DYNAMICS IN PARTISANSHIP DURING AMERICAN PRESIDENTIAL CAMPAIGNS

CORWIN D. SMIDT*

Abstract Despite their potential importance, little is known about the nature and prevalence of party identification dynamics within American presidential campaigns. This study reviews existing research to propose three basic contrasting models. It then introduces multivariate state space methods that account for sampling error and survey design effects to evaluate each model’s relative support within daily national survey data of the 1984, 2000, 2004, and 2008 presidential campaigns. The results indicate that the balance of party identifiers had near-certain changes during three of the four campaigns, with campaign events often being associated with these changes. These findings suggest that polls and analyses that fail to allow for sudden shifts in party identifications will mask changes in public opinion. More generally, the findings demonstrate that campaigns shape party coalitions on Election Day, and possibly thereafter.

A common way to cast doubts on a survey result is to claim the survey is biased from a skewed sample of party identifiers. This was often the case during the 2004 presidential campaign, when interest groups, pollsters, political scientists, and the news media engaged in prominent debates over whether polls should treat party identification as a relatively stable factor and, thus, use weights or not (MacFarquhar 2004; Memmott 2004; Abramowitz 2006; Newport 2006). Similar debates surfaced in 2012, to the point where conservatives sought out websites like unskewedpolls.com, which adjusted published poll results to account for a believed systematic undersample of Republicans.

CORWIN D. SMIDT is an assistant professor of political science at Michigan State University, East Lansing, MI, USA. The author thanks Paul Abramson, Brandon Bartels, and Jan Box-Steffensmeier for their help and comments, and especially thanks Herb Weisberg for providing the 1984 polling data. Data used in this study were collected by the Annenberg Public Policy Center of the University of Pennsylvania and Decision Making Information, Incorporated. Additional codes needed for replication purposes are available from the author upon request. *Address correspondence to Corwin D. Smidt, Department of Political Science, Michigan State University, South Kedzie Hall, 368 Farm Lane, S303, East Lansing, MI 48824, USA; e-mail: smidt@msu.edu.
Skeptical partisans typically initiate these debates over survey methodology, but their concerns remain in many ways valid and appropriate. Nonetheless, despite partisanship’s considerable influence on voting behavior, scholars know little about the stability of party coalitions over the course of the campaign and whether weighting is viable. Knowing if and how party identifications change during campaigns has direct implications for survey methodology, but it also informs our understanding of campaigns more broadly. Candidates often attempt to attract voters by modifying the image and identity of their party. By examining whether these actions contribute to changes in party identification, we can clarify what role candidates and campaign events play in forming party coalitions. Moreover, researchers studying campaign effects often control for partisanship within their analysis of campaign effects but fail to consider the implications of doing so. If the campaign’s influence on voters is directed partly through changes in partisanship, then studies that include partisanship as a controlling factor mask the total effect campaigns have on public opinion.

Accordingly, this study explores the prevalence and nature of campaign dynamics in aggregate party identification. I review extant studies of party identification to generate three competing models of party coalition dynamics: a stability model, an enhanced trend model, and a campaign events model. Using Bayesian state space models that test for dynamics while accounting for missing data, sampling error, and survey design effects, I compare the relative performance of these models within national daily survey data from the 1984, 2000, 2004, and 2008 campaigns.

Model estimates are near certain that the balance of party identifiers changed during three of the four campaigns. Moreover, the 2000 and 2008 estimates suggest that party coalitions changed in response to campaign events and in a manner beyond the reflection of retrospective forces. These findings demonstrate that the balance of party identifiers often fluctuates during the campaign and that this movement is at times conditional on campaign events. Consequently, the use of party identification as a weighting or controlling variable will bias estimates of public opinion if partisanship’s dynamics are not accurately identified. More generally, it indicates that campaigns can foster changes in party identification, but the nature of partisanship’s responsiveness varies by election.

### Presidential Campaigns and Party Identifications

Candidates are focused primarily on winning over voters during presidential campaigns, but they commonly attempt to do so by modifying the public’s perception of their party. By emphasizing issue positions (Petrocik 1996) or attending to ethnic or other social groups (Philpot 2004), parties attempt to strengthen or counter partisan stereotypes (Rahn 1993) and broaden the
appeal of the party label. Campaigns consequently increase citizen knowledge of party symbols and issue positions, especially among the young (Sears and Valentino 1997). Along these lines, the effects of the campaign can go beyond election-specific attitudes and last beyond the campaign. If a campaign effectively modifies the party’s brand, then the distribution of party identifications among Americans is also likely to change.

Surprisingly, little is known about whether campaigns have effects on party identification. Studies of dynamics in partisanship over multiple years are extensive and prominent (e.g., Clarke and Stewart 1998; Erikson, MacKuen, and Stimson 2002; Green, Palmquist, and Schickler 2002). These studies tend to agree that party identifications change, but they disagree on the meaning and durability of these perturbations. Campbell et al. (1960) originally proposed that party identifications were psychological attachments that were highly durable compared to other attitudes. Party identifications may change in response to external forces, but often revert to their original state after such aberrations, a claim most recently emphasized by social-identity perspectives (Green, Palmquist, and Schickler 2002; Weisberg and Greene 2003). The contention of revisionists is that changes in partisanship reflect more than temporary disturbances. Changes represent a meaningful accumulation of retrospective evaluations or prospective gains that have lasting consequences for future political behavior (Fiorina 1981; Achen 1992). Revisionist arguments are supported by examinations of aggregate dynamics by Erikson, MacKuen, and Stimson (2002), who find that trends in economic evaluations and presidential evaluations have permanent repercussions for future partisanship.

However, both theoretical camps are relatively agnostic about the reaction of party identifications to presidential campaigns. Social-identity perspectives recognize that changes in partisanship are possible during campaigns but claim they are unlikely to last (Green and Yoon 2002). For instance, Converse (1976, 124) characterizes noticeable movements in partisanship preceding the elections of 1956, 1968, and 1972 as “wobbles.” Revisionists also allow for changes, but their estimates suggest that presidential approval or economic evaluations produce relatively small immediate effects that take time to accumulate. Erikson, MacKuen, and Stimson (2002) estimate that a one-percentage-point change in presidential approval results in only a .13-percentage-point permanent change in macropartisanship one quarter later. Consequently, they describe most of the change in macropartisanship during the 1984 campaign as a large temporary deviation from equilibrium expectations.

Moreover, we currently have scattered perspectives and evidence about partisanship’s interaction with campaigns. Evidence of sharp movements that occur right before an election is either from the American National Election Studies (ANES) data (Converse 1976), which have relatively large rates of sampling error, or an aggregation of many Gallup polls each quarter (Erikson, MacKuen, and Stimson 2002), where Gallup’s measure enhances partisanship’s responsiveness to current conditions (Abramson and Ostrom 1994).
Likewise, some studies find that campaigns recruit independents such that their numbers decline from the prior year (Clarke and Stewart 1998), but such gains in partisanship may be specific to the Gallup question wording (Green, Palmquist, and Schickler 2002).

There are only a few studies of the dynamic behavior of party identification within campaigns. Allsop and Weisberg (1988) provide the first investigation of daily survey data from the 1984 campaign, finding that partisanship showed clear trends. These results are limited, however, by their inability to determine whether sampling error produced these dynamics. Examining the ANES’s four-wave 1980 major panel study, Brody and Rothenberg (1988) claim that much of the observed change in partisanship was systematic. However, Green and Yoon (2002) use the same 1980 ANES data and additional panel data from the 1976 campaign and find that individual-level changes in partisanship rapidly dissipate and revert to their original identification by the next time individuals are interviewed, suggesting that campaign fluctuations have a very short life. But Clarke and McCutcheon (2009) have contested these results, partly on methodological grounds, and use different methods to suggest that partisanship has much more fluid dynamics during the campaign.

THREE MODELS OF PARTY COALITION DYNAMICS

As outlined above, theory and evidence offer unclear expectations of whether presidential campaigns facilitate changes in party identifications. But it is possible to classify these theories and findings by their support for three contrasting models of party identification dynamics at the aggregate level.

The first potential model of coalition dynamics is simply the stability model, which assumes that the distribution of party identifications is best expressed as a constant. Even if retrospective forces have effects on partisanship, this model recognizes that they are so incremental and selective that they are essentially flat within the campaign’s time frame. Another theoretical justification for this model is that partisanship’s durability makes it appear stable in the aggregate. Perturbations in partisanship are temporary and quickly erased. Scholars have long suggested that campaign events and the intensity of campaign information serve as a very strong reinforcement mechanism (Berelson, Lazarsfeld, and McPhee 1954); group and other allegiances come to the forefront and create an environment that makes it difficult for party identifications to stray for too long. The strongest empirical support for this perspective comes from Green and Yoon (2002), who find that changes in partisanship within presidential campaigns do not have significant consequences in the future.

If campaigns facilitate partisan change, then there are contrasting expectations of how these changes emerge over the duration of the campaign. One model of party identification changes within the campaign is a trend
The trend model recognizes that campaigns are a mechanism for establishing or strengthening the effects of fundamental forces on political behavior (Finkel 1993; Gelman and King 1993; Erikson, Panagopoulos, and Wlezien 2010). Elections increase the public’s motivation to pay attention to politics and their opportunity to be exposed to political information, a process Gelman and King (1993) refer to as “enlightenment.” This makes voters more certain about which candidate matches their preferences (Alvarez 1997) and enhances their ability to match their party identifications with current retrospective considerations or other determinants of partisanship. Accordingly, changes in partisanship should trend at a rate corresponding to the campaign’s progression. Evidence for this type of process is supported by findings that the percentage of individuals identifying with either major party increases as the presidential campaign intensifies (Clarke and Stewart 1998). Further aspects of an enhanced trend model would include the campaign’s progression strengthening gains or losses in the percentage of incumbent party identifiers in a direction consistent with current economic and political conditions.

A different model of partisan dynamics within the campaign is the campaign events model. Both an events and a trend model suggest that party coalitions change in reaction to the campaign, but an events model stresses that these movements are conditional on the actions of the candidates and campaign events. Shifts in partisanship can operate in different directions depending on a party’s rhetoric and actions during the campaign, and these shifts may even go against retrospective trends. For instance, Vavreck (2009) finds that positive economic conditions are associated with improved incumbent party evaluations among voters, but these structural conditions have stronger associations in years when parties and candidates emphasize these considerations and weaker associations when parties emphasize other considerations.

Campaigns may cause shifts in party identifications at any time, but events like debates and conventions stand out as potential focal points since they are typically associated with swings in candidate support (Holbrook 1996; Hillygus and Jackman 2003; Shaw 2006). Conventions are attempts by parties to present their core identity to the greater public as a reflection of the presidential nominee (Schattschneider 1942; Philpot 2004). Likewise, party rhetoric within debates and advertisements influences the issue coverage of campaign news (Johnston, Hagen, and Jamieson 2004), allowing for the introduction or emphasis of wedge issues that redefine the basis of partisan divisions and attract opposing partisans or independents toward a party if salient (Carsey and Layman 2006).

These three models of campaign dynamics in party coalitions are not exhaustive, but remain informative since they outline contrasting perspectives of partisan change that require different types of methodological accommodation. Investigating each model’s applicability also has consequences for our understanding of what role candidates and campaigns play in shaping voting
behavior and party politics. If the balance of party identifications shows strong trending, then it suggests that presidential campaigns provide a context for party recruitment, where identifications face a stronger pull to the party’s recent track record and other factors that influence partisanship. Moreover, if partisanship fluctuates in response to distinct campaign events, this would suggest that partisan movements depend on how campaigns capitalize on economic and political contexts or promote a party’s issue positions or leaders.

Data and Methods

I evaluate campaign dynamics in partisanship using daily national telephone survey data from Decision Making Information’s (DMI) 1984 continuous monitoring study for the Republican National Committee (Allsop and Weisberg 1988) and the 2000, 2004, and 2008 National Annenberg Election Survey’s (NAES) rolling cross-section surveys (Romer et al. 2006). The four surveys of American adults asked identical versions of the party identification item originated by the American National Election Studies. Importantly, both wordings request how respondents “usually” consider their identification and, thus, provide a stringent test of the campaign’s influence.

The three time series from the NAES are relatively long, with surveys in the field for over 300 days before Election Day and only a few missing dates. However, the sample sizes for early dates are often below 100 observations and increase to only around 300 in July of each campaign year. The 1984 DMI survey ran only from June to Election Day (158 days), but it has consistently larger sample sizes that reach 1,000 observations during the last week. To maximize comparability with the DMI results and eliminate effects not clearly attributable to the presidential general election, I exclude respondents interviewed prior to April in each NAES survey.

I analyze two different categorizations of partisanship: one that codes all independents as independents, and a second that classifies independents as partisans if they report being closer to either party in a follow-up question. The latter categorization recognizes that independents with partisan leanings appear more like partisans than pure independents in their electoral behavior (Keith et al. 1992). However, I focus mostly on the former categorization. A change in the leanings of an independent does not technically represent a change in identification, since a respondent still claims to be

1. Although the models vary in their association with existing theories, none provide a basis for rejecting traditional or revisionist perspectives of partisanship. For example, if party identifications change in response to campaigns, a social-identity perspective can still claim that these changes dissipate over a longer time frame.

2. Both the NAES and DMI asked individuals: “Generally speaking, do you usually think of yourself as a Republican, a Democrat, an independent, or something else?” I provide further details about response rates and the sampling universe in appendix A.
independent in the original question. Similarly, the party leanings of independents may have strong associations with voting within an election, but the long-term consequences of party leanings are less certain, since their association with future voting behavior exhibits greater attenuation (Bartels 2000, 46–48).

I calculate sample proportions from each survey using poststratification weights, in which missing values (Don’t Knows, Refused) are excluded from the calculations and sample size. I calculate proportions for all adults, since errors in likely voter filters add artificial movements to campaign dynamics (Erikson, Panagopoulos, and Wlezien 2004). For the NAES data, after accounting for number of telephones and adults in household, I calculate poststratification weights to match the population targets (as provided by the NAES) in age, race, gender, region, and education using an iterative raking procedure. The 1984 data were archived in aggregate form with the weights developed by DMI.3

A STATE SPACE MODEL OF PARTY COALITION CHANGE

Relatively small daily sample sizes and high levels of sampling error reduce the power of traditional time-series testing when using observed measures. Consequently, I test the nature of partisan dynamics using a Bayesian state space model framework. State space models and their use of the Kalman filter offer an ability to account for sampling error effects and missing data while testing the nature of dynamics within an opinion series (Beck 1989; Green, Gerber, and De Boef 1999). The model takes each day’s estimate of partisanship and its sampling error and compares them with across-time patterns in a survey series to estimate an aggregate opinion series most likely to produce the observed data. The following specification expands upon earlier models by allowing a survey’s error to be a function of both sampling error and its potential design effects.

I follow Reilly, Gelman, and Katz (2001) by summarizing the composition of the three partisan groups using two different series.4 A partisanship series, \( y_{pt} \), represents the proportion of the population that identifies with either major political party on day \( t \). A second series, \( y_{mt} \), represents the daily macropartisanship split (proportion Democrat) of those who are partisans.

The state space model assumes that each series is an unbiased estimate of its corresponding population percentages (\( \pi_{pt} \) and \( \pi_{mt} \), respectively), but with varying degrees of measurement error. With sufficient sample sizes and

---

3. Access to these data was provided by Professor Herbert Weisberg.
4. Jointly estimating dynamics for the three percentages is difficult, since the daily measurement errors and the transition errors sum to zero and the combinations of each response option’s latent series sum to one each day; a gain (loss) in one series has to be accounted for by an equal total of losses (gains) among all other series. This makes the error variance-covariance matrices not of full rank and not invertible.
since both percentages are away from the boundaries, each measurement error is well approximated as following an independent normal distribution with a variance equal to the product of two components. The first component is the estimate of a survey’s design effect, which represents its decreased precision in repeated samples from variations in participation rates and questionnaire form (e.g., Tourangeau et al. 1989) or the inefficiencies of population weighting adjustments (e.g., Kish 1992). The product’s second component is the known sampling error estimate under simple random sampling. Depending on a survey’s expected sampling error and the model’s estimate of a survey’s design effect, the observed percentage is considered a more or less certain estimate of the population percentage.

State space models combine these estimates of $\pi_{pt}$ and $\pi_{mt}$ with a transition model estimate that specifies how these parameters change over time to form an optimally weighted average. Each of the three models of campaign dynamics proposes a different transition model. The campaign stability model expects that day-to-day changes in partisanship are quickly erased, such that both series are best expressed as constant across time:

$$\pi_{pt} = \alpha_p + w_{pt},$$

$$\pi_{mt} = \alpha_m + w_{mt},$$

where the effects of $w_{pt}$ and $w_{mt}$, the normally distributed transition errors, are erased by the next day.

The trend enhancement model expects that day-to-day changes in party identifications occur in a mostly consistent direction that corresponds to the intensity of the campaign. As the campaign intensifies, it will clarify and emphasize retrospective conditions or other existing characteristics of the two parties and candidates that traditionally influence party support. More formally, the model specifies party identification levels as a function of a campaign trend variable ($\text{Campaign}_t$) that represents the accumulated level of campaign activity:

$$\pi_{pt} = \alpha_p + \beta_p \text{Campaign}_t + w_{pt},$$

$$\pi_{mt} = \alpha_m + \beta_m \text{Campaign}_t + w_{mt}.$$
coverage. I tested many of these measures but present results only for a daily trend variable, since more complex specifications did not alter the findings. Since party conventions occur as early as mid-July, the daily trend variable is set at zero for dates before July and linearly increases until it equals one on the day before Election Day for each year.

The campaign events model allows day-to-day changes in party identifications to occur in any direction in response to the events of the campaign. Since it is unclear when these change points might occur, two sets of explanatory variables were included to capture campaign effects. To capture the possibility that a change at any point of the campaign can have lasting consequences, I include a first-order autoregressive process. Second, I include a set of post-event dummy variables corresponding to each party’s convention and the presidential debates:

\[
\pi_{pt} = \alpha_p + \zeta_p \pi_{pt-1} + \sum_{i=2}^{3} \beta_{pi} \text{Convention}_i + \sum_{i=3}^{K} \beta_{pi} \text{Debate}_i + w_{pt} \\
\pi_{mt} = \alpha_m + \zeta_m \pi_{mt-1} + \sum_{i=2}^{3} \beta_{mi} \text{Convention}_i + \sum_{i=3}^{K} \beta_{mi} \text{Debate}_i + w_{mt}.
\]

In 1984, there were only two presidential debates; the other years had three. Each party’s convention effect is specified to start on the final date of the convention. 7

BAYESIAN MODEL SELECTION AND ESTIMATION

The relative empirical support for each model is evaluated using Bayesian estimation and model comparison methods. This approach offers strong advantages over testing one general model that includes unnecessary independent variables. For example, even if the stability model were true in all four campaigns, a 5 percent error rate associated with traditional null hypothesis testing produces approximately a 94 percent chance that at least one of the 54 variable tests will reject the null hypothesis. 8 By comparison, a Bayesian model comparison makes a relative assessment of how likely it is that each model generated the data by combining the estimated marginal likelihood of each

7. The convention and debate dummy variables coupled with the autoregressive parameter allow for either sudden or smooth changes in party identification. If events produce sudden shifts in partisanship, then their coefficient estimates will be relatively large and the estimate of autoregression relatively small. However, if partisan fluctuations are smooth and gradual, then the autoregressive parameter will have a relatively large estimate and the coefficient estimates of events will be much smaller.

8. For joint hypothesis testing, there is still approximately a 34 percent chance that the stability model would be falsely rejected once when testing against the eight alternative transition models \((1 - .95^8)\).
model with prior beliefs of each model’s suitability to estimate the relative probability that each model produced the observed data. Further details about prior specification and model estimation are provided in appendix B.

Results

The model selection results are presented within each row of table 1. The top entry in each row contains the log of the marginal likelihood for each model. These estimates are compared within each year to calculate the posterior probability that each model generated the data, as presented in the parentheses. There are two results for each year, corresponding to whether leaners are categorized as independents or partisans. These estimates are nearly certain in choosing the model most likely to produce each year’s data and agree across

Table 1. Comparing Log Marginal Likelihoods (relative probability of each model generating data in parentheses)

<table>
<thead>
<tr>
<th>Election year</th>
<th>Leaners as:</th>
<th>Stability</th>
<th>Trend enhancement</th>
<th>Campaign events</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>Independent</td>
<td>–1,302.22</td>
<td>–1,269.05</td>
<td>–1,288.49</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(1.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>Partisan</td>
<td>–1,510.02</td>
<td>–1,487.25</td>
<td>–1,493.13</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(1.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>2000</td>
<td>Independent</td>
<td>–1,826.09</td>
<td>–1,799.94</td>
<td>–1,775.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(1.00)</td>
</tr>
<tr>
<td></td>
<td>Partisan</td>
<td>–2,103.80</td>
<td>–2,111.59</td>
<td>–2,071.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(1.00)</td>
</tr>
<tr>
<td>2004</td>
<td>Independent</td>
<td>–1,712.56</td>
<td>–1,742.40</td>
<td>–1,770.74</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>Partisan</td>
<td>–2,008.00</td>
<td>–2,038.08</td>
<td>–2,070.75</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>2008</td>
<td>Independent</td>
<td>–1,774.98</td>
<td>–1,787.57</td>
<td>–1,743.13</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(1.00)</td>
</tr>
<tr>
<td></td>
<td>Partisan</td>
<td>–2,066.19</td>
<td>–2,093.62</td>
<td>–2,044.374</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(1.00)</td>
</tr>
</tbody>
</table>

Note.—Marginal likelihood estimates calculated based on the reciprocal importance sampling estimate with importance density defined by Frühwirth-Schnatter (1995). Relative probabilities are estimated with a uniform prior. See appendix B for greater details.
the two different measures. Only one campaign year, 2004, provides evidence supportive of America’s balance of partisans being stable. During 1984, the trend enhancement model is most likely to have produced the data, whereas the campaign events model is the most likely in 2000 and 2008. In combination, these estimates strongly indicate that America’s balance of party identifiers often changes during presidential campaigns.

The estimates are largely consistent across the two codings of independents. Table 2 presents the coefficient estimates from each year’s selected model when coding leaners as independents. Results from the alternative coding are presented in appendix C. Both dependent variables are measured on the proportion scale ranging between zero and one, such that percentage-point effects require multiplying the coefficient estimates by 100.

Before we discuss the estimated changes in partisanship, note the design effect estimates presented at the bottom of each column, which represent how much larger the survey’s error variance is relative to what is expected under simple random sample. These results indicate that sampling error expectations alone fail to account for a survey’s measurement error across time. In all cases, the estimate of the design effect is greater than one. Of these, DMI’s 1984 survey results exhibit the smallest design effect. This is perhaps to be expected, since its weighted estimates were based on a larger sample size and the survey’s questionnaire form was short and stable across time. In contrast, the larger design effects for the NAES series are likely a function of added inefficiencies from weighting, since these surveys often have daily sample sizes below 100 and rarely have sample sizes above 400, and added measurement errors, since the NAES used various questionnaire versions across daily samples.

The results for each partisanship series represent changes in the proportion of Americans identifying with either major party. For the 1984 estimates, by subtracting the constant from one, we find that about 35.4 percent of Americans are estimated to be independents prior to July. But the proportion of partisans exhibits a downward trend as the campaign progresses, such that independents grow to approximately 36.9 percent of Americans on Election Day. Since the Democrat and Republican series are measured via a macropartisanship split, the estimates test whether there are clear changes in the balance of these identifiers. In this case, it is also evident that the Democrat advantage among partisans declines by 4.6 percentage points over the duration of the campaign, and this shift is estimated to be even larger (5.4) if one includes leaning independents.

To understand the dynamics specific to each group, figure 1 displays the combined effect of these dynamics for partisanship estimates over the course of the 1984 campaign. The coefficient estimates indicate a drop in the proportion of partisans and a drop in the proportion of partisans who are Democrats. In combination, the total decline in Democratic identifiers is large, as they move from comprising 36.6 to 32.8 percent of American adults. In contrast,
Table 2. Selected State Space Regression Model Estimates (posterior standard deviations in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Partisan</td>
<td>Macro.</td>
<td>Partisan</td>
<td>Macro.</td>
</tr>
<tr>
<td>Constant</td>
<td>0.646*</td>
<td>0.566*</td>
<td>0.693*</td>
<td>0.664*</td>
</tr>
<tr>
<td></td>
<td>(.004)</td>
<td>(.006)</td>
<td>(.164)</td>
<td>(.124)</td>
</tr>
<tr>
<td>Daily trend</td>
<td>–0.015*</td>
<td>–0.046*</td>
<td>–0.095</td>
<td>–0.222</td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.009)</td>
<td>(.259)</td>
<td>(.229)</td>
</tr>
<tr>
<td>Lagged value</td>
<td></td>
<td></td>
<td>–0.045*</td>
<td>0.054*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.014)</td>
<td>(.018)</td>
</tr>
<tr>
<td>Dem. convention</td>
<td>0.012</td>
<td>–0.028*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.012)</td>
<td>(.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rep. convention</td>
<td>–0.003</td>
<td>0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.015)</td>
<td>(.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Debate 1</td>
<td>0.015</td>
<td>–0.046</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.022)</td>
<td>(.026)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Debate 2</td>
<td>0.020</td>
<td>0.025</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.019)</td>
<td>(.023)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Debate 3</td>
<td>1.060</td>
<td>1.101</td>
<td>1.576</td>
<td>1.430</td>
</tr>
<tr>
<td></td>
<td>(.105)</td>
<td>(.109)</td>
<td>(.139)</td>
<td>(.125)</td>
</tr>
<tr>
<td>Design effect</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_w$</td>
<td>0.003</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.002)</td>
<td>(.002)</td>
<td>(.002)</td>
</tr>
<tr>
<td>N</td>
<td>158</td>
<td>158</td>
<td>220</td>
<td>220</td>
</tr>
</tbody>
</table>

Note.—Estimates when coding leaning independents as independents. Posterior means with standard deviations in parentheses. * indicates that 95 percent Bayesian credible interval excludes zero.
Figure 1. Party Coalition Dynamics in 1984. Dots indicate observed percentages, and dark lines represent state space smoothed estimates. 95 percent BCI indicated with shaded vertical gray lines. Democratic and Republican conventions and the two presidential debates indicated, respectively, with vertical markers.

Republican identifiers grow from 27.4 to 30.3 percent of American adults. These gains could have come from either Democrats becoming Republicans or from both Democrats becoming independents and independents becoming Republicans.
It is unclear why 1984 exhibits consistent trending whereas the other years do not. One possibility is that it is an artifact of differences in how campaigns and political information environments operated in the past. Another possibility is that the nation’s economic growth rate was so sudden, consistent, and strong in 1984 (7.2 percent change in real GDP) that it made a periodic trend more likely. Regardless, the observed survey percentages indicate that the drop in Democrats of almost four percentage points began near the time of the conventions. Therefore, although this trend likely reflects favorable economic conditions, both its size and the nature of its timing support interpretations that the campaign enhanced Republican gains.

Contrast these movements with those in 2000, as shown in figure 2. The results for this year and 2008 provide evidence that partisan movements can also vary in direction in response to campaign events. Economic conditions and Clinton’s popularity provided an opportunity for Democratic gains, but scholars have suggested that the campaign lessened this prospect because of candidate positioning and Gore’s personal distancing from Clinton (Fiorina, Abrams, and Pope 2003). This perspective is supported by the sizable degree of fluctuation in party support, with inconsistent benefit to either party. There was a clear increase in Republicans following their convention, but this gain was soon washed away by the Democratic convention. The convention’s coefficient estimates indicate that the percentage of partisans decreases by 4.5 points, but among partisans the percentage of Democrats increases by 5.4 percentage points. By combining these estimates with each other and those of the lagged dependent variables, the total decline in Republican identifiers is estimated to be a large 4.7 percentage points. What is most intriguing, however, is that the Democratic convention did not boost Democratic numbers, but rather grew independents by 4.2 percentage points. These percentages remained roughly at similar levels until the second and third debates. Republicans show an average combined gain of 2.9 percentage points following the second debate, with a corresponding decline mostly for Democrats. But Democrats show a 2.3-point gain following the third debate, with a corresponding decline in independents. The campaign clearly produced a sharp increase in independents following the convention, but then ultimately produced partisan gains during the debates.

Figure 3 displays the results from the stability model estimates of the 2004 campaign. In contrast to 2000, each observed series shows what is best described as random fluctuations around a constant population value. This degree of

10. These two estimates have a greater than 95 percent probability of excluding zero. The results for leaners indicate that the boost among Democrats is larger and pure independents smaller, suggesting that the Democratic national convention was associated with Republicans becoming independents and with some independents becoming leaning Democrats.

11. These respective effects are estimated to be greater than zero with greater than 95 and 90 percent probability.
stability in partisanship is perhaps not surprising. With a middling economy, the issues of Iraq and national security dominated the campaign. However, the policies and arguments surrounding these issues had been discussed and debated for over a year ahead of the campaign. Voters already had high levels of

Figure 2. Party Coalition Dynamics in 2000. Dots indicate observed percentages, and dark lines represent state space smoothed estimates. 95 percent BCI indicated with shaded vertical gray lines. Republican and Democratic conventions and the three presidential debates indicated, respectively, with vertical markers.
information on these issues, and the presidential campaign’s focus was mostly a replication of the same partisan debates from recent years. In this light, there was little new information or change in party positions or image during the campaign to act as a catalyst for changes in party identifications.

**Figure 3. Party Coalition Dynamics in 2004.** Dots indicate observed percentages, and dark lines represent state space smoothed estimates. 95 percent BCI indicated with shaded vertical gray lines. Democratic and Republican conventions and the three presidential debates indicated, respectively, with vertical markers.
Finally, four years later, short-term forces in 2008 strongly favored the Democratic party and Democrats entered their convention with significant advantages, comprising 39.4 percent of national adults, compared to Republicans at 28.3 percent. The convention managed to add to those numbers. As shown in table 2, with over 95 percent probability, Obama’s official nomination provided even further Democratic gains and Republican losses. On average, the combination of its effects on the partisanship and macro-partisanship series result in an estimate of a 2.8-point gain for Democrats and a 2.3-point loss for Republicans. Although the estimated changes following the Republican convention are not as certain, they indicate a decline in Democratic numbers following this event. Perhaps the initial reaction to McCain’s selection of Palin as his running mate managed to pare back some of the Democrats’ surge. But, as figure 4 shows, as the financial crisis unfolded and the debates progressed, the campaign’s net outcome was an increase in the proportion of independents and a decline in Republicans. Compared to before the conventions, the estimates are over 95 percent certain that the independent portion of the American public increased, with a combined effect of 1.9 percentage points. These gains came mostly from a decline in Republicans, as the estimated proportion of Democrats is equal to their preconvention levels.

Discussion

Partisanship plays a persistent and pervasive role in shaping American public opinion, but there are few and conflicting perspectives of its behavior immediately prior to Election Day, the time of its greatest influence. These results strongly indicate that the balance of party identifications changed across at least three recent presidential campaigns, and often in association with campaign events. However, these estimates also fail to find a consistent pattern in how partisanship changes during the campaign.

On a practical level, these findings inform evaluations of campaign polling methodology. There are two major limitations in the use of party identification weights to estimate the public’s support of a candidate or policy. First, target-population distributions of partisanship are never observed from sources like U.S. Census data. Second, partisanship is a psychological attachment that is not set in stone. Assuming that samples are sufficiently representative, it is possible to overcome the first limitation by using statistical models in combination with past sample survey data (Reilly, Gelman, and Katz 2001). But the use of any such method largely requires that researchers specify a model of how sample estimates of partisanship relate to one another across time.

12. The convention estimates are much smaller when defining leaners as partisans, suggesting that both convention effects produced changes in the strength of identifications among leaners.
Along these lines, the estimated variability in partisanship’s dynamics during these four campaigns illustrates the difficulties in estimating population party distributions and how it risks both bias and less precision. As this study demonstrates, statistical methods allow one to estimate when and how

Figure 4. Party Coalition Dynamics in 2008. Dots indicate observed percentages, and dark lines represent state space smoothed estimates. 95 percent BCI indicated with shaded vertical gray lines. Democratic and Republican conventions and the three presidential debates indicated, respectively, with vertical markers.

Along these lines, the estimated variability in partisanship’s dynamics during these four campaigns illustrates the difficulties in estimating population party distributions and how it risks both bias and less precision. As this study demonstrates, statistical methods allow one to estimate when and how
partisanship changes. But these estimates are inexact, especially when calculated without many future observations following a change. Pollsters who seek to take a snapshot of opinion at a single moment in time also risk bias if they specify the wrong model of how partisanship changes. What may appear to be a trend in partisanship following one party convention can quickly be erased following another, and target population weight estimates need to allow for the possibility of either large sudden breaks or no changes at all from prior sample estimates.

Similar concerns apply to political science and communication studies of campaign effects. Since partisanship is foundational to many individual attitudes and reactions to the campaign, studies often control for its influence on public opinion when testing campaign effects. However, if campaigns shape political behavior partially through their ability to change the partisan composition of the electorate, then controlling for partisanship masks the campaign’s total effect. Therefore, it is prudent for researchers to recognize and accommodate for a campaign’s indirect influence on public opinion through partisanship.

The broader relevance of these findings, however, speaks to our understanding of how presidential campaigns influence or reflect shifting partisan coalitions. Regardless of how independents are measured, the findings do not support claims that the general election portion of presidential campaigns makes the country more partisan (Clarke and Stewart 1998). Independents never declined in number, and their proportions exhibited near certain increases in two out of the four presidential campaigns. During the 1984 and 2008 campaigns, partisans on the losing side declined and independents increased. Furthermore, only the 1984 estimates are near certain that the winning party also experienced a gain in identifiers. In short, these four presidential campaigns were less effective at recruiting partisans than they were at weakening or driving away existing partisans.

Aggregate data analysis is limited in its ability to pinpoint whether each party’s gain (or loss) in identifiers came from (or went to) independents or the other party. When considering the patterns across both codings, the 2008 results are suggestive of the campaign mostly modifying the strength of identifications among each party’s supporters. But estimates show that campaign dynamics had double-sided consequences during 1984 and 2000. Gains on one side often occurred as the other side lost identifiers, a pattern that is also consistent with party recruiting or switching.

When sitting presidents were not running during the 2000 and 2008 campaigns, the timing of campaign events is also associated with shifts in partisan identities. This suggests that campaigns can act as catalysts for changes in partisan coalitions and not merely reflect them. The 2000 and 2008 debates and conventions were focal points where the new standard-bearers of the parties modified each party’s positions and image, and these points were associated
with changes in party coalitions. Thus, partisan change is conditional partly on when campaigns promote their images and messages. In contrast, events during the two reelection campaigns exhibited a much weaker association with changes in partisanship. These different patterns may reflect differences specific to reelection campaigns, since they are often referendums on existing party stances and performance. Alternatively, the degree of trending found in 1984 may represent a type of influence specific to past elections or its unique economic context.

The relevance of these shifts in partisanship for politics after the election depends on which model of partisanship’s long-run durability is accurate. If partisanship is largely a durable identity, then these deviations may represent only temporary wobbles, with little future consequence. However, if partisan shifts have greater permanence (Box-Steffensmeier and Smith 1996) or if campaigns act as catalyzing events (Sears and Valentino 1997), then an identification that is formed in reaction to the campaign will continue to influence mass political behavior long after the election.

Likewise, although the net change in partisanship was substantial during 1984, another potential qualification to finding large swings in 2000 and 2008 is that both culminated in a small net change in the distribution of partisanship. Finding a small net change is perhaps indicative of partisanship’s tendency to return from deviations. But if party competition and campaign events spur this process, then existing characterizations miss part of the story. By observing that partisan numbers are regained after a convention or debate, it is apparent that campaign activities influence the strength and duration of such movements. In short, the observed durability of partisanship across time is likely enhanced by the ability of party elites to emphasize party images that bring their supporters back to the fold. Along these lines, a complete understanding of how party coalitions change across time requires that we look beyond individual behavioral tendencies and examine how individuals respond to party attempts to capitalize on favorable circumstances or attacks on one another.

Appendix A. Survey Information


Each survey study was a national landline telephone survey of adults 18 years of age or older, via random digit dialing of area codes in the continental United States. Interviews were conducted in English or Spanish. When more than one adult lived in the household, respondents were randomly selected by age or closest birthdate. Response rates for the entire 2000 rolling cross-section study are reported at 25 percent, completed interviews divided by the number of eligible households of known and unknown status, or 31 percent, completed interviews divided by only the number of known eligible households. Using the same calculations, the respective response rates for the entire 2004 and
2008 rolling cross-section study are reported at 22 and 19 percent (or 25 and 23 percent). Further details about the survey’s sampling procedures are provided by Romer et al. (2006) and at www.annenbergpublicpolicycenter.org/political-communication/naes/.

1984 DECISION MAKING INFORMATION SURVEY

The continuous monitoring survey was a national telephone survey of adults via random digit dialing with a sampling universe consisting of all U.S. citizens 18 years of age or older. Response rates for the survey were not archived. Allsop and Weisberg (1988) provide further details of the DMI survey and validate its estimates by comparing them to the ANES’s Continuous Monitoring Study estimates (weekly samples).

Appendix B. Model Specification and Estimation Details

MODEL SPECIFICATION

Each state space model has the same observation equation specification:

\[
\begin{pmatrix}
y_{pt} \\
y_{mt}
\end{pmatrix} = \begin{pmatrix}
\pi_{pt} \\
\pi_{mt}
\end{pmatrix} + \begin{pmatrix}
\varepsilon_{pt} \\
\varepsilon_{mt}
\end{pmatrix}, \text{ where } \varepsilon_t \sim N_2(0, R_t)
\]

and \( R_t \) is a 2 x 2 matrix with diagonal elements \( \delta_{pp}(1 - y_{pt})/n_{pt} \) and \( \delta_{mm}(1 - y_{mt})/n_{mt} \), where \( \delta \) represents the design effect, and zeroes in the off-diagonal. The transition model specifications vary, but follow from the stability model specification:

\[
\begin{pmatrix}
\pi_{pt} \\
\pi_{mt}
\end{pmatrix} = \begin{pmatrix}
\alpha_{pt} \\
\alpha_{mt}
\end{pmatrix} + \begin{pmatrix}
w_{pt} \\
w_{mt}
\end{pmatrix}, \text{ where } w_t \sim N_2(0, W)
\]

and \( W \) is the 2 x 2 variance-covariance matrix of the transition errors \( \varepsilon_t \).

REGRESSION ESTIMATION

Estimates were generated using Gibbs sampling and the forward-filtering, backward-sampling algorithm (Frühwirth-Schnatter 1994). For each model, define \( b \) as the set of associated regression coefficients \( (\beta, \alpha, \zeta) \). The estimation task is to summarize the joint posterior \( p(\pi, b, W, R_t | y, x) \), which I evaluate via simulations using the Gibbs sampler. Starting with a set of proper initial values, the sampler was implemented in the following order:

1. Sample \( p(\pi_t | b, W, R_t, y_t, x_t) \): Updated estimates of state vector \( \pi_t \) were first calculated using the Kalman filter recursions, and then posterior
samples were drawn jointly using the backward-sampling approach. To initiate the Kalman filter chain, the initial unobserved state vector must also be defined. I implement a semidiffuse multivariate normal prior, where \( \pi_0 \sim N(\hat{\pi}_0, P_0) \), where \( \hat{\pi}_0 \) equals the observed average of both proportions in the first month and \( P_0 \) is given diagonal values equal to \( .02^2 \).

2. Sample \( p(\mathbf{b} | \pi, W, R, y, x) \): Given the error variance-covariance matrix \( W \) and a multivariate-normal prior for nonzero elements of \( \mathbf{b} \), we have a seemingly unrelated regression with a conditionally conjugate multivariate normal posterior distribution for the regression parameters. I specify relatively uniform prior expectations for the regression parameters, centered on the stability model, with \( E(\alpha_p = \bar{y}_p) \) and \( E(\alpha_m = \bar{y}_m) \) and all other expectations centered on zero. Although these priors are diffuse and contribute little information to the posterior estimates, to the extent they are informative these priors favor the stability model.

3. Sample \( p(W | \pi, \mathbf{b}, R, y, x) \): Define \( T \) as the number of days sampled. By specifying a diagonal inverse Wishart prior for the 2-by-2 square matrix representing the variance-covariance matrix for \( w_{pt} \) and \( w_{mt} \) (with diagonal elements expecting a standard shock of .5 percentage points, \( .005^2 \)) with \( \nu_0 = 4 \), this implies an inverse Wishart posterior with degrees of freedom \( \nu = 4 + T \).

4. Sample \( p(R | \pi, \mathbf{b}, W, y, x) \): Each diagonal element of \( R \), contains the error variance for \( \varepsilon_i (= y_i - \pi_i) \) scaled by the estimated sampling error based on simple random sampling. This reduces to estimating an error variance with known scalar. Defining \( T \) as the total number of daily observations, and by specifying an inverse Gamma prior, the posterior distribution of each \( \delta \) becomes \( \text{inverse-Gamma}(\nu/2, \nu s^2/2) \),

where \( \nu = 60 + T \) and \( s^2 = 60(1.25) + \sum_{i=1}^{T} \left( \frac{\varepsilon_i}{\sqrt{y_i(1-y_i)/n_i}} \right)^2 \).

Using different starting values, three separate simulation chains were run for 30,000 iterations. The first 10,000 simulated draws were discarded as burn-in simulations, and then 20,000 posterior simulations were included from each chain. Examination and the Gelman-Rubin comparison of the within- and between-chain variance all indicated proper convergence over each posterior distribution.

MARGINAL LIKELIHOOD AND RELATIVE PROBABILITY ESTIMATION

Bayesian model comparisons use estimates of the marginal likelihood \( (p(\text{Model} | y)) \) in combination with prior beliefs of each model’s suitability \( (p(\text{Model})) \) to estimate the relative probability of the data having produced each model. Using Bayes’s theorem to choose among three candidate models,
the posterior probability that the data support one model over the others is calculated as follows:

\[ p(\text{Model}|y) = \frac{p(\text{Model}) p(y|\text{Model})}{\sum_{k=1}^{n} p(\text{Model}_k) p(y|\text{Model}_k)} \]

Depending on the researcher, different prior probabilities may be placed on each model. In these results, I use a uniform prior such that I assume each model is equally likely.

Estimates of the marginal likelihood are calculated using the reciprocal importance density sampling procedure with the importance density defined by Frühwirth-Schnatter (1995).

Define \( \theta_m \) as the respective set of estimated model parameters \( (\alpha, \beta, \delta, \ldots) \) for each model \( j \) at each draw \( m \). Following Frühwirth-Schnatter (1995), a subset of 400 simulation draws of \( \pi_t \) were selected for use to approximate an importance density function \( q(\theta_m) \) such that the reciprocal importance sampling estimate of the marginal likelihood is

\[ p(y_j|\text{Model}_j) = \left( \frac{1}{M} \sum_{m=1}^{M} \frac{q(\theta_m)}{p(y_j|\theta_m) p(\theta_m)} \right)^{-1}, \]

where each tenth draw of the 60,000 posterior samples was included for estimation, resulting in \( M = 6000 \).
Appendix C. Estimates When Coding Leaners as Partisans

Appendix Table. Selected State Space Regression Model Estimates (posterior standard deviations in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Partisan</td>
<td>Macro.</td>
<td>Partisan</td>
<td>Macro.</td>
</tr>
<tr>
<td>Constant</td>
<td>0.901* (.004)</td>
<td>1.081* (.226)</td>
<td>0.924* (.001)</td>
<td>1.221* (.212)</td>
</tr>
<tr>
<td></td>
<td>0.537* (.004)</td>
<td>0.671* (.117)</td>
<td>0.537* (.003)</td>
<td>0.773* (.140)</td>
</tr>
<tr>
<td>Daily trend</td>
<td>–0.007 (.005)</td>
<td>–0.194 (.250)</td>
<td>–0.241 (.217)</td>
<td>–0.341 (.233)</td>
</tr>
<tr>
<td>Dem. convention</td>
<td>–0.005 (.009)</td>
<td>–0.005 (.018)</td>
<td>0.047* (.104)</td>
<td>0.003 (.022)</td>
</tr>
<tr>
<td>Rep. convention</td>
<td>–0.008 (.009)</td>
<td>–0.008 (.019)</td>
<td>–0.023 (.019)</td>
<td>–0.006 (.014)</td>
</tr>
<tr>
<td>Debate 1</td>
<td>–0.008 (.011)</td>
<td>–0.008 (.018)</td>
<td>–0.004 (.012)</td>
<td>0.004 (.020)</td>
</tr>
<tr>
<td>Debate 2</td>
<td>–0.008 (.015)</td>
<td>–0.008 (.024)</td>
<td>–0.049* (.017)</td>
<td>0.011 (.027)</td>
</tr>
</tbody>
</table>

(Continued)
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Debate 3</td>
<td>0.026* (.013)</td>
<td>0.046* (.020)</td>
<td></td>
<td></td>
<td>–0.018 (.017)</td>
<td>–0.003 (.026)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Design effect</td>
<td>1.386 (.141)</td>
<td>1.092 (.107)</td>
<td>1.684 (.154)</td>
<td>1.500 (.131)</td>
<td>1.530 (.146)</td>
<td>1.680 (.146)</td>
<td>2.006 (.179)</td>
<td>1.636 (.143)</td>
</tr>
<tr>
<td>$\sigma_w$</td>
<td>0.002 (.002)</td>
<td>0.002 (.001)</td>
<td>0.002 (.002)</td>
<td>0.002 (.002)</td>
<td>0.002 (.001)</td>
<td>0.002 (.001)</td>
<td>0.002 (.002)</td>
<td>0.002 (.001)</td>
</tr>
<tr>
<td>N</td>
<td>158</td>
<td>158</td>
<td>220</td>
<td>220</td>
<td>215</td>
<td>215</td>
<td>217</td>
<td>217</td>
</tr>
</tbody>
</table>

Note.—Estimates when coding leaning independents as partisans. Posterior means with standard deviations in parentheses. * indicates that 95 percent Bayesian credible interval excludes zero.
References


