# STATISTICAL AND ANALYTICAL SIGNIFICANCE COMPARED: A MORE SCIENTIFIC APPROACH TO APPLIED ECONOMICS

## Impoverished Mental Models, False Assumptions, Path Dependency, and Bad Science

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# Introduction

- I argue that the statistical methodology or approach that one uses is often conditional upon the assumptions one makes about the methodology or ones mental models.
- A key focus of social scientists, certainly of economists, is on correlation and statistical significance to determine the validity of ones model.
- The assumption here is that correlation and statistical significance represent truth tests of a model.

# Correlation and the Illusion of Causality

- The focus on correlation stems, most recently, from modeling assumptions of Freidman.
- The focus is on analytical prediction, irrespective of the realism of the assumptions.
- The latter remains the mainstay of conventional economics.
- Correlation is often inferred to imply causation.
- Typically, no discussion is takes with regards to how high the correlation coefficient need to be of some analytical consequence.

# Correlation and the Illusion of Causality

- This distracts attention from causal analysis and convolutes prediction with causality.
- This approach increases the probability of ignoring or simply not searching for other variables that are of more substantive significance and that are empirically derived.
- Omitted variable problems.

# Correlation and the Illusion of Causality

- This prediction-focused approach is also subject to spurious correlation and misleading policy prescriptions at both the micro and macro level.
- Correlation is simply a useful indicator of whether a given model is possibly of substantive significance.
- Behavioral economics (Herbert Simon—bounded rationality approach), focus is on the realism of assumptions and their pertinence to the analytical questions being asked.

# Correlation and the Illusion of Causality

- Identifying realistic assumptions which can be causally pertinent would be the focus of this approach.
- Correlation can be part of this modeling narrative, but not the core.

# Statistical Significance versus Analytical Significance

- The misuse of tests of statistical significance in economics and other fields of study has been highlighted by McCloskey and Ziliak.
- These tests have been subject to severe criticism in other disciplines as well.
- These tests are not derivative of the predictive-correlation analysis dominating conventional economics.

# Statistical Significance versus Analytical Significance

- Rather, they are rooted in the assumption that tests of statistical significance demonstrates the substantive significance of particular variables…
- And, that statistical insignificance demonstrates the substantive or analytical insignificance of particular variables.

# Statistical Significance versus Analytical Significance

- When an empirical result is found to be statistically significant, the finding is thought to be scientifically important, often even giving rise to the reasoning that if A is statistically significant than A must be the cause of B.
- And if A is not statistically significant, A can’t be a cause of B.
- In this view, statistical significance/insignificance brings causality to the correlation analysis.

# Statistical Significance versus Analytical Significance

- Note that even if a behavioralist approach is taken to model building, tests of statistical significance can still be used (and are) to test for the analytical significance of particular variable.
- But, this would (and does) generate misleading analytical results.
- Simply finding that a psychological or sociological variable is statistically significant or insignificant does not imply that this variable is analytically significant or insignificant.

# Statistical Significance versus Analytical Significance

- It is important to note that statistical significance can only indicate the extent to which ones mean estimate is plausible (not a fluke) given the size of ones sample, at a certain level of confidence.
- This is its scientific value and, one might argue, nothing more.

# Statistical Significance versus Analytical Significance

- One can actually design ones study such that ones results should be statistically significant.
- Increasing sample size to generate a statistically significant result, does not make ones selected variable(s) substantively significant.
- But as Ziliak, McCloskey, and others point out, too many researchers focus on statistical significance as the key determinant of substantive significance.

# Statistical Significance versus Analytical Significance

- To reiterate some points made in the critical literature:
  - Statistical significance tests can only be applied to a randomly drawn sample.
  - Statistical significance tests should not be applied to an entire population.
  - Statistical significance tests are all about determining the probability of the flukiness of ones results.
  - Confidence intervals used are not God-given and alternatives will generates different results for statistical significance.

# Statistical Significance versus Analytical Significance

- To reiterate some points made in the critical literature:
  - Related to above, tests for statistical significance are used non-random samples, this includes social science experiments, historical data, and case studies.
  - This violates first principles for using tests for statistical significance.
  - Correlation is often used to infer causation without carefully examining the robustness (underlying) of the relevant variables.

# Mental Models and Biased Modeling in Statistics

- I argue that mental models about statistical tools are key determinants of how applied researchers use use tests of statistical significance or correlation analysis.
- Mental models (Altman 2014) relate to the model that individuals use implicitly or explicitly to engage in decision making (discussed famously by Keynes).
- False models represent false representations of causality, best practice rules or heuristics, and of reality.

# Mental Models and Biased Modeling in Statistics

- Using statistical significance and correlation analysis inappropriately can be a function of adopting false or biased mental models with regards to what these tools can be used for and the limits of these tools.
- Just like economists are want to forget that much of economic theory is conditional upon the ceteris paribus assumptions, and needs to be adjusted for this where and when appropriate.

# Determinants of Mental Models

- Which mental models are adopted I would argue are a function of a number of key variables such as:
  - Path dependency, confirmation bias, education, loss aversion, status quo bias, defaults, power relationships, identity, and herding.
- Path dependency, status quo bias are closely related.
- In a world of bounded rationality, individuals will stick with what they know.
- Hence one can expect individuals to revert to the default practice, which yields path dependency and related to this, a bias to the status quo in the statistical methodologies adopted.

# Path dependency, status quo bias

- Also important here is herding.
- Given bounded rationality, individuals will often follow the heard in the expectation that the herd knows better than they.
- This would be especially true when herd leaders are in a position of authority and/or respect.

# Determinants of Mental Models

- Mental models can be reinforced by prior and current learning, be they true or false.
- I would hypothesize that even if education does against the a prevailing false mental model, this mental model might still be applied if it conforms to standard practice--path dependency, status quo bias.
- The latter also relates to individuals desire, on average to avoid, cognitive dissidence.

# Determinants of Mental Models

- This often involves conforming to conventional norms (related to identity economics).
- What is very important here is which identity one wishes to conform with.
- One can hypothesize, that the average individual will tend to identify with the herd, with the pack, and with the herd leader—related to defaults and bounded rationality and power relationships.

# Determinants of Mental Models

- In addition, one has loss aversion.
- Shifting to new methodologies can be viewed as a loss, when one has invested heavily in used particular analytical tools.
- This has to weighted against the gains of shifting to new methodologies; which be quite low if the current methodology is the dominant one.

# Costs versus Benefit

- Of particular importance is power relationships, where the current methodology to the dominant one.
- Not conforming can come at significant costs to the researcher.
- With regards to applied research, in many domains, certainly in economics, there is little competition with regards to the use of of test of statistical significance and correlation analysis as to alternative approaches in the use of these tools, including their scientifically current use.
- The dominant view has a quasi-monopoly position on the market.

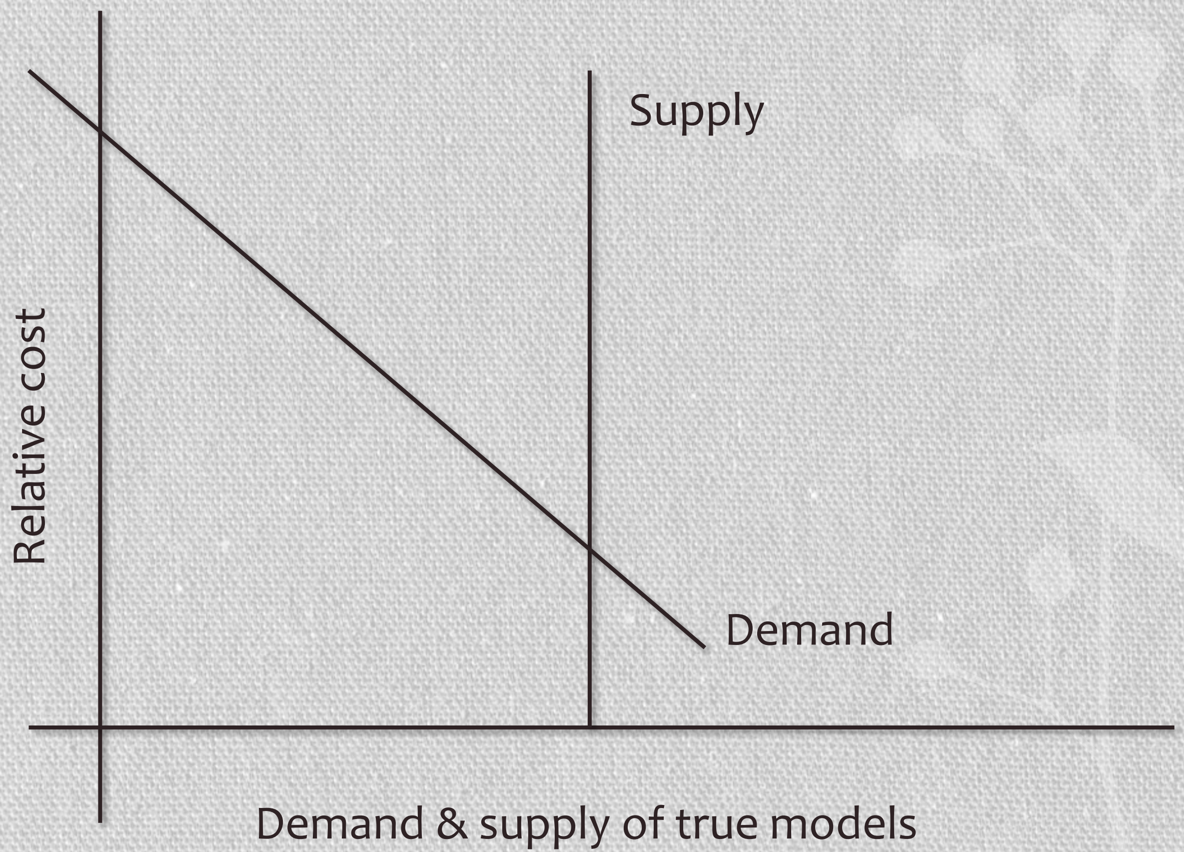
# Determinants of Mental Models

- Overall, It is the relatively lower cost (psychic and economic) and lower risk option, to maintain current practices.
- This would be the case even if one believes that these practices are biased or scientifically inappropriate.

# Risk Taking and Entrepreneurial Scholarship

- Where mental models (and related use of methodologies) are false, entrepreneurial scholarship can generate relatively high returns.
- But the capabilities to engage in such behaviour must be present.
- Also, one must understand when, where, and the extent to which particular mental models and related methodologies are false or biased.
- Increasing environmental capabilities and education re models and methodologies can be expected to increase the extent of entrepreneurial scholarship, ceteris paribus.

# Demand & supply of true models



# Concluding Comments

- To increase the probability of adopted true models and related practices, it is important contextualize tests of statistical significance and correlation analysis in terms of their scientific value and their limitation.
  - Most applied researchers apply these tools and accept that there is value in their use.
- The misapplication of these tools remain dominant.
- Ideally it would best to construct a template for best practice for these statistical tools.
  - An easily accessible (low cost) default template for applied research.

# Simple Rules

- **Some simple rules to avoid bad practice use of the tests of statistical significance and correlation:**
- Statistical significance test and correlation analysis could play an important role of the empirical narrative.
- Carefully assess the ‘realism’ of the variables underlying correlation analysis.
- Correlation analysis need to be contextualized in terms of the realism of the underlying theory.
- Understand that statistical significance can’t validate or refute causality in correlation analysis.

# Simple Rules

- Recognize that tests of statistical significance provide no information on analytical significance.
- Pay special attention and assess the size of the relevant estimated coefficients (size effect).
  - Discuss the impact of the variable in terms of the size effect on the dependent variable.
- Pay attention to the confidence level. Do not blindly accept statistical insignificance at a high level as definitive, without first checking significance at lower levels of confidence—going from 99 to 95 to 90 to 85 to 80 percent, for example.
- Pay attention to the variation about the mean (such as standard deviation)—less variation implies a more robust size effect, ceteris paribus.

# Simple Rules

- Pay attention to the structure and representativeness of your sample.
- Small samples, especially ones that are not representative, are more akin to case studies, and need to be repeated in other locales, to determine robustness. What one finds to be true for Prince Albert, Saskatchewan, Canada, might be quite different from what one finds in Bristol, England, San Francisco, USA, or Capetown, South Africa. And, what is true for a student sample may be different from what one finds in a low income ethnic ghetto.
- Statistical significance tells us nothing about these important issues.

# Simple Rules

- Avoid using tests of statistical significance to reject or accept null hypotheses in terms of their scientific validity.
- Otherwise, you are prone incorrectly reject a true null hypothesis (type I error) when your result is statistically insignificant but the size effect is large.
- On the other hand, you'd be prone to incorrectly accept a false null hypothesis (type II error) when your result is statistically significant, but the size effect is rather small.
- And, this does not at all touch upon sample selection issues, which are especially pertinent to behavioral and experimental economics.

# Simple Rules

- Statistically insignificant results should not be rejected when the size effect appears analytically significant.
- A particular independent variable might be of consequence, but the sample size might be too small, such that there is a high probability that the result is a fluke.
- But there is also a positive probability that the result is true—not a fluke.
- This calls additional experiments to test the hypothesis at hand.