A Framework for Unifying Formal and Empirical Analysis

Jim Granato University of Houston
Melody Lo University of Texas at San Antonio
M. C. Sunny Wong University of San Francisco

An important disconnect exists between the current use of formal modeling and applied statistical analysis. In general, a lack of linkage between the two can produce statistically significant parameters of ambiguous origin that, in turn, fail to assist in falsifying theories and hypotheses. To address this scientific challenge, a framework for unification is proposed. Methodological unification *leverages the mutually reinforcing properties of formal and applied statistical analysis to produce greater transparency in relating theory to test. This framework for methodological unification, or what has been referred to as the* empirical implications of theoretical models (EITM)*, includes (1) connecting behavioral (formal) and applied statistical* concepts*, (2) developing behavioral (formal) and applied statistical analogues of these concepts, and (3) linking and evaluating the behavioral (formal) and applied statistical analogues. The elements of this EITM framework are illustrated with examples from voting behavior, macroeconomic policy and outcomes, and political turnout.*

> Empirical observation, in the absence of a theoretical base, is at best descriptive. It tells one what happened, but not why it has the pattern one perceives. Theoretical analysis, in the absence of empirical testing, has a framework more noteworthy for its logical or mathematical elegance than for its utility in generating insights into the real world. The first exercise has been described as "data dredging," the second as building "elegant models of irrelevant universes." My purpose is to try to understand what I believe to be a problem of major importance. This understanding cannot be achieved merely by observation, nor can it be attained by the manipulation of abstract symbols. Real insight can be gained only by their combination.
>
> —John Aldrich (1980, 4)

> . . . there is still far too much data analysis without formal theory—and far too much formal theory without data analysis.
>
> —Larry Bartels and Henry Brady (1993, 148)

An important disconnect exists between the current use of formal analysis and applied statistical techniques.[1] Among other things, this discontinuity contributes to an overemphasis on attaining

Jim Granato is the Director of the Hobby Center for Public Policy and Professor of Political Science, University of Houston, 104 Heyne Building, Houston, TX 77204-5021 (jgranato@uh.edu). Melody Lo is Associate Professor of Economics, University of Texas at San Antonio, College of Business, Department of Economics, San Antonio, TX 78249-0631 (melody.lo@utsa.edu). M. C. Sunny Wong is Associate Professor of Economics, University of San Francisco, 2130 Fulton Street, San Francisco, CA 94117-1080 (mwong11@usfca.edu).

Versions of this article have been presented at the 2004 EITM Summer Program (Duke University), the 2005 annual meeting of the Southern Political Science Association (New Orleans, Louisiana), the 2005 annual meeting of the Canadian Political Science Association (London, Ontario), Ohio State University, Penn State University, the University of Texas at Austin, the 2006 EITM Summer Program (University of Michigan), and the 2007 and 2008 Essex Summer School in Social Science Data Analysis and Collection Program (University of Essex, Colchester, UK). We thank Chris Achen, Jim Alt, Mary Bange, Harold Clarke, Eva Coffey, Michelle Costanzo, John Freeman, Mark Jones, Skip Lupia, Elinor Ostrom, David Primo, Frank Scioli, Shalendra Sharma, and Miao Wang for their comments and assistance.

[1]The discussion focuses on formal analysis and applied statistical analysis. Formal analysis refers to deductive modeling that includes a theorem and proof presentation or computational modeling requiring simulation. Applied statistical analysis involves data analysis using statistical tools. We use the terms *analysis* and *modeling* interchangeably.

In addition, the linkage of formal and applied statistical analysis—the form of methodological unification described in this article—possesses important attributes that aid in falsification and, ultimately, scientific cumulation. Formal models, for example, force clarity

American Journal of Political Science, Vol. 54, No. 3, July 2010, Pp. 783–797

 ISSN 0092-5853

statistical significance through the manipulation of standard errors, exercises in data mining, and an overall inattention in relating theoretical specifications to applied statistical tests (see Achen 2002, 2005; Granato and Scioli 2004; Granato, Lo, and Wong 2010). A more general scientific problem with decoupling formal analysis from applied statistical procedures centers on a failure to *identify invariant* parameter estimates. This, in turn, impairs falsification of theories and hypotheses.[2]

What factors contributed to this methodological status quo? Conventional quantitative methodological practice is based in part on a tradition that borrows and applies statistical tools, which improves upon the use of older techniques. As this process took hold, the creation of methodologies isolating and identifying structural parameters became secondary to the use of hand-me-down applied statistical techniques. These techniques often end up as an exercise in implementing statistical "patches."[3] In a very real sense the emphasis on applied statistical technique, as opposed to identifying structural parameters, is based on a pedagogical tradition containing an aversion to mathematical modeling (Arrow 1951). This aversion has a cost. Absent mathematical modeling, the discipline lacks a basic tool to help identify causal mechanisms.

Even scholars who are sensitive to establishing robustness in their applied statistical results find the available tools inadequate when used in isolation. For example, augmenting applied statistical tests with *Extreme Bounds Analysis* (EBA; Leamer 1983) provides a check on parameter stability, but the test is performed *ex post* and therefore does not allow for *ex ante* prediction.[4] This should not be surprising when one considers the effects of previously unspecified covariates in this procedure. Each time an applied statistical model is respecified, the entire model is subject to change. But without a priori use of equilibrium conditions (e.g., stability conditions) in a formal model, the parameter "changes" in a procedure such as EBA are of ambiguous origin.

The scientific consequences of this methodological status quo are far-reaching. Among other things, current practices, because they are largely *ex post*, do not model an agent's behavior and responses to alternative policies or other social, political, and economic factors. Consequently, we cannot predict how the behavioral response of an agent influences the success or failure of a policy or treatment. The reason, as Lucas (1976) has argued, is that in-sample estimation provides little guidance in predicting the effects of policy changes because the parameters of the applied statistical models are unlikely to remain stable under alternative stimuli.[5]

To address these shortcomings, we argue for methodological unification—the linkage of formal and empirical analysis. Linking mutually reinforcing properties of formal and empirical analysis provides the necessary transparency between theory and test to aid in valid hypothesis testing. This linkage also contributes to the identification of invariant parameter estimates suitable for improving the accuracy of both *ex post* and *ex ante* predictions.[6]

Methodological unification is not new. Prior incarnations include research by scholars from organizations

about assumptions and concepts; they ensure logical consistency, and they describe the underlying mechanisms, typically behavioral, that lead to outcomes (Powell 1999, 23–39). The other component part of methodological unification—applied statistical models and tests—provides generalizations and rule out alternative explanations through multivariate analysis. Applied statistics assist in distinguishing between causes and effects, allow for reciprocal causation, and also help assess the relative size of the effects.

[2]The intuition behind the terms *identify* (i.e., identification) and *invariant* (i.e., invariance) are as follows. For applied statistical models, *identification* relates to model parameters (e.g., $\widehat{\beta}$) and whether they indicate the magnitude of the effect for that particular independent variable. Or, in more technical terms, "a parameter is identifiable if different values for the parameter produce different distributions for some observable aspect of the data" (Brady and Collier 2004, 290).

In applied statistical practice, *invariance* refers to the constancy of the parameters of interest. More generally, "the distinctive features of causal models is that each variable is determined by a set of other variables through a relationship (called 'mechanism') that remains invariant (constant) when those other variables are subjected to external influences. Only by virtue of its invariance do causal models allow us to predict the effect of changes and interventions" (Pearl 2000, 63).

[3]Heckman defines *structural causal effects* as "the direct effects of the variables in the behavioral equations" (2000, 59). Furthermore, "when these equations are linear, the coefficients on the causal variables are called *structural parameters* (emphasis added), and they fully characterize the structural effects" (59). Heckman also notes there is some disagreement about what constitutes a structural parameter. The disagreement centers on whether one uses a linear model, a nonlinear model, or, more recently, a fully parameterized model. In the latter case, structural parameters can also be called "deep" to distinguish between "the derivatives of a behavioral relationship used to define causal effects and the parameters that generate the behavioral relationship" (60).

[4]We will use the word *inference* to refer to a parameter in a regression or likelihood (b). We use the word *prediction* to refer to a model's forecast of a dependent variable ($\hat{y}$). For a technical treatment of these two concepts, see Engle, Hendry, and Richard (1983).

[5]The Lucas critique is based on the following intuition: "given that the structure of an econometric model consists of optimal decision rules . . . and that optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models" (Lucas 1976, 41).

[6]There is a large literature devoted to identification problems (see, e.g., Fisher 1966; Manski 1995). Some researchers treat the issue of simultaneity and identification as one and the same. We consider identification in a broader sense that includes simultaneity, but not limited to simultaneity.

such as the Cowles Commission.[7] We propose a framework which is consistent with what has been termed *empirical implications of theoretical models* (EITM).[8] EITM builds on the Cowles Commission approach and then places an emphasis on *developing behavioral and applied statistical analogues and linking these analogues*.[9]

This article is organized as follows. In the next section, we introduce an EITM framework by treating social, behavioral, political, and economic concepts (analogues) and applied statistical concepts (analogues) as linked entities. The following section illustrates—from literature in voting behavior, macroeconomic policy and outcomes, and political turnout—how the framework has been used in prior work and how this work provides a foundation for extension. We then summarize the discussion and provide some concluding comments.

A Framework for Methodological Unification

Background and Challenges

Methodological unification provides analytical transparency to support cumulative scientific practice. In more concrete terms, the EITM framework provides the necessary steps in attaining valid inference and prediction. For example, it is well known that when we specify that variable Y is a function of variable X, the statistical "tests" estimating a correlation between X and Y cannot determine causation between the two *even when their correlation is statistically significant*. Without unifying formal and empirical analysis we lack a basic analytical attribute suitable for identifying the following possibilities defining the relation between X and Y. A significant statistical result between X and Y can be due to (a) X causing Y directly; (b) X causing an unknown variable, Z, which causes Y; and (c) X and Y being caused by an unknown common factor, W, but there is no causality between X and Y. Too often researchers, using applied statistical methods, end up inferring the significant correlation to be result "a."

There have been numerous applied statistical attempts addressing these challenges to inference and prediction. Most econometric textbooks provide "solutions" such as instrumental variables (IV) estimation and different robustness checks, including EBA (Leamer 1983). However, these applied statistical tools, when used in isolation, lack power since they are not linked to a formal model.[10] Of course, formal models are simplifications of what is studied. Nevertheless, they systematically sort rival arguments and confounding factors in relating X to Y.[11] If formalized predictions *are inconsistent* with empirical tests, theory—as represented in the formal model—needs adjustment.[12]

Past academic research provides a scientific foundation for unifying formal and empirical analysis. The Cowles Commission, for example, established conditions in which structural parameters are identified within a model. It explored the differences between structural and reduced-form parameters. Along with their work on structural parameters, Cowles Commission members also gave formal and empirical specificity to issues such as exogeneity and policy invariance (Aldrich 1989; Christ 1994; Heckman 2000; Morgan 1990).

These contributions rested, in part, on a scientific vision merging formal and applied statistical analysis. The basis for this linkage was the idea that random samples were governed by some *latent* and *probabilistic* law of motion (Haavelmo 1944; Morgan 1990). This viewpoint meant formal models, when related to an applied statistical model, could be interpreted as creating a sample draw from the underlying law of motion. A test of a theory was accomplished by relating a formal model to an applied statistical model and testing the applied statistical model.

While sharing some similarities with the Cowles Commission approach, the EITM framework possesses modifications. First, if one were to adhere to the Cowles

[7] Morgan (1990) provides an extensive historical account of the contributions of the Cowles Commission. For further background on the Cowles Commission, consult http://cowles.econ.yale.edu/.

[8] The linking of formal and empirical analysis is part of the Empirical Implications of Theoretical Models (EITM) initiative supported by the National Science Foundation. For more information, see http://www.nsf.gov/sbe/ses/polisci/reports/eitmreport.jsp and http://www.nsf.gov/pubs/2003/nsf03552/nsf03552.pdf.

[9] Analogues are related to operationalizing a concept. An analogue is a device represented by variable—and measurable—quantities. Analogues include variables, operators, or an estimation process that mimics the concept of interest. They serve as analytical devices—not categorical indicators—for behavior and, therefore, provide for changes in behavior as well as a more transparent interpretation of the formal and applied statistical model.

[10] This criticism extends to progressive applied statistical research strategies (see Hendry 1995). Despite their rigor, specification searches that rely on diagnostics, goodness-of-fit metrics, and comparisons to rival models fail to account for *ex ante* changes in parameters that a formal model can provide. These applied statistical approaches succeed in improving in-sample accuracy, but lack power out-of-sample, particularly where behavioral responses to policy interventions or various shocks occur. Ultimately, the most powerful tests of formal models reside in predictions for other cases and over earlier or future periods.

[11] See Krugman (1994, 1998), Jasso (2002), and Wagner (2007) for general discussions on the utility of the formal modeling process.

[12] Experiments serve as empirical tests too. See Ostrom (2010, 71) for a discussion on how empirical results in experiments contributed to the development of an alternative preference function.

Commission approach, we forego the chance of modeling new uncertainty created by shifts in behavioral traits. The consequence of this omission directly affects the issues of identification and invariance because these unaccounted behavioral shifts of variables would not be linked with the other variables and specified parameters. *Ex ante* predictions are adversely affected (Lucas 1976). To address this issue, and to give greater support for *ex ante* predictions, we emphasize modeling human behavior so new uncertainties due to shifts in behavioral traits such as public tastes, attitudes, expectations, and learning are properly studied.

A second issue concerns the modeling process itself. A discipline such as political science studies the interactions between agent behavior and public policies all the time, but current research practices do not typically create formal models to predict or analyze these interactions. The Cowles Commission is associated with building a system of equations and then following rules (rank and order conditions) for identification that count equations and unknowns. In contrast, our EITM framework is agnostic on the choice to build and relate a system or to partition the system (via assumption) into a smaller set of equations, even a single equation. Priority is given to leveraging the mutually reinforcing properties of formal and empirical analysis.

A final point on model specification addresses the critiques of the structural approach leveled by Sims (1980). It is well known that structural parameters are not identified from reduced form estimates. The practice of finding ways to identify models leads to "incredible" theoretical specifications (Freeman, Lin, and Williams 1989; Sims 1980). The proposed EITM framework, through the use of behavioral concepts and analogues, addresses Sims's criticisms in a theoretically meaningful way. Analogues, in particular, have important scientific importance since they hold the promise of *operationalizing mechanisms.*[13]

The EITM Framework

This EITM framework is summarized as follows.

[13]Operationalizing mechanisms, as opposed to operationalizing variables, involves the creation of measurable devices (i.e., analogues) on both the formal side and the empirical side. An example of operationalizing a mechanism is in Converse (1969). For his theory, party identification (and voting behavior) is primarily a function of intergenerational transmission plus the number of times one had voted in free elections. To operationalize his proposed mechanism—intergenerational transmission—he used the following analogue: the Markov chain. This particular analogue allowed for a particular dynamic prediction he tested against actual voting data.

Unify Theoretical Concepts and Applied Statistical Concepts

Concepts of particular concern in this framework reflect many overarching social and behavioral processes. Examples include (but are not limited to) decision making, expectations, and learning.

It is also important to find an appropriate statistical concept to match with the theoretical concept. Examples of applied statistical concepts include (but are not limited to) persistence, measurement error, nominal choice, and simultaneity.

Develop Behavioral (Formal) and Applied Statistical Analogues

To link concepts with tests, we need analogues. An analogue is a device representing a concept via a continuous and measurable variable or set of variables. Examples of analogues for the behavioral (formal) concepts such as decision making, expectations, and learning include (but are not limited to) decision theory (e.g., utility maximization), conditional expectations (forecasting) procedures, and adaptive and Bayesian learning (information updating) procedures.

Examples of applied statistical analogues for the applied statistical concepts of persistence, measurement error, nominal choice, and simultaneity include (respectively) autoregressive estimation, error-in-variables regression, discrete choice modeling, and multistage estimation (e.g., two-stage least squares).

Unify and Evaluate the Analogues

The third step unifies the mutually reinforcing properties of the formal and empirical analogues. There are various ways to establish the linkage. For example, when researchers assume citizens (voters) or economic agents are rational actors who make decisions to maximize their own payoffs, a common analogue is utility (or profit) maximization. With this theoretical analogue in place, the other step is to determine the appropriate statistical concept and analogue to test the theoretical relation. Consider a basic Downsian model of voting. Voters decide to vote for one of the parties to maximize their utilities. This theoretical concept and analogue can be unified with the applied statistical concept, nominal choice, and its analogue, discrete choice modeling.

Applying the EITM Framework

In this section, we discuss four EITM examples. These examples contain, to varying degrees, the basic steps of the EITM framework. We also leverage the authors' EITM approach to show how their respective models and tests extend to new formalizations or tests or a combination of both.

Example 1: Voting with Compensational and Representational Preferences

The act of voting provides a useful window into methodological unification. In Hotelling (1929) and Downs (1957), voters choose one party over the others based on the relative political positions of parties—proximity voting theory. Voters are more likely to vote for a political party if the position of the party is closer to voters' ideal position. As the party's position further deviates from a voter's ideal position, the voter receives less utility and is less likely to vote for it.[14] While the voting literature finds some empirical support for the proximity model (see Blais et al. 2001), Kedar (2005) believes this effect diminishes if the institutional environment involves more power sharing.

The Relation between Decision Theory and Discrete Choice Models. In this example, decision theory and discrete choice serve as the EITM relation. Kedar (2005) asserts that, along with the proximity of parties' positions, voters are also concerned about each party's contribution to the aggregate policy outcome. She begins with the proximity model:

$$U_{ij} = -\beta_1 (v_i - p_j)^2, \tag{1}$$

where U_{ij} is the utility of voter i for party j, v_i is the ideal point of voter i, p_j is the position of party j, and β_1 is a scalar representing the importance of party-position deviations. In Kedar's analogue for decision making, equation (1), voter i perceives disutility from party j when the position of party j deviates from voter i's ideal point. On the other hand, if the position of party j is equivalent to his ideal point (i.e., $v_i = p_j$), no disutility is perceived.

Assuming party positions affect policy outcomes, Kedar (2005) specifies the policy outcome as a weighted average of policy positions of the respective parties:

$$P = \sum_{k=1}^{m} s_k p_k, \tag{2}$$

where there are m parties in the legislature, $0 < s_k < 1$ is the relative share of party k, and $\sum_{k=1}^{m} s_k = 1$ for all k.

If voters are policy-outcome oriented and concerned the policy outcome may deviate from their ideal point if party j is not elected, then the utility of voter i pertaining to party j becomes:

$$U_{ij} = -\beta_2 \left[(v_i - P)^2 - (v_i - P_{-p_j})^2 \right], \tag{3}$$

where:

$$P_{-p_j} = \left(\frac{1}{\sum_{k \neq j} s_k} \right) \sum_{k \neq j} s_k p_k. \tag{4}$$

Equation (4) represents the policy outcome if party j is not in the legislature and β_2 is a scalar weighting the deviations of the policy outcome when party j is excluded.

Equation (3) provides an important insight on how voters view the contribution of party j to the policy outcome affecting their utility. If party j takes part in policy formulation and makes the policy closer to voter i's ideal point v_i, that is, $(v_i - P_{-p_j})^2 > (v_i - P)^2$, then voter i gains positive utility when party j is involved (i.e., $U_{ij} > 0$). However, if the inclusion of party j makes the policy outcome increase in distance from voter i's ideal point such that $(v_i - P_{-p_j})^2 < (v_i - P)^2$, then the utility of voter i for party j is negative.

Now assume voter i has expectations concerning party j based on the weighted average of both the party's relative share position and its contribution to policy outcomes. With this analogue for expectations, voter i's utility for party j is:

$$U_{ij} = \theta \left\{ -\gamma (v_i - p_j)^2 - (1 - \gamma) \times \left[(v_i - P)^2 - (v_i - P_{-p_j})^2 \right] \right\} + \delta_j z_i, \tag{5}$$

where θ is a scalar, δ_j is a vector of coefficients on voter i's observable variables z_i for party j, and $\gamma \equiv \beta_1/(\beta_1 + \beta_2)$. When $\gamma \to 1$, voters are solely concerned with a party's positions—which is termed *representational voting behavior*. On the other hand, $\gamma \to 0$ implies voters choose a party where the policy outcome is placed at the voter's desired position(s). This outcome is called *compensational voting behavior*.

From equation (5) voter i's optimal or "desired" position for party j is obtained by solving the first-order condition of U_{ij} with respect to p_j:

[14] Applications of this particular utility function abound. Erikson, Mackuen, and Stimson (2002), for example, assume voters' utility is an inverse function of the squared distance of party political position and the voters' ideal position.

$$p_j^* = v_i\left[\frac{\gamma(1-s_j)+s_j}{\gamma\left(1-s_j^2\right)+s_j^2}\right] - \frac{(1-\gamma)\left(s_j \sum_{k=1,k\neq j}^{m} s_k p_k\right)}{\gamma\left(1-s_j^2\right)+s_j^2}. \tag{6}$$

When $\gamma \to 1$ (representational voting), the optimal position for party j is:

$$p_j^* = v_i. \tag{7}$$

But, if $\gamma \to 0$ (compensational voting), then:

$$p_j^* = \frac{v_i - \sum_{k=1,k\neq j}^{m} s_k p_k}{s_j}, \tag{8}$$

with the policy outcome:

$$\begin{aligned} P|_{\gamma\to 0,\, p_j=p_j^*} &= \sum_{k=1}^{m} s_k p_k = s_j p_j + \sum_{k=1,k\neq j}^{m} s_k p_k \\ &= s_j p_j^* + \sum_{k=1,k\neq j}^{m} s_k p_k \\ &= s_j \frac{v_i - \sum_{k\neq j}^{m} s_k p_k}{s_j} + \sum_{k=1,k\neq j}^{m} s_k p_k \\ &= v_i. \end{aligned} \tag{9}$$

Unifying and Evaluating the Analogues. The empirical tests follow directly from the theoretical model (i.e., equation 5). In equations (7)–(9), voters make an optimal voting decision based on representational (proximity) and compensational voting considerations. The theoretical prediction, γ is between zero and one, reflects the degree of political bargaining in different institutional systems. In majoritarian systems, where the winning party implements its ideal policy with less need for compromise, voters are expected to place greater value on γ and vote for the party positioned closest to their ideal position. However, in the case where institutional power sharing exists (i.e., γ is small), voters select a party whose position is further from their ideal positions to draw the collective outcome closer to their, the voters', ideal point.

Methodological unification occurs when Kedar derives an empirical analogue for discrete choice. The log-likelihood multinomial model is based on equation (5), and it estimates issue voting in four political systems using three measures: (1) seat shares in the parliament, (2) vote shares, and (3) portfolio allocation in government. The following hypotheses are tested:

H1: Voters' behavior in the countries with a majoritarian system follows the proximity model more closely (larger γ) than those in the countries with a consensual system (smaller γ).[15]

H2: The pure proximity model ($\gamma = 1$) does not sufficiently represent voting behavior.

Kedar tests these empirical implications (based on the value of γ) using survey data from Britain, Canada, the Netherlands, and Norway. The empirical results support the first theoretical hypothesis: voting behavior in the majoritarian systems (i.e., Britain and Canada) is more consistent with the proximity model relative to consensual systems (i.e., the Netherlands and Norway). Hypothesis 2 is tested using a likelihood ratio test. Kedar shows that γ is significantly different from 1 in all four political systems. This result suggests compensational voting behavior exists in the particular sample. The pure proximity model is an insufficient explanation.

Leveraging EITM and Extending the Model. In forming the behavioral mechanism of decision making, Kedar chooses utility maximization as an analogue: voters select their ideal party position or policy outcome or both by maximizing their utility. The author links the theoretical findings of the optimal choice model to multinomial estimation. One way to build on her formal model is to relax the behavioral assumption that voters' expectations are error free since it is well known that equilibrium predictions change when expectations are based on imperfect or limited information. The extension amends the formal model of voter expectations to incorporate modern refinements on how voters adjust and learn from their expectation errors. Leveraging Kedar's EITM design allows us to draw (empirical) implications on how voter expectations and learning affect *ex ante* model predictions.

Example 2: Economic Voting

A substantial economic voting literature exists. One specific area starts with Kramer (1983) and extends to Alesina and Rosenthal (1995). The features of these studies are the refinements in voter sophistication and applied statistical tests. In the former regard, voters possess the capability

[15]For H1, Kedar (2005) first identifies the institutional features of Britain, Canada, Norway, and the Netherlands. Using the indicators for majoritarianism and power sharing (see Lijphart 1984), she concludes Britain and Canada are more unitary and the Netherlands and Norway are more consensual.

to deal with the *uncertainty* in assigning blame or credit toward incumbents for good or bad economic conditions. For the latter, applied statistical tests include some of the more advanced tools in time-series analysis. In this example, we focus on Alesina and Rosenthal (1995).

The Relation between Expectations, Uncertainty, and Measurement Error. The formal model contains the behavioral concepts of expectations and uncertainty (Alesina and Rosenthal 1995, 191–95). Their model of economic growth is based on an *expectations-augmented* aggregate supply curve:

$$y_t = y^n + \gamma\left(\pi_t - \pi_t^e\right) + \varepsilon_t, \tag{10}$$

where y_t represents the rate of economic growth (GDP growth) in period t, y^n is the natural economic growth rate, π_t is the inflation rate at time t, π_t^e is the expected inflation rate at time t formed at time $t-1$, and ε_t is an unobservable shock to economic growth. Equation (10) shows the economic growth rate (y_t) exceeds the natural rate (y^n) when the actual inflation rate (π) is higher than the public's expected inflation rate (π_t^e).

With voter inflation expectations established, we turn to the concept of uncertainty. Assume voters try to determine whether to attribute credit or blame for economic growth (y_t) outcomes to the incumbent administration. However, they face uncertainty in determining what part of economic performance comes from incumbent competence (i.e., policy acumen) or simply good or bad luck. Uncertainty is based on the stochastic shock in equation (10). The analogue in equation (11) is commonly referred to as a "signal extraction" or measurement error problem:

$$\varepsilon_t = \eta_t + \xi_t, \tag{11}$$

where ε_t is composed of the two unobservable characteristics noted above—competence or luck. The first, represented by η_t, reflects competence attributed to the incumbent administration relative to the other party. The second, symbolized as ξ_t, are shocks to growth beyond administration control (and competence). Both η_t and ξ_t contain zero mean with variance(s) σ_η^2 and σ_ξ^2 respectively.

Competence can persist and support reelection. This feature can be characterized as an MA(1) process:

$$\eta_t = \mu_t + \rho\,\mu_{t-1}, \quad 0 < \rho \le 1 \tag{12}$$

where μ_t is $iid(0, \sigma_\mu^2)$. The parameter ρ represents the strength of persistence, and the lag or lags allow for retrospective voter judgements.

Alesina and Rosenthal (1995) tie economic growth performance to voter uncertainty. If "rational" voters predict inflation with no systematic error (i.e., $\pi_t^e = \pi_t$), then economic growth rate deviations from the average are attributed to administration competence or chance events:

$$y_t - y^n = \varepsilon_t = \eta_t + \xi_t. \tag{13}$$

Equation (13) shows when $\varepsilon_t = \eta_t + \xi_t > 0$, the actual economic growth rate is greater than its average or "natural rate" (i.e., $y_t > y^n$). Voters determine whether this above-average economic growth is due to the incumbent's competence (η_t) or the stochastic economic shocks (ξ_t) or both. Because competence can persist, voters use this property to make forecasts and give greater or less weight to competence over time.

To demonstrate this behavioral effect, the authors make use of conditional expectations as an analogue for the optimal forecast of competence (η_{t+1}). In particular, let rational voters form conditional expectations of η_{t+1} in equation (14) by observing the composite error $(\mu_t + \xi_t)$ given all available information y_t, y^n, and μ_{t-1} at time t:

$$\begin{aligned} E_t(\eta_{t+1}) &= E_t(\mu_{t+1}) + \rho\,E(\mu_t \mid \mu_t + \xi_t) \\ &= \rho\,E(\mu_t \mid \mu_t + \xi_t) \\ &= \rho\,E(\mu_t \mid y_t - y^n - \rho\,\mu_{t-1}), \end{aligned} \tag{14}$$

where:[16]

$$\mu_t + \xi_t = y_t - y^n - \rho\,\mu_{t-1}, \tag{15}$$

and $E_t(\mu_{t+1}) = E(\mu_{t+1} \mid \mu_t + \xi_t) = 0$. Using this analogue for expectations, competence, η_{t+1}, is forecasted by predicting μ_{t+1} and μ_t. Since there is no information available for forecasting μ_{t+1}, voters can only forecast μ_t based on the available information (at time t) from equation (15).

Unifying and Evaluating the Analogues. Using the method of recursive projection and equation (15), we link the behavioral analogue for expectations to the empirical analogue for measurement error (an error-in-variables "equation"):

$$\begin{aligned} E_t(\eta_{t+1}) &= \rho\,E(\mu_t \mid \mu_t + \xi_t) \\ &= \rho\,\frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\xi^2}\,(y_t - y^n - \rho\,\mu_{t-1}), \end{aligned} \tag{16}$$

where $0 < \rho\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\xi^2} < 1$. Equation (16) shows voters can forecast competence using the difference between $y_t - y^n$ and the weighted lag of μ_t (i.e., $\rho\,\mu_{t-1}$).

In equation (16), the expected value of competence is *positively* correlated with economic growth rate deviations. Voter assessment is filtered by the coefficient, $\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\xi^2}$, which represents the proportion of competence voters

[16]Equation (15) is obtained by substituting (12) in (13).

observe and interpret. The behavioral implications are straightforward. If voters interpret that variability of economic shocks comes solely from the incumbent's competence (i.e., $\sigma_\xi^2 \to 0$), then $\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\xi^2} \to 1$. On the other hand, the increase in the variability of uncontrolled shocks, σ_ξ^2, confounds the observability of incumbent competence since the signal coefficient $\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\xi^2}$ decreases. Voters assign less weight to economic performance in assessing incumbent competence.

Equations (10)–(12) serve as the formalization for tests using U.S. data on economic outcomes and political parties for the period 1915 to 1988. The theoretical model is based, in part, on equation (12). It specifies that competence, η_t, follows an MA(1) process. The MA process is important since it has properties to capture short-term changes. When the incumbent party is in office for the second period, the authors argue the covariance of ε_t is larger for the incumbent party than if a new party had taken office in that same period.

Alesina and Rosenthal estimate and compare the size of covariances within party and between parties to test this argument. They first estimate equation (10) to collect the estimated exogenous MA shocks, ε_t, and restrict the variance-covariance structure of ε_t. The authors report null findings (i.e., equal covariances) and conclude there is little evidence suggesting voters are retrospective and use incumbent competence as a basis for support.

Leveraging EITM and Extending the Model. Alesina and Rosenthal provide an EITM connection between equations (10), (12), and their empirical tests. They link the behavioral concepts—expectations and uncertainty—with their respective analogues (conditional expectations and measurement error) and estimate the variance-covariance structure of the residuals to test this relation. Yet, Alesina and Rosenthal's model is tested in other ways. For example, the empirical model resembles an error-in-variables specification, which is testable using dynamic methods such as rolling regression (Lin 1999). Alternatively, one could evaluate the competence equation (16) and use different measures for uncertainy such as the empirical tests and measures Suzuki and Chappell (1996) use for permanent and temporary changes in economic growth.[17]

Example 3: Macroeconomic Policy and Outcomes

In the post–World War II era there have been several regime shifts in U.S. macroeconomic policy (e.g., Bernanke et al. 1999; Taylor 1999). One line of research has focused on the use of interest rate rules in new Keynesian models (see Clarida, Gali, and Gertler 2000). These models are not generally used in political science since classic work in macro political economy does not typically rely on structural models.[18] While structural models are few in number, Granato and Wong (2006) derive a model with new Keynesian properties to determine the relation between inflation-stabilizing policy, inflation persistence and volatility, and business cycle fluctuations. Extending this model to various political phenomena, particularly as it pertains to policy (e.g., policy rules), is feasible.[19]

The Relation between Expectations, Learning, and Persistence. This example demonstrates an EITM relation between expectations, learning, and persistence.[20] Based on Fuhrer (1995) and Fuhrer and Moore (1995), this small structural model of macroeconomic outcomes and policy follows the Cowles Commission tradition, but it also contains behavioral analogues for expectations and learning.[21] The details in the model are as follows. First, a two-period contract is assumed where prices reflect a

[17]Recall the competence analogue (η_t) in Alesina and Rosenthal's model is part of the aggregate supply (AS) shock ($\varepsilon_t = \eta_t + \xi_t$). Competence ($\eta_t$) is defined as the incumbent's ability to promote economic growth via policies along the AS curve (e.g., protection of property rights, public infrastructure). Assume voters believe AS policy provides the source for long-lasting "permanent" economic growth since it adds to productive capacity. On the other hand, voters punish incumbent politicians for unusual economic growth due to a "temporary" shift in aggregate demand (AD) policy because of the inflationary consequences.

[18]See Hibbs (1977) as an example of the nonstructural tradition. However, Chappell and Keech (1983), Alesina and Rosenthal (1995), and Freeman and Houser (1998) are exceptions.

[19]See Drazen (2000) for a review of the literature.

[20]The intuition of the model is as follows: policy influences public expectations by encouraging the public to substitute an inflation target for past inflation. The testable prediction is a negative relation between aggressive inflation-stabilizing policy and inflation persistence. Granato and Wong (2006) define an aggressive inflation-stabilizing policy as a willingness to respond forcefully to deviations from a prespecified implicit or explicit inflation target.

[21]The particular analogues for expectations and learning in this example are developed in Evans and Honkapohja (2001). The analogue for expectations involves the use of conditional expectations tools and finding *rational expectations equilibria* (REE). Rational expectations (RE) are agent forecasts based on all available information (in the model). Intuitively, these forecasts equal the actual outcome on average. An REE imposes the consistency condition that each agent's choice is a best response to the choices of others. Adaptive learning procedures serve as the analogue for learning. Under adaptive learning, agents do not initially obtain the REE, but they update their forecasts as new information becomes available. This learning process occurs provided a convergence condition is satisfied (E-stability). E-stability determines the feasibility of reaching the REE and it also (1) shows whether RE is a useful technique for solving for long-run equilibria and (2) serves as a selection criterion when a model possesses multiple equilibria (e.g., quadratic

unitary markup over wages. The price at time t, p_t, is expressed as the average of the current (x_t) and the lagged (x_{t-1}) contract wage:[22]

$$p_t = \frac{1}{2}\left(x_t + x_{t-1}\right), \tag{17}$$

where p_t is the logarithm of the price level, and x_t is the logarithm of the wage level at period t. Assume agents are concerned about their real wages over the lifetime of the contract:

$$x_t - p_t = \frac{1}{2}\left[x_{t-1} - p_{t-1} + E_t\left(x_{t+1} - p_{t+1}\right)\right] + \theta z_t, \tag{18}$$

where $x_t - p_t$ represents the real wage rate at time t, $E_t(x_{t+1} - p_{t+1})$ is the expectation of the future real wage level at time $t+1$ formed at time t, and z_t is the excess demand for labor at time t. The inflation rate (π_t) is defined as the difference between the current and lagged price level $(p_t - p_{t-1})$. Next, substitute equation (18) into equation (17) and obtain:[23]

$$\pi_t = \frac{1}{2}\left(\pi_{t-1} + E_t\pi_{t+1}\right) + \theta z_t + u_{1t}, \tag{19}$$

where $E_t\pi_{t+1}$ is the expected inflation rate over the next period and is an additive supply shock.

Equation (19) captures the behavioral characteristics contributing to inflation persistence. Since agents make plans about their real wages using both past and future periods, the lagged price level (p_{t-1}) is taken into consideration as they adjust (negotiate) their real wage at time t. This model feature allows the inflation rate to depend on both the expected inflation rate as well as past inflation.

Equation (20) represents a standard IS curve where the quantity demanded (signified by (z_t)) is negatively associated with the changes in real interest rates:

$$z_t = -\varphi\left(i_t - E_t\pi_{t+1} - r^*\right) + u_{2t}, \tag{20}$$

where i_t is nominal interest rate, r^* is the target real interest rate, u_{2t} is $iid(0, \sigma^2_{u_2})$, and $\varphi > 0$.

Policymakers are assumed to follow an interest rate rule, the *Taylor rule*, when conducting monetary policy (Taylor 1993):

$$i_t = \pi_t + \alpha_z z_t + \alpha_\pi(\pi_t - \pi^*) + r^*, \tag{21}$$

where positive values of α_π and α_z indicate a willingness to raise (lower) nominal interest rates in response to the positive (negative) deviations from either the targeted inflation rate $(\pi_t - \pi^*)$, the output gap (z_t), or both.

To determine the equilibrium inflation rate, first substitute equation (21) into equation (20). Next, solve for z_t and then put that result into equation (19). The expression for π_t is:

$$\pi_t = \Gamma_0 + \Gamma_1\pi_{t-1} + \Gamma_2 E_t\pi_{t+1} + \xi_t, \tag{22}$$

where:

$$\begin{aligned}
\Gamma_0 &= (\theta\varphi\alpha_\pi\pi^*)\,\Phi^{-1},\\
\Gamma_1 &= (1+\varphi\alpha_z)\,(2\Phi)^{-1},\\
\Gamma_2 &= (1+\varphi\alpha_z + 2\theta\varphi)\,(2\Phi)^{-1},\\
\xi_t &= [\theta u_{2t} + (1+\varphi\alpha_z)\,u_{1t}]\,\Phi^{-1},\\
\text{and}\quad \Phi &= 1 + \varphi\alpha_z + \theta\varphi\,(1+\alpha_\pi).
\end{aligned}$$

Equation (22) shows current inflation depends on the first-order lag of inflation (π_{t-1}), expected inflation $(E_t\pi_{t+1})$, and composite stochastic noise (ξ_t). When (22) is "closed," the *minimum state variable* (MSV) solution is expressed as an AR(1) process.[24] The AR(1) process is the applied statistical analogue for persistence.

Unifying and Evaluating the Analogues. Methodological unification occurs when we solve for the REE since this step involves merging the behavioral analogue of expectations with the applied statistical analogue for persistence. Take the conditional expectations at time $t+1$ of equation (22) and substitute this result into equation (23):

$$\pi_t = A + B\pi_{t-1} + \tilde{\xi}_t, \tag{23}$$

where $A = \Gamma_0(1 - \Gamma_2 B - \Gamma_2)^{-1}$, $B = (1 \pm \sqrt{1 - 4\Gamma_1\Gamma_2})(2\Gamma_2)^{-1}$, and $\tilde{\xi}_t \equiv \xi_t(1 - \Gamma_2 B)^{-1}$. Equation (23) is the MSV solution of inflation—which depends solely on the lagged inflation rate.

A final step in the modeling process is to use the adaptive learning analogue and determine if the REE is unique and stable.[25] Based on the magnitude of the model's parameters, we determine the properties of the quadratic

terms). For this example, the use of these particular behavioral analogues mimics how agents learn from policy makers: under the REE, aggressive implementation of an inflation target guides agents to the stable equilibrium and reduces inflation persistence.

[22] See Wang and Wong (2005) for the details of the general theoretical framework.

[23] To obtain equation (19), subsitute (17) into (18): $(1/2)(x_t - x_{t-1}) = (1/2)((1/2)(x_{t-1} - x_{t-2}) + (1/2)E(x_{t+1} - x_t)) + \theta z_t$. Then insert the inflation rate derived from equation (17), $\pi_t = p_t - p_{t-1} = (1/2)(x_t - x_{t-1}) + (1/2)(x_{t-1} - x_{t-2})$, into this new expression. The output term in equation (19) is a moving average of the current and lagged output gap $(z_t - z_{t-1})$. Fuhrer (1995) assumes the output term is the current output gap (i.e., θz_t).

[24] As part of the method of undetermined coefficients, the *minimal state variable* (MSV) solution or "fundamental" solution is suggested by McCallum (1983).

[25] The adaptive learning analogue serves as an important selection criterion (i.e., determining stable solutions; McCallum 2003). If conditions for uniqueness and stability are established, then the *ex ante* prediction—as represented in equation (23)—is that an increase in α_π reduces B.

solutions and solve for the relation between aggressive inflation-stabilizing policy (α_π) and inflation persistence (B). The two values are defined as:

$$B^{+} = \frac{1+\sqrt{1-4\Gamma_1\Gamma_2}}{2\Gamma_2},$$
$$B^{-} = \frac{1-\sqrt{1-4\Gamma_1\Gamma_2}}{2\Gamma_2}.$$

Granato and Wong (2006) show that one of the two values, B^{-}, is a unique and learnable stationary solution when $\alpha_\pi > 0$: if policymakers adopt an aggressive inflation-stabilizing policy, then a stationary AR(1) solution is obtained (i.e., B^{-}).

Quarterly U.S. data (for the period 1960:I to 2000:III) are used to test the relation between the policy parameter(s) and inflation persistence. According to the model, inflation persistence should fall under an aggressive inflation-stabilizing policy.[26] From equation (23) Granato and Wong estimate a first-order autoregressive process (i.e., AR(1)) of the U.S. inflation rate. The formal model predicts a positive inflation stabilization policy parameter (α_π) reduces inflation persistence, B_t. Granato and Wong also estimate equation (21) in order to contrast the parameter movements in α_π and α_z.[27]

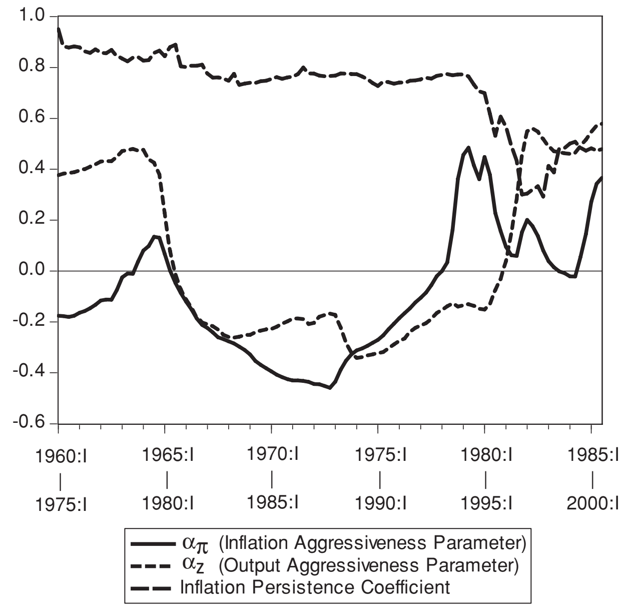
Figure 1 provides point estimates of inflation persistence (B_t) and policy rule parameters, α_π and α_z, for a 15-year rolling sample starting in the first quarter of 1960 (1960:I). Figure 1 shows both α_π and α_z de-emphasize inflation and output stability in approximately 1968. Prior to 1968, countercyclical policy emphasized output stability ($\alpha_z > 0$). Aggressive inflation-stabilizing policy occurs only after 1980, when $\alpha_\pi > 0$. Consistent with the model's predictions, inflation persistence falls after this policy change in 1980.

Leveraging EITM and Extending the Model. The model presented here, in some respects, is a mirror of Kedar's (2005) model. Kedar emphasizes microfoundations but makes assumptions about voter expectations. This example, on the other hand, has an explicit analogue for expectations, but little in the way of microfoundations or in the strategic interaction between policymakers and the public. In addition, the policy rule (21) is devoid of any political and social factors. Both the inflation target variable (π^*) and the response parameters (α_π, α_z) could be made endogenous to political and social factors, including (but not limited to) partisanship, elections, and social interaction where information levels are heterogeneous (Granato, Guse, and Wong 2008).

[26]As a consequence of the more aggressive inflation-stabilizing policy stance during the Volcker-Greenspan period (August 1979 through August 2000), the inflation-persistence parameter (B_t) is predicted to be smaller (statistically) relative to the pre-Volcker period.

[27]See also Granato and Wong (2006, 198–211).

FIGURE 1 Inflation Persistence and Policy Parameters



Example 4: Political Turnout

In previous studies of turnout, researchers have used discrete choice models to estimate the probability of voting. The explanatory variables in these empirical models include ad hoc transformations and lack a formal theoretical foundation. For example, age, the square of age, education level, and the square of education level are used. The variables are included typically for the sake of a better statistical fit within the sample, but they lack power for policy and intervention analysis where behavioral responses are important modeling considerations. Achen (2006) uses an EITM framework to link an *ex ante* theoretical prediction, based on Bayesian analysis, with an applied statistical analogue—"double-probit." He finds the fit of his model is superior to a traditional and rival applied statistical specification.

The Relation between Decision Theory, Learning, and Discrete Choice Models. Achen assumes a voter receives positive expressive utility of voting if he expects the true value of the difference between two parties in the next period, u_{n+1}, to be different from zero (where n is the number of prior elections that the voter experiences). Voters also possess imperfect foresight about the true value of the party differences. Instead, the voter "learns" the expected value based on his information set (updated using a Bayesian mechanism).

The subjective (expected) distribution of u_{n+1} is written as:

$$f\left(u_{n+1}\,|I\right), \tag{24}$$

where $f(\cdot)$ is the probability density distribution based on the voter's information set I given n periods. The corresponding cumulative distribution function (cdf) from equation (24) is:

$$F\left(u_{n+1}\,|I\right), \tag{25}$$

where $F(\cdot)$ is the cdf with mean $\hat{u}_{n+1}$ and variance σ^2_{n+1}.

For theoretical convenience, Achen (2006) assumes $\hat{u}_{n+1}$ is nonnegative: the voter only votes for the party valued higher than another. Following Downs (1957), Achen (2006) suggests the utility of voting in period $n+1$ is the difference between the expected benefit of voting, $E(u_{n+1})$, and the cost of voting:

$$U = E\left(u_{n+1}\right) - c. \tag{26}$$

Achen argues voters use a Bayesian updating procedure (assuming a normal distribution of u_{n+1}) and learn the true u_{n+1} based on (1) the difference(s) in party identification (PID) from the last period, u_n; (2) campaign information, c_{n+1}; and (3) a trusted information source, $q_{n+1,}$ possibly affiliated with a political party.[28]

The learning process is characterized as follows. The voter's observed difference in party benefits is:

$$u_t = \delta + v_t, \tag{27}$$

where $v_t \sim N(0, w^2)$ and $u_t \sim N(\delta, w^2)$. The voter first updates the posterior mean δ of his PID up to time n using the standard Bayesian formulation:

$$\hat{\delta}_n = \frac{h_1 \bar{u}_n}{h_0 + h_1}, \tag{28}$$

where $\bar{u}_n = \sum u_t/n$ is the mean of PID based on past voting experience, $h_1 = (w^2/n)^{-1}$ is the inverse of the sample variance, and $h_0 = (\sigma_0^2)^{-1}$ represents the inverse of the prior variance, σ_0^2. In the next period, the voter receives new information from the party campaign:

$$c_{n+1} = u_{n+1} + \theta_{n+1} + \epsilon_{n+1}, \tag{29}$$

where $\theta \sim N(0, \varphi^2)$ and $\epsilon \sim N(0, \tau^2/m)$.

The same Bayesian procedure is used to update the posterior mean of the PID difference $\hat{u}_{n+1}$. It is based on the posterior mean of PID at time n (i.e., $\hat{\delta}_n$, in equation (28)), campaign information, c_{n+1} in equation (29), and the trusted information source, q_{n+1}, at time $n+1$:

$$\hat{u}_{n+1} = \frac{h_c \hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{h_c + h_\tau + h_q}, \tag{30}$$

where $h_c \equiv [(h_0 + h_1)^{-1} + w^2]^{-1}$, $h_\tau \equiv (\varphi^2 + \tau^2/m)^{-1}$, and h_q is the inverse of known variance of the trusted information source. The posterior variance of $\hat{u}_{n+1}$ is presented as:

$$\sigma^2_{n+1} = \frac{1}{h_c + h_\tau + h_q}. \tag{31}$$

Achen shows that $\hat{u}_{n+1}$ is a monotonically increasing, bounded above, concave function of the information sources, and the sum of such functions has the same properties. Moreover, if no information comes from any source, then the value of voting is zero.

Unifying and Evaluating the Analogues. Achen approximates the population mean probability of voting given the information as follows. Let there be a critical level of utility, call it U^*, such that if $U > U^*$, the voter will vote, otherwise the voter will not. Given the normality assumption for the utility distribution, we construct the probability that U^* is less than or equal to U based on the normal cdf:

$$\begin{aligned}
&\Pr\left(vote = 1\,\middle|\,\text{PID, Campaign Information, and Trusted Source}\right)\\
&\quad = \Pr\left(U^* \leq U\right)\\
&\quad = \Phi\left(\alpha\left[2\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{\left(h_c + h_\tau + h_q\right)^{1/2}}\right) - 1\right] - c\right).
\end{aligned} \tag{32}$$

Here the function, $2\Phi(\cdot) - 1$, has only nonnegative arguments and is monotonically increasing, bounded, and concave. Therefore, in equation (32), we can see the inner normal cdf represents the Bayesian learning process and the outer normal cdf is used for the purpose of discrete choice estimation. Unification is achieved at this point.

To estimate the determinants of voting turnout, Achen presents the probit model which follows from equation (32). Using maximum likelihood estimation, Achen (2006) estimates simultaneously two normally distributed cdf's in equation (32): a *double-probit*. To interpret the coefficients, we first focus on the inner normal cdf. If the voter does not have any accurate information about the future, that is, $(h_c + h_\tau + h_q)^{1/2} = 0$, then $\Phi(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{(h_c + h_\tau + h_q)^{1/2}}) = \Phi(0) = 1/2$. In this case, equation (32) is equivalent to:

[28]Trusted information can also come from the voter's spouse or some interest groups.

$$\begin{aligned}
\Pr(vote = 1 \mid I) &= \Phi\left(\alpha\left[2\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{\left(h_c + h_\tau + h_q\right)^{1/2}}\right) - 1\right] - c\right) \\
&= \Phi\left(\alpha\left[2\Phi(0) - 1\right] - c\right) \\
&= \Phi(-c). \qquad (33)
\end{aligned}$$

Since c is a z-value, expected theoretically to range between 2 or 3, then $\Phi(-c)$ will range between -2 and -3, implying that the probability of voting will be very low.

On the other hand, if the voter is fully informed and the posterior precision of information is quite large, that is, $(h_c + h_\tau + h_q)^{1/2} \to \infty$, then $\Phi(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{(h_c+h_\tau+h_q)^{1/2}}) = \Phi(\infty) \to 1$. Therefore, we have:

$$\begin{aligned}
\Pr(vote = 1 \mid I) &= \Phi\left(\alpha\left[2(1) - 1\right] - c\right) \\
&= \Phi(\alpha - c). \qquad (34)
\end{aligned}$$

Given that α is expected to range between 4 and 5, $\Phi(\alpha - c)$ will range between 2 and 3. This relation shows the probability of voting will be high and close to 1.

To estimate equation (32), Achen uses the variables *systemtime* and *education* as the proxies for PID, $\hat{\delta}$, and campaign information, c_{n+1}, respectively. *Systemtime* is defined as the voter's age minus 18 years. Education is classified as six categories: (1) No High-School, (2) Some High-School, (3) High-School Degree, (4) Some College, (5) College Degree, and (6) Postgraduate Level.

Achen argues the age of voters (*systemtime*) shows the strength of PID while education level is an attribute in understanding campaign information.[29] Based on the availability of data, the theoretical model (32) is used to estimate the following double-probit model:

$$\begin{aligned}
\Pr(vote = 1) &= \Phi\left(\lambda_0 + \lambda_1\left[2\Phi\left(\beta_1 systemtime + \beta_2 education\right) - 1\right]\right), \qquad (35)
\end{aligned}$$

where the empirical component, $\Phi(\beta_1 systemtime + \beta_2 education)$, approximates the Bayesian learning procedure $\Phi(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{(h_c+h_\tau+h_q)^{1/2}})$, and λ_0 and λ_1 are equivalent to $-c$ and α in equation (32), respectively.

Achen (2006) uses voter turnout data from the 1998 and 2000 Current Population Surveys (CPS) and the Annenberg 2000 presidential election study. When he contrasts his EITM-based model with traditional applied statistical models in the existing literature, he finds his model has a better fit. Equally important, when the focus turns to the parameters in Achen's model, the empirical estimates are consistent with the theoretical predictions of his model (see equation (32)). For example, the estimated values of c and α range between 1.212 and 2.424 and between 3.112 and 4.865, respectively. These values are statistically indistinguishable from the values predicted in his model.

Leveraging EITM and Extending the Model. Achen uses the behavioral concepts of rational decision making and learning. His behavioral analogues are utility maximization and Bayesian learning, respectively. He links these behavioral analogues with the applied statistical analogue for discrete choice: probit. To accomplish this EITM linkage he assumes the voting decision and Bayesian learning are normally distributed events. With that assumption in place, his formal model is tested using two probit regressions simultaneously.

There are many ways to leverage Achen's EITM model. One of the more important extensions is to take advantage of the dynamic properties in his theory and model. Retrospective evaluations are assumed in the model, but there is no specification or test on how long these evaluations persist or how long a voter's memory lasts. We know, for example, that in matters of policy, retrospective judgments by the public have a profound influence on policy effectiveness. Equally important, persistence analogues exist to complete the unification process.

Summary and Discussion

In this article, we demonstrate a framework that provides formalized behavioral explanations suitable for statistical inference and prediction. EITM not only builds on the Cowles Commission's work to recover a model's parameters, but it also addresses both Lucas's (1976) and Sims's (1980) critiques of conventional applied statistical estimation practice. A way to address these criticisms is to ensure analogues are tied to concepts. We work through the properties of the analogues and focus on the relation between the formal-theoretical parameter(s) and the applied statistical parameter(s). Explicit emphasis on the parameters allows for greater likelihood of knowing what is being tested. Ultimately, EITM means a clean break from the methodological status quo. No half-measures will suffice if the goal is to build a cumulative science based on the transparency between theory and test.

The EITM framework, because it runs counter to current practice, raises new challenges. One challenge is practical. The overall process of methodological unification, applying the EITM framework, and the diverse

[29]Note that there is no proxy measure used for trusted source. Therefore q_{n+1} is dropped from equation (32).

examples used means a reorientation in methodological training. There are well-known differences between formal and empirical approaches, and current training reflects the siloed thinking. This framework serves as a way to create courses and teaching modules where research questions dictate the analogues used and make the "how" we examine the problem equal in emphasis to "what" we study.

Two technical challenges emerge. One technical challenge is the development of analogues. Unlike the natural sciences, the social sciences study human subjects who possess expectations affecting their current behavior. This "dynamic" creates moving targets for many social science questions. How to improve upon current analogues for distinctly human behavioral traits (e.g., expectations and learning) is a key future hurdle to scientific cumulation.

A second technical challenge relates to the framework's emphasis on *parameters* as a building block for *ex post* and *ex ante* prediction (see Bamber and van Santen 1985, 2000). It is almost impossible to capture all parameters in complex political, social, and economic systems. However, the EITM framework is useful since it helps researchers open the "black box" relating different theoretical parameters to the estimated coefficients in an empirical model.[30] *A more general point is the EITM framework's focus on parameters separates variables that aid in fundamental prediction from other variables considered "causal" but are of minor predictive importance.*

The EITM framework is part of an ongoing process geared toward methodological unification (see Morton 1999). What we describe can be extended in many ways. Unified methodological frameworks now exist across different levels of analysis (Freeman and Houser 1998; Kydland and Prescott 1982), make explicit use of game theory (Mebane and Sekhon 2002; Signorino 1999), or are part of a mutiple-method research design (Poteete, Janssen, and Ostrom 2010). Experiments also provide a rich alternative or complement to the secondary data analysis we use in this article and are a natural outlet for methodological unification. A good deal of EITM research will no doubt take place using experimental methods because of the relative ease in connecting a formal model and prediction to tests.[31]

[30]Although isolating the effects of all parameters is unlikely, one possible alternative is to set up experiments in a laboratory or via numerial simulation and create an artificial but controlled environment. In this setting, one can examine how one variable, *holding everything constant* (i.e., the free parameters are unchanged for all subjects), affects the other variables of interest.

[31]Experiments not only serve as transparent tests of formal models, but they also (1) advance the integration of a variety of methods (qualitative and quantitative); (2) advance a dialogue between these methods to produce cumulation; and (3) produce data where secondary data sources, particularly in comparative analysis, are of poor quality. An example of these various attributes is demonstrated in the following sequence of studies (Cardenas 2000; Cardenas, Stranlund, and Willis 2000; Casari and Plott 2003; Ostrom, Walker, and Gardner 1992).

References

Achen, Christopher H. 2002. "An Agenda for the New Political Methodology: Microfoundations and ART." *Annual Review of Political Science* 5: 423–50.

Achen, Christopher H. 2005. "Let's Put Garbage-Can Regressions and Garbage-Can Probits Where They Belong." *Conflict Management and Peace Science* 22(4): 327–39.

Achen, Christopher H. 2006. "Expressive Bayesian Voters, Their Turnout Decisions, and Double Probit: Empirical Implications of a Theoretical Model." Princeton University, Typescript.

Aldrich, John H. 1980. *Before the Convention: Strategies and Choices in Presidential Nomination Campaigns*. Chicago: University of Chicago Press.

Aldrich, John. 1989. "Autonomy." *Oxford Economic Papers* 41(1): 15–34.

Alesina, Alberto, and Howard Rosenthal. 1995. *Partisan Politics, Divided Government, and the Economy*. New York: Cambridge University Press.

Arrow, Kenneth. 1951. "Mathematical Models in the Social Sciences." In *Policy Sciences*, ed. Daniel Lerner and Harold D. Lasswell. Stanford, CA: Stanford University Press, 129–54.

Bamber, Donald, and Jan P. H. van Santen. 1985. "How Many Parameters Can a Model Have and Still Be Testable." *Journal of Mathematical Psychology* 29(4): 443–73.

Bamber, Donald, and Jan P. H. van Santen. 2000. "How to Assess a Model's Testability and Identifiability." *Journal of Mathematical Psychology* 44(1): 20–40.

Bartels, Larry M., and Henry E. Brady. 1993. "The State of Quantitative Political Methodology." In *Political Science: The State of the Discipline II*, ed. Ada Finifter. Washington, DC: American Political Science Association, 121–59.

Bernanke, Ben S., Thomas Laubach, Frederick S. Mishkin, and Adam S. Posen. 1999. *Inflation Targeting: Lessons from the International Experience*. Princeton, NJ: Princeton University Press.

Blais, André, Richard Nadeau, Elisabeth Gidengil, and Neil Nevitte. 2001. "The Formation of Party Preferences: Testing the Proximity and Directional Models." *European Journal of Political Science* 40(1): 81–91.

Brady, Henry E., and David Collier. 2004. *Rethinking Social Inquiry: Diverse Tools, Shared Standards*. Lanham, MD: Rowman and Littlefield.

Cardenas, Juan-Camilo. 2000. "How Do Groups Solve Local Commons Dilemmas? Lessons from Experimental Economics in the Field." *Environment, Development and Sustainability* 2(3–4): 305–22.

Cardenas, Juan-Camilo, John K. Stranlund, and Cleve E. Willis. 2000. "Local Environmental Control and Institutional Crowding-Out." *World Development* 28(10): 1719–33.

Casari, Marco, and Charles R. Plott. 2003. "Decentralized Management of Common Property Resources: Experiments with a Centuries-Old Institution." *Journal of Economic Behavior and Organization* 51(2): 217–47.

Chappell, Henry W., Jr., and William R. Keech. 1983. "Welfare Consequences of the Six-Year Presidential Term Evaluated in the Context of a Model of the U.S. Economy." *American Political Science Review* 77(1): 75–91.

Christ, Carl F. 1994. "The Cowles Commission's Contributions to Econometrics at Chicago, 1939-1955." *Journal of Economic Literature* 62(1): 30–59.

Clarida, Richard H., Jordi Gali, and Mark Gertler. 2000. "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory." *Quarterly Journal of Economics* 115(1): 147–80.

Converse, Philip. 1969. "Of Time and Partisan Stability." *Comparative Political Studies* 2(2): 139–71.

Downs, Anthony. 1957. *An Economic Theory of Democracy*. New York: Harper and Row.

Drazen, Allan. 2000. *Political Economy in Macroeconomics*. Princeton, NJ: Princeton University Press.

Engle, Robert F., David F. Hendry, and Jean-Francois Richard. 1983. "Exogeneity." *Econometrica* 51(2): 277–304.

Erikson, Robert S., Michael B. Mackuen, and James A. Stimson. 2002. *The Macro Polity*. Cambridge: Cambridge University Press.

Evans, George W., and Seppo Honkapohja. 2001. *Learning and Expectations in Macroeconomics*. Princeton, NJ: Princeton University Press.

Fisher, Franklin. 1966. *The Identification Problem in Econometrics*. New York: McGraw-Hill.

Freeman, John, and Daniel Houser. 1998. "A Computable Equilibrium Model for the Study of Political Economy." *American Journal of Political Science* 42(2): 628–60.

Freeman, John, Tse–min Lin, and John Williams. 1989. "Vector Autoregression and the Study of Politics." *American Journal of Political Science* 33(4): 842–77.

Fuhrer, Jeffrey. 1995. "The Persistence of Inflation and the Cost of Disinflation." *New England Economic Review*. Jan./Feb.: 3–16.

Fuhrer, Jeffrey, and George Moore. 1995. "Inflation Persistence." *Quarterly Journal of Economics* 110(1): 127–59.

Granato, Jim, Eran Guse, and M. C. Sunny Wong. 2008. "Learning from the Expectations of Others." *Macroeconomic Dynamics* 12(3): 345–77.

Granato, Jim, Melody Lo, and M. C. Sunny Wong. 2010. "The Empirical Implications of Theoretical Models (EITM): A Framework for Methodological Unification." *Política y gobierno* 17(1): 25–57.

Granato, Jim, and Frank Scioli. 2004. "Puzzles, Proverbs, and Omega Matrices: The Scientific and Social Consequences of the Empirical Implications of Theoretical Models (EITM)." *Perspectives on Politics* 2(2): 313–23.

Granato, Jim, and M. C. Sunny Wong. 2006. *The Role of Policymakers in Business Cycle Fluctuations*. Cambridge: Cambridge University Press.

Haavelmo, Trygve. 1944. "The Probability Approach in Econometrics." *Supplement to Econometrica* 12 (July): S1–115.

Heckman, James. 2000. "Causal Parameters and Policy Analysis in Economics: A Twentieth Century Retrospective." *Quarterly Journal of Economics* 115(1): 45–97.

Hendry, David. 1995. *Dynamic Econometrics*. New York: Oxford University Press.

Hibbs, Douglas. 1977. "Political Parties and Macroeconomic Policy." *American Political Science Review* 71(4): 1467–87.

Hotelling, Harold. 1929. "Stability and Competition." *Economic Journal* 39(153): 41–59.

Jasso, Guillermina. 2002. "Formal Theory." In *Handbook of Sociological Theory*, ed. Jonathan H. Turner. New York: Kluwer Academic/Plenum, 37–68.

Kedar, Orit. 2005. "When Moderate Voters Prefer Extreme Parties: Policy Balancing in Parliamentary Elections." *American Political Science Review* 99(2): 185–99.

Kramer, Gerald. 1983. "The Ecological Fallacy Revisited: Aggregate versus Individual-Level Findings on Economics and Elections and Sociotropic Voting." *American Political Science Review* 77(1): 92–111.

Krugman, Paul. 1994. "The Rise and Fall of Development Economics." In *Rethinking the Development Experience*, ed. Lloyd Rodwin and Donald A. Schon. Washington, DC: The Brookings Institution and Cambridge: The Lincoln Institute for Land Policy, 39–58.

Krugman, Paul. 1998. "Two Cheers for Formalism." *The Economic Journal* 108(451): 1829–36.

Kydland, Finn, and Edward Prescott. 1982. "Time to Build and Aggregate Fluctuations." *Econometrica* 50(6): 1345–70.

Leamer, Edward. 1983. "Let's Take the 'Con' Out of Econometrics." *American Economic Review* 73(1): 31–43.

Lijphart, Arend. 1984. *Democracies: Patterns of Majoritarian and Consensus Government in Twenty-One Democracies*. New Haven, CT: Yale University Press.

Lin, Tse-min. 1999. "The Historical Significance of Economic Voting, 1872-1996." *Social Science History* 23(4): 561–91.

Lucas, Robert E., Jr. 1976. "Econometric Policy Evaluation: A Critique." *Carnegie-Rochester Conference on Public Policy* 1(1): 19–46.

Manski, Charles. 1995. *Identification Problems in the Social Sciences*. Cambridge, MA: Harvard University Press.

McCallum, Bennett T. 1983. "On Nonuniqueness in Linear Rational Expectations Models: An Attempt at Perspective." *Journal of Monetary Economics* 11(2): 134–68.

McCallum, Bennett T. 2003. "Multiple-Solution Indeterminacies in Monetary Policy Analysis." *Journal of Monetary Economics* 50(5): 1153–75.

Mebane, Walter, and Jasjeet Sekhon. 2002. "Coordination and Policy Moderation at Midterm." *American Political Science Review* 96(1): 141–57.

Morgan, Mary. 1990. *The History of Econometric Ideas*. Cambridge: Cambridge University Press.

Morton, Rebecca B. 1999. *Methods and Models: A Guide to the Empirical Analysis of Formal Models in Political Science*. New York: Cambridge University Press.

Ostrom, Elinor. 2010. "Revising Theory in Light of Experimental Findings." *Journal of Economic Behavior and Organization* 73(1): 68–72.

Ostrom, Elinor, James Walker, and Roy Gardner. 1992. "Covenants with and without a Sword: Self-Governance Is Possible." *American Political Science Review* 86(2): 404–17.

Pearl, Judea. 2000. *Causality: Models, Reasoning, and Inference*. Cambridge: Cambridge University Press.

Poteete, Amy R., Marco A. Janssen, and Elinor Ostrom. 2010. *Working Together: Collective Action, the Commons, and Multiple Methods in Practice*. Princeton, NJ: Princeton University Press.

Powell, Robert. 1999. *In the Shadow of Power*. Princeton, NJ: Princeton University Press.

Signorino, Curt. 1999. "Strategic Interaction and the Statistical Analysis of International Conflict." *American Political Science Review* 93(2): 279–97.

Sims, Christopher. 1980. "Macroeconomics and Reality." *Econometrica* 48(1): 1–48.

Suzuki, Motoshi, and Henry W. Chappell Jr. 1996. "The Rationality of Economic Voting Revisited." *Journal of Politics* 58(1): 224–36.

Taylor, John. 1993. "Discretion versus Policy Rules in Practice." *Carnegie-Rochester Conference Series on Public Policy* 39(1): 195–214.

Taylor, John. 1999. "A Historical Analysis of Monetary Policy Rules." In *Monetary Policy Rules*, ed. J. B. Taylor. Chicago: University of Chicago Press, 319–41.

Wagner, R. Harrison. 2007. *War and the State: The Theory of International Politics*. Ann Arbor: The University of Michigan Press.

Wang, Miao, and M. C. Sunny Wong. 2005. "Learning Dynamics in Monetary Policy: The Robustness of an Aggressive Inflation Stabilizing Policy." *Journal of Macroeconomics* 27(1): 143–51.