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Connecting Micro- and Macropartisanship

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This paper extends models of micro- and macropartisanship in two ways. It first develops a model of individual partisanship that accommodates changes in partisan utilities. Achen's Bayesian partisan updating is a special case of our model. This more general micromodel is then aggregated to create a model of macropartisanship. This macromodel is a more general version of the models of macropartisanship estimated by various authors. The less restricted version incorporates possible individual and temporal heterogeneity. We present an example using real data that offers a possible way to estimate the parameters in the full aggregate model.

1 Introduction

This paper proposes a set of models to improve our understanding of individual and macropartisanship and how they are connected. Partisanship is a central concept in modern political science, but it is safe to say that a consensus on precisely what partisanship means, on its stability and on whether and how it influences other aspects of political behavior, has been elusive. We do not wish to enter into nor certainly attempt to settle any of these debates here. In fact, given particular parameter values, the models are sufficiently general to accommodate many of the prevailing interpretations at both the micro- and macrolevels. These models, because of their generality, can contribute to the debates.

The individual and the aggregate models contain identical terms measuring individual and temporal heterogeneity in the stability of partisanship and in the response to new information. The micro- and macromodels allow individuals to differ in their attachments to a party and in their reactions to events that might alter partisanship. Both models also allow the relationships between new information and partisanship to vary over time so as to accommodate periods of high stability and periods of realignment. The consistency of the micro- and macromodels means that information gained or propositions made at one level can be passed easily to the other level, and researchers can connect the two levels conceptually. Substantively, consistent micro- and macromodels facilitate better understanding of the connections between individual partisanship and the balance between the parties at the national level in the United States, for the parties' regional composition, and for presidential, congressional, and subnational politics. The methodological strategy can be adopted to study and to connect micro- and macropartisanship in other contexts, such as countries with multiparty systems and different electoral rules.

Authors' note: This paper continues a project that began with a paper on partisanship and path dependence presented at the 2007 Meeting of the Society for Political Methodology, State College, PA, July 2007. We express our thanks to Chris Achen, Neal Beck, and John Freeman for their comments on that paper and for pushing us to explore this connection. Jude Hays offered suggestions that improved the model. Lastly, we want to thank the editors and reviewers for their requests and suggestions, which led us to do more that we thought possible. All errors are, of course, our own.

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It is valuable to have consistent micro- and macromodels for empirical analysis as well as for conceptual and substantive arguments. Models that incorporate varying amounts of stability are likely to involve time-varying parameters. Accurate estimation of these parameters requires data with temporal variations, which is most readily available with aggregate time series data. Other parameters, particularly those related to individual heterogeneity, will be better estimated with cross-sectional individual data. Comparability of results across these two empirical efforts requires consistency between the structure of and parameters in the individual and aggregate models. Our models depict a dynamic process where voters can update their partisanship after observing new information. In one form, this is a Bayesian-style approach, but the model incorporates other ways to understand partisanship, partisan change, and stability. Individuals may differ in the amount of updating they do in response to this new information. We also incorporate an expanded version of an error correction model commonly used in macropartisanship studies. We show how our micromodel can be aggregated to specify a model of macropartisanship with precisely the same terms. We then offer an initial attempt using American partisanship data from the 1950s to 2000 to estimate time-varying parameters and parameters that indicate heterogeneity among individuals. While our data analysis here is offered as a demonstration of possibilities rather than as an exploration of the substantive debates, our initial attempt points the way toward further progress and reveals the types of data and methods necessary to test for partisanship change at multiple levels of analysis.

2 Individual Partisanship

Achen (1992) and Gerber and Green (1998) propose a Bayesian-type model of individual partisanship in a two-party system in which current partisanship is a weighted sum of past partisanship, $P_{i,t-1}$, and the current utility differential associated with the parties, $U_{i,t}$,

$$P_{it} = \rho_t P_{i,t-1} + (1 - \rho_t)U_{it} + V_{it}. \quad (1)$$

The utility term is sufficiently general at this point to accommodate various types of decision processes, such as proximity, directional, or valence voting. A stochastic term V_{it} is added to make the model more general and because we are interested in empirical applications where the observed values for P_{it} are not given deterministically by $P_{i,t-1}$ and U_{it}.[1]

In the Bayesian-type models, the value of ρ_t is inversely proportional to the uncertainty of past partisanship and directly proportional to the uncertainty in U_{it} as indicators of true partisanship. The two models differ in the treatment of U_{it}. Achen assumes that it is a constant true utility plus error, $U_{it} = U_i^* + \omega_{it}$, with U_i^* varying across individuals but not over time for any given individual. Achen (1992, 199) says his "... model describes a stable period between realignments." Gerber and Green also treat realized utility as true utility plus error, $U_{i,t} = U_{i,t}^* + \omega_{it}$ but assume individuals' true party utility changes temporally as an autoregressive process, $U_{it}^* = \alpha U_{i,t-1}^* + \nu_{it}$, where α is the amount of autoregressivity and ν_{it} is another stochastic term. The models of Achen and Gerber and Green are identical if $\alpha = 1$ and the variance of $\nu = 0$.

Neither model accommodates an exogenous shift in conditions that might result in a restructuring of partisan utility and thus in partisanship. What occurs during periods of party system change and instability is substantively interesting and important. Burnham (1970, 16) argues that abrupt shifts in partisan voting occurred around 1874, 1894, and 1930, which correspond to crises in the U.S. economy (see also Nardulli 1995). He further shows (p. 57) these changes occurring on a regional level. At the individual level, both Miller (1992) and Green, Palmquist, and Schickler (2002) show that among African-Americans and among southern Whites, particularly southern White males, there were important partisanship changes among age cohorts beginning with the Goldwater candidacy in 1964. Even if these systematic changes in partisanship occur infrequently and/or only among subgroups within the electorate, they can have significant consequences for the national party structure.[2] Thus, it is valuable to have a model that accommodates both periods of stability and episodes of systematic change.[3]

[1] If the variance of V_{it} equals zero, equation (1) is the Achen and the Gerber and Green model.

[2] See Mickey (2011), for an innovative study of the national consequences of this southern realignment.

[3] The model and we are agnostic on whether systematic partisan shifts occur abruptly as Burnham contends or over an extended period as both are possible and consistent with the model.

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We alter the structure and notation of these models to incorporate explicitly the possibility of systematic shocks to the utility term. Let $U_{it} = f(S_t) + \omega_{it}$, where S_t represents the state of the world at time t, such as economic conditions, party platforms, foreign policy crises, scandals, or candidate attributes, and ω_{it} is the same random term used by Achen and Gerber and Green to indicate the random component in realized utility. Individuals do not know the precise functional form and parameters in $f(S_t)$. In any period, they only know the state of the world, S_t, and their utility.

When people compare the difference in current utility to their previous partisanship and there is no change in S so that $\Delta S_t = 0$, this difference is attributable to the draw from the distribution of ω_{it} and to how previous partisanship differs from their true partisanship. This is Achen's Bayesian model with $\Delta S_s = 0$ for all $s \leqslant t$, so that $S_t = S_0$. Partisanship at $t-1$ is an increasingly accurate predictor of true partisanship. Over $t-1$ elections, individuals acquire $t-1$ realizations of $U_{is} = f(S_0) + \omega_{is}$, which correspond to $t-1$ draws from the distribution of ω. The expectation is that $P_{i,t-1}$ will differ from $f(S_0)$ by $\bar{\omega}_{i,t-1} = \frac{1}{t-1}\sum_{s=1}^{t-1}\omega_{is}$ and the imprecision, or variance, of $P_{i,t-1}$ as an estimate for $f(S_0)$ is $\sigma_\omega^2/(t-1)$.

If the observed difference between current utility and past partisanship is accompanied by a change in S, individuals are uncertain how much of that difference is a systemic change related to the fact that $\Delta S_t \neq 0$ and how much is the realized value for ω_{it}. The larger the systemic change in S_t, the larger the change in party utility and in true partisanship and the less weight individuals give to previous partisanship as it becomes a less reliable predictor of their true partisan utility. The expected squared difference between past partisanship and currently realized utility is related to the variance in the observational error, ω_t, and to the absolute difference in the state of the world, $|\Delta S_t|$. In regression terms, the former is the random and the latter is the systematic components of this difference. The larger the systematic component, the more weight individuals give to the currently realized utility and the less weight to past partisanship. This makes ρ_t directly related to σ_ω^2 and inversely related to $|\Delta S_t|$.

This discussion in effect provides a partial specification for ρ_{it} in equation (1), which determines the relative weights given to past partisanship and currently realized utilities in selecting a current partisanship. These relationships can be expressed as

$$\rho_{it} = \frac{[a_0 + h(i)_t]}{g(|\Delta S_t|)} = [a_0 + h(i)_t]\gamma_t, \tag{2}$$

where a_0 incorporates but may not be identically equal to σ_ω, $h(i)_t$ represents the importance of accumulated experience with $\partial h(i)_t/\partial t > 0$, and $1/g(|\Delta S_t|) = \gamma_t$ is the relationship between ρ_t and the change in the state of the world. A reasonable condition is that $\gamma_t = 1$ when $\Delta S_t = 0$, indicating that with no change in the state of the world ρ_t is only related to the variance of ω and individuals' experience. Equation (1) can now be written as

$$\begin{aligned} P_{it} &= \rho_{it} P_{i,t-1} + (1-\rho_{it})U_{it} + V_{it} \\ &= [a_0 + h(i)_t]\gamma_t P_{i,t-1} + \{1 - [a_0 + h(i)_t]\gamma_t\}U_{it} + V_{it}. \end{aligned} \tag{3}$$

Equation (3) has several implications for the dynamics of individual partisanship and ultimately for aggregate partisanship. It encompasses most common models of individual partisanship and whether and how partisanship changes over time. In periods of stability, meaning there is no change in the state of the world so that $\Delta S_t = 0$ and $\gamma_t = 1$, and if $a_0 = 0$ and $h(i) = (t-1)/t$, where t is the number of elections in which i has participated, equation (3) is Achen's Bayesian model of how people update, or learn, their partisanship during stable periods. It is also quite general in that $h(i)_t$ and γ_t can accommodate specifications for how experience or other individual-specific and temporal factors affect the amount of updating when new information is available.

Equation (3) is consistent with empirical studies of individual partisanship, though these models do not consider temporal heterogeneity with ρ_{it} varying over time. Franklin (1984), Franklin and Jackson (1983), Fiorina (1981), and Stewart and Clarke (1998) find that $\rho_i < 1$ and that variations in U_{it} are strongly associated with differences in P_{it}. Though the specifications for the composition of U_{it} vary these results imply that voters regularly update their partisanship in response to current utility evaluations and changing conditions. Green, Palmquist, and Schickler (2002) and Schickler and Green (1996), in contrast, conclude that ρ_i is close to 1 and that there is little association between measures of U_{it} and P_{it},

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meaning individuals' partisanship is temporally stable and not responsive to changes in the state of the world. Green and Yoon (2002) conclude that the stability in individual partisanship is all attributable to stable individual effects and not to a strong autoregressive process. This result implies that $\rho_i = 0$ and $U_{it} = U_i$, a constant for each individual that is not responsive to changes in the state of the world or that the state of the world is unchanging. Wawro (2002) disputes this result and using an estimator he says is more appropriate and reliable estimates ρ_i to be about 0.45. He also finds significant uniform shifts in partisanship at each election period, implying $U_{it} = U_i + D_t$ where D_t is a time dummy.

A few of the micro studies include individual heterogeneity in ρ_i, as proposed in equation (3). Franklin and Jackson (1983) model ρ_i as a function of age and find that it increases with age, and presumably with political experience, as in Achen's model. Green and Yoon (2002) estimate their model stratified by age and political interest and find that ρ_i does not differ from zero for any group. Bartels et al. (2011) estimate a multinomial logit model similar in specification to Green and Yoon's with similar results, except they find that the coefficient on past partisanship is higher among the oldest voters, a result consistent with Achen's Bayesian model.[4] Clarke and McCutcheon (2009) propose and estimate a model where the electorate is composed of movers and stayers. The former, who shift their partisanship from one period to the next in a Markovian fashion, are estimated to be 30%–35% of the British electorate and 45%–55% of the U.S. and Canadian electorates. Stayers are those who maintain the same partisanship across periods. The models of Green and Yoon, Bartels et al., and Clarke and McCutcheon do not include a utility term, so the stability could be interpreted as being the result of stable utilities, as in Achen's model. These, and any other, individual differences can be incorporated in equation (3) with appropriate specifications for α_0 and $h(i)_t$. For example, in the model of Clarke and McCutcheon with $\alpha_0 = 0$, $h(i)_t = 0$ for movers and $h(i)_t = 1$ for stayers at time t. Other propositions about individual heterogeneity, such as any related to age, political knowledge, or ethnicity, can be accommodated by appropriate specifications for $h(i)_t$. These must be developed for particular political contexts and with appropriate substantive justification.

If $\gamma_t = c$, a constant, meaning the amount of updating does not depend on changes in the state of the world, partisanship updating proceeds in a temporally constant manner as individuals observe new utilities and accumulate experience with their partisanship. This is the specification estimated (as far as we are aware) in existing models of individual partisanship. If γ_t is not a constant but varies with changes in the state of the world then only in the absence of exogenous shocks, $\Delta S_t = 0$, will partisan updating take place as in the Achen model designed for periods of stability. But when there are shocks that alter individual utilities, such that $|\Delta S_t| > 0$, people give increased weight to their utilities and less weight to past partisanship in choosing their current partisanship.

One important implication if γ_t in equation (3) varies with changes in the state of the world is that models of individual partisanship estimated with data from different elections will estimate different values for the coefficients on lagged partisanship and on any exogenous variables in the model. These temporal differences will be determined by the magnitude of γ_t, which is related to the magnitude of $|\Delta S_t|$.

Equation (3) is altered in an important way before developing the model for macropartisanship. The alteration is the addition of an error correction term. In the common error correction model, the value for P_{it} adjusts to the deviation between $P_{i,t-1}$ and its equilibrium value, given by $U_{i,t-1}$, $(P_{i,t-1} - U_{i,t-1})$ (see Clarke and Stewart 1994). In our model, the adjustment is to the deviation of $P_{i,t-1}$ from its systematic component in equation (3), $P_{i,t-1} - [\rho_{i,t-1}P_{i,t-2} - (1-\rho_{i,t-1})U_{i,t-1}]$. The error correction term relative to $P_{i,t-1}$'s equilibrium value is nested within our specification:

$$\begin{aligned} P_{it} &= \rho_{it}P_{i,t-1} + (1-\rho_{it})U_{it} - \delta\left\{P_{i,t-1} - [\rho_{i,t-1}P_{i,t-2} - (1-\rho_{i,t-1})U_{i,t-1}]\right\} + \epsilon_{i,t} \\ &= \rho_{it}P_{i,t-1} + (1-\rho_{it})U_{it} - \delta(P_{i,t-1} - U_{i,t-1}) + \delta\rho_{i,t-1}(P_{i,t-2} - U_{i,t-1}) + \epsilon_{it}. \end{aligned} \tag{4}$$

The $\delta(P_{i,t-1} - U_{i,t-1})$ term in equation (4) is the error correction term where adjustments are based on how lagged partisanship differs from its equilibrium value that period. Equation (4) shows that this standard error correction model is nested within the error correction model proposed here. Another coefficient d added to the last term enables a statistical test to discriminate between the two models:

$$P_{it} = \rho_{it}P_{i,t-1} + (1-\rho_{it})U_{it} - \delta(P_{i,t-1} - U_{i,t-1}) + d\delta\rho_{i,t-1}(P_{i,t-2} - U_{i,t-1}) + \epsilon_{it}. \tag{5}$$

[4]The Green and Yoon model includes an individual-specific constant term, whereas the Bartels et al. model treats this as a random coefficient specific to each respondent.

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The error correction based on deviations from expected equilibrium values implies $d = 0$, whereas the error correction model proposed here implies $d = 1$.

There is a substantive difference in the two models. The implication of equation 5 with $d = 1$ is that individuals adjust their partisanship at time t to the difference between their partisanship at $t - 1$ and its expected value given their partisanship at $t - 2$ and their partisan utility at time $t - 1$. Think of the terms $\rho_{it} P_{i,t-1} + (1 - \rho_{it})U_{it}$ as the sequence or path of values that P_{it} would follow given the exogenously determined values for U_{it}. In the model proposed here, corrections are made to deviations from this path rather than to deviations from the equilibrium values, which are $U_{i,t-1}$. A consequence of this difference is that the model that corrects for deviations from the equilibrium value will adapt to a permanent change in U_{it} faster than the one that corrects for deviations from the expected sequence but both converge to the same equilibrium given by U_{it}.

We have to this point proposed a rich model of the dynamics of individual partisanship. The model in equation (5) contains both temporal and individual heterogeneity and two possible error correction mechanisms. By varying the specification of different components, such as the $h(i)_t$ and γ_t functions, and parameters, such as α_0 and d, the equation accommodates the various common models of individual partisanship, including Achen's Bayesian model, the slow random walk proposed by Erikson, Michael, and Stimson (1998), and the models where some individuals adapt to new information more rapidly than others.[5] Any macromodel derived from this structure should also be general and consistent with these various propositions.

3 Aggregate Partisanship

We now turn to the question of how the model of micropartisanship aggregates to a model of macropartisanship. Achen and Shively (1995) argue for macroconsistency, meaning that models relating aggregate level variables, such as macropartisanship, should be derivable from theoretically justifiable microlevel models and an explicit aggregation process. "Without that constraint, macrolevel research too easily slips into studies of the interrelationships of meaningless statistical aggregates. Only when both macrotheoretical propositions and statistical assumptions are rigorously inferred from the microlevel can we have faith in macrolevel studies" (Achen and Shively 1995, 25). We agree with Achen and Shively, but this consistency is often elusive. In their seminal paper on macropartisanship, MacKuen, Erikson, and Stimson (1989) state that "... [their] findings will neither support nor undermine particular models of individual partisanship" (1129). In later work, Erikson, Michael, and Stimson (1998, 2002) estimate a macropartisanship model and link it descriptively to a micromodel, but they do not present the algebra connecting the two models.[6]

The work on macropartisanship is extensive, methodologically diverse, and often susceptible to the criticism of Achen and Shively about the lack of microfoundations. Our purpose is not to review or assess these studies and their associated methodologies. (See Brandt and Freeman 2009 for a sophisticated critique and results that contradict the proposition that macropartisanship is affected by economic conditions.) The theme here is to begin with a rich microfoundation, to develop its aggregate properties, and where relevant to relate existing results to the terms in this integrated micro- and macro models.

The absence of an explicit link from the micromodel to the macromodel of partisanship has been a missed opportunity and goes beyond the satisfaction of logical consistency. Substantive conclusions about empirical changes in partisanship differ depending on whether the focus is the microsurvey-based public opinion literature or the macropartisanship literature. With tight conceptual connections across levels of analysis, we might possibly improve some of the debates—what is the typical length of time that a negative opinion of the incumbent president influences individuals' partisanship, for instance? The desired transportability requires consistent micro- and macromodels. This objective motivates what follows.

[5] See Franklin and Jackson (1983), Jackson (1975), Mebane and Wand (1997), and Zaller (1992).

[6] We tried to derive the Erikson, Michael, and Stimson (1998) macromodel from the equations for individual partisanship but do not believe that it aggregates to their macromodel without additional assumptions.

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The model of macropartisanship aggregates equation (5) for any group of interest, including the electorate as a whole. Assume that this group has N members so that

$$\begin{aligned}
\bar{P}_t &= N^{-1}\sum P_{it} \\
&= N^{-1}\sum \langle [\alpha_0 + h(i)_t]\gamma_t P_{i,t-1} + \{1 - [\alpha_0 + h(i)_t]\gamma_t\}U_{it} \\
&\quad - \delta(P_{i,t-1} - U_{i,t-1}) + d\delta[\alpha_0 + h(i)_{t-1}]\gamma_{t-1}(P_{i,t-2} - U_{i,t-1}) + \epsilon_{it}\rangle \\
&= N^{-1}\left\{\alpha_0\gamma_t\sum P_{i,t-1} + (1-\alpha_0\gamma_t)\sum U_{it} - \delta\left(\sum P_{i,t-1} - \sum U_{i,t-1}\right)\right. \\
&\quad + d\delta a_0\gamma_{t-1}\left(\sum P_{i,t-2} - \sum U_{i,t-1}\right) + \gamma_t\left(\sum h(i)_t P_{i,t-1} - \sum h(i)_t U_{it}\right) \\
&\quad \left. + d\delta\gamma_{t-1}\left[\sum h(i)_{t-1}P_{i,t-2} - \sum h(i)_{t-1}U_{i,t-1}\right] + \sum \epsilon_{it}\right\} \\
&= \alpha_0\gamma_t\bar{P}_{t-1} + (1-\alpha_0\gamma_t)\bar{U}_t - \delta(\bar{P}_{t-1} - \bar{U}_{t-1}) + d\delta a_0\gamma_{t-1}(\bar{P}_{t-2} - \bar{U}_{t-1}) \\
&\quad + \gamma_t\left(N^{-1}\sum h(i)_t P_{i,t-1} - N^{-1}\sum h(i)_t U_{it}\right) \\
&\quad + d\delta\gamma_{t-1}\left[N^{-1}\sum h(i)_{t-1}P_{i,t-2} - N^{-1}\sum h(i)_{t-1}U_{i,t-1}\right] + \bar{\epsilon}_t. \qquad (6)
\end{aligned}$$

Equation (6) indicates that current mean partisanship is a function of current and lagged mean utilities, mean partisanship lagged one and two periods, the cross products of the current experience term and past partisanship and current utilities, and the cross products of lagged experience and lagged utilities and the second lag of partisanship plus the mean value of the contemporaneous stochastic element. The weight given to some of these different components, γ_t and γ_{t-1}, varies temporally depending upon the magnitude of the changes in the state of the world, $|\Delta S_t|$. The structure described in equation (6) is very general with important and interesting implications for models of macropartisanship and their estimation.

3.1 *Individual Homogeneity*

First consider the model with individual homogeneity, meaning $h(i)_t = 0$, so the cross product terms in equation (6) drop out leaving,

$$\bar{P}_t = \alpha_0\gamma_t\bar{P}_{t-1} + (1-\alpha_0\gamma_t)\bar{U}_t - \delta(\bar{P}_{t-1} - \bar{U}_{t-1}) + d\delta a_0\gamma_{t-1}(\bar{P}_{t-2} - \bar{U}_{t-1}) + \bar{\epsilon}_t. \qquad (7)$$

3.1.1 Temporal homogeneity

Temporal homogeneity means that $\gamma_t = \gamma_{t-1} = 1$. What remains is the conventional model of macropartisanship that describes aggregate partisanship at time t as a function of lagged aggregate partisanship, aggregate party utilities, and the error correction terms with the parameter d distinguishing between the two forms of the error correction model,

$$\bar{P}_t = \alpha_0\bar{P}_{t-1} + (1-\alpha_0)\bar{U}_t - \delta(\bar{P}_{t-1} - \bar{U}_{t-1}) - d\delta\alpha_0(\bar{P}_{t-2} - \bar{U}_{t-1}) + \bar{\epsilon}_t. \qquad (8)$$

The difference between the common error correction model of macropartisanship and equation (8) is the inclusion of the $d\delta\alpha_0(\bar{P}_{t-2} - \bar{U}_{t-1})$ term, as discussed with the individual model.[7] A subtle but important

[7]There are two other minor differences between the most common macropartisanship models and equation (8). In equation (8), aggregate partisanship is the mean of individual partisanship, presumably measured on some interval scale. In studies of macropartisanship, this variable is routinely measured as the proportion of Democrats among those who identify with a party, defined formally as $\bar{P}_t$ = %Dem/(%Dem + %Rep), where %Dem and %Rep are the proportions of Democrats and Republicans in the survey at time t. Though this conventional measure omits Independents and is bounded between zero and one, it correlates very highly with measures of mean partisanship constructed by assigning arbitrary values to the ANES seven-point scale and aggregating that measure for electoral groups, suggesting very little empirical difference. Also Erikson, Michael, and Stimson (1998, 2002) use a cumulative measure of partisan utility based on the indices of consumer sentiment and presidential approval to define the lagged equilibrium rather than the lagged values themselves.

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implicit assumption in all the macropartisanship studies is contained in equation (8). The $\bar{P}_{t-1}$, $\bar{P}_{t-2,}$ and $\bar{U}_{t-1}$ terms all refer to the mean lagged values for the respondents in the survey done in period t from which $\bar{P}_t$ is determined. These lagged values are being approximated by the mean values calculated from the surveys done in periods $t-1$ and $t-2$, which constitute different individuals.

3.1.2 Temporal heterogeneity

Temporal homogeneity may be reasonable in stable periods where there are no large long-term changes in the state of the world. In such periods, individual partisan utilities "are drawn independently over time from a common distribution" (Achen 1992, 199). Thus, it is likely that successive elections are homogenous with respect to the amount and type of individual partisan change.

This homogeneity condition is more questionable in periods where there are large changes in the state of the world that might trigger significant systematic shifts in individuals' true party utilities, leading them to change the weights given to past partisanship and to current utility assessments in updating their partisanship. These different weights are indicated by values for γ_t that vary over time. If the factors causing people to change their true party utilities persist over several elections, then we expect variations in the persistence of past partisanship over this period.[8] Models of macropartisanship with temporal heterogeneity are not prominent in the literature. Lebo and Box-Steffensmeier (2008) use a dynamic conditional correlation (DCC) technique to show that the monthly correlation between the Index of Consumer Sentiment and Presidential Approval varies between 1978 and 2004, often in association with observable events such as foreign policy crises. Though they do not include macropartisanship in their analysis, their findings could easily extend to the relationship between these or other variables and aggregate partisanship.[9]

The Carmines and Stimson study of issue evolution (1989) is a natural candidate for the estimation of a macropartisanship model with temporal heterogeneity. They document both an abrupt shift and a longer term evolution in both public opinion and party positions on civil rights beginning in 1963–64. They do not, however, estimate an explicit model for macropartisanship that incorporates these two distinct but related shifts. Their discussion clearly cites the evolution in civil rights attitudes and party positions as a basis for shifts in partisanship among both the mass public and political elites. They conclude that the history of opinions and partisanship constitutes a process of punctuated equilibria consisting of short periods of structural change followed by longer periods of stability. Equation (7) captures the possibility of this punctuated equilibria. For appropriate specifications for a_0, γ_t, and $f(S_t)$, there will be periods of substantial partisan change followed by stable periods.

The presence of temporal heterogeneity has an important implication for the conventional microlevel models of individual partisanship estimated with cross-sectional data. These data, even when using panel data, refer to a given election where the shocks that might lead people to alter their partisan utilities and the weight given to these current evaluations in updating their partisanship are common to all or at least to large groups of respondents. Consequently, the cross-sectional studies can estimate these coefficients for each election but cannot assess how they change with altered external circumstances, such as a shift in party positions as Carmines and Stimson document with their civil rights study. Time series data are required to estimate this model as that is the only way to observe the variations in S_t that are hypothesized to produce the variations in ρ_t. (For a seminal discussion of estimating models with time-varying parameters, see Beck 1983.) The payoff to such an analysis, however, could be high if one's goal is to understand partisan evolution and punctuated equilibria.

3.2 *Individual Heterogeneity*

An important part of the models of individual partisanship is the individual heterogeneity in the weights given to past partisanship and current utilities, meaning that $h(i)_t \neq 0$. With this addition, equation (6)

[8]The model can be expanded easily to incorporate propositions about the length of the instability by including lagged values of ΔS in the model for the updating weights, $g(\Delta S_t, \ldots, \Delta S_{t-s})$. In such a model, individuals' updating at time t is related to current and lagged changes in the state of the world, allowing for a more dynamic learning process.

[9]The DCC method is of limited use here, however, because it estimates the variations in the correlations between variables rather than in a specified set of parameters in the relationship among these variables. This will make it difficult if not impossible to talk about the consistency of micro- and macromodels of partisanship, our main objective, because correlations are sample specific and there is no model that explicitly links these correlations.

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includes the cross product terms that explicitly model individual differences in the updating of partisanship, as denoted in equation (3). In Achen's model, this heterogeneity is created by individual differences in the length of experience with their current partisanship. This heterogeneity, and the variables included in $h(i)_t$, can be generalized to any set of factors that create differences in how individuals respond to new partisan evaluations, exogenous events, and to their past partisanship. Frequently mentioned variables in addition to experience are political interest and knowledge. More generally, such variables could be social and socialization factors that create attachments to a party independent of utilitarian evaluations. The $h(i)_t$ could also denote purely random variations in individuals' updating processes, but this possibility is not pursued here. The only restriction on $h(i)_t$ is that it is assumed to be linear in its parameters to permit the aggregation in equation (6).

Box-Steffensmeier and Smith (1996) and Box-Steffensmeier and DeBoef (2001) estimate fractionally integrated models of macropartisanship. The Box-Steffensmeier and Smith model does not include any exogenous variables that could proxy $\bar{U}_t^*$, so they are only estimating the autoregressive coefficient, a_0. Following proofs from Granger, they conclude that fractional integration rules out individual homogeneity in the degree of persistence, meaning $\alpha_{i0} \neq a_0$ for all i. They do not model the individual heterogeneity directly, denoted here as $h(i)_t$, but assume that $h(i)_t$ is distributed as a beta distribution on the range zero to one. Their specification and assumption limit what can be concluded about the sources of individual heterogeneity and about partisan adjustment, but their results argue strongly that heterogeneity exists.

Box-Steffensmeier and DeBoef include a measure of macroideology in their study and stratify respondents by education.[10] In the macropartisanship equations, they observe fractional integration, meaning heterogeneity, but do not observe significant differences in the degree of fractional integration among their four education levels. They do, however, observe different Granger causal patterns between macroideology and macropartisanship at different education levels. These results indicate there is heterogeneity related to years of schooling in the link between macroideology and macropartisanship. This implies heterogeneity related to education in the relationships in equation (6).

The univariate time series specification in the two papers by Box-Steffensmeier and coauthors differs from the structure of the macropartisanship model in equation (6). The analyses in these two papers omit any exogenous variables that might lead to systematic partisan shifts, which are a central part of the micro- and macromodels in equation (3) and (6). Less obviously, the fractionally integrated models consider individual variation in a_0 but do not associate it with any explicit variables. In the macropartisanship model in equation (6), it is the correlations of these variations, the $h(i)_t$, with past partisanship and current party utilities each time period that are important.

Computing the cross product between $h(i)_t$ and U_{it} is relatively straightforward, though we are not aware of any macropartisanship model that does so. Both terms refer to the current election so that appropriate variables should be available in the surveys used to measure aggregate partisanship and attitudes. For example, and to anticipate our empirical example, if the individual heterogeneity is related to age, Age_{it}, and current utilities are a function of attitudes on civil rights, Att_{it}, the cross product between age and attitudes for each time period can be calculated from the available survey data, $C_{\text{AgeAtt}_t} = N_t^{-1} \sum \text{Age}_{it}\text{Att}_{it}$.

The big difficulty is computing the cross product between $h(i)_t$ and $P_{i,t-1}$, $P_{i,t-2}$, and $U_{i,t-1}$ because this involves information from two time periods, which is not usually available in a given survey. To continue with the age example, the required correlation between age and past partisanship is, $C_{\text{Age}P_{t-1}} = N_t^{-1} \sum \text{Age}_{it} P_{i,t-1}$. Unless one has a panel study, it is not possible to associate the age of person i at time t with her or his partisanship at $t-1$. As we suggest in our example, it might be possible, by adopting certain assumptions, to estimate these cross products, but only for some variables.

The presence of both temporal and individual heterogeneity, meaning $\gamma_t \neq 1$ and $h(i)_t \neq 0$ in equation (6), adds considerable complications to the model and to any estimation effort. They also place considerable demands on the type of data required for any estimation. There are the usual requirements, such as consistently and accurately measured variables at appropriate time periods for partisanship and for the

[10] Macroideology is defined as $\%Liberal/(\%Liberal + \%Conservative)$, where the variables refer to the percent of respondents in each survey who identify themselves as Liberals and Conservatives, respectively. As with macropartisanship, this measurement approach omits respondents who do not claim to be in either of the two categories, for example, moderates for ideology or independents for partisanship.

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variables that constitute the expression for party utilities. In addition, the data must permit the calculation, or at least adequate estimation, of the cross-product terms in these equations. These are daunting tasks, and a full exploration is beyond the scope of this paper. We try, however, to make headway and use some readily available data to illustrate how such an estimation might proceed and to present the results of this estimation.

4 An Empirical Example

In what follows we build on the important work of Carmines and Stimson (1989) on civil rights attitudes to illustrate how one might estimate a full model of macropartisanship. We use data collected by the American National Election Studies (ANES) on partisanship, attitudes towards civil rights policy, and the perceived positions of the two parties on this issue for different subgroups of the electorate between the mid-1950s and 2000. Extending the Carmines' and Stimson's analysis with the ANES data provides a natural opportunity to show how one might estimate a model of macropartisanship that is linked to a model of micropartisanship with time-varying parameters and individual heterogeneity. Given the limitations of these data, discussed below, we stress that this is presented as an illustration of how one can, or might, estimate the model of macropartisanship presented above with time-series data. Better and more carefully constructed data are required in order to make anything beyond suggestive substantive claims.

Our basic variable definitions are:

$$
\begin{aligned}
\bar{P}_{jt} &= N^{-1}\sum P_{ijt} = \text{ mean partisanship of members of group } j \text{ at time } t,\\
\bar{A}_{jt} &= N^{-1}\sum A_{ijt} = \text{ mean civil rights attitudes of members of group } j \text{ at time } t,\\
\bar{D}_{jt} &= N^{-1}\sum \mathrm{Dem}_{ijt} = \text{ group } j'\text{s location of Democratic elites at time } t,\\
\bar{R}_{jt} &= N^{-1}\sum \mathrm{Rep}_{ijt} = \text{ group } j'\text{s location of Republican elites at time } t,\\
\Delta D_{jt} &= |\bar{D}_{jt} - \bar{D}_{j,t-1}|,\\
\Delta R_{jt} &= |\bar{R}_{jt} - \bar{R}_{j,t-1}|,\\
\Delta G^2_{jt} &= \Delta D^2_{jt} + \Delta R^2_{jt},\\
\bar{L}_{jt} &= \text{ mean civil rights loss } = N^{-1}\sum(|A_{ijt} - R_{ijt}| - |A_{ijt} - D_{ijt}|),\\
\Delta\mathrm{GDP}_t &= \text{ percent change in national real GDP per capita in the year preceding the election},\\
I_t &= \text{ incumbent administration in year } t,\ \mathrm{Dem} = 1,\ \mathrm{Rep} = -1\\
E_t &= \text{ Retrospective economic evaluation } = \Delta\mathrm{GDP}_t \times I_t.
\end{aligned}
$$

The groups referenced by j are northern Whites, southern Whites, northern Blacks, and southern Blacks. We expect the sequences of partisanship, attitudes, and perception of party positions to be different between these groups. This would make it unwise to aggregate these into a single time series. Higher values of $\bar{D}_{jt}$ or $\bar{R}_{jt}$ indicate that members of group j associate the Democrats, or Republicans, with more pro-civil rights policies. The variable $\bar{L}_{jt}$ is the mean difference in the absolute distance between individual civil rights preferences and the two party's positions for members of group j at election t.[11] Berinsky and Lewis (2007) find that the absolute spatial differences are a better fit to associations between utilities and various outcomes than the more theoretically tractable quadratic utility function, hence our use of it for empirical purposes. The expression for party utility in equation (6) is,

$$\bar{U}_{jt} = \beta_0 + \beta_1\bar{L}_{jt} + \beta_2 E_t. \tag{9}$$

[11]Recent literature shows the importance of proximity measures in electoral decisions, for example, Jessee (2009), Lacy and Paolino (2010), and Tomz and Van Houweling (2008). Sanders et al. (2011) say that valence considerations are more important than proximity calculations in vote choices, though both are important. They then show that proximity assessments are important contributors to valence considerations, making proximity calculations important in a reduced form vote equation.

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Temporal heterogeneity is modeled as

$$\gamma_{jt} = \mathrm{e}^{-\gamma\left(\Delta G_{jt}^2 + \Delta G_{j,t-1}^2 + \Delta \mathrm{GDP}_t^2 + \Delta \mathrm{GDP}_{t-1}^2\right)}. \tag{10}$$

The rate of adjustment in partisanship is related to the amount of current and lagged change in party positions and to the amount of change in real per capita GDP in the two years before the election. The implication, as discussed above, is that the larger the changes in the state of the world, in this case party positions and the economy, the less weight given to previous partisanship and the more weight to current utilities. The squared values follow the regression analogy given earlier and mean that small changes in party positions or the economy receive disproportionally less weight in calculating how γ_{jt} differs from one.

Individual heterogeneity has two components. The first is taken from Achen's Bayesian model with updating. Data on how many times individuals participated in elections, and hence might have acquired new information with which to update their partisanship, are not available in ANES surveys. This information variable is proxied by the number of elections, n_{ijt}, people could have participated in, given their age. The proxy for election information is $I_{ijt} = (n_{ijt} - 1)/n_{ijt}$. The second source of heterogeneity is individuals' education. Zaller (1992) proposes a rising then falling relationship between political awareness and the stability of partisanship and the impact of new information. Awareness is proxied by years of schooling beyond eighth grade, S_{ijt}, and the nonlinear proposition by a spline function, $S_{ijt}^* = (S_{ijt} - S^*)d_{ijt}$, where S^* is the knot in the spline function and d_{ijt} is a dummy variable that equals one if $S_{ijt} \geqslant S^*$. The expression for individual heterogeneity is

$$h(i)_t = \alpha_0 + \alpha_1 I_{it} + \alpha_2 S_{it} + \alpha_3 S_{it}^*. \tag{11}$$

Denote by C_{XZ} the cross product between the variables X and Z during a given election and by $C_{XZ_{t-1}}$ the cross product between X and lagged Z. For example, the cross product between information and spatial loss in the current election would be $C_{IL} = N^{-1}\sum I_{ijt}L_{ijt}$ and between schooling and lagged partisanship would be $C_{SP_{t-1}} = N^{-1}\sum S_{ijt}P_{ij,t-1}$, and so on. Combining terms in equations (6) and (11) gives the following macropartisanship equation for group j,

$$\begin{aligned}
\bar{P}_{jt} = {} & \alpha_0\gamma_{jt}\bar{P}_{j,t-1} + (1-\alpha_0\gamma_{jt})\bar{U}_{jt} - \delta(\bar{P}_{j,t-1} - \bar{U}_{j,t-1}) \\
& + \gamma_{jt}\left[a_1\left(C_{IP_{t-1}} - C_{IU}\right) + a_2\left(C_{SP_{t-1}} - C_{SU}\right) + a_3\left(C_{S^*P_{t-1}} - C_{S^*U}\right)\right] \\
& + d\delta\gamma_{j,t-1}\left[a_0\left(\bar{P}_{j,t-2} - \bar{U}_{j,t-1}\right) + a_1\left(C_{I_{t-1}P_{t-2}} - C_{I_{t-1}U_{t-1}}\right)\right. \\
& \left. + a_2\left(C_{S_{t-1}P_{t-2}} - C_{S_{t-1}U_{t-1}}\right) + a_3\left(C_{S_{t-1}^*P_{t-2}} - C_{S_{t-1}^*U_{t-1}}\right)\right] + \bar{\epsilon}_{jt}.
\end{aligned} \tag{12}$$

The estimation substitutes the expression for party utilities in equation (9) for the $\bar{U}_{jt}$ and U_{ijt} terms and the expression for temporal heterogeneity in equation (10) for the γ_{jt} terms. The cross products between information and schooling and past partisanship and the variables that constitute current utilities, $\bar{L}_{ijt}$ and E_t, must be calculated from survey data. This is not straightforward because the terms involving $P_{ij,t-1}$, $P_{ij,t-2}$, and $U_{ij,t-1}$ require the value of a variable in previous periods. Part of the reason we refer to the subsequent effort as an illustration is that strong assumptions are required to produce these cross-product terms.

4.1 *Data*

We estimate the model using data available in the ANES Time Series Cumulative Data File (American National Election Studies 2010).[12] The election studies asked two questions about attitudes on aid to African-Americans. We splice together these two attitude questions to approximate a continuous series. The first, from 1956 to 1968, asks if the respondent supports or opposes federal government actions to insure that Blacks have equal access to jobs and housing.[13] The post-1968 question asks about more generic support for federal government aid for minorities without reference to a particular venue or policy. The

[12] The party placements for 1956 and 1958 had to be obtained from the separate study files for those two years.

[13] There is a change in the question wording and response categories between 1960 and 1964 as well. Before 1964, the question asked only about access to jobs and responses were based on a five-point Likert agree/disagree scale. In 1964 and 1968, the reference to housing was added and the question format changed to ask if this was something the federal government should do or not do.

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post-1968 question was also restructured as a seven-point scale with two opposing policy options located at each end, and respondents were asked to locate themselves and the two parties on this scale, relative to the two policy options. Responses to all questions are recoded on a minus three to three scale, so the overall metrics are comparable.

Assessing party positions also changes in 1970. For the 1956–1968 period, which is critical for any model involving attitudes on civil rights issues, the ANES does not ask respondents to place each party on a civil right dimension but simply asks which party is more likely to follow a specific policy.[14] The post-1968 question asks people to place the parties on the same opinion scale measuring respondents' preferences. For the pre-1970 data, $\text{Dem}_{jt} = 2$ and $\text{Rep}_{jt} = -2$ if a respondent thinks the Democrats are more likely to pursue a pro-civil rights policy, both equal zero if there is no difference, and $\text{Rep}_{jt} = 2$ and $\text{Dem}_{jt} = -2$ if the Republicans are more pro-civil rights. For the post-1970 questions, Rep_{jt} and Dem_{jt} are the respondents' placements of the Republicans and Democrats on the seven-point scale, rescaled to the minus three to three format.[15] The only variable measured consistently over this time period is partisanship, which is the standard ANES seven-point scale, with minus three indicating a strong Republican, zero an Independent, and three a strong Democrat.

The terms in equation (12) that include current utilities are constructed from the cross-products from the individual data in each election survey. For example, one term is the cross product of information and spatial loss, $C_{IL} = (1/N_t)\sum I_{ijt}L_{ijt}$. This can be calculated with the responses in each election's ANES survey. Similarly for the cross products with S, S^*, E, etc. The difficulty arises with the cross products that include $P_{ij,t-1}$ as this variable refers to information from the previous election, which is not in most ANES surveys.[16] Our methodology requires two assumptions. The first is that the value for the variable measured at $t-1$, such as $I_{ij,t-1}$ or $S_{ij,t-1}$, can be used to calculate the value for that variable at time t. For example, since $I_{ijt} = (n_{ijt}-1)/n_{ijt}$, in the election at $t-1$, $I_{ijt} = n_{ij,t-1}/(n_{ij,t-1}+1)$. From this, we estimate $\hat{C}_{IP_{jt}} = (1/N_{t-1})\sum \frac{n_{ij,t-1}}{(n_{ij,t-1}+1)}P_{ij,t-1}$. In the case of years of schooling, we make the assumption that $S_{ijt} = S_{ij,t-1}$, which is reasonable for older voters but less so for younger ones, who may still be in school. Thus, $\hat{C}_{SP_t} = (1/N_{t-1})\sum S_{ij,t-1}P_{ij,t-1}$.

The second assumption is that these cross products calculated from the data collected during the survey during the election at time $t-1$ would equal the cross products that would exist in the survey data collected during the election at time t, if these data were available. We are also maintaining the previous set of assumptions from above. In other words, $(1/N_t)\sum \frac{(n_{ijt}-1)}{n_{ijt}}P_{ij,t-1} = (1/N_{t-1})\sum \frac{n_{ij,t-1}}{(n_{ij,t-1}+1)}P_{ij,t-1}$ and $(1/N_t)\sum S_{ijt}P_{ij,t-1} = (1/N_{t-1})\sum S_{ij,t-1}P_{ij,t-1}$. The weakness of this assumption is that a representative sample of the electorate at election $t-1$ may not match a representative sample during the election at t because of the changing demographics and mobility of the electorate. Our defense is one of practicality and necessity, as we do not have the necessary panel data for each election.

4.2 *Estimation*

Substituting the expressions for $\bar{U}_{jt}$ and γ_{jt} from equations (9) and (10) into equation (12) and rearranging some terms gives the full model to be estimated,

$$\begin{aligned}\bar{P}_{jt} = {} & \beta_0 + \beta_1\bar{L}_{jt} + \beta_2 E_t - \delta[\bar{P}_{j,t-1} - (\beta_0 + \beta_1\bar{L}_{j,t-1} + \beta_2 E_{t-1})] \\ & + e^{-\gamma\,(G_{jt}^2 + G_{j,t-1}^2 + \Delta GDP_t^2 + \Delta GDP_{t-1}^2)}\left\{\alpha_0\left[\bar{P}_{j,t-1} - (\beta_0 + \beta_1\bar{L}_{jt} + \beta_2 E_t)\right]\right. \\ & + \alpha_1\left[C_{I_j P_{j,t-1}} - (\beta_0\bar{I}_{jt} + \beta_1 C_{I_j L_j} + \beta_2 C_{I_j E_j})\right] \\ & \left. + \alpha_2\left[C_{S_j P_{j,t-1}} - (\beta_0\bar{S}_{jt} + \beta_1 C_{S_j L_j} + \beta_2 C_{S_j E_j})\right]\right\}\end{aligned}$$

[14] There are actually two variations. In 1956 and 1958, respondents were asked which party was more likely to pursue the policy the respondent preferred, which with the reponses to the policy question we can infer which party the person perceived as more pro-civil rights at the federal level. Beginning in 1960, the ANES asked the respondent which party was most likely to promote equal treatment for Blacks.

[15] The ANES did not ask for party placements in 1986, 1996, and 1998. The placements for these years have been interpolated from the preceding and succeeding surveys.

[16] The exception would be the few years where the ANES conducted a panel study, but we want a methodology that is consistent for all elections.

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$$+\alpha_3\left[C_{S_j^* P_{j,t-1}} - (\beta_0 \bar{S}_{jt}^* + \beta_1 C_{S_j^* L_j} + \beta_2 C_{S_j^* E_j})\right]\Big\}$$
$$+d\delta e^{-\gamma\,(G_{j,t-1}^2 + G_{j,t-2}^2 + \Delta \mathrm{GDP}_{t-1}^2 + \Delta \mathrm{GDP}_{t-2}^2)}\Big\{a_0\left[\bar{P}_{j,t-2} - \left(\beta_0 + \beta_1 \bar{L}_{j,t-1} + \beta_2 E_{t-1}\right)\right]$$
$$+a_1\left[C_{I_{j,t-1}P_{j,t-2}} - (\beta_0 \bar{I}_{j,t-1} + \beta_1 C_{I_{j,t-1}L_{j,t-1}} + \beta_2 C_{I_{j,t-1}E_{j,t-1}})\right]$$
$$+\alpha_2\left[C_{S_{j,t-1}P_{j,t-2}} - (\beta_0 \bar{S}_{j,t-1} + \beta_1 C_{S_{j,t-1}L_{j,t-1}} + \beta_2 C_{S_{j,t-1}E_{j,t-1}})\right]$$
$$+\alpha_3\left[C_{S_{j,t-1}^* P_{j,t-2}} - (\beta_0 \bar{S}_{j,t-1}^* + \beta_1 C_{S_{j,t-1}^* L_{j,t-1}} + \beta_2 C_{S_{j,t-1}^* E_{j,t-1}})\right]\Big\} + \bar{\epsilon}_{jt}. \tag{13}$$

Equation (13) contains a lot of terms but only ten parameters: (β_0, β_1, and β_2) in the utility equation; (a_0, a_1, a_2, and a_3) in the equation for the individual heterogeneity in the autoregressive parameter, ρ_{it}; γ for the time varying component of ρ_{it}; δ, the error correction term; and d, which distinguishes between the two forms of error correction. This is a total of ten parameters. The model, however, is nonlinear in the coefficients, which is accommodated using a nonlinear least squares estimator (see Davidson and MacKinnon 1993, 2004). All of the cross product and lagged cross product terms were constructed in the manner and with the assumptions discussed above.

Following the procedure in Clarke and Stewart (1994), we first checked to see if the key time series variables—partisanship, civil rights loss, and change in GDP per capita—are stationary. Because the data closely resemble a pooled cross-section time series structure with the same time periods observed for the four groups, the augmented Dickey-Fuller tests are conducted within this framework.[17] The evidence rejects the null hypothesis of unit roots. The chi-squared values for the three series are 18.48(8), 34.10(8), and 6.96(2), respectively, which with appropriate degrees of freedom shown in parentheses have p values of 0.018, 0.000, and 0.031. From this, we conclude that the series are stationary and equation (13) can be estimated as shown.

4.3 *Estimated Parameters*

Five different models are estimated for comparative purposes. The first is the more conventional macropartisanship model with no heterogeneity as shown in equation (8). The next two introduce temporal and individual heterogeneity, equations (7) and (6) with $\gamma_t = 1$, respectively. The fourth model contains both temporal and individual heterogeneity, as shown in equation (13). The last model is the full model but with the specification parameter $d = 1$, which is the stochastic error correction model proposed here. The estimated equations, sum of squared residuals, log likelihood, and R^2 corrected for degrees of freedom are shown in Table 1. The results support the error correction model proposed here, in contrast to the model with corrections to the equilibrium value, as in all four models $d > 0$ and in fact $d > 1$. The value of $d = 1.17$ in the fourth model is not statistically significant from one according to a likelihood ratio test computed with from the log likelihood functions. This is consistent with our expectation, and thus, we discuss this fourth model subsequently.

The equation with both temporal and individual heterogeneity fit the partisanship series much better than the equation without heterogeneity and better than the equations with only one type. All the coefficients assessing heterogeneity of both types are statistically significant at well below the 0.001 level. To the extent the data and method for estimating the cross-product terms are credible, the results indicate that heterogeneity, both over time and across individuals, is an important part of macropartisanship.

The estimates of individual heterogeneity are consistent with expectations. The knot in the relationship between schooling and the weight given to past partisanship occurs at twelve years of schooling or a high school education.[18] The weight given to past partisanship increases by 0.19 for each year of schooling up to twelve years and then decreases by 0.07 for each year above twelve.

[17] The Stata xtunitroot program with the Fisher test and the augmented Dickey-Fuller option is used. The Fisher test permits gaps in the data, which exist in 1962 and 1966. For change in GDP per capita, the test was conducted for only one group as the variable is identical for all groups.

[18] The fit was best with the knot equal 12.5 years, but the difference in the log likelihood function was only 0.08. Because twelve years of schooling has a direct substantive interpretation and schooling is only measured in two year increments, it seemed best to set the knot at twelve years.

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Table 1 Estimated macropartisanship equations without and with heterogeneity

	Model heterogeneity				
	None	*Temporal*	*Individual*	*Both*	
	equation (8)	*equation* (7)	*equation* (6), $\gamma_t = 1$	*equation* (13)	
Party utility					
b_0 – Constant	0.49	0.38	0.38	0.35	0.38
	(0.14)	(0.19)	(0.20)	(0.18)	(0.16)
b_1 – Civil rights	0.89	0.77	0.73	0.71	0.68
	(0.14)	(0.14)	(0.14)	(0.13)	(0.11)
b_2 – Economic	1.54	1.61	1.85	1.77	1.70
evaluations	(0.57)	(0.67)	(0.68)	(0.69)	(0.68)
Autoregressive term					
a_0 – Constant	0.75	1.05	−0.41	−0.18	−0.25
	(0.06)	(0.07)	(0.44)	(0.54)	(0.58)
a_1 – Experience	–	–	0.79	0.76	0.89
			(0.42)	(0.51)	(0.54)
a_2 – Schooling	–		0.20	0.18	0.19
			(0.05)	(0.05)	(0.06)
a_3 – Schooling $\geqslant$ 12	–	–	−0.24	−0.23	−0.26
			(0.08)	(0.09)	(0.10)
γ – Temporal	–	0.19	–	0.11	0.13
heterogeneity		(0.06)		(0.05)	(0.05)
Error correction term					
δ	0.26	0.31	0.38	0.39	0.43
	(0.11)	(0.10)	(0.11)	(0.11)	(0.10)
Model specification test					
d^a	1.47	1.18	1.27	1.17	1
	(0.33)	(0.19)	(0.16)	(0.14)	
L^{*b}	3.14	15.75	18.66	21.93	20.62
SSR^c	4.33	3.16	2.94	2.71	2.80
$\tilde{R}^{2d}$	0.91	0.97	0.97	0.98	0.98

Note. Asymptotic standard errors in parentheses.
[a] Test of equilibrium error correction (d = 0) versus stochastic error correction (d = 1).
[b] Value of the log likelihood function.
[c] Sum of squared residuals.
[d] R^2 corrected for degrees of freedom.

The effect of accumulated information from more elections increases the weight of previous partisanship, as the Bayesian model predicts. The coefficient is not statistically significant, but this illustrates a difficulty with estimating some relationships with aggregate data. The electorate's age distribution does not vary much, even over forty-five years, which means that the information variable has only a small variance for this sample. The range, for example, is only 0.77–0.91 and a standard deviation of 0.024. The result is consistent with the Bayesian model and some individual level studies that relate partisan stability to age, but we are left with little confidence in this estimate.

The estimate for γ indicates that there is considerable temporal heterogeneity, with γ_{jt} varying from 0.60 to 0.99. The latter value implies very stable aggregate partisanship if party positions and the economy are stable. The values for γ_{jt} were greater than 0.95 in 1958, 1990, 1994, and 1996. The first three are midterm elections with stable presidential administrations and the fourth was President Clinton's reelection campaign. By contrast, values of γ_{jt} were lowest in 1964, 1972, 1974, and 1984. The first two featured presidential candidates who departed dramatically from traditional party positions, the third was the first post-Watergate election, and the fourth was after Reagan's first term, where he was trying to lead the Republicans, if not the country, in new directions.

Macropartisanship is sensitive to the utilities people associate with the civil rights positions of each party and to changes in real GDP per capita. Members of groups that support aid to minorities and perceive the Democrats as more likely to provide that aid are stronger Democrats. Conversely, those who oppose

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aid and see the Republicans as opposing aid are stronger Republicans. GDP growth increases the partisan advantage of the incumbent party, and conversely for GDP decreases, which benefit the opposition. One sample SD difference in utilities and in per capita GDP change is associated with 0.76 and 0.53 differences in long-run partisanship, respectively. The yearly change then depends on the estimated values for the individual and temporal heterogeneity terms. The estimates for δ provide evidence that people adjust their partisanship if it deviated from its expected value in the previous period. The estimated values for δ are consistently about 0.4 and are statistically significant. An alternative model with no error correction terms, the null hypothesis that $\delta = 0$, was soundly rejected.

The important conclusion is that a properly specified model of macropartisanship derived from a micromodel includes both temporal and personal heterogeneity. The empirical results are consistent with this specification, indicating that such heterogeneity likely is present in the electorate. If the data, and therefore the results, are credible, the empirical results imply that it is possible with aggregate data to obtain estimates for the evolution of partisanship that can be interpreted at the individual level. More importantly, aggregate data are necessary to estimate the temporal heterogeneity, as that requires substantial information from variables that only vary across many elections. The results from this estimation are only useful in understanding the evolution of individual behavior if the micro- and macromodels are consistent with each other.

5 Conclusions

This paper specifies a model of aggregate partisanship derived from a model of individual partisanship that contains the individual heterogeneity found in most micromodels and that accommodates periods of partisan stability and restructuring. The individual heterogeneity is maintained in the aggregate model through complex cross-product terms. The ability of the individual model to capture both partisan stability and change requires temporal heterogeneity in that these same relationships are likely to vary over time depending upon the political context. This feature of the individual model is represented in the aggregate model with time varying parameters. The advantage of this model is that information about these parameters and how they vary can be passed between the models at each level, which provides conceptual and empirical consistency and can incorporate empirical studies at both levels.

Estimating the fully specified model poses serious challenges and likely requires analysis of individual and aggregate data. Estimation of the individual heterogeneity, such as that associated with electoral experience, is better done with the variations available at the microlevel. Estimation of the time varying parameters, however, requires time series data, which is likely to be available only at the aggregate level.

Creation of adequate data with which to estimate the full macromodel is a daunting task, as should be evident from the illustration presented here. This requires the calculation of cross-product terms, some of which must be estimated from data in different surveys because of the lagged variables. For certain types of variables, some approximations should be acceptable, as illustrated here.

Even defining the right data is a challenge. The model with partisan change is predicated on there being a change in the state of the world, S_t, that leads to a restructuring of partisan utilities such that there might be a new equilibrium partisanship. The civil rights issue from the late 1950s onward fits this description nicely, particularly during the 1960s. The party's positions on foreign and defense policy before and after the Vietnam War might be another possibility. The heavy reliance of most work on macropartisanship on short-term economic fluctuations as measures of partisan utility is unlikely to capture the type of restructuring envisioned here. These economic changes are largely cyclical fluctuations around a relatively stable economic equilibrium that is unlikely to stimulate long-term shocks to partisanship the way the civil rights issue did. Were one to have the data available to examine macropartisanship before, during, and after the Depression of the 1930s, one would likely see quite different results compared to what is seen in the macropartisanship literature.

Developing data that captures this type of permanent change and where the variables and measures are consistent over a long time period for this issue is likely to require herculean efforts and maybe herculean budgets. The inability of the available ANES data to meet these needs for the civil rights issue is apparent in the previous discussion. Compiling the necessary data requires careful decisions about the relevant time periods. It requires assumptions about the frequency with which people update their partisanship, about what constitutes the state of the world and changes in that state, and about the level of aggregation. We

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chose to aggregate by region and race for the example here as that seemed to be the best balancing of within and between group differences with respect to perceptions of the state of the world and partisan change and sample size within the aggregate. Too high a level of aggregation will miss important partisan realignment if different groups of voters are moving between both parties.

We wish to emphasize that this is primarily a methods paper designed to develop a model of macropartisanship that is consistent with a microfoundation and to explore the types of data and methods that could be used to estimate that model. The model's value goes beyond just arguing for better data. Accepting Achen's and Shively's (1995) caution that credible macromodels require strong microfoundations means that it is important to have consistent micro- and macromodels. This paper provides that consistency for macropartisanship research in the U.S., which should improve assessments of conclusions based on previous research. Macro models that lack either or both individual and temporal heterogeneity are subject to potentially serious omitted variable bias. The model also provides insight into the limitations of much micro level research on partisanship which cannot accommodate temporal heterogeneity and may well miss the importance of factors that contribute to shifts in individual and aggregate partisanship. We further wish to emphasize that this paper is not intended as a substantive contribution to the debate about macro partisanship, though we have pointed to comparisons between our model and results with those in this literature. The model, as formulated, is specific to a two-party system like the United States, with its first-past-the-post system. The modeling strategy, however, could be followed for other electoral contexts. Such efforts must begin with a model of individual partisanship specified for the particular electoral context, such as the existence of multiple viable parties, the votes-to-seats rules, and the factors contributing to individual heterogeneity. The aggregate implications of this model can then be derived following the strategy shown here. This paper is presented as a challenge to scholars in this field to explore the micro-macro connections with better data than we have used here; to some extent, this paper poses rather than fulfills an agenda. The structure offered here and its challenges should move the study of partisanship forward.

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