HOW QUICKLY WE FORGET:
THE DURATION OF PERSUASION EFFECTS FROM MASS COMMUNICATION

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ABSTRACT

Scholars do not usually test for the duration of the effects of mass communication, but when they do, they typically find rapid decay. Persuasive impact may end almost as soon as communication ends. Why so much decay? Does mass communication produce any long-term effects? How should this decay color our understanding of the effects of mass communication? We examine these questions with data from the effects of advertising in the 2000 presidential election and 2006 sub-national elections, but argue that our model and results are broadly applicable within the field of political communication. We find that the bulk of the persuasive impact of advertising decays quickly, but that some effect in the presidential campaign endures for at least six weeks. These results, which are similar in rolling cross-section survey data and county-level data on actual presidential vote, appear to reflect a mix of memory-based processing (whose effects last only as long as short-term memory lasts) and on-line processing (whose effects are more durable). Finally, we find that immediate effects of advertising are larger in sub-national than presidential elections, but decay more quickly and more completely.
Joseph Klapper’s classic argument that exposure to mass communication rarely causes significant opinion change is no longer persuasive to many scholars (Klapper, 1960). In the laboratory and in the field, multiple studies have demonstrated fairly large and seemingly consequential effects of exposure to mass communication.¹

A handful of recent studies, however, has found that persuasion effects can be quite short-lived, decaying in a few weeks or even a few days. Best known is the Texas advertising study, which found no persistence of persuasion effects in the week following exposure to the ads (Gerber, Gimpel, Green, and Shaw, 2011). But other recent studies show similar results. For example, Mutz and Reeves (2005) found that exposure to “uncivil behavior” on TV talk shows reduced the public’s level of political trust, but that trust bounced back to baseline levels in a follow-up survey.

Social psychologists have grappled for decades with findings that persuasive communication often produces only short-lived effects (Cook and Flay, 1978; Petty and Wegener, 1998). But most scholars of mass communication, perhaps too eager to show that early persuasion research as summarized by Klapper was wrong, have until recently paid little heed (Gaines, Kuklinski and Quirk, 2007, p. 6). This neglect has left large gaps in our understanding of the effects of communication. At what rate do persuasion effects decay? Can persuasion effects that are very short-lived affect behavior in the short period before they decay? What are, in Klapper’s classic question, the lasting effects of mass communication? These questions, which have hardly been raised, much less investigated, are the focus of this paper. We answer them with evidence on the effects of political advertising, but our analysis is framed in terms generally applicable within the field of mass political communication.

The paper begins with the theoretical observation that, in politics as in the rest of life, citizens

¹ For reviews, see Iyengar and Simon, 2000; Kinder 2003.
form opinions by one of two routes (Hastie and Park, 1986). In the first, memory-based evaluation, people express opinions on the basis of information available in memory when asked. In this model, the effect of persuasive messages is to create opinions that may persist only as long as the messages underlying them remain accessible in memory, which may not be long. In the second route, termed online-processing, people evaluate persuasive communication as they receive it, updating an online tally of overall opinion after each message and storing the tally in memory. In this model, opinion change can survive long after the message that caused it has been forgotten.

Both types of citizen “information processors” are likely to be present in most situations of mass persuasion. But because, as much evidence suggests, few citizens think carefully about the communications they encounter, memory-based processing is more common. Hence, two kinds of opinion change are expected to occur, a larger amount of short-term change and a smaller increment of more durable change.

Empirical investigation of this expectation requires a large number of opinion measurements over a lengthy time. We obtain the necessary data by linking media market-level advertising data with surveys of candidate preference during the 2000 presidential elections and in a set of gubernatorial, Senate, and House elections in the 2006 midterms. Testing effects of short-lived opinion on behavior requires data on actual voting. For this purpose we use county-level advertising and voting data from the 2000 presidential election.

Our main statistical models are from the extensive psychological literature on learning and forgetting (Rubin and Wenzel, 1996). Results from the presidential election show that, as expected from theoretical analysis, most persuasion effects decay quickly, but that small effects survive six weeks and perhaps longer. The half-life of persuasion effects in the 2000 election is about four days. Over the six-week period of our study, about half of the advertising effects that survived to Election Day were due to ads from the last week of the campaign and the other half were due to the accumulation of all surviving effects from the previous five weeks.

A separate estimate based on county-level data on the 2000 presidential election found that,
as in the rolling cross-section survey data, advertising produced mainly short-lived effects. Importantly, however, these short-lived effects carried over into actual behavior on Election Day. If we had found otherwise – if short-term persuasion effects did not govern even short-term behavior – it would indicate that the bulk of the communication effects that occur have little political importance.

Our final finding is that, in lower level races, advertising causes preference shifts that have half-lives of only one to two days and no discernible long-term survival.

These results entail a different view of the effects of mass communication than offered by either Klapper or contemporary scholarship. In our account, most communication effects are minimal in the particular sense that they are likely to be short-lived. But communication effects may be, and perhaps often are, held in place by a long-term flow of communication. Examples of such communication include ideological warfare between the parties (Zaller, 1996), uncivil political discourse (Mutz and Reeves, 2005, p. 12), war-time propaganda, “mainstream political norms,” and some political advertising. For such cases, the minimal effects thesis is wrong: Short-term effects become long-term effects – including behavioral effects – if the communication causing them is continuously present. Communication may also produce a small amount of durable change that, over a long period of time, can add up to a sizeable effect.

When, however, a long-term communication flow is not present, effects may be truly minimal. Examples are a one-time government report on the health of the Social Security Trust Fund (Jerit and Barabas, 2010) and a short-term advertising campaign (Gerber, Gimpel, Green, and Shaw, 2011), which did not produce lasting effects on opinion.

The paper has four parts. The first reviews research on the persistence of opinion change. The second describes data and methods, and the third reports the empirical analysis. The final section concludes the paper with the implications of our findings for the study of elections and, more generally, citizen learning from political communication.

**PERSISTENCE OF ATTITUDE CHANGE**
We begin our argument with laboratory and Internet research on basic mechanisms of attitude change. The major implication of this research for our study is that, under typical conditions of political persuasion, most but not all attitude change should be expected to decay fairly rapidly. In the next section we review leading field studies of attitude change. The major result here is that, for reasons that no field research has attempted to explain, rapid decay of the effects of mass communication is common.

_Laboratory and Internet studies of persuasion_

Most laboratory studies of persuasion by social psychologists in the 1960s and 1970s found that opinion change decayed rather quickly, usually within a few days or weeks. This gave rise to an effort to discover conditions that would produce durable change. Researchers tested whether opinion change was more likely to persist when subjects were: exposed to the message multiple times (Johnson and Watkins, 1971); heard the persuasive message from a “gruff and stern” voice (Schopler, Gruder, Miller, and Rousseau, 1968); were reminded on retest that the message had come from a high credibility source (Kelman and Hovland, 1953); required to write out their reactions to the persuasive message (Greenwald, 1968); confronted with the value-implications of their views (Rokeach, 1975); and told that peers thought that the message was convincing (Cook and Insko, 1968). Often these manipulations worked as expected to increase duration of change, but their strength and obtrusiveness underscore the difficulty of achieving lasting opinion change under ordinary circumstances. As Cook and Flay commented: “much of what has been labeled ‘attitude change’ in past experiments may have been nothing more than short-lived and situationally determined ‘elastic shifts’ in response” (Cook and Flay, 1978, p. 3)

Some 30 years after this observation, persuasive communication continues to produce “elastic shifts in response,” but scholars of mass communication regard them differently. Even when opinion change is found to be short-lived, scholars take it seriously as an expression of actual attitude change. This is related to a more fundamental theoretical development, as described by the social psychologists Wilson, Lindsey, and Schooler (2000):
In recent years, a different view of attitudes has emerged. Instead of viewing attitudes as stored evaluations of objects and issues, researchers have found that people construct on-the-spot attitudes on the basis of information that happens to be accessible at that point in time. Some researchers have argued that evaluations are so context-dependent that there is no such thing as a “true” attitude... Drawing on such findings, [one scholar] proposed that attitudes may best be viewed as the current state of activation of a connectionist system, rather than as evaluations stored in memory (p. 102-103).”

For most scholars, however, constructed attitudes have not displaced the more classic notion of attitude as evaluations stored in memory. Rather, both kinds of attitudes are assumed to exist side-by-side. Thus when a researcher elicits opinions from members of a large population, she may get a mix of constructed opinions and retrieved evaluations.

Leading studies of attitude change posit “dual process models” to account for the different kinds of attitudes that may form. One is the memory-based versus online model of attitude formation, as outlined earlier. The key variable in this model is effortful processing of information (Hastie and Park, 1986). If subjects expect, after receiving a message, to make an evaluation of a particular object, they weigh each bit of evidence as they receive it, adjusting an online tally up or down and storing the resulting evaluation in memory. But if surprised by the need to make an unexpected evaluation, they construct an opinion from whatever information they can recall. There is no expectation that memory-based evaluations are stored in memory.

The most prominent of the dual process models of attitude change is the Elaboration Likelihood Model (ELM) of Richard Petty and John Cacioppo (1986). As in the Hastie and Park formulation, the subject’s motivation for effortful information processing is critical. If subjects find the topic of persuasive communication to be engaging, they elaborate the messages they receive, evaluate their elements, and adopt new attitudes as indicated. Lacking such motivation,
people attend only to peripheral aspects of the message, such as the number of arguments or the credibility of its source, and express opinions on this basis. Petty and Cacioppo reason that the former kind of message processing is more likely, *inter alia*, to result in a new attitude that is stored in permanent memory. Petty and Cacioppo favor the terms “weak” and “strong” attitudes to the terms “constructed attitudes” and “online tallies,” but the two sets of terms are based on similar causes and effects – effortful vs. non-effortful processing, and storage and non-storage in long-term memory. In effect, the leading dual response models repackage some of Cook and Flay’s “elastic response shifts” as a kind of genuine opinion change (in the form of weak or constructed attitudes).

The dual process models raise two important questions for our analysis. The first is whether changes in memory-based (constructed) attitudes can influence actual behavior. To our knowledge, no one has demonstrated that they can. We must therefore argue from theory. On one hand, one might argue, in the language of Cook and Flay, that attitude change in the form of newly constructed attitudes is a situationally induced response shift that will likely disappear when the stimulus that caused it has been removed. This view, however, may be outmoded. In the constructionist view that many researchers now favor, all attitudes are more or less situationally induced, and the only question is which cognitions are accessible in memory. With more effortful processing, cognitions from persuasive communication become more deeply embedded in what psychologists call associative networks and therefore remain available to influence behavior over a longer time. New cognitions that have been subjected to less effortful processing do not become as deeply embedded and are therefore less likely to be recalled after a long time has passed, but in the period in which cognitions, however processed, do come to mind, they may still guide behavior.

The second key question raised by the dual process models is relative prevalence of effortful

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2 In a review of evidence on this point, Petty, Haugtvedt, and Smith argue that strong attitudes are more likely to persist than weak attitudes (1995, p. 100 – 108). But the number of studies reviewed is small and, as the authors note, some have validity problems. Even in psychology, duration of opinion change appears to be a peripheral concern.
versus non-effortful processing of messages in typical situations of mass persuasion. In two high profile papers, Milton Lodge and colleagues have argued that, as regards candidate evaluation, effortful processing predominates over less motivated processing (Lodge, McGraw and Stroh, 1989; Lodge, Steenbergen, and Brau, 1996). The procedure in the 1996 study is to ask subjects to state their own views on a set of issues, read a list of positions of fictitious candidates on these issues, and (after delay) evaluate the candidates. But just before the delayed evaluation of candidates, subjects are asked to recall as many candidate positions as they can. The key test is then whether subjects evaluate the candidates on the positions they have been able to remember, or on the full set of positions they have read. It turns out to be the full set.3

This striking finding strongly supports the notion that subjects kept an online tally when initially reading the candidate positions and used it as the basis of their evaluations. The conclusion that citizens behave similarly in real world election campaigns is, however, open to question. As a basic matter, laboratory studies have limited value for establishing the population frequencies of the mechanisms they examine.

One unrealistic feature of the Lodge studies is that subjects read candidate positions all at once. In a recent study, Mitchell (2012) repeats the basic Lodge procedure, but runs the study over several weeks, providing a new candidate position each week and getting a new evaluation. She finds that subjects’ response to each week’s new issue position dominates evaluations, overriding effects of previous issue positions. Under more realistic conditions, then, memory-based processing prevailed over online processing4

Recent experimental evidence from outside of electoral politics also suggests the limited prevalence of online processing under more natural conditions. Focusing on attitudes toward

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3 Lodge, Steenbergen, and Brau find a small effect from recall for one of the two candidates, but the effect of the full set of positions was dominant (see Table 2). The study included an experimental manipulation, but it did not figure in these results, which we take to be their key results.

4 Mitchell reports that her subjects did maintain an online tally summarizing reaction to previous stories; they didn’t, however, use it in making weekly evaluations, relying instead on information from the current week’s story.
urban growth in an Internet sample, Chong and Druckman (2011) found that strong arguments produced opinion change that mostly decayed on follow-up 21 days later, with this important exception. Subjects took a “Need for Cognition” test to measure disposition for effortful processing of arguments they encounter. The small number who scored at the highest level of this Need for Cognition exhibited durable attitude change, as consistent with the online model, but the majority formed attitudes that decayed rapidly. Thus, while online processing of communication can occur and produce durable effects, it is not the dominant mode of information processing.

Taken all together, results from dual process models give rise to our key theoretical expectation: Most attitude change in response to mass communication, because based on non-effortful processing, will decay quickly, but some, because based on effortful processing, will persist.\(^5\)

An important wrinkle is that the mix of people available for persuasion is likely to be different in different contexts. All of the candidate evaluation studies mentioned above ask subjects to evaluate fictitious candidates – that is, candidates about whom subjects have no prior opinions. All subjects are therefore available for persuasion. But in field studies of persuasion, research does not usually begin at the point at which everyone is a blank slate. This is certainly true for the cases we examine -- the last two months of a presidential campaign and the last weeks of a set of Governor, Senate, and House races. For cases like these, citizens who are habitual online or central route processors – often dubbed by political scientists as issue voters – are likely to have preferences before the study begins; those available for persuasion are likely to consist disproportionately of less motivated, memory-based evaluators.\(^6\) These considerations

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\(^5\) In studies that do not distinguish on-line from memory-based processing, the typical pattern is rapid decay of persuasion effects (Gaines, Kuklinski, and Quirk, 2007). A study following this pattern but not cited is de Vreese (2004, p. 203). However, an exception is an experiment in News that Matters, which checks for and finds duration over a one-week period (Iyengar and Kinder, 1987, p. 25-6, 44).

\(^6\) Late deciders in elections are likely to care less, know less, and be less educated, all of which traits would incline them toward less effortful processing (Campbell et al., 1960)
strengthen our theoretical expectation that, for the candidate data we shall study, most preference change in response to mass communication will decay quickly and that only a small amount will persist.

**Field studies of political persuasion**

Most field studies do not examine the duration of communication effects, sometimes because they cannot. For example, the path-breaking Fox News study by Della Vigna and Kaplan (2007) could not show how long Fox’s pro-Republican effect would continue if Fox were to cease broadcasting. But when field researchers can and do test for the decay of communication effects, they find substantial amounts of it.

The most sophisticated field study to measure the duration of persuasion effects is, to our knowledge, Shaw’s (1999) study of presidential campaign events, such as scandals and major speeches. He finds that most produce slight or fleeting effects on candidate preference, but some create effects that persist over the 10-day window he studies. Presidential debates are a leading example of the latter, but their significance is unclear. First, Shaw does not show a debate (or any other) effect that lasts until Election Day; second, he notes that the appearance of a durable effect may be due to continuing media coverage, declaring who has won or lost and why, rather than to durability per se.

Studies of political advertising make clear that the effects of ads decay over time, but none pins down the rate of decay. In one study, Johnston, Hagen, and Jamieson (2004) aggregate advertisements by blocks as short as five days, a procedure that implies, but does not prove, substantial decay of effects. But in another study, Huber and Arceneaux (2007) aggregate advertisements over a 30-day period, and in still another, Franz and Ridout (2010) aggregate ads in blocks of one, two, and multiple months. The Texas advertising study aggregates data by the week and finds no evidence that any effects survive from one week into the next. But we know from the other studies that advertising effects survive at least a day or two – else there would be
no effect on Election Day – and the Texas study gives no estimate of what this survival period might be.

Even taken altogether, these advertising studies leave wide gaps in our knowledge: Do ads have individually tiny effects that cumulate over the course of the campaign into large effects? Or do only ads close to Election Day have important effects? Do very early ads matter at all? From several points of view – knowing when to buy advertising, understanding elections, or assessing voter competence – one would like to answer these questions.

In a markedly different kind of election study, Healy, Malhotra, and Mo (2010) find that victories by college football teams on the weekend before elections boosted vote share of incumbent candidates by about one percentage point, but had no effect at longer delays. The authors interpret their findings to mean that incumbent support is higher when feelings of personal well-being are higher. For our purposes, the key points are that the football effect decays rapidly, and that, though presumably due to non-effortful memory-based processing, the football effect was able to govern an important political behavior.

We have located two other studies of mass persuasion that include estimates of the duration of the effects. Each finds that reports of casualties during the Iraq War reduced popular support for the war, but that support bounces back. Hayes and Myers (2009) find that the negative impact on war support lasted about 30 days; Althaus, Bramlett, and Gimpel (2012) find that the half-life of the effect is about 30 days.\footnote{This is our eyeball estimate from Figure 4a. Althaus et al. report effect sizes at lags of 14, 28, 42, 56 days, plus an estimate for all days, but do not report an initial impact.}

Summary

Laboratory studies show that persuasive communication tends to produce durable opinion change when subjects have been induced to engage in effortful processing. But most evidence also indicates that relatively few people habitually engage in effortful processing. Hence we should expect that, under the uninvolving conditions of mass persuasion, some persuasive effects will be durable, but most will be short-lived. Field studies show rapid decay in the effects of
mass communication, but do not estimate the rate of decay or determine whether any long-term change occurs.

Data and Methods

Overview of data

The data for our study come mainly from rolling cross section designs of the kind pioneered by Johnston, Blais, Brady and Crete (1992), in which independent samples of potential voters are polled over each day of a multi-day survey. Ads that have run up to the day of interview in the respondent’s market constitute our persuasive message.

The data for our first study are roughly 12,000 respondents from the 2000 National Annenberg Election Study (NAES) who were interviewed by telephone between September 1 and Election Day, the period of the traditional fall presidential campaign. NAES was designed as a representative sample of the general population, and despite lower-than-desirable response rates, demographics of NAES respondents match up reasonably well with U.S. population characteristics.

The advertising data for the 2000 analysis cover advertisements aired on broadcast television, collected by the Campaign Media Analysis Group (CMAG), for the 75 largest media markets in the United States, which cover more than 80 percent of the U.S. population (see Goldstein and Freedman 2000). We use the replication dataset of Huber and Arceneaux (2007).  

The data for our study of 2006 elections are from the 2006 Cooperative Congressional Election Study (CCES), an Internet survey conducted during October and November of 2006. CCES was administered by the survey research firm, Polimetrix, Inc. Interviewed respondents were selected from the Polimetrix PollingPoint Panel using sample matching (Rivers and Bailey 2009; Vavreck and Rivers 2008). The interviews we analyze were fielded between October 13 and November 7 (Election Day), 2006.

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8 We rescaled the data to make ad volumes comparable to those reported by Shaw (2006); that is, we divided by 10.
9 Quality of Internet samples has been challenged and defended (Malhotra and Krosnick 2007; but also see Sanders, Clarke, Stewart, and Whitely 2007; Hill, Lo, Vavreck, and Zaller 2007).
The CCES survey data used in this study are from a module purchased by teams at [REDACTED] and [REDACTED]. The 3,002 respondents in our CCES module are drawn to be representative of nine media markets in five states: Illinois, Indiana, Michigan, Minnesota, and Ohio. The limited set of media markets was chosen for reasons of an unrelated research project with content analysis. To these survey data from 2006 we append campaign advertising data purchased directly from Nielsen, Inc. for all Governor, Senate, and House races in these markets. These data enable us to study advertising in up to three races for many of the 3002 respondents.

Rates of advertising in both studies are denominated in Gross Ratings Points (GRPs). GRPs are defined as “reach” multiplied by frequency. Given this definition, an ad that runs for 100 GRPs is expected, on average, to be seen one time by 100 percent of targeted households in its media market; an ad with 500 GRPs is expected, on average, to be viewed five times in all target households, and so on. Two comments are in order here. First, to achieve 500 GRPs an ad would need to air many times on many stations and time slots; it would not air just five times. Second, the GRP-metric is obviously approximate; ads will be seen more often in some households than others and, depending on media consumption habits, may not be seen at all in some.

For ease of understanding, we discuss advertising in this paper in units of expected ad viewings per household in the target population. Thus, if one candidate airs 500 GRPs more than another, we will say that she has an advantage of 5 ad viewings. We denominate advertising in our regressions in units of GRPs/100 to facilitate similar interpretations.

Our survey respondents are mainly interviewed during the evening. We would like to link each respondent to ads that have run in their market up to the exact time of interview and ignore other ads. Unfortunately, our GRP data are summed over the calendar-day, which creates errors in our measure of ad exposure. For example, some respondents (mainly in the Internet survey) complete their interviews between midnight and 3 a.m.; these people may have seen many ads over the course of the previous evening, but few or none on the calendar day on which they take

\[^{10}\text{Where “reach” is the percentage of the target population that sees an ad at least once.}\]
their survey. We can significantly ameliorate but not eliminate this problem. We begin with the assumption that most exposure to campaign advertising begins at the time of the late afternoon local news and continues through the primetime evening. Respondents who complete interviews between 5 p.m. and midnight are then coded as potentially exposed to ads from the entire calendar day of their interview. The few people who complete interviews between midnight and 3 a.m. are assigned to ads from the previous calendar day. We code respondents who complete their interviews between 3 a.m. and 5 p.m. as exposed to no ads on their calendar-day of interview, since they complete their interview before the main period of prime-time advertising begins.\footnote{If we code advertising exposure strictly by calendar day, results degrade somewhat, but the main patterns remain.}

Figures 1 and 2 give an overview of our advertising data. Figure 1 shows the daily number of average ad viewings by targeted households in the last three weeks of the one presidential, five governor, four Senate, and 60 House races in our study (on a log scale). In the Bush-Gore contest, the candidates together bought close to 40 ad viewings per capita, per day in battleground states. Most sub-national races had much less advertising than the presidential election and often none at all. In the most intense sub-national races, advertising was one fifth that in the presidential battlegrounds of 2000. This would be 40 presidential ads per day, or eight ads per hour, or one or two ads during each commercial break. In the most intense sub-national race, by comparison, the average viewer would see roughly two ads per hour, or one ad every third break.

(Figures 1 and 2 here)

Figure 2 shows average ad viewings by day and party for candidates in four competitive races over the last six weeks of the campaign. For the Bush-Gore race, we show advertising in CNN-defined battleground states. We also examine two nationally visible House races from our 2006 sample: The Illinois 2\textsuperscript{nd}, which paired Peter Roskam and Tammy Duckworth for the seat vacated by Henry Hyde; and the Ohio 15\textsuperscript{th}, which was between Republican incumbent Deborah
Pryce and challenger Mary Jo Kilroy. We also show totals for the one close gubernatorial contest in our set, the Wisconsin battle between Democrat Jim Doyle and Republican Mark Green. (Note that the scale of the y-axis is different in the Bush-Gore race than in the other three.)

An important point in Figure 2 is that ad volumes tend to increase in the last weeks of the campaign. Indeed, one of the sub-national races had little advertising in the early weeks of the campaign. This lack of early advertising makes it difficult to identify long-term ad effects in sub-national races, as we discuss further below. Note also the jagged pattern of on- and off-advertising in all races; this reflects weekend lulls, which help to identify decay effects in these races.

A final preliminary point about the data involves respondents’ use of television. The 2000 survey has no overall measure of TV use, but does ask people how many days a week they watch local, national, and cable news programs. About seven percent of the subjects gave a response of 0 to all three questions, which we use in some of our analysis below. The 2006 study asks whether respondents have a TV; we limit analysis of the 2006 data to the 98.8 percent of respondents who do.

The response model

Existing research on persuasion provides scant guidance on how to model the decay of advertising. Accordingly, we begin our analysis with an open-minded examination of the data to determine, as best we can, the basic pattern of decay. More specifically, we aggregate daily advertising into blocks of various lengths and lags – e.g., effect of first 20 days of ads versus effect of next 20 days – and test the blocks against one another. Having learned from these results the general pattern of decay, we fit several closed-form models to the data, evaluating results in light of the more open-form analysis.

The response model in our analysis is an ordered probit in which the dependent variable is pre-election preference for the Democrat, neither candidate, or the Republican. We discard respondents who express preference for a third party, say they will not vote, or have cast an early
ballot at the time of interview. We use the difference in the sums of logged candidate ad viewings at the media market level on a given date as our principal independent variable. Our models control for standard covariates, including party attachment and county-level presidential vote in 1996. Methodological issues pertaining to these specifications are discussed in the Appendix. We show there that our results are robust to various alternatives.

Campaigns produce other kinds of communication besides advertising for which we try to account. The first is news. To control for streaks of good and bad news (e.g., candidate Bush’s drunk driving arrest reported late in the 2000 campaign), we employ fixed effects for each week. A second is the ground campaign, a combination of phone calls, canvassing, and mailings. As Huber and Arceneaux (2007) have pointed out, the effects of ground campaigns are collinear with advertising and may lead to inflated estimates of advertising effects. Their solution is to estimate effects in non-battleground states in which ground campaigns do not occur. We replicate our results with this strategy to demonstrate robustness, but our main strategy is to rely on the fact that ground campaigns generally operate in the last days of campaigns. To capture ground campaign effects, we use Fixed Effect terms for each DMA in the last 14 days of the campaign. This strategy avoids the substantial loss of cases, and the attendant loss of precision, of the Huber and Arceneaux method. For confirmatory purposes, we then estimated the same models in non-battleground states, relying, as Huber and Arceneaux did, on spillover advertising from adjacent media markets to obtain causal identification. These results, which are similar to our first results except for larger standard errors, are presented and discussed in the Appendix.

In the 2006 House races, in which each media market contains multiple contests, we use a fixed effect for each race; these terms capture the net effect of all candidate-level differences,

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12 Controls are: gender, race, age, income, education, political information, party identification, a PID and political information interaction, Republican vote share in the respondent’s county from 1996, Perot vote share in respondent’s county in 1996, church attendance, fixed effects for interview week, media market, and state separately, and indicators for “don’t know” responses on the income and church attendance variables.

13 Results are unchanged if instead we use fixed effects for the last four, seven or 10 days.
including incumbency advantage, and potentially capture average advertising advantages, which could lead us to underestimate the net effect of the advertising, a conservative bias. In the governor and Senate contests, we employ state fixed effect terms. Finally, we use a set of media market fixed effect terms across all 2006 races. Our data contain insufficient power to control for ground campaigns in the sub-national races. However, we note that our main finding in these races – large but very short-lived ad effects – cannot be explained by other campaign efforts unless those efforts co-vary, day-by-day, with advertising rates, which is unlikely to be the case.

**Main Results**

*Overview of effects using ad block models*

We begin with simple models of advertising in the 2000 presidential election. Table 1 presents the effects on vote preference of ad blocks of different lengths, where each block is a sum of the difference in logged ads in the period indicated. The table presents results only for the ad variables, but all models contain the standard set of controls.\(^\text{14}\)

(Table 1 here)

In column 1, ads are broken into two groups – those running on the day of interview and those running over the previous 42 days. Coefficients for the ad variables are statistically significant and, as a separate matter, statistically different from one another, thus showing that very recent ads have more effect than less recent ones. The difference, moreover, is large: Ads on the respondent’s day of interview have 38 times more impact, viewing for viewing, than do ads run over the previous six weeks.

As noted, about seven percent of respondents report zero exposure to TV news, which we take as a proxy for very low rates of TV use. As a placebo test, we examine the effect of advertising on this subset. As columns 2 and 3 show, presidential ads affect only those who report heavier TV use, suggesting that our specification captures, as intended, the effects of TV...

\(^{14}\) Full model results available in the Appendix.
advertising rather than political activity that may be associated with it.

Our results so far are based on crude division of ads into only two time periods, day of interview and all previous days. Results in columns four to eight of Table 1 ("TV news viewers only") employ ad blocks of varying length to provide a finer-grained view. Results continue to show that ads running on the day of interview have a larger effect than ads from only a few days earlier. But while the table shows that initial ad effects fall off quickly, the effects of ads do not continue in freefall. For example, estimates in column six show that the impact of ads from the 10 days prior to interview is only modestly larger than the impact of ads from days 11 to 42 days before interview. Ad effects thus seem to undergo rapid initial decay, followed by a long period of much slower decay. Standard errors here are large, but our more structured decay models below confirm that the pattern is real. We would like to test still finer divisions of the ad flows, but when more than three ad blocks are specified, we get irregular patterns that seem unlikely to reflect real trends in the data (see column 7).

These results are consistent with the expectation that advertising would produce mostly short-term effects and some long-term effects. Because, however, these results have been obtained from simple block models, we defer detailed consideration of this issue until later.

Next, we present an overview of ad effects in the 2006 sub-national elections.

**Ad decay in sub-national elections**

Most of the 3,002 respondents in the 2006 CCES midterm study voted in three separate elections – for governor, Senate, and House of Representatives. The size of the sample is too small to permit reliable estimation of ad effects in each type of election, so we stack the data into one dataset having a total of 7,400 cases. We present results in the same form as the 2000 results in Table 2; full results are in the Appendix.

![](Table 2 here)

Results from models of the 2006 data are comparable to results from the presidential data in

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15 The basic pattern of ad effects is similar within each type of race.
that effects of ads on the day of interview are consistently larger, and usually much larger, than effects of less recent ads. However, results from the presidential and non-presidential data differ in two ways. First, the effects of ads from the day-of-interview are larger in the 2006 data than in the 2000 data (compare column one of Table 1 and Table 2). This difference is short of statistical significance, but is substantively large. Second, advertising effects decay more rapidly in the 2006 data. Indeed, the 2006 data offer essentially no evidence that persuasive effects last beyond five days and slight evidence that long-term effects may be negative. These findings are consistent with those of Gerber et al., who found no evidence that ad effects in a state gubernatorial primary lasted as long as a week, the lag period of their study.

The block model results in Tables 1 and 2 are imprecise, but more restrictive models of impact and decay continue to support the two main patterns they disclose: Very recent ads have much more effect on current preference than more distal ads, and advertising effects are initially larger but decay more rapidly in sub-national elections compared to the presidential one. These results are what we might expect if voters were engaged in mainly peripheral or memory-based processing of communication, but not what we would expect from central or online processing.

Having developed a sense of the rate of ad decay from the block models above, we turn now to closed-form models of decay based on known statistical distributions.

*Decay Models*

Rubin and Wenzel (1996) provide an excellent review of models for fitting the decay of memory for simple facts and words, e.g., nonsense syllables that laboratory subjects have been asked to learn. (No one, to our knowledge, has made a comparable study of models for studying the decay of persuasion effects.) We considered the set of four models which they identified as

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16 We are skeptical that the long-term effect of ads in these races is negative or zero, as the data weakly suggest. Although we are using ad data from up to 42 days prior to each interview, few races were competitive enough to deploy long-term advertising. This means that, in contrast with presidential elections, we have little leverage for identifying long-term effects and their decay; the perverse coefficients should be viewed in this light.
best performers (p. 750):17 The logarithmic, power, hyperbolic-power, and Weibull functions.18 We present each function in Table 3, along with the exponential form, which is widely used (e.g., Lodge et al, 1995). In each model, the parameter $I$ specifies the impact of advertisements on vote choice, and $d$ specifies the decay of that impact as time ($t$) passes. Each day’s net advertising – that is, log of Republican ad viewings (plus 1) minus the log of Democratic ad viewings (plus 1) – is weighted by the value of the decay function on its day, summed across all days into a summary ads variable, and made to affect vote choice via an ordered probit response function. The $XB$ terms refer to the set of control variables and fixed effects described earlier. All functions are monotonic and have an asymptotic value, which are desirable properties in decay functions. 

(Table 3 here)

The four functions have distinctive mathematical properties. For example, the logarithmic function specifies that decay occurs in ratios of time, such that a change from day 1 to day 2 is the same as change from 10 to 20. The exponential specifies that a fixed proportion of an ad’s impact decays within each time period. Our aim in the analysis below is to identify the function(s) that best capture whatever pattern of decay may be present in our data.

Estimates of key parameters from these models are shown in Table 4 for the 2000 presidential contest and Table 5 for the 2006 sub-national contests. We plot graphical representations of survival rates of advertising influence, based on the tables, in Figures 3 and 4.19 The graphs show the percent of ad impact from each lagged day (1 to 42) that survives at Day 0, the day of interview. However, these survival rates say nothing about the size of the initial effects, which we shall examine separately below.

(Tables 4 & 5, and Figure 3 here)

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17 They actually identify five top models, but two are close cousins, so we dropped the weaker of this pair.
18 Rubin and Wenzel refer to this function as the exponential-power, but it is better known to political scientists as a variant of the Weibull function.
19 Estimation of the hyperbolic power model would not converge in either dataset.
We begin with survival rates of presidential ad effects, as shown in Figure 3. The results suggest that (depending on the function) about five to 10 percent of the impact of ads aired 42 days before Day 0 survives and affects preference at Day 0. But differences across the functions are substantial. Using the exponential function, we estimate the half-life of advertising is 11 days, while using the power function we estimate the half-life of advertising at 2 days. (Half-life values can be seen by projecting a horizontal line from the value of .5 on the y-axis). According to the estimate from the exponential-power function, 80 percent of an ad’s initial impact is gone after three days; yet results based on the logarithmic and exponential functions suggest that this point is not reached for 28 days. These differences bear out a warning by Rubin and Wenzel that results can “depend in dramatic ways on the function used” (p. 753).

So which function to use? The purpose of the earlier block models was to develop a view of the data relatively free of modeling constraints. The conclusion was that decay was rapid in the first days after ads appear and then flattens out. Graphical results from the power and Weibull functions best fit this pattern. The statistical results in Table 4 favor the same two models, showing slightly higher log likelihoods for them.20

We turn now to results from the gubernatorial, Senate, and House elections in Figure 3. The results show, as in the block model analysis, very rapid decay and scant evidence of long-term survival of ad effects. (Again, the results pertain exclusively to rate of decay and not at all to size of effect.) Yet, as with the presidential ad data, results differ by functional form of the model. The power, Weibull, and exponential functions estimate the most rapid decay, with no effect lasting longer than about five days. This pattern is broadly consistent with the earlier block model analysis.21 The regression statistics in Table 5 show that the exponential form fits the data slightly better than the others, but, from Figure 3, one can see that the exponential generates essentially the same fit as the power and the Weibull.

20 No likelihood ratio test is necessary for this comparison because all decay models have the same number of parameters.
21 The logarithmic function finds that ad effects survive about 10 days, but fits the data poorly, pushing survival rates into negative territory after about 12 days.
Recall that, in the block models, decay appeared more rapid in the 2006 elections than in the presidential election. This pattern is also present in results from the closed-form models. For example, decay in the power function model of the midterm data is 1.93 (se=.86) and .62 (se=.29) in the presidential data.\textsuperscript{22}

In each set of elections, then, effects of advertising decay very rapidly in the first few days, as would be expected if most voters were making memory-based evaluations that are not stored in long-term memory. In the case of presidential advertising, however, the rate of decay slows after a few days and never reaches the asymptote of complete decay. This long-term survival is the pattern that would be expected if some citizens were processing ad messages via the central route or online model.\textsuperscript{23}

There is little evidence of durable change in the sub-presidential elections. Note, however, that our decay functions are capable of tracing a pattern of complete overnight decay if the data so indicated; what the results instead show are effects that rapidly extinguish over about five days. This pattern is qualitatively similar to the pattern from the more open form models in Table 2.

We turn now to the size of ad effects, which is estimated separately from decay rates. 

\textit{Size of Ad Effects}

Because the heaviest advertising occurs in the most competitive races, most advertising simply cancels out other advertising. Imbalances do nonetheless occur, and in this section we simulate a hypothetical campaign in which one candidate continuously runs two ad views per day for six weeks and the other runs one ad view per day. These values are mid-range for 2006 midterm races but below the level of the 2000 election (see Figure 1). In a later section, we

\textsuperscript{22} A statistical test involving this difference is reported below. 
\textsuperscript{23} From the derivative of the best fitting Weibull function, one can see that if the Impact and Decay coefficients are positive (as they are), \( f'(x) \) is always negative and \( f''(x) \) is always positive. This means that the functions are strictly decreasing and convex, which is to say that the rate of decay is always increasing, but at an increasingly slow rate.
simulate effects with values from real campaigns, including the last week of the 2000 presidential election.

The left panel of Figure 4 shows the effects of two simulated campaigns, as these effects survive to the day of interview.24 One simulation is based on coefficients from the presidential election (dashed line) and the other on coefficients from sub-national elections (solid line). As can be seen, the effect of our 2-1 ad advantage in a presidential election, as measured on the day of interview (Day 0), is about .5 percentage points of vote share for the favored candidate. The same-day effect of this 2-1 advantage in a sub-national election is about 2.5 points. Thus, the day 0 impact of ads is greater in sub-presidential elections by a factor of five, a difference that is significant at the .05 level.

(Figure 4 about here)

We saw earlier that decay is more rapid in sub-national races. Close examination of Figure 4 confirms that result: The (dashed) impact curve for ads that survive to Day 0 from Days 10-42 in presidential elections is higher than the (solid) curve for ads from Days 10-42 in sub-national elections, a mean difference that is also significant at p < .05 on a non-parametric bootstrap test.

If presidential ads have less initial effect than ads in sub-national races, but also longer lasting effect, the question arises: In which type of election is the total Election Day effect of ads greater?25

To estimate the total impact on Election Day of a 2-1 advertising lead over the period of study, we sum impacts for each day from Day 1 to Day 42 that survive to Day 0. (Because ads do not usually run on Election Day, we omit Day 0 ads from the calculation.) These total impacts, from the top panel of Figure 4, are 2.9 points in presidential elections and 2.6 points in sub-national elections.26 These results show that a substantial advertising advantage in either

24 The simulation calculates the marginal effect for a respondent whose baseline probability of voting for the first candidate is .5.
25 A significance test of differences in the coefficients in Tables 4 and 5 does not strictly bear on the difference in effect sizes because of differences in cut-points of the models.
26 The non-parametric bootstrap estimates of the standard errors are 1.14 and 1.30.
presidential or sub-national elections can have a potentially decisive impact. 27

(Insert Table 6 about here)

Advertising is, of course, only one influence on vote choice, and far from the biggest. As in all partisan elections, the partisan, ideological and group attachments of voters have large effects. For example, 82 percent of self-identified Republicans voted for Bush in 2000, while 83 percent of Democrats voted for Gore. Effects of partisanship in sub-national elections are almost as large. Yet, large as they are, they leave plenty of room for advertising to have important effects, as we have just seen.

A final point: previous field studies have measured opinion change in a single estimate of both short- and long-term impacts. Table 6, however, breaks the total effect into unique short-term (ads from previous week) and long-term (ads in weeks two to six) effects. For presidential advertising, the effect of an advantage of two ads to one in the last week before interview is roughly equal to the cumulative effect of these ads from the previous five weeks – about two percentage points for each set of ads.

Note, however, that the long-term effect rivals the short-term effect only because messages have run continuously over the whole six-week period. If the effect of a single ad were measured in week one and week 6, it would be greatly larger in week one. Table 6 does, however, make the important point that, in situations of continuous information flow, small long-term effects can cumulate into a significantly large impact. Meanwhile, for sub-national advertising, there is no evidence of a long-term effect.

27 We note that our estimate of short-term ad impact in Governor, Senate, and House elections is close to the estimate from the state gubernatorial primary contest of Gerber et al. They tested the impact of ad buys of 1,000 GRPs per week or, in our units, 1.4 ad viewings per day on average (10 ads a week divided by seven days). Their estimated impact was about five percentage points, which they took to be constant over the week-long period in which they surveyed voters. We calculate the comparable effect in our modeling framework as the effect of seven days of exposure to 1.4 ad viewings per day from one candidate and none from the other, as measured on the seventh day. This effect, as calculated form the best fitting model in Table 5, is 8.07 points (with a standard error of 2.41). About half of this eight-point effect would carry over to the eighth day.
Does Very Short-term change have behavioral effects?

We come now to a central question in our analysis: Do short-term and most likely memory-based evaluations have behavioral consequences? More pointedly, do vote intentions, as reported in rolling cross section surveys, represent actual preferences, or just politically irrelevant survey behavior? We are able to provide a direct test of this question. We use aggregate data from Secretaries of State offices and map county-level voting returns from the 2000 presidential election into media markets.28 Using these election returns instead of survey data, we test whether ads run on the last day of the 2000 presidential campaign had the same effect as previously run ads -- or, as in our survey analysis, much more effect – on actual voting behavior, rather than reported attitudes. The model in this test is as similar as we could make it to the models used above. The most important difference is that, because we have only one vote observation per media market, we cannot deploy market-level fixed effects; however, we have used state fixed effects to capture state-level differences in campaign activity.

(Table 7 here)

The key results are in column 2 of Table 7, which show that ads aired on the day before Election Day in 2000 had about 28 times more impact (.83) – viewing for viewing -- than ads aired in the previous 42 days (.03). This ratio is consistent with the ratio for day 0 to day 1-42 in column 1 of Table 1.29 Results from other specifications with different ad-blocks are also in line with survey-derived estimates of decay.30

In the survey analysis, respondents interviewed at different times in the fall campaign were always most responsive to the ads that had run just before their particular interview. This

28 We use the replication dataset from Wand et al., 2001.
29 Coefficients themselves cannot be directly compared because the forms of the response models are different, OLS and probit.
30 We obtain the following next-day estimate for a county in which one candidate runs two ad viewings and the other runs one: a .34 point impact (standard error of .09). The individual-level estimate (from the Weibull model) gave an impact of .22 points (.07). The county data suggest a bigger next-day effect than the survey data, however, given the uncertainty of the estimates they are best regarded as comparable.
implied that ad-driven opinions were mostly very short-lived. But would people actually vote on the basis of these short-lived opinions? Results of the aggregate analysis suggest that they would – and do.

A Theoretical Puzzle

One might suppose that bigger initial ad impacts, as observed in midterm elections, would be associated with greater duration, since ads strong enough to produce big effects would also cause more durable effects. But we earlier found the opposite. Moreover, this pattern is repeated in the right panel of Figure 4, which shows ad impacts in the presidential election by levels of education. Among the less educated, large initial effects decay rapidly; among the middle educated, smaller initial effects last longer; among the most educated, there is minimal change and hence no clear pattern of decay (see the Appendix for coefficients).

Why might big initial impacts go along with more rapid decay? As argued above, opinion change in response to communication probably reflects a mix of memory-based and on-line processing. The initially large impact of ads may then be due to memory-based processing, in which content salient in memory overrides long-term dispositions, while long-term impact may be due to on-line processing, which actually alters dispositions. Memory-based processing cannot produce effects any longer than short-term memory lasts, which means that initial effects, even when large, fade rapidly; the on-line process acts on dispositions that are, by definition, more deeply embedded, leading to smaller but more durable persuasion effects.

McGraw, Lodge, and Stroh (1990) suggests that individuals are more likely to engage in memory-based processing when they care less about the subject. If sub-national elections seem less important than a presidential election, and if the less educated are less engaged than the middle educated, it would lead to more memory-based processing and hence to initial effects that are larger but that decay more quickly in sub-national elections and among the less educated – which is the pattern we observe.

Although the elements of this explanation are established in the experimental literature, additional field research is necessary to confirm it.
DISCUSSION

Our principal finding is that, consistent with the logic of dual process models of attitude change, the bulk of the persuasive effect of advertising decays quickly (as if most citizens were engaged in memory-based processing), but some effect endures (as if a smaller number of citizens stored their new attitudes in long-term memory, where they decay much more slowly). Two kinds of statistical models – relatively open-form ordered probit models, and closed-form models from psychological studies of learning and forgetting – confirmed the theoretically expected pattern.

We obtained two other important findings. The first is that short-lived attitude change affects behavior in the period before it has decayed. Healy, Malhotra, and Mo (2010) foreshadowed this finding, but our fuller analysis – an explicit model of decay and use of both survey and aggregate data – puts the finding on a stronger footing. The finding is important because most of the persuasive effect of mass communication appears to be short-lived. If this attitude change had no consequences for behavior, the field of political communication would be set back toward the “minimal effects” world of Samuel Klapper.

Our second important finding is that persuasive effects decay more rapidly in sub-national than in presidential elections. In the next section, we demonstrate the political significance of these differences in decay rates.

Significance of findings for political campaigns

In their study of the 2000 election, Johnston, Hagen, and Jamieson (2004) found that that Bush’s come-from-behind win over Gore was due to a slim advertising advantage in battleground states during the last week. Here we seek to corroborate that finding. We base our estimate on coefficients of the Weibull model in column 4 of Table 5, taking into account that voting occurs the day after the last ad has run. We find that Bush’s advantage in battleground markets – an average of 25 ad viewings per day to Gore’s 20 per day for 7 days – would net Bush .64 percentage points of vote share (standard error = .18). This estimate is broadly
consistent with the report of Johnston et al.\textsuperscript{31}

The story in sub-presidential elections appears quite different. Significant advertising occurred in 16 of the 60 House contests in our study, and in 6 of these contests, one of the candidates had a late advantage of one or more ad viewings (100 GRPs). The heaviest advertiser in our sample was incumbent Republican Congresswoman Deborah Pryce in the Ohio 15\textsuperscript{th} congressional district, as depicted in Figure 2. Based on the estimates in column 3 of Table 4, and again taking into account that voting occurs on the day after advertising has ended, we calculate that a last week advantage of the size enjoyed by Pryce would be expected to produce a vote swing of 2.23 (se = 1.13) percentage points. Since Pryce won her race by less than one percentage point, her late advertising advantage was potentially decisive.

Due to power limitations and the infrequency of long-term advertising in 2006, we cannot rule out the existence of long-term ad effects in sub-presidential races. But the data are strong enough to establish that late advertising can easily swamp earlier advertising. If campaign practitioners accept this analysis, it could affect strategies in sub-national elections, especially those of less resourced candidates. These candidates should save their limited funds to match or exceed their opponents at the end of the race, even if this means allowing their opponents to dominate earlier advertising.

The implications of our analysis for well-resourced candidates are less clear. They might reasonably wish to buy early ads to impress journalists or donors of their viability, or to deter weaker candidates from entering the race. Their reasons, however, should not include belief that heavy early advertising can build a durable lead.

One prominent politician to discover the limited value of early spending is California gubernatorial candidate Meg Whitman. She outspent her Democratic opponent Jerry Brown $140 million to $25 million in their 2010 race, mostly on summer advertising that kept her ahead

\textsuperscript{31} Johnston et al report that Bush’s ad advantage in the last week of the campaign netted four points. Their analysis, however, differs from ours in important ways. \textit{Inter alia}, they do not appear to have added either previous week or next day decay.
of Brown until mid-September. But Whitman fell behind as Brown began to spend and she lost
soundly on Election Day. Only political consultants and local TV stations appear to have
profited from her early spending strategy.

Somewhat paradoxically, then, our findings of rapid decay of ad effects imply a previously
unrecognized limit to what campaign advertising can do in sub-national (but not presidential)
races. Votes, it appears, can be rented in these elections but not bought. If it were otherwise – if,
that is, ad effects cumulated over the whole campaign – well-resourced candidates like Whitman
could get much more advantage from their money than they do.

Most of the time when scholars turn up cognitive limitations of voters, it’s bad news for
democracy. Our findings, with their implied limit on the power of money to buy indefinitely
large numbers of votes, might have at least this upside. The downside, however, is that political
amnesia extends to other political messages that voters would do well to retain, as we explain in
the next section.32

Conclusions

We see two main implications of our analysis. The first – obvious, but still worth stating -- is
that decay of the effects of political persuasion is too important to be ignored, as it routinely has
been. It is a basic feature of mass persuasion in most if not all political contexts. Scholars
should therefore try harder to build measurement of decay into their research designs. When this
is not feasible, they should explicitly acknowledge the likely existence of decay and assess its

32 The effects of advertising in the 2012 presidential election appear to have been similar to those in 2000.
John Sides and Lynn Vavreck (2013) demonstrate sizable impacts of same-day ads and a rapid rate of decay,
but their model uses a different functional form and different controls. Sides and Vavreck have made their
data available to us for a robustness test of our models. The survey data are from the 2012 Cooperative
Campaign Analysis Project, which is broadly similar in design to the 2006 CCES described above. The
advertising data are from Nielsen under license to Lynn Vavreck and John Geer. With fairly minor exceptions,
these data have the same form as our data from the 2000 election and permitted tests that are very similar to
the tests reported in Table 5 above. We found that initial impact of ads in the 2012 election was greater than
in the 2000 election, but decay was also greater. The half-life of an ad’s impact was about three days
(compared to four in 2000). In both initial impact and decay, results fall between those obtained for the 2006
sub-national elections and the 2000 presidential election. Coefficients, however, are imprecisely estimated
because the 2012 sample was only 60 percent as large as the 2000 sample. In view of this lack of precision,
we do not offer an interpretation for such differences as appear to exist from 2000.
implications for their argument. Scholars should not, as studies of political advertising have until recently done, present average or aggregate results that fail to make clear the degree of decay that occurs.

A second implication is that effects of political communication -- and therewith the public’s capacity for durable learning -- may be sharply limited. No one would expect citizens to remember the myriad details in media reports of public affairs. One might, however, hope that the information would make a lasting imprint on opinion. Indeed, if the on-line model were to operate for most citizens, this is exactly what would happen – citizens would internalize the implications of communication while forgetting its details.

But our review of existing research indicates that the kind effortful processing accounts for only a small portion of the public’s response to mass political communication. On this basis, we hypothesized that most mass political communication produces a mix of sizeable short-term and small long-term effects. Sizeable long-term effects occur only when communication is repeated over a long period of time.

We emphasize that nothing in our argument implies that mass communication cannot have large and durable effects. It implies only that communication is unlikely to have such effects unless citizens pay thoughtful attention to it. The problem for durable learning and persuasion – and, more broadly, for the creation of an informed electorate – is that few citizens engage in effortful processing of the political communication they receive.
References


Petty, R.E., C.P. Haugtvedt and S.M. Smith. 1995. “Elaboration as a determinant of attitude strength: Creating attitudes that are persistent, resistant, and predictive of behavior.”


Figure 1: Total Advertising Volume in Four Types of Races

- President (1)
- Senate (4)
- Governor (5)
- House (60)

Log of expected total number of ad views per household per day for both candidates over last 21 days of race

Figure 1: Total Advertising Volume in Four Types of Races: Results are expected total number of ad views per household per day for both candidates over last 21 days of race.
Figure 2: Total Advertising Volume Across Four Races: All units are in GRP/100.
Decay rates, 2000 Presidential Election

Decay rates, 2006 Subnational Elections

Figure 3: Advertising Decay Rates, 2000 vs. 2006 Election: Plots show percent of initial impact that remains at Day 0 from each previous day. Model estimates shown in Tables 4 and 5.
Figure 4: Estimated Advertising Impacts in Presidential and Sub-National Elections: Left panel plot compares the percent change in vote probability from 2-1 ad view advantage in presidential vs. subnational elections. Decay curves are plotted from the 2000 Weibull model and the 2006 Exponential model estimates in Table 4. Right panel compares the percent change in vote from 2-1 ad view advantage in the 2000 presidential election by education. All estimates by education are conducted using the Weibull model, and coefficients are included in the online appendix. Simulations are specified to calculate the marginal effect for a respondent whose baseline probability of voting for the candidate is 0.5.
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Table 1: Models of advertising effects in 2000 presidential election: Dependent variable is ordered choice of Gore, undecided, or Bush. Main cell entries are ordered probit coefficients, with standard errors in parentheses. TV news watchers are 93 percent of sample. All ad variables are in units of logged Bush GRPs/100 minus logged Gore GRPs/100. Standard control variables are described in text. Full results are reported in Online Appendix.
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<td>Day 6-10 ads</td>
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<td>(0.023)</td>
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<tr>
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<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td>7541</td>
<td>7541</td>
<td>7541</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-4958.53</td>
<td>-4956.89</td>
<td>-4956.71</td>
<td>-4956.91</td>
<td>-4956.80</td>
<td>-4958.09</td>
<td>-4956.17</td>
</tr>
</tbody>
</table>

Table 2: Models of advertising effects in 2006 Midwest elections: Dependent variable is ordered choice of Democrat, undecided, or Republican. Main cell entries are ordered probit coefficients, with standard errors in parentheses. Sample includes only respondents who own a TV. All ad variables are in units of logged Republican GRPs/100 minus logged Democratic GRPs/100. Standard control variables are described in text. Full results are reported in Online Appendix.
Table 3: Functional Forms for Modeling Persuasion and Decay:  
Functional Forms are the best-performing models described in Rubin and Wenzel (1996) to estimate decay. I refers to the impact parameter and $\delta$ refers to the decay parameter in Table 4. Vote choice is ordered preference between Democrat, undecided, and Republican. $X\beta$ includes all control and fixed effects described in text.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Functional Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logarithmic</td>
<td>$\text{Vote} = \sum_{t=0}^{T} [I - \delta \ast \log(t + 1)] \ast \text{grp}_t + X\beta$</td>
</tr>
<tr>
<td>Exponential</td>
<td>$\text{Vote} = I \ast \sum_{t=0}^{T} \exp(-\delta \ast t) \ast \text{grp}_t + X\beta$</td>
</tr>
<tr>
<td>Weibull</td>
<td>$\text{Vote} = I \ast \sum_{t=0}^{T} \exp(-\delta \ast t^{0.5}) \ast \text{grp}_t + X\beta$</td>
</tr>
<tr>
<td>Power</td>
<td>$\text{Vote} = I \ast \sum_{t=0}^{T} (t + 1)^{-\delta} \ast \text{grp}_t + X\beta$</td>
</tr>
</tbody>
</table>

Table 4: Parametric Decay Estimates, 2000 Presidential Election:  
Coefficients are from the functions in Table 4. Standard errors in parentheses. Dependent variable is vote preference for Democrat, undecided, or Republican. All models contain standard controls and fixed effects described in text. Results at right are for null model with term for net advertising GRPs but no term for decay.

<table>
<thead>
<tr>
<th></th>
<th>Exponential</th>
<th>Logarithmic</th>
<th>Weibull</th>
<th>Power</th>
<th>Null Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impact</td>
<td>0.014</td>
<td>0.019</td>
<td>0.033</td>
<td>0.029</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>—</td>
</tr>
<tr>
<td>Decay</td>
<td>0.071</td>
<td>0.005</td>
<td>0.494</td>
<td>0.616</td>
<td>—</td>
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<tr>
<td></td>
<td>(0.064)</td>
<td>(0.002)</td>
<td>(0.237)</td>
<td>(0.290)</td>
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<td>12,467</td>
<td>12,467</td>
<td>12,467</td>
<td>12,467</td>
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<tr>
<td>Log Like</td>
<td>-7831.643</td>
<td>-7831.041</td>
<td>-7830.328</td>
<td>-7830.482</td>
<td>-7834.043</td>
</tr>
</tbody>
</table>

41
Table 5: Parametric Decay Estimates, 2006 Subnational Elections: Coefficients are from the functions in Table 4. Standard errors in parentheses. Dependent variable is vote preference for Democrat, undecided, or Republican. All models contain standard controls and fixed effects described in text. Results at right are for null model with term for net advertising GRPs but no term for decay.

<table>
<thead>
<tr>
<th></th>
<th>Exponential</th>
<th>Logarithmic</th>
<th>Weibull</th>
<th>Power</th>
<th>Null Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impact</td>
<td>0.161</td>
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<td>0.175</td>
<td>0.179</td>
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<td></td>
<td>(0.086)</td>
<td>(0.023)</td>
<td>(0.087)</td>
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<tr>
<td>Decay</td>
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<td>1.435</td>
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<tr>
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<td>(0.449)</td>
<td>(0.007)</td>
<td>(0.632)</td>
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<td>N</td>
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<tr>
<td>Log Like</td>
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<td>-4958.27</td>
<td>-4957.84</td>
<td>-4957.97</td>
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</tr>
</tbody>
</table>

Table 6: Effect of Ads, Week before Interview vs. Previous 5 Weeks: Compares the net effect of advertising from 0-6 days before date of interview to the effect of advertising 7-42 days before date of interview. Models are based on results from Figure 4. The simulation assumes a 2-1 daily ad view advantage for the candidate, and simulates the effect on a respondent whose baseline probability of voting for the candidate is 0.5. 95% confidence intervals are derived from non-parametric percentile bootstrap.

<table>
<thead>
<tr>
<th></th>
<th>Baseline Vote Probability</th>
<th>Vote Probability After Ads</th>
<th>Net Effect</th>
<th>95% CI</th>
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<td>2000 Election</td>
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<td></td>
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<tr>
<td>Week before Interview</td>
<td>50%</td>
<td>51.89%</td>
<td>1.89%</td>
<td>(1.19%, 3.52%)</td>
</tr>
<tr>
<td>Previous 5 weeks</td>
<td>50%</td>
<td>52.05%</td>
<td>2.05%</td>
<td>(0.04%, 3.23%)</td>
</tr>
<tr>
<td>2006 Election</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week before Interview</td>
<td>50%</td>
<td>54.94%</td>
<td>4.94%</td>
<td>(2.49%, 8.08%)</td>
</tr>
<tr>
<td>Previous 5 weeks</td>
<td>50%</td>
<td>50.03%</td>
<td>0.03%</td>
<td>(0.0%, 0.9%)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>----------------------</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td><strong>Days 1-1</strong></td>
<td>1.20</td>
<td>0.83</td>
<td></td>
<td>1.08</td>
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<tr>
<td></td>
<td>(0.21)</td>
<td>(0.23)</td>
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<td>(0.24)</td>
</tr>
<tr>
<td><strong>Days 2-42</strong></td>
<td>0.03</td>
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<tr>
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<td>(0.01)</td>
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<td><strong>Days 3-42</strong></td>
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<td><strong>Clinton 3-Party Share 1996</strong></td>
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<tr>
<td><strong>Perot 3-Party Share 1996</strong></td>
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<tr>
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<td>(0.13)</td>
<td>(0.13)</td>
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<tr>
<td><strong>Std. Error of Regression</strong></td>
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<td>2.87</td>
<td>2.88</td>
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</table>

Table 7: Models of advertising effects in 2000 presidential election, logged advertising version: *Dependent variable is county Bush vote share percentage. Main cell entries are multiple regression coefficients, with robust standard errors in parentheses. All ad variables are in units of logged Bush GRPs/100 minus logged Gore GRPs/100. Day 1 is day before Election Day, day 2 two days before Election Day, and so forth. Advertising in each county is measured by the advertising in that county’s modal media market. All models include state fixed effects.*