THE DYNAMICS OF PARTY IDENTIFICATION RECONSIDERED

by

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Abstract

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This paper uses mixed Markov latent class models and data from multiwave national panel surveys to investigate the stability of individual-level party identification in three Anglo-American democracies — the United States, Britain and Canada. Analyses reveal that partisan attachments exhibit substantial dynamism at the latent variable level in the American, British and Canadian electorates. Large-scale partisan dynamics are not a recent development; rather, they are present in all of the national panel surveys conducted since the 1950s. In all three countries, a generalized "mover-stayer" model outperforms rival models including a partisan stability model and a "black-white" nonattitudes model that specifies random partisan dynamics. The superiority of generalized mover-stayer models of individual-level party identification comports well with American and British studies that document nonstationary long-memory in macropartisanship. The theoretical perspective provided by party identification updating models is consistent with the mix of durable and flexible partisans found in the United States and elsewhere.

THE DYNAMICS OF PARTY IDENTIFICATION RECONSIDERED

Controversies concerning the dynamics of party identification are protracted and unresolved. Over a half-century after the concept was first introduced (Belknap and Campbell, 1952; see also Campbell, Gurin and Miller, 1954; Campbell et al., 1960, 1966), political scientists continue to debate whether party identification exhibits high levels of individual- and aggregate-level stability. Much of this debate has focused on the properties of party identification measure employed by the American National Election Studies (ANES) surveys. However, MacKuen, Erikson and Stimson's (1989) study of American "macropartisanship" also has sparked a lively dispute about the aggregate dynamics of party identification as measured in monthly Gallup polls and other public opinion surveys.[1] Box-Steffensmeier and Smith (1996, 1997, 1998) have linked the aggregate- and individual-level controversies by conjecturing that the nonstationary "long-memoried" time series dynamics they observe in American macropartisanship is consistent with individual-level heterogeneity in the stability of partisan attachments.[2] Recently, Green and his colleagues (2002) have challenged many of these findings and interpretations. Reasserting the older conventional wisdom, they claim that partisanship in the United States and elsewhere is highly stable at both the individual and aggregate levels.

In this paper, we reconsider the individual-level dimension of the partisanship dynamics controversy. We begin by reviewing central theoretical and methodological aspects of the debate. We then present basic data on responses to standard party identification questions asked in multiwave national panel surveys conducted in the United States since the 1950s. Similar data from British and Canadian national surveys are employed to place the American data in comparative perspective. Next, we consider methodological aspects of the debate about individual-level partisan instability, and demonstrate that Green et al. (2002) misinterpret their key analyses of multiwave panel surveys. We then introduce the mixed Markov latent class model for assessing individual-level dynamics of party identification, and estimate rival models for the United States, Britain and Canada. The conclusion discusses major findings and theoretical implications.

An Unmoved Mover?

Theoretical Challenges: As originally formulated by social psychologists at the University of Michigan in the 1950s, party identification was defined as "an individual's affective orientation to an important group-object in his environment" (Campbell et al., 1960:121; see also Miller, 1991; Miller and Shanks, 1996). Although this conception does not require that partisan attachments are directionally immutable, Campbell et al. contended that, except in rare periods of partisan realignment, directional stability was the norm for the vast majority of Americans. They claimed that partisan attachments typically are products of early life socialization experiences which, once acquired, tend to strengthen over time as a result of attitudinal and behavioral reinforcement processes (Campbell et al., 1960:ch.7; Converse, 1969, 1976; Jennings and Niemi, 1974).

This social-psychological conception of party identification and the accompanying directional stability hypothesis has been contested by numerous critics. In the United States, the principal challenge has its theoretical lineage in works by Downs (1957) and Key (1968) (e.g., Achen, 1992; Erikson, MacKuen and Stimson, 2002; Fiorina, 1981; Franklin, 1984, 1993; Franklin and Jackson, 1983; MacKuen, Erikson and Stimson, 1989). Although differing in detail, these critics emphasize that the psychological processes generating party identification are primarily cognitive and evaluative, rather than affective. In Fiorina's (1981) formulation, party identification is a summary "running tally" of present and (discounted) past party performance evaluations. Party identification at any time t is the product of an updating process that involves voters' reactions to ongoing flows of information. Since these reactions can vary markedly over time, party identifications can change. Voters assess party performance, and parties found wanting will be abandoned.

In other countries, two principal theoretical challenges have appeared. Some critics (e.g., Budge, Crewe and Farlie, 1976; Fleury and Lewis-Beck, 1993; Scarbrough, 1984) argue that a complex of legal-institutional factors including a single-member plurality electoral system with legally mandated candidate selection processes (primary elections), voter registration requirements, a two-party system, federalism, and the separation of executive and legislative powers generate durable partisan identities in the American electorate. Such identities either do not develop elsewhere, or they are wholly determined by, and hence redundant to, socio-demographic and ideological cleavages. In consequence, party identification is a concept that cannot be profitably exported from Ann Arbor to, say, Colchester or Cologne.

Other critics (e.g., Alt, 1984; Clarke et al., 2004; Clarke, Stewart and Whiteley, 1997a, 1997b; Stewart and Clarke, 1998) do not dismiss the concept of partisanship as inapplicable for non-American political settings. Rather, they adopt conceptualizations similar to those advocated by Fiorina and other American revisionists, arguing that cognitively oriented views of partisanship are consistent with the observed instability in party identification in panel surveys, as well as rapid, large-scale, reversals in party fortunes that occasionally occur in countries such as Canada and Great Britain.

Empirical Challenges: Empirical challenges to the claim that party identifications are stable rest largely on data gathered in national panel surveys.[3] The first such survey was conducted by the

ANES between 1956 and 1960. As Figure 1.A shows, "turnover tables" generated using this and subsequent American panel surveys tell very similar stories — large numbers of respondents indicate that they do not maintain directionally stable partisan attachments.[4] When interviewed four times between 1956 and 1960, only 58% of the ANES panelists identified with the same party. Comparable figures for the 1980 and 1992-94-96 four-wave panels are 50%, and 41%, respectively. As Figure 1 also shows, the dominant pattern of movement is for substantial minorities to go back and forth between identification and independence (31% on average). Relatively few people switch parties (5% on average) and, among multiple movers, there is a tendency to return to the party that had been abandoned earlier (Clarke and Suzuki, 1994). The same pattern obtains in the ANES 1972-74-76 and 2000-2002-2004 three-wave panels. Between 2000 and 2004 46% reported directionally stable identifications, 4% changed parties, and 29% moved between identification and independence. Comparable numbers for the 1972-74-76 panel are 44%, 5% and 32%, respectively. The pattern also is echoed in the 2004 National Annenberg Election Study (NAES) two-wave (pre- and post-election) panel survey where 57% were stable identifiers, 5% switched parties, 19% went between identification and independence, and 19% were stable independents.[5]

(Figure 1 about here)

Turnover table evidence of substantial partisan instability in American panel surveys is not an artifact of a decision to classify as independents persons who initially decline a party identification but then state that they feel closer to a party. The long-running controversy about whether such "leaners" are really "hidden" partisans (Dennis, 1992; Keith et al., 1992; Weisberg, 1980) suggests that one also should assess instability in partisan attachments categorizing leaners as identifiers rather than independents. Doing so magnifies instability, with the number of inter-party switchers increasing substantially. For example, assuming leaners are really identifiers, 27% of the respondents in the 1980 U.S. four-wave panel have directionally unstable identifications, 15% move between an identification and independence, and 12% switch parties (data not shown).

Unfortunately, multiwave panels have not been a regular feature of the ANES, and they are in short supply in most other countries as well. Great Britain and Canada are exceptions — several multiwave panels have been conducted in these countries.[6] Turnover tables constructed using these data reveal dynamics similar to the American ones in certain respects, but different in others. The most important similarity is the consistent presence of large groups with directionally unstable partisan attachments. For example, British panels regularly show that about one-third change their party identifications at least once over three- to seven-year periods (Figure 2). However, unlike Americans, sizable minorities (from 12% to 28%) indicate that they switch from one party to another rather than move between identification and non-identification.[7] A large percentage of these inter-party switches involve movements between the Conservative and Labour parties, on the one hand, and the Liberal Party (or Liberal-SDP Alliance), on the other. Direct or indirect (via the halfway house of non-identification) switches from Conservative to Labour or vice versa are relatively rare.

(Figure 2 about here

As in the United States, decisions regarding the classification of persons who indicate in the first question of the British party identification battery that they are not identifiers, but subsequently state that they feel closer to a party, are not responsible for the measured instability. Nor is this finding altered by decisions about how to categorize respondents who are Liberal identifiers. In this regard, it often has been observed that Liberal support is the functional equivalent in Britain of independence in the United States (e.g., Clarke and Zuk, 1989). Classifying Liberals with non-identifiers shows approximately one-third of the 1963-70 and 1974-79 four-wave panelists have unstable identifications.

Multiwave panels also indicate large-scale partisan dynamics in Canada. As in Britain, direct inter-party moves are quite common, and sizable number move between identification and non-identification. For example, across a 1988-93 national four-wave panel, fully 43% identified with different parties, and an additional 17% went between identification and non-identification (see Figure 3). Comparable figures for 1979-84 and 1983-88 four-wave panels are 29% and 21%, and 28% and 22%, respectively. Similarly, a 2004-06 four-wave panel reveals that only 33% maintained stable party ties, 35% moved between identification and non-identification, and 20% traveled between parties (Figure 3).[6] Such high levels of partisan instability — if credible — are impressive.

(Figure 3 about here)

A Conventional Wisdom Reinstated?

Responses to party identification questions in panel surveys invite one to infer that partisan instability is substantial. However, Green et al. (1990, 1993, 1997, 2002) argue that the inference is unwarranted. If a researcher uses structural equation modeling techniques (e.g., Bollen, 1989) that account for random measurement error in responses, directional stability in *latent* party identification is much greater than critics of the traditional "Michigan model" would allow. This is true not only in the United States, but in Britain and Canada as well (Green, Palmquist and Schickler, 2002: ch. 7; Schickler and Green, 1997). Substantial latent instability is found only for Canadian data gathered in the late 1980s and early 1990s. Schickler and Green (1997:478) plausibly attribute this latter finding to resurgent regional and ethno-linguistic group identities that overturned a long-lived national party system. Absent such extraordinary circumstances, party identification in

Canada approximates the "unmoved mover" of Michigan lore.

Although Green et al.'s counterrevolutionary analyses are intriguing, there are reasons for skepticism. First, levels of instability in turnover table analyses of multiwave panel data are always large and sometimes massive. It strains credulity to conclude that such large-scale variation in responses to straightforward questions about orientations toward highly salient entities such as political parties are largely, or wholly, products of random measurement error. Second, the structural equation models are problematic. Since these models use only a single indicator of party identification at any time point, and most available panels have four or fewer waves, the amount of data (i.e., variances and covariances) available for estimation and testing purposes is minimal.[8] For example, as Green et al. (2002) note, a three-wave panel model is exactly identified, leaving no degrees of freedom for goodness-of-fit tests. The parameters and goodness-of-fit of plausible, less restrictive, rival models (e.g., ones specifying non-zero error covariances for observed indicators, or non-zero covariances for the structural-level error process) cannot be estimated (Wiley and Wiley, 1970, 1974: see also Bartels and Brady, 1983; Palmquist and Green, 1992).[9]

Some readers may conclude that these criticisms are not compelling because in more recent work Green and his colleagues use an alternative methodology, and continue to report very high levels of partisan stability. Specifically, they specify a dynamic panel model with an *unobserved* individual effect parameter (Green, Palmquist and Schickler, 2002:66-73). The model is:

$$Y_{it} = \gamma Y_{it-1} + \alpha_i + \nu_{it} + \varepsilon_t \qquad (1)$$

where: Y_{it} = party identification for individual i at time t
Y_{it-1} = party identification for individual i at time t-1
α_i = unobserved effect on individual i, all time periods
ν_{it} = stochastic shock on individual i at time t
ε_t = stochastic shock on all individuals at time t

Because of α_i, (1) suffers from simultaneity bias and an estimate of γ will be biased and inconsistent (Arellano, 2003; Wawro, 2002). Following Anderson and Hsiao (1982), Green et al. take first differences to remove α_i:

$$Y_{it} - Y_{it-1} = \gamma(Y_{it-1} - Y_{it-2}) + \nu_{it} - \nu_{it-1} + \varepsilon_t - \varepsilon_{t-1} \qquad (2)$$

Since (2) continues to produce biased and inconsistent estimates because of correlation between Y_{it-1} and ν_{it-1}, Green et al. follow Anderson and Hsiao's suggestion to use an instrumental variables approach to estimation. They report that, with one exception, γ is not significantly different from zero and conclude that:

$$Y_{it} = \alpha_i + \nu_{it} + \varepsilon_t \qquad (3)$$

Accordingly, for any voter i, the expected value of party identification at any time t is simply the individual constant α_i, and perturbations caused by $\nu_{it} + \varepsilon_t$ will temporarily drive it off this value. However, this conclusion is incorrect because the equation Green et al. *estimate* is not (1) but rather (2). For technical convenience, they have changed the *theoretical specification* of the dynamics of their model. The correct conclusion from their analysis is that:

$$Y_{it} = Y_{it-1} + \nu_{it} - \nu_{it-1} + \varepsilon_t - \varepsilon_{t-1} \qquad (4)$$

Equation (4) is a random walk with *assumed* noninvertible moving average errors. Absent this implausible assumption, party identification is a variance nonstationary process in which shocks are never forgotten (e.g., Enders, 2004). The full value of any shock at time t is never discounted in the future.

In addition, there is no individual-specific constant, α_i. That term also is not included on the right-hand side of (2). Absent this "drift" parameter, partisan attachments move in response to an ongoing combination of individual and general shocks, ν_{it} and ε_t, at time t. Substantively, the absence of the drift term means that the model has no "Converse-like" (Converse, 1969) property that would cause initial attachments to strengthen over time. Party identification thus manifests no proclivity in the short- or long-term to return to any particular position; nor does it have an individual-specific deterministic trend as would be implied by an α_i term. As $t \rightarrow \infty$, the party identifications of all voters theoretically can be expected to take on all possible values.

There are two more general problems. One — and Green et al. are aware of it — is the assumption that party identification can be measured as an interval-level variable. Although legions of researchers have made this assumption using the famous ANES seven-point scale of party identification (running from 0 "strong Democrat" to 6 "strong Republican"), the data clearly are at best ordinal. The cardinality assumption remains problematic if one analyzes party identification using only responses to the first question in the ANES party identification battery. Moreover, if one wishes to study partisanship in countries with multiparty competition on multiple issue dimensions, assumptions of ordinal, let alone interval, measurement may be unwarranted. What is needed is an analytic technique that allows for random measurement error and demands only nominal-level measurement.

A second problem is the assumption of homogeneity in the evolution of partisan attachments over time spans such as those encompassed by multiwave national panel surveys. As discussed above, Green et al. (2002) recently have relaxed this assumption by introducing unobserved individual-specific effects (α_i's) in their model of otherwise uniform partisan (non)dynamics. But, no compelling *theoretical* reason is provided for this latter specification. Here, we propose a simple two-group model for *describing* partisan dynamics — one group (stayers) for whom party identification is stable over the time span encompassed by a multiwave panel survey, and one group (movers) for whom it is unstable. Membership in the mover and stayer groups is *not fixed*. People who change their party identification over one time span may not do so subsequently. Similarly, stayers in one time period may become movers in a later one.[10]

The conjecture that political attitudes manifest heterogeneous dynamics is not new. Converse (1964; see also Converse 1970) concluded that homogeneous models could not possibly account for the over-time correlations observed for attitudinal variables in the 1956-58-60 ANES panel. He reacted by advancing the famous "non-attitudes" (black-white) model which specified perfect over-time stability in the responses of one group with pure randomness in the responses of a second one. It is not necessary to accept this particular model to appreciate the utility of allowing for heterogeneity in the (in)stability of party identification.[11] In the next section, we employ mixed Markov latent class analysis for this purpose, while simultaneously taking account of random measurement error.

Mixed Markov Latent Class Models

Statistical models for analyzing categorical (discrete) measures in panel survey data have been available since the 1970s (Wiggins 1973, see also Poulsen 1982, van de Pol and Langeheine 1990). User-friendly computer programs developed by van de Pol et al. (1991) and others have made these models accessible for applied research.[11] Here, we employ one of these models — the mixed Markov latent class (MMLC) model — to analyze processes of individual-level partisan stability and change.

Latent class models estimate a set of unobserved, categorical outcomes with discrete (categorical) indicator variables, while assuming observed indicator variables are subject to measurement error. Although the logic of latent class analysis was introduced in the early 1950's (Lazarsfeld,1951a, 1951b), nearly a quarter century lapsed before Goodman's (1974, 1979) development of the EM algorithm for solving the parameter estimation problem for the latent class model (Dempster et. al 1977; McCutcheon 1987). Wiggins (1973) combined latent class and Markov models to examine change in discrete outcomes in instances in which error-prone indicator variables are available in panel data. A combination of the EM algorithm with the latent class and Markov models, as well as the introduction of multiple Markov chains to capture unobserved heterogeneity in the population, was first proposed by Poulsen (1982) and further developed van de Pol and Langeheine (1991; see also McCutcheon 1996; van de Pol et al. 1991).

Latent class analysis is useful when survey responses are available for several discrete, categorically-scored variables (Hagenaars and McCutcheon 2002; McCutcheon 1987). When the categorical variables are answers to the same panel survey question at multiple points in time, it is possible to model changes in responses using the Markov latent class model, or its variant, the mixed Markov latent class model (Hagenaars, 1990; Langeheine and van de Pol 2002; McCutcheon 1996; van de Pol and Langeheine, 1990).

Briefly, a Markov model is a discrete-time change process model in which a set of outcomes, such as panel survey responses, has some probability of either changing or remaining the same as at the prior wave of the panel. If respondents are asked their party identification at four different times we designate the responses as the variables A_i, B_j, C_k, and D_l, where, $i = 1, \dots, I$, and I indicates the number of parties at time 1 that represent the I response categories. The indices j, k, and l are similarly defined for waves 2 through 4. The $I * J * K * L$ distribution of cases for the four waves can be viewed as a Markov model as illustrated in Figure 4, Panel A.

(Figure 4 about here)

We can express the model for the $I * J * K * L$ distribution of party identifications across the four waves of the panel as a Markov model

$$\pi_{ijkl}^{ABCD} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{l=1}^{L} p_i^A \tau_{j|i}\tau_{k|j}\tau_{l|k}, \qquad (1)$$

where π_{ijkl}^{ABCD} is the expected joint probability distribution of party identifications for the four waves, p_i^A is the observed distribution of party identifications in wave 1, and $\tau_{j|i}$ is an I-by-K matrix of probabilities. In the tau matrices, the main diagonal (e.g., $I = j$) is the proportion of a party who remain (stayers), and the off-diagonal elements are the proportions that change party identification between the two waves.

Generally, one can identify unique estimates for all parameters of a model if the number of degrees of freedom in the data is greater than the number of parameters that must be estimated. For an $I * J * K * L$ contingency table, we have $I * J * K * L - 1$ degrees of freedom. For the Markov model expressed in (1), we must use I-1 of these degrees of freedom for the distribution of party identification at wave 1, and we must estimate $I(J\text{-}1) + J(K\text{-}1) + K(L\text{-}1)$ for the first, second, and third set of tau parameters. If we have more degrees of freedom in the table than the number of parameters, we can estimate a unique set of parameters for the Markov model. Restrictions may be imposed that reduce the number of parameters that need to be estimated — for example, researchers have often imposed the restriction that $\tau_{j|i=} \tau_{k|j=} \tau_{l|k}$, the so-called “stationarity” restriction.

Wiggins (1973) first introduced the *latent* Markov (LM) model that permits measurement error at each wave of data collection. The observed values are used to estimate a set of latent variables, and the Markov model is then used to estimate the change in the latent party identification variables over the waves of the panel.[12] Consider a set of four latent variables W_s, X_t, Y_u, and Z_v that correspond to the four observed variables (A_i, B_j, C_k, and D_l), where $S = T = U = V = I = J = K = L$ (i.e., the latent and manifest variables have the same number of political parties). As Figure 4 Panel B indicates, the change (τ) matrices relate the latent variables in the LM model, while the measurement matrices (ρ) characterize the associations between the latent and observed variables. In the LM model, the observed association between any two waves of survey responses is a function of 1) measurement error (ρ) between the observed and true (latent) values, and 2) change (τ) in the latent value between waves of the panel.

The association among the four waves of observed data in the LM model is stated formally as

$$\pi_{ijkl}^{ABCD} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{l=1}^{L} p_i^A \; \rho_{i|s} \; \tau_{t|s} \; \rho_{j|t} \; \tau_{u|t} \; \rho_{k|u} \; \tau_{v|u} \; \rho_{l|v}, \qquad (2)$$

where the rho (e.g., $\rho_{i|s}$) parameters represent the measurement error that relates the latent values to the observed survey responses and each of the other parameters is defined as before. In the unrestricted LM model, the measurement error at each wave of the panel is regarded as different from the measurement error at each of the other waves. Thus, the unrestricted LM model requires $I(S - 1) + J(T - 1) + K(U - 1) + L(V - 1)$ additional degrees of freedom for estimating the model. It is, of course, possible to test the hypothesis of "time homogeneous" measurement error, i.e., the hypothesis that the measurement error associated with measuring party identification does not change. This hypothesis requires estimating only a single set of rho parameters, which means that this restriction requires the estimation of fewer parameters than the unrestricted model.

The final elaboration of the LM is the mixed Markov latent class model in which more than a single Markov chain is estimated for the data (Langeheine and van de Pol 2002, van de Pol and Langeheine 1990). Figure 4 Panel C is an example. The MMLC model is stated formally as:

$$\pi_{ijkl}^{ABCD} = \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{l=1}^{L} p_i^A \, \delta_r \; \rho_{ir|sr} \; \tau_{tr|sr} \; \rho_{jr|tr} \; \tau_{ur|tr} \; \rho_{kr|ur} \; \tau_{vr|ur} \; \rho_{lr|vr}, \qquad (3)$$

where the delta (δ_r) parameter represents the differing Markov chains, and the other parameters are defined as above.

The MMLC model requires the estimation of many parameters, since a different set of tau and rho parameters must be estimated for each chain — with the example of a four-wave panel with three categories, there are insufficient degrees of freedom to estimate an unrestricted MMLC model with two (or more) latent chains. However, there are a number of theoretically cogent models in the MMLC class. In particular, the “mover-stayer” model is one in which the change (i.e., tau) parameters for the “stayer” chain are set equal to identity matrices a priori — in effect, this model tests the hypothesis that there is one group of respondents who are "stayers" who will not change their partisanship over the panel, and another (“movers”) who are prone to change. Additional restrictions (e.g., time homogeneous error rates in one or both chains) yield identified models that are of theoretical interest to those studying the dynamics of latent-level change.

MMLC Models of Party Identification

We first consider the 1980 ANES year-long four-wave panel data. Respondents were classified as Democrat, Independent, or Republican, according to their response to the first question of the ANES party identification question battery (i.e., "leaners" were classified as Independents). The three response possibilities, at each of the four waves of the panel, yields an 81 cell contingency table (3 x 3 x 3 x 3) for analysis. The cell counts for this four-way cross classification constitute the empirical basis for the analysis.

We estimate four competing models, all of which permit random measurement error in the indicator variables. The first, Model A, is the classic latent class model, where all party identifications are stable at the latent level. The second, Model B, is the latent Markov model which also assumes homogeneity, with everyone having the same, possibly non-zero, probability of changing their partisanship from one time point to the next. Models C and D are mover-stayer models. Model C is Converse's "black-white" model, with movers switching with equal probability from any one alternative (Democrat, Independent, Republican) at time t to any another alternative at time t+1. Model D relaxes the equal probability transition assumption, although it imposes time invariant measurement errors.

Fit statistics for the four competing models are summarized in Table 1. As judged by likelihood ratio and Pearson chi-square statistics, the classic latent class model, the latent Markov model and black-white MMLC model (Models A, B and C) do not fit the data well. In contrast, the generalized mover-stayer model (Model D) performs quite well. This latter model has better, i.e., smaller, chi-square statistics. Model D also has statistically insignificant likelihood ratio and Pearson chi-squares. Moreover, it outperforms its rivals according to the Akaike model selection criterion (AIC), having smaller AIC values than competing models (Hagenaars and McCutcheon, 2002; see also Burnham and Anderson, 2002).

The superior performance of the generalized mover-stayer model is not an artifact of treating leaners as Independents. Rather, if people who say that they are Independents but feel closer to the Democrats or the Republicans are classified as identifiers, the analyses are basically unchanged (data not shown). The generalized mover-stayer models continue to have considerable smaller chi-square statistics and better (smaller) AIC values than various rivals.

(Table 1 about here)

Table 2 summarizes properties of the generalized mover-stayer model for the 1980 ANES panel data. As shown, the 1980 American electorate was composed of two approximately equal parts, with nearly half (.48) classified as movers and just over half (.52) estimated to be stayers. Among the movers, over half (.56) are estimated to have the initial state of true Independents, while just over one-third (.37) are estimated to be latent Democrats and fewer than one in 10 (.07) are estimated to latent Republicans. Among stayers, partisan identification is far more prevalent; nearly half (.48) are estimated to be latent Democrats, well over one third (.38) are latent Republicans, and fewer than one-sixth (.15) are latent Independents. Fewer than one-fourth were true Republicans during the first wave in January 1980 (.07 x .48 + .38 x .52 = .23), and about two in five (.37 x .48 + .38 x .52 = .42) were true Democrats. We find a higher proportion of party loyalists (stayers) among Republicans ([.38 x .52]/.23 = .86) than among Democrats ([.48 x .52]/.42 = .59).

As one might expect, there is less measurement error associated with the partisan stayers than with the partisan movers. Among stayers, there appears to be no measurement error among the self-identified Democrats regarding their latent state, whereas among movers, only about four of five (.81) who self-identify as Democrats are estimated to be true Democrats. A similar, though less dramatic, pattern is found among Republican identifiers; among stayers, the measurement error of the indicator variable is less than half (1.0 - .98 = .02) the measurement error found for Republican identifiers among movers (1.0 - .96 = .04). In contrast, greater measurement error is found for Independents (1.0 - .57 = .43) among the stayers than among the movers (1.0 - 98 =.02).

(Table 2 about here)

Transition probability matrices for movers are also reported in Table 2. There is a consistent pattern in which movement is more likely the further one is from the election. Thus, from wave one (January-February 1980) to wave two (June-July 1980), we see .15 (1.0 - .85) of the wave one latent Democrats changed their identification to either Independent or Republican, .22 (1.0 -.78) of latent Independents changed to either Democrat or Republican, and .27 (1.0 - .73) of latent Republicans changed to either latent Democrats or latent Independents. From wave one to wave two, the losses of Democrats and Independents to Republicans, coupled with the Republicans' retention rate over this period, resulted in a sizable GOP gain by the end of the primary season (.37 x .06 + .56 x .09 + .07 x .73 = .13). However, by September (wave three), the proportion of movers who remain Republican decreased substantially (.13 x .61 + .39 x .02 = .08).

Table 3 summarizes results for the 1956-58-60 and the 1992-93-94-96 ANES panels. In both cases, the classic latent class (all stayer) and black-white models again perform relatively poorly in comparison with the generalized mover-stayer models. The latter consistently have the best fits as judged by chi-square statistics, and the best (smallest) AIC values. And, again, it does not matter how one classifies leaners — the generalized mover-stayer models prevail (data not shown). These results indicate that the superiority of the generalized mover-stayer model is not an idiosyncratic feature of circumstances surrounding the 1980 election; rather, the model works well for ANES party identification data gathered nearly four decades apart. The 1950's analyses are particularly interesting because they testify that partisan stability was far from ubiquitous even when the Michigan model was first advanced. Moreover, the mover chain is always substantial — 47% and 55%, respectively, are classified as movers in the 1956-58-60 and 1992-93-94-96 panels.

(Table 3 about here)

Analyses of British and Canadian four wave panels yield results similar to the U.S. ones. We do not discuss all of them here. However, typical patterns are summarized in Table 4. For both the British 1963-64-66-70 panel and the Canadian 1979-80-83-84 panel, the generalized MMLC model outperforms its rivals, as evidenced by the chi-square and AIC statistics. Also similar to the U.S. case, the British and Canadian generalized MMLC model analyses indicate that there are sizable numbers of people in the mover chains — 31% and 45%, respectively (see Figure 5). Once again, these numbers are not atypical. The percentages of movers in six British four-wave panels spanning the four decades between 1963 and 2001 varies from a low of 29% to a high of 37%. Similarly, the Canadian percentage of movers in four-wave panels ranges from 41% to 57%. The average number of movers in the British and Canadian panels is 32% and 46%, respectively. These figures and their American equivalents accord well with the simple accounting exercises performed using turnover tables. Partisan instability is common in all three countries.

(Table 4 and Figure 5 about here)

Conclusion: Dynamic Partisanship

Controversy concerning the nature of party identification began shortly after the concept was introduced in the 1950s. This paper has joined this long-running debate by using mixed Markov latent class models and multiwave panel data to analyze the dynamics of individual-level party identification in three Anglo-American democracies — the United States, Britain and Canada. These models have desirable theoretical and statistical properties for the task at hand. They admit the existence of stable (stayer) and unstable (mover) groups, assume only nominal-level measurement of observed indicator variables, and permit measurement error in survey responses. Analyses of multiwave panel data clearly indicate that partisan attachments exhibit substantial dynamism at the latent level in the American, British and Canadian electorates. However, movements in party identification are not random in the sense that a “black-white” model does not fit the data well. The latter finding is inconsistent with Converse's classic conjecture (1964) that the observed instability in variables such as party identification in panel surveys is due to the presence of a sizable group of "non-attitude" respondents.

The substantive bottom line is that the American, British and Canadian electorates are — and long have been — composed of varying mixtures of people with durable and flexible partisan attachments. Over the past several decades, the flexible partisan groups have always been large enough to make consequential political change in successive elections an ongoing possibility. At least since the 1950s, the fortunes of American, British and Canadian political parties have not been firmly anchored by the ubiquitous presence of durable party identifications. The venerable Michigan model of voting behavior admits the presence of short-term forces associated with orientations towards issues and party leaders. Present findings indicate short-term forces typically are more important for many voters than the spirit of that model would allow.

There is another point. One might attempt to effect a theoretical compromise given that the present analyses document large groups of stayers, as well as large groups of movers. The temptation is to conclude that the former are Michigan-style partisans and the latter are revisionist-style partisans. But, the compromise is not required. Cognitively oriented models of partisanship such as those advanced by Achen, Fiorina, Franklin and others generate partisan dynamics, but they also admit partisan stability.[14] Voters evaluating party performance may well decide to stay where they are. Key's (1968) famous edict that "voters are not fools" does not mean that everyone will be a partisan mover across any particular time period. Equally, Key's other famous dictum, that voters make "standing decisions" in favor of a particular party, does not mean that they are impervious to novel information about party performance. Voters may stand pat for now, but not necessarily forever. Stayers may become movers and vice versa. *Theoretical heterogeneity* is not required to explain the patterns of stability and change we have described in party identification panel data.

ENDNOTES

1. See, e.g., Abramson and Ostrom (1991); Green, Palmquist and Schickler (1997, 1998, 2002); MacKuen et al. (1992).

2. In making this argument, Box-Steffensmeier and Smith (1996) rely on the aggregation theorem developed by Granger (1980). Erikson, MacKuen and Stimson (2002), in contrast, argue that macro-level partisan dynamics are consistent with findings of Green, Palmquist and Schickler (2002) that individual-level partisanship is highly stable. According to Erikson, MacKuen and Stimson (2002:145), the perceived difference in aggregate- and individual-level dynamics is a "statistical illusion." Analyses presented below challenge Green et al.'s findings and, hence, make Erikson et al.'s effort to reconcile aggregate dynamics with individual stability unnecessary.

3. The ANES party identification question battery is: (a) "Generally speaking, do you usually think of yourself as a Republican, a Democrat, and Independent, or what?" (b) [If respondent names a party in (a)] "Would you call yourself a strong [Democrat/Republican] or a not very strong [Democrat/Republican]?" (c) [If respondent does not name a party in (a)] "Do you think of yourself as closer to the Republican Party or to the Democratic Party?" The data are available from the ANES website (www.electionstudies.org).

4. Measurement error aside (see below) and absent use of recall questions, estimates of partisan dynamics provided by panel data are *minimum* figures. Consider a two-wave panel. It is possible that everyone changed their partisanship after t1 and then changed back before t2. If so, measured partisan change is 0%. In contrast, if 30% have different identifications at t1 and t2 this is the minimum number of possible changers. Others may have changed and changed back, but we do not detect this. Whatever the time interval between panel waves, and however many waves, measured change is always a minimum.

5. The 2000 and 2004 Annenberg election survey data are available from the NAES website: www.annenbergpublicpolicycenter.org.

6. The British and Canadian party identification batteries are similar to the ANES battery (see note 3. above). Given the sizes of the British four-wave panel data sets, we use three party identification options for the MMLC analyses presented below: Conservative, Labour and others (non-identifiers, nationalists and miscellaneous minor party identifiers). Similarly, the Canadian party identification options are: Conservative (Conservative Party of Canada for the 2004-06 panel), Liberal, and others (non-identifiers, NDP, Bloc Québécois and miscellaneous minor party identifiers.

Recent British election study (BES) data and documentation may be accessed from the 2001 and 2005 BES website (www.essex.ac.uk/bes). Earlier British data are available at the UK Data Archive at the University of Essex (www.data-archive.ac.uk). The 2004 and 2006 Canadian election study (CES) data and questionnaires are available from the CES website (ces-eec.umontreal.ca) and the Political Support in Canada (PSC) data are available from the principal investigators' website (www.utdallas.edu/~hclarke). The 1980 and earlier CES data are available from the ICPSR Data

Archive (www.icpsr.umich.edu).
7. The terms "Independent" and "independence" are seldom used outside the United States. Hence, we use terms "non-identifier" and "non-identification" to refer to respondents in the British and Canadian surveys who do not designate a party when answering the party identification questions.

8. The number of non-redundant elements in the sample variance-covariance matrix S is N(N+1)/2 where N is the number of measured (indicator) variables. For example, for a three-wave panel, the number of party identification measures is 3 and S has 6 non-redundant elements. This is the number of parameters to be estimated in the Wiley-Wiley (1970) model for a three-wave panel.

9. It is possible that a model as whole will not be identified, but that there will be sufficient information to identify particular parameters of interest. See, e.g., Bollen (1989).

10. As Brady's (1993) analytic work and Box-Steffensmeier and Smith's (1997) Monte Carlo study have shown, individual-level heterogeneity can inflate the autoregressive (over-time stability) parameters in Wiley-Wiley-type models that assume homogeneity.

11. For early analyses of the applicability of the black-white model to the dynamics of party identification see Dobson and St. Angelo (1975) and Dryer (1973).

12. The models are analyzed with van de Pol, Langeheine and de Jong's PANMARK program.

13. A pioneering analysis using Markov models to study instability in party identification is Dobson and Meeter (1974).

14. Erikson, MacKuen and Stimson (2002:131-32) theorize that the *observed* dynamics in macropartisanship result from aggregating *individuals*, each of whom mixes two types of over-time change in partisanship. Their research problem is that all one can observe empirically is what they call M_t, an aggregated time series measure of macropartisanship. The explanatory power of rival time series models of macropartisanship, such as those advocated by Erikson et al. and Box-Steffensmeier and Smith, is an interesting topic for future research.

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Table 1. Alternative Models of the Dynamics of Party Identification, 1980 ANES Four-Wave Panel

Model	Likelihood Ratio χ^2	Pearson χ^2	AIC
A. Classic Latent Class	121.43, 54 df, p = .000	91.66, 25 df, p = .000	71.43
B. Latent Markov†	86.05, 48 df, p = .001	76.58, 20 df, p = .000	46.05
C. Black-White Mixed Markov Latent Class with time homogeneous error rates	132.57, 66 df, p = .000	83.19, 40 df, p = .000	52.57
D. Mixed Markov Latent Class with time homogeneous error rates	50.63, 54 df, p = .261	23.39, 17 df, p = .137	15.63

† - response probabilities of first and last indicator set equal to those of nearest indicator.

Table 2. Mixed Markov Latent Class Model of the Dynamics of Party Identification, ANES 1980 Four-Wave Panel

	Movers	*Stayers*
Mixture Proportion (Π)	.48	.52
Initial State (δ)		
Republican	.07	.38
Independent	.56	.15
Democrat	.37	.47
Response Probability (ρ)	*True*	*True*
Republican	.96	.98
Independent	.98	.57
Democrat	.81	1.00

Transition Probabilities (τ) for Movers

		Republican	Independent	Democrat
Republican:	Wave 1 - Wave 2	.73	.28	.00
	Wave 2 - Wave 3	.61	.33	.07
	Wave 3 - Wave 4	.84	.16	.00
Independent:	Wave 1 - Wave 2	.09	.78	.13
	Wave 2 - Wave 3	.00	.93	.08
	Wave 3 - Wave 4	.03	.97	.00
Democrat:	Wave 1 - Wave 2	.85	.08	.06
	Wave 2 - Wave 3	.98	.01	.02
	Wave 3 - Wave 4	.95	.00	.05

Latent Turnover Table – Mover Chain - Wave 1 to Wave 4
(Horizontal Percentages)

			Wave 4	
		Republican	Independent	Democrat
	Republican	38.8	54.6	6.5
Wave 1	Independent	8.1	74.0	17.9
	Democrat	9.1	11.1	79.8

Note: probabilities may not sum to 1.0 because of rounding.

Table 3

Alternative Models of the Dynamics of Party Identification,
1956-58-60 and 1992-93-94-96 ANES Four-Wave Panels

I. 1956-58-60

Model	Likelihood Ratio χ^2	Pearson χ^2	AIC
A. Classic Latent Class	261.15, 72 df, p = .000	240.52,63 df, p = .000	135.15
B. Latent Markov†	100.52, 48 df, p = .000	83.47, 31 df, p = .000	38.52
C. Black-White Mixed Markov Latent Class with time homogeneous error rates	216.05, 66 df, p = .000	168.63, 56 df, p = .000	104.05
D. Mixed Markov Latent Class with time homogeneous error rates	68.79, 45 df, p = .013	44.97, 26 df, p = .012	16.79

II. 1992-93-94-96

Model	Likelihood Ratio χ^2	Pearson χ^2	AIC
A. Classic Latent Class	152.38, 60 df, p = .000	162.29, 29 df, p = .000	156.65
B. Latent Markov†	78.87, 48 df, p = .012	40.16, 16 df, p = .000	40.87
C. Black-White Mixed Markov Latent Class with time homogeneous error rates	164.58, 66 df, p = .000	102.95, 38 df, p = .000	88.58
D. Mixed Markov Latent Class with time homogeneous error rates	59.89, 45 df, p = .068	27.48, 13 df, p = .016	33.89

† - response probabilities of first and last indicator set equal to those of nearest indicator.

Table 4

Alternative Models of the Dynamics of Party Identification, British and Canadian National Four-Wave Panels

I. Britain 1963-64-66-70

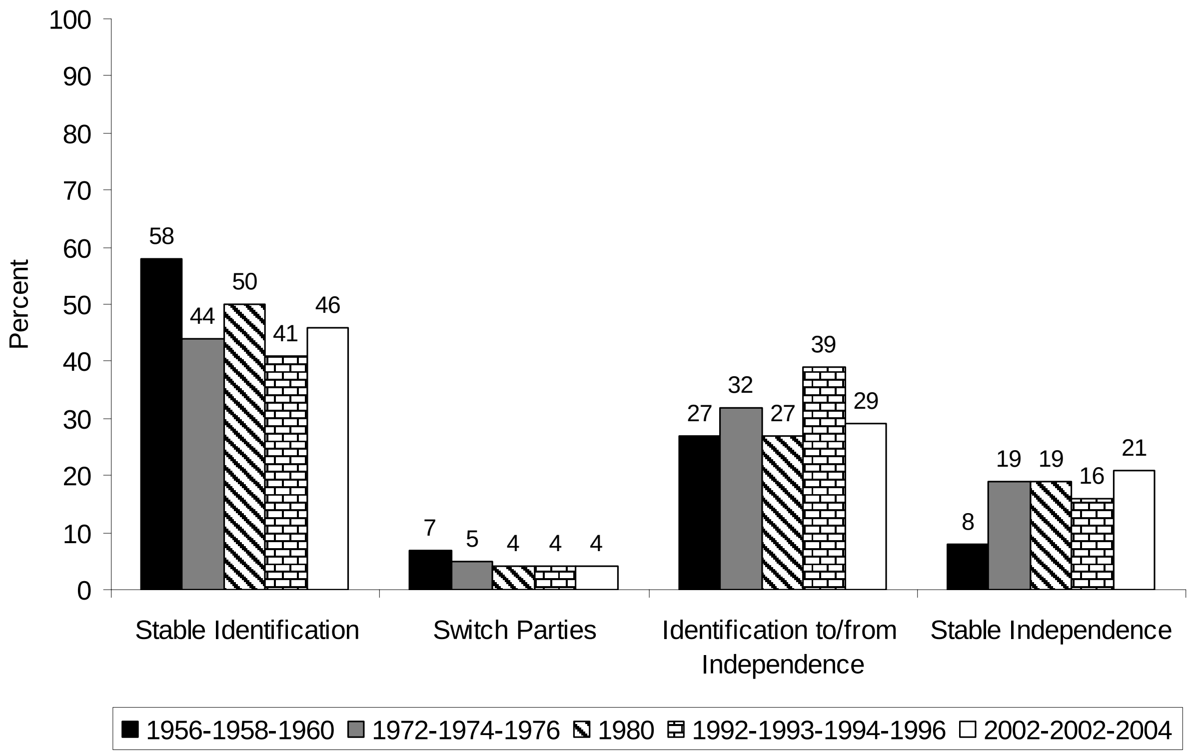
Model	Likelihood Ratio χ^2	Pearson χ^2	AIC
A. Classic Latent Class	158.79, 54 df, p = .000	149.95, 42 df, p = .000	74.79
B. Latent Markov†	114.80, 48 df, p = .000	107.35, 36 df, p = .000	42.80
C. Black-White Mixed Markov Latent Class with time homogeneous error rates	223.02, 66 df, p = .000	218.72, 65 df, p = .000	93.02
D. Mixed Markov Latent Class with time homogeneous error rates	82.57, 45 df, p = .001	54.42, 30 df, p = .004	22.57

II. Canada 1979-80-83-84

Model	Likelihood Ratio χ^2	Pearson χ^2	AIC
A. Classic Latent Class	149.77, 54 df, p = .000	163.06, 35 df, p = .000	79.77
B. Latent Markov†	83.61, 48 df, p = .001	68.53, 28 df, p = .000	27.61
C. Black-White" Mixed Markov Latent Class with time homogeneous error rates	222.06, 66 df, p = .000	269.82, 60 df, p = .000	102.06
D. Mixed Markov Latent Class with time homogeneous error rates	81.89, 45 df, p = .001	64.18, 29 df, p = .000	23.89

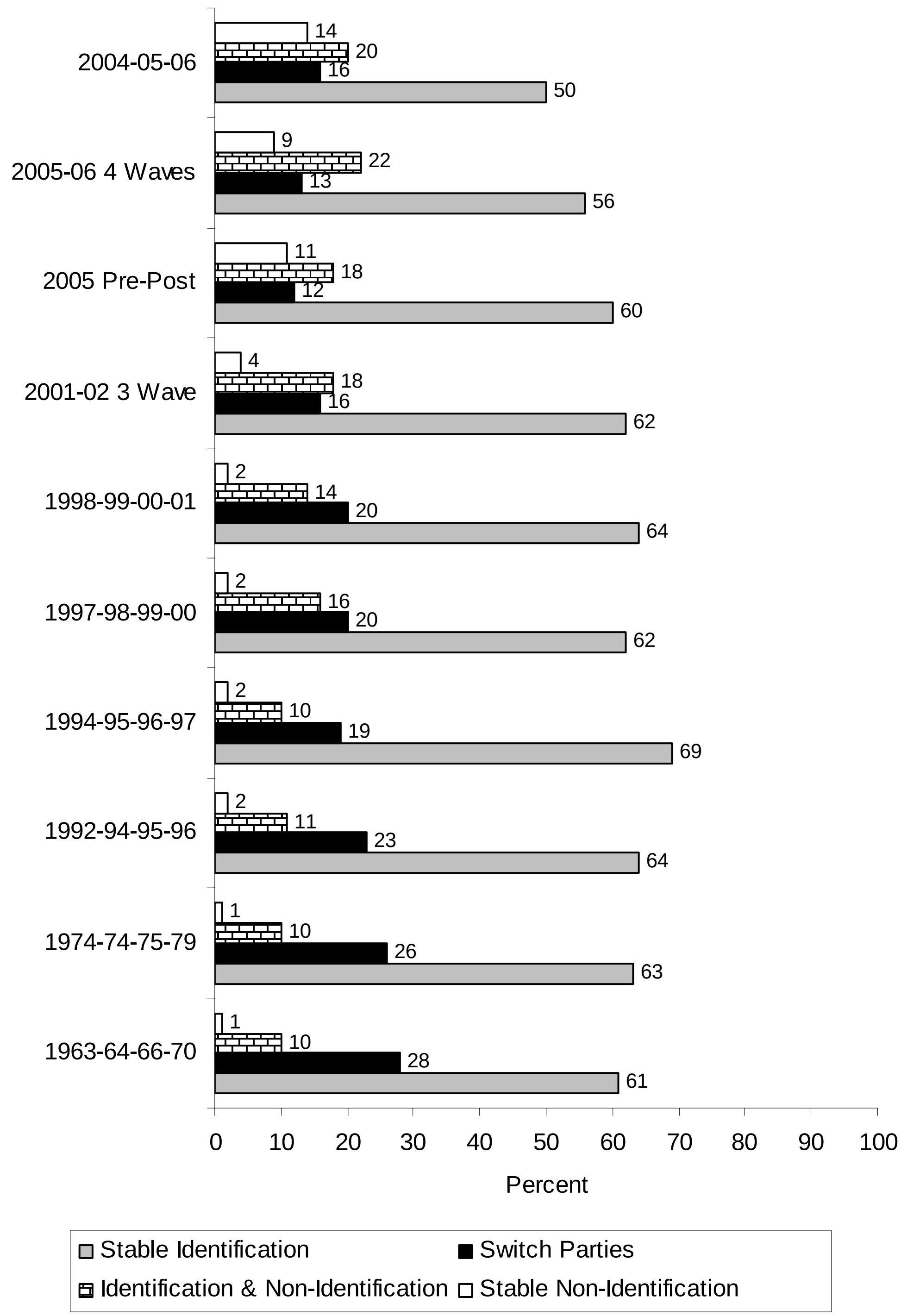
† - response probabilities of first and last indicator set equal to those of nearest indicator.

Figure 1. Dynamics of Party Identification in American National Multiwave Panels



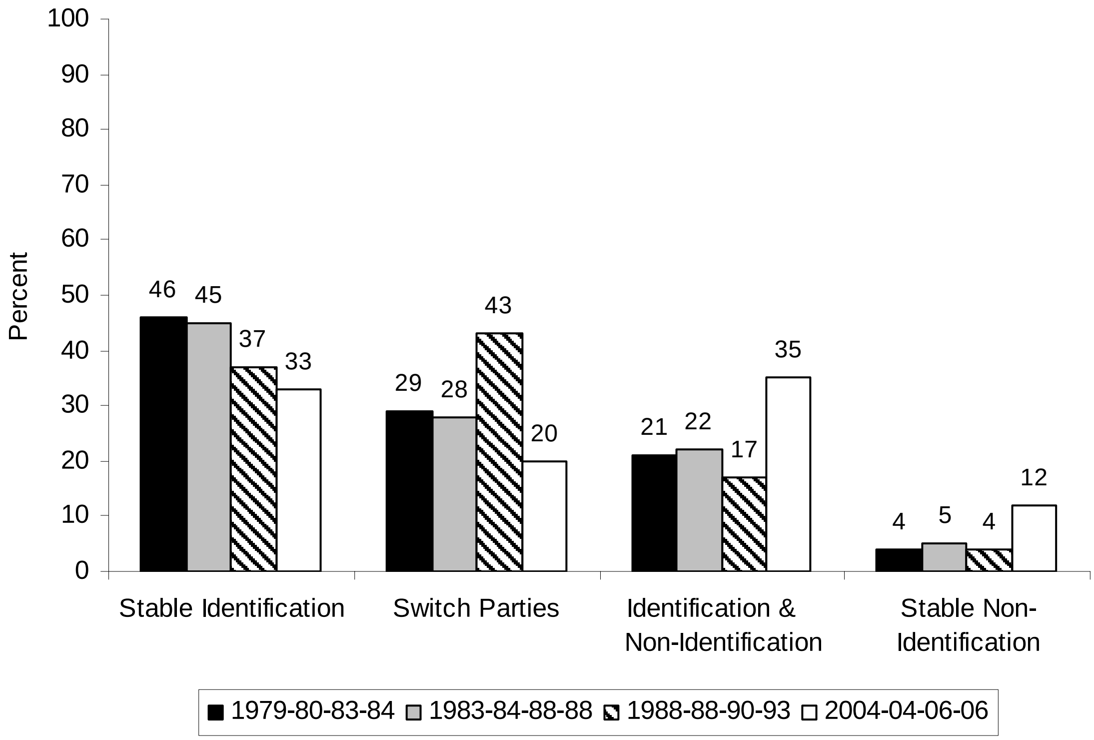
Source: ANES panel surveys.

Figure 2. Dynamics of Party Identification in British National Multiwave Panels



Source: BES, BEPS, and DPSCB panel surveys.

Figure 3. Dynamics of Party Identification in Canadian National Multiwave Panels



Source: CES and PSC panel surveys.

Figure 4. Markov Models, Markov Latent Class Models, and Mixed Markov Latent Class Models

Panel A

$$
\begin{tikzcd}
A_i \arrow[r, "\tau_{j|i}"] & B_j \arrow[r, "\tau_{k|j}"] & C_k \arrow[r, "\tau_{l|k}"] & D_l
\end{tikzcd}
$$

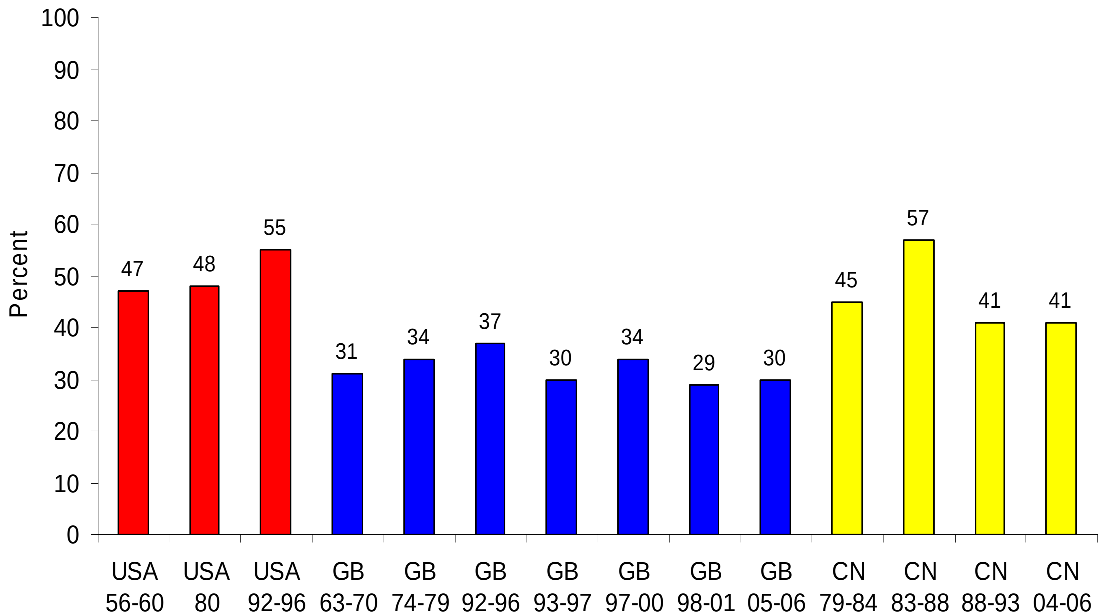
Panel B

$$
\begin{tikzcd}
A_i & B_j & C_k & D_l \\
W_s \arrow[u, "\rho_{i|s}"'] \arrow[r, "\tau_{t|s}"] & X_t \arrow[u, "\rho_{j|t}"'] \arrow[r, "\tau_{u|t}"] & Y_u \arrow[u, "\rho_{k|u}"'] \arrow[r, "\tau_{v|u}"] & Z_v \arrow[u, "\rho_{l|v}"']
\end{tikzcd}
$$

Panel C

$$
\begin{tikzcd}
W_{s1} \arrow[r, "\tau_{t1|s1}"] \arrow[d, "\rho_{i|s1}"] & X_{t1} \arrow[r, "\tau_{u1|t1}"] \arrow[d, "\rho_{j|t1}"] & Y_{u1} \arrow[r, "\tau_{v1|u1}"] \arrow[d, "\rho_{k|u1}"] & Z_{v1} \arrow[d, "\rho_{l|v1}"] \\
A_i & B_j & C_k & D_l \\
W_{s2} \arrow[u, "\rho_{i|s2}"'] \arrow[r, "\tau_{t2|s2}"] & X_{t2} \arrow[u, "\rho_{j|t2}"'] \arrow[r, "\tau_{u2|t2}"] & Y_{u2} \arrow[u, "\rho_{k|u2}"'] \arrow[r, "\tau_{v2|u2}"] & Z_{v2} \arrow[u, "\rho_{l|v2}"']
\end{tikzcd}
$$

Figure 5. Size of Mover Chains in MMLC Analyses of American, British and Canadian Four-Wave Panel Data



Note: CN = Canada, GB = Great Britain, USA = United States