of the budget and the level of voters' knowledge (specifically, how much they know without exposure to ads). Furthermore, for a subset of the parameter space, negativity increases in both knowledge and budget. As pointed out previously, these findings are interesting because close races are not only characterized by higher negativity but also by larger budgets and more intense media coverage (which can lead to high levels of knowledge). In this sense, our model can tie together these three empirical regularities.

Using data on the elections for the U.S. House of Representative in 2000, 2002, and 2004, we examine the model and its implications by applying both nonstructural and structural estimation. The nonstructural estimation demonstrates that negativity is indeed positively related to voters' knowledge. For example, we find that candidates who became well known by their vote on the Iraq resolution tended to be more negative. Other variables that measure knowledge on the candidates, such as media coverage, are also supportive of the model. We also find that negativity is positively related to the candidates' budgets even when we account for endogeneity of the budgets via a control function treatment. Furthermore, as hypothesized, we find evidence that the relationship between the closeness of the race and negativity is mediated by knowledge and budget.

In the structural estimation we treat both the budget and its division between negative and positive ads as endogenous variables. The results reinforce the findings from the nonstructural estimation—we find that the model's parameters are within the subset of the parameters space discussed above. Thus, the evidence implies that the model is not only helpful in shedding a light on the incentive to go negative but also in explaining the interesting empirical regularity—the closer the race, the higher the negativity.

2. Related Literature

Negative advertising has been researched broadly under a variety of names, including comparative, contrast, disparaging, and attack ads. The effect of positive and negative advertising on consumers has

[1] See http://www.ftc.gov/bcp/policystmt/ad-compare.htm for the FTC statement on comparative (negative) advertising.

[2] For a few examples of the Mac versus PC campaign, search for the following codes in YouTube: ci2D1ig4df4, 1EbCyibkNB0, GQb_Q8WRL_g, and eU9EflLJuf8. Check out the many spoofs of these commercials in YouTube. They reflect the involvement level that these commercials encourage. For the "1984" commercial, search for 6h3G-lMZxjo. Note also that comparative ads tend to be more memorable (Grewal et al. 1997).

[3] Notice that we are using the terms "comparative" and "negative" to refer to cases in which the ad discusses the firm's competitor. The precise meaning in the formal theory is presented in §3.

[4] In presenting the findings of Goldstein and Freedman (2002b), we combine "contrast" and "attack" ads because each specifically mentions the opponent and implies a negative statement.

been examined in commercial settings and even more intensely in political campaigns. Research in commercial settings finds that comparative ads garner more attention, awareness, message processing, and favorable attitudes toward the sponsored brand than noncomparative ads (Grewal et al. 1997). A related stream of research examines the psychological response to negative advertising (e.g., Shiv et al. 1997) and related psychological processes (e.g., Thompson and Hamilton 2006).

In contrast, much of the early evidence in political campaigns (Lau et al. 1999) was equivocal on whether negative ads have different effects than positive ads. However, more recent research has begun to garner less ambiguous results. With improved measures of advertising tone and exposure, Goldstein and Freedman (2002a) find that negative ads increase voter involvement. Phillips et al. (2008) find that the impact of negative and positive advertisements depends on prior preferences. Che et al. (2007) examine the effect of negative political advertising on election outcomes, finding that the average voter responds positively to negative ads and not at all to positive ads. Thus, studies of negative advertising in both commercial and political settings have found that negative and positive advertising can influence viewer response differently.

As mentioned in §1, most scholars that studied negative advertising examined consumers' reactions to them rather than firms' motivation to use them. Still, this issue was not completely ignored by scholars. In the commercial setting, for instance, Chen et al. (2009) model "combative" advertising, which can shift customer preferences away from a competitor's product, and show the effect of such advertising on equilibrium prices and profits. Similarly, Yang and Gerstner (2006) explore a theoretical model of negative comparative advertisements and demonstrate that such advertisements can reduce price competition, cause customers to exit, and decrease social welfare. However, we differ from both of these papers because they neither consider the choice between positive and negative advertising nor the conditions in which one or the other is optimal. Shaffer and Zettelmeyer (2009) show how the inclusion of a retailer and in-store displays in the model discourages the manufacturer from engaging in comparative advertising. Although there are various differences between their approach and ours, the most fundamental one is that we introduce knowledge as the mechanism through which ads affect individuals.

Two earlier theoretical studies also explore the reasons for going negative in political campaigns—Skaperdas and Grofman (1995) and Harrington and Hess (1996). Both studies focus on the difference between the front-runner and his competitor in the tendency to go negative. Although both predict that front-runners will be less negative than trailing candidates, their explanations are different. Theilmann and Wilhite (1998) test both models using a pseudoexperimental study of political consultants' responses to hypothetical campaign scenarios. They find no support for the Harrington and Hess model, but they do find support for the Skaperdas and Grofman prediction. However, the overall evidence on the front-runner effect is mixed. (See Damore 2002, Sigelman and Buell 2003, Benoit 1999, Sigelman and Shiraev 2002.) As apparent, previous studies were interested in the impact of the front-runner, but none of them considered voters' knowledge or candidates' budgets as a fundamental ingredient in candidate motivation to go negative.

Finally, two more recent papers are quite related to our subject of interest. Soberman and Sadoulet (2007) present a theoretical model of targeted campaign advertising under different campaign spending limits. They suggest that candidates use broader, less targeted campaigns with high budgets and narrow campaigns targeted at the opponent's supporters with lower budgets. Che et al. (2007) focus on estimating the effect of negative and positive ads on voters' choices, but they also present a model of strategic communication and use their "demand" estimates in a candidate choice model of advertising tone. Interestingly, they find that the demand estimates help them to explain the "supply" of negative ads.

Unlike the studies above, we both present an equilibrium model of negative advertising *and* test it empirically (using nonstructural and structural estimation). Our theory introduces factors (knowledge and budget) that were ignored by previous studies but are supported by the data. Finally, our model not only explains the incentive to go negative but also sheds light on an interesting empirical regularity—the positive relationship between negativity and the closeness of the race.

Before presenting the model, it is worth noting its role in this study. Although the main contribution of this study is to demonstrate empirically that two variables that were previously ignored (budget and knowledge) play an important role in the tendency to go negative and that they can explain the relationship between the closeness of the race and negativity, the model also has a critical role. First, it identifies these variables. Second, it offers a way to tie together three interesting empirical regularities about close races. Third, it puts some (theoretically based) structure on the estimation.

The next section presents the model. The data, preliminary results, and the nonstructural estimation are described in §3. The fourth section discusses some estimation issues and the results of the structural estimation, and the last section concludes.

3. Model

This section presents a model of candidate decisions about the negativity of their advertising. Although the central element of the model is negativity, its scope is widened to include both individuals' voting choices and the candidates' choices of the advertising budget. Voters' choices reflect the incentive of the candidate, and the budget represents the candidates' constraint. The sequence of events is the following: (i) candidates decide on their spending/budgets, (ii) they choose the proportion of their budgets that is devoted to negative ads (versus positive ads), and finally, (iii) the individuals make their voting choices. We solve the model, of course, in the opposite order.

In the model, two candidates, d and r, represent the Democratic and Republican parties, respectively. Each candidate has good traits denoted by a (e.g., effective manager) and bad traits denoted by b (e.g., performs badly under pressure). Throughout the exposition, we will refer to the voter as a male, to the focal candidate as a female, and to her rival as a male.

3.1. The Voter

We consider a representative consumer framework. However, the results hold for a more general setting with two loyal segments and one segment of independents (à la Narasimhan 1988).

A central ingredient of our theory is voters' knowledge. Thus, we start this subsection by discussing our formulation of knowledge, and we only then describe individuals' voting choices.

3.1.1. Knowledge. Not all of the candidates' traits are known to the public. Accordingly, the voter's knowledge can be thought of as the stock of candidate traits to which he has been exposed. The total stock is the sum of two components: prior knowledge and knowledge attained through candidates' political advertisements; i.e., advertisements are informative. Stated formally, let a_j represent the voter's knowledge level of candidate j's good traits at the time of the voting decision and decompose it into two parts: (i) knowledge of her good traits prior to seeing ads (denoted by a_{j0}) and (ii) knowledge learned from her advertisements (denoted by a_{j1}). Thus, $a_j = a_{j0} + a_{j1}$. Define b_j, b_{j0}, and b_{j1} similarly with respect to the bad traits. Below, we specify (a) the impact of knowledge on utility and (b) the production function of a_{j1} and b_{j1} (i.e., how candidates' ads are transformed to voter knowledge).

3.1.2. The Dual-Channel Assumption. Following previous studies (including experimental, survey, and brain research), we assume that the voter does not combine the information on the good and bad traits into one construct. Instead, he keeps a separate record for each type of trait, and his utility is additive and separable in both. We refer to this assumption as a "dual channel."

The idea that good and bad are different constructs and that people are likely to mentally account for them separately has a strong foundation in the psychological and behavioral economics literature (Thaler 1985, Cacioppo et al. 1997, Baumeister et al. 2001). This research has found that the effect of negative information is greater than that of positive (e.g., Klein and Ahluwalia 2005, Lau 1985) and that the response to positive and negative is not only asymmetric but also nonlinear (e.g., Holbrook et al. 2001). Brain research has identified significant differences in event-related brain potentials for positive and negative evaluation objects (Ito and Cacioppo 2000, Ito et al. 1998), and such a biological basis has been suggested to be an evolutionary adaptive smoke-alarm-type system (Baumeister et al. 2001). Overall, this body of research provides considerable evidence that thinking about positive and negative information as distinct may be essential to the way humans process information and form attitudes.

3.1.3. Voting Choices. Based on this dual-channel assumption, the voter's utility from candidate j is

$$g(a_j) - f(b_j) + \varepsilon_j, \tag{1}$$

where ε is the individual's evaluation of the candidate that is uncorrelated with knowledge and not observed by the candidates (i.e., a random variable). Notice that the representative consumer assumption can be replaced by assuming that ε_js are independent and identically distributed (i.i.d.) across individuals.

We further assume that $g(a_j) = a_j^\alpha$ and $f(b_j) = b_j^\beta$. The solution of the model will obviously depend on whether α and/or β are greater or less than 1 and which one of them is higher. We discuss these issues as well as the reasonability of each assumption later.[5]

Under the assumption that ε_js come from an "extreme value" distribution with function $\exp(-\exp(-\varepsilon))$, the probability that the individual votes for candidate j (denoted by p_j) is

$$p_j = \frac{\exp(a_j^\alpha - b_j^\beta)}{\exp(a_j^\alpha - b_j^\beta) + \exp(a_{-j}^\alpha - b_{-j}^\beta)}, \tag{2}$$

where $-j$ indexes the rival of j.[6]

[5] This formulation assumes that the effect of a trait on the utility is either concave or convex. An alternative specification is an S-shaped function. Given that we estimate this model using congressional data, and voters' knowledge about their congresspersons is usually quite low, it is unlikely that our data would cover both the convex and concave parts of an S-shaped function. Therefore, and to maintain a parsimonious model, we employ a power function instead.

[6] This model of consumer voting behavior is a standard Bradley–Terry–Luce model (Bradley and Terry 1952, Luce 1959). Although

3.2. Candidates' Negativity

Given voter responses, each candidate decides how to divide her or his total budget, denoted by E_j, between negative and positive ads. Let e_j represent candidate j's spending on positive advertising (i.e., about her good traits). It is easy to show that under the model's assumptions, candidates will always exhaust their budgets. Thus, her spending on negative advertising (i.e., about the bad traits of her opponent) is $E_j - e_j$.

3.2.1. Knowledge Production Function. We assume a standard convex cost function of producing knowledge—i.e., $a_{j1} = e_j^\gamma$ and $b_{-j1} = (E_j - e_j)^\gamma$, where $\gamma < 1$.[7] Although the production function of knowledge could take the more common Bayesian format (e.g., Narayanan et al. 2005), this formulation (i.e., $\gamma < 1$) captures the same essential relationship between ad spending and knowledge. Specifically, in Bayesian learning one gets decreasing marginal returns because more observations mean more precision, and hence an automatic reduction in the impact of each additional observation. This same decreasing marginal returns property holds in the above formulation for each trait type. Because this formulation allows certain simplifications in the analytical model, we opt for it.

It is important to distinguish between the following three parameters—α, β, and γ. Whereas γ represents the learning aspect of the informative advertising that results in decreasing marginal returns, α and β do not pertain to the learning process. Instead, they are preference parameters that capture the impact of knowledge about candidate traits (good and bad) on utility.

3.2.2. Optimal Negativity. Candidates choose the level of spending on positive and negative advertising to maximize the winning probability, which is equal to p_j in a representative consumer model. Thus, subject to the budget constraint, candidate j maximizes $vp_j(e_j)$, where v is the value of winning and

$$p_j(e_j) = \frac{\exp([a_{j0}+e_j^\gamma]^\alpha - b_j^\beta)}{\exp([a_{j0}+e_j^\gamma]^\alpha - b_j^\beta)+\exp(a_{-j}^\alpha - [b_{-j0}+(E_j-e_j)^\gamma]^\beta)}. \quad (3)$$

Recall that the candidate can affect her winning probability either by increasing knowledge about her own good traits (where $a_j = a_{j0} + a_{j1} = a_{j0} + e_j^\gamma$) or by increasing knowledge about the bad traits of her opponent (where $b_{-j} = b_{-j0} + b_{-j1} = b_{-j0} + (E_j - e_j)^\gamma$).

The first-order condition for candidate j, denoted by λ_j, is then

$$vp_j(e_j^*)[1-p_j(e_j^*)](\alpha\gamma(e_j^*)^{\gamma-1}[a_{j0}+(e_j^*)^\gamma]^{\alpha-1} - \beta\gamma(E_j-e_j^*)^{\gamma-1}[b_{-j0}+(E_j-e_j^*)^\gamma]^{\beta-1}) = 0, \quad (4)$$

where e_j^* denotes the optimal value of e_j. The optimal negativity depends on the voter's prior knowledge and the candidate's budget—$e_j^*(a_{j0}, b_{-j0}, E_j)$. Of course, the effect of these variables on negativity depends on the model's parameters—α, β, and γ. We explore the effect of knowledge and budget in the following subsection and use them to guide our empirical analysis.

It is important to point out that (because of the dual channel of knowledge) e_j^* does not depend on e_{-j}^*. In other words, the negativity of one candidate is independent from the negativity of her rival. However, we soon solve for the equilibrium values of E_j and E_{-j} and demonstrate that the candidate's budget depends on her rival's budget. This means that, given the budget (i.e., in the second stage of the game), the negativity decisions of the candidates are independent, but with endogenous budgets, all players' decisions depend on each other.

3.2.3. The Effect of Knowledge and Budget on Negativity. We start by studying the effect of the voter's prior knowledge about j's good traits or her rival's bad traits (i.e., a_{j0} and b_{-j0}) on j's optimal level of negativity. Note that the formal foundation of the discussion in this subsection appears in Web Appendix 1 of the electronic companion, available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

The effect of these prior knowledge elements depends on α and β. Specifically, an increase in a_{j0} leads to a decrease in e_j^* if $\alpha < 1$ and to an increase if $\alpha > 1$. The logic behind this result is simple. If $\alpha < 1$, the marginal utility of good traits is diminishing. Thus, when a_{j0} increases, the marginal utility of a good trait (which determines the effectiveness of a positive ad) decreases, reducing the tendency to send positive ads. Of course, the opposite holds for increasing marginal utility in the good traits (i.e., $\alpha > 1$).

The effect of prior knowledge about the rival's bad trait on negativity depends on β in the same fashion. Specifically, an increase in b_{-j0} leads to a decrease in negative ads (i.e., an increase in e_j^*) if $\beta < 1$ and leads to an increase in negative ads (a decrease in e_j^*) if $\beta > 1$.

These implications suggest that data on voters' knowledge of the candidates coupled with information on campaign's negativity can identify the parameters α and β. For example, if candidates whose good

estimating such models have been the subject of attention in the statistics literature (e.g., Glickman 1999, 2001), we will not ultimately estimate this model from paired-comparison data. Instead, as will be clarified in §4, our statistical model will depend on the candidates' decisions rather than voters' choices. Note, though, that the two are related because the voter model forms the basis for the candidate decisions.

[7] Of course, it is possible that the γ parameter is different in producing good and bad traits. However, because such differences are inconsequential, we ignore them.

traits are well known have a higher propensity to go negative than similar candidates with fewer well-known good traits, it would suggest that α is likely to be smaller than 1. It is worth noting that prior studies of the effect of political advertising have ignored this issue and cannot assist us in determining the relationship among α, β, and 1. Interestingly, though, as we will soon see, the empirical regularity that serves as one of the motivations for this study (i.e., that negativity is higher in close elections) can guide us in forming some expectations about these parameters.

Before formally examining the effect of the budget on negativity, we describe the intuition. Recall that the candidate is using her advertising budget to inform the voter about her good traits and her opponent's bad traits. Thus, larger budgets ultimately mean that the voter is more knowledgeable, and as we have just shown, under certain conditions, knowledge has a direct effect on negativity. Accordingly, the effect of the budget on negativity is unambiguous for a subset of the parameter space ($\alpha < 1 < \beta$ or $\beta < 1 < \alpha$) and ambiguous for the rest.

To understand the logic behind this result, consider the case where $\alpha < 1 < \beta$. It can be shown that for these parameters the proportion of the budget allocated to negative ads is an increasing function of the budget (i.e., $\partial(E_j - e_j^*)/E_j/\partial E_j > 0$). Because the marginal utility is diminishing in good traits (i.e., $\alpha < 1$), more knowledge about her good traits would lead the candidate to become more negative in her campaign. Accordingly, because the marginal utility is increasing in bad traits (i.e., $1 < \beta$), as the voter becomes more knowledgeable about her rival's bad traits, she will also tend to go more negative. Thus, for $\alpha < 1 < \beta$, knowledge, and hence, budget, has an unambiguous effect on the campaign's negativity—the higher the budget, the more negative the campaign.

When $\beta < 1 < \alpha$, exactly the opposite holds, and as the budget increases, the negativity of the campaign decreases. When both α and β are either below or above 1, the effect of budget on negativity is ambiguous. Furthermore, in such cases the effect depends not only on these two parameters but also on the prior knowledge variables.

As discussed in §1, we estimate this model directly, and thus we will have structural estimates of the parameters α and β. However, it turns out that we can form expectations about these parameters even before the structural estimation. Recall that close races are characterized by (i) higher negativity, (ii) higher budgets, and (iii) higher media coverage. An appealing aspect of the suggested model is that it can tie together all these characteristics of close races for a specific subset of α and β—specifically, $\alpha < 1 < \beta$. As discussed previously, under this condition both knowledge and budget have an unambiguous positive effect on negativity. Because intense media coverage is likely to lead to more knowledgeable voters, close races are characterized by greater knowledge and higher budgets, and these two lead to higher negativity. This means that for $\alpha < 1 < \beta$, it might be possible to fully explain the relationship between closeness and negativity via knowledge and budget. In other words, it is possible that when budget and knowledge are included in the empirical analysis, closeness will not have a direct effect on negativity.

Finally, note that even when $\alpha > 1$ or $\beta > 1$, the second-order conditions can hold (i.e., concavity) as long as some mild conditions are satisfied. For example, for $\alpha < 1 < \beta$, a sufficient condition is $\beta\gamma < 1$. We enforce such conditions in the structural estimation. Note that it is easy to show that under such conditions the marginal effect of both positive and negative ads on the utility is diminishing. In other words, in the solution of this model, advertising always has a wearout effect.

3.3. Budget

As discussed previously, in the first stage of the model, the candidates decide on their budgets. This stage is included in the model mostly for empirical reasons. Specifically, we wish to account for the endogeneity of the budgets in the estimation, and this subsection provides a theoretical framework that is consistent with the other two parts of the model—the negativity decision of the candidates and the voting decisions of the individual.

Candidates' spending has, of course, received a lot of attention from previous scholars. They have identified two major incentives to contribute to political candidates: the investment incentive (Baron 1989) and the partisan incentive (Wand 2006). The "investors" donate to the candidate who is more likely to win. They hope to get their money's worth after the election via regulatory favors. The "partisans" donate to the candidate whose ideological positions they prefer. In our analysis we include variables that allow for both types of contributions.

In the second stage of the model (after the budget has been determined), the candidate maximizes her value-weighted winning probability, vp_j, which depends on the negativity of both candidates and their budget—i.e., $p_j[e_j^*(E_j), e_{-j}(E_{-j}), E_j, E_{-j}]$. However, in the first stage of the model she needs to account also for the cost of collecting the donations that form the budget. The cost function is denoted by $\acute{C}_j(E_j)$, and we assume that $\partial\acute{C}_j/\partial E_j > 0$ and that $\partial^2\acute{C}_j/\partial^2 E_j > 0$. The cost function is indexed by j because in the empirical work we will allow it to depend on candidate-specific characteristics such as her wealth and ability to collect contributions.

Thus, the objective function of candidate j is $vp_j(E_j) - \acute{C}_j(E_j)$, and her first-order condition (recall that $\partial p_j/\partial e_j$ is equal to zero at e_j^*) is[8]

$$p_j(E_j, E_{-j})[1-p_j(E_j, E_{-j})]\delta_j(E_j) - \frac{\partial C_j}{\partial E_j} = 0, \tag{5}$$

where

$$\delta_j(E_j) \equiv \beta\gamma(E_j - e_j^*(E_j))^{\gamma-1}[b_{-j0} + (E_j - e_j^*(E_j))^{\gamma}]^{\beta-1} \tag{6}$$

and

$$\frac{\partial C_j}{\partial E_j} \equiv \frac{1}{v}\frac{\partial \acute{C}_j}{\partial E_j}. \tag{7}$$

The second-order condition is presented and discussed in Web Appendix 1 of the electronic companion.

The first-order condition has three factors: (1) the closeness of the race ($p_j[1-p_j]$), (2) the marginal effect of budget on the voting probability ($\delta_j(E_j)$), and (3) the marginal cost of the budget ($\partial C_j/\partial E_j$). Whereas the second two factors depend only on the budget of candidate j, the first one also depends on the budget of her competitor. As a result, the optimal budget of candidate j (denoted by E_j^*) depends on the budget of her competitor. Furthermore, the relationship is not monotonic. Specifically, when j is more likely to win, an increase in her competitor's budget shrinks the winning margin and leads to a closer race. The closeness of the race encourages her to collect more donations (even at a higher cost). On the other hand, when j is the more likely loser, an increase in the budget of her competitor further decreases the closeness of the race, and the focal candidate will be less likely to seek contributions.

Although the reaction functions are not monotonic, it turns out that there exists a unique pure-strategy equilibrium to this game, as stated in the following proposition (where $E_j^*(E_{-j})$ represents the optimal reaction function of j to the budget of her opponent).

Proposition 1. *There exists a pair* $(\dot{E}_j, \dot{E}_{-j})$ *such that* $\dot{E}_j = E_j^*(\dot{E}_{-j})$ *and* $\dot{E}_{-j} = E_{-j}^*(\dot{E}_j)$. *Furthermore, for any* $E_j' \neq \dot{E}_j$, *we have* $E_j^*(E_{-j}^*(E_j')) \neq E_j'$.

Proof. See Web Appendix 1 of the electronic companion. □

The uniqueness of the equilibrium will be useful in the estimation of this model.

Candidates' spending in equilibrium depends on the closeness of the race, the knowledge of the voters, and any variables that affect the cost of collecting contributions. The effect of closeness is clear and intuitive—the closer the race, the higher the budgets. This result is consistent with previous theoretical and empirical studies (Shachar 2009). The effect of knowledge is ambiguous and (as discussed in the previous subsection) depends on the parameters α and β. The effect of the variables that affect the cost function is quite straightforward—any variable that decreases the marginal cost (e.g., ability to collect contributions) increases the budget.

Before moving to the data and the estimation, we highlight the role of the model in this study. First, the model identifies two types of variables that were ignored by previous studies of campaign negativity—candidates' spending and voters' knowledge. Second, as discussed previously, the model offers an elegant and intuitive way to tie together three interesting empirical regularities about close races (i.e., in close races, the budgets, the media attention, and negativity are all high). Specifically, a sufficient condition to tie these regularities together is $\alpha < 1 < \beta$. Finally, the model enables us to put (theoretically based) structure on the estimation. For example, our model takes into account that voters' knowledge affects both the budget of the candidates and the negativity of the campaign. Thus, the structure allows us to ensure the consistency and efficiency of our estimates.

4. Data, Preliminary, and Nonstructural Results

4.1. Data

The data set focuses on three U.S. congressional elections held in 2000, 2002, and 2004. We observe advertising behavior for all candidates who ran in races contained in the top 75 Nielsen designated media areas (DMA) in 2000 and in the top 100 DMAs in 2002 and 2004. However, we exclude races in which more than the two major parties garnered a significant share of the vote. This results in 416 districts in which both candidates air ads and 12 in which only one is advertising.

The data are drawn from a number of sources. We begin by describing the measures of the two endogenous variables, E and e^* (i.e., budget and negativity). The primary source of data for advertising quantity and cost is the Campaign Media Advertising Group (CMAG hereafter). CMAG employs a technology that records and creates storyboards for every ad that is shown on network TV and some cable channels for the DMAs it monitors. The Wisconsin Advertising Project then systematically codes these ads for tone. From these data we construct our measures of budget and negativity. For the budget measure, we sum the estimated costs of each ad aired by a candidate or party in the congressional district, and accordingly, our measure of negativity is the portion of total

[8] See Shachar (2009) and Gordon and Hartman (2010) for some recent alternative formulations of the objective function of the candidate. Ours is most similar to Gordon and Hartman (2010).

ad budget allocated to negative ads. The Wisconsin Advertising Project codes ads into three broad categories: attack, promote, and contrast. We use as negative ads those coded as attack ads and those coded as contrast ads that are subdivided by the coders as mostly attack ads. We code contrast ads (that discuss both the good traits of the candidate and the bad traits of the opponent) as either negative or positive to ensure consistency with our model in which an ad either discusses the good traits of a candidate or the bad traits of her rival.

We now turn to our measures of closeness. We use a measure regularly discussed in the media and in campaigns—an industry publication ranking of closeness called Cook's Political Report. For each House race, the report indicates which party is leading and how close the race is. The closeness is grouped into four categories—not competitive, likelys (least close), leanings (next closest), or toss-ups (closest). We use these four categories as our measures of closeness.

We control for a number of potential alternative explanations for negativity, such as the "front-runner effect" (Theilmann and Wilhite 1998, Buell and Sigelman 2008), and for some district-level characteristics. The details of these variables are available in the appendix.

Finally, we use variables that can measure the cost of fundraising, i.e., variables that might affect C_j. First, we consider variables that capture contributor incentives to either invest in the likely winner or to support a partisan platform. Specifically, we include an indicator variable for the front-runner of the race and for the partisan leaning of the district to capture these incentives. Second, we include other cost-shifters that are specific to the district or candidate, such as incumbency (e.g., franking privileges), the wealth of the candidate, and whether there was a senate race in the state. The variables not already discussed are presented at more length in the second section of the appendix.

We leave discussion of the knowledge variables to the next section.

4.2. Preliminary Results

Before employing our structural model to study the data, we first seek to understand some basic relationships. In this subsection we take a preliminary look at the relationship between knowledge and negativity.

American voters are not very knowledgeable about their congressional candidates (Mann and Wolfinger 1980, Neuman 1986). Thus, in this initial look at the data, we focus only on information that voters most likely know. Fortunately, within the time frame of our study, Congress held a vote that received a lot of media attention—"Public Law 107-243: Authorization for Use of Military Force Against Iraq." Because of the media coverage, voters are likely to know how their representative voted. Furthermore, those that voted against their party are likely to stand out to voters. Specifically, 82 Democrats voted with President Bush and 6 Republicans voted against him.

We consider "voting against your party on the Iraq resolution" as a good trait of a candidate, because a candidate is likely to behave in such a way if the party affiliation of her district differs from her party. Indeed, in our data the tendency to vote against a party is higher the lower the support for this party is in the district.[9]

The data support our hypothesis. The negativity (i.e., the share of ads that are negative in the 2002 and 2004 elections) of those who voted against their party is 34% versus 16% among those who voted with their party, and this difference is significant at the 1% level.[10] This result, which is somewhat counterintuitive—a representative does a good thing (voted with her district and against her party) and as a result she goes more negative—is consistent with our hypothesis that $\alpha < 1$. In §§4.5 and 5 we use richer (structural and nonstructural) tests of our theory in which we account for a range of control variables. For now, we consider this finding as preliminary and encouraging.

4.3. Nonstructural Estimation

In this subsection we use nonstructural estimation to examine the main implication of the model: that negativity depends on budget and knowledge. Furthermore, we also aim to test the secondary implication of the model: that the effect of closeness on negativity is mediated by knowledge and budget (i.e., it does not hold when these variables are included in the analysis). We have already described many of the variables needed for this estimation (e.g., negativity, budget, and closeness). Now we need to describe our measures of voters' knowledge. Note that one of these measures was already described—the vote on the Iraq resolution. The summary statistics of all the variables are reported in Table 1.

4.3.1. Knowledge. As discussed previously, voters know little about their congressional candidates. In which conditions will voters' knowledge about a candidate go beyond the minimum? Such conditions

[9] For candidates that voted with their party on Iraq, 57% of people in her district voted for the candidate's party in the last presidential election. In contrast, for candidates that voted against their party on Iraq, the support for the party in the previous presidential election was only 47%. This difference is significant at the 1% level.

[10] Furthermore, we regress the difference in negativity between 2002 and 2000 on the Iraq vote. Consistent with the previous analysis, voting against the party leads to 18% more negativity than voting with the party and is (marginally) significant ($p < 0.05$ for a one-tailed test).

Table 1 Summary Statistics

	Mean	Min	Max	Std. dev.
Positive knowledge				
Media coverage—Self	3.33	0	5.82	1.13
Prior exposure—Self	0.25	0	1	0.43
Iraq vote against party	0.07	0	1	0.25
Negative knowledge				
Incumbent—Opponent	0.31	0	1	0.47
Media coverage—Opponent	3.06	0	5.82	1.26
Prior exposure—Opponent	0.28	0	1	0.45
Budget				
Total ad spend ($1,000s)	532.5	0.2	3,175	617
Ex ante closeness				
Likelys (3rd-closest)	0.49	0	1	0.50
Leanings (2nd-closest)	0.28	0	1	0.45
Toss-ups (closest)	0.10	0	1	0.30
Controls				
Incumbent	0.47	0	1	0.50
Front-runner	0.59	0	1	0.49
Partisanship	0.58	0	1	0.49
Party = Republican	0.52	0	1	0.50
Year = 2002	0.35	0	1	0.48
Year = 2004	0.34	0	1	0.47
Republican in 2002	0.18	0	1	0.39
Republican in 2004	0.18	0	1	0.38
Demographic factor—Educated and income	0	−3.3	6.5	1.15
Demographic factor—Foreign	0	−4.9	8.3	1.40
Demographic factor—Poor nonwhite	0	−4.3	6.6	1.34
Demographics—Violent crime	0.01	0	0.31	0.02
Cost instruments				
Wealth	0.16	0	1	0.36
Past contributions ($millions)	0.23	0	2.85	0.38
Close presidential race	4.68	1	7	1.81
Any senate race	0.67	0	1	0.47
Any governor race	0.39	0	1	0.48

include if the news media cover her and if the voters were exposed to her when she previously held a public position. To capture these sources of knowledge, we collected data on media coverage, prior exposure, and incumbency status.

Our media coverage variable is denoted as *Media coverage—Self* for the candidate and *Media coverage—Opponent* for her opponent. This variable is an estimate of the number of news articles covering a candidate. We count (via NewsLibrary.com) the number of articles in local newspapers that mention the name of the candidate in the two months prior to Labor Day. To ensure an accurate count, we use multiple variations of each candidate's name. We use a log transform to capture diminishing returns on media and to account for skewness of the measure.

The second variable is binary and is denoted as *Prior exposure—Self* for the candidate and *Prior exposure—Opponent* for her opponent. It is 1 if the candidate previously ran for a U.S. congressional seat or held a public office with reasonable districtwide exposure (e.g., not to a school board in a small town). This measure is based on various sources (e.g., VoteSmart).

The third variable is also binary and is denoted as *Incumbent—Self* for the candidate and *Incumbent—Opponent* for her opponent. It is 1 if the candidate was a representative in the prior U.S. Congress (i.e., an incumbent). The incumbent campaigned in a previous election and acted as the district's representative for at least two years, leading voters to know her better. That said, prior research (see Lau and Rovner 2009) suggests there may be important effects of *Incumbent—Self* on negativity other than a knowledge effect. We are unable to separate these effects and thus consider *Incumbent—Self* a control variable.

Unlike the vote on Iraq, the other knowledge variables are not specific on whether the knowledge is about the candidate's good traits or bad traits. Although they are not specific, these variables can still be used to examine the model's implications. Specifically, unless $\alpha = \beta = 1$, we expect the knowledge variables to have a significant effect on negativity. Furthermore, when voters are more knowledgeable about a candidate (say, because of high media coverage), they are more familiar with both her bad and good traits. Thus, greater knowledge about the candidate implies higher a_{j0} and therefore, from the model, higher negativity if $\alpha < 1$ (lower if $\alpha > 1$). Accordingly, greater knowledge about the opponent implies higher b_{-j0} and thus, from the model, higher negativity if $\beta > 1$ (lower if $\beta < 1$). Notice also that for the subset of the parameter space discussed previously ($\alpha < 1 < \beta$), any increase in knowledge is expected to lead to higher negativity. Of course, it would have been better if all of our variables were specific on whether the knowledge is about the good traits or bad traits, and thus we return to this issue when we report results and suggest being cautious in interpreting them.

4.3.2. Estimation Results. Table 2 presents estimates of four models used to assess the relative importance of various parts of the model. In the estimation, we account for the censoring of the dependent variable at 0 and 1 (i.e., the proportion of negativity cannot be smaller than 0 nor bigger than 1) and include various controls: (1) random effects (at the congressional district level), (2) time fixed effects, (3) party effects, (4) district demographic characteristics, (5) two common explanatory variables (*Incumbent* and *Front-runner*), and (6) whether the median voters support the candidate's party. For brevity, we do not discuss the coefficients of these control variables.

The first model includes the control and closeness variables. The results provide strong support to the empirical regularity that we wish to explain—the closer the race, the more negative it is.

Table 2 Nonstructural Estimation Results

Variable	Model 1: Closeness only	Model 2: Knowledge only	Model 3: Full w/closeness	Model 4: Full no closeness
Positive knowledge				
Media coverage—Self		0.05 (1.67)**	−0.04 (−1.16)	−0.04 (−1.24)
Prior exposure—Self		0.10 (1.79)**	−0.00 (−0.04)	−0.01 (−0.27)
Iraq vote against party		0.35 (4.70)*	0.26 (3.06)*	0.25 (3.17)*
Negative knowledge				
Incumbent—Opponent		0.05 (0.67)	0.16 (2.24)*	0.15 (2.41)*
Media coverage—Opponent		0.15 (5.23)*	0.12 (4.00)*	0.12 (3.99)*
Prior exposure—Opponent		0.10 (1.85)**	0.02 (0.45)	0.01 (0.29)
Budget				
Log(*Total ad spend*)			0.21 (2.72)*	0.21 (2.71)*
Ex ante closeness				
Likelys (3rd-closest)	0.46 (8.16)*		0.07 (0.59)	
Leanings (2nd-closest)	0.15 (2.42)*		−0.06 (0.82)	
Toss-ups (closest)	0.11 (1.39)		0.04 (0.64)	
Controls				
Incumbent	−0.19 (−2.92)*	−0.30 (−3.75)*	−0.26 (−3.40)*	−0.26 (−3.97)*
Front-runner	−0.26 (−3.83)*	−0.13 (−1.62)*	−0.14 (−1.78)*	−0.14 (−2.16)*
Partisanship	0.00 (0.06)	0.06 (1.17)	0.01 (0.27)	0.01 (0.31)
Party = Republican	0.03 (0.35)	0.08 (1.04)	0.09 (1.19)	0.09 (1.24)
Year = 2002	−0.25 (−3.33)*	−0.44 (−5.76)*	−0.38 (5.21)*	−0.39 (−5.55)*
Year = 2004	−0.04 (−0.47)	−0.24 (−3.18)*	−0.13 (−1.93)*	−0.13 (−1.92)*
Republican in 2002	0.13 (1.18)*	0.14 (1.42)	0.16 (1.65)	0.16 (1.77)*
Republican in 2004	0.07 (0.61)	0.05 (0.53)	0.02 (0.24)	0.02 (0.22)
Demographic factor—Educated and income	−0.01 (−0.58)	−0.01 (−0.23)	−0.08 (−2.59)*	−0.08 (−3.28)*
Demographic factor—Foreign	−0.02 (−0.98)	−0.02 (−0.78)	−0.03 (−1.22)	−0.03 (−1.13)
Demographic factor—Poor nonwhite	−0.03 (−1.38)	−0.01 (−0.50)	0.02 (0.94)	0.03 (1.27)
Demographics—Violent crime	−0.24 (−0.25)	−1.65 (−1.60)	−0.47 (−0.60)	−0.50 (−0.64)
Budget residual			−0.10 (−1.13)	−0.11 (−4.15)*
Scale/random effect scale	0.48/0.005	0.46/0.02	0.43/0.004	0.43/0.004
Log-likelihood/McFadden's R-square	−463.5/26.2%	−452.8/27.9%	−318.7/49.3%	−319.5/49.1%

Note. Tobit regressions with negativity as the dependent variable.
*p-value < 0.05; **p-value < 0.05 for a one-tailed test.

The second model adds to the control variables only the knowledge variables. The results are very encouraging. We find that the higher the knowledge, the higher the negativity—as expected when $\alpha < 1 < \beta$. All the variables have positive signs. Two have t-values of above 4.5 (*Iraq vote against party* and *Media coverage—Opponent*), and the other four are jointly significant at the 5% level. These results imply that the more knowledgeable the voter (i.e., the more he knows about the candidate and/or the rival), the greater the tendency to go negative. As the candidate gets more media attention, she tends to focus more on the opponent, and her tendency to go negative also grows as her opponent gets more media attention. Recall that this variable counts coverage prior to Labor Day and negativity uses advertising after Labor Day.

The tendency toward negativity with greater knowledge also holds for the prior exposure variables. We find that prior exposure to either of the candidates (via prior campaigns or time in public office) leads to higher negativity. The prior exposure variable is another proxy for the knowledge level of voters (i.e., voters exposed to a candidate in the past are more likely to know her better).

The final knowledge variable that supports the model's implication is the vote on the Iraq resolution. It is quite encouraging to find that its effect on negativity remains statistically significant at the 0.1% level even after accounting for various additional variables and controls.

After examining the separate impact of two sets of variables (closeness and knowledge) on negativity, we move to an examination of their joint effect. The third column presents the results when all elements of our theory—closeness, knowledge, and budget—are included. We account for the endogeneity of the budget via a control function treatment (details of the first-stage regression are in the third section of the appendix) and for the skewness in the budget variable via a log transform.

The most important finding of this model is that the inclusion of budget and knowledge dramatically changes the impact of the closeness variables.

Specifically, as suggested by our theory, when budget and knowledge are included, closeness no longer has a significant effect on negativity. All three closeness variables turn from significant to insignificant. Furthermore, removing the closeness variables (as done in the fourth column of Table 2) hardly changes the fit of the model (McFadden's R-square decreases from 49.3 to 49.1, and there is an insignificant change in log-likelihood). This result suggests that the finding of previous studies about the relationship between closeness and negativity is due to the exclusion of the knowledge and budget variables. Put differently, this result implies that closeness affects negativity through (higher) budget and knowledge.[11]

Given that the closeness variables do not have a significant effect, we drop them from the analysis in the fourth column of Table 2 to provide the closest test of our theory. In this model we exclude closeness and include the two sets of variables suggested by our model (knowledge and budget). The results are very supportive. Consistent with the earlier findings, more knowledge leads to higher negativity by the candidate, and a larger budget leads to a more negative campaign.

As discussed in §3, under the model's assumptions, the negativity of one candidate does not directly depend on the negativity of her rival. Web Appendix 4 of the electronic companion provides a preliminary examination of this independence result. We find that although the evidence is not strong enough to make a compelling argument against the direct effect of a rival's negativity, it certainly demonstrates that such a direct effect cannot be supported convincingly *with our data*. The data also seem to suggest that the empirical findings reported in Table 2 are not sensitive to the inclusion of a rival's negativity.

Although we view the results of Table 2 as somewhat preliminary and focus our attention on the estimates of the structural model, these results start to draw an interesting picture.

- Budget and knowledge significantly relate to negativity, and once included in the estimation, the impact of the closeness variables vanishes. This suggests that the effect of closeness on negativity is mediated (i.e., the relationship is spurious) by our theoretical variables. Furthermore, one of the knowledge variables is based on the media coverage and thus reinforces the idea that the high negativity of close races is due to the intense media coverage (which leads to greater knowledge) and large budgets. These results provide empirical support for the importance of our theoretical variables.
- Using our model, we interpret the effects of the budget and knowledge variables to suggest that the parameters satisfy the following condition: $\alpha < 1 < \beta$. First, the evidence that greater knowledge about the candidate increases her negativity suggests that $\alpha < 1$, and the evidence that greater knowledge about the opponent increases negativity implies that $1 < \beta$. Second, the evidence on the budget is consistent with $\alpha < 1 < \beta$. That said, we have to stress that this is purely an interpretation. Given that most of our knowledge variables are not specific on whether the knowledge is about the candidate's good traits or bad traits, such interpretation should be taken with some caution.
- Another encouraging result from the nonstructural estimation is that the three knowledge variables that turn out to be significant come from different domains. First, two are about the opponent and one is about the candidate. Second, one is related to media, another to incumbency, and the third to a well-known vote. The diversity of measures gives greater support to the underlying concept of knowledge as being important to negativity decisions.

5. Structural Estimation

Using structural estimation has three main advantages in our case. First, obtaining measures of knowledge for congressional races is a significant empirical challenge. Although we are pleased with our knowledge variables, it is clear that some aspects of knowledge are left unobserved. In the estimation below, we structurally account for the unobserved knowledge. Second, the choice of budget in the first stage of the game depends on the resulting negativity in the second stage, and both decisions depend on the knowledge. Whereas we have accounted for the endogeneity of the budget in the nonstructural estimation via a control function approach, the structural estimation will enable us to impose this rich relationship among budget, negativity, and knowledge on the estimation. Third, the structural estimation provides us, of course, with the parameters of the theoretical model and can thus directly address the question about the values of α and β.

[11] It is important to note, though, that the effect of knowledge when closeness and budget are included is not as strong. Although one knowledge variable, *Incumbent—Opponent*, becomes positive and significant at the 5% level, three of the knowledge variables turn from being significant to insignificant. Interestingly, two of the variables that lose their significance, *Media coverage—Self* and *Prior exposure—Self*, turn out to have a significant effect in the first-stage estimation of the budget. The other variables that assist in predicting the budget are (1) two demographic variables that represent the income of the district (the higher the income, the higher the budget), (2) the closeness variables (the closer the race, the higher the budget), (3) total contributions for the candidate in the previous campaign, and (4) the wealthy candidate indicator. These results seem very intuitive and give some face validity to the estimation. A discussion of the estimates of the first-stage regression are included in the second section of the appendix.

This section proceeds as follows. The first subsection describes functional form and distribution assumptions used in the structural estimation, and the second subsection presents the results.

5.1. Estimation Issues

We use a Bayesian approach to estimate the parameters. To define the likelihood we select functional forms for the cost and prior knowledge functions and make some distributional assumptions.

We assume that the marginal cost function faced by candidate j in market m is

$$C'_{j,m}(E_{j,m}) = x^c_{j,m}c_x + \rho E_{j,m} + \omega_{j,m}, \tag{8}$$

where (i) the row vector $x^c_{j,m}$ includes variables such as the demographic factors (e.g., income and education in the district) and contributions from the most recent campaign, and the parameter vector c_x represents their effect on the marginal cost; (ii) the parameter ρ is the term that generates convex costs for collecting contributions; and (iii) ω is a random variable observed by the candidates but not by the econometrician drawn from a normal distribution with a mean of 0 and a variance of σ^2_ω.

The prior knowledge also differs across candidates and markets for observed and unobserved reasons. Specifically, the prior knowledge about the good traits of candidate j in market m is

$$a_{j,0,m} = x^a_{j,m}a_x + \nu^a_{j,m}, \tag{9}$$

where (i) the row vector $x^a_{j,m}$ includes variables such as the media coverage of candidate j in market m, and the parameter vector a_x represents their effect on the prior knowledge; and (ii) $\nu^a_{j,m}$ is a random variable observed by the candidates but not by the econometrician.[12] This formulation has two nice features. First, it maps in a flexible way all the possible measures of knowledge considered in the nonstructural estimation into the one structural knowledge variable. Second, because the knowledge variables are partially unobserved, the model practically includes unobserved heterogeneity that affects both the size of the budget and the negativity of the campaign. Thus, the structural estimation not only endogenizes the budget but also accounts for its correlation with the negativity for some unobserved sources. The prior knowledge about the bad traits of candidate j in market m is formulated in a similar way. Specifically,

$$b_{j,0,m} = x^b_{j,m}b_x + \nu^b_{j,m}. \tag{10}$$

[12] The prior exposure variables that were included in the nonstructural estimation are not included here for two reasons. First, their coefficients in the nonstructural estimation were close to zero in magnitude and not significant. Second, it turns out that including them in the structural estimation leads to slower mixing.

Both of the prior knowledge variables are constrained to be nonnegative to match our theoretical model. We do so by assuming that the joint distribution of the random variables is

$$\begin{pmatrix}\nu^a_{j,m}\\ \nu^b_{j,m}\end{pmatrix} \sim f_{\mathrm{TMVN}}\left[\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma^2_a & \eta\sigma_a\sigma_b\\ \eta\sigma_a\sigma_b & \sigma^2_b\end{pmatrix}, \begin{pmatrix}-x^a_{j,m}a_x\\ -x^b_{j,m}b_x\end{pmatrix}\right], \tag{11}$$

where $f_{\mathrm{TMVN}}(m, v, t)$ is a truncated bivariate normal with a mean m and a covariance matrix v, and it is truncated below at t.

Next, we need to account for the possibility of measurement errors (MEs hereafter) in the negativity. It is reasonable to assume that there are MEs in the CMAG advertising data for two reasons. First, although the CMAG data cover 80% of the population, they do not cover all television markets in the United States. Second, MEs can be introduced in the coding of the advertisements. We account for the possibility of MEs of the negativity in a fully structural way—that is, formulating the ME function and incorporating it into the likelihood.

The formulation of MEs is standard. We let the observed proportion of negativity of candidate j in market m, denoted by $N_{j,m}$, to be

$$N_{j,m} = \begin{cases} 1 & \text{if } \dfrac{E^*_{j,m} - e^*_{j,m}}{E^*_{j,m}} + \varepsilon^e_{j,m} > 1, \\[2ex] \dfrac{E^*_{j,m} - e^*_{j,m}}{E^*_{j,m}} + \varepsilon^e_{j,m} & \text{if } 1 > \dfrac{E^*_{j,m} - e^*_{j,m}}{E^*_{j,m}} + \varepsilon^e_{j,m} > 0, \\[2ex] 0 & \text{otherwise}, \end{cases} \tag{12}$$

where $e^*_{j,m}$ is the unobserved optimal level of negativity from the theoretical model and $\varepsilon^e_{j,m}$ is a random variable drawn from a normal distribution with mean $\mu_{j,m} = x^e_{j,m}e_x$ and variance σ^2_e. Specifically, the vector $x^e_{j,m}$ includes the same variables used in the nonstructural estimation: incumbency, front-runner, party, year, partisanship, and district demographics.

We control for budget endogeneity by including the probability of $E^*_{j,m}$ derived from the first-order condition in Equation (5). Furthermore, we also account for potential measurement error in the budget when it is very small. Specifically, for the 12 observations where we observe zero budget, we set it to half of the minimum observed positive budget.

In Web Appendix 2 of the electronic companion, we describe the construction of the likelihood, prior, and the sampler for the estimation. The likelihood accounts for endogeneity of both the budget and negativity. In constructing the likelihood, we use the result that there is a unique equilibrium given the second-order conditions and enforce the second-order conditions for both stages (budget and negativity) through the prior. We use a Gibbs sampler with Metropolis-Hastings steps. In addition to estimating the full endogenous budget model, we estimate (for comparison) a model with an exogenous budget. In the latter case, we have only the negativity in the likelihood.

In Web Appendix 3 of the electronic companion, we discuss identification of the parameters and demonstrate via Monte Carlo evidence that the estimation procedure yields reliable estimates. Although γ is theoretically identified, it is not reliably estimable in our data. Thus, we set γ to a specific value and verify that the results are not sensitive to this value. Specifically, we set it to 0.7 but also estimate the model for values above and below 0.7. We find that the substantive results remain the same and plot marginal posterior density estimates for α and β in the Web Appendix 2 of the electronic companion.

5.2. Estimation Results

We present results from two models—one with an exogenous budget and one with an endogenous budget. The conclusions from these models are largely the same, so we focus on the latter.

We start with the parameters of the knowledge functions (a_x and b_x) presented in Table 3. Whereas these estimates provide similar results to the ones from the nonstructural estimation, the structural estimates are even more supportive when it comes to a_x. Specifically, we find that both *Media coverage—Self* and *Iraq vote against party* have the expected sign and are significant. The estimates of b_x draw a similar picture to the one from the nonstructural estimation. Specifically, *Media coverage—Opponent* has a significant effect in both models, and *Incumbent—Opponent* is significant in the exogenous budget model.

Whereas a_x and b_x represent the effect of the observable variables on knowledge, σ_a^2 and σ_b^2 capture the role of unobservables. Although a significant fraction of the knowledge on the bad traits is left unobserved, the observables capture most of the knowledge on the good traits. These conclusions are based on a decomposition of the variance of the total knowledge into the unobserved component and the part that is due to the observed variables. The posterior means for the percentage of the observed out of the total

Table 3 Structural Estimation Results—Main Results

Parameter	Model with exogenous budget	Model with endogenous budget and partially observed knowledge
Positive knowledge		
α	0.520 (0.37, 0.72)[a]	0.439 (0.36, 0.50)[a]
a_x—Intercept	0.014 (0.00, 0.05)[a]	0.248 (−0.36, −0.14)[a]
a_x—*Media coverage—Self*	0.037 (0.01, 0.11)[a]	0.055 (0.02, 0.09)[a]
a_x—*Iraq vote against party*	0.671 (0.07, 3.44)[a]	0.487 (0.08, 0.92)[a]
σ_a		0.036 (0.02, 0.06)
Negative knowledge		
β	1.356 (1.29, 1.40)[a]	1.363 (1.32, 1.40)[a]
b_x—Intercept	0.010 (0.00, 0.04)[a]	−0.281 (−0.37, −0.18)[a]
b_x—*Incumbent—Opponent*	1.124 (0.26, 3.50)[a]	−0.099 (−0.39, 0.17)
b_x—*Media coverage—Opponent*	0.017 (−0.00, 0.06)[b]	0.080 (0.01, 0.17)[a]
σ_b		0.599 (0.47, 0.71)
Negativity controls		
e_x—*Intercept*	−0.020 (−0.16, 0.20)	0.079 (0.02, 0.14)[a]
e_x—*Incumbent*	−0.269 (−0.39, −0.15)[a]	−0.381 (−0.48, −0.30)[a]
e_x—*Front-runner*	−0.141 (−0.28, −0.01)[a]	−0.259 (−0.36, −0.15)[a]
e_x—*Partisanship*	0.031 (−0.06, 0.12)	−0.030 (−0.08, 0.02)
e_x—*Party = Republican*	0.106 (−0.04, 0.25)	−0.045 (−0.18, 0.08)
e_x—*Year = 2002*	−0.320 (−0.48, −0.17)[a]	−0.476 (−0.56, −0.40)[a]
e_x—*Year = 2004*	−0.132 (−0.28, 0.00)[b]	−0.263 (−0.35, −0.15)[a]
e_x—*Republican in 2002*	0.083 (−0.13, 0.29)	0.260 (0.11, 0.36)[a]
e_x—*Republican in 2004*	0.001 (−0.19, 0.20)	0.175 (0.00, 0.36)[a]
e_x—*Demographic factor—Educated and income*	−0.043 (−0.08, −0.00)[a]	−0.011 (−0.06, 0.03)
e_x—*Demographic factor—Foreign*	−0.027 (−0.07, 0.02)	−0.011 (−0.06, 0.03)
e_x—*Demographic factor—Poor nonwhite*	0.005 (−0.04, 0.04)	−0.001 (−0.04, 0.03)
e_x—*Demographics—Violent crime*	−0.604 (−1.50, 1.17)	0.599 (−1.02, 1.91)
σ_e	0.201 (0.17, 0.24)	0.235 (0.20, 0.28)
η—Unobserved knowledge correlation		0.551 (0.25, 0.79)[a]

[a]95% credible interval does not overlap with 0.
[b]90% credible interval does not overlap with 0.

variance are 88% for a and 26% for b. These results illustrate two points. First, unlike good traits, bad traits are likely to be idiosyncratic and unique and not likely to be captured by our observables. Second, the unobservable part of knowledge (which can be captured via structural estimation) plays an important role. Furthermore, we also find the correlation parameter, η, to be positive and significant. This finding is very reassuring because it is consistent with the notion that some candidates are better known than others, which means that voters are more familiar with both their good and bad traits.

We are now ready to discuss one of the most interesting findings of the structural estimation—α and β. The results are quite clear—the posterior means are 0.44 for α and 1.36 for β. This means that the marginal utility from a good trait diminishes, whereas the marginal disutility from a bad trait increases. Furthermore, the posterior mean for $\beta\gamma$ is 0.95, indicating both that the second-order conditions are satisfied and that negative ads have a wearout effect. In other words, whereas the effect on utility is convex for knowledge about bad traits, the effect of advertising is concave. Furthermore, we can easily reject the hypothesis that $\beta \leq 1$ and the hypothesis that $\alpha \geq 1$. In other words, the structural estimates place us in a subset of the parameter space for which the theoretical model ties together the empirical regularities presented in the introduction. That is, close races increase negativity through their effect on media coverage and budgets. Specifically, such races attract more media coverage (that educate the voters about the candidates) and higher budgets. The resulting high levels of knowledge and budget lead (according to this model) to higher negativity.

Finally, Table 3 also presents the estimates of e_x—the parameters that determine the mean of the negativity measurement error. The variables that are significant are quite similar to those in the nonstructural estimation in Table 2. For brevity, we do not discuss them again.

Table 4 presents the estimates of c_x—the parameters of the cost function. We find that the cost of fundraising is lower for the front-runner, for candidates with higher past campaign contributions, and for Republicans in 2002 and 2004. We find that fundraising costs are lower in close races than less close races but lowest in the category that is second-closest (*Leanings*).

Table 4 Structural Estimation Results—Cost Variables

Parameter	Model with endogenous budget
Fund-raising costs	
ρ	0.153 (0.12, 0.19)
c_x—Intercept	0.441 (0.40, 0.49)[a]
c_x—*Incumbent*	0.000 (−0.04, 0.03)
c_x—*Front-runner*	−0.045 (−0.08, −0.01)[a]
c_x—*Partisanship*	−0.010 (−0.03, 0.02)
c_x—*Wealth*	−0.002 (−0.03, 0.02)
c_x—*Past contributions* ($millions)	−0.053 (−0.08, −0.02)[a]
c_x—*Demographic factor—Educated and income*	0.027 (−0.01, 0.07)
c_x—*Demographic factor—Poor nonwhite*	−0.032 (−0.07, 0.01)
c_x—*Party = Republican*	−0.029 (−0.07, 0.01)
c_x—*Year = 2002*	−0.024 (−0.08, 0.02)
c_x—*Year = 2004*	−0.031 (−0.09, 0.02)
c_x—*Republican in 2002*	−0.123 (−0.16, −0.09)[a]
c_x—*Republican in 2004*	−0.108 (−0.14, −0.07)[a]
c_x—*Likelys*	−0.075 (−0.12, −0.03)[a]
c_x—*Leanings*	−0.031 (−0.04, −0.02)[a]
c_x—*Toss-ups*	0.026 (0.02, 0.03)[a]
σ_ω	0.014 (0.01, 0.02)

[a]95% credible interval does not overlap with 0.

6. Conclusion

To gain a better understanding of the tendency of firms to "go negative," we have focused on an interesting industry (political campaigns) and empirical regularity (the tendency to go negative is higher the closer the race). We have offered a model of electoral competition that identifies two variables that were completely ignored by previous studies of campaign negativity—candidates' spending and voters' knowledge. Furthermore, this model offers an elegant and intuitive way to tie together three interesting empirical regularities about close races (i.e., in close races, the budgets, the media attention, and negativity are all high). Using data on U.S. congressional races in 2000, 2002, and 2004, and both nonstructural and structural estimation, we find that the data support the model and its implications. Specifically, we find that (i) negativity is increasing in both knowledge and budget and (ii) that the relationship between the closeness of the race and negativity is mediated by knowledge and budget.

The structural estimates suggest that whereas the marginal utility of good traits is diminishing, the marginal disutility of bad traits in increasing. Although these results might have an intuitive appeal, they should be treated with some caution for at least three reasons. First, our estimates are not based on directly observing voters' choices as a function of candidates' good and bad traits but rather on candidates' strategies (i.e., tendency to go negative). As such, the estimates of α and β should be viewed mainly as an interpretation of the data. Second, although our data include a variety of knowledge measures, only one of them (the vote on Iraq) is specific to the candidates' good or bad traits. Third, our estimates are based on congressional races only. As mentioned previously, voters' knowledge about their congresspersons is usually quite low. Thus, if the utility has an S-shaped response structure with respect to the candidates' traits, it is possible that the marginal utility will be increasing in the congressional races but decreasing in, say, presidential races, in which the knowledge level is much higher.

The results of this study are specific for political campaigns not only because the data are based on congressional races but also because the model was structured to capture such a setting (e.g., a fund-raising competition in the first stage of the game). As such, it is difficult to generalize the findings to commercial settings. However, our findings might highlight interesting avenues to examine negative commercial advertising. For example, it seems reasonable to assume that consumers' knowledge is higher in mature product categories. If knowledge plays a similar role in commercial competition, we should expect to find more negative advertising in such markets. It is also interesting to examine whether budget and negativity have a similar relationship in the commercial setting by comparing markets with intense advertising to those with fewer ads. A final possible parallel between the political case and the commercial setting relates to the empirical regularity that we have focused on (about the relationship between closeness and negativity). It seems that a somewhat similar relationship may exist in commercial markets. It was recently suggested that "as the economy gets ugly, marketers get nasty" (Vranica 2008). Another way to frame this observation is that when the going gets tough (i.e., close races or slowing economy), the tough get going (i.e., ads tend to be more negative). Furthermore, when the economy is not growing, the only way that a firm can grow is at the expense of its competitors. This means greater competition for the same consumers, and the parallel to political races is fairly immediate.

An interesting alternative explanation, based on emotional reactions, exists for why "when the going gets tough, the tough get going." It is possible that the tendency to go negative is higher when the decision maker is under stress. Because close elections (as well as slowing economy) can raise the level of stress, it can also lead to a higher tendency to go negative. We find this alternative mechanism an interesting avenue for future research.

The model can be enriched in future research by allowing negative and positive ads to have different effects on either the awareness of candidates or the resulting word of mouth. For example, it seems likely that negative ads are more effective in generating buzz about a candidate. Another interesting topic for future research is the dynamic aspects of negativity. Our model is static when it comes to negativity. However, in practice, the dynamics are quite interesting. For example, it turns out that as the election draws nearer, candidates tend to become more negative (Goldstein and Freedman 2002b). Interestingly, this observation seems consistent with the knowledge theory presented here for the following reason. At the start of the campaign, voter knowledge is low. Thus, our theory would predict that candidates should start by focusing on positive ads. However, as voters gain knowledge about candidates, the candidates should shift to more negative messages. Although it seems that the theory presented here might be able to explain an important aspect of the dynamics of negativity, it is reasonable to believe that a dynamic model would do a better job in such a task. Furthermore, such a dynamic model might be able to capture some competitive effects that do not show up in the static model.

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

Acknowledgments

The authors' thanks go to Preyas Desai, Ken Goldstein, Dan Horsky, Ganesh Iyer, Barak Libai, and the review team, as well as participants at their Marketing Science Conference session, at the Marketing and Politics Track at the Invitational Choice Symposium, and at the University of Chicago, Stanford, the University of Rochester, Michigan State, and the University of California, Los Angeles research seminars who were kind enough to share some of their expertise with them. The authors also thank their research assistants who helped in the construction of the data, including Kenji Yakamoto, Roger Cordero, Iulia Bejan, Thejas Krishe Gowda, Rama Sethuraman, Saroopya Vidhya Ramachandran, June Tang, and Ashwin Haleyur. The second author's work was partially financed by the Henry Crown Institute of Business Research in Israel.

Appendix

Control Variables for Negativity

Motivated by previous studies (e.g., Lau and Pomper 2001, Damore 2002, Peterson and Djupe 2005), we include the following controls: *Party* (Republican), *Year* (2002 and 2004), *Party* × *Year*, *Incumbent*, *Partisanship*, and *Front-runner*. To define *Partisanship*, we first identify the median voter in each district as belonging to the party that won the district in the previous presidential election. The indicator variable *Partisanship* is 1 only if the candidate's party is the same as that of the median voter. The *Front-runner* measure is based on Cook's Political Report data.

We also control for a large range of demographics at the district level using Bureau of Labor Statistics, Census, and Federal Bureau of Investigation data. The measures are the percentage in the district that (1) is white and not Hispanic, (2) holds a bachelor's degree, (3) is unemployed, (4) is considered a family in poverty, (5) speaks a foreign language, (6) was born in a foreign country, (7) earns in the top income bracket, (8) owns a home, (9) lives in an urban area, (10) migrated within the United States in the last year, (11) migrated to the United States in the last year, as well as (12) average household income and (13) violent crime rate.

These measures are highly correlated (e.g., educated districts have higher incomes, districts with high unemployment have larger poverty rates), which makes interpretation difficult. We use factor analysis to reduce the dimensionality and identify meaningful variation. We found a solution with three factors to be the best. Table A.1 presents the factor loadings based on a promax rotation. All variables are standardized, only significant variables are displayed, and the three most influential variables for each factor are bold. Clearly, the separation between these three variables and the other variables is fairly large, and interpretation is straightforward. We name the first factor *Educated and income*, the second *Foreign*, and the third *Poor nonwhite* and include them as controls for the basic demographics along with the measure *Violent crime*.

Cost Shifters

This subsection presents the variables that are exclusive to the cost function. These variables can be divided into two types: district-specific and candidate-specific. The district-specific variables include indicators for whether the current presidential race was close in the state (from Cook's Political Report) and whether there was a senate or governor race in the state. These concurrent variables capture potential cost increases as a result of higher demand (i.e., crowding the airwaves with political ads).

We use two candidate-specific variables. First, we include an indicator for whether the candidate was wealthy to capture any idiosyncratic ability to pay out of pocket. To measure wealth, we collected candidate biographical data from VoteSmart and publicly available sources. Two independent judges then used this information to code whether each candidate was wealthy. The intercoder reliability was 82%, and discrepancies were resolved by a third coder. The second candidate-specific variable is a measure of her innate ability to raise funds. This measure is based on the total contributions the candidate received in the previous campaign (*Past contributions*) collected from the Federal Elections Commission mandatory filings.

Table A.1 Factor Loadings of Demographic Variables

Variable	Factor 1 *Educated and income*	Factor 2 *Foreign*	Factor 3 *Poor nonwhite*
Earns in top income bracket	**0.95**		0.19
Average household income	**0.91**		−0.13
Holds bachelor's degree	**0.88**		
Lives in urban area	0.40	0.47	
Born in foreign country		**1.02**	
Speaks foreign language		**0.89**	0.10
Migrated from outside the United States in last year		**0.67**	−0.14
Owns a home	0.22	−0.41	−0.27
White, not Hispanic		−0.25	**−0.61**
Unemployed	−0.38	0.17	**0.61**
Family in poverty	−0.41		**0.83**
Migrated within the United States in last year	−0.16	0.15	−0.22

Budget Estimation for Control Function Approach

In the nonstructural estimation, we correct for budget endogeneity via a control function approach. Following this tradition, in the second-stage regression, we include the *Budget* and the residuals from a first-stage regression, which proxy for the endogenous component of the *Budget* variable. In the first stage, we regress the log of the budget on the exogenous variables from the second stage and the cost shifters. We use a log transform on the budget to correct for its empirical skewness.

Table A.2 presents the first-stage results. The statistically significant variables are the three closeness variables, *Media coverage—Self*, *Prior exposure—Self*, two demographic factors (*Educated and income* and *Poor nonwhite*), *Past contributions*, and *Wealthy candidate*. The sign of these coefficients are as expected except *Wealthy candidate*, which is only marginally significant. Importantly, some of the significant variables (*Past contributions*, *Likelys*, *Leanings*, and *Toss-ups*) are our excluded variables (i.e., are not in the second-stage regression).

Table A.2 First-Stage Nonstructural Estimates

Variable	Budget model
Intercept	10.1 (31.0)[a]
Media coverage—Self	0.19 (2.81)[a]
Prior exposure—Self	0.32 (2.22)[a]
Iraq vote against party	−0.00 (−0.02)
Incumbent—Opponent	−0.09 (−0.46)
Media coverage—Opponent	−0.02 (−0.32)
Prior exposure—Opponent	0.08 (0.63)
Likelys (3rd-closest)	1.50 (11.3)[a]
Leanings (2nd-closest)	0.75 (4.74)[a]
Toss-ups (closest)	0.38 (1.93)[b]
Incumbent	0.19 (0.90)
Front-runner	0.18 (0.85)
Partisanship	0.16 (1.38)
Party = Republican	−0.13 (−0.69)
Year = 2002	0.10 (0.53)
Year = 2004	0.11 (0.50)
Republican in 2002	−0.09 (−0.37)
Republican in 2004	0.09 (0.35)
Demographic factor—Educated and income	0.26 (4.84)[a]
Demographic factor—Foreign	0.02 (0.42)
Demographic factor—Poor nonwhite	−0.21 (−4.19)[a]
Demographics—Violent crime	−0.40 (−0.20)
Wealthy candidate	−0.23 (−1.70)[b]
Past contributions ($\times 10^{-5}$)	0.57 (3.78)[a]
Close current presidential race	0.03 (1.02)
Any senate race	−0.10 (−0.97)
Any governor race	0.19 (1.53)
R-square/adjusted R-square	0.513/0.493

Note. Linear regression with log(budget) as the dependent variable.
[a]Significant at the 0.05 level in two-tailed test.
[b]Significant at the 0.05 level in one-tailed test.

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