I. Module 1: An Overview

Current Research Practices that Undermine Scientific Cumulation

- Emphasis on statistical technique leads distracts from the search for causal linkages.

- Non-cumulation is the consequence.

Merging Formal Models with an Empirical Test (EITM) can Arrest this Problem

- Has been done before.
    - Friedman (1957), Lucas (1973), West (1988), Converse (1969), Signorino (1999), Mebane (2003).
    - For the most part these works take well known concepts that receive a good deal of informal discussion and put them in a technical-analytical framework (i.e., expectations).
- There is a scientific basis for this.
    - Our goal, then, is to take a set of plausible facts or axioms, model them in a rigorous mathematical manner, and identify causal relations that explain empirical regularities.
    - What you would develop is a road map for others to modify, correct, or follow. More importantly, you would be providing a transparent linkage between your theory and test.
    - This is not to say your model is correct.
    - Instead, what you would be doing is meeting a minimal requirement that what your theory and test are related.
    - In that case you rise to the level of showing where your model is wrong.

Current Practices that Contribute to Research that is **Not Even Wrong**

- The following ratio is the subject of much attention by applied statistical analysts because it is the basis for which "theories" survive or perish:

$$\frac{\beta}{(s.e.)}$$

- This identity is commonly referred to as a "t-statistic."

- The denominator, the standard error (s.e.), also is susceptible to numerous forces that can make it artificially large or small. In either case, avoiding false rejection of the null hypothesis (Type I error) or false acceptance of the null hypothesis (Type II error) is imperative.

- While the concern with Type I and Type II errors should be of prime importance that is not the case. Instead, the focus is on the size of the t-statistic and whether one can get "significant" results.

Three practices: Data Mining, Garbage-Cans, and Omega Matrices

- **Data mining** is the practice of putting data into a statistical program with minimal theory, and run regression after regression until a researcher gets either statistically significant coefficients or coefficients they like. This search is not random and can wither away the strength of causal claims.

- **Garbage cans** refers to regressions or likelihood estimation practices whereby a researcher includes, in a haphazard fashion, as many independent variables into a statistical package and gets significant results somewhere. More often than not there is little or no attention paid to the numerous potential confounding factors that could corrupt statistical inferences.

- **Omega Matrices** refers to -- statistical patching (i.e., the use of weighting procedures to adjust the standard errors (s.e.) in the t-statistic identity above).

    - Data mining and garbage-can approaches are almost guaranteed to break down statistically.

    - Consider the t-statistic above again and the incentive to achieve significant results. One can do this by using statistical patches that *deflate* the standard error and *inflate* the t-statistic which, of course, increases the chance for statistical significance. Unfortunately, with the advances in computing power and the simplification of statistical software packages, this practice is only a click on the "enter" key away.

- There are elaborate ways of using (error) weighting techniques to “correct” model misspecifications or to use other statistical patches that substitute for a new specification.

- For example, in almost any intermediate econometric textbook (see, for example, Johnston and DiNardo 1997: 189-190) one finds a section that has the Greek symbol: Omega **(Ω).**

- This symbol is representative of the procedure whereby a researcher weights the data that are arrayed (in matrix form) so that the statistical errors, ultimately the standard error noted above, are reduced in size and the t-statistic now becomes significant.

Using EITM as a Way to Minimize Non-falsifiable Research Practices

- We choose three applied statistical concepts, familiar to us all, and hence are dealt with in well known ways:
  - Persistence, Measurement error, and Simultaneity
  - These concepts have direct applied statistical solutions. For persistence we have various autocorrelation corrections, for measurement error we have the error in variables regression or instrumental variables regression, and for simultaneity we typically use a multi-stage estimation process.
  - We show these applied statistical concepts can be tied to important social, behavioral, and economic concepts. The three we choose are expectations, learning, and social interaction.
  - In addition, we use these concepts in a macro sense. Our applied statistical technique will be least squares.
  - Tests can involve actual data, simulation, experiments, or a mix of all three.
  - We place an emphasis on dynamics.

An Example of How Conventional Research Practices Produce Results that are <u>not even wrong</u>.

Example: Aggressive Policy Inflation Stabilizing Policy and Price Level Indeterminacy

- **Solving reduced form**
- **Focusing on correct sign and significance**
    - **Aggressive policy stabilizes the price level**

HOW THIS MISLEADS.

- **CORRECT SIGN, BUT COULD MEAN A DESTABILIZING OUTCOME**

Consider the small scale macroeconomic model:

AS: $$y_t = y_t^n + a_1\left(\pi_t - E_{t-1}\pi_t\right) + u_{1t}$$

IS: $$y_t = b_1 + b_2\left[i_t - \left(E_t\pi_{t+1}\right)\right] + b_3 E_t y_{t+1} + u_{2t}$$

Policy

Rule: $$i_t = \pi_t + c_1\left(y_t - y_t^n\right) + c_2\left(\pi_t - \pi_t^*\right) + r_t^*,$$

where: $y_t^n = \alpha + \beta t,\ a_1 \equiv \lambda\left(\dfrac{\sigma_{rel}^2}{\sigma_{rel}^2 + \sigma_\pi^2}\right).$

Solving the System:

In this system we first solve for π_t. Simply combine the AS, IS, and Policy Rule equations:

$$y_t^n + a_1\left(\pi_t - E_{t-1}\pi_t\right) + u_{1t} \;=$$

$$b_1 + b_2\left[\pi_t + c_1\left(y_t - y_t^n\right) + c_2\left(\pi_t - \pi_t^*\right) + r_t^* - \left(E_t\pi_{t+1}\right)\right] +$$

$$b_3 E_t y_{t+1} + u_{2t}.$$

Note that $E_t y_{t+1} = y_{t+1}^n$ from the AS equation and

$$y_{t+1}^n = \alpha + \beta\left(t+1\right) \;= \alpha + \beta t + \beta = y_t^n + \beta.$$

Collect terms:

$$\pi_t \left[a_1 \left(1 - b_2 c_1\right) - b_2 \left(1 + c_2\right) \right] \qquad =$$

$$\left(b_1 - b_2 c_2 \pi_t^* + b_2 r_t^* + b_3 \beta\right) +$$

$$\left(a_1 - b_2 c_1 a_1\right) E_{t-1} \pi_t - b_2 E_t \pi_{t+1} +$$

$$\left(b_3 - 1\right) y_t^n + \left(b_2 c_1 - 1\right) u_{1t} + u_{2t}.$$

Therefore,

$$\pi_t = J_0 + J_1 E_{t-1} \pi_t + J_2 E_t \pi_{t+1} + J_3 y_t^n + X_t,$$

where,

$$J_0 = \frac{b_1 - b_2 c_2 \pi_t^* + b_2 r_t^* + b_3 \beta}{a_1 \left(1 - b_2 c_1\right) - b_2 \left(1 + c_2\right)},$$

$$J_1 = \frac{a_1 - b_2 c_1 a_1}{a_1 \left(1 - b_2 c_1\right) - b_2 \left(1 + c_2\right)},$$

$$J_2 = \frac{b_2}{a_1 \left(1 - b_2 c_1\right) - b_2 \left(1 + c_2\right)},$$

$$J_3 = \frac{b_3 - 1}{a_1 \left(1 - b_2 c_1\right) - b_2 \left(1 + c_2\right)},$$

and,

$$X_t = \frac{\left(b_2 c_1 - 1\right) u_{1t} + u_{2t}}{a_1 \left(1 - b_2 c_1\right) - b_2 \left(1 + c_2\right)}$$

Using the method of undetermined coefficients, we can solve for the MSV asserting the solution takes the form:

$$\pi_{\mathrm{t}} = A + By_t^n + X_t,$$

and,

$$E_{t-1}\pi_t = A + By_t^n,$$

with,

$$E_t\pi_{t+1} = A + B\left(y_t^n + \beta\right).$$

Now the two identities above into the reduced form and solve for A and B:

$$\pi_{\mathrm{t}} = \left(\frac{J_0}{1-J_1-J_2} + \frac{J_2 J_3 \beta}{\left(1-J_1-J_2\right)^2}\right) + \left(\frac{J_3}{1-J_1-J_2}\right) y_t^n + X_t$$

Simulation Parameters (Steps = 100):

AS :

$\alpha = 5.0$; $\beta = 0.05$; $y^n{}_0 = 1.0$; $a_1 = 10$; $\sigma_{u1} = 1.0$;

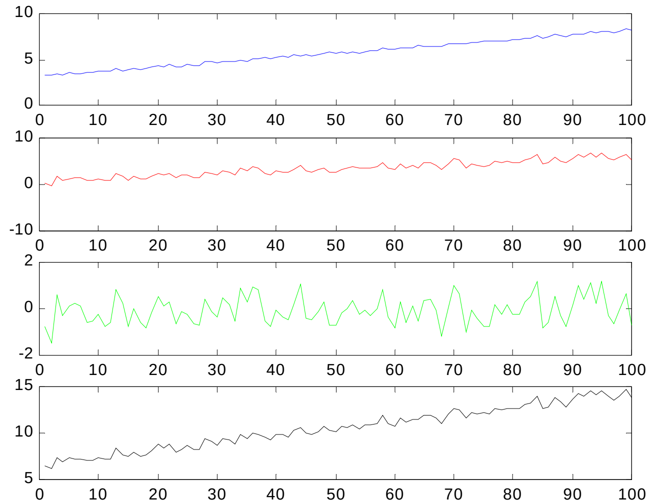
IS:

$b_1 = 3.0$; $b_2 = -1.0$; $b_3 = ?$; $\pi^* = 2$; $\sigma_{u2} = 1.0$;

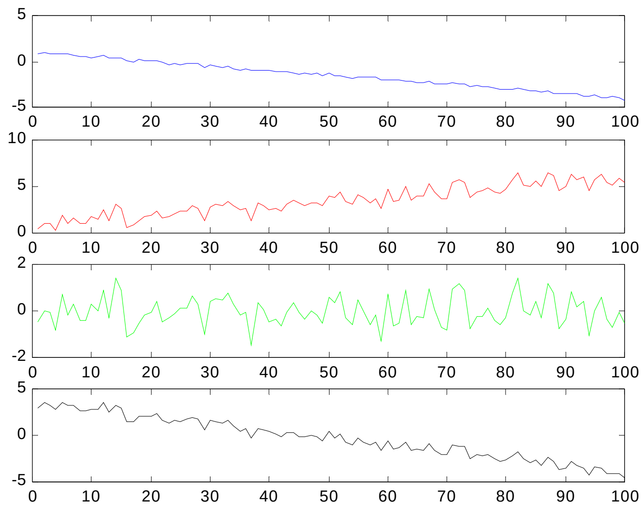
Policy
Rule:

$c_1 = .5$; $c2 = .5$; $r^* = 3.0$.

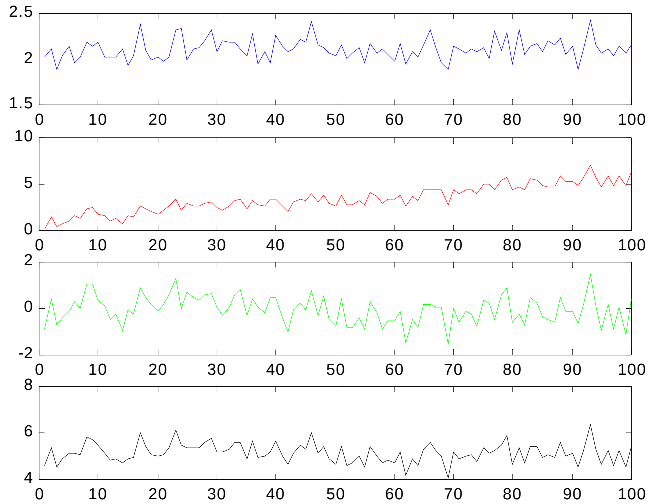
NOTE: FOCUS ON TOP PANEL (Inflation Outcome)



b_3 is greater than 1.0, $b_3 = 1.5$ in this case.



b_3 is less than 1, $b_3 = 0.5$ in this case.



b_3 = 1.0 in this case.