Latent Variables and Rolling Panels
A New Approach to Modeling Campaign Effects
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OVERVIEW
What effects do political campaigns have on voters? Many researchers have argued that they have only "minimal effects", given the stability of voters' choices and the influence of factors such as partisanship and the economy. But in recent years, a growing body of evidence has suggested that campaigns indeed affect voters in a meaningful way. Exactly how campaigns' influences manifest, however, is still an unsettled debate.

I argue that difficulty of identifying campaign effects reflects the limitations of existing data and methods, not the absence of effects. In the paper from which this poster is drawn, I investigate campaign effects in the present election using by combining panel data from the National Annenberg Election Survey (NAES) with detailed records of campaign ads from the WiscCAM dataset. My paper is the first to present direct measures of campaign messages and panel data with regard to specific issues, and the results point to a far greater role for campaigns than previously believed. I demonstrate that campaigns can choose to clarify or obfuscate their positions effectively, that voters are persuaded by ads to change their policy preferences, and that these effects ultimately lead to substantial changes in vote choice.

While these findings are made possible through the use of over-time data on campaigns and voters, such data present a number of analytical challenges which threaten the ability of the analysis to credibly discern any causal relationships. As this is the point of using panel data in the first place—and existing models for panel data offer little guidance—I develop an original modeling approach and present it. With existing panel data being more common, this method could prove incredibly valuable.

MODELING CAMPAIGN EFFECTS
I look at three dependent variables to study the effects of campaign messages on candidate positions, policy preferences, and vote choice. To illustrate my general modeling strategy, I present below the model of how advertising affects voters' perceptions of candidates. The perception by individual i of the position of candidate j on issue t at time t – Tij – is assumed to be oriented so that positive values are closer to the candidate's true position. This perception then leads to Cijt, an indicator for whether the respondent would vote for the candidate in a survey:

Cijt = 1 if Zij > 0.0 otherwise.

The perception Zij at time t – T is modeled as a linear function of ads by each candidate, on that issue in the respondents' market up until that date, and a set of control variables:

Zij = β0 + β1*KittyAdsijt + β2*BushAdsijt + β3*Demographics + β4*Media1in + β5*Party1ij + β6*Idea + β7*Interest + β8*Time + εijt

Since the dependent variable in the applied models is the survey response Cijt, a binary probit model can be used for the latent Zij:

P(Cijt = 1 | Zij) = Φ(Zij).

Because the only factors in this model which vary across panel waves are the ads and the time trend, post-election perceptions (T – T) can be modelled as a function of these variables and pre-election perceptions (T = 0):

Zij = β0 + β1*KittyAdsijt + β2*BushAdsijt + β3*Demographics + β4*Media1in + β5*Partyij + β6*Idea + β7*Interest + β8*Time + εijt

We observe Zij directly, this model would be simple to implement. But because we have both lagged and continuous (while its observed counterpart, Cijt, is categorical), the best approach is not so obvious. What is needed is a way to proxy for Zij. Given the challenges of using the NAES panel described earlier, a suitable approach for implementing these models in the NAES data would need to meet three criteria:

1. It would avoid overfitting in a moderately-sized sample.
2. Missing pre-election responses could be imputed and used in a straightforward manner.
3. Bias from time-correlated measurement error would be minimized.

EXISTING METHODS
There are a variety of common techniques for analyzing panel data, but none meets all three criteria:

<table>
<thead>
<tr>
<th>Method</th>
<th>Alleviate Overfitting</th>
<th>Imputation OK?</th>
<th>Minimize Bias?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>First Differences</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Lagged DV</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>LDV + Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
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</table>

The Markov model, in which separate analyses of post-election responses are run based on pre-election responses, can have sample-size problems when response distributions are skewed, requires categorical initial responses (complicating M↓), and does not address bias concerns. Using first differences solves the sample-size problem, but the others remain. Using a lagged dependent variable would meet the first two criteria, but still does not address bias. Finally, including the full set of controls (e.g., demographics, media consumption) in an LDV model would help to minimize bias (by taking weight off of the LDV), but risks overfitting the model μijt.

A NEW APPROACH
As proxies for the lagged latent variables in models of post-election responses, I use survey responses such as perceptions of pre-election latent variables based upon models of cross-sectional responses (using the much-larger RSC sample, which allows for more precise estimates). Mathematically, the motivation behind using both variables is as follows. Let yijt be an individual's categorical survey response at time t. This response is the sum of the latent continuous variable yijt and a measurement error ϵijt (discussed at the end of the second section) produced by converting yijt into the categorical response yijt:

yijt = yijt + ϵijt

The latent variable yijt is itself the sum of xijt, the product of a vector of coefficients and a vector of observable independent variables, λijt, which reflects the individual's unobservable heterogeneity, and εijt, reflecting a random error term in the present period. Thus:

yijt = xijtλijt + εijt

Because yijt never observed, the goal is to find the best proxy for yijt to use as a control variable in the follow-up period, t + 1. By modeling yijt as a function of xijt, I can generate efficient, unbiased estimates of yijt – βijt – which I assume to be the true value for this purpose. To proxy for yijt, I use the weighted average of θij and yijt:

yijt = θij + yijt(1 – θij)

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yijt = θij + yijt(1 – θij)

The weight variable θij is not known a priori, but instead determined empirically: the coefficients produced by the t + 1 model are correlated with the t + 2 model. The true weight is then an increased precision from greater weight on θij and increased error from greater weight on εijt and τijt. Determining these weights empirically allows the weight given to the individual and random error terms to be adjusted while keeping the weight on xijt constant. In expectation, if the coefficients on the time-invariant IVs are the same in both models, my approach will place the same weights in the LDV + Controls model discussed above, without the associated cost to the post-election model's degrees-of-freedom.

COMPARING MODELS OF PERCEPTIONS
To compare how these approaches compare in practice, I use each to model perceptions of Bush's position on stem cell research (1 = correct placement, 0 = incorrect). The model fits (as expected) proportional reduction in error—see Herron 1999), sample sizes, and estimated effects of ads (as the average change in probability of correctly placing Bush from $1 in per-household spending; SEs in parentheses) are listed below:

<table>
<thead>
<tr>
<th>Model</th>
<th>Effect of $1 per Household of Bush Ads</th>
<th>Model</th>
<th>Effect of $1 per Household of Kerry Ads</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDV &amp; Controls</td>
<td>0.165 (0.03)</td>
<td>LDV &amp; Controls</td>
<td>0.133 (0.03)</td>
</tr>
<tr>
<td>LDV</td>
<td>0.145 (0.04)</td>
<td>LDV</td>
<td>0.116 (0.04)</td>
</tr>
<tr>
<td>First Differences</td>
<td>0.134 (0.04)</td>
<td>First Differences</td>
<td>0.111 (0.04)</td>
</tr>
<tr>
<td>Lagged DV</td>
<td>0.140 (0.04)</td>
<td>Lagged DV</td>
<td>0.126 (0.04)</td>
</tr>
<tr>
<td>LDV + Controls</td>
<td>0.173 (0.04)</td>
<td>LDV + Controls</td>
<td>0.158 (0.04)</td>
</tr>
</tbody>
</table>

While most models show effects in the same direction (Bush's ads making voters' perceptions less accurate, Kerry's ads making them more so), the last two—lagged DVs with full controls, and my original approach—show the best fit and the most significant effects. Though there is little evidence of overfitting in the LDV + Controls results here (a potential problem noted above), models of policy preferences on the same issue tell another story.

MODELS OF POLICY PREFERENCES
I next look to see whether voters are persuaded to change their policy positions. One common methodological approach is by respondents place themselves on 5-pt scales (which I rescale to range from –1 to 1 strongly oppose to 1 = strongly favor), though I treat these scales as continuous, they still carry potential measurement error. (Effect sizes are the estimated average change in self-placements from $.1 in per-household-asset spending, with SEs in parentheses.)

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<td>LDV &amp; Controls</td>
<td>0.058 (0.02)</td>
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<td>0.055 (0.02)</td>
</tr>
<tr>
<td>LDV</td>
<td>0.046 (0.02)</td>
<td>LDV</td>
<td>0.043 (0.02)</td>
</tr>
<tr>
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</tr>
<tr>
<td>LDV + Controls</td>
<td>0.069 (0.02)</td>
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<td>0.067 (0.02)</td>
</tr>
</tbody>
</table>

Here the full set of controls (which includes many factor variables and interactions) offers little advantage over the prediction in terms of model fit, but the resulting coefficients on ads are of substantially-diminished magnitude and significance. Across all of the models, these results demonstrate how the use of ill-considered methods can lead to null or even perverse findings. With my approach, however, the results confirm what we would expect to see if persuasion were truly occurring: that Bush's ads made voters' perceptions more conservative, while Kerry's made them more liberal.

SUBSTANTIVE RESULTS
In my paper, I look at how each candidate's ads affect voters' candidate perceptions and policy preferences across 10 issues, then test whether such changes lead voters to update their vote preferences. I find that
- Contrary to recent studies of campaign advertising, ads do not uniformly make voters better informed about candidates' positions. Rather, ads by competing candidates tend to have a negative effect on a candidate's ads clarify the candidates' positions for voters, the opponent's ads often serve to obfuscate them.
- Advertising can also have a persuasive effect on voters' policy preferences, even after controlling for partisan cue-taking.
- When these effects occur, individuals do update their vote choice, moving toward the candidates whose positions better fit their own preferences.

These results present a robust counterargument to those who dismiss campaigns as insignificant, and demonstrate that the effects of campaigns are meaningful rather than minimal.

CONCLUSION
The failure of previous studies to find campaign effects says less about the existence of these effects than it does about the inadequacy of common methodological approaches. By improving upon these approaches, I find stronger evidence for both informing and persuasiveness than any other study to date, and further show that such effects have a meaningful impact on votes. To be certain, this achievement was largely made possible by the advent of more precise data than was previously available. But as illustrated above, great data is not sufficient on its own—to be used effectively, it must be paired with a thoughtful modeling approach such as that presented here.

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