A New Approach to the Study of Rolling Cross-Sectional Design Surveys

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Abstract

At present, there are two methods for analyzing rolling cross sectional (RCS) data, the likes of which are generated by the National Annenberg Election Survey. One method is to aggregate the data by day and analyze these aggregated units as a time series. Doing so allows the researcher to test hypotheses about the effects of campaign or other aggregate events (e.g. the nominating conventions). The second method keeps the individual as the unit of analysis and looks at each time point or set of points as a separate cross section. This method allows the research to make inferences about individual level behavior, but sacrifices the ability to directly assess the effects of aggregate phenomena. We propose a solution to this problem by using a simple mathematical procedure within the framework of a hierarchical model. The multilevel model will allow us to retain the individual level dependent variable while giving us the ability to examine how coefficients change over time. In addition, the procedure that we demonstrate will also allow us to study the impact of events like nominating conventions and how these effects dissipate over time.

The National Annenberg Election Survey (NAES) and its rolling cross-section (RCS) design offer a distinct opportunity for political scientists to examine the dynamics of the campaign trail and the effects on their polity. To date, there are two generally accepted approaches to tap this relationship. First, researchers have aggregated individual survey responses to generate time series data to examine such things as presidential approval and vote intent (Johnston and Brady 2002; Johnston and Hagen 2003; Johnston, Hagen, and Jamieson 2003); through aggregation, researchers can look at the influence of campaign and election specific events like party conventions and debates. While this approach offers much to the study of the implications of campaigns, aggregation of the data sacrifices much in terms of the ability to make inferences at the individual level.

Second, others have examined the individual level also taking advantage of the RCS design, which allows for grouping of respondents by day, month, or some other pooled period (Carey and Lebo 2003; Johnston and Hagen 2003; Johnston, Hagen, and Jamieson 2003). To date, the most general approach involves estimating separate regressions for each day and comparing the coefficients or changes in predicted probabilities as the election nears. With such a large number of days to analyze, one can have ample model coefficients to compare throughout the election. Unfortunately, this method also makes a trade off. There is a distinct inability to apply any direct link of causality for the changes in the model's expectations or predictions to the specific dynamic characteristics at the aggregate level. More simply, using this approach, one can not say with certainty that a shift in the coefficients or predicted probabilities for a given day was due to events that occurred on that day.

Because of the importance of being able to draw conclusions of aggregate factors influencing individual level behavior and cognitive evaluations, we offer a possible solution to

the problem of the two approaches. We believe that a multilevel model, with some minor adjustments to the specification, will allow us to maintain the individual level heterogeneity, make causal inferences of aggregate level measures influencing individual level actions, and, therefore, better sift out the dynamic effects of campaigns and elections.

Two concerns are of particular interest here. First, we are interested in the dynamics between egocentric, or personal, and sociotropic, or national, economic evaluations.[1] Countless studies have been conducted at the individual and aggregate levels on the effects of economic evaluations, especially in the United States. Most of these works, however, focus on the tension between national retrospections and expectations, giving little specific attention to the relationship between national and personal evaluations. Some research has found that the electorate is generally forward looking (Fiorina 1981; MacKuen, Erikson, and Stimson 1989, 1992, 2000; Nadeau, et al. 1999). Still other research has found that voters tend to evaluate the economy retrospectively (Fiorina 1981; Hetherington 1996; Norpoth 1996, 1996b; Nickelsburg and Norpoth 2000). Most of the recent work (post-1989) agrees that individuals in the United States tend to weigh their evaluations of the national economy more than their evaluations of their own personal financial situation in matters of voting and approval.

This is not necessarily the case outside of the United States. Weyland (1998) finds that it is personal evaluations that matter more in Peru. Personal evaluations can affect vote intention in Britain (Carey and Lebo 2003) and party support (Clarke, Stewart, and Whiteley 1997; Clarke and Lebo 2003). Even the United States, applying proper methods to an aggregate time series

[1] The 2000 NAES does not ask questions regarding prospective evaluations until after Election Day. We will, therefore, analyze the dynamics between personal and national economic retrospections. The personal retrospective question is phrased as follows: "*Over the past year, would you say that the economic policies of the federal government have your own personal economic situation better, worse, or haven't they made much difference either way?*" The national retrospective question asks: "*Over the past year, would you say that the economic policies of the federal government have made the nation's economy better, worse, or haven't they made much difference either way?*"

shows that personal evaluations have an effect on presidential approval (Clarke and Stewart 1994). Given that there are dynamics between retrospections and evaluations, we will examine, looking only at retrospections, whether there are dynamics throughout the 2000 campaign between personal and national evaluations. We expect that as the election draws near, national considerations will have a larger effect than personal evaluations, but personal evaluations will have an important roll to play throughout the campaign season.

Our second concern relates to modeling the effects of aggregate level phenomena on an individual level dependent variable. The events we are concerned with here are the nominating conventions of both major parties. As we demonstrate below, there are several difficulties that arise when trying to link the two levels of analysis, difficulties we feel our procedure partially overcomes. Specifically, individual level models often require either qualitative explanations for changes in coefficients, assuming the method is to analyze each cross section separately, or else the researcher is forced to move several steps beyond the data, looking at the coefficients or other values in a time series.

This paper will proceed as follows. First, we attempt to sift out the effects of personal and national economic evaluations on vote intent at the aggregate level—using the approach of aggregating each cross-section by day and analyzing the aggregate time series. Second, we proceed to parcel out these effects at the individual level, following the approach mentioned briefly above. Third, we apply the same theory to our proposed specification of the multilevel model. Lastly, we discuss the implications and conclusions drawn from examining all three methods.

Rolling Cross-Sectional Design as Time Series

Simply put, the RCS is just a cross-section, but the assignment of the day in which a respondent is interviewed is randomly assigned. By taking into account and modeling the day in which a respondent is called, completed surveys for that day allow for researchers to examine the heterogeneity and dynamics of the campaign under real-time conditions. Comparing several alternatives, Johnston and Brady (2002) conclude that telephone surveying under the RCS method may indeed be best conducted in this manner because it makes the temporal heterogeneity of survey research an object of the analyses. More specifically, through the RCS method, they were indeed able to sift out campaign effects using the 1993 Canadian Election Study.[2]

In regards to the specifics of campaign effects, we can show the very dynamic nature of vote intent and how it is affected by personal and national retrospections. As briefly mentioned above, one approach that takes advantage of the RCS is to aggregate the individual level responses to survey questions and track the changes as time marches to the final voting act on Election Day. For our purposes here, we use the 2000 NAES and create a time series based on aggregated daily percentages of survey responses. The power of a time series approach to the RCS, again, is that it also allows for integration of day-specific factors into the model.

First, the dependent variable is aggregated vote intention, which is originally coded 1 if the respondent intends to vote for Bush in the coming election, 0 otherwise. Figure 1 graphs the percentages of vote intention aggregated by day. The two main independent variables are personal economic retrospections and national retrospections. We theorize that only individuals who believed that their personal economic situation had gotten worse would punish the

[2] For a more detailed discussion regarding the benefits of RCS, please also see Romer et al (2003), which speaks specifically to the National Annenberg Election Survey (NAES).

incumbent and vote for the challenger. Given that our dependent variable is coded in favor of the non-incumbent party, we therefore coded personal economic retrospections 1 if the respondent thought their personal economic welfare had gotten worse in the past year, 0 otherwise. The same was done for national evaluations; if the respondent indicated that she believed the nation's economy had gotten worse, the variable was coded 1, 0 otherwise. The two variables were aggregated to daily percentages.

[Figure 1 here]

We also control for partisan identification of the respondents. The variable for party identification was coded 1 if the respondent indicated affiliation with the Republican Party, 0 otherwise. All variables were aggregated by day. Moreover, we include interventions for each of the party national conventions and model decay parameters for each. Each convention is coded 1 on the last day of the Convention, 0 otherwise, suggesting temporary interventions. The expectation is that any bumps in vote intention at the aggregate level should come after each national convention for the respective parties; this effect though should dissipate as the number of days since the convention increases.

For each of the dependent and independent variables, we tested for the level of integration and differenced appropriately prior to estimation of the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model.[3] Also, we include one period lags, for all

[3] The reason for using the ARFIMA model is that most variables would not fall directly in line with either being stationary or not. This assumption is quite hefty given the dynamic nature of most measures. Under most conditions, it would be difficult to find situations where solely level form or only first differencing would keep a model from violating the stationarity assumption in time series. Thus, applying a fractional integration technique prior to estimation is most appropriate under these circumstances. For a further discussion of fractional integration, please see Lebo et al (2000) as well as Carey and Lebo (2003).

independent variables.[4] The results of the time series are presented in Table 1. Overall the model performs quite well and in accordance with our loose theoretical expectations.

[Table 1 here]

As anticipated, personal economic retrospections, at least in the aggregate, have a positive relationship with the vote intention. A one percentage point increase leads to a 0.26 point bump in the percentage of individuals indicating an intention of voting for Bush in the 2000 presidential election. The negative coefficient of personal evaluations indicates that an increase in the previous period leads to about a 0.23 percentage decrease in vote intention for Bush; the relationship of these two variables suggests that there is indeed a cyclical tendency to the effects of personal evaluations in the aggregate. Moreover, the coefficient for national economic retrospections suggests that a one percent bump leads to about a 0.20 percentage rise in vote intention for Bush; this variable is statistically insignificant, but in the correct direction; the lagged value indicates a lasting positive effect. The coefficient predicts an additional 0.293 percentage increase in Republican vote intention when national retrospections increased in the day before. Turning to party identification, as expected, a rising percentage of respondents that share party congruence with Bush leads to about a 0.65 percentage increase in support for the eventual act at the booths on Election Day. The lag of this variable also points to cyclical effect where the total effect for an increase of one point each day leads to about a 0.40 point increase in vote intention for Bush.

[4] Please also note that we estimated a model using a Dynamic Conditional Correlations model similar to Box-Steffensmeier and Lebo (2006). The parameter of interest to test if the variables of personal and national retrospections varied conditionally across the period of examination was insignificant at a p-value of .395 and thus we could not reject the null that there is constant correlation across the 2000 NAES survey period of the two independent variables of concern. Full model coefficients and specifications are available from the authors upon request.

In regards to the interventions, there is as expected an increase in vote intention for the Republican candidate after the party's national convention. According to the results in Table 1, George W. Bush received a 0.06 point increase in the percentage of specifying an intention to vote for him. The decay parameter, at 0.75, suggests a strong decline in terms of the effects of the Convention's boost in numbers. The Democratic National Convention, on the other hand, had the opposite effect. It led to about a 0.02 point decrease in the percentage of individuals indicating an intention to vote Republican for president in the final voting act. This effect erodes at a definitively slow rate considering the rather large coefficient of 0.99 for the Democratic National Convention decay parameter.

Logit Analysis by Day: Moving to the Individual Level

The time series estimated above can tell us much about the dynamics of vote intention and how various factors influence it. As discussed, the results from our loose model of vote intention indicated that the conventions did indeed lead to bumps in the percentage of vote intention for the respective parties. Unfortunately, we could not make any inferences as to what was occurring at the individual level. For example, what was the impact of or how heavily did personal economic retrospections weigh on individual vote choice? Time series does not leave much room to make inferences upon questions regarding the individual level. It is a thin line before one crosses into the territory of the ecological fallacy.

Individual level inferences have been made mostly treating data as pure cross-sectional or pooled cross-sectional. There generally can be two accepted approaches to using the rolling cross-section. First, one can sift out campaign effects by estimating two cross sections for two separate time points—one prior to the campaign and one after. The change in the coefficient of a

particular variable of interest would be considered the effect of the campaign itself. This also has its problems because it is assumed that the change in the coefficient is strictly due to the campaign and not some other possible aggregate effect.

A second approach would be to estimate models by day and track the changes in the predicted probabilities. The need to use predicted probabilities, when analyzing data from the RCS design, can be justified under two characteristics of the data.[5] Each day or time period represents a completely different sample. RCS is not panel data and therefore one can not treat the respondents from one time period as the same as those from another point in the survey. Two, the number of observations per day varies. The 2000 NAES generally has an average completion rate of surveys that hovers between about 30 and 50 respondents up until July of the election year. And, then, as the campaigns begin to take off and as the official presidential candidates become formalized, the number of respondents per day for the 2000 NAES rise into the triple digits and remains so until the completion of the survey. Due to these two aspects of the data, comparing across samples—if one were to estimate the individual level by day—is properly done by generating the predicted probabilities.

The method just discussed is exactly the strategy we employ to analyze the individual level. We developed models for each day keeping all the variables that were aggregated in the time series presented above in their original recoding. From there, we estimated models of vote intent as a function of personal and national evaluations as well as party identification. We will not show results for all 215 logit models because such a presentation is daunting and inefficient.[6] Instead, we present the predicted probabilities. Please note that we only show results since July

[5] The use of predicted probabilities is, of course, only proper with a limited dependent variable. If the dependent variable was continuous and ordinary least squares could be used to estimate the daily models, one could use the percent of the variance explained by a particular variable on each day to create a series.
[6] Of course, the estimated model coefficients are available from the authors upon request.

6th. This is so because, with a smaller number of observations at the front end of the survey period, most of the model's variables perfectly predicted vote choice. For example, on certain days early in the survey period, Republican Party affiliation perfectly predicted vote intent for the party's candidate. As a result, we only present predicted probabilities from the point at which all models generated estimated coefficients for all variables in the model. A graphical presentation of the predicted probabilities is found in Figure 2.

[Figure 2 here]

Please note that the predicted probabilities held party constant at its modal category which happens to be 0 meaning non-Republican Party identifiers. Moreover, for the two series, we held the other variable at 0. Thus, when looking at national retrospections, we held the variable at 1 while keeping personal retrospections at 0; the reverse is true when examining personal economic retrospections. A quick perusal of Figure 2 indicates much volatility in the measure. In order to sift through the effects of each, we decided to test the relationship between the two variables. Understanding the dynamics of personal and national retrospections should reveal much as to what enters into the individual level voting calculus on Election Day. Because we have no a priori expectations as to the direction of causality in this relationship, we estimate a Seemingly Unrelated Regression (SUR) model.

In order to test the validity of this (non)assumption and the appropriateness of the model, we examined the relationship first by applying Granger causality tests.[7] According to the tests, neither variable Granger causes the other. We also estimated two Vector Autoregressions (VAR)

[7] Turning the predicted probabilities into time series analyses also required tests for the precise level of fractional integration. Although the Dickey-Fuller and Variance Ratio tests led to the conclusion that both variables individually should not be first differenced because we rejected the null that d=1, simple Box-Jenkins models of for each variable with only AR(1) parameters indicated almost complete random walks, or unit roots, of both variables. Leaving each in level form is unfeasible and a violation of the stationarity assumption. Thus, considering the strength and significance of the AR(1) parameters for both models—one with only personal retrospection predicted probabilities and the other with only national, we opted to first difference each variable in for the analyses to follow.

to examine the relationship between the dependent variables—national retrospection predicted probabilities and personal retrospection predicted probabilities—and the lagged values of both. We included lags of up to three periods of each variable and estimated the models. Intuitively, the predicted probabilities for national retrospections are strongly predicted by all three lagged values that we included, but, oddly are not related to the lagged values of the personal predicted probabilities. The reverse is true when the predicted probabilities for personal economic retrospections are used as the dependent variable. Moreover, a VAR model may not be the best estimation strategy in this case because the cross-correlation function indicates a moderately strong, contemporaneous negative correlation between the predicted probabilities for national and personal retrospections.

Given that a VAR cannot be estimated using contemporaneous values, we estimated the model with 2SLS and OLS. Estimating a 2SLS model will allow us to do two things. First, it gives us consistent estimates in the face of endogenous relationships such as the possible one between the predicted probabilities from personal and national retrospections. Second, it allows us to test whether our instruments—the three lagged values of each variable—are proper instruments, which implies strongly predicting the endogenous variable of interest as well as being uncorrelated to the other endogenous variable in the system of equations. In this case, we use the three lagged values of the predicted probabilities for personal retrospections to predict its contemporaneous value. The same is done for national retrospections. There is indeed proper exclusion[8] and, moreover, the Hausman test showed that the efficient estimator, OLS, can be used instead of 2SLS.[9] Because we have the fortune of not only having proper exclusion, strong predictors of our two dependent variables, and over-specification of both models in a system of

[8] The actual Sargan Test statistic for over-identification test of all instruments, which is distributed χ^2 with 2 degrees of freedom, is 0.524 with a p-value of 0.7696.
[9] The actual test statistic χ^2 with 4 degrees of freedom is 1.57 with a p-value of 0.8134.

equations, a SUR as an estimation procedure is possible. Again, since we have no theoretical expectation as to which variable should be on the left hand side of the question and which on the right, we estimate a SUR. The results are presented in Table 2.

Overall, the models perform quite well. Moreover, we can see the significant and negative effect the predicted probabilities of personal and national evaluations have on one another. A one point increase in predicted probabilities of negative personal economic retrospections leads to a 0.393 decrease in the predicted probabilities of vote intent for the Republican candidate. Moreover, a decrease of 0.258 occurs for personal retrospections when there is a one percentage increase in predicted probabilities of national retrospections. As one can see, the interpretation and inferences from analyzing predicted probabilities seems quite difficult. The individual level should allow the researcher much more room and ease in terms of making inferences. The preceding analysis demonstrates that this is not the case.

[Table 2 here]

To date, the best method to be used has been to take predicted probabilities and examine the relationship as we have done above or to plot them on a graph as in Figure 2. Although graphical presentation of the results may indeed prove useful, any connection to increases or decreases in the predicted probabilities to any day specific events are cancelled out and thus subject only to qualitative reasoning and supposition as to the causes of such a shift. For example, if predicted probabilities fell on a given day, the relationship to such a decrease to a particular political event can be offered. But, any explanation can not truly be empirically tested unless one were to use the predicted probabilities of each day as time series, which would allow for specification of interventions and transfer functions at a daily level. Keeping in mind that examinations of predicted probabilities are solely contingent and conditional on the values of the

independent variables that were held constant to generate them, the inferences and interpretations hardly allow for simple analyses and presentation. Moreover, predicted probabilities treated at time series, although aggregated from the individual level, leads one back to the problem of possible ecological fallacy now, even worse, tied into the conditional values generated. Although this can be done and interpreted well, it is hardly an ideal situation.

The Multilevel Model: Using Aggregate Predictors in an Individual Level Model

As previously discussed, one of the drawbacks to aggregate level analyses is that we lose the ability to draw inferences about the individual level. Looking at each day as a separate cross section, however, we lose some of the ability to study the dynamics of the series. In studying the individual level relationships between personal and national retrospections with each other and with vote intention, we might also want to consider the effects of "aggregate" events like the nominating conventions. Using the logit method we previously discussed, we could have examined changes in predicted probabilities holding all variables at zero across time. This would have given us predicted probabilities based solely on changes in the intercept for each day. Doing this, we would probably observe a positive spike on August 3rd. We could assume that the increase in the predicted probability of intending to vote for Bush is due to an increase in the intercept caused by the Republican Convention. How much of the increase, however, is actually caused by the Convention? How long does this effect last? These are questions that cannot be answered by examining series of predicted probabilities.

A second problem arises when we want to examine relationships between coefficients. In the logit-by-day method, we examined the series of predicted probabilities because it would be inappropriate to compare coefficients across these models; each day has a different dependent

variable and different observations. In order to draw inferences about the individual level and keep the ability to model "aggregate" variables, like the nominating conventions, we propose using multilevel modeling, nesting individual respondents within days. A multilevel model will afford us the ability to do the following, which we present below:

1. By specifying the coefficients for personal and national retrospections as random, we can examine the relationship between them, looking at the correlation or covariance between the coefficients;
2. We can examine changes in the coefficients over time by including a simple time counter as a predictor in the equations for the coefficients;
3. We can model the effects of aggregate, or period-specific, phenomena like the nominating conventions or other interventions as part of a random coefficient, here are part of the intercept;
4. With a simple method, which we explain below, we can model the decay of the effects of these interventions.

As with the logit models discussed above, the multilevel model uses the same individual level variables. Vote intention is a function of personal economic retrospections, national economic retrospections, party identification, and idiosyncratic error. The individual level equation is presented as follows:

[1] $$Vote\ Intent_{it} = \beta_{0t} + \beta_{1t}\ Personal\ Retro_{it} + \beta_{2t}\ National\ Retro_{it} + \beta_{3t}\ Party\ ID_{it} + r_{it}$$

In order to study the relationships described above, we modeled the intercept and the effects of personal and national retrospections as random coefficients that also vary systematically.[10] The time level equations (Level 2) for the coefficients are modeled as follows:

[10] Our decision to use the multilevel model is supported by two results. First, we pooled the data and estimated the individual level coefficients using a logit, including a dummy variable for each day, excluding the first day. A Wald

[2] $\beta_{0t} = \gamma_{00} + \gamma_{01}\ Rep\ Convention_t + p\delta_{01}\ ln(Time\ After\ RC_t) + \gamma_{02}\ Dem\ Convention_t + p\delta_{02}\ ln(Time\ After\ DC_t) + u_{0t}$

[3] $\beta_{1t} = \gamma_{10} + \gamma_{11}\ T_t + u_{1t}$

[4] $\beta_{2t} = \gamma_{20} + \gamma_{21}\ T_t + u_{2t}$

[5] $\beta_{3t} = \gamma_{30}$

The intercept is a function of two interventions, the Republican and Democratic National Conventions, and the log of the amount of time since those conventions. These coefficients, which we refer to as *pseudo-δ* coefficients (abbreviated as *pδ*), are where we include a standard concept from time series methods into the analysis of rolling cross sectional data, decay parameters. One of the benefits of analyzing rolling cross sectional data as an aggregate time series is having the ability to perform impact analysis. As we did above, we could examine the initial impact of an event (e.g. the Republican National Convention) and we could explicitly model the dynamic properties of that impact; how long the effect lasts and how much of it remains in each subsequent time period. In time series analysis, an impact decays exponentially as time increases. In general, an intervention will have the following impact: $\omega\delta^t$. The initial impact is estimated by ω. At the first period after the initial impact, the effect is $\omega\delta$. At the second period, it is $\omega\delta^2$.

In an effort to model a similar exponential decay, we first operationalized the Republican and Democratic Conventions as "permanent" interventions; the variable is scored "1" for the last

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test on the coefficients of the period dummies showed that we could reject the null of no period effects ($\chi^2 = 301.37$, p-value = 0.0001 for 214 degrees of freedom). Second, we estimated fixed effects and random effects logit models. We could not reject the null of the Hausman test ($\chi^2 = 0.92$, p-value = 0.8209 for 3 degrees of freedom), which compares the consistent fixed effects estimator to the efficient random effects estimator. The results suggest that our individual level independent variables are not correlated with the period effects, freeing us to specify the intercept as random. Aside from these results, in a multilevel model we can specify random slope coefficients, which allow us to examine the correlation between the effects of personal and national retrospections.

day of the Convention and each day thereafter.[11] The initial impact of each convention is measured by γ_{01} and γ_{02}. The subsequent decay is measured by the natural logarithm of the number of days since each convention (starting from the last day), raised to the power of *pseudo-*δ, which is a parameter to be estimated.[12] For example, on August 3rd, the last night of the Republican Convention, the total effect is equal to $\gamma_{01} + p\delta_{01}\ ln(1)$. The log of 1 equals 0, which gives the initial impact of γ_{01}. On August 4th, the effect of the Convention is equal to $\gamma_{01} + p\delta_{01}\ ln(2)$. We expect $p\delta$ to have the opposite sign of the initial effect. We therefore expect γ_{01} to be positive (increase the likelihood of intending to vote for Bush) and $p\delta_{01}$ to be negative, thereby decreasing the impact of the Convention. We expect the opposite for the Democratic Convention; γ_{02} should have a negative effect on the likelihood of intending to vote for Bush and $p\delta_{02}$ should be positive, lessening the initial impact of the Convention.

As an illustration of the effects we expect from our decay function, we present Figure 3. Each of the curves shows how much of an initial impact would be decreased in each subsequent time period. Unlike decay parameters in aggregate time series analysis, larger estimates for *pseudo-*δ in our framework lead to faster decay. The one drawback to modeling decay using parameters that are linear and additive is that the possibility exists for the total effect (initial impact – decay) to be negative for interventions with a steep decay as the time since the initial impact increases. This framework, however, can give us a good idea of how many periods it

[11] Modeling the interventions as permanent here is necessary to estimate a total effect for the intervention as the series moves past the initial impact. The equation for the intercept is additive in its parameters therefore the decay must be subtracted from some baseline effect. The baseline effect of the Republican Convention, for example, is constant from the first day the Convention is modeled until November 6th. The decay parameter will establish how much is subtracted from this effect in each subsequent time period.

[12] Decay was modeled in this way to keep the equation linear and additive in the parameters. Our modeling strategy stems from a desire to keep the proposed technique as accessible as possible while allowing for the possibility of exponential decay. Such models could then be estimated using software most researchers currently own. While this model was estimated using HLM6, the technique we describe here could be implemented in STATA 9 using the "xtmixed" command, given that the dependent variable is continuous and the model is linear, or the GLAMM add-on to STATA, which would be appropriate for linear or nonlinear models. We settled on decreasing the initial impact of an event by $ln(T^{p\delta})$, which is mathematically equivalent to $p\delta\ ln(T)$, the formulation of the decay found in the multilevel model.

takes for the effect of an intervention to completely decay. We will examine this in more detail below in our discussion of the estimates for these parameters.

[Figure 3 here]

The coefficients for personal and national retrospections are modeled as random to allow these slopes to vary idiosyncratically by day. The correlation and covariance between the slopes will give us an idea of how the effects of one relate to the other. The literature suggests that the key tension between types of evaluations is whether retrospection or expectations matter more. Unfortunately, the 2000 NAES does not afford us the ability to examine the dynamics between these two. We can, however, state that as one type becomes more or less important—as people think more or less retrospectively—both national and personal retrospections become more or less important at the same time. This would be supported by a positive correlation between the slopes.

The second dynamic we examine is how these slopes change over time. The effect of personal and national retrospections is modeled with an interaction between retrospections and a time counter. We expect that this interaction will have a larger effect for national retrospections than personal retrospections. We theorize that as Election Day draws closer, the national focus of the presidential campaign makes national retrospections more important than personal retrospections. Put another way, given the linear equations for each coefficient (equations 3 and 4), we expect the coefficient for national retrospections (β_{2t}) to have a steeper slope—the absolute value of γ_{21} will be greater than the absolute value of γ_{11}. Finally, we simply model the effect of party identification as fixed or constant across individuals and time.

[Table 3 here]

Table 3 presents the estimates for the multilevel model. The model correctly predicted 75.443% of the outcomes, which gives a 48.817% reduction in error. We have a total of 34,438 individuals nested within 215 days. There is an average of 160.2 respondents per day with only three days that had fewer than thirty respondents. There were no days with less than twenty-five respondents. Neither the intercept nor the slope of personal retrospections showed significant random variation, suggesting that our time level variables sufficiently model any time-based variation in those coefficients. The slope of national retrospections, however, does exhibit significant random variation ($p = 0.058$).

Looking at the relationship between personal and national retrospections, we find a large positive correlation. The covariance between the coefficients is also positive, but, given the absence of random variation in the slope of personal retrospections, this covariance is quite small. Using the correlation, we find that the effects of personal and national retrospections move together—if a respondent is thinking retrospectively, both personal and national retrospections increase in importance. The reverse is true for respondents who show smaller effects for retrospections. As retrospections in general become less important, both personal and national retrospections would show decreased effects.

One important note about the effects of personal and national retrospections is that they are conditional on the proximity of the election. Both coefficients are modeled to vary linearly with a simple counter for time. Along with conditional effects, however, we must also consider conditional significance. Looking at table 3, we see that the fixed effect for national retrospections is not significant, but this effect is never possible; we modeled our time counter so that the first day of the rolling cross section is counted as 1 not 0. Figure 4 shows the conditional significance of personal and national retrospections. Each line shows the t-score for the slopes of

personal and national retrospections for each day in the analysis with 1.978 as the two-tailed critical value for 213 degrees of freedom. The slope for personal retrospections is always significant, but the slope for national retrospections does not become significant until May 3rd. Generally, we can conclude that national retrospections do not have an effect very early in the campaign season. It might be the case that before the heavy summer campaigning begins, respondents have less of a national focus in considering their evaluations of the economy and who they intend to vote for. This could also be the case if the presidential candidates focused more on local or regional issues during the primary season, trying to attract support locally before winning the nomination and focusing on the nation.

[Figure 4 here]

Table 4 shows how the effects of personal and national retrospections change over time. The conditional effect is the value of β_{jt} given the estimated coefficients (γ_{j0} and γ_{j1}) and the value of the time counter. For the purposes of presentation, the first column of the table shows how many days remain until Election Day. As an example, one day remaining in the last row implies the day is November 6th and the value of the counter is 215.

[Table 4 here]

Clearly, as time increases both personal and national retrospections become more important. As predicted, however, at some point in the campaign national retrospections become slightly more important than personal retrospections. In the final column of table 4, we show the difference between the slope coefficients. A negative difference means national retrospections have a larger slope. This relationship is depicted in Figures 5 and 6. Figure 5 shows the conditional effects of personal and national retrospections. Figure 6 plots the difference between these coefficients. We estimate that after August 27th, which is after each party has held its

nominating convention, respondents become more national in their focus giving more weight to national as opposed to personal retrospections.[13]

[Figures 5 & 6 here]

Turning to our intervention analysis, we estimate the initial impact of the Republican Convention as 0.465, which suggests an increased likelihood in intending to vote for Bush. *Pseudo-δ* for the Republican Convention is estimated to be -0.189. This means that the effect of the Republican Convention for any period starting from the last day of the Convention equals: *0.465 – 0.189 ln(Time Since)*. The initial impact of the Democratic Convention is -0.248 and this effect has a *pseudo-δ* of 0.083. This gives a total effect for any period of: *-0.248 + 0.083 ln(Time Since)*. These relationships are depicted in Figure 7.

[Figure 7 here]

We can see in Figure 7 that the total effects "flip" signs at certain points and we discussed this possibility above. We find that the effect of the Republican Convention becomes negative after eleven days, which coincides with the beginning of the Democratic Convention, and the effect of the Democratic Convention becomes positive after twenty-two days. We stated above that the *pseudo-δ* estimate would give us an idea of how long it took an initial impact to decay. To check our findings, we also examined the effects of the Conventions in the aggregate time series. Note, however, that the initial impact of the Democratic Convention in the ARFIMA model was not significant and the estimated decay suggested a "near-permanent" effect of zero. These effects are pictured in Figure 8.

[Figure 8 here]

[13] For simplicity, we have estimated the effects of personal and national retrospections as linear with respect to time. Future work need not be bound by this restriction. We have also estimated models in which the coefficients are quadratic functions. These results suggest that the effect of personal retrospections has a linear relationship with time ($\gamma_{10} + \gamma_{11} T$) and the effect of national retrospections has a quadratic relationship ($\gamma_{20} + \gamma_{21} T^2$).

The figures look like they match quite well for the effects of the Republican Convention. The Democratic Convention curves have different shapes owing to the different ways in which the decay is estimated; time series methods have decay parameters bounded between zero and one and the multilevel approach we take has a technically unbounded decay parameter. Another note of comparison to make is that we find very significant effects at the individual level for the Conventions. In the aggregate time series, the p-values are 0.10 and 0.12 for the Republican and Democratic Conventions respectively.

[Figure 9 here]

Looking more closely at the effects of the Republican Convention, we graphed the total effects of the Convention in the time series and the multilevel model between August 3rd and August 16th (Figure 9). Our purpose here is to compare how long it takes the initial effect to decay towards zero in each model. While the total effect of the Convention becomes negative in the multilevel model, this figure demonstrates more clearly that our decay function produces results strikingly similar to those found in the aggregate time series.

Conclusion

We conclude several things from the preceding analysis. Substantively, there is a place for personal economic evaluations in research on the American voter. We have shown both at the aggregate and individual levels that vote intention is significantly affected by personal as well as national economic retrospections. Multilevel modeling has also allowed us to conclude that while national retrospections are more important to potential voters on Election Day, personal retrospections can play a crucial role in determining vote intention throughout the campaign and possibly set a tone for voters as the campaign progresses.

Methodologically, we have demonstrated a new technique for the analysis of RCS data. Our technique is an improvement over other methods of individual level analysis, given we no longer have to estimate a separate model for each period, and it is accessible in that it could be implemented using standard software. The multilevel approach also allows for the longitudinal analysis that is often lacking in studies making use of RCS or pooled cross-sectional time series data. In this paper, we included only intervention analysis as it affects mean vote intention—working through the intercept of the individual level. The technique, however, could also be used to assess the effects of aggregate level phenomena on the slopes of individual level variables. For example, we could assess the initial impact of the first Swift Boat Veterans for Truth advertisement on the effect of partisanship on vote intention in 2004. Furthermore, we could examine the decay of this effect as time goes on. One area of improvement that we recognize is in the possibility for our decay parameter to push an effect past zero. In traditional time series analysis, an intervention decays exponentially so that its impact approaches zero; this is not the case for our mathematical procedure. In the future, however, we plan to develop an estimator that can incorporate exponential decay into the time level of the multilevel model. We feel this approach would better estimate the impact of interventions in our framework, but might sacrifice accessibility if the appropriate program would need to be written in R, which at present is the most likely starting point for creation of the estimator.

Finally, we see potential for this framework beyond analyzing pure RCS designs like the NAES. As demonstrated in Carey and Lebo (2003), surveys that are traditionally pooled for aggregate level analysis (e.g. monthly Gallup polls in the study of presidential approval) could be examined at the individual level. In addition to the creation of a new estimator, we intend to look at new sources of RCS data, specifically the 2004 NAES, and monthly polls that have long

series like Gallup and New York Times / CBS News polls. We feel that our framework can help answer questions at the individual level while still incorporating the effects of interventions and other time level, or aggregate, factors and serve as a means to better bridge the study of cross-sectional and longitudinal variation.

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Figure 1
Aggregate Vote Intention (Percent Intending to Vote for Bush)

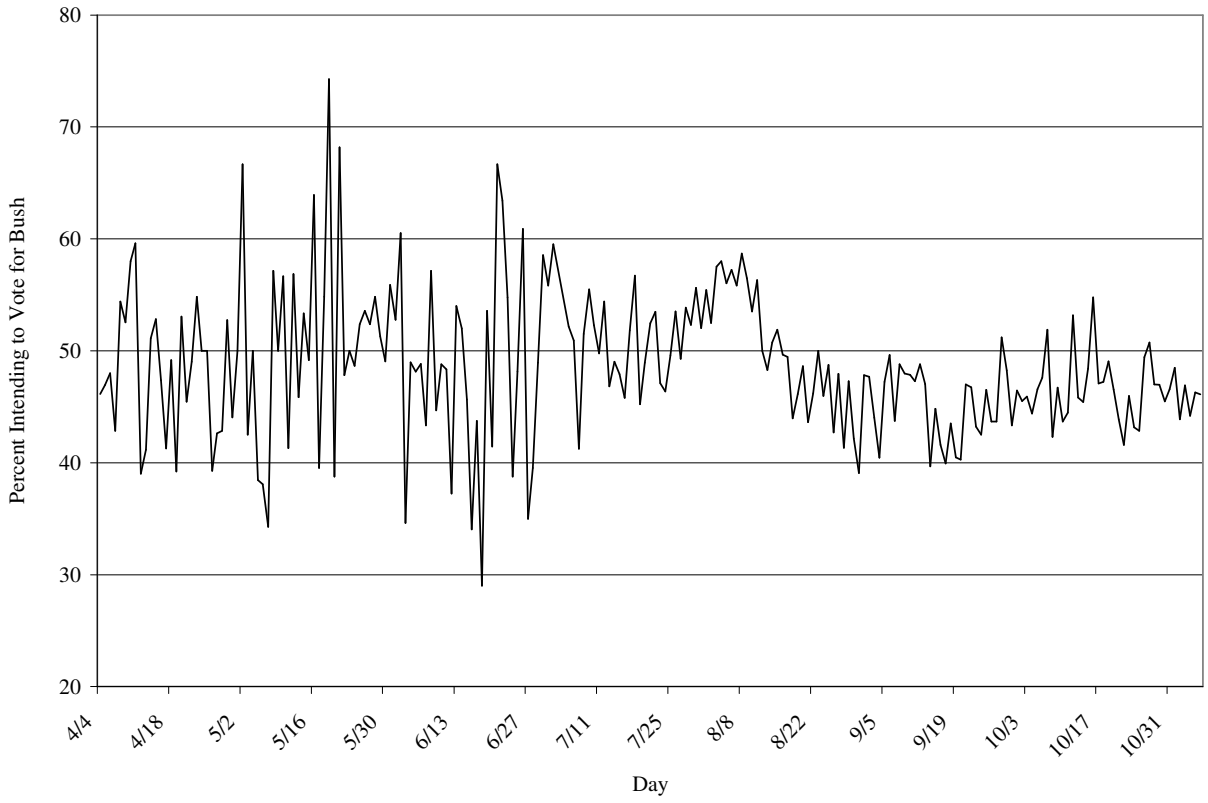
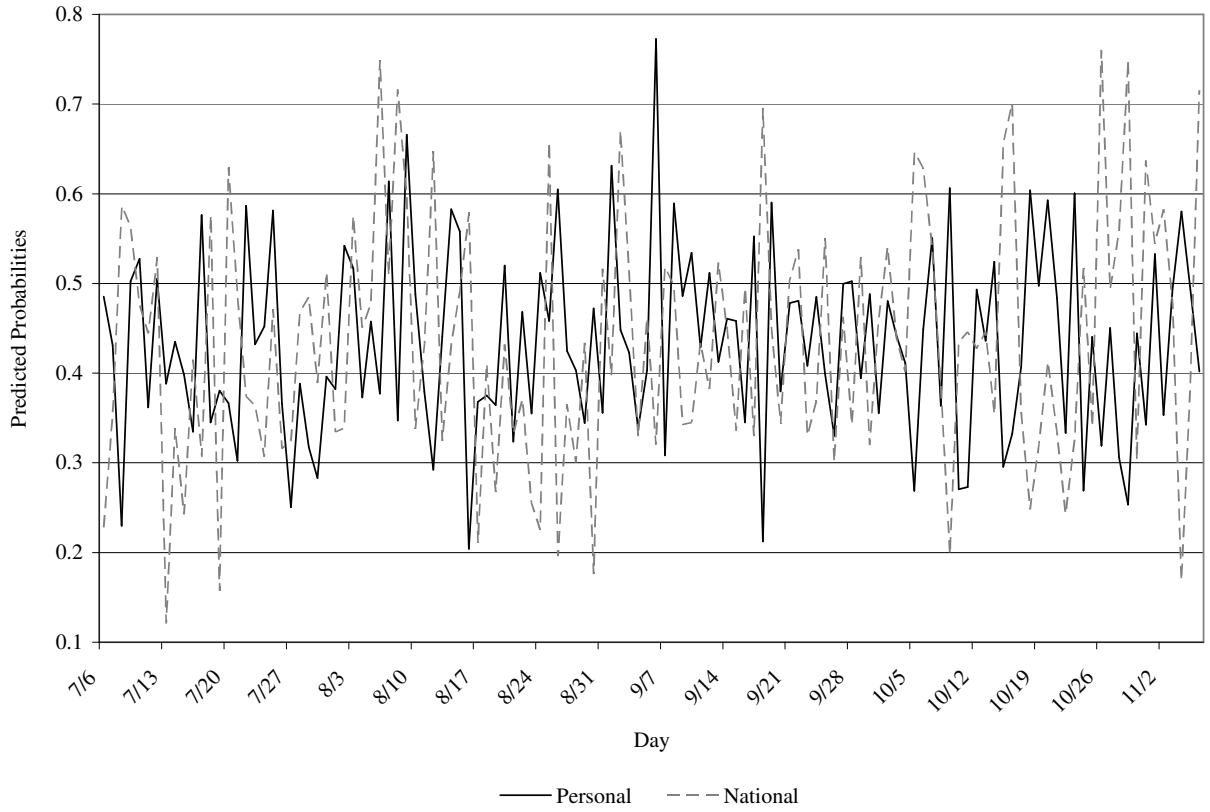


Figure 2
The Effects of Personal and National Retrospections on the Likelihood of Intending to Vote for Bush



Note: The predicted probabilities series for personal retrospections was generated by setting the values of personal retrospections to 1 (personal financial situation is worse compared to 12 months ago), national retrospections to 0 (national economy is same or better), and party identification to 0 (Democrat and Independent). The series for national retrospections set the values of national retrospections to 1 and personal retrospections to 0, keeping party identification at 0.

Figure 3
Amount of Decay for Hypothetical Values of *pseudo-δ*

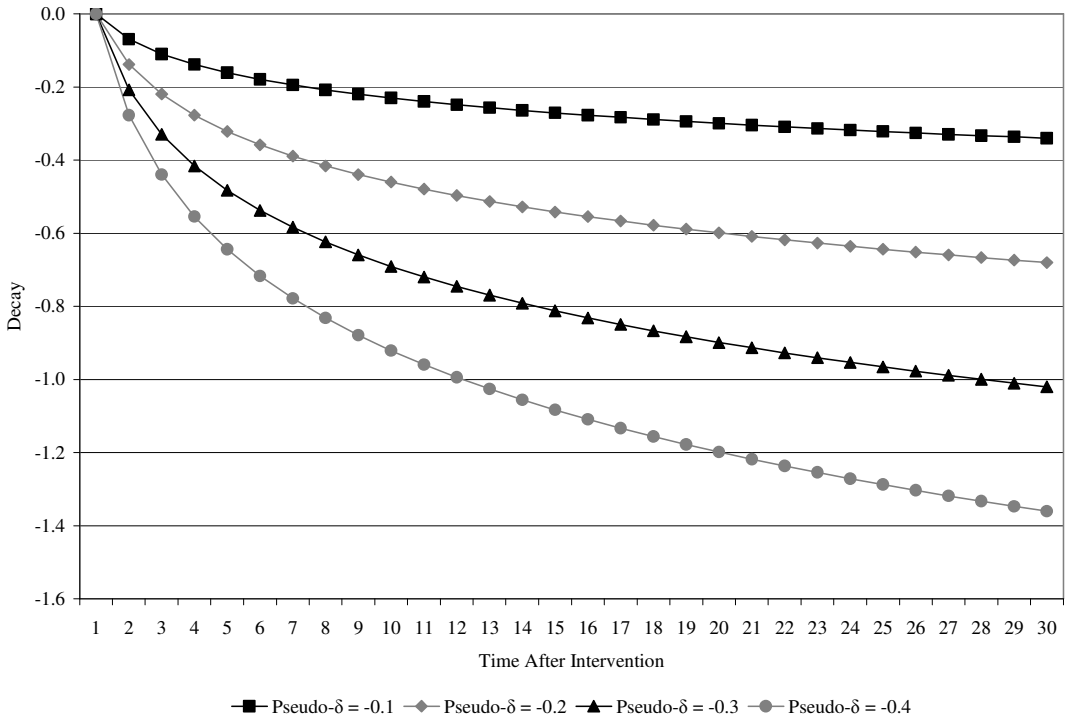
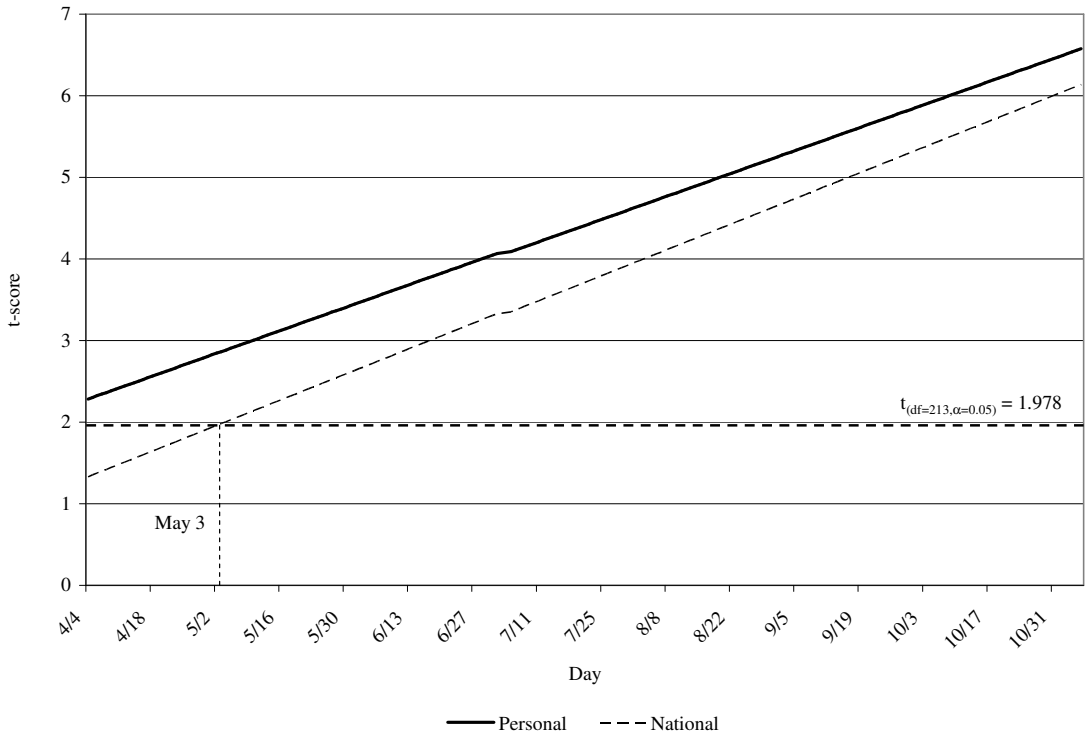


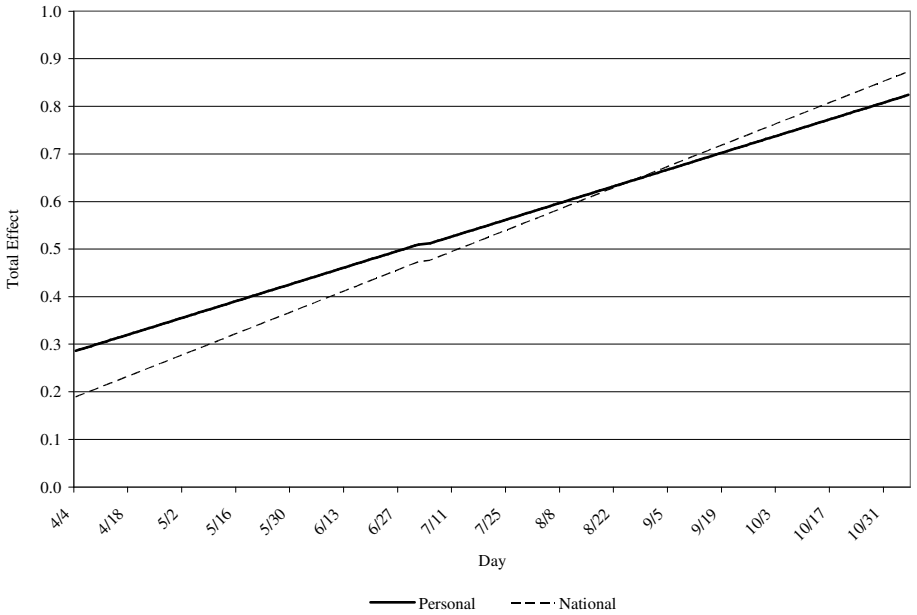
Figure 4
Conditional Significance of Personal & National Retrospections



Note: The significance of β for both personal and national retrospections is conditional on time. Therefore, we can assess the significance of the overall effect of each evaluation for each day in the sample. The conditional significance of β was calculated as follows:

$$t - score_t = \frac{\gamma_{k0} + \gamma_{k1} T_t}{\sqrt{var(\gamma_{k0}) + var(\gamma_{k1}) + 2 \cdot cov(\gamma_{k0}, \gamma_{k1})}}$$

Figure 5
Conditional Effects of Personal & National Retrospections



Note: The total effect is the value of the β coefficient for personal and national retrospections. The β for each variable is the sum of a constant and the effect of time: $\beta_{kt} = \gamma_{k0} + \gamma_{k1} T$.

Figure 6
Difference between the Effects of Personal & National Retrospections

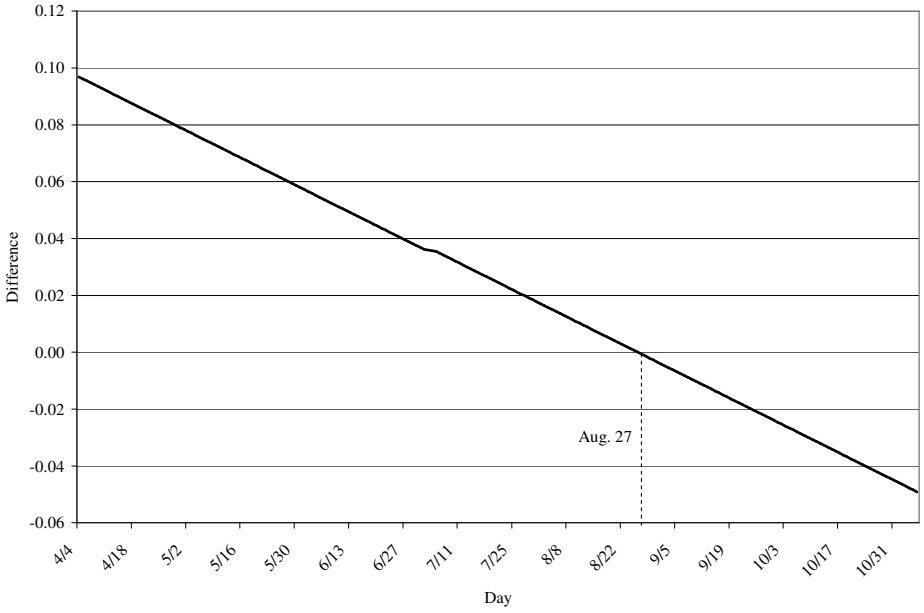
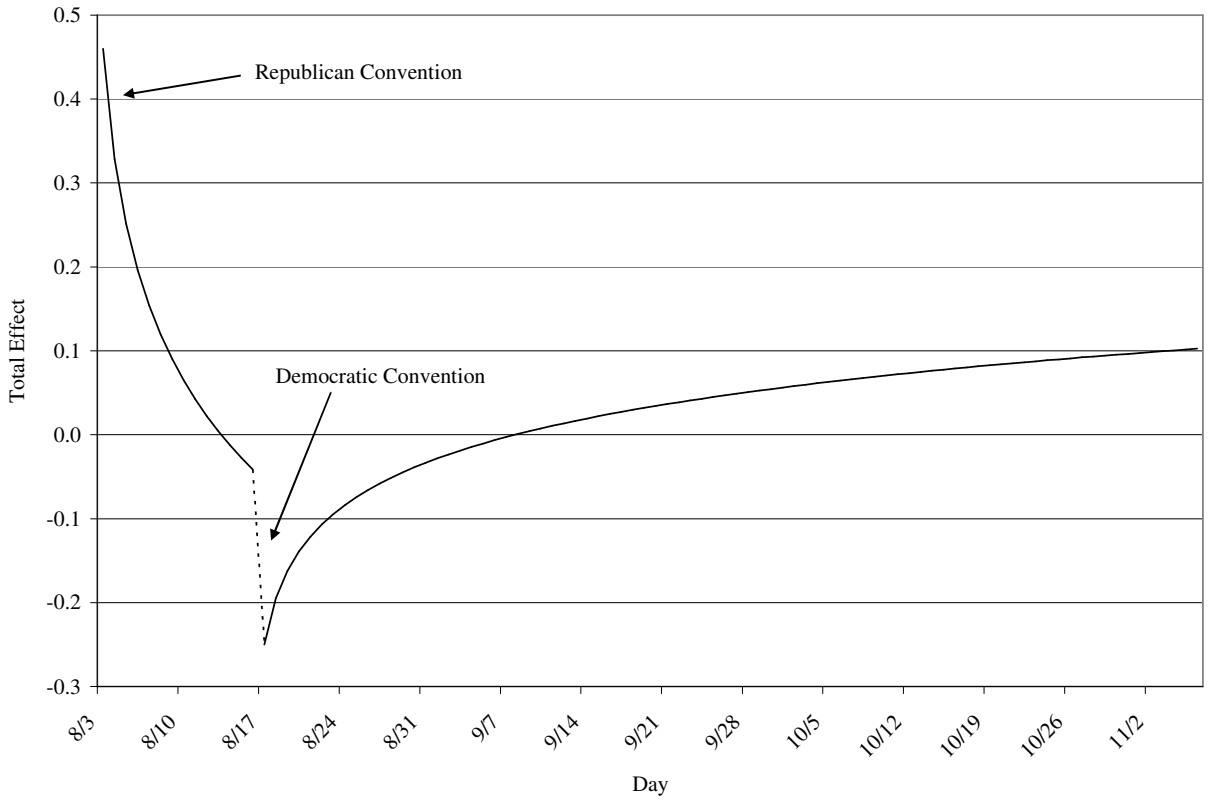
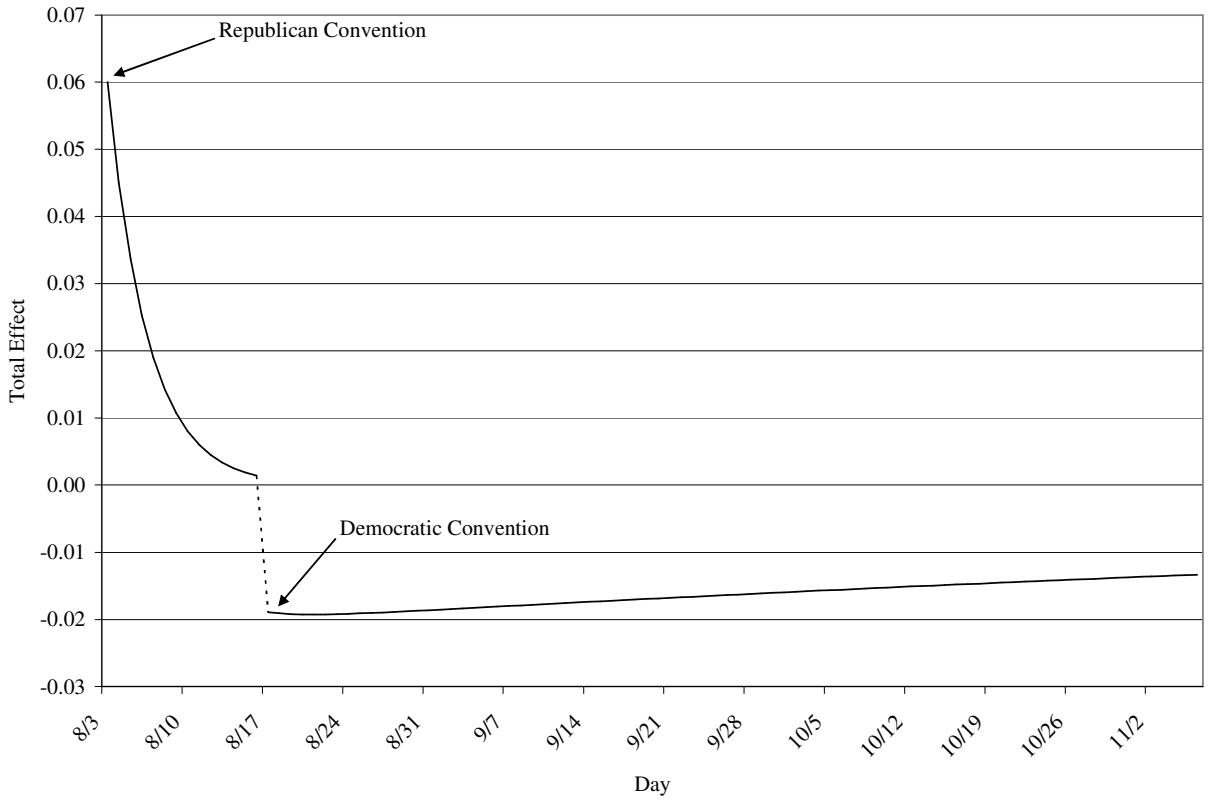


Figure 7
Total Effects of Both Conventions (Multilevel Model Estimates)



Note: The total effects here are the effects of the Republican Convention until the last day of the Democratic Convention and then the effects of the Democratic Convention thereafter.

Figure 8
Total Effects of Both Conventions (Aggregate Time Series)



Note: The total effect is the product of the initial impact (ω) and the decay parameter (δ^T), where T is the number of periods after each convention.

Figure 9
Effects of the Republican Convention in the Aggregate Time Series and Multilevel Model

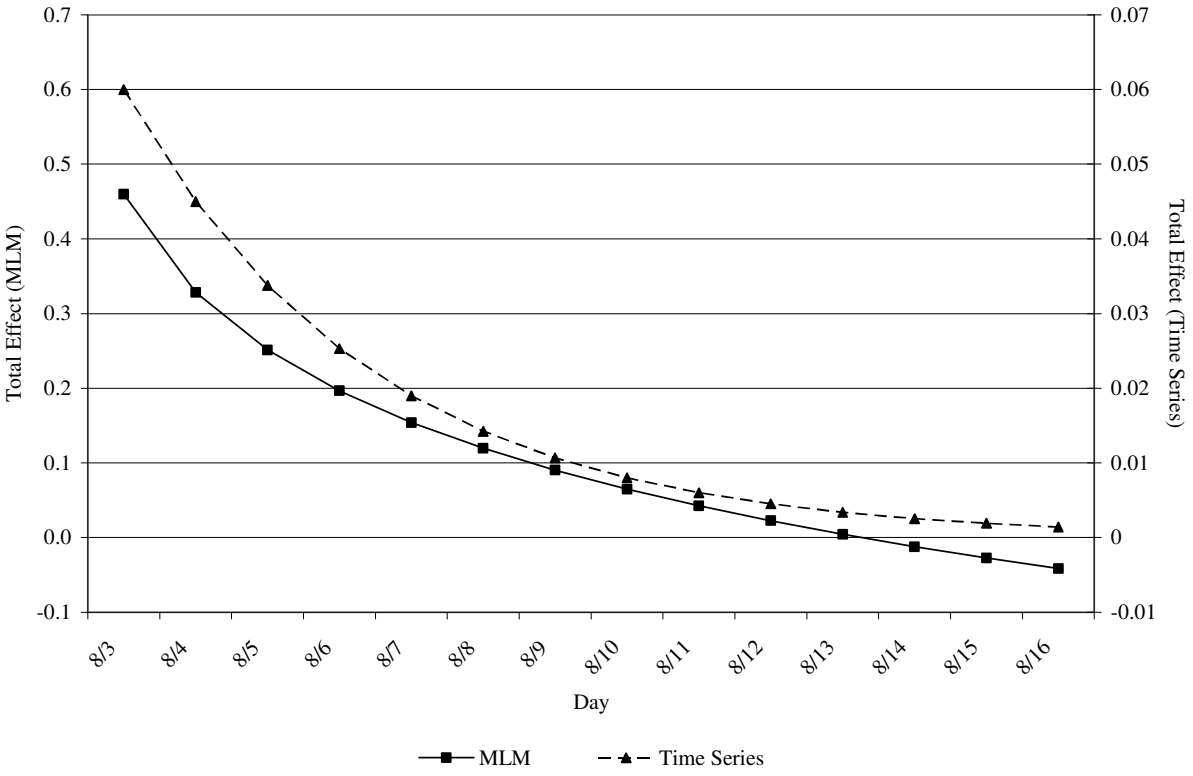


Table 1. Model of Vote Intention Aggregated By Day	
Independent Variables	**Coeff. (Std Err)**
National Retrospections$_t$	.197
	(.126)
National Retrospections$_{t-1}$	.293*
	(.125)
Personal Retrospections$_t$	.263**
	(.106)
Personal Retrospections$_{t-1}$	-.229*
	(.105)
Party Identification$_t$	.651***
	(.076)
Party Identification$_{t-1}$	-.257***
	(.075)
Republican National Convention	.062
	(.037)
Republican National Convention (Decay)	.754***
	(.208)
Democratic National Convention	-.017
	(.011)
Democratic National Convention (Decay)	.995***
	(.014)
MA$_{t-1}$	-.182**
	(.070)
Constant	.010
	(.017)
Centered R^2	.400
Durbin-Watson Statistic	1.979
Ljung-Box Q (35)	42.148
N	213

Note: All dependent and independent variables were tested for the exact level of integration and were differenced accordingly. The values for d were: 0.24 for vote intention, 0.00 for personal retrospections, 0.21 for national retrospections, and 0.10 for party identification.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 2. Seemingly Unrelated Regression Model of Personal & National Retrospections

Independent Variables	Personal Retrospections	National Retrospections
National Retrospections$_t$	-.258***	---
	(.055)	
National Retrospections$_{t-1}$	---	-.693***
		(.089)
National Retrospections$_{t-2}$	---	-.467***
		(.103)
National Retrospections$_{t-3}$	---	-.188**
		(.086)
Personal Retrospections$_t$	---	.394***
		(.085)
Personal Retrospections$_{t-1}$	-.730***	---
	(.088)	
Personal Retrospections$_{t-2}$	-.379	---
	(.106)	
Personal Retrospections$_{t-3}$	-.139	---
	(.010)	
Constant	.001	-.0005
	(.010)	(.013)
R^2	.497	.455
N	120	120

Note: All dependent and independent variables were tested for the exact level of integration and were differenced accordingly. Also, all values of the variables are generated from the predicted probabilities obtained from individual logit models holding party identification at its mode, 0.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 3. Multilevel Model Results

Variable	*Coeff.*[2]	*Robust Std Err*
Intercept	-0.824**	0.026
Personal Retrospections	0.284**	0.120
Personal x Time	0.0025**	0.001
National Retrospections	0.186	0.152
National x Time	0.0032**	0.001
Party Identification	2.894**	0.037
Interventions		
Republican Convention	0.465**	0.060
pseudo-δ	-0.189**	0.057
Democratic Convention	-0.248**	0.033
pseudo-δ	0.083**	0.019
Model Statistics		
$\hat{\tau}^2_{00}$ (Intercept)[1]	0.0009 (206.863)	
$\hat{\tau}^2_{11}$ (Slope of Personal Retrospections)[1]	0.0123 (209.771)	
$\hat{\tau}^2_{22}$ (Slope of National Retrospections)[1]	0.0130* (243.208)	
$\hat{\tau}_{12}$ (Covariance between Personal & National)	0.0074	
Correlation between Personal & National[2]	0.582	
N (individuals)	34,438	
T (days)	215	
Average N per day	160.2	
Percent Correctly Predicted	75.443%	
Percent Reduction in Error	48.817%	

* p < 0.1, ** p < 0.05

[1] τ^2 measures the variance of the random coefficients in the model. There are three random coefficients, which are listed in the table. χ^2 test statistics for the variance components are given in parentheses. The null hypothesis is: $\tau^2 = 0$.

[2] The covariance and correlation measures are between the *slopes* of personal and national retrospections.

Table 4. Conditional Effects of Personal & National Retrospections			
Days until Election	***Personal Retrospections***	***National Retrospections***	***Difference (Personal - National)***
210	0.304	0.212§	0.092
180	0.379	0.307	0.072
150	0.454	0.403	0.051
120	0.525	0.493	0.032
90	0.600	0.589	0.012
60	0.676	0.685	-0.009
30	0.751	0.780	-0.029
15	0.789	0.828	-0.040
7	0.809	0.854	-0.045
1	0.824	0.873	-0.049

§ This is the only effect that is not statistically significant at the α = 0.05 level.