The Seeds of Negativity: Knowledge and Money*

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Abstract

This paper studies the tendency of firms to "go negative" in their 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 on the good traits of the candidate or on the bad traits of his opponent. We find that in equilibrium the proportion of negative ads increases with (a) voters' knowledge, (b) the candidate's budget, and (c) the proportion of politically-involved voters. We test these implications using data on US congressional races in 2000, 2002 and 2004 and presidential races in 2000 and 2004, and find that the data is quite supportive for the effects of knowledge and budget on negativity but not so for the role of involvement. Furthermore, we also find that the model can explain well the empirical regularity about the relationship between the closeness of the race and its negativity.

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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. 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 in 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 2002a). We present a model of electoral competition in which ads inform voters either on the good traits of the candidate or on the bad traits of his opponent. We find that in equilibrium the proportion of negative ads increases with (a) voters' knowledge, (b) the candidate's budget, and (c) the proportion of politically-involved voters. Interestingly, close races are not only characterized by high negativity, but also by (a) high media coverage (West 1994) which can lead to high knowledge and (b) large marketing spending (i.e., large budgets) by the candidates (Goldstein and Freedman 2002a). In this sense, our model can tie together these three empirical regularities. Using data on the elections for the US House of Representative in 2000, 2002 and 2004 and for US president in 2000 and 2004, we examine the model and its implications. The data is quite supportive for the effects of knowledge and budget on negativity but not so for the role of involvement. Furthermore, the theory helps to explain why close political races are more negative.

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). While 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, two of the most memorable and probably also influential ads of 2007 were the

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

"Mac versus PC" ones and "1984" by supporters of Barack Obama against Hillary Clinton.[2]

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

In order to learn the most about negative advertising we focus on an application in which negativity is frequent and exhibits high variation – political campaigns. Furthermore, we aim to explain one of the most interesting empirical regularities about negativity in political campaigns – that is, 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 noncompetitive races but 65% in competitive races (Goldstein and Freedman 2002a).[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. Thus, 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 three types of voters – Democrats, Republicans, and Independents. Each candidate 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. Furthermore, voters differ in their knowledge and these differences are correlated with their type (e.g., the Democratic voters know more good traits of the Democratic candidate than the Independents). Each candidate decides how to divide his budget between ads that present his good traits (i.e., positive advertising) and ads that present his opponent's bad traits

[2] For a few examples of the "Mac versus PC" search for the following codes in youtube: ci2D1ig4df4, 1EbCy-ibkNB0, GQb_Q8WRL_g and eU9EflLJuf8. Check out the many spoofs of these commercials in youtube. They reflect the involvement level these commercials encourage. For the "1984" commercial search for 6h3G-lMZxjo. Comparative ads tend to be more memorable (Grewal et al. 1997) and thus it is not surprising that although most 2007 ads were not negative, the memorable ones are.

[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 will become clear soon.

[4] In presenting the findings of Goldstein and Freedman, we combine "Contrast" and "Attack" ads, as each specifically mentions the opponent and implies a negative statement.

(i.e., negative advertising).

In equilibrium, the portion of negative ads in a campaign is an increasing function of the size of the budget, the level of voters' knowledge (specifically, how much they know even without any exposure to ads), and the size of the partisan segment of voters. As pointed out above, these findings are interesting since close races are not only characterized by higher negativity, but also by larger budgets and more intense media coverage (which can lead to high knowledge). In this sense, our model can tie together these three empirical regularities.

We collect data on elections for the US House of Representative in 2000, 2002 and 2004 and for US president in 2000 and 2004. There are various challenges in the data collection. The most dramatic is getting information on voters' knowledge. Furthermore, this task is especially difficult for the congressional elections. Still, the evidence is supportive for our theory. We find that, as expected by our model, the tendency to "go negative" is an increasing function of the candidate's budget and voters' knowledge. However, the prediction on the effect of voters' involvement on negativity is not supported by the data.

The evidence also 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 on consumers of positive and negative advertising has 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 more favorable attitudes toward the sponsored brand than noncomparative ads (Grewal et al. 1997). A stream of research has examined the psychological responses to negative advertising (e.g., Shiv et al. 1997) and psychological processes that moderate the response to comparative ads (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 advertisements have different effects than positive advertising. However, more recent research has begun to garner less ambiguous results. With improved measures of advertising tone and exposure, Goldstein and Freedman (2002b) find that negative ads increase voter involvement.[5] Phillips et al. (2008) find that the impact of negative and positive advertisements differs once prior preferences are considered. They find that negative ads have an advantage in increasing commitment of voters that support the candidate. The effect on voters that support the opponent, on the other hand, is mixed: while some shift their support to the advertising candidate, others feel more strongly in favor of the opponent. Finally, 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 the introduction, 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. (2008) 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 since they neither consider the choice between positive and negative advertising nor the conditions in which one or the other is optimal.

There are also two earlier theoretical studies that explored the reasons for going negative in political campaigns – Skaperdas and Grofman (1995) and Harrington and Hess (1996). Both studies focused on the differences between the frontrunner and his competitor in their tendency to "go negative". While both predict that frontrunners will be less negative than trailing candidates, their explanations are different. Theilman and Wilhite (1998) tested both models using a pseudo-experimental study of political consultants' responses to hypothetical campaign scenarios. They find no support for the Harrington and Hess model, but do find support for the

[5] They find that voter turnout increases with negative ads and suggest that this increase is due to greater voter involvement and interest in the election.

Skaperdas and Grofman prediction. However, the overall evidence on the frontrunner effect is rather mixed.[6] As apparent, previous studies were interested in the impact of the frontrunner, but none of them considered voters' knowledge as a fundamental ingredient in candidate motivation to "go negative".

Finally, while Che et al. (2007) focus on estimating the effect of negative and positive ads on voters' choices, they also use these 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. Furthermore, our theory introduces factors (such as knowledge and budget) that were ignored by previous studies, but are supported by the data. Finally, our model does not only explain the incentive to "go negative", but also shed light on an interesting empirical regularity – the positive correlation between negativity and the closeness of the race.

3 Model

This section presents a model of candidate decisions on the negativity of their advertising. Since candidates' strategies rely on voters' behavior, we start by modeling individual choices. The model and its solution are used to identify some implications that can be tested empirically. Specifically, we explore the effect of several variables of interest (such as budgets and voter knowledge) on candidates' choice of negativity in equilibrium.

However, before presenting our model, we discuss in the following subsection a simpler story that we believe is important to explaining non-competitive election negativity. A terminology clarification: a non-competitive race in one in which the winner is known a priori. In this sense, the closeness of the race is zero. Within the competitive races the closeness of the race varies. In other words, while in some competitive races the uncertainty about the winner is very large in others one of the candidate seems to have some advantage on his competitor.

[6] Damore (2002) provides further support for the frontrunner effect using data on the tone of appeals in Presidential general election ads for the 1976 to 1996 elections. Again using Presidential races but from 1960 to 2000, Sigelman and Buell (2003) find that in non-competitive races frontrunners attack less than trailing candidates, but in competitive races the pattern was unpredictable (see also Benoit 1999 for similar results using overlapping data). However, the frontrunner effect was not supported in Sigelman and Shiraev's (2002) study of Russian presidential races.

3.1 Lack of negativity in non-competitive races

One of the main aims of this study is to explain the relationship between the closeness of the race and its negativity. In this subsection we claim that the rareness of negativity in non-competitive races is actually straightforward. Specifically, we suggest that in noncompetitive races the degree of negativity should be very small because it does not provide a benefit to either candidate.

Competitive and noncompetitive races may have fundamentally different strategic considerations. When races are competitive, the main concern of the candidates is winning the current elections. Post-election considerations have a smaller weight in their mind. However, when the election is not competitive, candidates are likely to weigh more heavily the post-election future than the current election.

These differences are directly relevant for the degree of negativity in a campaign. Consider the role of positive and negative advertisements for future benefits. Generating positive image via ads benefits the candidate not only in the current race but also in the future. It can help him govern if he wins the elections, but it can also assist him if he loses the election. For example, it can create a good reputation that will become useful if the candidate becomes a business person after losing the elections. In contrast, negative advertisements (i.e., presenting the negative traits of the opponent) have basically no future value. If the candidate wins the election, he is likely to face a different opponent in the future. If he loses, he is not likely to run again. Thus, the probability that the image of his current opponent will be relevant to him in the future is slim.

Thus, we suggest that in races that are not competitive, candidates will largely focus on positive advertising. In subsection 4.2 we use our data to demonstrate that this is indeed the case for congressional races, but not so for presidential races, where the race typically reflects the pinnacle of a political career.

Because non-competitive congressional contests are not likely to produce significant amounts of negativity, we find them less interesting to study and so don't include them in our empirical analysis of congressional races. We discuss later the advantages of this strategy. Recall, though, that even within the competitive races there is variation in the closeness of the race. Furthermore, in section 5 we show that campaign negativity is a function of closeness even when non-competitive races are excluded. Thus, we now examine in more detail voter and candidate decisions in competitive races.

3.2 Individual citizens' decisions

There are three types of individuals indexed by j. A central ingredient of our theory is voters' knowledge. Thus, we start this subsection by discussing our formulation of knowledge and only then discuss the characteristics of the three segments and their voting choices.

3.2.1 Knowledge

We assume there are two candidates: one represents the Democratic party and is denoted by d and the other represents the Republican party and is denoted by r. Each candidate has good traits denoted by a (e.g., effective manager) and bad traits denoted by b (e.g., performs badly under pressure). Of course, voters' utility increases in candidate's good traits and decreases in his bad traits, but not all of the traits are known to the public.

Voters' knowledge can be thought of as the stock of candidate traits to which they have 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.[7] Formally, let κ represents knowledge on either good or bad traits (i.e., $\kappa \in \{a, b\}$), κ_0 be the prior knowledge and κ_1 be knowledge from candidate advertisements. Thus, the stock of knowledge that the individual has about each of the characteristics of each of the candidates at the time of decision is $\kappa_0 + \kappa_1$. Below we (a) add indexes to these in order to make them more specific, (b) specify the impact of knowledge on utility, and (c) specify the production function of κ_1 (i.e., how candidates' spending are transformed to knowledge).

3.2.2 Segments

Some individuals are more involved in politics than others. To capture this heterogeneity in voter involvement, we assume two broad segments of citizens, the active and the inactive and denote the size of these segments, respectively, as q_l and q_n where $q_l + q_n = 1$. We also assume

[7] As will become evident soon, we are formulating informative advertising differently then the common Bayesian learning approach (see, for example, Narayanan, Manchanda, and Chintagunta 2005).

that those that are more active in politics also have well-defined preferences that lead them to have skewed knowledge about each of the candidates. Hence, we further segment the active segment into two parts, one which favors the Democratic party, d, and the other which favors the Republican party, r. The proportions q_d and q_r correspond to the size of these segments (where $q_d + q_r = 1$). As a result, three segments exist, denoted by $j \in \{d, n, r\}$ with respective sizes $q_l q_d$, q_n, and $q_l q_r$. Of course, such a three-segments model is quite common in marketing (Narasimhan 1988).

The individuals in these segments also differ in their knowledge. We make two related assumptions to distinguish the active and inactive segments. First, the active segment has more positive knowledge about the candidate they favor than the inactive segment (i.e., $a_{0kk} > a_{0nk}$, where κ_{0jc} is the prior knowledge of segment j on candidate c and $c \in \{d, r\}$). Second, the active segment has more negative knowledge about the opponent than the inactive segment has (i.e., $b_{0c,-c} > b_{0n,-c}$ where $-c$ denotes the opponent of c).[8]

The segments differ also in their willingness to "listen" to the candidates. Following previous studies, we assume that active citizens do not "listen" to advertisements by the unfavored candidates.[9] Hence, regardless of the actual advertising by either candidate, $a_{1rd} = a_{1dr} = b_{1rr} = b_{1dd} = 0$.[10]

Finally, we define the segment specific participation rates as τ_l and τ_n. It is basically "by definition" that we assume that $\tau_l > \tau_n$. Notice also that we implicitly assume that the participation rates do not depend on candidates' advertisements. Given that we allow the ads to affect the voting choices, this assumption can be considered as a normalization.

3.2.3 Voting choices

Any individual can vote for either candidate (consider Reagan-Democrats as an example of Democrats who voted for the Republican candidate). The utility of individual i of segment j

[8] (a) In the data section we examine this assumption empirically.
(b) Notice that we do not make any assumptions about various other pairs (e.g., a_{0cc} and $a_{0c,-c}$) because they do not have any consequences on the results.

[9] It was found that partisans are largely influenced by only ads sponsored by their favored candidate (Ansolabehere and Iyengar 1997).

[10] Our theoretical results do not change qualitatively if loyals also listen and respond (in a reduced manner) to the opponent's messages.

from candidate c is

$$g(a_{jc}) - f(b_{jc}) + u_{ijc}$$

where u is an individuals evaluation of the candidate that is uncorrelated with knowledge and not observed by the candidates (i.e., a random variable). Thus, individual i from segment j votes for the Democratic candidate, d, if

$$g(a_{jd}) - f(b_{jd}) - g(a_{jr}) + f(b_{jr}) + u_{ij} > 0$$

where $u_{ij} \equiv u_{ijd} - u_{ijr}$. We assume that (i) u_{ij} follows a uniform distribution on the interval $[-\frac{1}{2}, \frac{1}{2}]$, (ii) $g(a) = \alpha_0 a^{\alpha_1}$, $f(b) = \beta_0 b^{\beta_1}$, (iii) $\alpha_0 > 0$, $\beta_0 > 0$, and (iv) $0 < \alpha_1 < 1 < \beta_1$, which implies that while the g-function is concave, the f-function is convex.

The assumption about α_1 and β_1 deserves some discussion and explanation. Previous studies that estimated the effects of positive versus negatives ads focused on linear structures and thus cannot be used to directly shed light on this assumption. Thus one of the aims of our empirical analysis is to test this assumption. Indeed, as demonstrated briefly, we can test it using data on candidates' strategies, since the effect of knowledge on negativity depends on the relationship among α_1, β_1 and 1.

Furthermore, while the model can be solved for any combination of α_1 and β_1, we prefer to solve it for this subset of the parameter space because we find this assumption reasonable. Specifically, it seems reasonable that good traits of candidates can only generate so much good for citizens, whereas bad traits can have increasingly bad effects on citizens' lives. Put another way, the positive traits (and thus ads) can only generate so much hope and affirmation, whereas negative traits fuel fear that fuels even more fear.

Finally, as demonstrated below, when $0 < \alpha_1 < 1 < \beta_1$ the model predictions are consistent with the three empirical regularities simultaneously (i.e., that close races are associated with high negativity, high marketing budgets and high news media coverage). This brings another layer of credibility to this assumption.

We are now ready to discuss candidates strategies.

3.3 Candidates' decisions

Each candidate decides how to divide his total budget, denoted by E_c, between negative and positive ads.[11] In other words, candidates' expenditures on positive advertising (about his good traits), denoted by e_{ca}, and negative advertising (about the bad traits of his opponent), denoted by e_{cb}, are constrained by $e_{ca} + e_{cb} \leq E_c$.

3.3.1 Knowledge production function

We assume a standard convex cost function of producing knowledge – i.e., $a_{1jc} = e_{ca}^{\gamma}$ and $b_{1j,-c} = e_{cb}^{\gamma}$ where $\gamma < 1$ and as above c, and $-c$ represent the candidate and his opponent.[12] Of course, the production function of knowledge can take the more common Bayesian format. However, it seems that the formulation above captures the relationship between spending and knowledge well, and it allows certain simplifications in the analytical model.

3.3.2 Candidates' objective function

The candidates choose the level of expenditures on positive and negative advertising to maximize the total votes that they expect to receive. Candidates are interested in total votes in order to maximize both the probability of success and the mandate for their desired policies (this is supported empirically in Shachar 2009). Recall that ads contribute to voters' knowledge and thus affect the election results.

Thus, subject to the budget constraint, the objective function of candidate c is:

$$q_l q_c \tau_l \lambda_{cc}(e_{ca}, e_{cb}) + q_n \tau_n \lambda_{nc}(e_{ca}, e_{cb}) + q_l q_{-c} \tau_l \lambda_{-c,c}$$

where λ_{jc} is the expected votes for candidate c from segment j – specifically:

$$\lambda_{jc}(e_{ca}, e_{cb}) \equiv g(a_{0jc} + e_{ca}^{\gamma}) - f(b_{jc}) - g(a_{j,-c}) + f(b_{0j,-c} + e_{cb}^{\gamma}) + 0.5 \qquad (1)$$

[11] Since E_c is not a function of candidates' choice of negative versus positive, we treat it in our analysis as exogenous.

[12] (a) Recall that we assume the advertisements sent by the unfavored candidate of an active political segment do not produce any additional information.

(b) Of course, it is possible that the γ parameter is different in producing good and bad traits. However, since such differences are inconsequential we ignore them.

and where we have explicitly dropped the dependence of λ_{rd} and λ_{dr} on the respective candidate's advertising decision. Intuitively, candidates choose their positive and negative advertising to maximize the weighted sum of segment votes (respectively, λ_{cc}, λ_{nc}, or $\lambda_{-c,c}$), where the weight for each segment is its size (respectively, $q_l q_c$, q_n, or $q_l q_{-c}$) multiplied by its turnout rate (respectively, τ_l, τ_n, or τ_l).

3.3.3 Candidates' optimal decision

For explication purposes let's denote by e_c the positive advertising and by e_c^* the optimal value of this variable. Since the voter response to both positive and negative advertisements is always positive, the candidate will always exhaust the budget. Thus, we can use $E_c - e_c$ to represent the negative advertising expenditures for candidate c.[13]

The first order condition for candidate c is then

$$q_l q_c \tau_l \lambda_{1c} + q_n \tau_n \lambda_{1nc} = 0 \tag{2}$$

where $\lambda_{1c} \equiv \frac{\partial \lambda_{cc}}{\partial e_c}$ and $\lambda_{1nc} \equiv \frac{\partial \lambda_{nc}}{\partial e_c}$. Notice that the first order condition cannot be solved explicitly for e_c^* and that it can be written also as

$$\left(\frac{e_c^*}{E_c - e_c^*}\right)^{\gamma-1} \frac{\alpha_1 \alpha_0}{\beta_0 \beta_1} = \frac{q_l q_c \tau_l \left(b_{0c,-c} + (E_c - e_c^*)^{\gamma}\right)^{\beta_1 - 1} + q_n \tau_n \left(b_{0n,-c} + (E_c - e_c^*)^{\gamma}\right)^{\beta_1 - 1}}{q_l q_c \tau_l \left(a_{0cc} + (e_c^*)^{\gamma}\right)^{\alpha_1 - 1} + q_n \tau_n \left(a_{0nc} + (e_c^*)^{\gamma}\right)^{\alpha_1 - 1}}. \tag{3}$$

3.4 Theoretical Predictions

From either equation (2) or equation (3) we can get $e_c^*(b_{0c,-c}, b_{0n,-c}, a_{0cc}, a_{0nc}, q_l, q_c, E_c)$. In other words, we can identify the effect of some key parameters on the optimal decision. Specifically, we are interested in the impact on negativity of prior knowledge $(b_{0c,-c}, b_{0n,-c}, a_{0cc}, a_{0nc})$, the size of the active segment (q_l, q_c), and the budget (E_c). These theoretical predictions will guide our empirical analysis.

[13] The convexity of the utility with respect to bad traits might create a concern that the objective function is not strictly concave. In the appendix (subsection 7.1) we show that under mild conditions the concavity of the objective function is guaranteed. For example, a *sufficient* condition is $\beta_1 \gamma < 1$. Of course, when the objective function is strictly concave, the possibility of a bang-bang solution (i.e., where the candidate always either chooses all positive or all negative ads) does not exist.

3.4.1 The effect of prior knowledge

In this subsection we examine the effect of an increase in prior knowledge about one of the candidates on the degree of negativity of both candidates. For example, what if a_{0dd}, a_{0nd}, b_{0rd}, and b_{0nd} increase (i.e., the Democratic candidate is better known)?[14]

Our model predicts that as a candidate becomes better known he allocates a larger portion of his budget to negative ads about his opponent. Specifically, an increase in a_{0dd} or a_{0nd} has the following effect

$$\begin{aligned} \frac{\partial e_d^*}{\partial a_{0dd}} &= \frac{-q_l q_d \tau_l \lambda_{1d,a_{0dd}}}{\lambda_2} \text{ and } \frac{\partial e_d^*}{\partial a_{0nd}} = \frac{-q_n \tau_n \lambda_{1n,a_{0nd}}}{\lambda_2} \\ \text{where } \lambda_{1j,a_{0jd}} &= \alpha_0 \alpha_1 (\alpha_1 - 1) \left(a_{0jd} + (e_d^*)^\gamma\right)^{\alpha_1 - 2} \gamma \left(e_d^*\right)^{\gamma - 1} \text{ and } \lambda_2 \equiv \frac{\partial \lambda_{1j}}{\partial e_j} \end{aligned}$$

Since $\alpha_1 < 1$ and $\lambda_2 < 0$ (i.e., the second order condition is negative) we get $\frac{\partial e_d^*}{\partial a_{0jd}} < 0$.[15]

The effect of b_{0rd} (and symmetrically for b_{0nd}) on e_r^* has the same effect – i.e., as the Democratic candidate becomes better known his opponent allocates a larger portion of his budget to negative ads. Specifically, the derivative in this case is

$$\frac{\partial e_r^*}{\partial b_{0rd}} = \frac{-q_l q_r \tau_l \lambda_{1rb_{0rd}}}{\lambda_{2r}}$$

where

$$\lambda_{1rb_{0rd}} = -\beta_0 \beta_1 (\beta_1 - 1) \left(b_{0rd} + (E - e_r^*)^\gamma\right)^{\beta_1 - 2} \gamma \left(E - e_r^*\right)^{\gamma - 1}$$

Since $\beta_1 > 1$, and $\lambda_2 < 0$ we find $\frac{\partial e_r^*}{\partial b_{0rd}} < 0$.

Taken together, we find that as a candidate becomes better known both he and his opponent increase the proportion of negativity, matching the empirical observation related to media attention and negativity. While the condition $\alpha_1 < 1$ is critical for the behavior of the candidate that becomes better known, the assumption $\beta_1 > 1$ is critical for the strategic reaction of his opponent.

The rationale behind these results is intuitive. When $\alpha_1 < 1$ the marginal impact of the

[14] Notice that we do not discuss the impact of a_{0rd} since this element does not enter into the first order condition for candidate d. In other words, the Republican loyals do not listen to the positive messages about the Democrat, so the derivative is zero.

[15] See the appendix (subsection 7.1) for conditions in which the second order condition is negative (i.e., $\lambda_2 < 0$).

good traits is diminishing. Thus, as voters are better informed about a candidate's good traits, his tendency to send ads with additional positive information diminishes. As a result, the proportion of negativity used by him increases. When $\beta_1 > 1$ the marginal impact of bad traits is increasing. Thus, as voters are better informed about a candidate's negative traits, the tendency of his opponent to send ads with additional negative information increases as well. As a result, once again, the proportion of negativity increases.

Recall that the parameters α_1 and β_1, which are central for these results, were completely ignored in previous studies of negative advertising. Our theoretical results suggest that one can test our assumption (i.e., $0 < \alpha_1 < 1 < \beta_1$) not only directly (via data on voters' response to negative and positive advertising) but also indirectly through candidates' allocation of their budget between negative and positives ads. Specifically, with $\beta_1 < 1$ the effect of knowledge about bad traits on the negativity of the ads reverses. This means that when voters' prior knowledge on the bad traits of a candidate increase, his opponent will go more negative if $\beta_1 > 1$ but less negative if $\beta_1 < 1$.[16] Thus, the effect of knowledge about bad traits on negativity provides a clean test for whether β_1 is greater or less than one. Similarly, this is true for $\alpha_1 < 1$ versus $\alpha_1 > 1$ with positive knowledge. We follow this approach in section 5.

3.4.2 The effect of total budget

In appendix section 7.2, we show that when $0 < \alpha_1 < 1 < \beta_1$ both $(E_c - e_c^*)$ and $\frac{(E_c - e_c^*)}{E_c}$ increase when E_c increases. Together these relationships show that as his budget increases, the candidate will spend both absolutely and proportionately more on negative advertising.

The intuition of this result is the following. The advertising budget is used to inform consumers about the good traits of candidate c and the bad traits of the opponent, $-c$. Thus, larger budgets ultimately mean that voters will be more knowledgeable, and as we have already seen as the voters become more familiar with the candidates the effectiveness of negative ads (over positive ads) increases. In other words, the effect of the budget works via voters' knowledge.

As mentioned earlier, close races are characterized by relatively large advertising budgets.

[16] This dichotomy between $\beta_1 < 1$ and $\beta_1 > 1$ does not exist for the effect of the other two variables of interest – budget and involvement. In other words, for some parameter values when $\beta_1 < 1$ the effect of budget and involvement on negativity are the same as when $\beta_1 > 1$. As a result, only the knowledge variable provides an unambiguous test for whether $\beta_1 > 1$ or $\beta_1 < 1$ (and likewise for α_1).

Thus, it is possible that the theoretical result in this subsection can explain the relationship between closeness and negativity. In other words, close races lead to larger budgets which then lead to more negativity.

3.4.3 Impact of the active segment

In appendix subsection 7.3, we also examine the effect of a change in the size of the politically active segments, q_l, on negativity, $E_c - e_c^*$. We find that as the portion of active citizens increases, candidates advertising campaigns become more negative. Intuitively, because we assume active citizens are more knowledgeable than the inactive ones, as the portion of active citizenry increases, the average knowledge in the population increases, and the higher knowledge leads to more negativity. Hence, this effect, as well, operates through knowledge.

The analysis in appendix subsection 7.3 goes further by examining the impact of an increase in the size of the active citizenry that favors candidate c, (i.e., q_c) on $(E_c - e_c^*)$ and $\left(E_{-c} - e^*_{-c}\right)$. We find that as q_c increases, candidate c increases his spending on negative ads. Of course, we also find that the opponent (for whom q_{-c} decreases when q_c increases) decreases his spending on negative ads.

The intuition of this result is the following. An increase in q_c increases the portion of the population that knows relatively more about the good traits of c and about the bad traits of $-c$. Because $0 < \alpha_1 < 1 < \beta_1$ this increase implies that the marginal productivity of information on the good traits of c diminishes while the marginal productivity on the bad traits of $-c$ increases, and this immediately leads to the result above.

3.5 Summary of model predictions

To conclude, we briefly summarize the key predictions of the theoretical model. First, the model predicts that as a candidate becomes better known both he and his opponent increase the proportion of negativity. Specifically, an increase in knowledge about the candidate's good traits will lead to more negativity by the candidate, and an increase in knowledge about the candidate's bad traits increases the negativity of the competitor. This latter prediction relies critically on the assumption $\beta_1 > 1$ and, as a result, provides an empirical test for this assumption based on candidate behavior. Second, an increase in the budget leads to an increase in the level and portion of the candidate's advertising that is negative. Third, the model predicts that an increase in the politically active segment will lead to more negative advertising for both candidates. At the same time, when the portion of active citizens that favor one candidate increases, that candidate increases his spending on negative ads, while his opponent decreases it.

4 Data

We test our theory using two distinct types of races in the US– races for the White House and for Congress. Specifically, we use data from US presidential elections in 2000 and 2004 and from US House of Representatives elections in the 2000, 2002 and 2004. For congressional races, each candidate in a congressional district is one observation. For presidential races, each candidate in each Nielsen media market serves as an observation.

The main advantage of using data from House elections is the availability of many races. The main advantage of the presidential data is the (relative) reliability of the measures. Specifically, as discussed shortly, for House elections it is difficulty to acquire reliable measures of knowledge.

The data we use for analysis is compiled from a number of publicly available and privately held sources.[17] We integrate these sources in order to develop the variables discussed below. Like previous studies (e.g. Shachar 2009) we restrict our attention to the post-Labor day period (when campaign activity greatly increases) and to candidates from the major parties (Democrats and Republicans).

In the first subsection we describe the dependent variable (negativity) and one independent variable (competitiveness/closeness). These two variables enable us to test, in the following subsection, whether – as we suggest earlier (subsection 3.1) – non-competitive races are rarely negative. We then present the rest of the variables used in the analysis – prior knowledge, involvement, budget, and control variables.

[17] These sources include The Wisconsin Advertising Project, which has enhanced data from the Campaign Media Advertising Group (CMAG) with textual analysis, the Annenberg National Rolling Cross-section Election Surveys, the National Election Survey (ANES) supplemental files, the Congressional Quarterly Special Election Reports, and The Cook's Political Report.

4.1 Negativity and Competitiveness

4.1.1 Negativity

Our data on the proportion of negativity come from the Campaign Media Analysis Group (CMAG). The data was collected through technological monitoring of the transmissions of the national networks (ABC, CBS, NBC, Fox), 25 national cable networks (e.g., CNN, ESPN, and TBS), and local advertising in the top 75 media markets. These represent media covering at least 80% of the population (Goldstein and Freedman 2002a). This data provides detailed information about the content and tone of every advertisement for each candidate who advertised in these markets.

Based on their tone the ads were coded by independent raters as part of the Wisconsin Advertising Project into three major categories – promote, contrast, or attack. Contrast ads were coded further into three sub-categories – (a) mostly attack, (b) equally divided between attack and promote, or (c) mostly promote. We define an ad as negative if it was coded either as "attack" or as sub-categories *a* and *b* of "contrast".[18] Otherwise, it is coded as positive.

Finally, our variable (*Negativity*) is the ratio between the negative ads that a candidate airs and the total ads that he airs.[19]

4.1.2 Competitiveness

We follow previous studies which have used *The Cook Political Report* as a measure of competitiveness (e.g., Goldstein and Freedman 2002a). This periodical publishes a rating of competitiveness for each House race and for each state (in presidential races). The rating is based on a range of quantitative factors, including polls, historical voting patters, and expert opinion. The ratings are published on an irregular basis throughout the election year, and we select the report closets to Labor day, making the measure ex ante.

The rating has four categories based on the competitiveness of each race. Accordingly we create three indicator variables (i) *Toss Up* which represents the highest category of competi-

[18] In 2000, the data did not include the break-out of contrast ads. Thus, for this election year, we include all contrast ads under the definition of negative. Our empirical analysis incorporates fixed time effects to account for any level differences this produces.

[19] Of course, this means that (by definition) our analysis and results are only for the candidates that used ads in their campaigns. Notice that our theory is also for these cases only.

tiveness, (ii) *Leaning* which represents the highest two categories, and (iii) *Likely* for the highest three categories. Notice that (a) these variables are inclusive, and (b) when *Likely=0* the race is defined by *Cook* as non-competitive.[20]

4.2 Negativity in non-Competitive Races

One of our research aims is to explain the higher negativity in close races. In subsection 3.1 we have suggested that in non-competitive races (i.e., the lowest level of closeness) negativity should be rare, because the candidate benefits little from negative ads. The reason for the low benefit is that the result of the current campaign is practically determined and in the future the candidate is not likely to meet this same opponent. Here we test this simple story before moving to an empirical examination of the more complex model.

Figure 1 presents density plots of the negativity of competitive and noncompetitive races. The left plot presents the congressional campaigns. The contrast between competitive and non-competitive races is clear with most of the negativity and variation in negativity occurring in competitive races. The mean negativity for competitive and non-competitive congressional races are 56% and 22% respectively. Using a variety of tests[21] we find significant differences between the competitive and non-competitive races. These tests indicate that competitive races are considerably more negative. Further, while over 60% of races have zero negativity in non-competitive races, in close races less than 10% do. Thus, in non-competitive races very little negativity occurs, supporting our theoretical prediction for congressional races.

The right plot in figure 1 is for presidential advertising. In presidential elections, considerable variation occurs for both low and high competition media markets. Thus, the "long-term incentives story" does not hold in presidential races. This result is quite reasonable. Congressional candidates are relatively unknown and it makes sense for them to use advertising money in order to build their image for future benefits in noncompetitive races. Presidential candidates are well known and thus do not have this incentive.

[20] For the presidential races, the measure is available for each state. Whenever a media market has more than one state, we average over all relevant states (assuming an interval scale) and then recategorize using the original interval breaks. Hence, if a media market covered two states one with a leaning race (2) and one with a likely race (1) it would receive a 1.5 rating and be classified as a leaning race. For congressional races, the measure is available for each race.

[21] We test for equality of means and distributions using parametric t-tests and nonparametric Kolmogorov-Smirnov two sample test.

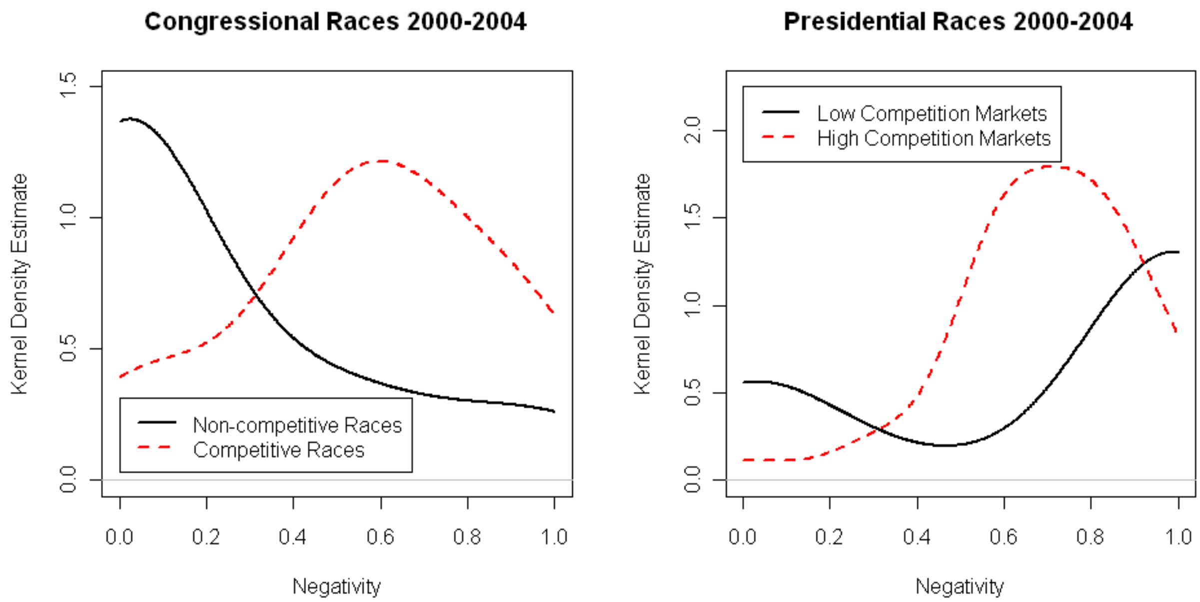


Figure 1: Negativity of competitive and noncompetitive races

The results of this subsection encourage us to focus our attention (just for the congressional races) only on the competitive cases. In other words, we focus on races that are defined as *Toss up*, *Leaning*, or *Likely*. These are the races in which, according to the evidence above, "the action is." Such focus makes sense for two main reasons: (1) competitive races has proved in prior research to be less predictable (Sigelman and Buell 2003), suggesting that by focusing on competitive congressional races we provide a more challenging test for our predictions; and (2) as will become evident soon, collecting data for congressional races is a challenging task. Reducing the set of races facilitates collection of some variables that otherwise would have significant missing data.

4.3 Data Summary and Variable Descriptions

Our congressional data include 162 competitive districts and 306 observations, while the presidential data include 222 observations. Tables 1 and 2 present descriptive statistics of our variables for the congressional and presidential data respectively. In the following subsections, we describe each of the variables introduced by our theory – voters' prior knowledge, voters' involvement and loyalty, and candidates' budget. We also present several control variables. The variables are described for both data sets, and we note differences where appropriate.

4.3.1 Voter Prior Knowledge

Recall that the optimal spending of candidate c on positive ads is $e_c^*(b_{0c,-c}, b_{0n,-c}, a_{0cc}, a_{0nc}, q_l, q_c, E_c)$, where the first four elements are various measures of knowledge. Specifically, while $b_{0c,-c}$ and $b_{0n,-c}$ represent (respectively) the prior knowledge of the supporters of c and the independents about the bad traits of his opponent, a_{0cc} and a_{0nc} represent the prior knowledge of these segments about the good traits of the candidate. This means that we need to create four knowledge variables that differ based on whether they are (i) about good or bad traits, and (ii) for the candidate's supporters or independents.

For presidential elections we have good measures of knowledge based on the Annenberg National Election Survey, a large national survey of citizens. This data is collected for each presidential election year and includes approximately 80,000 respondents in both 2000 and 2004. We use respondents who were interviewed during the period of April 19 to September 1 (i.e., before labor day), to verify that we measure *prior* knowledge.

While we use the term "traits" in the model, we were able to find characterizations of "good" and "bad" with respect to issues and stands. Specifically, respondents were asked "Do you favor X?" where X is a particular issue or stance, and then they were asked whether each candidate supported the issue. In this follow-up question respondents were allowed to say "do not know." The combination of these two questions is very informative for us. The first question allows us to code whether the knowledge is about a "good" or "bad" stand. The second question indicates whether the respondent knows or doesn't if the candidate has this good or bad stand. Our measures of "good" and "bad" knowledge are based on the summation of all the relevant questions.[22]

We also need to identify whether the respondent is a supporter of the candidate or an inde-

[22] Political surveys on presidential candidates include some direct questions about characteristics (e.g., "Candidate X changes his mind"). There are three major problems with using these questions to measure a and b: (i) although the characteristics are generally framed as "good traits", some respondents might perceive them as "not so good" or even as "bad", (ii) while respondents are asked to state the degree of each characteristic for the candidate, for variety of reasons (e.g. scales is subjective) these scales do not provide a clean cut answer as to whether the candidate has the trait or not, and (ii) relatively few people indicate that they do not know how well the characteristic fits the candidate – thus providing us with little insights about the real differences in knowledge. The measures that we use do not suffer from these problems.

pendent. For this purpose we use the respondents' self-reported party affiliation (Republican, Democrat, or Independent). In this way, we generate good measures of $b_{0c,-c}$, $b_{0n,-c}$, a_{0cc}, and a_{0nc}. We aggregate these by media market to form an average knowledge measure and z-score these measures by year to control for any differences in measurement across years.

These variables enable us to test one of the model's assumptions – that loyals are more knowledgeable than the independents. Indeed, we find significant differences in means between the two segments (0.39 versus 0.30 for "good" and 0.37 versus 0.29 for "bad" – these differences are significant at the 1 percent level).

In the analysis below we will not use all four variables but rather one composite variable (labeled *Knowledge*) constructed via factor analysis. We use a composite variable since these four variables are significantly positively correlated as illustrated in Table 3. This is quite intuitive – some media markets are more knowledgeable about presidential politics than others. In these markets both the loyals and the independents are quite knowledgeable and they are knowledgeable about both candidates. Table 3 also presents the loading of the variables.

Our theory suggests that as long as $0 < \alpha_1 < 1 < \beta_1$ the direction of effect of each one of these four variables on negativity should be the same (i.e., more knowledgeable voters, more negativity). In order to test this assumption we also estimated the models reported in the next section several times with each of these variables individually. We found that, as expected by the theory, the coefficients of all the variables were positive. Still, only the effects of $b_{0c,-c}$, and a_{0cc} were significant.[23] While we find this evidence reassuring, we return to this point when discussing the estimation with the congressional data. For the congressional races we have a clear measure of the bad traits of the opponent, and thus we can test again the assumption that $\beta_1 > 1$. Notice that this assumption is more interesting to test than whether $\alpha_1 < 1$, since the assumption about α_1 is quite standard.

For congressional races, the Annenberg Survey and other data sources do not have questions that are specific to the candidate. Lacking such comprehensive data, we use multiple measures. While each measure in its own right might have flaws, taken together they might be able to shed

[23] Furthermore, we have, of course, estimated the models reported in the next section with all four variables instead of the composite one. We found that multicollinearity ruled out effective interpretation. Moreover, when we estimated the models with each of these variables individually, we found that the credible intervals for all four measures overlapped. Thus, we find the same coefficient constraint (and direction of effect) based on the factor loadings to be reasonable.

light on the role of prior knowledge in congressional elections.

Incumbent and *Opponent Incumbent*: First, we consider the role of incumbency. The incumbent campaigned in a previous election and acted as the district's representative for at least two years. Thus, in general, voters know him better than his challenger. Of course, voters are likely to be knowledgeable about his good traits as well as about his bad traits. Thus, following the model's predications, we expect that both indicator variables *Incumbent* and *Opponent Incumbent* would have a positive impact on the proportion of negativity.[24] Specifically, if a candidate is an incumbent, his good traits are relatively known and thus he tends to be more negative. Accordingly, if the candidate opponent is an incumbent, the opponent's bad traits are relatively known and thus, again, the candidate tends to be more negative.

The disadvantage of the *Incumbent* variable is that incumbency comes with additional features that might be related to the tendency to go negative. For example, incumbents generally have had more time to build local organization, political favors, endorsements, and other forms of support that could potentially substitute for advertising as a means of fueling support, particularly among the politically active. Hence, incumbents' negativity may be lower due to these alternative ways to garner loyal support. In contrast, the variable *Opponent Incumbent* does not share this disadvantage. In other words, while it might change the incentives of the opponent to go negative, the only effect that it should have on the candidate is via the knowledge channel.

Supporters' Knowledge and *Independent Knowledge*: Some questions in the Annenberg Survey can assist us in measuring the *general* political knowledge of respondents. For example, respondents were asked "How much of a majority is required for the U.S. Senate and House to override a presidential veto?" Incorrect answers to such questions were marked as indicators of an unknowledgeable respondent. In other cases the respondent was asked to form an opinion on a political manner. When the respondent answer was "do not know" he was considered as not knowledgeable.[25] We calculate the portion of questions for which the respondent was knowl-

[24] We are able to separately identify the effect of *Incumbent* from *Opponent Incumbent* because there are districts in which redistricting created multiple incumbents for a particular race and because some incumbents do not run for re-election, leading to an open seat and no incumbent.

We define as an incumbent any candidate that won in the immediately preceding election cycle, even if redistricting somewhat altered the constituency.

[25] An example of these second set of questions: "Over the past year, would you say that the economic policies of the federal government have made the nation's economy better, worse, or haven't they made much difference either way?"

edgeable and use this as an individual level measure of knowledge. We then average across two types of individuals within a district in order to form two variable: (a) those who are strongly identified with the candidate's party (and name this variable *Supporters' Knowledge*), and (b) those who consider themselves independents, *Independent Knowledge*. We note that unlike our theoretical assumption about segment knowledge, *Supporters' Knowledge* is on average smaller than *Independent Knowledge*. We return to this point when we discuss the results.

A clear disadvantage of these measures is that (i) the knowledge is not content-specific (i.e., positive versus negative) and (ii) the political questions are general and are not candidate specific. There is some evidence that general knowledge about current political issues is related to specific knowledge about congressional candidates and their platforms (Brians and Wattenberg 1996). However, it seems that in our data this relationship is rather weak.[26] While this suggests that these variables are not very good measures of the knowledge variable in our model, we nonetheless include them because it allows us to ask whether general political knowledge is sufficient to garner the knowledge effects.

Scandal: Scandals get a lot of attention and thus are likely to have a major impact on important elements of the model: $b_{0c,-c}$ and $b_{0n,-c}$ (i.e., knowledge on the bad traits of the opponent). Thus, we gathered data on races in which scandals occurred,[27] and created an indicator variable, *Scandal*, for observations in which the candidate's opponent faced a scandal. Six percent of the candidates' opponents, in our data, faced scandals.

Relative to the other measures of prior knowledge, *Scandal* has several advantages. In particular, the valence of knowledge is established (a scandal by definition is information about bad traits) and the knowledge is specific to a particular candidate.

To summarize, for congressional races we are unable to attain direct measures of voter prior knowledge about the good and bad traits of candidates. Instead, we use multiple proxies. These measures suffer from various problems. Still, some of the measures (e.g., *Scandal*) are less

[26] For a small subsample of our data (78 candidates) we have indicators of whether respondents said they could name the congressional candidates in the race. It turns out that while the correlations between our knowledge measures and this congressional candidate recall measure are positive, they are small in magnitude and insigificant (Pearson correlation of 0.10 for Own and 0.08 for Independent Knoweldge).

[27] This indicator is constructed from analyzing the Special Election Report of the *Congressional Quarterly*, which summarizes the campaigns and main issues involved, and where that report was inconclusive, from investigating other publically available summaries of candidate's and their campaigns. Separate coders were used to gather this information and to score the information as a scandal or not.

problematic than others.

4.3.2 Voter Involvement and Loyalty

As pointed above e_c^* is also a function of q_l and q_c. Specifically, (i) the greater the active segment, q_l (who can also be referred to as the "involved segment") the more negative the campaign, and (ii) the greater the proportion of a candidate's supporters (among the active voters), q_c, the higher his tendency to go negative.

Using the Annenberg Survey we create two variables, *Loyals* and *Party Loyals*, to represent q_l and q_c. We base these variable on an often used question about party affiliation, in which respondents are asked to identify themselves as Republican, Democrat, or Independent. The variable *Loyals* is equal to the proportion of those who define themselves are either Republican or Democrat. Out of these respondents, the proportion of those who favor the party of the candidate is the *Party Loyals* variable.

In the congressional data, *Party Loyals* (to a given party) range from 15% to 80% and the *Loyals* range from approximately 36% to 78% with an average of 60%. In the presidential data, *Party Loyals* range from 24% to 75% and the *Loyals* range from approximately 43% to 78% with an average of 61%.

4.3.3 Candidate Budget

Finally, e_c^* is also a function of E_c. Specifically, the higher the budget, E_c, the greater the negativity. Our measure of E_c (termed *Budget*) is the logarithm of the sum of all advertising spots for candidate c. We use the sum of ads rather than the total monetary costs of the ads in order to be consistent with the formulation of the dependent variable, $Negativity$. In the presidential data, the average budget is 6.9 with a standard deviation of 2.1.[28] In the congressional data, because non-close races were dropped, the congressional district budgets are somewhat larger and less dispersed than the presidential media market budgets with an average of 7.0 and standard deviation of 1.1.

[28] Notice that $Budget = 6.9$ represents a case in which the candidate aired about 1,000 ads in a media market during the campaign. If we average the number of ads directly (i.e., without taking the log transformation first) we find that it is 2506 for the presidential data (with a standard deviation of 2003), and 1600 for the congressional data (standard deviation of 1325). This number is not as huge as it looks since they are spread over multiple channels.

4.3.4 Control Variables

In the estimation we control for (i) random effects (at the media market or congressional district level), (ii) time fixed effects, and (iii) two commonly used explanatory variables. The first of these explanatory variables ($Frontrunner$) is an indicator variable for candidates who are frontrunners. Previous research has indicated that frontrunners are less negative than the trailing candidate. For the congressional races, we get the information about the frontrunner status from the *Cook Report*, that indicates which candidate is favored to win. For the presidential races, due to the coincidence of the Republican being the frontrunner in both election years, the effect is indistinguishable from the party fixed effects. The second explanatory variable ($Party$) is an indicator variable for candidates from the Republication party. We use this variable since several studies have suggested that Republicans conduct more negative campaigns (e.g., Lau and Pomper 2001; Goldstein and Freedman 2002a; Peterson and Djupe 2005; but see Sigelman and Buell 2003 for an exception).

5 Estimation and Results

We estimate a model in which the dependent variable is *Negativity* and the explanatory variables are (i) the closeness variables, (ii) the variables suggested by our theory (e.g., knowledge) and (ii) the control variables. We use standard Bayesian techniques for estimation. We also (a) account for the censoring of the dependent variable at 0 and 1 (i.e., the proportion of negativity cannot be smaller than 0 and bigger than 1), (b) allow random effects for congressional districts (media markets) in the congressional (presidential) data, and (c) correct for heteroskedasticity (see appendix section 7.4 for estimation details).

5.1 Testing our predictions

The estimation results enable us to address the two main goals of this study. First, they can shed a light about the incentives to go negative. Specifically, we can test whether the variables presented by the model (e.g., knowledge) indeed affect the proportion of negativity. Second, we can examine whether the model can explain the empirical regularity according to which close races are more negative. Specifically, our model predicts that negativity is increasing in both knowledge and budget. Since close races are characterized by large budgets and large news media coverage (which should lead to high levels of knowledge) it is possible that the relationship between closeness and negativity can be explained by our model.

To examine this idea we would estimate (i) a benchmark model in which the variables presented by our model are excluded and (ii) a theory-based model in which they are included. If our model can fully explain the empirical regularity, we expect that the coefficient of closeness will be significantly different from zero in the benchmark model but not in the theory-based one. If our model can only partly explain the empirical regularity, the coefficient of closeness would diminish but still be different from zero. Of course, it is also possible that the effect of closeness would be the same in both estimations, which would mean that our model cannot explain the empirical regularity. Table 4 presents the results of the benchmark model for our two data sets (congressional and presidential), while Table 5 presents the estimates of the theory-based model.

5.2 The Benchmark Model

The results in Table 4 demonstrate that the empirical regularity identified by previous studies – close races are more negative – also exists in our data.[29] Recall that the three variables that represent closeness are inclusive. Specifically, *Toss Up* represents the highest category of competitiveness, *Leaning* represents the highest two categories, and *Likely* the highest three. Because the variables are inclusive, we don't necessary expect all of them to be significant. Still, in the congressional data (in which the non-competitive races are excluded from the analysis) the two variables have a significant effect. Specifically, *Leaning* and *Toss Up* are positive and significantly different from zero at the five percent level with magnitudes of 19% and 14% respectively (i.e., *Toss Up* races are 33% more negative than *Likely* ones). In the presidential data, we find *Leaning* is significant and positive with a magnitude of 8%, but the other two closeness variables are not.

Thus, we have established closeness and negativity are related in the benchmark model and we are ready to examine whether this relationship remains when the variables presented by our model are included in the analysis.

[29] Furthermore, these results also mean that the relationship between closeness and negativity exists in the congressional data although we have removed the non-competitive races from the data (and thus include only the subset of competitive races).

5.3 The Theory-based Model

By including the variables suggested by the theory – voter prior knowledge, voter involvement, and candidate budgets – we improve the fit of the model in terms of the log marginal likelihood. Specifically, for the presidential data the improvement is 36.8 and for the congressional data it is 91.5, both of which are large improvements in odds ratios.

Furthermore, and more importantly, once these variables are included in the estimation, the effect of the closeness variables diminishes. In particular, for the presidential data, all of the closeness variables decrease in magnitude and none are significant (i.e., the previously significant *Leaning* variable diminishes in magnitude from 8% to 5.8%). In the congressional data, both variables decrease in magnitude. The *Leaning* variable decreases from 19% to 13%, but is still statistically significant. The *Toss Up* variable decreases from 14% to 8% and is no longer statistically significant.

This result suggests that our theory can explain pretty well the empirical regularity about the relationship between closeness and negativity. Furthermore, notice that the only remaining significant effect (of closeness on negativity) is for the congressional data in which the measure of knowledge is far from perfect.

We are now ready to describe the effect of the variables suggested by the theory. In general, the data is quite supportive for the effects of knowledge and budget on negativity but not so for the role of involvement.

5.3.1 Voter Prior Knowledge

We begin with the measures of voter prior knowledge – *Candidate Knowledge, Incumbent*, *Opponent Incumbent*, *Supporters' Knowledge*, *Independent Knowledge*, and *Scandal*. All of these variables are operationalized so that an increase in them reflects an increase in the underlying knowledge. Hence, in all cases we expect to find positive coefficients.

Turning first to the presidential data (in which our measure of knowledge is direct and quite reliable), we find a positive significant effect of *Candidate Knowledge*. The magnitude of the effect is moderate with approximately a 6% shift in negativity at the mean for a two standard deviation change. Recall that *Candidate Knowledge* is a composite variable of the good traits of the candidate and the bad traits of his opponent. Furthermore, the initial measures (which are combined to create *Candidate Knowledge*) are separate for the loyals and the independents. Thus, the presidential data, where we directly observe a_{0cc}, $b_{0c,-c}$, a_{0nc}, and $b_{0n,-c}$, supports the expected role of knowledge in determining the negativity of the campaign.

While the estimation using the congressional data leads to weaker results, it is reassuring to find that the impact of the most reliable variable, *Scandal*, supports our theory. As mentioned above, *Scandal* has a couple advantages: (i) the valence is clear, and (ii) it is candidate-specific. We find that a candidate tends to be more negative if his opponent was involved in a scandal. Specifically, the tendency increases by 27% at the mean and it is significantly different from zero at the five percent level. Furthermore, the impact of *Scandal* also supports the assumption $\beta_1 > 1$. Recall that for $\beta_1 > 1$ a candidate responds to an increase in knowledge on the bad traits of the opponent by increasing the negativity, while for $\beta_1 < 1$ the reaction of the candidate is a decrease in negativity. Thus, the finding that *Scandal* leads to an increase in negativity not only supports the role of knowledge in general, but also the assumption that $\beta_1 > 1$. The rest of the results using the congressional data are not so reassuring.

The only other "knowledge variable" that has a statistically significant effect is *Incumbent*, but its coefficient is negative. While this finding is consistent with past results for incumbents, it is not consistent with our knowledge theory. Still, it is important to remember that incumbency brings with it other advantages (e.g., better organization, political favors, etc.) that could serve as substitutes for negative campaigning and may offset any knowledge effects.

The remaining "knowledge variables" do not have a significant effect on negativity. This includes both candidate specific (*Opponent Incumbent*) and segment specific (*Supporters' Knowledge* and *Independent Knowledge*) variables. Note that the segment specific knowledge variables are admittedly problematic since the knowledge is general rather than candidate specific.

Overall, despite weaknesses in our congressional measures, the results provide support for a role of voter knowledge in determining negativity.

It is worth noting that we included in the analysis a few variables that we were a-priori concerned about their ability to reflect a_{0cc}, $b_{0c,-c}$, a_{0nc}, and $b_{0n,-c}$ well, because they were the best measures that we were able to construct after examining various data sources. As discussed in the conclusion, we hope that our findings will encourage future data collection efforts to include questions that are specific about a_{0cc}, $b_{0c,-c}$, a_{0nc}, and $b_{0n,-c}$.

5.3.2 Voter Involvement and Loyalty

The model predicts that negativity should increase with both *Loyals* and *Party Loyals* that represent q_l and q_c. In three out of the four cases, the coefficient is indeed positive. Specifically, in the congressional data the *Loyals* variable has a positive effect but the coefficient of *Party Loyals* is negative, and in the presidential data both coefficients are positive. However, in none of the cases the effect is statistically different from zero (even at the ten percent level).

This means that the role of involvement in campaign negativity is not supported by the data. It is important to note that the model can be easily rewritten without the distinction among the three segments (Democrats, Independents and Republicans) and that all the other theoretical results will not change. Thus, the lack of empirical support on this point has no bearing on the other parts of the model. Furthermore, the theoretical result about the impact of q_l and q_c on negativity depends on some assumptions including that the independents are less knowledgeable than the loyals (i.e., $a_{0cc} > a_{0nc}$ and $b_{0c,-c} > b_{0n,-c}$). Recall, that for the congressional races this assumption was not supported by the data.

5.3.3 Budget

The model also predicts that the higher the budget, the higher the proportion of negativity. As expected by the theory, the coefficient of *Budget* in both data sets is positive and statistically significant at the five percent level. Specifically, an increase of two standard deviations in *Budget* leads to a large increase in negativity: 34% at the mean in the congressional data and 29% in the presidential data. This represents a significant role for the budget in determining campaign negativity.

Thus, the data clearly support our theoretical prediction that campaigns with more ads will also be more negative. Furthermore, notice that the role of budget in determining negativity was ignored by previous studies.

5.3.4 Control Variables

Finally, we briefly describe the effect of the control variables. First, the only significant difference in negativity across election years in between 2004 and 2000 in the presidential elections – 2004 was more negative. Second, the effects of the two variables that were found important by prior studies, *Frontrunner* and *Party*, are insignificantly different from zero. Interestingly, the effect of *Frontrunner* is negative and significant in the benchmark model (as in previous studies).[30]

As explained formally in the appendix our model includes two unobserved random variables, ξ_{jt} and ε_{ijt}. Interestingly, the variances of the random effects (i.e., ξ_{jt}) are quite similar across all models and data sets. However, these need to be interpreted in terms of the variance of ε_{ijt} (which is scaled down by the heteroskedastic power function). Taking all these together, the congressional data have much larger variation in ξ than the presidential data for 90% of the observations.

This result is quite reassuring, since the unit of analysis in the congressional data (voting district) is more disaggregated than the unit of analysis in the presidential data (media market). Thus, one should expect to find more heterogeneity at the congressional level. Finally, as expected, the heteroskedastic variance power function appears to play an important role with estimated values far from zero.

6 Conclusion

In order to gain a better understanding into 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 and found that in equilibrium the degree of negativity increases when (a) voters' knowledge increases, (b) the proportion of potential voters who are politically-involved increases and (c) the budget (of the candidates) is larger. Using data on U. S. congressional races in 2000, 2002 and 2004 and presidential races in 2000 and 2004, we find that while the data is quite supportive for the effects of knowledge and budget on negativity but not so for the role of involvement. We also find that our model can explain well the empirical regularity about the relationship between

[30] Notice that as discussed in section 4 the frontrunner effect is captured by the party variable in the presidential data, because in both elections the Republican candidate, George Bush, was the frontrunner.

the closeness of the race and its negativity.

It seems that the theory presented here might be able to shed some light on another empirical regularity – as the election draws nearer candidates tend to become more negative (Goldstein and Freedman 2002a). 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.

The empirical findings provide preliminary support for the model and suggest that further examination of its theoretical foundations and implications is likely to be fruitful. First, future empirical research on candidate negativity should improve on the measure of knowledge. The measures used in this study, though reflecting considerable effort, were still less than ideal, particularly in congressional elections. We hope that our findings would encourage institutions who are involved in collecting data on political campaigns to include in their surveys questions on the good and bad traits of congressional candidates. Second, while we have tested the assumption about β_1 indirectly via candidates' strategies, it makes sense to examine it also directly through individual level data that includes voters' response to positive and negative advertising. Interestingly, while previous studies have implicitly estimated the first derivative of consumers' attitudes and choices with respect to positive versus negative ads (see Lau et al. 1999 for a review of these studies), we are not aware of studies that have directly focused on differential effects of the second derivative. However, this study shows that it is the second derivative that determines the tendency to "go negative".

While our knowledge-based model was able to identify an important incentive to "go negative", the empirical results also imply that there is room for improvement. There are at least two directions that scholars can adopt in order to make progress. First, one can add details to the model presented here. For example, we have not distinguished between the vertical and horizontal attributes of candidates, although this distinction is clearly important in political campaign. Second, it is possible that the decision to "go negative" is due to some emotional situation. For example, is the tendency to "go negative" higher when the decision maker is under stress? If this is the case, it is possible to explain the correlation between close elections (and thus stress) and the tendency to "go negative".

Finally, our model can be applied to commercial settings. In particular, the results can be directly transferred to settings with two products (or two competing firms or brands), where we would suggest greater knowledge and advertising intensity is likely to lead to higher negativity. Further, recently it was suggested that we should expect to find an increase in negativity in commercial advertising since (based on past evidence) “as the economy gets ugly, marketers get nasty” (Vranica 2008). If this observation is true, it means that (i) negative ads in commercial setting would become even more important, and (ii) a similar phenomenon to the empirical regularity we were interested in exists also in commercial setting. Specifically, 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 over the same consumers, and the parallel to political races is fairly immediate. Finally, it seems that our theory might be able to explain the shift to negative advertising in bad times. When the economy is bad consumers' knowledge is likely to increases since they are paying more attention to the attributes and prices. In such a case, our theory suggest that ads should be more negative.

7 Appendix

7.1 Condition for $\lambda_2 < 0$

Define the following:

$k_1 = \alpha_0\alpha_1\gamma > 0$

$k_2 = \beta_0\beta_1\gamma(E-e)^{\gamma-2} > 0$

$k_3 = (\beta_1\gamma - 1)(E-e)^{\gamma}$

$k_4 = q_l q_c \tau_l > 0$

$k_5 = q_n \tau_n > 0$

$k_6 = (\alpha_1 - 1)\gamma e^{2\gamma-2} < 0$

$k_7 = (\gamma - 1)e^{\gamma-2} < 0$

Then the second derivative of the objective function, V, in terms of positive advertising is

$$
\begin{aligned}
\frac{\partial^2 V}{\partial e^2} \;=\;& k_1 k_6 [k_4 (a_{0cc} + e^\gamma)^{\alpha_1 - 2} + k_5 (a_{0nc} + e^\gamma)^{\alpha_1 - 2}] \\
& + k_1 k_7 [k_4 (a_{0cc} + e^\gamma)^{\alpha_1 - 1} + k_5 (a_{0nc} + e^\gamma)^{\alpha_1 - 1}] \\
& + (\gamma - 1) k_2 [k_4 b_{0c,-c} (b_{0c,-c} + (E - e)^\gamma)^{\beta_1 - 2} + k_5 b_{0n,-c} (b_{0n,-c} + (E - e)^\gamma)^{\beta_1 - 2}] \\
& + k_2 k_3 [k_4 (b_{0c,-c} + (E - e)^\gamma)^{\beta_1 - 2} + k_5 (b_{0n,-c} + (E - e)^\gamma)^{\beta_1 - 2}]
\end{aligned}
$$

We analyze this second derivative line by line. The first two elements (which appear in the first two lines) represents the effect of positive ads. Since the effect of good traits is concave and costs are convex, we expect these two elements to be negative. Since $k_6 < 0$ and all other terms in the first element are greater than zero, the first element is negative. The second element is negative because $k_7 < 0$ and all other terms are positive. Thus, as expected these two elements are negative.

The last two elements represent the effect of negative ads. Because the effect of bad traits is convex and costs are convex, the effect of negative ads is ambiguous. Since all terms on the third line are positive except the $(\gamma - 1)$ term and since $\gamma < 1$, the element in the third line is also negative. The element on the fourth line, however, is only negative if $(\beta_1 \gamma - 1) < 0$, since all other terms are negative. Thus, a *sufficient* condition for the second derivative to be negative is $(\beta_1 \gamma - 1) < 0$.

Intuitively, this sufficient condition requires that the convexity of the bad traits is not too strong compared to the convexity of costs. In such a case the objective function will be concave and we have an internal solution. Also, note that a necessary condition can be established by using the above equation.

7.2 Proofs Relating to Impact of Total Budget

We begin by showing that $(E_c - e_c^*)$ increases in E_c. By the implicit function theorem,

$$
\frac{\partial \left(E_c - e_c^*\right)}{\partial E_c} = \frac{\lambda_2 + \lambda_{1E}}{\lambda_2}
$$

where λ_{1E} is the derivative of the first order condition with respect to E_c. Because $\lambda_2 < 0$ at e_c^*, the total derivative is positive if $\lambda_2 + \lambda_{1E} < 0$. It is easy to show that

$$\begin{aligned} \lambda_2 + \lambda_{1E} &= \alpha_0\alpha_1\gamma(\alpha_1 - 1)\gamma e^{2\gamma-2}[k_4(a_{0cc} + e^{\gamma})^{\alpha_1-2} + k_5(a_{0nc} + e^{\gamma})^{\alpha_1-2}] \\ &\quad +\alpha_0\alpha_1\gamma(\gamma - 1)e^{\gamma-2}[k_4(a_{0cc} + e^{\gamma})^{\alpha_1-1} + k_5(a_{0nc} + e^{\gamma})^{\alpha_1-1}] \end{aligned}$$

and since $\alpha_1 < 1$ and $\gamma < 1$ while all other elements are positive, we get that $\lambda_2 + \lambda_{1E} < 0$.[31] Thus, as the budget increases the candidate increases his spending on negative advertising.

Next we show that when E_c increases not only that $(E_c - e_c^*)$ increases but also $\frac{(E_c-e_c^*)}{E_c}$ increases which can be stated also as $\frac{e_c^*}{E_c}$ decreases. We show this using a contradiction.

Assume that $\frac{e_c^*}{E_c}$ is a *non-decreasing* function of E_c. Thus, when E_c increases, $\left(\frac{e_c^*}{E_c-e_c^*}\right)^{\gamma-1}\frac{\alpha_1\alpha_0}{\beta_0\beta_1}$ is non-increasing, since $\gamma < 1$ and $\frac{\alpha_1\alpha_0}{\beta_0\beta_1} > 0$. Recall that the FOC (eq. 3) is:

$$\left(\frac{e_c^*}{E_c - e_c^*}\right)^{\gamma-1}\frac{\alpha_1\alpha_0}{\beta_0\beta_1} = \frac{q_l q_c \tau_l \left(b_{0c,-c} + (E_c - e_c^*)^{\gamma}\right)^{\beta_1-1} + q_n\tau_n \left(b_{0n,-c} + (E_c - e_c^*)^{\gamma}\right)^{\beta_1-1}}{q_l q_c \tau_l \left(a_{0cc} + (e_c^*)^{\gamma}\right)^{\alpha_1-1} + q_n\tau_n \left(a_{0nc} + (e_c^*)^{\gamma}\right)^{\alpha_1-1}}$$

Since $\left(\frac{e_c^*}{E_c-e_c^*}\right)^{\gamma-1}\frac{\alpha_1\alpha_0}{\beta_0\beta_1}$ is non-increasing in E_c so is the right hand side (denoted h). Since $\beta_1 > 1$ and (as just shown) $(E_c - e_c^*)$ is a positive function of E_c the numerator of h is increasing. Hence, in order for h to be non-increasing, the denominator must increase. Since (by assumption) $\frac{e_c^*}{E_c}$ is non-decreasing in E_c, e_c^* must increase when E_c increases. Since $\alpha_1 < 1$, however, an increasing value of e_c^* causes the denominator to be decreasing and, hence, h to further increase. This produces the contradiction and proves $\frac{e_c^*}{E_c}$ is a negative function of E_c. Thus, as the budget increases the portion of negative advertisements increases.

7.3 Proofs Relating to Impact of Active Segment

We start by showing that $\frac{\partial(E_c-e_c^*)}{\partial q_l} > 0$. Substituting $q_n = 1 - q_l$ in eq. (2) and once again applying the implicit function theorem, we have

$$\frac{\partial\left(E_c - e_c^*\right)}{\partial q_l} = \frac{q_c\tau_l\lambda_{1c} - \tau_n\lambda_{1nc}}{\lambda_2}$$

[31] Note, that when $\beta_1\gamma < 1$, it is easy to show that $\frac{\partial e^*}{\partial E}$ is also positive. Intuitively, this implies that in absolute terms as budget increases, both negative and positive ads increase.

where we already know that $\lambda_2 < 0$. In the appendix subsection 7.3.1, we show that $\lambda_{1c} < 0$ and $\lambda_{1nc} > 0$. Since $q_c \tau_l$ is non-negative and τ_n is positive, we know that $q_c \tau_l \lambda_{1c} - \tau_n \lambda_{1nc} < 0$ and thus $\frac{\partial(E_c - e_c^*)}{\partial q_l} > 0$. Further, since λ_{1c} and $\lambda_{1,-c}$ are symmetric, we also know that $\frac{\partial\left(E_{-c} - e_{-c}^*\right)}{\partial q_l} > 0$.

Next we show that $\frac{\partial(E_c - e_c^*)}{\partial q_c}$ is also positive. Again, from the implicit function theorem, it is easy to show that

$$\frac{\partial\left(E_c - e_c^*\right)}{\partial q_c} = \frac{q_l \tau_l \lambda_{1c}}{\lambda_2}$$

Since $\lambda_{1c} < 0$ and $\tau_l > 0$, we get that $\frac{\partial(E_c - e_c^*)}{\partial q_c} > 0$ as long as q_l is non-zero. Finally, recall that $q_r = 1 - q_d$, so that

$$\frac{\partial\left(E_{-c} - e_{-c}^*\right)}{\partial q_c} = \frac{-q_l \tau_l \lambda_{1,-c}}{\lambda_{2,-c}}$$

Hence, by symmetry and the opposite sign on the numerator, we get $\frac{\partial\left(E_{-c} - e_{-c}^*\right)}{\partial q_c} < 0$ with the same restriction on q_l.

7.3.1 Proof that $\lambda_{1c} < 0$ and $\lambda_{1nc} > 0$

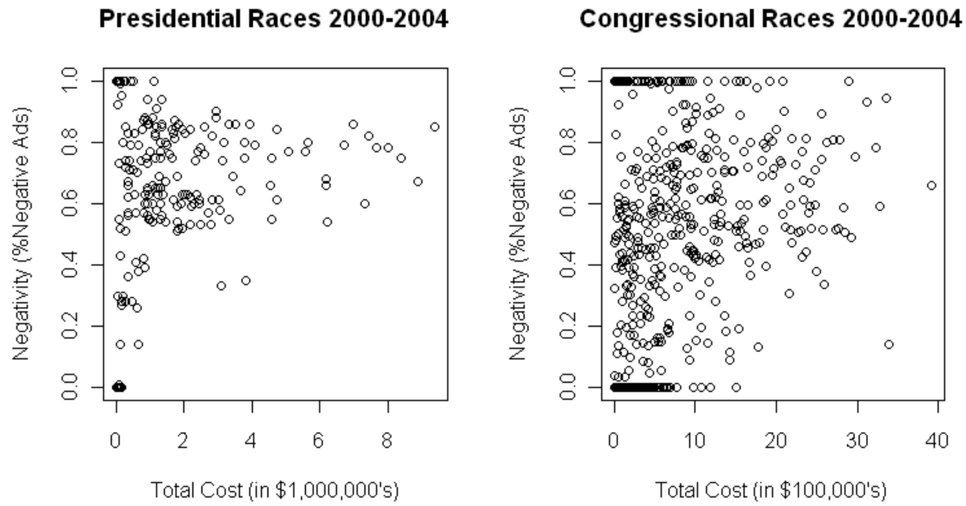
Notice that

$$\begin{aligned} \lambda_{1nc} - \lambda_{1c} &= \gamma \alpha_1 \alpha_0 \left(e^*\right)^{\gamma-1} \left[\left(a_{0nc} + \left(e^*\right)^{\gamma}\right)^{\alpha_1 - 1} - \left(a_{0cc} + \left(e^*\right)^{\gamma}\right)^{\alpha_1 - 1}\right] \\ &\quad - \gamma \beta_0 \beta_1 (E - e^*)^{\gamma-1} [(b_{0n,-c} + (E - e^*)^{\gamma})^{\beta_1 - 1} - (b_{0c,-c} + (E - e^*)^{\gamma})^{\beta_1 - 1}]. \end{aligned}$$

Since $\gamma \alpha_1 \alpha_0 \left(e^*\right)^{\gamma-1}$and $\gamma \beta_0 \beta_1 (E - e^*)^{\gamma-1}$ must be positive, the terms in brackets determine the sign of $\lambda_{1nc} - \lambda_{1c}$. Recall that by assumption $a_{0cc} > a_{0nc}$, $b_{0c,-c} > b_{0n,-c}$, $\alpha_1 < 1$, and $\beta_1 > 1$. This directly implies that $\lambda_{1nc} > \lambda_{1c}$. Finally, the first order condition is $q_l q_c \tau_l \lambda_{1c} + q_n \tau_n \lambda_{1nc} = 0$. This, in turn, implies that $\lambda_{1c} < 0$ and $\lambda_{1nc} > 0$.

7.4 Empirical Model and Estimation

We use the following specification for the proportion of negativity of party i (where $i \in \{d, r\}$) in market j (where a market is either congressional district or media market and $j = 1, ...J$) at time t (where $t \in \{2000, 2002, 2004\}$):



$$\widetilde{Negativity}_{ijt} = \theta_{1i} + \theta_{2t} + \boldsymbol{\theta}_3 \mathbf{X}_{ijt} + \xi_{jt} + \varepsilon_{ijt} \tag{4}$$

where the θ's are random parameters of interest: θ_{1i} is the party fixed effect, θ_{2t} is the time fixed effects, and θ_3 is the vector of parameters for the variables $\mathbf{X}_{ijt}$ (which includes the closeness variables, the variables introduced by our theory and the control variables). The ξ_{jt} are random effects for each combination of market and time and they are assumed to be i.i.d. and normality distributed. Specifically, $\xi_{jt} \sim N(0, V_1)$ where V_1 is a parameter to estimate. Of course, the model also includes the unobserved random variable ε_{ijt} which is also assumed to be i.i.d with a normal distribution. Furthermore, the model incorporates a heteroskedasticity correction based on Gelman, Carlin, Stern, and Rubin (2004). Specifically, the variance of ε, denoted by V_{2ijt}, is $V_{2ijt} = \sigma_\varepsilon^2 (H_{ijt}^2)^\varphi$, where σ_ε^2 is the variance scale, φ is the power function parameter, and H_{ijt} is the variable that we use to control for heteroskedasticity. The variable we use is Total Cost. Each advertising spot has an estimated cost based on the timing and market of the spot. We sum these estimated costs for each candidate and use that sum as the measure, *Total Cost*. As total cost increases, the variance of negativity decreases dramatically and particularly the frequency of 1's and 0's decreases to zero, as depicted in figure 7.4.

Note that $\widetilde{Negativity}_{ijt}$ is observed when $Negativity_{ijt} \in (0, 1)$ but unobserved when $Negativity_{ijt} \in \{0, 1\}$. We treat values of 0 as left censored and values of 1 as right censored and assume that the parametric form (i.e., equation 4) holds for both censored and uncensored data. This censoring is important for us to handle because a meaningful portion of our observations are all negative (16.7% in presidential data and 12.1% in congressional data) or not negative at all (4.5% in presidential data and 9.4% in congressional data).

To estimate the model, we use a Gibbs sampler with sampling blocks. The priors are as follows: diffuse normal mean zero priors for the linear parameters, diffuse inverted-gamma prior for the linear model variance, diffuse inverted-gamma prior for the variance of the random effects, normal mean zero random effects, and improper flat prior for the heteroskedastic power function parameter. The resulting posterior sampling blocks include the linear block of parameters (including the θ's and ξ_{jt}'s), the linear model variance, σ_ε^2, the augmented data, $\widetilde{Negativity}_{ijt}$, for the censored cases, the random effect variance, V_1, and the parameter for the heteroskedastic variance power function, φ. The implementation uses standard posterior sampling approaches for this type of model (see Gelman, Carlin, Stern, and Rubin 2004).

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