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Persistence and aggregations of survey data over time: from microfoundations to macropersistence☆

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Abstract

The repeated cry for analysts to provide microfoundations for aggregate research is particularly relevant for the over time analysis of aggregations of survey data. In this paper I look at the microfoundations of some important macro processes, how they relate to aggregation theorems and the persistence of macro processes. In addition, I look at what we can learn about macro persistence from macro theory and models. The paper gives a broad treatment of each of these. While the choices at each stage often involve substantial ambiguity, microfoundations, aggregation theorems, as well as macro theory and evidence each help us to make decisions about persistence that enable us to make reliable inferences about the dynamics of aggregated preferences. © 1999 Elsevier Science Ltd. All rights reserved.

Persistence, or memory, is a feature of many political processes. Persistence may be thought of as the tendency for a political process to exhibit time dependence. This time dependence may take many forms and arises in many ways. Typically in the case of political processes, it arises from the tendency of individuals to use yesterday as a starting point, as when deciding today's partisanship or national budget, for example. It may also be a product of slowly evolving social norms or

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technology, say as nations modernize. For most political processes this time dependence is an important feature of both our theory and our data. But the nature of time dependence is often debated. The debate is an important one because the nature of persistence has both theoretical and statistical implications. In particular, the statistical models used to test hypotheses about political change rely for their validity on the adequacy of assumptions about persistence.

Much of the debate over persistence in the political science literature involves the best characterization of aggregations of survey data. Analyst decisions about the memory inherent in these time series are typically debated on three levels: the implicit consistency of the "microfoundations" for the aggregate data with what we know about individual behavior; the implications of the aggregation process itself for macro persistence; and the weight of theory and evidence in the aggregate. At the crux of these debates are fundamental questions about central political concepts. I argue that the points of debate need to be critically considered. It is important that we ask what can microfoundations, aggregation theorems and macro level theory and evidence tell us about macro persistence? Given our current understanding, how much can they be relied upon to justify our characterizations of aggregate persistence?

The purpose of this paper is to assess what we can learn from microfoundations, aggregation theorems and macro level theory and evidence about the kinds of persistence that might reasonably characterize aggregations of survey data. I show that while each of these factors is related in important ways to aggregate persistence, each provides only limited information to guide the analyst in the cases considered here. Throughout the paper the discussion is centered on three processes: macropartisanship, presidential approval, and Stimson's (1991) public policy mood. The paper proceeds with a discussion of aggregations of survey data over time and the types of persistence that are typically offered to characterize this type of data. This follows with sections on microfoundations, aggregation, and macro theory and evidence. The paper concludes with suggestions for further research.

1. Aggregations of survey data

Political scientists often aggregate over individuals and across time, as in the case of survey responses of individuals, say as to their partisanship. Other commonly analyzed time series take this form: presidential approval, economic expectations, and public policy mood (Stimson, 1991), for example. The attraction of this type of data for political scientists is clear. If we wish to understand the dynamics of these political processes, we must appeal to aggregated data.[1] Aggregations of survey data offer analysts other advantages as well. First, aggregation allows us to focus on the effects of common or system level, as opposed to idiosyncratic, shocks

[1] Panel data offers one way to assess individual level dynamics, but there are obvious limitations to this approach, most notably short panels.

on preferences. Large portions of the variance of individual opinions may have little to do with politics while a much larger proportion of the variance in the aggregate can be attributed to political factors. Further, we cannot estimate the effects of macro political shocks on opinions at a single point in time with cross-sectional survey data. For example, if we wish to estimate the effect of the impeachment hearings on American opinions about President Clinton, then we need measures of Americans' opinion before and after the impeachment hearings, as well. More generally, if macro political shocks are continuous, the only way to assess the effect of these system level forces is through aggregations of survey data over time. Finally, we often ask questions about electoral systems, which can only be answered with macro data.

Unlike many other types of political processes — budget data, conflict/cooperation scores, poverty, for example — these data are built directly from individual behavior. As a result, decisions about the persistence of aggregations of survey data are often criticized for lacking consistency with our understanding of individual level persistence. Such criticisms imply that solid microfoundations exist, that aggregation theorems can be directly applied to the micro data to justify characterizations of macro persistence, and that macro level evidence will follow directly from this process. But such criticisms presuppose a great deal. We need to ask several questions before we can assess their validity. What are the microfoundations that underlay our understanding of aggregations of survey data? How solid are they? How does the aggregation process affect macro persistence for these processes? Do we have enough information from microfoundations and aggregation theorems to draw specific inferences about macro persistence? Finally, what can we infer from measured persistence? Before I consider these questions, I outline the types of persistence offered to characterize aggregations of survey data.

2. Types of persistence

It is reasonable to expect persistence in aggregations of survey data: often we have theory and some evidence that individuals use past behavior as a starting point in determining current behavior. But it is not clear whether this dependence is short term, long term, or permanent. In short, it is not clear whether stationary, near integrated, fractionally integrated, or unit root characterizations of the persistence are most reasonable. In this section, I discuss these alternative characterizations of persistence. The definitions are brief and focus on the theoretical conceptualizations and the intuition associated with each type of persistence. Definitions are illustrated with reference to macro processes, but the logic extends to micro processes as well. I focus here on macropartisanship, presidential approval, and mood.

2.1. Stationary processes

Early treatments of both macropartisanship (see for example, Allsop and Weisberg, 1988; MacKuen et al., 1989; Weisberg and Smith, 1991; Abramson and Ostrom,

1991) and presidential approval (see for example, Mueller, 1970; MacKuen, 1983) either implicitly or explicitly argued that these series were best characterized as autoregressive, stationary series. Analysts assumed, for example, that political events and conditions might affect the dynamics of macropartisanship in the short run, but that any effect on current macropartisanship would be transient. This is the defining characteristic of a stationary series; shocks to a stationary process will dissipate, and do so relatively quickly, so that the series will return to its mean.[2]

Consider the following first-order autoregressive process (AR(1)), where the error term μ_t, is normally distributed with a mean of zero and a variance of σ^2,

$$y_t=\alpha+\rho y_{t-1}+\mu_t$$

where ρ is a parameter linking past values of say macropartisanship with current values. In the stationary case, $|\rho|<1$. It is easily seen that any shocks, represented by μ, will exert a transient effect on macropartisanship.[3]

2.2. Unit root processes

Presidential approval and public policy mood have been characterized as unit root processes (Ostrom and Smith, 1992; Durr, 1993; Wlezien, 1996). Under this characterization, shocks to the process are permanent. Public policy mood today, for example, represents the sum of past shocks to policy preferences. Events are not forgotten but completely determine current preferences. Given the autoregressive process above, ρ=1. Changes in the political environment thus have an additive effect. Integrated series tend to wander over time so that the variance grows as a function of time, $\sigma^2 t$.

2.3. Strongly autoregressive near integrated processes

DeBoef and Granato (1997) suggested the possibility that macropartisanship and presidential approval may be near integrated. Near integrated processes have a root close to, but not quite unity, $\rho=1+\varepsilon$, where ε is small and negative, in the autoregressive representation.[4] While asymptotically stationary, these near integrated processes mimic integrated processes in finite samples and are indistinguishable from them

[2] This has implications for the variance of a stationary process — that it is finite and does not depend on time. This type of stationarity is often called *weak* because only the first two moments need be independent of time.

[3] More generally, we can extend this representation of stationary processes to allow additional autoregressive effects as well as moving average effects.

[4] Ignore cases in which ε is positive. Positive values imply explosive rather than strongly autoregressive processes.

(Phillips 1987a,b, 1988; Banerjee et al., 1993; Blough, 1992; Hamilton, 1994).[5] These strongly autoregressive series contain features of both integrated and stationary processes. In particular, like integrated processes, near integrated processes are strongly persistent, however, shocks to a near integrated system die out given long enough time spans.[6] As such, near integrated time series may wander from their mean for extended time periods in finite samples. In the case of macropartisanship, for example, events like the great depression still exert an influence on the party balance today, but much less so than in previous time periods.[7]

2.4. Fractionally integrated processes

Box-Steffensmeier and Smith (1996 and 1998) introduced political scientists to fractional integration. They argued that macropartisanship is best characterized as a fractionally integrated process. In general, fractionally integrated processes exhibit long memory like an integrated process, but like stationary processes the effect of these shocks decays over time. Fractionally integrated processes will wander, manifesting random local cycles or trends, of all sizes and different spans of time.[8]

Economic and political shocks have a long run effect on macropartisanship if the process is fractionally integrated, but the effect of these shocks does decay. Specifically, the autocorrelations of a fractionally integrated process decay hyperbolically. rather than geometrically as stationary processes. The rate of the decay is given by the factional parameter, d.[9] The size of the autocorrelations depends on the short run behavior of the series.

Consider the simplest fractional process, an autoregressive, fractionally integrated, moving average or ARFIMA (0,d,0) process, also called fractional noise:

$$(1-L)^d y_t=\mu_t$$

where L is the lag operator and d refers to the order of integration and can take on

[5] Phillips (1987b, 1988) establishes the following relationship for near-I(1) processes: ρ=exp(ε) where ε is characterized as a "noncentrality" parameter (Phillips 1987a,b, 1988). As ε changes, ρ assumes different values and y_t, is characterized as integrated or some local alternative — near-integration. (In the first case, when ε=0, ρ=1 and the process y_t contains a unit root or is integrated of order 1. When $\varepsilon>0$ and T is finite, $0<\rho<1$ so that the series is strongly autoregressive and stationary. When ε is positive in a finite sample, $\rho>$l, in which case the process is explosive.)

[6] Because they are asymptotically stationary, near integrated processes fall into the class of ARMA models.

[7] The variance of a near integrated time series depends on time in finite samples (DeBoef and Granato, 1997) and reduces to $\sigma^2/(1-\rho)$ as the sample size grows.

[8] Given this feature of fractionally integrated processes, it is not surprising that local nonstationarity — structural breaks or changes in the underlying structure of the data — may manifest itself in the apparent form of long memory.

[9] It is the rate of decay that is key. It may be that all autocorrelation estimates are individually not statistically significant even if there is long range dependence in the process. Further for small values of d, we will need large samples before the autocorrelations will be jointly statistically significant. Beran (1994) notes that in spite of this, if we ignore the dependence in the data, our confidence intervals will be too small, perhaps substantially so.

values between 0 and 1. For this reason we denote fractionally integrated series as $I(d)$. Fractionally integrated processes are stationary for values of d in the range from -0.5 to 0.5. Values of d greater than or equal to 0.5 imply nonstationarity. In the autoregressive representation:

$$y_t = \rho y_{t-1} + \zeta_t$$

where

$$(1-L)^{d'} \zeta_t = \mu_t$$

and

$$d' = d-1$$

so that the error ζ_t is no longer white noise, but is fractional noise.[10] See Box-Steffensmeier and Smith (1998) for a discussion of fractional integration and political processes.

2.5. Explosive processes

Few analysts have argued that political processes are explosive. For a process to be explosive implies that the effect of a shock grows over time rather than dissipates. If partisanship, approval or mood are explosive processes then the depression, for example, has more effect on these processes today than it did at any previous time since the depression occurred. In the autoregressive representation above, $\rho > 1$. Arguments about path dependence or institution-building may imply explosive dynamics. However, explosive characterizations seem to have little applicability to the case of aggregations of survey data.

3. Assessing persistence

Which of these types of persistence represent reasonable characterizations for aggregations of individual level survey data? How does the analyst decide? I consider microfoundations, aggregation theorems and macro theory and evidence. Specifically, how does each inform us and what are the limits of this information?

3.1. Assessing micro persistence: providing "microfoundations"

When working with aggregations of survey data, it is clear that the data is a function of individual level opinions. As a result, we may be able to gain some insight into the persistence of the aggregate data by considering the persistence in individual opinions and attitudes. Such "microfoundations" can then be used to help

[10] See also Beran (1994) and Baillie (1996) and Baillie (1996) for a more formal treatment of fractional integration.

understand the implications of aggregation for the behavior of the macro process and to suggest classes of persistence that may be reasonable characterizations for our time series. In this section of the paper, I discuss the case for microfoundations — what they are, how we might provide them, and the limitations of microfoundations for assessing aggregate persistence.

What are microfoundations? The basis for microfoundations may be found in theories of individual level behavior and evidence from individual level models. When we ask what are the microfoundations of time series of aggregated survey data, we are asking what do our theories and data tell us about individual level attitudes and opinions?

3.2. Individual level persistence: theory

To the extent that political scientists have theories about the persistence of individual attitudes and opinions, they tend to be fairly general and often are contradictory. Consider partisanship. A long-standing tradition tells us to expect persistence, but precisely how much is not clear. Partisanship has been conceptualized as a psychological attachment to a political party (Campbell et al., 1960), a "running tally" of evaluations of the party (Fiorina 1977, 1981) and as an expected cost benefit calculation (Achen, 1992). While these conceptualizations allow for different predictions about persistence, most analysts agree that theory tells us that partisanship is highly stable, that attachments to the parties tend to endure. It is not clear, however, precisely what form that persistence might take.

We have very little theory about individual evaluations of presidential performance. We might expect that the fickleness of voters plays a larger role and produces less persistence in approval than in partisanship. It may be harder to imagine that what an individual thinks of President Clinton during his first month in office has much to do with his or her view today, for example, than it is to think in such a manner about partisanship. Even more difficult to imagine is that one's view of President Ford's performance in office over two decades ago affects one's evaluation of President Clinton's performance today. Yet it is not unreasonable to argue that some standard of evaluation used today may be built on evaluations of past presidents.

For public policy mood, there is even less to guide us. Public policy mood (Stimson, 1991) taps society's underlying preference for more or less government in social policy. It is derived from patterns in changes in opinions about social policy across a variety of policy domains. It is not easy to imagine the microfoundations of a process conceptualized as a characteristic of society, rather than of individuals, and made up of policy preferences aggregated across policy domains, as well as across individuals and over time. One way to think about the microfoundations of mood might be to draw parallels with individual preferences on single-issue domains or with ideological thinking. Yet we know that there is a general lack of consistency in individual preferences across the very questions that make up public policy mood. Individuals often support more spending on education, for example, and less spending on welfare (Converse, 1964). We also know that many individuals reply to these questions in what appears to be a random matter over time (Converse, 1964). As such, individual theory may provide us little, or mixed, guidance as to micro persistence.[11]

3.3. Individual level persistence: evidence

From a statistical standpoint, determining micro persistence is even more difficult than determining macro persistence, in part because we are hampered by a lack of individual level time series data. Panel data, the only available dynamic individual level survey data, afford us few observations with which to measure persistence. Analyses of partisanship using panel data all suggest that it is highly persistent, with debate over the true extent of that persistence (see for example, Green and Palmquist, 1990; Franklin and Jackson, 1983; and Fiorina, 1981). Similar individual level analyses of presidential approval and public policy mood have not been undertaken.

It is important to note, however, that the methods for assessing individual persistence with panel data have important limitations. This is easily seen by looking at a theoretical individual level univariate model of a process like partisanship (where we assume a latent partisan continuum):

$$y_{it}=\alpha_i+\beta_i y_{it-1}+\mu_{it}$$

Each individual has his or her own mean partisanship, α_i, as well as his or her own dynamic parameter, β_i, which represents the persistence of partisanship from one period to the next. We do not, however, estimate this model. Instead something like the Wiley–Wiley (1970) model is used to estimate a pooled panel model like that given below.

$$y_{it}=\alpha+\beta y_{it-1}+\mu_t$$

Neither mean partisanship nor the dynamic parameter varies across individuals.[12] Coefficients on lagged y from Wiley–Wiley models do not tell us much about micro persistence. They indicate the persistence of the distribution of partisans, rather than the persistence of individual partisanship. Average micro persistence can only be estimated with a model that estimates α_i. An assessment of the heterogeneity in persistence requires an estimate of both β_i and a_i.[13] While other analytical methods might assess individual level persistence, analyses to date do not provide us with much evidence as to the persistence of individual level behavior measured by survey data.

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[11] These discussions of micro theory are very oversimplified.

[12] Using the Wiley and Wiley (1970) method for estimating this equation, β (the average persistence) will be recovered only in the special case when α is constant across individuals, an unreasonable assumption.

[13] Typically heterogeneity is assessed by estimating separate models for different samples of the population.

Many different characterizations of persistence are broadly consistent with what we know about these micro processes and may represent approximations to the true micro data generating process. In short, individual level theory and evidence — microfoundations — tell us only generally that individual level processes should exhibit some type of persistence.

3.4. Aggregation and macro persistence

The fact that we are considering aggregations of individuals over time has other implications for understanding macro level persistence as well. Microfoundations are the basis for making the assumptions necessary to appeal to aggregation theorems. A large body of literature has examined the problem of aggregation in a variety of contexts (see for example, Thiel, 1954; Green, 1964; Granger, 1980; Forni and Lippi, 1997). I highlight a few relevant results from this literature and show that aggregation theorems link micro persistence to macro persistence in a way that depends very specifically on the particulars of micro behavior. I argue further that we typically do not have a sufficient grasp of the microfoundations to justify specific links.

Granger (1980) derived the persistence properties of aggregations of (heterogeneous) individuals over time under a specific set of assumptions about individual behavior. Granger showed that if we assume individual preferences follow a stationary autoregressive process (autoregressive parameters range between 0 and 1) and follow a beta distribution, fractional dynamics can arise in aggregations of survey data. Box-Steffensmeier and Smith (1996) drew on this work to offer a microfoundation for the fractional characterization of the persistence of macropartisanship. This important work lays a foundation for the fractional characterization of other aggregations of survey data, as well.

It is important to note, however, that more general assumptions about the distribution of the autoregressive parameters lead to different kinds of persistence in aggregate series. Gourieroux and Monfort (1997) demonstrate that aggregation may produce increased autocorrelation (unless all individuals have the same autoregressive coefficient) in the aggregate series, but not necessarily fractional integration under the assumption that the density for the autoregressive parameter is defined over positive real numbers. Chambers (1995) made no distributional assumptions and allowed a general contemporaneous correlation structure for the process shocks. He found that the macro process is integrated of an order equal to the maximum order of integration of the underlying variables. He notes that "simple linear aggregation by itself does not produce long memory in aggregate variables." Chambers notes that distributional assumptions account for the disparity in implied macro persistence between this result and Granger's results.

Other types of heterogeneity may be relevant to aggregations of survey data as well. We know that some individuals respond quickly to revelations about political misconduct, for example, while others withhold judgment pending more information and respond only after deliberation. Similarly, some voters make up their minds early in a campaign while others are undecided virtually until they enter the voting booth.

When the magnitude of autoregressive coefficients, the number of political shocks, and the structure of the timing of effects varies across individuals, then a variety of different Wold representations may be produced in the aggregated data. The nature of persistence produced in the aggregate depends on the precise nature of the varying lag structures, the number of shocks entering the system, and the heterogeneity in the autoregressive coefficients themselves (Forni and Lippi, 1997).

Finally, Granger (1980) notes that the presence of a single individual with unit root dynamics will produce a unit root process in the aggregate. Summing across individuals, the aggregate process will be integrated of an order equal to the maximum of the component series. Little has been made of the implications of potential unit root behavior in individual level survey data, but it suggests that we might expect to see more unit root behavior in aggregate series than has been suggested to date (see Wlezien, this issue).

Aggregation results do help us to assess the macro persistence of processes like partisanship and presidential approval. If these processes are themselves autoregressive, the aggregated process will also exhibit persistence and unless there is no heterogeneity, more persistence than the average persistence of the individuals. Fractional integration may be a reasonable characterization if we are willing to make specific assumptions, near integration, stationarity, or unit roots may be more reasonable under other distributional assumptions. Much work remains before we can rely on specific aggregation results to justify specific macro characterizations of persistence. At a minimum we need a better understanding of individual level persistence, better microfoundations, so that we can make appropriate distributional assumptions and draw on the appropriate aggregation theorems.

3.5. Assessing macro persistence

If we wish to answer questions about the dynamics of preferences or assess the extent to which common shocks influence behavior, or if we wish to answer questions at the system level, we must eventually come face to face with the macro data. Microfoundations and aggregation theorems can inform us as to the nature of persistence in macro processes, but they are often inconclusive (or debatable) and macro level theory and statistical evidence are equally important for understanding the dynamics of these kinds of processes.

From a theoretical standpoint we are often little informed about macro persistence. Theories and hypotheses are typically stated in terms of analogies: as the economy falters, more *individuals* are likely to negatively evaluate the president or his party, or more people are likely to choose conservative policy options, for example. We expect more or less persistence, in part because we expect individuals' evaluations to exhibit persistence. However, in addition to these appeals to individual level behavior, we can often make more macro arguments. We might argue that the processes to which the evaluations respond are themselves evolving slowly so that the macro process is highly persistent. This can occur even if individual preferences are not terribly persistent as a result of the effects of idiosyncratic factors on individual preferences.[14]

It seems reasonable to come to this point and ask what is the measured persistence of the aggregate series? Traditionally we approach this question in two stages. Fist, the analyst uses some visual "tests" to identify the process and/or conducts a series of pretests on the individual time series to determine whether the data exhibit evidence of nonstationarity. In the second stage a univariate model is estimated. Diagnostics are used to ensure that the model is consistent with the data. This procedure is relatively straightforward if the analyst considers stationary processes or unit root processes. When we expand our consideration to include near integrated and fractionally integrated processes, both identification and estimation present unique difficulties.

3.5.1. Identification

Identifying fractionally integrated processes and distinguishing them from stationary, near integrated processes or unit root processes, as well as alternative fractional processes, is extremely difficult. The problem stems primarily from two facts. First, the defining characteristics of these processes are hard to distinguish in finite samples. Second, our samples tend to be small. Typically we have at best just over 100 observations, often we have fewer. Identifying long memory and estimating its nature in relatively short time series is definitionally problematic, regardless of the true nature of the memory of the process. These problems are easily seen when we consider the autocorrelation function (ACF) and hypothesis tests for stationarity and unit roots.

Not all stationary processes look near integrated or like unit root or fractionally integrated processes, but for many members of these classes of processes, *theoretical* patterns of decay are very similar. Fractionally integrated processes may be represented by high order autoregressive moving average models, for example. *Sample* autocorrelations for each process will be even harder to distinguish. In general, the ACF for a fractionally integrated process should exhibit slow, hyperbolic decay while a stationary process should exhibit geometric decay and a unit root should show no evidence of decay. But these patterns are likely to be obscured for a variety of reasons. Fist, if the sample is small many of the estimated autocorrelations are likely to be within $+/-2\sqrt{T}$ confidence bounds. This makes it hard to distinguish patterns that characterize many members of each of these classes of processes. It makes it doubly hard to identify and distinguish alternative fractionally integrated processes because the autocorrelations between observations at increasingly large intervals — those key for assessing long memory — are estimated with the least certainty. Second, if the process is fractionally integrated with a small fractional parameter, d, the problem is compounded. For some values of d it is likely that few, or even none, of the autocorrelations will

[14] We also expect stronger persistence in the aggregate series because much of the "noise" in individual survey data (whether from measurement error of from idiosyncratic causes) cancels in the aggregate.

be individually significant and very large numbers will fail to be jointly significant. Third for stationary but near integrated processes, the evidence of decay in the autocorrelations is by definition statistically indistinguishable in sample from unit root processes. Further, fractional processes with large values of d will themselves evidence behavior that is indistinguishable from both these processes in some samples. Finally, the addition of high order processes, those with multiple autoregressive and/or moving average components, simply makes it harder to estimate any parameter with efficiency, reducing the certainty with which we draw our inferences.

Pretesting poses problems for the same reasons. The analyst's task is to distinguish reasonable alternative characterizations that may represent local alternatives to the null hypothesis, whether that null is stationarity, unit root, or fractional integration. But statistical tests have low power against local alternatives. Tests for unit roots have low power against near integrated alternatives (Evans and Savin, 1984; Phillips, 1988) and fractional alternatives (Diebold and Rudebusch, 1991). Tests for stationarity have low power against fractional alternatives (Lee and Schmidt, 1996),[15] and estimates of fractional integration may also have low power against some near integrated and stationary alternatives (Beran, 1994). In many cases, the dominant features of these processes are simply hard to distinguish.

Consider the commonly used Augmented Dickey Fuller (ADF) tests (1979) and the less commonly used asymptotic confidence intervals (Stock, 1991) for estimates of the autoregressive parameter, ρ. Table 1 presents results for macropartisanship, 1945:2–1994:4, monthly presidential approval over the 12 consecutive years of Republican administrations from 1981 through 1992, and public policy mood 1958:4–1994:4.[16] A quick look at the table shows that for none of these series can we reject the null hypothesis of a unit root using the ADF test.[17] The estimates of

[15] The KPSS test is the most common test for stationarity (Kwiatkowski et al., 1992). The size of the test is too low for strongly autoregressive processes so that information about autocorrelation from a larger number of lags is needed to discriminate a strongly autoregressive stationarity series from nonstationary alternatives. As a result, we will tend to overreject the null hypothesis that the series is stationary for near integrated processes if (a) number of lags used to calculate the test is small and/or (b) the sample size is small. However, as lag length increases, a larger sample is needed to maintain the power of the test. Thus there is a trade off between choosing a lag length large enough to discriminate between even mildly strong autoregressive series and nonstationary alternatives, but small enough to limit power losses. Further, while the KPSS tests are consistent against fractional alternatives, they cannot distinguish fractionally integrated series (particularly with small d) from those with strong autoregressive components in small samples (Lee and Schmidt, 1996). Rejecting the null may indicate that the series is either integrated of order d or that it is strongly autoregressive. Rejection of the null of stationarity may indicate a variety of nonstationary processes. Acceptance of the null, however, does not rule out fractional processes.

[16] Selecting this monthly sample period allows us to avoid problems associated with the changing partisanship of the president associated with series spanning longer time periods and allows a reasonably large sample size.

[17] The decision as to whether the series contain a deterministic (and linear) trend is an important one, with implications for the characterization of the memory process. Trends reduce the estimated role of persistence. Analysts do not typically entertain the prospect that these series contain deterministic trends. However, inferences are unchanged when the series is detrended.

Table 1
Dickey Fuller tests and asymptotic confidence intervals for ρ

Series	Date	N	k	ADF	Estimated ρ	Confidence intervals 80%	Confidence intervals 90%
Gallup Partisanship quarterly	1945:2-1944:4	197	1	−2.413	0.957	(0.920,1.004)	(0.910,1.008)
Public Mood quarterly	1958:2-1944:4	143	1	−1.791	0.986	(0.924,1.020)	(0.936,1.015)
Republican Presidential Approval	1981:1-1992:12	142	1	−2.302	0.949	(0.884,1.014)	(0.898,1.008)

ρ are all large, ranging from 0.949 for the presidential approval series to 0.986 for mood. In all cases, the asymptotic confidence intervals for ρ include 1.0 (and explosive values as well) and drop quite low.[18] While these tests lead us to infer that each process exhibits strong persistence, the results are all consistent with a stationary, near integrated process, a unit root, and also fractionally integrated alternatives. This information, like that from the microfoundations and from aggregation theorems presents important information for assessing macro persistence, but it is also incomplete information.

3.5.2. Estimation

Given the difficulties with identification, an analyst characterizing the persistence of aggregate time series typically engages in a three-step process. First, the analyst estimates a set of ARFIMA models, usually $(0,d,0)$, $(1,d,0)$, (2.60),…, $(0,d,1)$,…, $(0,d,2)$,…, $(3,d,3)$. Then the best ARFIMA model is selected using some information criterion, typically Akaike's (1973) information criterion (AIC) or the Schwarz (1978) information criterion (SIC).[19] Finally, the analyst conducts tests to see if the estimate of the fractional parameter, d, is different from 0 (stationary) and 1.0 (unit root). If it is, the process is assumed to be fractionally integrated.

There are, however, several considerations that need to be made when estimating ARFIMA models. First, there is some debate over the best estimator. Most analysts use Sowell's exact maximum likelihood estimator (EMLE) (Sowell 1989, 1990; Sowell, 1992a,b). Others have found that the Whittle likelihood, the profile likelihood and other estimators perform better than the EMLE for some processes and in some cases (see Hauser 1997, 1998). Whether these alternative estimators work better for aggregations of survey data is not clear. Preliminary work with political popularity

[18] KPSS tests of the null hypothesis that the series is stationary and variance ratio tests (Diebold and Rudebusch, 1989) of the unit root null hypothesis lead to similar inferences.

[19] The SIC penalizes more for additional parameters so that model selection using the SIC till typically yield a more parsimonious model than the AIC.

data across countries suggests that the estimators produce similar inferences when each converges (Byers et al., 1998).

A second difficulty with estimation involves the decision of how to treat the constant. If $d<0.5$, then the process is stationary and has a meaningful mean value. However, a fractionally integrated process may wander away from its mean for extended time periods. This increases the likelihood that the process may not cross the mean very often in our sample and implies that care must be take as to how to estimate the mean. We might use the sample mean, or we might impose a mean on the data, for example. When care is taken, it does appear that this decision has limited effects on the model parameters in many cases (Beran, 1994).

While analysts need to think carefully about these and other issues in estimation, it appears to be the case that aggregations of survey data are often well-characterized by ARFIMA models (Byers et al., 1998; Box-Steffensmeier and Smith, 1996; Box-Steffensmeier et al., 1998; Box-Steffensmeier and DeBoef, 1998; Box-Steffensmeier et al., 1997; Lebo et al., 1998). In these applications, estimated ARFIMA models were found to fit political approval, partisanship, macro ideology, and other processes; estimates of d were found to be significantly different from both 0 and 1.0.

I present Sowell's EML estimates for a set of ARFIMA models for Gallup macropartisanship, monthly presidential approval, and Stimson's public policy mood in Table 2. All series were first-differenced prior to estimation.[20] Results presented are for the first-differenced data so that 1.0 must be added to all estimates of d. Estimates of d for Gallup macropartisanship for all estimated models are significantly different from 0 and 1.0. Estimated values of d range from 0.559 to 0.855, indicating a nonstationary range of fractional processes. Both the AIC and SIC lead us to infer that the process is pore fractional noise, or $(0,d,0)$, with an estimated d of 0.855 and a standard error of 0.061.[21] Estimation in the frequency domain using the Whittle likelihood also leads to similar inferences (results not reported), selecting the fractional noise model with d=0.837 (0.060).

Estimation suggests that monthly presidential approval exhibits features of both long memory and short memory. Both model selection criteria lead us to select a $(1,d,0)$ model for presidential approval. This model predicts that shocks will have a substantial long run effect (d=0.788); the effect of shocks decays slowly over a long period of time. In addition, the significant autoregressive parameter (ρ=0.836) suggests that some of the effect of shocks does decay relatively quickly. In contrast frequency domain estimation (not reported) selects a $(3,d,1)$ model with d=0.934

[20] The properties of fractionally integrated processes are not known for nonstationary values of d ($d\geq.5$). Estimation is thus typically done on first differenced data, to ensure stationarity. The analyst must then add 1.0 to the estimated value of d to retrieve the estimate of d for the levels data. If estimates of d are less than 0.5, then estimation may be undertaken with the levels data. In the examples here, Robinson's (1994) semiparametric estimate of d was used to determine whether or not to first difference the data before estimation.

[21] The Box-Pierce test is used to determine whether the model residuals are white noise. Across the range of data, values of the test less than 20 indicate white noise residuals.

Table 2

Number of AR parameters	Number of MA parameters			
	0	1	2	3
(a) Gallup Macropartisanship, 1945:2-1994;4. Exact maximum likelihood ARFIMA estimation[a]				
0 *d* (differences)	−0.145 (0.061)	−0.207 (0.095)	−0.209 (0.115)	−0.264 (0.115)
ARMA estimates				
		0.081 (0.114)	0.089 (0.130)	0.124 (0.125)
			0.010 (0.080)	0.051 (0.085)
				0.099 (0.084)
Log likelihood	−407.808	−407.576	−407.568	−406.889
AIC	−817.616*	−819.156	−821.136	−821.778
SIC	−820.909*	−825.739	−831.016	−834.951
Box-Pierce test Q(12)	11.500	10.722	10.659	8.534
1	−0.213 (0.116)	−0.379 (0.215)	−0.389 (0.236)	−0.399 (0.174)
	0.095 (0.140)	0.651 (0.217)	0.670 (0.254)	0.514 (0.297)
		−0.403 (0.178)	−0.408 (0.178)	−0.255 (0.211)
			−0.013 (0.098)	0.018 (0.085)
				0.118 (0.082)
	−407.558	−407.042	−407.033	−406.116
	−819.116	−820.085	−822.067	−822.231
	−825.703	−829.964	−835.239	−838.699
	10.600	8.697	8.614	6.680
2	−0.260 (0.178)	−0.385 (0.226)	−0.407 (0.243)	−0.241 (0.094)
	0.140 (0.192)	0.682 (367)	0.252 (1.05)	0.925 (0.052)
	0.039 (0.106)	−0.13 (0.125)	0.306 (0.678)	−0.877 (0.043)
		−0.426 (0.278)	0.034 (1.01)	−0.837 (0.113)
			−0.216 (0.400)	0.835 (0.114)
				0.165 (0.111)
	−407.491	−407.037	−406.942	−403.745
	−820.981	−822.074	−823.883	−819.490
	−830.862	−835.247	−840.351	−839.250
	10.061	8.566	8.114	9.125
3	−0.401 (0.215)	−0.397 (0.209)	−0.287 (0.132)	−0.380 (0.201)
	0.275 (224)	0.385 (0.390)	1.14 (156)	0.848 (0.247)
	0.066 (0.087)	0.032 (0.125)	−1.08 (0.143)	−1.031 (0.077)
	0.113 (0.077)	0.103 (0.084)	0.197 (0.146)	0.565 (0.235)
		−0.116 (0.348)	−1.00 (0.023)	−0.609 (0.184)
			1.00 (0.027)	1.091 (0.069)
				−0.269 (0.186)
	−406.485	−406.432	−403.616	−402.327
	−820.971	−822.864	−819.232	−818.654
	−834.143	−839.331	−838.992	−841.707
	6.956	6.960	582.267	240.255

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continued

Number of AR parameters	Number of MA parameters			
	0	1	2	3
(b) Gallup Presidential Approval, 1981:1-1992;12. Exact maximum likelihood ARFIMA estimation				
0 *d* (differences)	0.481 (0.025)	0.346 (0.095)	0.338 (0.118)	0.128 (0.136)
ARMA estimates				
		0.378 (0.123)	0.385 (0.139)	0.597 (0.154)
			0.014 (0.113)	0.296 (0.176)
				0.246 (0.109)
Log likelihood	−247.844	−242.826	−242.819	−240.360
AIC	−497.687	−489.652	−491.638	−488.719
SIC	−500.650	−495.592	−500.547	−500.599
Box-Pierce test Q(12)	18.755	12.310	12.536	7.545
1	−0.212 (0.137)	−0.434 (0.189)	−0.351 (0.241)	−0.609 (0.288)
	0.836 (0.086)	0.888 (0.068)	0.880 (0.071)	0.902 (0.071)
		0.227 (0.176)	0.162 (0.208)	0.399 (0.256)
			−0.085 (0.136)	0.114 (0.241)
				0.168 (0.125)
	−240.222	−239.537	−239.342	−238.220
	−484.445*	−485.074	−486.684	486.440
	−490.384*	−493.938	−498.563	501.289
	11.989	11.985	10.789	7.947
2	−0.467 (0.331)	−0.340 (0.148)	−0.326 (0.223)	−0.556 (0.284)
	1.131 (0.356)	0.293 (0.296)	0.276 (0.320)	0.632 (0.449)
	−0.216 (0.280)	0.735 (0.202)	0.491 (0.300)	0.610 (0.383)
			0.705 (0.406)	0.181 (0.257)
				0.168 (0.137)
	239.671	−238.660	−238.657	238.078
	485.343	−485.321	−487.313	488.156
	−494.251	−497.199	−502.163	−505.975
	13.525	7.521	7.374	6.836
3	−0.378 (0.482)	−0.308 (0.278)	−0.488 (0.199)	−0.456 (0.163)
	1.044 (0.483)	276 (0.320)	1.33 (0.290)	−0.164 (0.104)
	−0.182 (0.250)	0.482 (0.293)	0.147 (0.529)	0.004 (0.086)
	0.031 (0.162)	0.027 (0.194)	−0.507 (0.248)	0.826 (0.082)
		0.717 (0.250)	−0.198 (0.204)	1.344 (0.126)
			0.674 (0.208)	1.290 (0.127)
				0.371 (0.134)
	−239.657	−238.651	−236.385	−234.076
	−487.313	−487.303	−484.770	−482.152
	−499.193	−500.979	−502.589	−502.941
	13.649	9.386	37.057	144.204

(continued on next page)

continued

Number of AR parameters	Number of MA parameters			
	0	1	2	3
(c) Public Policy Mood, 1958:4-1994;4. Exact maximum likelihood ARFIMA estimation				
3 *d* (differenced data)	−0.032 (0.071)	−0.037 (0.112)	−0.013 (0.176)	−0.008 (0.189)
		0.104 (0.136)	0.079 (0.196)	0.074 (0.202)
			−0.021 (0.116)	−0.023 (0.119)
				−0.008 (0.095)
Log likelihood	−266.972	−266.715	−266.699	−266.694
AIC	−535.943*	−537.430	−539.398	−541.391
SIC	−528.967*	−543.383	−548.328	−553.299
Box-Pierce test Q(12)	8.980	8.335	7.918	7.891
1	−0.43 (0.140)	−0.026 (0.126)	−0.013 (0.178)	−0.006 (0.182)
	0.107 (0.167)	0.112 (0.798)	0.028 (1.21)	−0.542 (0.954)
		0.204 (0.723)	0.080 (1.24)	0.605 (0.987)
			−0.023 (0.152)	0.005 (0.216)
				−0.046 (0.101)
	−266.739	−266.706	−266.699	−266.602
	−531.417	−539.412	−541.398	−543.703
	−543.431	−548.342	−553.305	−558.088
	8.618	8.121	7.913	7.502
2	−0.006 (0.188)	−0.004 (0.700)	0.028 (0.071)	−0.016 (1.24)
	0.059 (203)	0.040 (0.858)	−0.246 (0.024)	−0.246 (0.24)
	−0.040 (0.120)	−0.038 (0.151)	−0.985 (0.019)	−0.985 (0.020)
		−0.021 (0.909)	0.286 (0.032)	0.304 (0.149)
			1.000 (0.032)	1.005 (0.056)
				0.018 (0.149)
	−266.686	−266.685	−264.098	−264.091
	−539.371	−541.371	−538.196	−540.182
	−548.302	−553.271	−553.080	−558.042
	7.589	7.601	31.439	31.784
3	−0.785 (0.213)	−0.058 (0.208)	0.014 (0.133)	−0.050 (0.098)
	0.822 (0.222)	−0.525 (0.814)	−0.226 (0.161)	−1.195 (0.494)
	−0.011 (0.129)	−0.056 (0.231)	−0.980 (0.043)	−1.144 (0.397)
	0.089 (0.101)	−0.072 (0.121)	0.020 (0.150)	−0.329 (0.428)
		0.533 (0.868)	0.286 (0.032)	1.361 (0.443)
			1.000 (0.036)	1.431 (0.383)
				0.501 (0.446)
	−265.015	−266.580	−264.090	−261.993
	−538.029	−543.161	−540.180	−537.986
	−549.937	−558.044	−558.040	−558.823
	7.233	6.809	27.976	62.866

[a] Standard errors are in parantheses. Data was differenced before estimation. Sample mean of first differenced data (−0.134) was used for estimation. AR parameters are listed before MA parameters. Box-Pierce test (levels) Q(12) that the residuals are white noise should be less than about 20 for p=0.05.

(0.179). The remaining model parameters are stationary and invertible, but not all are significant in this model. Model residuals are well behaved for the selected models for both estimators.

Our best inference from the ARFIMA estimation is that Stimson's mood series is extremely persistent. Both the AIC and SIC lead us to select the lowest order model, pure fractional noise. Adding 1.0 to the estimate, d=0.968 (0.071). This finding of very strong persistence is robust across most of the model specifications and to estimator. Estimation in the frequency domain (not reported) also selects a (0,d,0) model with an estimated d of 1.05 (0.059). Taken together, the evidence is consistent with a near integrated, unit root, fractionally integrated, or perhaps an explosive process.

The estimation of macro persistence typically stops here, with inferences about persistence drawn from the ARFIMA estimation. It is important to note, however, that selecting the best ARFIMA model is not the same thing as selecting the best model. Ideally we would compare these ARFIMA models to ARMA and ARIMA models to see whether ARMA or ARIMA models describe the data as well as or better than ARFIMA processes. To date there has been no research that I am aware of that compares the best ARFIMA model with the best ARMA (or ARIMA) model. Comparing the models directly is problematic, however, as estimation is typically in first differences for the ARFIMA models and in levels for the ARMA models. This suggests that the next step for analysts is to consider out of sample prediction. Forecasting may be a valuable tool for selecting persistence characterizations, especially where our time series span large chunks of political time. This is an important avenue for future research on persistence for several reasons. First, just as the power of tests is often low, we have reasons to expect that some ARMA model is arbitrarily close to a given ARFIMA model in samples of the size we see. Second, if we cannot distinguish these classes of processes empirically, we may proceed to estimation on the solid foundation of more traditional analysis.

4. Conclusions

Persistence is an important feature of political processes. Questions about the nature of political change are asked more and more frequently as the number and regularity of surveys conducted increases to span decades. If we are to understand the dynamics of opinions and test hypotheses about change, the issues raised are paramount. Microfoundations, aggregation theorems, and macro theory and evidence tell us much about the dynamics of important political processes. They suggest persistence, and pretty strong persistence, in at least some aggregations of survey data. However. there may be a great deal of ambiguity involved in characterizing the precise form of persistence in these types of processes. Information of the kind considered here does increase the likelihood that inferences drawn from aggregate data are reliable. As such, each careful analysis provides us with a greater understanding of the dynamics of political processes. But clearly more work remains to be done.

We need better microfoundations. a broader appreciation of aggregation theorems and we need to compare the performance of fractionally integrated models with those from stationary and integrated models of persistence. The agenda for future research is large, but it is essential if we hope to understand the causes and consequences of political change.

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