A Generational Model of Political Learning

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I propose a mathematical framework for modeling opinion change using large-scale longitudinal data sets. The framework encompasses two varieties of Bayesian learning theory as well as Mannheim's theory of generational responses to political events. The basic assumptions underlying the model are (1) that historical periods are characterized by shocks to existing political opinions, and (2) that individuals of different ages may attach different weights to those political shocks. Political generations emerge endogenously from these basic assumptions: the political views of identifiable birth cohorts differ from each other, and evolve distinctively through time, due to the interaction of age-specific weights with period-specific shocks. I employ this model to examine generational changes in party identification using data from the 1952-1996 American National Election Studies. My estimates of the age-specific weights characterizing various points in the life-span are generally consistent (at least between the ages of 15 and 60) with a simple Bayesian model in which an individual's opinion at any given time is a simple average or "running tally" of past political experiences. I find no support for the hypothesis that more recent events receive disproportional weight, and only slight (and statistically uncertain) support for the notion that events experienced during a crucial period encompassing late adolescence and early adulthood have more powerful effects than those experienced later in life.

Prepared for presentation at the annual meeting of the American Political Science Association, San Francisco, September 2001.

A Generational Model of Political Learning [1]

Do political experiences in adolescence and early adulthood powerfully shape subsequent attitudes and behavior? Are citizens responsive to political information throughout their lives? Is their incorporation of new information consistent with the precepts of rational political learning? And how do individual responses to political events add up to large-scale shifts in political opinions over decades or generations?

My aim here is to develop and apply a mathematical model of opinion change that can shed light on these questions. The model is quite simple, with only two "moving parts" – (1) a sequence of parameters characterizing the political events of successive historical periods and (2) a sequence of parameters representing the (potentially) distinctive weights attached to those events by individuals of various ages. Despite its simplicity, the model is sufficiently flexible to subsume a variety of more specific models, ranging from Bayesian learning theories (Achen 1992, Gerber and Green 1998) to Mannheim's (1952) generational theory of political change.

My empirical analysis employs longitudinal data to estimate the two sequences of parameters that interact to produce political change over time and across generations. In this respect, my work is firmly situated in the long and vibrant research tradition of "cohort analysis" exemplified by the work of Campbell et al. (1960, chap. 7), Carlsson and Karlsson (1970), Converse (1969; 1976), Abramson (1975), Markus (1983), Miller and Shanks (1996), and Brady

[1] I am grateful to Princeton University's Woodrow Wilson School of Public and International Affairs for financial support of the research reported here, to the American National Election Studies project for providing a half-century of high-quality political data, and to Charlie Parker, Billy Strayhorn, and Gerald Wilson for invaluable computing assistance.

and Elms (1999), among others. However, my analysis departs in some important ways from the theoretical framework underlying most of this work, the so-called "Age-Period-Cohort" framework.

The Age-Period-Cohort framework treats political attitudes or behavior as a function – typically a simple additive function – of variables indexing each individual's age, year of observation ("period"), and year of birth ("cohort"). One fundamental (and much-remarked) problem with this approach is that the model in its general form is statistically underidentified; the age, period, and cohort variables are collinear.[2] As a result, distinct age, period, and cohort effects cannot be disentangled without additional, more or less arbitrary assumptions.

An even more significant (but less-remarked) limitation of the Age-Period-Cohort framework is that it lacks a clear theoretical rationale. As Markus (1983, 720) put it, "the APC model is primarily an accounting equation rather than an explanatory one. That is, its purpose is to partition variation into distinct bundles (age, period, cohort); it is rarely purported to represent in mathematical form the underlying process generating the observed data."

In combination, these two limitations of the Age-Period-Cohort framework seem to produce a pernicious mixture of empirical complexity and conceptual confusion. For example, analysts often impose constraints on the various age, period, and cohort effects to overcome the identification problem that have odd and presumably unintended implications for observed patterns of generational change. And since no analyst really believes that an individual's birth year has a direct causal impact on her political attitudes or behavior, "cohort" effects in the Age-

[2] Any given individual's year of birth can be deduced from her age and the year in which she was interviewed; or her age can be deduced from her year of birth and year of interview; or the year in which she was interviewed can be deduced from her age and year of birth.

Period-Cohort framework are often loosely interpreted as reflecting some mysterious combination of past "period" effects and (unmodelled) generational imprinting – a state of affairs that inspired Converse (1976, 80) to ask "who is responsible for insisting on the conceptual partition between 'period effects' and 'generational effects,' since it seems to verge on a distinction without a difference."[3]

My aim here is to develop an alternative to the Age-Period-Cohort framework that is more explicitly grounded in theories of political learning. Rather than attempting to partition observed variance into additive "period" and "cohort" components, I posit a single process of political learning in which the two important elements are (1) period-specific "shocks" reflecting the distinctive political events of a given time period, and (2) age-specific "weights" reflecting the extent to which these shocks are internalized by individuals at various points in the life-span. Generational patterns of political change arise endogenously from the interaction of these basic elements – a form of interaction that cannot be captured within the conventional additive Age-Period-Cohort framework.[4]

[3] Converse's monograph is a small masterpiece of dyspeptic commentary on the theoretical and empirical difficulties of cohort analysis, replete with references to conceptual distinctions that "blur badly in practice" (23), "hunting for a needle in the disheveled haystack of sampling error" (46) and the possibility that shifting parameters may "add a whole new level of indeterminacy to a problem already near death in indeterminacy" (33).

[4] Brady and Elms (1999) proposed an Age-Period-Cohort model of political participation in which period effects multiply age- and cohort-specific baseline levels of participation. Their model transcends the conventional additive Age-Period-Cohort framework; but from the perspective proposed here it does so in a way that is precisely backward. For Brady and Elms, time periods may be more or less intense but have no distinctive political character, while cohort-specific baseline levels of participation presumably reflect (unspecified) differences in political socialization. In my model, the defining characteristic of each time period is a distinctive political "shock" and age plays the role of multiplier, causing individuals of different ages to respond to these period effects more or less intensely.

My empirical analysis focuses on partisan learning as reflected in changing levels of party identification in the American National Election Studies (NES) data from 1952 through 1996. Party identification provides a useful empirical focus for a variety of reasons even more cogent now than they were for Converse a quarter-century ago, including “the demonstrated importance of these abiding feelings of party attachments in the determination of voting choices,” the fact that “few time series available in sample survey data ... are now as rich or as long,” and the fact that partisanship has been “a workhorse in efforts to develop a proper methodology of cohort analysis” (Converse 1976, 9). However, the model is intended to be sufficiently general to apply to a wide variety of political attitudes and beliefs, and I shall conclude by calling precisely for such comparative analysis.

Three Models of Political Learning

I begin by laying out three distinct models representing alternative hypotheses regarding the nature of political learning through the life-span. There are strong family resemblances among these three distinct models, and indeed all three will turn out to be encompassed by a more general framework in which each appears as a special case. The more general framework will serve as the basis for my empirical analysis, so that available data can be used to assess the adequacy of the special assumptions underlying each of the distinct models presented here. However, from the standpoint of fixing ideas it seems preferable to proceed from the simplest model to more complex alternatives rather than beginning with the general framework and deriving the distinct models as special cases.

All three models are *generational* in the sense that they differentiate individuals at any point in time solely on the basis of when they were born. It would certainly be possible – and, for some purposes, desirable – to elaborate the generational framework in order to incorporate other politically relevant individual characteristics such as race, region, and socio-economic status. However, in the simple formulation offered here, all the respondents of similar age in a given survey are treated as homogeneous, and their political views are accounted for on the basis of the sequence of political events they experience in common at different points in their shared life-history up to the point at which they are interviewed.

In each model, the relevant sequence of political events is represented as a sequence of observations shedding light on some unknown parameter of interest. For example, a survey response to the familiar NES party identification question may be thought of as a report of an individual's subjective assessment of the current value of an unknown parameter representing her appropriate partisan loyalty. Political events are relevant to the extent that they shed (subjective) light on the value of this unknown parameter.

The key distinction among the three models considered here is in how individuals are supposed to incorporate relevant information at various points in their lives. In the simplest model, an individual's attitude reflects a simple average of all the relevant political events she has experienced throughout her life. In the second model, recent events receive more weight than those experienced in the distant past. In the third model, events experienced during the formative years of late adolescence and early adulthood receive more weight than those experienced earlier or later in life.

A key simplifying assumption common to all three models is that age has no independent impact on political attitudes. If members of a given cohort become more Republican (or

Democratic) as they grow older, their changing partisanship is assumed to reflect the accumulation of specific political experiences to which they have been exposed rather than the process of aging per se. Moreover, the political experiences to which they have been exposed are assumed to be unaffected by their age at the time of exposure. Thus, a given war, scandal, or economic boom cannot be interpreted by some cohorts as a pro-Republican event but by other cohorts as a pro-Democratic event.[5]

These simplifying assumptions will obviously be more or less plausible depending on the specific research context. For example, direct effects of aging seem more likely to be consequential in an analysis of political involvement than in an analysis of party identification (Converse 1969; Converse 1976; Brady and Elms 1999), and political events with clear age-specific ramifications (say, the imposition of a military draft or the collapse of a public pension system) seem more likely than other kinds of events to produce distinctive responses in different birth cohorts (Delli Carpini 1989). Limitations of this sort notwithstanding, the framework developed here seems sufficiently flexible to be potentially fruitful in analyzing a variety of specific instances of political learning.

The Running Tally

The first model to be considered here is a simple Bayesian learning model (Zeckman 1979; Achen 1992). The model posits a sequence of observations $\{\pi_1, \ldots \pi_t, \ldots \pi_T\}$, with

{1} $$\pi_t = \mu + \delta_t ,$$

[5] This is not to deny that the *impact* of such an event may, and in general will, be age-dependent – a point I shall elaborate in due course.

where μ is a constant (unknown) parameter and δ_t is a normally-distributed random variable with mean zero and (known) variance σ^2.[6] In Achen's (1992) formulation, μ represents a partisan differential in expected (prospective) benefits for a given voter, and the observations $\{\pi_1, \ldots \pi_t, \ldots \pi_T\}$ represent a sequence of actual benefits experienced by that voter in successive time periods.[7] Actual benefits are more or less affected by random factors (reflected by the variance σ^2); nevertheless, favorable (or unfavorable) experience with either party inclines the voter to adjust her beliefs about the unknown value μ accordingly.[8] For the specific case of party identification, Achen's model represents a mathematical formalization of Fiorina's (1977, 611) notion of party identification as a "running balance sheet" of retrospective evaluations of the competing parties' performance in office.

More generally, μ may be thought of as representing any political attitude of interest, with the observations $\{\pi_1, \ldots \pi_t, \ldots \pi_T\}$ representing political experiences influencing that

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[6] More realistically, the variance σ^2 may also be treated as an unknown parameter. That complication is of no great importance, so is omitted here.

[7] Even this rather modest degree of specificity regarding the interpretation of the parameter μ and the observations $\{\pi_1, \ldots \pi_t, \ldots \pi_T\}$ is not strictly necessary, and may be theoretically objectionable. Thus, for example, Gerber and Green (1998, 798-801 and 815-816) suggest that Achen's "net benefits" formulation goes astray by ignoring the distinction between partisan *evaluations* and party *identification*. For my purposes here it is sufficient for μ to represent whatever political assessment respondents have in mind when they answer the party identification questions, and for $\{\pi_1, \ldots \pi_t, \ldots \pi_T\}$ to represent whatever political observations or experiences are relevant to shaping that assessment.

[8] Achen's formulation includes informative prior beliefs produced by parental socialization in addition to direct experience. Since the available longitudinal data do not include reliable information on parental partisanship, I dispense with that complication here and assume that each individual begins life

attitude. For example, μ may represent a given citizen's level of confidence in the federal government, and the sequence $\{\pi_1, \ldots \pi_t, \ldots \pi_T\}$ a series of relevant political experiences such as scandals, economic booms or busts, and successful or unsuccessful wars.

In this simple "running tally" model, the optimal estimate $m_{C,T}$ of the underlying value μ at time T for an individual born at time C is a simple average of the observed π values from birth through time T:

$$\{2\} \qquad m_{C,T} = \left(\textstyle\sum_{C+1 \leq t \leq T} \pi_t \right) / (T-C).$$

Since the characteristics of the distribution of expected benefits are assumed to be constant over time, inferences about the unknown value μ are unaffected by the temporal order of the observations – an economic boom or bust in the distant past is just as relevant as today's headlines. However, the incremental impact of each new observation does depend on the number of previous observations, as may be seen from the recursive relationship between the current estimate $m_{C,T}$ and the previous estimate $m_{C,T-1}$:

$$\{3\} \qquad m_{C,T} = m_{C,T-1}\,(T-C-1)/(T-C) + \pi_T/(T-C)\,.$$

For individuals in a given birth cohort C, the marginal impact of a new experience π_T declines over time (that is, the weight $1/(T-C)$ attached to π_T declines as T increases) even though experiences at different times enter identically in equation {2}. Alternatively, at any given time T, the marginal impact of a new experience π_T declines with age (since the weight

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without partisan predispositions.

$1/(T–C)$ attached to π_T declines as the birth year C decreases). As Achen (1992) pointed out, this fact provides a theoretical rationale for a familiar pattern in the empirical literature on political attitudes: the greater stability of observed opinions among the old than among the young.

It is also worth noting that the incremental impact of any given experience depends upon the discrepancy between that experience and previous experiences as encapsulated in the prior belief $m_{C,T-1}$. Subtracting $m_{C,T-1}$ from each side of equation {3} and simplifying,

$$\{4\} \qquad m_{C,T} - m_{C,T-1} = (\pi_T - m_{C,T-1})/(T-C) \ .$$

One implication of equation {4} is that experience consistent with prior beliefs leaves those beliefs unaltered (albeit more confidently held). Another is that the same experience π_T may pull different cohorts in opposite directions (if $m_{C,T-1} < \pi_T < m_{D,T-1}$ for cohorts C and D, respectively).

Achen's (1992) discussion of the Bayesian model focused primarily on the dynamic relationship between current and past partisanship represented by equation {3} rather than on the reduced-form impact of the sequence of period shocks highlighted by equation {2}. Thus, he suggested models and methods for capturing the age-dependent relationship between current and past partisanship in panel data – in effect, providing a more explicit theoretical rationale for empirical work along similar lines by Franklin and Jackson (1983), Markus (1983), and others. However, since my approach here is predicated on the use of longitudinal data rather than panel data, the key relationship for my purposes is equation {2}, which expresses the optimal estimate

$m_{C,T}$ of the partisan differential at any point in time as a simple average of the period shocks $\{\pi_{C+1}, \pi_{C+2}, \dots \pi_T\}$.

Partisan Change and Temporal Discounting

The simple "running tally" model assumes, rather implausibly, that the underlying political value of interest, μ, remains constant over time. Gerber and Green (1998) have proposed a more realistic dynamic model in which μ is subject to temporal drift:

$$\{5\} \qquad \mu_t = \gamma\, \mu_{t-1} + \varepsilon_t\,,$$

where γ is a constant parameter between zero and one and ε_t is a normally-distributed random variable with mean zero and variance φ^2. As Gerber and Green (1998) noted, the "running tally" model is a special case of this more general model in which $\gamma = 1$ and $\varphi^2 = 0$. The more general model is in turn subsumed within a broader class of Dynamic Linear Models analyzed by West and Harrison (1997).

The model defined by equations {1} and {5} does not fit neatly within the framework proposed here, because the optimal estimate $m_{C,T}$ of the current value μ_T for a member of birth cohort C at time T is not a weighted average of the observed π values. (Due to the mean reversion in μ_t produced by $\gamma<1$, the sum of the optimal weights is less than one.) However, setting $\gamma = 1$ but allowing $\varphi^2 > 0$ produces a random-walk model in which the partisan differential varies over time, albeit without mean reversion.[9] In that case, the optimal estimate $m_{C,T}$ of μ_T does turn out to be a weighted average of the period shocks $\{\pi_{C+1}, \ldots \pi_t, \ldots \pi_T\}$:

$$\{6\} \qquad m_{C,T} = (\textstyle\sum_{C+1 \le t \le T} \omega_{t-C}\, \pi_t) / (\textstyle\sum_{C+1 \le t \le T} \omega_{t-C}) ,$$

where the optimal weight ω_{t-C} for the observation π_t (experienced at age $t-C$) is

$$\{7\} \qquad \omega_{t-C} = [(v_{C,t-1} + \varphi^2)/ v_{C,t-1})]\, \omega_{t-C-1} ,$$

with $v_{C,t}$ (the variance of $m_{C,t}$) defined recursively as

$$\{8\} \qquad v_{C,t} = \sigma^2 (v_{C,t-1} + \varphi^2)/(v_{C,t-1} + \varphi^2 + \sigma^2) .$$

When $\varphi^2 = 0$ (that is, when the underlying partisan differential does not vary over time), $[(v_{C,t-1} + \varphi^2)/ v_{C,t-1})] = 1$ in equation {7}, which implies $\omega_{t-C} = \omega_{t-C-1}$. This is the special case represented by the "running tally" model, in which (as was clear from equation {2}) the optimal estimate $m_{C,T}$ is a simple average of the observations $\{\pi_{C+1}, \ldots \pi_t, \ldots \pi_T\}$. However, when $\varphi^2 > 0$ (that is, when the underlying partisan differential μ_t is allowed to vary over time), $[(v_{C,t-1} + \varphi^2)/ v_{C,t-1})] > 1$ in equation {7}, which implies $\omega_{t-C} > \omega_{t-C-1}$. In this case the

[9] The loss of theoretical generality entailed by setting γ=1 is not trivial, since it may well be reasonable to expect the existing partisan differential at any given time to erode. However, the generational pattern of political learning implied by the simpler random-walk model is qualitatively similar to that implied by Gerber and Green's more general model with mean reversion. Thus, my empirical test of the random-walk model will also shed light, albeit indirectly, on the adequacy of the more general model.

optimal estimate $m_{C,T}$ is a weighted average of the observations $\{\pi_{C+1}, \ldots \pi_t, \ldots \pi_T\}$, with the weights increasing with t. Viewed from the current period T, recent observations are more relevant than older observations for inferring the current value μ_T. Indeed, since $v_{C,t-1}$ is of order $1/(t-1)$, equation {7} implies that the weights increase at an accelerating rate, ensuring that old observations will (eventually) be heavily discounted even when the underlying rate of change in the partisan differential is quite modest.

The important point here is that the pattern of optimal weights distinguishes the "partisan change" model from the simpler "running tally" model. When μ is fixed, the optimal weights for observations $\{\pi_{C+1}, \ldots \pi_t, \ldots \pi_T\}$ are identical. But when μ is allowed to change over time, the optimal weights for observations from more recent periods (or, equivalently, for events experienced later in life) are greater than those attached to similar events experienced earlier.[10]

Generational Imprinting

In discussing the limitations of their Bayesian model of political learning, Gerber and Green (1998, 815) argued that "any such model must account for the 'period effects' that stamp different generations with distinctive partisan coloration. . . . Learning models that stress the influence of contemporaneous information have difficulty explaining the persistence of early formative experiences." Indeed, at least since the publication of Mannheim's (1952) classic essay on "The Problem of Generations," the notion that early formative experiences have some

[10] Allowing $\gamma<1$, as in Gerber and Green's (1998) more general formulation, would provide an additional reason to discount past experience, causing the optimal weights to increase even more markedly over the life-span. Thus, an empirical test of the random-walk model proposed here provides a "conservative" qualitative test of the more general model.

special power to stamp different generations with distinctive political attitudes and beliefs has been one of the most familiar and influential ideas in the literature on political socialization.

There is some disagreement – and a good deal of vagueness – about what it is that makes these formative experiences so important. Analysts of generational politics have pointed to a variety of potentially relevant psychological and sociological processes, but have done little to pursue their specific implications or even to distinguish clearly among them. Thus, for example, Markus (1983, 723) noted that generational analysts "posit that the socializing experiences of late adolescence and early adulthood are of crucial importance in forming political outlooks because of the heightened sensitivity of cohort members during this formative life stage," while Delli Carpini (1989, 18) referred to the "openness of youth to new ways of thinking." But to argue that "heightened sensitivity" or "openness" account for distinctive responsiveness to political stimuli is a not-very-enlightening tautology.

Fortunately, my own interest is not in mechanisms of political socialization but in the patterns of generational opinion change they may produce. Here the literature seems to me to be a good deal stronger, with careful empirical studies shedding light on the continuity of political attitudes over the life-span and on variations in political attitudes across cohorts or generations.[11] However, despite their manifest virtues, these studies fall short of providing a clear empirical test of what I take to be the heart of Mannheim's generational theory.

The best evidence adduced in support of the persistence of early formative experiences is derived from long-term panel studies of the same individuals over significant portions of the life-

[11] I have neither the space nor the expertise to improve upon Delli Carpini's (1989) thorough, insightful review of the relevant literature.

span (Newcomb et al. 1967; Jennings and Niemi 1981; Beck and Jennings 1991). However, the structure of these studies tends to preclude detailed analysis of the timing of political socialization, or detailed comparison of the experiences and attitudes of different cohorts. As a result, the attribution of patterns of generational change specifically to political experiences in late adolescence or early adulthood seems a good deal less solid than one could wish.

Many other studies (for example, Carlsson and Karlsson 1970; Glenn 1980; Franklin and Jackson 1983; Alwin and Krosnick 1991; Achen 1992) have adduced empirical support for the notion that political attitudes are more labile in early adulthood than at later points in the life-span. Typically, these studies employ short-term panel surveys (conducted over periods ranging from a few months to a few years) to demonstrate that older panel respondents have more stable political attitudes than their younger counterparts. But this fact is not, in itself, strong evidence of generational imprinting in Mannheim's sense. In order to grasp that point, it is necessary to distinguish clearly between the *weight* associated with each age and the corresponding *incremental impact* of events experienced at that age.

Within the framework of generational analysis I have proposed here, any given sequence of age-specific weights $\{\omega_1, \ldots \omega_a, \ldots \omega_A\}$ implies a corresponding sequence of incremental impacts $\{\alpha_1, \ldots \alpha_a, \ldots \alpha_A\}$, where

{9} $$\alpha_A = \omega_A / (\textstyle\sum_{a \leq A} \omega_a) .$$

Since the weights are, by assumption, non-negative, the denominator in equation {9} must be an increasing function of age. Thus, the incremental impact of events experienced at any given age will decrease even if the age-weights are constant over the entire life-span.

Of course, the special case of equal age-weights over the life-span corresponds exactly to what I have dubbed the "running tally" model. In that case, as equation {3} makes clear, the incremental impact of an event experienced at age A is $\alpha_A = 1/A$. Thus, for example, any given political shock will produce only half as much change in the views of a 40-year-old as in the views of a 20-year-old. However, it would be a mistake to conclude that political events experienced at age 20 are somehow more powerful or important than those experienced at age 40. From the perspective of understanding the current political beliefs of a 40-year-old (or, for that matter, a 60-year-old or 80-year-old), the events experienced at age 20 would deserve exactly as much weight as those experienced at age 40 – no more, no less. That does not seem to be what Mannheim and his followers had in mind.

A stronger, and correspondingly more interesting, version of the "generational imprinting" hypothesis would hold that the age-weights themselves, and not only the incremental impacts associated with those age-weights, peak during a crucial period of political development in late adolescence or early adulthood. Cast in this light, the "generational imprinting" hypothesis fits within the same framework of period-specific shocks and age-specific weights that I have used to represent the Bayesian "running tally" and "partisan change" models. In particular, the political attitudes of an individual in birth cohort C at age A can be represented as a weighted average of previous political experiences,

{10} $$m_{C,A} = \left(\sum_{a \leq A} \omega_a \pi_{C+a} \right) / \left(\sum_{a \leq A} \omega_a \right),$$

where π_{C+a} is the period-specific shock representing the distinctive political events of the period in which cohort C reached age a and ω_a is the age-specific weight representing the distinctive sensitivity to political experience of individuals at age *a*.

Equation {10} exactly parallels equation {6}, except that the notation has been slightly recast to emphasize the age-dependence of the weights $\{\omega_1, \ldots \omega_a, \ldots \omega_A\}$. Thus, in my formulation, the crucial distinction between the “generational imprinting” model and the Bayesian learning models is not in *how* political experiences are incorporated, but simply in the *extent* to which political experiences are incorporated at different points in the life-span.

The precise pattern of age-weights implied by the hypothesis of “generational imprinting” is somewhat unclear, but hardly so unclear as to render the hypothesis vacuous. In an extensive review of the relevant literature, Delli Carpini (1989, 20) conceded that “there is some disagreement on the specific years involved,” and cited various estimates (including 17 to 25, 18 to 26, 15 to 30, and 20 to 30) for the “critical” years of political development. An attractive feature of equation {10} as a representation of the “generational imprinting” hypothesis is that it is sufficiently flexible to capture any relevant variation in age-weights over the course of the life-span. Thus, evidence rather than assumptions can identify which (if any) stage of life is distinctively “formative.” More generally, data can be made to shed light on “the rate at which the life cycle affects learning and socialization” – a good thing, given that “almost any pattern can be defended” logically, from linear trends to step functions to curvilinear patterns (Delli Carpini 1989, 31).

Another attractive feature of equation {10} is that the *political content* of generational imprinting varies naturally from cohort to cohort with changes in the political environment. As Delli Carpini (1989, 18) summarized Mannheim’s generational hypothesis,

> The possibility of a new generation existed with the coming of age of each new

> cohort, but the actuality of a new generation, as well as the specific attitudes that developed and the specific ways in which those attitudes were expressed, depended on the external environment.

In my mathematical formulation, the contribution of the external environment is to produce a sequence of political experiences which may or may not depart markedly from those experienced in previous periods. When they do, the new cohort or cohorts most open to being shaped by those distinctive experiences develop markedly different political attitudes from previous cohorts, transforming a "potential generation" into an "actual generation."

Moreover, my formulation is sufficiently flexible to represent either sharp or gradual generational differences. If a crucial political experience occurs suddenly, and if the weight attached to political experiences varies sharply with age, then a relatively narrow birth cohort may develop quite distinctive attitudes by comparison with earlier and later cohorts. On the other hand, a political experience that extends over several years will tend to produce less sharp generational differences, as will a pattern of relatively equal age-weights over a significant fraction of the life-span.

Data and Estimation

The data analyzed here are from the American National Election Study (NES) Cumulative Data File.[12] The NES surveys conducted biennially between 1952 and 1996 include 39,549 respondents with identifiable birth years between 1853 and 1978. (My analysis omits

[12] The data are taken from the Cumulative Data File on the American National Election Studies 1948-1997 CD-ROM. A newer version of the Cumulative Data File including 1998 data is available on the NES website, *www.umich.edu/~nes*.

respondents whose age was not ascertained, including all of the respondents in the 1954 NES survey, in which age was only recorded in ten-year intervals.)

Given the biennial structure of the NES data set it seems natural to define birth cohorts and estimate period-specific political shocks in two-year increments. Thus, for example, I categorize respondents who were 18 or 19 at the time of the 1974 NES survey (born in 1955 or 1956) as members of a 1956 birth cohort. These respondents' partisan loyalties in 1974 are assumed to be the product of a series of ten biennial political shocks: a 1956 shock experienced at age 0-1, a 1958 shock experienced at age 2-3, and so on through a 1974 shock experienced at age 18-19. Since early birth years are very thinly represented (with only 30 respondents born between 1853 and 1870), I treat all respondents born before 1873 as members of a single (1872) cohort.

The resulting distribution of respondents by birth cohort is shown in Figure 1. The birth cohorts from 1910 through 1958 are well represented, with a minimum of 988 respondents in each. Cohorts born before or after this 50-year period are less well represented in the NES data, with fewer than 200 respondents in each of the cohorts born before 1887 or after 1972.

*** * * Figure 1 * * ***

The dependent variable in my analysis is the seven-point NES party identification scale, recoded to range from −50 (for Strong Republicans) to +50 (for Strong Democrats). The average Democratic partisanship on this 100-point scale of each successive two-year birth cohort in the pooled NES data is displayed in Figure 2. (Here and in subsequent figures, the upper and lower tails attached to each data point indicate the range of uncertainty associated with the indicated value, from minus one standard error to plus one standard error.)

*** * * Figure 2 * * ***

Figure 2 displays a clear pattern of changing partisanship by birth cohort. A rough parity between Democrats and Republicans born in the late nineteenth century gives way to a strong preponderance of Democrats in the cohorts born in the first three decades of the twentieth century; but that Democratic advantage is significantly eroded among the cohorts born after 1930, and especially among the cohorts born after 1950. The youngest cohorts represented in the figure display a rough parity in partisan loyalties reminiscent of the one prevailing 80 years earlier.

Converse (1976, 141) predicted in the mid-1970s that "if no new major realignment intrudes within the next decade, the static correlation between age and the direction component of party identification, so long a staple feature of the American political scene, will very nearly, if not completely, wither away." In fact, as should not be surprising in light of the pattern displayed in Figure 2, the correlation between age and partisanship has not withered away but reversed. In the 1950s, 65-year-olds were, on average, about 9 points less Democratic than 25-year-olds on the 100-point partisanship scale. In the 1990s, a typical 65-year-old was about 5 points *more* Democratic than a typical 25-year-old. Roughly speaking, the comparison between 65-year-olds and 25-year-olds in the 1950s was a comparison between the early and middle birth cohorts in Figure 2, whereas the comparison between 65-year-olds and 25-year-olds in the 1990s was a comparison between the middle and late cohorts in the figure.

The negative correlation between age and Democratic partisanship in recent NES surveys provides some empirical justification for my willingness to ignore potential life-cycle effects in my generational model. Obviously, the simple correlation does not rule out the possibility that life-cycle effects exist; but it does cast doubt on the once-commonsensical notion that Americans naturally become more Republican as they grow older.[13]

The general form of my weighted-average model is

$$\{11\} \qquad m_{i,T} = \left(\sum_{t \leq T} \sum_a x_{i,a,t} \; \omega_a \, \pi_t \right) / \left(\sum_{t \leq T} \sum_a x_{i,a,t} \; \omega_a \right) + \upsilon_{i,T} \;,$$

where $m_{i,T}$ is the party identification of respondent i at time T; $x_{i,a,t}$ is an indicator variable taking the value 1 if respondent i's age at time t is a and zero otherwise; $\upsilon_{i,T}$ is a stochastic disturbance term; $\{\omega_1 , \ldots \omega_a , \ldots \omega_{91}\}$ is a sequence of 46 age-specific weights to be estimated;[14] and $\{\pi_{1872} , \ldots \pi_t , \ldots \pi_{1996}\}$ is a sequence of 63 period-specific shocks to be estimated.

Equations {2}, {6}, and {10} – the corresponding expressions for the "running tally,"

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[13] Converse's (1976) prediction that the correlation between age and Republican partisanship would "wither away" was based on his empirical contention that what he referred to as the "direction component" of party identification is a product of generational effects rather than life-cycle effects. By contrast, he argued that the "strength component" of party identification – the intensity of partisan loyalties regardless of direction – tends to increase as a direct function of age (or, more precisely, of experience within a stable party system). As Achen (1992) pointed out, one advantage of Bayesian learning models of the sort considered here is that they provide a natural framework in which to derive variations in the "strength component" of party identification through the life-cycle from more basic theoretical principles. Indeed, if we are willing to equate "strength" with "certainty," the life-cycle effects posited by Converse follow directly from the fact that the variance of the estimated partisan differential necessarily declines over time in either the "running tally" model or the more general random-walk model under the assumptions outlined in the preceding section.

[14] I curtail the sequence of age-weights at 91, implicitly setting subsequent weights to zero. This simplification seems benign, since there are only 31 respondent in the NES Cumulative Data File over the age of 91, and since the incremental impact of political experiences at that point in the life-span are likely to be modest.

"partisan change," and "generational imprinting" models – are simply special cases of equation {11} with less explicit notation.

The stochastic disturbance term $\upsilon_{i,T}$ in equation {11} incorporates all of the factors that might account for heterogeneity in partisan loyalties among the members of any given birth cohort at any point in time. Given the obvious importance of these factors, it should not be surprising that the generational model defined by equation {11} will leave a great deal of the total variance in observed partisanship unaccounted for.

It is clearly unrealistic to assume that the sequence of period-specific shocks in equation {11} is identical for all the members of a given cohort, much less for the entire population. Since the NES samples are nationally representative, the parameter estimate for each period may reasonably be interpreted as representing the *average* value of the period-specific shocks for every individual in the national population in that period; however, the interpretation is only approximately valid given the non-linearity of the model. It would not be difficult (though it would be unwieldy) to incorporate distinct period-specific shocks for different sub-groups of the population; but that complexity is beyond the scope of the present analysis.

There is good reason to expect that the pattern of age-specific weights in equation {11} will be a more or less smooth function of age. If respondents are strongly affected by political events when they are 21, it seems reasonable to suppose that they are also strongly affected at 19 and 23, though perhaps not at 11 or 31. Thus, it is tempting to impose some simple functional form on the age-specific weights in order to reduce the complexity of the model and the number of parameters to be estimated. I avoid that temptation here, for two reasons. First, in the absence of previous research along the lines contemplated here, it seems far from clear what specific functional form would be appropriate. Even a seemingly unrestrictive choice could unintentionally miss or distort interesting features of the data. Moreover, the general expectation of continuity in the weights over the course of the life-span will provide a useful check on the plausibility of the empirical results: if the estimated weights display a reasonably smooth pattern when nothing in the analysis forces them to do so, their credibility will be correspondingly enhanced.

While my approach to the estimation of age-weights is as unrestrictive as possible, one restriction is imposed by the structure of the model. Since all of the age-weights always appear in both the numerator and the denominator of equation {11}, it should be clear that their absolute scale is indeterminate – multiplying each of the weights by the same positive constant would have no effect on the magnitudes of the period shocks or on the expected value of the dependent variable. Thus, it is necessary to normalize the age-weights. I do this by fixing the weight for one age category (age 17) at an arbitrary value (1.0), implicitly scaling the remaining age-weights relative to that one.

Once this normalization is imposed, the model embodied in equation {11} is a straightforward non-linear regression model in which the explanatory variables are the indicator variables $x_{i,a,t}$ identifying the age of each respondent in each time period (and thus, indirectly, the respondent's birth cohort). However, applying the model to the NES Cumulative Data File and unpacking the strings of terms lurking behind the summation signs in equation {11} produces a complex and rather cumbersome model, with 54 terms (one for each two-year birth cohort from 1872 through 1978), each of which is itself a non-linear expression with anywhere from 9 to 45 terms (one for each two-year age bracket) in the numerator and denominator. There are a total of 108 parameters to be estimated – 63 period-specific shocks $\{\pi_{1872}, \pi_{1874}, \ldots \pi_{1996}\}$ and 45 unnormalized age-specific weights $\{\omega_1, \ldots \omega_{15}, \omega_{19}, \ldots \omega_{91}\}$.

In principle, the sheer size of the model should not be a barrier to estimation. However, my attempts to convince my computer of that fact have (so far) been unavailing. Having failed to estimate the parameters of the model directly, I estimated them indirectly by iterating between two simpler non-linear regression models: one taking the period shocks as given and estimating the age-specific weights, and the other taking the age-specific weights as given and estimating the period shocks. Since the results of each iteration had to be transposed from periods to age brackets (or vice versa) separately for each birth cohort, this indirect approach was unhappily time-consuming. My convergence criterion was correspondingly primitive: I stopped iterating when the fit of the model stopped improving (after ten iterations). Given the complexity of the relevant parameter space and the limitations of the indirect estimation strategy, it is by no means clear that all of the parameter estimates did, in fact, converge to their optimal values. The sequences of parameter estimates from successive iterations revealed no obvious anomalies; nevertheless, further analysis will be required to verify the accuracy of the results presented here.

One important substantive challenge in estimating the parameters of the generational model is that the NES data provide little useful information regarding the period shocks for early years in the sequence $\{\pi_{1872}, \pi_{1874}, \ldots \pi_{1996}\}$. With no respondents interviewed before 1952 – and most interviewed after 1975 – it is obviously very difficult to disentangle the specific impact of events in, say, 1882 from those in 1884.[15] Of course, the NES data are far from being the

[15] One source of leverage is the fact that, under the assumptions of my generational model, survey respondents who were 78 or 79 years old in 1952 (or 82 or 83 years old in 1956, etc.) could have been

only available source of information regarding the political events of those years. In order to produce more accurate estimates of the period shocks (and thus, by extension, of the age-weights) I used congressional election outcomes to supplement the survey data. While election outcomes only indirectly reflect the political shocks relevant for my purposes, it would be odd indeed if future survey respondents routinely drew pro-Democratic partisan lessons from events that produced pro-Republican shifts in congressional representation at the time (and vice versa).

The specific partisan shocks implied by the congressional election results for each two-year period from 1872 through 1996 are reported in the second column of Table 1 and presented graphically in Figure 3.[16] The standard error of 40.0 attached to each value represents a subjective estimate of the uncertainty associated with the construction of these auxiliary estimates of the partisan shock in each period.[17]

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affected by events in 1884, but not by events in 1882. However, there are only a total of 143 NES respondents in this cohort; and even the evidence they can provide is clouded by the fact that political events "experienced" in their infancy may (and, as it turns out, do) have a very modest impact on their partisan attachments eight decades later. The situation is rather less bleak for later years, not only because there are more NES respondents in the relevant cohorts but also because those respondents are observed at younger ages (so that their observed partisan loyalties have to be decomposed into fewer distinct period-specific shocks).

[16] In keeping with the general approach pursued here, I used a simple Bayesian model to extract estimates of the partisan shock in each two-year period from observed changes in the partisan composition of Congress. In particular, I treated the Democratic proportion of seats in the House of Representatives in the wake of each election (rescaled to match the −50 to +50 range of the survey data on party identification) as a weighted average of the previous Democratic seat share and a partisan shock, with the previous Democratic seat share (somewhat arbitrarily but, I hope, not unreasonably) receiving five times as much weight as the partisan shock. Given this setup, it is a simple matter to solve for the value of the partisan shock in each period, and those values are reported in Table 1 and graphed in Figure 3.

[17] The standard error of 40.0 is obviously a very rough reflection of the uncertainty associated with these prior estimates. However, the choice of a specific value turns out not to have much impact on the results of my subsequent analysis, since under any reasonable construction the evidence available from

*** * * Table 1; Figure 3 * * ***

I used the prior values displayed in Figure 3 as starting values for the iterative estimation of age-specific weights. I also used them to stabilize the estimated period shocks from subsequent iterations. The effect of this stabilization is evident from a comparison of Figure 3 with Figure 4, which displays the posterior estimates of the period shocks from the final round of estimation. (The posterior estimates are also presented in the third column of Table 1.) For the early years of the analysis the NES data provide very little leverage, and the posterior estimates essentially replicate the prior estimates. (For example, the average weight of the NES data relative to the priors in computing the 20 estimates before 1912 is less than 2 percent. All of these shocks were 40 to 80 years in the past by the time their residual traces began to be recorded in the NES data.) For the later years the survey data are much more informative, and the posterior estimates are noticeably different from (and much more precise than) the prior estimates. (For the 20 estimates after 1956, the average relative weight of the NES data in computing the posterior estimates is more than 88 percent.)

*** * * Figure 4 * * ***

The sequence of estimated partisan shocks displayed in Figure 4 plays a crucial role in my generational model. Thus, it seems worth pausing briefly to verify that that sequence provides a plausible account of the political events that are supposed to have shaped the partisan

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the NES survey data is much less precise than the prior information before about 1926 and much more precise than the prior information after about 1956.

attachments of NES respondents over the past half-century. Perhaps the simplest way to do this is to focus on the largest partisan shocks recorded in Figure 4 and ask whether they correspond sensibly to the relevant political history. The four largest shocks (in 1894, 1874, 1890, and 1932) directly reflect shifts in the composition of Congress in response to major economic dislocations – events of precisely the sort that might be expected to leave durable traces in the partisan attachments of subsequent generations. The collapse and resurgence of the Republican majority in the period between 1910 and 1920 are nicely captured in the estimates, as are the sustained Democratic gains of the New Deal period. However, all of these estimates reflect the congressional election results much more than they do the NES survey data.

A sharper test of the generational model is provided by the estimates from the second half of the twentieth century, which are derived almost wholly from the survey data. The most notable partisan shocks in this period imply strong Democratic gains in 1964 (+70.3) and 1958 (+66.2) and, in the former case, a strong Republican rebound in 1966 (–57.3). These estimates seem quite reasonable. So do the Republican gains apparent in 1984 (–28.3), 1988 (–34.6), and 1994 (–41.2), though the magnitudes of the Democratic counter-surges in 1986 (+32.2), 1990 (+45.6), and 1996 (+46.4) strike me as surprising. The absence of notable Republican gains in the presidential landslide years of 1956 (–4.6), and 1972 (–13.8) may also seem surprising, but can easily be rationalized as reflecting the fact that these were *personal* rather than *partisan* triumphs. After all, the classic analysis of party identification in *The American Voter* (Campbell et al. 1960) was inspired in large part by the ability of Democratic identifiers in the 1950s to retain their partisan attachments while voting in significant numbers for Eisenhower.

It also seems worth noting that the posterior estimates of the period shocks after 1954 are strongly correlated with the prior estimates based on congressional election results (.71) and even more strongly correlated with the estimates in the first column of Table 1 derived from imposing equal age-weights over the entire life-span (.86). Since the posterior estimates are based much more on the survey data than on the prior estimates, the former correlation indicates considerable agreement between the two independent sources of information. And since the estimates derived from imposing equal age-weights involve neither the prior estimates derived from congressional election outcomes nor the iterative estimation strategy employed in my main analysis, the even closer correspondence between those estimates and the estimates shown in Figure 4 suggests that the pattern of political shocks I have extracted from the survey data is not unduly dependent on either my prior estimates or my iterative estimation strategy.

Political Learning Through the Life-Span

My key findings are presented in Table 2, which reports the estimated age-specific weights from my iterative non-linear regression analysis. The estimated weights are also presented graphically in Figure 5, along with standard error bars and a lowess (locally weighted) regression line summarizing how the estimated weights vary over the course of the life-span.[18]

*** * * Table 2; Figure 5 * * ***

The standard error bars presented in Figure 5 call attention to the fact that the precision of the estimated weights declines markedly over the course of the life-span; the estimates beyond

[18] The bandwidth for the lowess regression (Cleveland 1979) is .2; thus, the smoothed value at each point is based on a weighted average of the estimates from the previous decade and the subsequent decade, with estimates closer in time receiving more weight.

age 60 are not even clearly distinguishable from zero, while those beyond age 80 are so erratic that they disappear entirely from the range of values included in the figure. Primarily, this reflects the inevitable fact that the NES data set includes many more former 20-year-olds than former 60-year-olds, and very few former 80-year-olds. (To a lesser extent, it reflects the structure of the generational model, in which the current attitudes of 60-year-olds must be apportioned among 30 distinct period shocks, while the attitudes of current 20-year-olds are composed of only 10 distinct shocks.)

Within the limits set by the imprecision of the parameter estimates, three aspects of the results seem to be worth noting:

- Over the first twenty years of the life-span the estimated weights increase fairly linearly, roughly tripling from the first (age 0-1) age bracket to the eleventh (age 20-21) age bracket. This pattern suggests a plausible process of gradual partisan socialization from youth through early adulthood.

- Between the ages of 20 and 60 the estimated weights are essentially constant. There is some evidence of a trough visible in Figure 5, especially in the lowess summary line, around the age of 30; but the trough is of modest magnitude (reducing the weights by about 20 percent at most) and of fairly short duration (disappearing by the mid-40s).

- After the age of 60 there is a fairly sudden, albeit ragged, drop in the estimated weights. This drop seems to persist through the mid-70s, when the estimates become so imprecise that they are completely uninformative.

There is remarkably little support in these results for the notion that citizens rationally discount (or, for that matter, simply forget) past political events. The portion of the life-span over which the age-weights are clearly increasing ends around age 20, and the subsequent (more gradual) increase through the 30s and 40s merely reverses a decline through the 20s. (By contrast, simply discounting past political experience by, say, 10 percent every two years would produce an age-weight for 50-year-olds almost five times as large as the estimate shown in Figure 5!)

It would obviously be rash to conclude from these results that citizens never forget political events, or that they consciously give events from the distant past as much or even more weight than very recent events. A more plausible explanation for the estimated pattern of age-weights is that recent events are perceived in ways that reflect the indirect influence of past events. Thus, citizens who lived through the New Deal are more Democratic than they would otherwise be, not only because their memories of Hoover and FDR weigh heavily in their current thinking, but also because their impressions of Eisenhower and Kennedy were shaped, in part, by the partisan predispositions forged in the 1930s.

If the image of a citizenry acutely sensitive to political change fares poorly in this analysis, the hypothesis of generational imprinting does not fare much better. True believers may be tempted to seize upon the local maximum apparent in the estimated weights around age 20 as evidence of the special character of early adulthood, with the subsequent decline through the 20s marking the onset of a more settled adult political orientation. However, this interpretation puts a great deal of weight on a rather modest decline – especially since that decline is largely attributable to a single anomalous estimate (for the 28-29 age bracket). In any event, the decline seems to end by age 30, with a rebound in the estimated weights through the 30s and early 40s producing a level of responsiveness at age 50 essentially identical to that at age

20. If our aim was to account for the current political views of a typical 50- or 55-year-old, we would not go far astray by computing a simple average of the political shocks she had experienced over the preceding three decades of her life.

Of course, from another perspective the staying power of political impressions implied by a simple average computed over three decades is quite remarkable. The partisan loyalties of adults do seem to be strongly shaped by political experiences accumulated throughout their lives, including adolescence and early adulthood. However, the stronger version of the generational theory, in which these so-called "formative years" have an unparalleled impact on the course of subsequent political development, seems to receive rather modest support from my analysis.

It may be worth emphasizing once again that I interpret the generational theory as a claim about age-specific weights of the sort displayed in Figure 5, *not* as a claim about the *incremental* impact of political events at different points in the life-span. The latter clearly decline with age under any of the three theories considered here, simply because new experiences must be balanced against an increasing store of past experiences – unless past experiences are entirely forgotten or discounted as completely irrelevant (that is, in the "partisan change" model with γ=0, a world with absolutely no political continuity).

The pattern of incremental effects implied by the estimated age-weights in Figure 5 is presented in Figure 6. As in Figure 5, the temporal pattern is summarized with a lowess regression line. As expected, the incremental effect of partisan shocks decline steadily with age. The rate of decline decelerates over the life-span, and the estimates for the very oldest age brackets are ill-behaved; nevertheless, the basic pattern is clear, and (at least in this respect) clearly consistent with the implications of all three of the theories considered here. Indeed, the pattern is remarkably reminiscent of the simple reciprocal function implied by the "running tally" model.

*** * * Figure 6 * * ***

Another feature of the pattern of incremental effects in Figure 6 provides more leverage for distinguishing among the alternative theories of political learning. If we ignore the very imprecise estimates beyond age 80, the incremental effects clearly seem to approach an asymptotic value of zero. That is an important point because one of the characteristic features of the "partisan change" model (with or without mean reversion) is that the incremental effect of new information declines asymptotically to a positive value determined by the "signal to noise" ratio φ^2/σ^2.[19] Indeed, Gerber and Green (1998, 808) called attention to the "noteworthy" fact that "*even when the underlying party differential changes very little over time (in comparison to random fluctuations in observed party performance), rational learning nonetheless involves placing considerable weight on contemporaneous information*" (emphasis in original). That implication of the "partisan change" model seems to be strongly disconfirmed by the pattern of estimated incremental effects in Figure 6.

The weight of the past implied by the estimates presented in Figures 5 and 6 may well be disquieting to partisans of "rational" political learning. One can sympathize with Fiorina (1977, 611) wrestling with the implications of his own version of the "running tally" model:

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[19] Gerber and Green (1998, 806-807). Gerber and Green's parameters K_t, q, and h correspond to my α_a, φ^2, and σ^2.

> I would hesitate to call the model I have proposed a rational choice model. Why in the world would a sixty-five year-old union member vote for McGovern on the basis of what he thought of Roosevelt? Sunk costs are sunk, our colleagues in economics say.

The subsequent work of Achen (1992) and Gerber and Green (1998) clarified precisely when, and to what extent, it would be rational for memories of Roosevelt to motivate a vote for McGovern – when, and to the extent that, the continuity of Democratic (and Republican) personnel, policy commitments, and performance over the intervening decades produced a rational expectation of positive correlation between the partisan differential prevailing in the 1930s and the partisan differential prevailing in the 1970s.

The estimates presented in Figure 5 imply that a 65-year-old in 1972 would have given the events of the immediately preceding decade (from age 56 to age 65 – up through and including McGovern), 30 percent less weight than the events of the decade from 1933 to 1942 (that is, from age 26 to age 35) in the formulation of his current party identification. By this calculation, sunk costs appear to be anything but sunk! Nor is this apparent anomaly attributable to the particular features of the New Deal era or the1960s – given the structure of my model, the calculation would be exactly the same for a 65-year-old in 1992 looking back to the Eisenhower years, or for a 65-year-old in 1932 looking back to Theodore Roosevelt.

In my view, there is no convincing way to accommodate these estimates within a "rational" theory of political learning. The weight of the past is simply too heavy to be accounted for on the basis of tidy Bayesian reasoning. Ironically, the Bayesian approach comes closest to fitting the observed pattern of generational change when it is most implausible as pure theory – when we assume that the underlying partisan differential is absolutely constant for decades at a time, as in Achen's (1992) formulation. Given a choice between an implausible theory that fits the data reasonably well and a plausible theory that does not, I would suggest looking for a new theory.

Of course, as Gerber and Green (1998) have already noted, party identification may be a very atypical political attitude in this respect, since both the theory and the operationalization of party identification emphasize long-term psychological attachment rather than short-term political calculation (Campbell et al. 1960, chaps 6-7). Nothing in the results presented here is inconsistent with the notion that citizens update their beliefs about candidates, public policies, and other features of the political world – perhaps even their *evaluations* of the parties, as distinct from their party *identifications* – in good Bayesian fashion. The only way to find out is to look. Thus, despite my dislike of the hackneyed conclusion that "more research is needed," it seems to me that a good deal might be learned by applying the generational model proposed here to a variety of other political attitudes and beliefs.

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Table 1: Estimated Period-Specific Shocks

Standard errors in parentheses.

Year	With Equal Age-Weights	With Age-Specific Weights – Priors	With Age-Specific Weights – Posteriors
1872	–109.7 (326.2)	–70.2 (40.0)	–70.2 (40.0)
1874	+452.9 (370.2)	+143.2 (40.0)	+142.7 (39.9)
1876	–289.9 (322.2)	–35.2 (40.0)	–33.4 (40.0)
1878	–180.0 (201.0)	+7.2 (40.0)	+5.6 (40.0)
1880	+223.3 (182.0)	–35.5 (40.0)	–34.4 (39.9)
1882	–251.0 (162.9)	+79.1 (40.0)	+78.2 (39.9)
1884	–40.3 (140.0)	–18.3 (40.0)	–20.2 (39.9)
1886	+133.3 (124.8)	–11.0 (40.0)	–9.0 (39.9)
1888	–97.2 (114.4)	–25.0 (40.0)	–25.5 (39.8)
1890	+185.6 (101.1)	+122.4 (40.0)	+123.8 (39.8)
1892	–114.3 (88.9)	–21.6 (40.0)	–21.1 (39.8)
1894	+54.5 (77.7)	–155.9 (40.0)	–153.8 (39.7)
1896	–69.4 (74.2)	+28.2 (40.0)	+25.2 (39.6)
1898	–115.9 (70.7)	+26.4 (40.0)	+23.9 (39.6)
1900	+31.7 (62.8)	–19.2 (40.0)	–21.6 (39.5)
1902	+48.4 (59.6)	+6.6 (40.0)	+8.6 (39.4)
1904	–61.0 (55.0)	–58.8 (40.0)	–58.0 (39.3)
1906	–9.7 (49.4)	+21.7 (40.0)	+21.2 (39.3)
1908	–40.9 (45.4)	+0.0 (40.0)	–4.5 (39.2)
1910	+43.6 (42.5)	+66.5 (40.0)	+71.7 (39.0)
1912	–18.7 (40.0)	+63.5 (40.0)	+56.8 (38.7)
1914	–22.0 (37.4)	–55.5 (40.0)	–51.1 (38.6)
1916	–3.2 (34.8)	–21.5 (40.0)	–19.6 (38.3)
1918	+10.4 (33.3)	–24.2 (40.0)	–27.5 (37.9)
1920	+38.2 (31.5)	–75.4 (40.0)	–65.2 (37.6)
1922	+68.2 (29.3)	+67.1 (40.0)	+65.0 (37.4)
1924	–15.5 (28.3)	–28.6 (40.0)	–43.0 (37.0)
1926	–34.6 (27.8)	+5.1 (40.0)	+12.6 (35.9)
1928	+39.0 (26.8)	–40.9 (40.0)	–45.8 (35.5)
1930	+3.6 (26.6)	+47.4 (40.0)	+49.0 (34.9)
1932	+9.1 (27.0)	+114.8 (40.0)	+105.7 (34.2)
1934	+80.9 (27.4)	+37.8 (40.0)	+34.5 (34.0)
1936	–40.5 (27.4)	+41.3 (40.0)	+71.4 (33.8)
1938	+45.6 (26.8)	–61.6 (40.0)	–56.7 (33.6)
1940	–7.0 (25.5)	+17.8 (40.0)	+21.9 (33.5)
1942	+11.6 (23.6)	–41.3 (40.0)	–31.7 (32.6)
1944	–20.0 (22.7)	+24.5 (40.0)	+10.4 (32.1)
1946	–10.7 (21.8)	–57.9 (40.0)	–73.5 (31.0)

1948	+0.3 (20.9)	+79.8 (40.0)	+77.0 (30.5)
1950	+38.3 (21.0)	–22.4 (40.0)	–43.9 (29.6)
1952	+11.7 (18.3)	–20.5 (40.0)	+49.1 (25.4)
1954	–1.7 (18.1)	+20.1 (40.0)	–1.1 (22.5)
1956	+4.3 (18.1)	+5.8 (40.0)	–4.6 (22.2)
1958	+45.8 (15.4)	+58.8 (40.0)	+66.2 (14.9)
1960	–25.5 (16.8)	–8.2 (40.0)	–23.9 (16.2)
1962	+28.2 (17.5)	+6.2 (40.0)	+12.6 (16.2)
1964	+47.8 (17.3)	+51.4 (40.0)	+70.3 (15.0)
1966	–26.9 (18.2)	–36.2 (40.0)	–57.3 (14.9)
1968	–17.8 (18.9)	+1.5 (40.0)	+19.6 (14.6)
1970	+2.3 (18.6)	+18.9 (40.0)	+3.5 (14.3)
1972	–7.2 (17.1)	–6.5 (40.0)	–13.8 (12.7)
1974	+24.9 (18.2)	+62.5 (40.0)	+27.7 (12.5)
1976	–14.9 (19.4)	+17.9 (40.0)	–6.5 (13.1)
1978	+31.1 (17.4)	+0.1 (40.0)	+28.0 (11.8)
1980	–3.7 (18.9)	–25.3 (40.0)	–3.4 (12.5)
1982	+27.5 (21.7)	+36.4 (40.0)	–2.8 (13.9)
1984	–68.0 (20.3)	–7.5 (40.0)	–28.3 (13.1)
1986	+40.2 (17.8)	+14.1 (40.0)	+32.2 (12.1)
1988	–43.2 (18.5)	+11.8 (40.0)	–34.6 (12.7)
1990	+57.4 (19.1)	+18.3 (40.0)	+45.6 (13.1)
1992	–16.2 (18.3)	+1.0 (40.0)	–6.8 (12.7)
1994	–50.7 (19.4)	–52.6 (40.0)	–41.2 (13.6)
1996	+77.9 (21.7)	+1.0 (40.0)	+46.4 (15.0)

Table 2: Estimated Age-Specific Weights

Non-linear least squares parameter estimates; standard errors in parentheses.

Age	Weight	Age	Weight
1	.260 (.068)	**47**	.756 (.275)
3	.649 (.082)	**49**	1.137 (.315)
5	.503 (.079)	**51**	1.246 (.326)
7	.516 (.082)	**53**	.626 (.314)
9	.590 (.081)	**55**	.849 (.346)
11	.663 (.092)	**57**	.880 (.389)
13	.722 (.106)	**59**	1.194 (.446)
15	.988 (.098)	**61**	.433 (.430)
17	1.000 (---)	**63**	.244 (.477)
19	.917 (.095)	**65**	.086 (.521)
21	1.030 (.132)	**67**	.406 (.562)
23	.986 (.129)	**69**	.421 (.620)
25	.904 (.126)	**71**	.412 (.676)
27	.803 (.133)	**73**	.928 (.762)
29	.615 (.137)	**75**	.277 (.799)
31	.887 (.159)	**77**	–.552 (.922)
33	.919 (.173)	**79**	.350 (1.101)
35	.829 (.181)	**81**	.183 (1.222)
37	.785 (.195)	**83**	–2.130 (1.433)
39	.760 (.212)	**85**	5.889 (3.321)
41	.966 (.235)	**87**	5.168 (3.828)
43	1.156 (.267)	**89**	18.887 (10.810)
45	.785 (.259)	**91**	7.875 (10.474)

Table A1: Goodness of Fit Statistics

	Number of parameters estimated	Standard error of regression	F-statistic
Linear Year Effects	22	34.04	8.9
Linear Cohort Effects	54	34.01	33.9
Linear Year and Cohort Effects	75	33.96	26.4
Equal Age Weights	63	33.97	30.7
Variable Age Weights	108	33.97	42.5

Figures

Figure 1: Distribution of NES Survey Respondents by Two-Year Birth Cohort

Figure 2: Partisanship by Birth Cohort

Figure 3: Partisan Shocks – Priors

Figure 4: Partisan Shocks – Posteriors

Figure 5: Age-Specific Effects of Partisan Shocks

Figure 6: Incremental Effects of Partisan Shocks

Figure 1: Distribution of NES Survey Respondents by Two-Year Birth Cohort

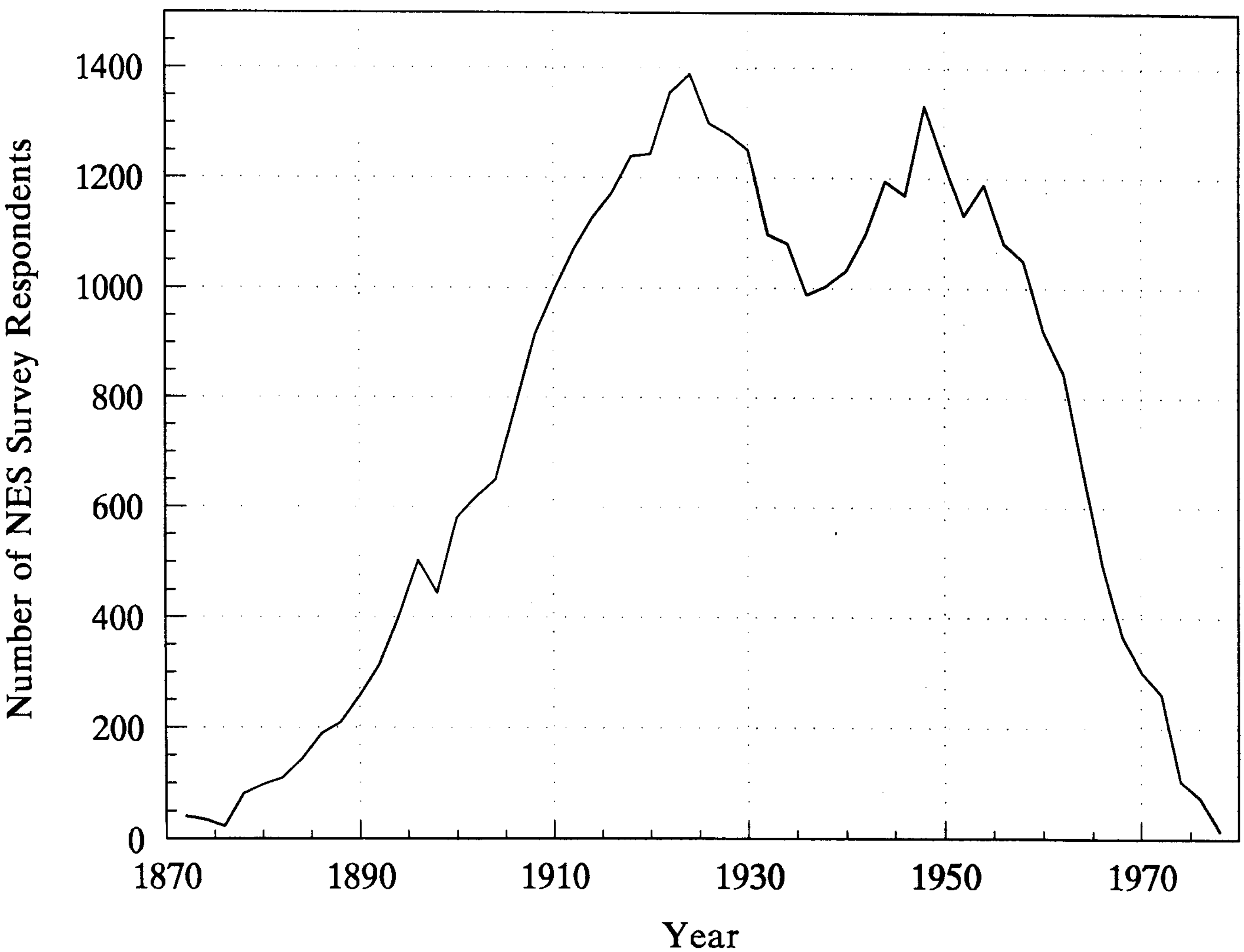

Figure 2: Partisanship by Birth Cohort

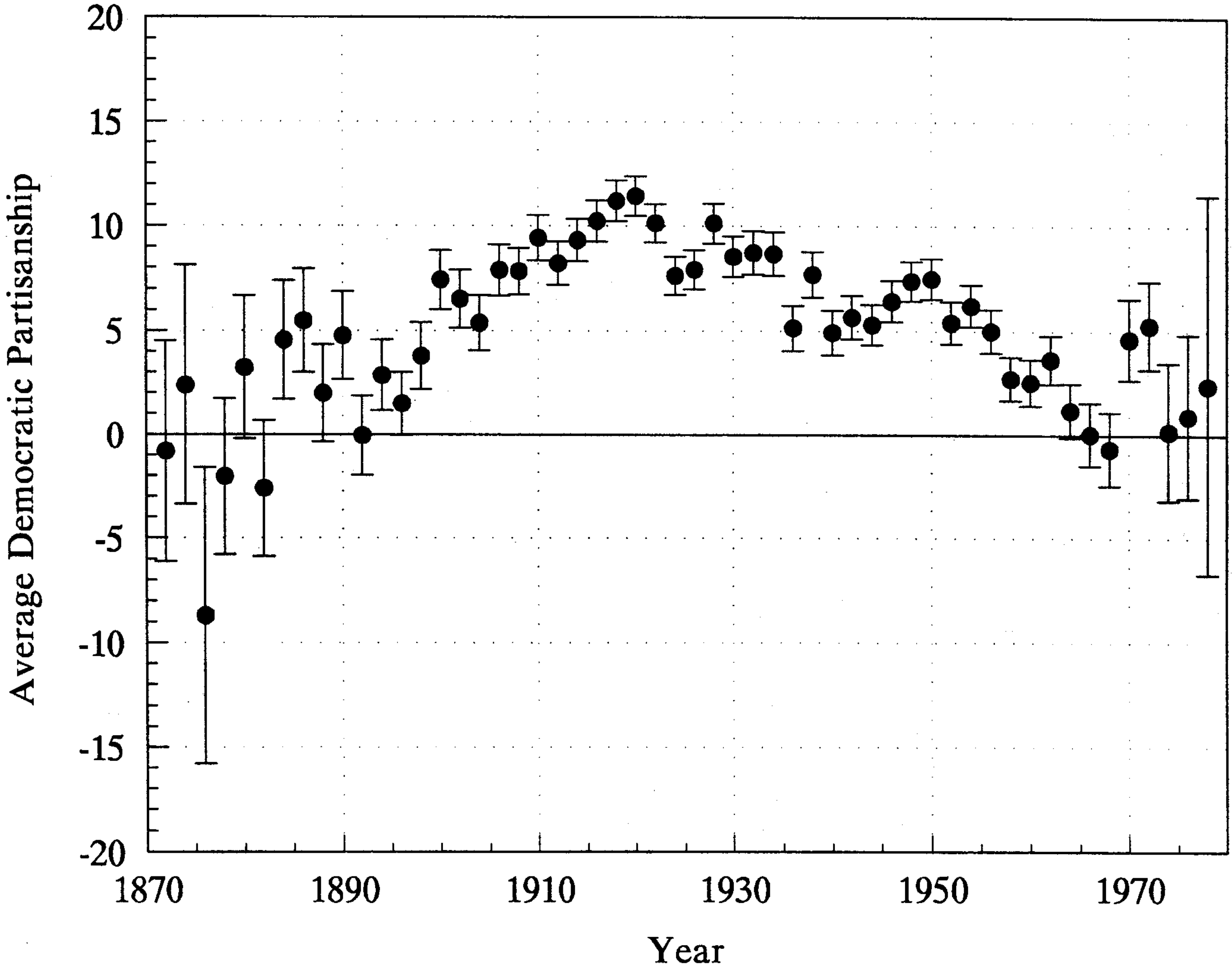

Figure 3: Partisan Shocks - Priors

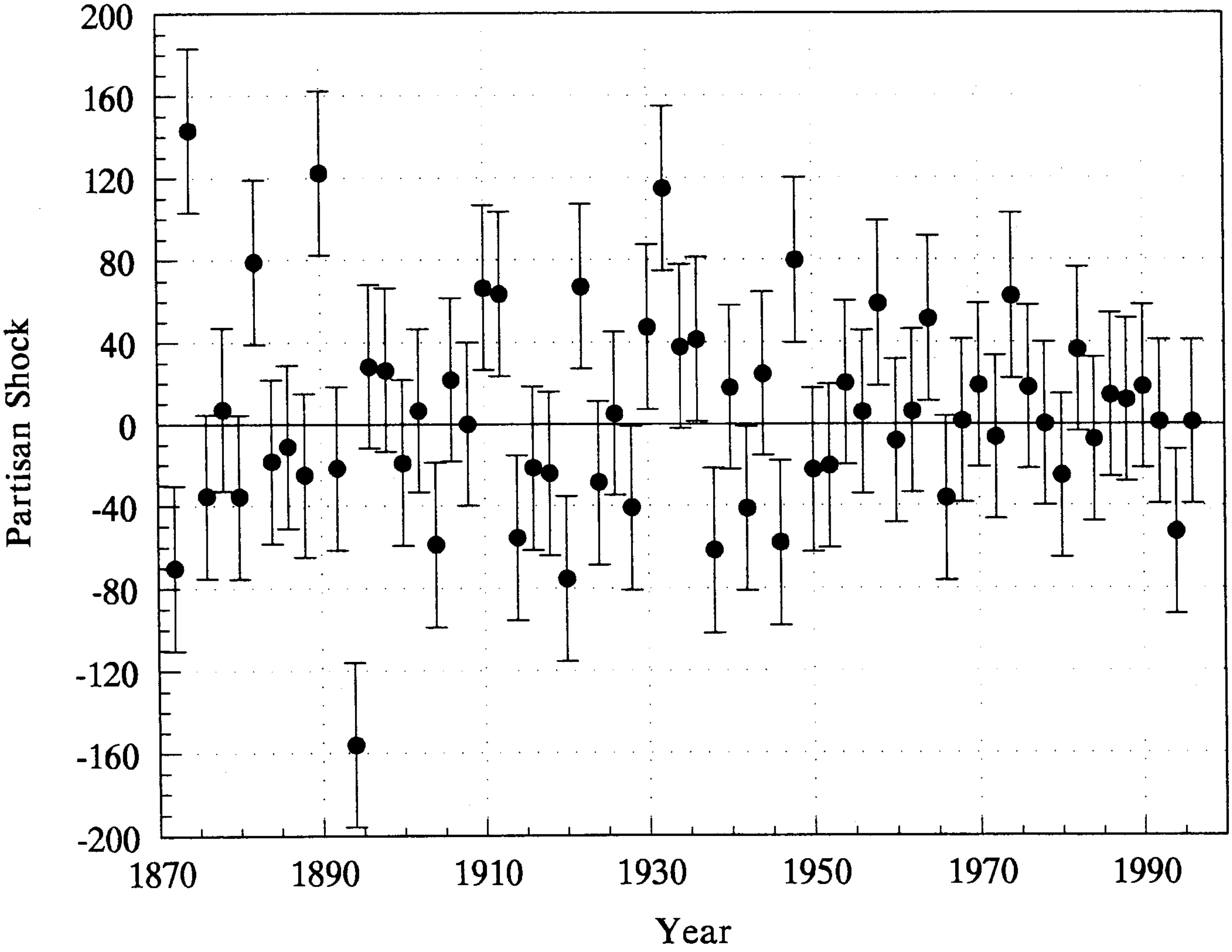

Figure 4: Partisan Shocks - Posteriors

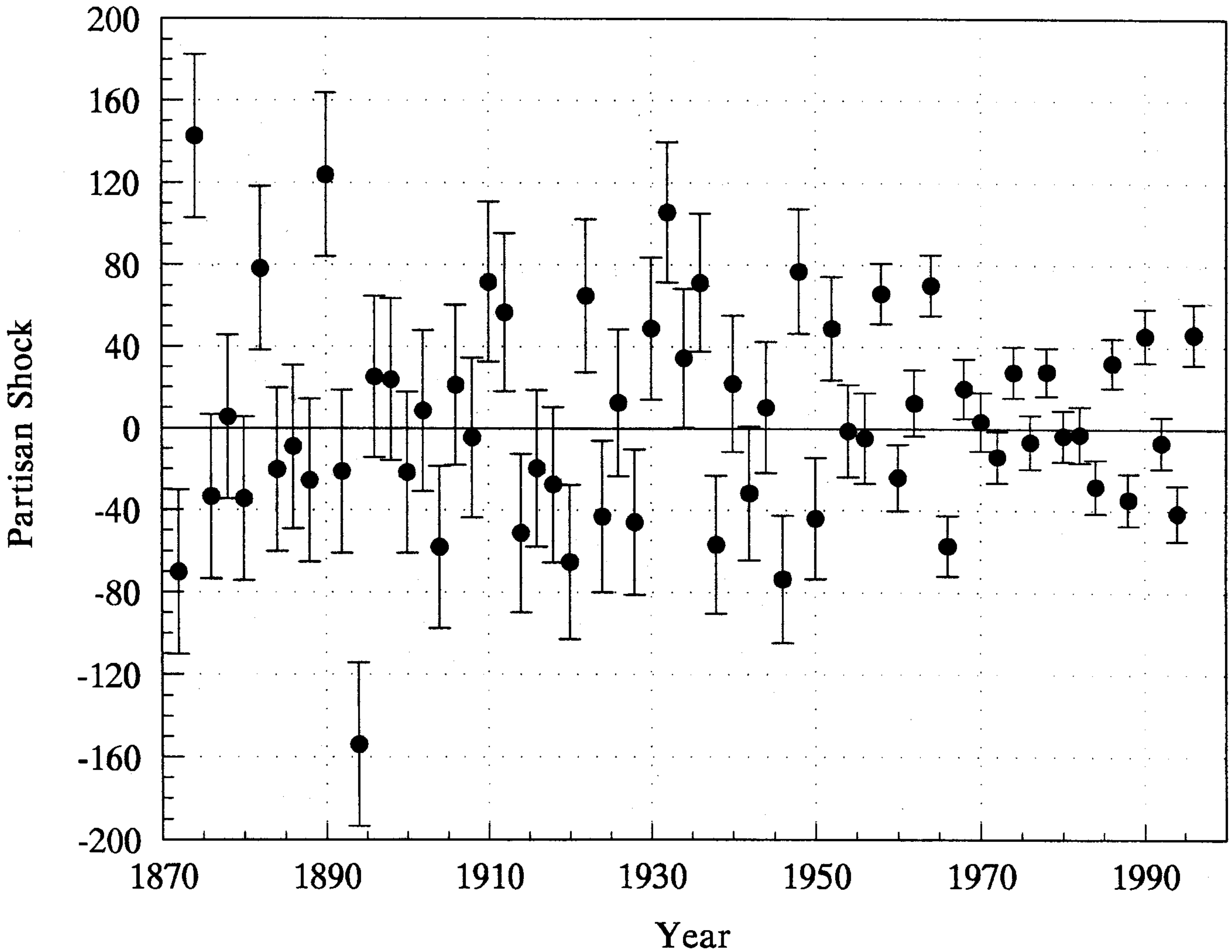

Figure 5: Age-Specific Effects of Partisan Shocks

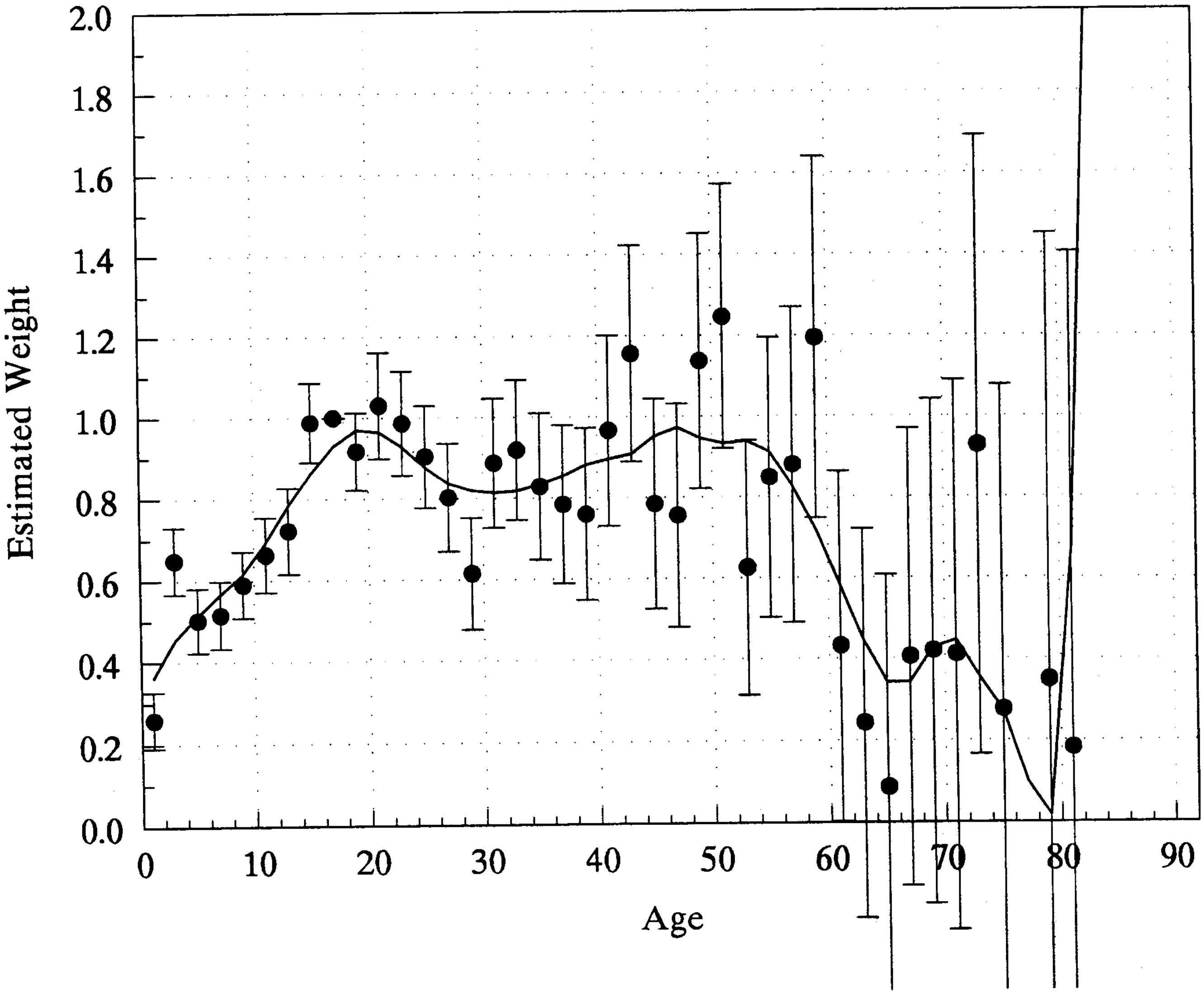

Figure 6: Incremental Effects of Partisan Shocks