A FRAMEWORK FOR UNIFYING FORMAL AND EMPIRICAL ANALYSIS*

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Abstract:
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 unifying formal modeling and applied statistical analysis is proposed. We argue *methodological unification* leverages the mutually reinforcing properties of formal and applied statistical analysis to produce greater transparency in relating theory to test. A 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. We demonstrate the various elements of this EITM framework with examples from voting behavior, the political economy of macroeconomic policy, 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." (Aldrich 1980, 4).

"...there is still far too much data analysis without formal theory – and far too much formal theory without data analysis." (Bartels and Brady 1993, 148).

1. Introduction

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 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). A larger and 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]

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[1] We center the discussion on formal analysis and applied statistical analysis. Formal analysis refers to deductive modeling that can include a theorem and proof presentation or computational modeling that requires the assistance of 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 we develop in this paper — possesses important attributes that aid in falsification and, ultimately, scientific cumulation. Formal models, for example, force clarity 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 — provide 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 *identification* and *invariance* is 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 (non)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

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 that improve upon the use of older techniques. But, as this process took hold, the creation of methodologies that isolated and identified structural parameters became secondary to the use of hand-me-down applied statistical techniques that end up doing things such as manipulating standard errors and their associated *t*-statistics.[3]

Even for scholars who are sensitive to establishing robustness in their applied statistical results find the tools available are inadequate when used in isolation. For example, augmenting the applied statistical tests with *Extreme Bounds Analysis* (EBA) (Leamer 1983) provides a check on parameter stability, but the test is ex-post and 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 when an applied statistical model is respecified the entire model is subject to change. All predictions are fragile in that sense, but without apriori use of equilibrium conditions (e.g., stability conditions) in a formal model, the parameter "changes" in a procedure such as EBA are of unknown origin.

In a very real sense the emphasis on applied statistical technique as opposed to identifying structural parameters can be traced back to a pedagogical tradition that involved an aversion to mathematical modeling (Arrow 1948). But, this aversion came with a cost. Absent mathematical

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a relationship (called "mechanism") that remains invariant 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). In short, the terms invariant or invariance, when applied to applied statistical models, centers on whether a relation (signified by a parameter) remains constant in the face of a treatment (or policy) shift.

[3] Heckman's (2000) defines *structural causal effects* as "the direct effects of the variables in the behavioral equations" 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." (page 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 non-linear 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" (page 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 a model's forecast of a dependent variable $(\hat{y})$. For a technical treatment of these two concepts see Engle, Hendry, and Richard (1983).

modeling, the discipline lacks a basic tool to identify causal mechanisms.

The scientific consequences of this methodological status quo are far reaching. Because the usual methodological approach cannot produce identified and invariant parameter estimates, policy recommendations, for example, lack a scientific basis since there is no useful information regarding the mechanism(s) on policy and treatment effectiveness. Among other things, current practices, because they are 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 the shortcomings in some current methodological practices, 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 suitable for valid hypothese testing and to support the identification of invariant parameter estimates. This, in turn, allows for both ex-post and ex-ante predictions.[6]

Methodological unification is not new. We propose a framework which is consistent with what has been termed *empirical implications of theoretical models* (EITM).[7] Prior incarnations include scholars from organizations such as the Cowles Commission.[8] We build on the Cowles

[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, for example, 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.

[7] 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.

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

Commission approach and then place an emphasis on *developing behavioral and applied statistical analogues and linking these analogues*.[9]

This paper 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. Section 3 demonstrates — 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. Section 4 summarizes these results and provides some concluding comments on how EITM can change evaluation procedures and apply to any number of research subfields.

2. A Framework for Methodological Unification

2.1. Background and Challenges

Methodological unification does not guarantee a model is correct. Rather, it provides analytical transparency to support cumulative scientific practice. In more concrete terms we use the EITM framework for purposes of attaining valid inference and prediction when we specify, say, a relation between two variables, X and Y. For example, it is well known that when we specify a variable Y is a function of variable X, the statistical "tests" that estimate 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 that define the relation between X and Y. In particular, 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 are caused by an unknown common factor W, but there is no causality between X and Y. In empirical studies, too often researchers end up inferring the significant correlation to be the true causal relation (i.e., result "a").

[9] In contrast to operationalization, an analogue can be thought of as a device in which a concept is represented by continuously variable — and measurable — quantities. Analogues 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. Analogues also emphasize measurement validity — the relation between a measure and the (unmeasured) concept it is meant to represent.

Of course, there have been numerous applied statistical attempts to address these challenges to inference and prediction. In any econometric text one can find solutions such as instrumental variables (IV) estimation and different robustness checks, including EBA by Leamer (1983). However, these applied statistical tools, when used in isolation, lack power since they are not linked to a formal model.

It is true that researchers can argue that a formal model is also an approximation of the relation between X and Y. This argument is correct since a formal model is not a true model. Yet, a formal model is a "map" that systematically sorts out other confounding factors and deals with the inferential challenges in relating X to Y.[10] If the theoretical predictions *are inconsistent* with the empirical tests, we then know that the theory as represented in the formal model needs to be reconsidered.

There have been systematic attempts to address these challenges to inference. Academic research exists that provides a scientific foundation for unifying formal and empirical analysis. The Cowles Commission, for example, has established conditions in which structural parameters can be identified within a model. It was the Cowles Commission that explored the differences between structural and reduced-form parameters. Conditions for parameter identifiability were introduced to aid in this differentiation. Along with their work on structural parameters, the Cowles Commission also gave formal and empirical specificity to issues such as exogeneity and policy invariance (Aldrich 1989; Morgan 1990; Christ 1994; and Heckman 2000).[11]

These contributions rested, in part, on a scientific vision that involved 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). Further, this viewpoint meant that formal models, when related to an applied statistical model, could be interpreted as creating a sample draw from the underlying law of motion. A well-grounded test

[10] See Chapter 1 in Wagner (2007) for a general discussion on the utility of the formal modeling process.

[11] With the passage of time, the Cowles Commission's approach has been criticized. Ironically, the effort to satisfy mathematical conditions for parameter "identification" led to practices that undermined the promise of methodological unification. In particular, Sims (1980) pointed out the "incredible" theoretical restrictions that were imposed.

of a theory could be accomplished by relating a formal model to an applied statistical model and testing the applied statistical model. This methodological approach was seen, then, as a valid representation and examination of underlying processes in existence.

While sharing some similarities with the Cowles Commission approach, the EITM framework we propose possesses some modifications. First, if one were to strictly adhere to the Cowles Commission approach, we would forego the chance of modeling new uncertainty created by shifts in behavioral traits. The scientific 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 place emphasis on modeling human behavior so that new uncertainty created by shifts in behavioral traits such as public tastes, attitudes, expectations, and learning can be 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.[12] We place emphasis on the mutually reinforcing properties of formal and empirical analysis.

A final and related point on model specification relates to the critiques of the structural approach leveled by Sims (1980). It is well known that reduced form estimates are not identified. The practice of finding ways to identify models can lead to "incredible" theoretical specifications (Sims 1980; Freeman, Lin, and Williams 1989). The proposed EITM framework, by way of adding behavioral concepts and analogues, can address Sims' criticisms in a theoretically meaningful way. Analogues, in particular, have important scientific importance since they hold the

[12] This debate about general and partial equilibrium model building can be traced back to at least the 1800s. See Friedman (1949, 1954) for descriptions and evaluation of "Walrasian" and "Marshallian" model building practice.

promise of *operationalizing mechanisms*.

Operationalizing causal 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 can be seen in the work of Converse (1969). He advanced the theory that strength of 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 made use of the following analogue: the Markov chain. This particular analogue allowed for a particular dynamic prediction that he tested against actual voting data.

2.2. The EITM Framework

The framework is summarized as follows:

1. Unify Theoretical Concepts and Applied Statistical Concepts

Given that human beings are the agents of action, concepts reflect overarching social and behavioral processes. Examples include (but are not limited to):

- decision making
- bargaining
- expectations
- learning
- social interaction

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
- simultaneity

2. Develop Behavioral (Formal) and Applied Statistical Analogues

To link concepts with tests, we need analogues. An analogue is a device in which a concept is represented by continuously variable — and measurable — quantities. 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
- 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
- multi-stage estimation (e.g., two-stage least squares)

3. 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 consideration is determine the appropriate statistical concept and analogue to test the theoretical relationship. Consider a basic Downsian model of voting. Voters decide to vote for one of the parties to maximize their utilities. This theoretical concept/analogue can be unified with the applied statistical concept, nominal choice, and its analogue, discrete choice modeling.

3. Applying the EITM Framework

In this section, we discuss EITM examples in detail. These examples contain to varying degrees the basic steps of the EITM framework. We also leverage the respective author(s) EITM approach to show how their respective models and tests can be extended.

3.1. Example 1: Voting with Compensational and Representational Preferences

The act of voting provides a useful window into methodological unification. Hotelling (1929) and Downs (1957) argue that 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 a 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.[13] While the voting literature finds some empirical support for the proximity model, Kedar (2005) believes this effect would be reduced if the institutional environment involves more power-sharing.

3.1.1. The Relation Between Decision Theory and Discrete Choice Models

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:

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

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 for 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 to result from party j.

Assuming that party positions can 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 that the policy outcome may deviate

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

from their ideal point if party j is not elected, then the utility of voter i pertaining to party j becomes:

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

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, $\left(v_i - P_{-p_j}\right)^2 > (v_i - P)^2$, then voter i will gain positive utility when party j is involved in the policy formation process (i.e., $U_{ij} > 0$). However, if the inclusion of party j makes the policy outcome increase in distance from voter i's idea point such that $\left(v_i - P_{-p_j}\right)^2 < (v_i - P)^2$, then the utility of voter i for party j is negative.

Now assume that voter i has expectations concerning party j that are based on the weighted average of both the party's relative position and its contribution to policy outcomes. With this analogue for expectations, voter i's utility for party j can now be written as:

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

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

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

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

When $\gamma \to 1$ (representational voting), we have:

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

But, when $\gamma \to 0$ (compensational voting), we have:

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

and the policy outcome would be:

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

3.1.2. Unifying and Evaluating the Analogues

In (7) thru (9), voters make an optimal voting decision based on representational (proximity) and compensational voting considerations. These two considerations reflect the levels of political bargaining in different institutional systems. In majoritarian systems, where the winning party is able to implement its ideal policy with less need for compromise, voters place greater value on γ and vote for the party positioned closest to their ideal position. However, in the case where institutional power sharing (γ is small) exists, voters select a party whose position is further from their ideal positions to draw the collective outcome closer to their, the voter's, ideal point.

Kedar tests these empirical implications using survey data from Britain, Canada, Netherlands, and Norway:

Hypothesis 1: *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).*

Hypothesis 2: *The pure proximity model ($\gamma = 1$) does not sufficiently represent voting behavior.*

For Hypothesis 1, Kedar (2005) first identifies the institutional features of Britain, Canada, Norway, and the Netherlands. Using the indicators of majoritarianism and power-sharing in Lijphart (1984), she concludes that Britain and Canada are more unitary whereas the Netherlands and Norway are more consensual.

Methodological unification occurs when Kedar derives an empirical analogue for discrete choice, the log-likelihood multinomial model based on equation (5), and estimates issue voting in four political systems using three measures: i) seat shares in the parliament; ii) vote shares; and iii) portfolio allocation in government.

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 that in the consensual systems (i.e., the Netherlands and Norway). Hypothesis 2 is tested using a likelihood ratio test. The results show that, in all four political systems, compensational voting behavior exists in the survey data. The pure proximity model is an insufficient explanation.

3.1.3. 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 and/or policy outcome 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 would amend 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.

3.2. Example 2: Economic Voting

A substantial economic voting literature exists. Consider a sub-sample that starts with Kramer (1983) and extends to work that includes Alesina and Rosenthal (1995), Suzuki and Chappell (1996), and Lin (1999). A feature of these studies are the refinements in voter sophistication and applied statistical tests. In the former regard, voters are now modeled to have the capability to deal with the uncertainty in assigning blame or credit toward incumbents for good or bad economic conditions. For the latter, applied statistical tests now include some of the more advanced tools in time series analysis. In this example we focus on Alesina and Rosenthal (1995).

3.2.1. The Relation Between Expectations, Uncertainty, and Measurement Error

We first start with the formal model that has the behavioral concepts of expectations and uncertainty. Alesina and Rosenthal (1995) provide the formal model (pages 191-195). Their model of economic growth is based on an expectations augmented aggregate supply curve:

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

where $\hat{y}_t$ represents the rate of economic growth (GDP growth) in period $t,$ $\hat{y}^n$ is the natural economic growth rate, π_t is the inflation rate at time $t,$ and π_t^e is the expected inflation rate at time t formed at time $t-1.$

With voter inflation expectations established we now turn to the concept of uncertainty. Let us assume that voters want to determine whether to attribute credit or blame for economic growth (y_t) outcomes to the incumbent administration. Yet, voters are faced with the uncertainty in determining what part of the economic outcomes is due to incumbent "competence" (i.e., policy acumen) or simply good luck.

If we base the uncertainty, in part, from equation (10), then equation (11) presents the analogue. It is commonly referred to as a "signal extraction" or measurement error problem:

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

The variable ε_t represents the shock that is comprised of the two unobservable characteristics noted above — competence or good luck. The first, represented by η_t, reflects "competence" that can be attributed to the incumbent administration. The second, symbolized as ξ_t, are shocks to growth that are beyond administration control (and competence). Both η_t and ξ_t have zero mean with variance(s) σ_η^2 and σ_ξ^2 respectively.

Note also that competence can persist *and support* reelection. This feature can be characterized as an MA(1) process:

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

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

If we reference equation (10) again, let us assume that voters' judgements include a general sense of the average rate of growth $(\hat{y}^n)$ and the ability to observe actual growth $(\hat{y}_t)$. Voters can evaluate their difference $(\hat{y}_t - \hat{y}^n)$. Equation (10) also implies that when voters predict inflation with no systematic error (i.e., $\pi_t^e = \pi_t$), the result is non-inflationary growth that does not adversely affect real wages.

Next, we tie economic growth performance to voter uncertainty. We formalize how economic growth rate deviations from the average can be attributed to administration competence or fortuitous events:

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

Equation (13) shows that when the actual economic growth rate is greater than its average or "natural rate" (i.e., $\hat{y}_t > \hat{y}^n$), then $\varepsilon_t = \eta_t + \xi_t > 0$. Again, the voters are faced with uncertainty in distinguishing the incumbent's competence (η_t) from the stochastic economic shock (ξ_t). However, 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, substitute equation (12) in (13):

$$\mu_t + \xi_t = \hat{y}_t - \hat{y}^n - \rho\mu_{t-1}. \tag{14}$$

We now determine the optimal estimate of competence, η_{t+1}, when the voters only see $\hat{y}_t$. We demonstrate this result by making a one-period forecast of equation (12) and then solve for its expected value (conditional expectation) at time t:

$$E_t\left(\eta_{t+1}\right) = E_t\left(\mu_{t+1}\right) + \rho E\left(\mu_t | \hat{y}_t\right) = \rho E\left(\mu_t | \hat{y}_t\right), \tag{15}$$

where $E_t\left(\mu_{t+1}\right) = 0$. Using this analogue for expectations in equation (15), we see that competence, η_{t+1}, can be 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 observable $\hat{y}_t$ (at time t) from equation

(14).

Using the method of recursive projection and equation (14) we illustrate how the behavioral analogue for expectations is linked to the empirical analogue for measurement error (an error-in-variables "equation"[14]):

$$E_t\left(\eta_{t+1}\right) = \rho E\left(\mu_t|\hat{y}_t\right) = \rho\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\xi^2}\left(\hat{y}_t - \hat{y}^n - \rho\mu_{t-1}\right), \tag{16}$$

where $0 < \rho\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_\xi^2} < 1$. Equation (16) shows that voters can forecast competence using the difference between $\hat{y}_t - \hat{y}^n$, but also the "weighted" lag of μ_t $\left(\text{i.e., } \rho\mu_{t-1}\right)$.

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 a proportion of competence that voters are able to interpret and observe. The behavioral implications are straightforward. If voters interpret that the variability of economic shocks come 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 the incumbent's competence.

3.2.2. Unifying and Evaluating the Analogues

Alesina and Rosenthal (1995) test the empirical implications of their theoretical model with U.S. data on economic outcomes and political parties for the period 1915 to 1988. They first use the growth equation (10) to collect the estimated exogenous shocks (ε_t) in the economy. With these estimated exogenous shocks, they then construct their variance-covariance structure. Since competence (η_t) in equation (12) follows an MA(1) process, they hypothesize that a test for incumbent

[14] The traditional applied statistical view of measurement errors is that the correlated signs of the measurement errors among independent variables can lead to inappropriate signs for regression coefficients. This is exactly what EITM and methodological unification accomplish. The theory — the formal model — implies an applied statistical model with measurement error. Consequently, one can examine, with a unified approach, the joint effects and identify the cause. Applied statistical tools cannot untangle conceptually distinct effects on a dependent variable. We hasten to add that Friedman (1957) and Lucas's (1973) substantive findings would not have been achieved had they just treated their research question as a pure measurement error problem requiring only an applied statistical analysis (and "fix" for the measurement error) that focused on a significant *t*-statistic.

competence, as it pertains to economic growth, can be performed using the covariances between the current and preceding year. The specific test centers on whether the changes in covariances with the presidential party in office are statistically larger than the covariances associated with a change in presidential parties. They report null findings (e.g., equal covariances) and conclude that there is little evidence to support that voters are retrospective and use incumbent competence as a basis for support.

3.2.3. 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 devise a signal extraction problem. While the empirical model resembles an error-in-variables specification, testable by dynamic methods such as rolling regression (Lin 1999), instead they estimate the variance-covariance structure of the residuals.

Alesina and Rosenthal's model can be tested in other ways. We can, for example, leverage equation (16) and account for other forms of uncertainty. Suzuki and Chappell (1996) (and many others) provide tests of that nature without any formalization. Here we leverage the formalization of Alesina and Rosenthal and link it to Suzuki and Chappell's test.

Now, to see the relation between this statement and Alesina and Rosenthal's model, recall that the competence analogue (η_t) in their model is set up to be part of the aggregate supply (AS) shock ($\varepsilon_t = \eta_t + \xi_t$). Accordingly, competence (η_t) is defined as the incumbent's ability to promote economic growth via policies along the AS curve. Let us assume voters are sophisticated enough so as to not reward incumbent politicians for unusual economic growth that is the result of an aggregate demand (AD) policy or shock. Rather, voters accept that AS policy provides the source for long-lasting (permanent) economic growth since it adds to productive capacity.[15] On the other hand, AD policy can at best produce temporary output gains and it eventually leaves the

[15] AS policies can provide positive technology shocks. These policies range from government protection of property rights to the provision of public infrastructure.

economy with higher inflation.

By leveraging the EITM framework, the these two studies would lead to direct relation between the parameters of the formal and empirical models. In particular, one could evaluate the competence equation (16) with the empirical tests and measures Suzuki and Chappell use for permanent and temporary changes in economic growth.

3.3. Example 3: The Political Economy of Monetary Policy

In the post World War II era there have been several regime shifts in macroeconomic policy. More recently, there has been a renewed emphasis on the study of overall monetary policy effectiveness (see Bernanke et. al., 1999 and Taylor 1999). One particular line of research has focused on the use of interest rate rules in new Keynesian models (see Clarida, Gali, and Gertler 2000). More recently, Granato and Wong (2006) have used a model with new Keynesian properties to determine the relation between inflation stabilizing policy, inflation persistence and volatility, and business cycle fluctuations.

3.3.1. The Relation between Expectations, Learning, and Persistence

In this example we demonstrate an EITM relation the between formal and behavioral concepts, expectations and learning, with the applied statistical concept of persistence. Substantively speaking, the model and test will show how the implementation and aggressiveness of maintaining an inflation target affects inflation persistence. 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 periods of aggressive inflation-stabilizing policy and inflation persistence.[16]

The model is a small structural model of macroeconomic outcomes and policy in the Cowles Commission tradition. The model, containing behavioral analogues for expectations and learning, has a unique and stable *rational expectations equilibrium* (REE) (Evans and Honkapohja 2001). The stability (E-stability) conditions are important because they have direct implications on how,

[16] We define an aggressive inflation-stabilizing policy as one that includes a willingness to respond forcefully to deviations from a prespecified implicit or explicit inflation target.

and if, agents learn from policymakers.[17] Under the REE, aggressive implementation of an inflation target guides agents to the stable equilibrium and reduces inflation persistence.

The model assumes a two-period contract. For simplicity, prices reflect a 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:[18]

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

where p_t is the logarithm of the price level, and x_t is the logarithm of the wage level at period t. In addition, agents are concerned with 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, $E_t\left(x_{t+1} - p_{t+1}\right)$ is the expectation of the future real wage level at time $t+1$ formed at time t, and $z_t = y_t - y_t^n$ 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 $(p_t - p_{t-1})$.

With this definition substitute equation (18) into equation (17) and obtain:

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

where $E_t\pi_{t+1}$ is the expected inflation rate over the next period and u_{1t} is $iid\left(0, \sigma_{u_1}^2\right)$. Equation (19) captures the main characteristic of inflation persistence. Since agents make plans about their real wages over 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 on output relative

[17] Adaptive learning allows agents to achieve the REE within the context of a stochastic (updating) process that is typically represented via adaptive learning. Agents do not initially obtain the REE, but they attempt to learn the stochastic process by updating their forecasts (expectations) over time as new information becomes available.

In more technical terms, adaptive learning is used so that agents update parameters of a forecasting rule — perceived law of motion (PLM) — associated with the stochastic process of the variable in question to learn an REE. This process requires a condition establishing convergence to the REE — the E-stability condition. The E-stability condition determines the stability of the equilibrium in which the PLM parameters adjust to the implied actual law of motion (ALM) parameters. See Evans and Honkapohja (2001) for details.

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

to natural output (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 $iid\left(0, \sigma^2_{u_2}\right)$, and $\varphi > 0$.

We assume that policymakers use an interest rate rule — the Taylor rule (Taylor 1993) — when conducting monetary policy:

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

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

The equilibrium inflation rate can be found by taking the reduced form of the system. It is derived by substituting equation (21) into equation (20). Next solve for z_t and then put that result into equation (19). If we solve that expression for π_t the result is:

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

where:

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

Equation (22) shows that current inflation depends on the first-order lag of inflation and also expected inflation. When (22) is "closed," the *minimum state variable* (MSV) solution can be expressed as an AR(1) process. Of course, the AR(1) process is the empirical analogue for persistence.

Methodological unification occurs when we solve for the REE since this will involve merging the behavioral analogue of expectations with the empirical analogue for persistence. Simply 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 $A = \Gamma_0 (1 - \Gamma_2 B - \Gamma_2)^{-1}$, $B = \left(1 \pm \sqrt{1 - 4\Gamma_1\Gamma_2}\right)(2\Gamma_2)^{-1}$, 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.

This solution also highlights an important formal modeling and analogue attribute. Because we are using an adaptive learning analogue, one potential confounding factor we are alerted to, with important empirical implications, is the nature of the coefficient of lagged inflation, B. This parameter is a quadratic where the two values are defined as:

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

Based on the behavior of the model's parameters, we determine the properties of the quadratic solutions and solve for the relation between aggressive inflation-stabilizing policy (α_π) and inflation persistence (B).

Granato and Wong (2006) show that B^- is a unique stationary solution when $\alpha_\pi \geq 0$. Behaviorally speaking, when policymakers adopt an aggressive inflation-stabilizing policy, a stationary AR(1) solution can be obtained (i.e., B^-) while an explosive AR(1) solution (i.e., B^+) would also be possible. However, the technique of adaptive learning (McCallum 2003) serves as an important selection criteria (i.e., determining stable solutions) where only the stationary solution (i.e., B^-) is attainable and that the explosive solution (i.e., B^+) is not possible. In other words, if agents learn the equilibrium in an adaptive manner and they form expectations as new data becomes available over time, B^- is the only learnable (E-stable) equilibrium when policymakers aggressively stabilize inflation (i.e., $\alpha_\pi > 0$).

As a final matter, Granato and Wong (2006) point out that equation (23) represents the AR(1) process of the inflation rate. The empirical implications of the model — and ex-ante prediction — as represented in equation (23) is that an increase in α_π reduces persistence under B^-. The stability condition(s) show that this hypothesis is possible in this model.

3.3.2. Unifying and Evaluating the Analogues

To test the relation between the policy parameter(s) and inflation persistence quarterly U.S. data are used (for the period 1960:I to 2000:III). According to the model, inflation persistence should fall significantly under an aggressive inflation-stabilizing policy. From equation (23) we estimate a first-order autoregressive process (i.e., AR(1)) of the U.S. inflation rate. As a consequence of the more aggressive inflation-stabilizing policy stance during the Volcker-Greenspan period (August, 1979 through August, 2000), we expect that the inflation-persistence parameter (B_t) in the Volcker-Greenspan period to be smaller (statistically) relative to the pre-Volcker period.

(Figure 1 About Here)

The formal model predicts that a positive inflation stabilization policy parameter (α_π) reduces inflation persistence, B_t. We also estimate equation (21) in order to contrast the parameter movements in α_π and α_y.[19] Figure 1 provides point estimates of inflation persistence (B_t) and policy rule parameters, α_π and α_y, for a 15-year rolling sample starting in the first quarter of 1960 (1960:I). The results show that after 1980, inflation persistence starts falling. Figure 1 also shows that both α_π and α_y de-emphasize inflation and output stability in approximately 1968. Prior to 1968, countercyclical policy emphasize output stability $(\alpha_y > 0)$. Aggressive inflation stabilizing policy occurs only after 1980, when $\alpha_\pi > 0$.

3.3.3. Leveraging EITM and Extending the Model

The model presented here, in some respects, is a mirror of the model proposed by Kedar (2005). Kedar's model emphasizes micro foundations but makes assumptions about voter expectations. However, in this example, there is 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_y) could be made endogenous to political and social factors, including (but not limited to) partisan-

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

ship, elections, and social interaction where information levels are heterogeneous (Granato, Guse, and Wong 2008).

3.4. 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. For example, age, the square of age, education level, and the square of education level are used. However, there is weak theoretical justification for the squared terms. The variables are included typically for the sake of a better statistical fit within sample. Achen (2006) uses an EITM framework that not only provides an estimated model with a theoretical interpretation (i.e., no “squared" variables) but he also shows that his “double-probit” model is a better fit to the actual data.

3.4.1. The Relation between Decision Theory, Learning, and Discrete Choice

In his theoretical model, Achen assumes a voter receives positive 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). He also assumes that the voter does not have perfect foresight on the true value of the party differences. Instead the voter "learns" the expected value based on his information set (updated by a Bayesian mechanism).

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

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

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

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

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

For theoretical convenience, Achen (2006) assumes that $\hat{u}_{n+1}$ is non-negative: the voter only votes for the party valued higher than another. The probability of the voter making a correct decision is when $u_{n+1} \geq 0$, is therefore:

$$\Pr(\text{correct}) = 1 - F(0\,|I\,), \tag{26}$$

whereas the probability of an incorrect decision is:

$$\Pr(\text{incorrect}) = F(0\,|I\,). \tag{27}$$

If we assume a voter will vote only if the probability of making a correct decision exceeds that of making an incorrect decision, then we can present the expected benefit of voting, $E(D_{n+1})$, in the next period given by the difference between the two probabilities:

$$\begin{aligned} E(D_{n+1}) &= \alpha\left[\Pr(\text{correct}) - \Pr(\text{incorrect})\right] \\ &= \alpha\left[1 - F(0\,|I\,) - F(0\,|I\,)\right] \\ &= \alpha\left[1 - 2F(0\,|I\,)\right], \end{aligned}$$

where $\alpha > 0$ represents the weight (importance) of voting.

Following Downs (1957), Achen (2006) suggests that the utility of voting in period $n+1$ is the difference between the expected benefit of voting, $E(D_{n+1})$, and the cost of voting:

$$\begin{aligned} U &= E(D_{n+1}) - c \\ &= \alpha\left[1 - 2F(0\,|I\,)\right] - c, \end{aligned} \tag{28}$$

where c is the cost of voting. Assuming that u_{n+1} is normally distributed, we can transform equation (28) to:

$$U = \alpha\left[1 - 2\Phi\left(-\hat{u}_{n+1}/\sigma_{n+1}\right)\right] - c, \tag{29}$$

where $\Phi(\cdot)$ is a standard normal cdf. Since $\Phi(-z) = 1 - \Phi(z)$, we can rewrite equation (29) as:

$$U = \alpha\left[2\Phi\left(\hat{u}_{n+1}/\sigma_{n+1}\right) - 1\right] - c. \tag{30}$$

Achen argues that voters use a Bayesian updating procedure (assuming a normal distribution of u_{n+1}) and voters "learn" the true u_{n+1} based on: i) the difference(s) in party identification (PID) from the last period, u_n; ii) the campaign information, c_{n+1}; and iii) a trusted information source, $q_{n+1,}$ received from a political party.[20]

[20] Achen (2006) also suggests that *trusted information* can also come from the voter's spouse or some interest groups.

The learning process can now be characterized. The posterior mean as it pertains to party identification is:

$$u_t = \delta + v_t, \tag{31}$$

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

$$\hat{\delta}_n = \frac{h_1 \bar{u}_n}{h_0 + h_1}, \tag{32}$$

where $\bar{u}_n = \frac{\Sigma u_t}{n}$ 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 also receives new information from the party campaign:

$$c_{n+1} = u_{n+1} + \theta_{n+1} + \epsilon_{n+1}, \tag{33}$$

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

Based on the posterior mean of PID at time n (i.e., $\hat{\delta}_n$, in equation (32)), the campaign information, c_{n+1}, in equation (33), and the trusted information source, q_{n+1}, at time $n+1$, we can use the same Bayesian updating procedure to update the posterior mean of the PID difference $\hat{u}_{n+1}$:

$$\hat{u}_{n+1} = \frac{h_c \hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{h_c + h_\tau + h_q}, \tag{34}$$

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

$$\sigma_{n+1}^2 = \frac{1}{h_c + h_\tau + h_q}. \tag{35}$$

To derive the utility function of voting with the feature of Bayesian learning, we substitute equations (34) and (35) into equation (30):

$$\begin{aligned} U &= \alpha \left[2\Phi \left(\left(\frac{h_c \hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{h_c + h_\tau + h_q} \right) \Big/ \left(\frac{1}{(h_c + h_\tau + h_q)^{1/2}} \right) \right) - 1 \right] - c \\ &= \alpha \left[2\Phi \left(\frac{h_c \hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{(h_c + h_\tau + h_q)^{1/2}} \right) - 1 \right] - c. \end{aligned} \tag{36}$$

3.4.2. Unifying and Evaluating the Analogues

To estimate the determinants of voting turnout, Achen presents the probit model which follows from equation (36). 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 can construct the probability that U^* is less than or equal to U based on the normal cdf:

$$\begin{aligned}
&\Pr\left(vote = 1\,|\text{PID, Campaign Information, and Trusted Source}\right) \\
&= \Pr\left(U^* \leq U\right) \\
&= \Phi\left(\alpha\left[2\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{\left(h_c + h_\tau + h_q\right)^{1/2}}\right) - 1\right] - c\right). \qquad (37)
\end{aligned}$$

In equation (37), we can see that 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.

Using maximum likelihood estimation, Achen (2006) estimates simultaneously two normally distributed cdf's in equation (37): a *double-probit*. To interpret the coefficients, we first focus on the inner normal cdf. If the voter does not have accurate information about the party, that is, $\left(h_c + h_\tau + h_q\right)^{1/2} = 0$, then $\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{\left(h_c + h_\tau + h_q\right)^{1/2}}\right) = \Phi\left(0\right) = 1/2$. In this case equation (37) is equivalent to:

$$\begin{aligned}
\Pr\left(vote = 1\,|I\right) &= \Phi\left(\alpha\left[2\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{\left(h_c + h_\tau + h_q\right)^{1/2}}\right) - 1\right] - c\right) \\
&= \Phi\left(\alpha\left[2\Phi\left(0\right) - 1\right] - c\right) \\
&= \Phi\left(-c\right). \qquad (38)
\end{aligned}$$

Given that c is the z-value which ranges between 2 or 3, then $\Phi\left(-c\right)$ 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, $\left(h_c + h_\tau + h_q\right)^{1/2} \rightarrow \infty$, then $\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{\left(h_c + h_\tau + h_q\right)^{1/2}}\right) = \Phi\left(\infty\right) \rightarrow 1$. Therefore, we have:

$$\begin{aligned}
\Pr\left(vote = 1\,|I\right) &= \Phi\left(\alpha\left[2(1) - 1\right] - c\right) \\
&= \Phi\left(\alpha - c\right). \qquad (39)
\end{aligned}$$

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

To estimate equation (37), Achen uses the variables, systemtime and education, as the proxies for PID, $\hat{\delta}_{n,}$ and campaign information, c_{n+1}, respectively. Systemtime is defined as the voter's age subtracted from 18 years. Education is measured as the level of education that the voter receives which is classified in 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 that the age of voters (systemtime) shows the strength of PID while voters' education level are attributes in understanding campaign information.[21] Based on the availability of data, the theoretical model (37) is used to estimate the following double-probit model:

$$\Pr(vote = 1) = \Phi\left(\lambda_0 + \lambda_1\left[2\Phi\left(\beta_1 systemtime + \beta_2 education\right) - 1\right]\right), \tag{40}$$

where the empirical component, $\Phi\left(\beta_1 systemtime + \beta_2 education\right)$, is theoretically equivalent to the Bayesian learning procedure $\Phi\left(\frac{h_c\hat{\delta}_n + h_\tau c_{n+1} + h_q q_{n+1}}{(h_c + h_\tau + h_q)^{1/2}}\right)$, and λ_0 and λ_1 are equivalent to $-c$ and α in equation (37), respectively.

To test his EITM relation, 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 models has a better fit. Equally important, when the focus turns to the parameters in Achen's model he finds the empirical estimates are consistent with the theoretical predictions of his model (see (37)). For example, he finds that 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.

[21] Note, there is no proxy measure used for trusted source. Therefore q_{n+1} is dropped from equation (37).

3.4.3. Leveraging EITM and Extending the Model

Achen uses the behavioral concepts of rational decision making and learning. His behavioral analogues are basic 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 that 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.

Achen's EITM model can be leveraged in a number of ways. 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 voter's memory lasts. We know, for example, that in matters of policy, retrospective judgements by the public can have a profound influence on policy effectiveness. Equally important, we have analogues for persistence that can be linked to a formal extension of the model.

4. Summary and Discussion

In this paper we demonstrate a framework that provides behavioral explanations suitable for statistical inference and prediction. The EITM framework we propose shares the Cowles Commission emphasis on structural parameters and devising ways to identify them. Yet, EITM not only builds on the Cowles Commission's work to recover a model's parameters, but it also addresses both Lucas' (1976) and Sims' (1980) critiques of conventional structural estimation practice.

A way to address these criticisms is to ensure analogues are tied to concepts. We then 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.

The EITM framework proposed here raises new challenges. Because this framework places emphasis on *parameters* as a building block for ex-post and ex-ante prediction, one issue is how to deal with *overparameterization*. This threat to the validity of our inferences is exemplified in the macroeconomic policy example (e.g., Example 3). In that example, we work out a mechanism between the policy parameter (α_π) and the persistence parameter (B_t), but also note there are other free parameters in the expression for the persistence parameter. The potential shifts in the remaining free parameters may be influencing the results.[22]

The fact that we are now focused on overparameterization and the issue of free parameters is indicative of the scientific potential of methodological unification. Still, the existence of free parameters constitutes a threat to valid hypothesis testing and inference. Consider Example 3 again. Because we have not worked out the behavior of certain parameters in the system, we are open to the criticism that an autonomous shift in one of the free parameters confounds the link between theory and test. Moreover, the policy example suggests the EITM framework must be extended to include a means "to map" as many parameters in the system as possible. The framework is flexible enough to accomplish this task. The issue will be making appropriate use of additional formalization — informed by empirical and contextual evidence — to provide greater specificity on the range of magnitudes that the previously free parameters take and whether all free parameters are subject to some restriction.

From these challenges to inference, we conclude that EITM can be thought of as having two levels, one level involving results that are consistent with the formal and applied statistical analogues' predictions. But, a second level requires even greater emphasis on identifying every structural relation in the formal model and analogue so that every estimate in the reduced form and applied statistical analogue are isolated.

While we are agnostic on whether to build or partition a system of equations, there is a need to address these inferential challenges posed by overparameterization. One avenue is to develop metrics on the degree to which free parameters can confound the results. Our conjecture is to think along the lines of creating some "tolerance" criteria on the relation between the structural equations, the number of free parameters, and the probability of committing a Type I or Type II

[22] Recall from (23) that $B = \left(1 \pm \sqrt{1 - 4\Gamma_1\Gamma_2}\right)(2\Gamma_2)^{-1}$.

error. It is possible that metrics on overparameterization may involve a mix of rank and order type conditions in conjunction with EBA (see Leamer 1983 and Bamber and van Santen 1985, 2000).

The EITM framework we use 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 that foster links to different levels of analysis (Kydland and Prescott 1982; Freeman and Houser 1998) or make explicit use of game theory (Signorino 1999; Mebane and Sekhon 2002) are just two examples. Experiments, too, provide a rich alternative or compliment to the secondary data analysis we use in this paper and are a natural outlet for methodological unification. People can sit in different pews but still be members of the same congregation. Ultimately, what EITM means is a clean break from the methodological status quo. No half-measures will suffice if the goal is build a cumulative science that relies on the transparency between theory and test.

5. References

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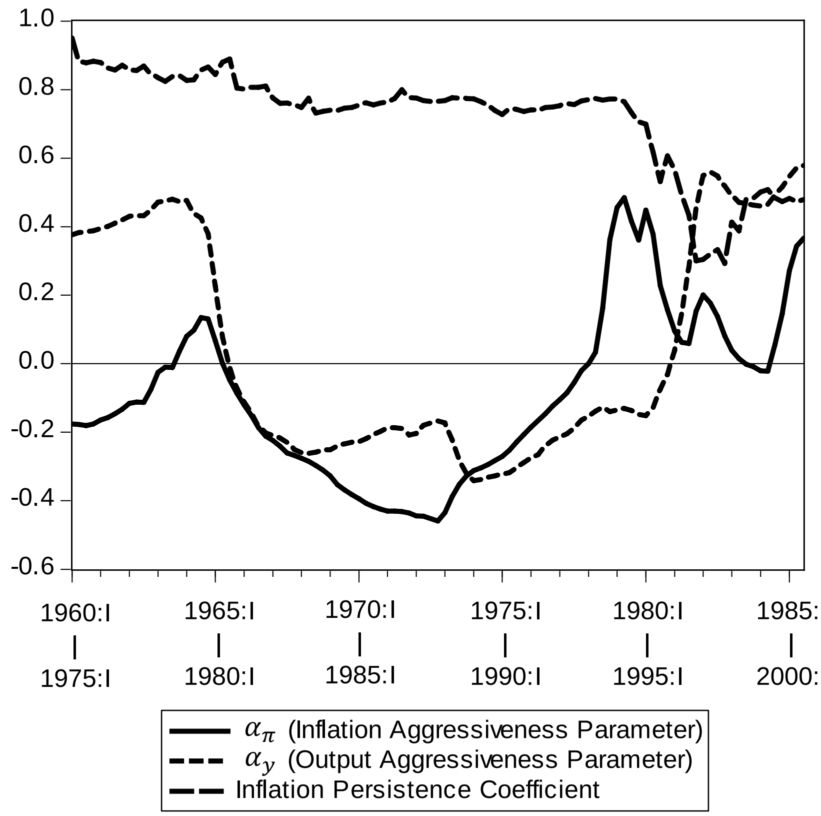
Figure 1



1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
1960:I
1975:I
1965:I
1980:I
1970:I
1985:I
1975:I
1990:I
1980:I
1995:I
1985:I
2000:I
α_π (Inflation Aggressiveness Parameter)
α_y (Output Aggressiveness Parameter)
Inflation Persistence Coefficient