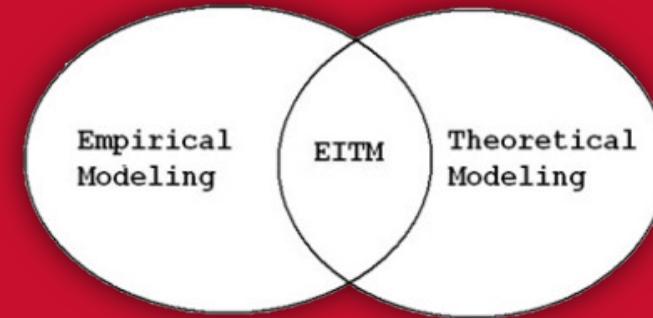


EITM



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Outline

1. Introduction and Background
2. EITM Definition and EITM Framework
3. The Benefits of Ensuring a Dialogue between Theory and Tests
4. EITM Application: Economic Voting (Chapter 4)

1. Introduction and Background

The 2001 Workshop convened by the Political Science Program at the National Science Foundation (NSF).

Why was EITM created?

1. Motivation.
2. Problem Diagnosis.
3. Remedies.

Motivation

Motivation 1: Perceived weakness of the political science discipline at National Science Foundation (NSF).

- Granato and Scioli (2004) cite the following report relating how political science was perceived at NSF.

“The recent *Report of the APSA Ad Hoc Committee on the National Science Foundation* found that political science had been characterized by as, “not very exciting, not on the cutting edge of the research enterprise, and in certain quarters as journalistic and reformist.” We disagree with this statement and believe there has been considerable improvement in political science in the past 40 years through the use of formal models, case studies, and applied statistical modeling (page 313).”

- This negative perception also led to skepticism as to whether the political science discipline – and its current training practices – was methodologically equipped to improve upon the existing methodological status quo. Social, Behavioral and Economic Sciences Division Director Bill Butz stated all was not certain about the outcome:

“Sometimes that works and sometimes you’re just pushing on a string because the field isn’t ready for it yet... And getting you all here and I judge from the papers it resonated with you, too. And we’ll see in the succeeding year or 2 or 3 whether this is pushing on a string or whether it’s really lighting a fire (EITM Workshop Transcript 2001: 18).”

Motivation

Motivation 2: Old antagonisms and the methodological status quo.

- Workshop participants were from varied methodological backgrounds where long antagonisms had existed and led to splits in departments as well as various subfields. But, EITM workshop panelist Dina Zinnes expressed hope that these old antagonisms between formal and empirical modelers could be overcome and lead to some meaningful advice.

“First let me just say what a pleasure it is to be amongst this group of people. I have to admit that when I got those initial memos I sort of put them on the side burners, thinking, well, okay, I’ll look at them eventually, because I was worried about the fights and the antagonisms that I thought would emerge. And it was with great delight that I read those and discovered, my gosh, there really is a consensus going on here. And listening to people this morning confirms that. I find that it’s wonderful to see that both the empirical and statistical side and the modeling side really all sort of agree on certain things. And I think that’s a fabulous beginning (EITM Workshop Transcript 2001: 113-114).”

Motivation

Motivation 3: Weaknesses in research design for NSF Competitions.

- In his role as Division Director over a six year period, Director Butz reviewed and approved over 16,000 proposals. He stated:

“And of those 16,000, about 2 years ago I formulated just a sort of a stylized FAQ what the principal ways are to be sure that you don’t get money from NSF. And out of all the possible reasons, there were three that came to the front...Now, it varies some across fields. And I don’t mean to say that this is particularly true of political science, but I want to show it to you because it may give you an additional context for the reasons why scientific proposals fail in the social and behavioral sciences –how to get zero money (EITM Workshop Transcript 2001: 14).”
- One reason is even though basic conceptualization exists, there is still a failure to connect theories to tests:

“there will be a well-developed deductive theory at the beginning, and then the next section will be data, the next section will be empirical equations, and you’ll look at the empirical stuff and it’s just – it’s not connected, or it’s only connected in the vaguest sense (EITM Workshop Transcript 2001: 14-15).”
- Another reason in his summary was inadequate specification:

“I don’t know how many panels I’ve sat in where people say, well, you know, we can’t really tell how they’re going to form this proxy from these variables, or we can’t really tell how they’re going to get over the statistical problem with such-and-such (EITM Workshop Transcript 2001: 17).”
- In concluding his presentation Director Butz states:

“There are many other things that are wrong with proposals, but these two –something wrong with the theory and something wrong with the data or the statistical methods are two of the three most common ones across – and I really don’t think there are very many exceptions to this – across the 18, I think now 19, programs in the social, behavioral, and economic sciences here. So I thought I would just point that out (EITM Workshop Transcript 2001: 16-17).”

Problem Diagnosis: Compartmentalization, Siloed Training and Thinking in Methodology

“Isolation – *compartmentalization* – of fields and sub-fields is the status quo in political science...current field and sub-field structure exacerbates the separation between formal and empirical modeling. For example, focusing on a question that is particular to American Politics increases specialization and, turn, discourages integrating approaches and theories that would best come about from studying a particular research question in many countries (EITM Report 2002: 6).”

- Moreover, field and sub-field isolation reinforces separation between formal and empirical analysis including the belief that an:
 - “outdated perspective about formal and empirical analysis is the assertion that these technical-analytical approaches are simply interesting intellectual enterprises that lack political and social relevance (EITM Report 2002: 6).”
- The consequence of this divide is not neutral in its effect; indeed the effect can be negative. In particular:
 - “a good deal of research in political science is competent in one technical area, but lacking in another, that is, a formal approach with substandard (or no) empirical tests or an empirical approach without formal clarity. Such impaired competency contributes to a failure to identify the proximate causes explicated in a theory and, in turn, increases the difficulty of achieving a meaningful increase in scientific knowledge (EITM Report 2002: 1).”

Problem Diagnosis: Compartmentalization, Siloed Training and Thinking in Methodology

Siloed Training

- Consequences for Formal Modeling

“Many formal modelers feel uncomfortable with powerful empirical concepts such as social norms, limited rationality, and psychological factors such as personality and identity. The usual argument is that formal models are not meant to fit data, or should not be. While there is much to be learned from pure theory and abstract formal arguments, the formal modeling isolation reinforces distance from basic circumstances that these abstract models could help to illuminate. This isolation also contributes to the basic misunderstanding noted above about the great attributes formal modeling brings to the scientific process (EITM Report 2002: 6-7).”

- Consequences for Empirical Modeling

“Empirical modeling isolation, on the other hand, is equally guilty of not advancing scientific understanding when it fails to incorporate their “more complex and general assumptions” into a mathematically identified model with direct and testable implications. Instead “errors” or “confounding variables” that derail the inferential process are treated as statistical problems that require only statistical fixes (EITM Report 2002: 7).”

Problem Diagnosis: Compartmentalization, Siloed Training and Thinking in Methodology

Factors reinforcing the status quo:

1. ***The Intellectual Investment:*** Scholars have to invest in different skill sets.
 2. ***Training Differences:*** Empirical modelers devote their energies to data collection, measurement, and statistical matters, and formal modelers focus on mathematical rigor.
 3. ***Research Practice:*** For empirical modelers, model failures lead to emphasis on additional statistical training or more sophisticated uses of statistics – usually to “patch over” – a model failure. Formal modelers, on the other hand, deal with model controversies by considering alternative mathematical formulations but this is usually done piecemeal.
- These implementation challenges are deeply rooted in the academic community – fostered by career incentives – taking years to overcome (Poteete, Janssen, and Ostrom 2010: 18-24). Consequently, “Old habits” learned in graduate school inhibit the desire to make the changes in skill development. But, the situation is worse since many things learned in graduate school tend to become out-of-date by mid-career.
 - When methodological instruction reflects these status quo forces, successive generations will only repeat the shortcomings. Indeed, disciplines failing to provide incentives for this type of risk taking and re-tooling reduce the threat of an:
“assembly-line model of research production that imperils innovative theories and methodologies and, in turn, scientific breakthroughs. One could make the argument that EITM or initiatives like it are unnecessary because the unfettered marketplace of ideas expedites best scientific practices and progress. But, it is precisely because there are significant rigidities (training and otherwise) in the current academic setting (imperfect competition) which makes EITM-type initiatives not only necessary – but imperative (EITM Report 2002: 8).”
 - We now see, and have repeatedly seen, practices unsuitable for addressing complex issues. Invalid policy prescriptions take place: prediction without basic understanding of how a system under study works is of little scientific or social value.

Proposed Remedies

The 2001 EITM Workshop participants recommended that the Political Science Program at the NSF address the technical-analytical divide between formal and empirical approaches in three priority areas:

1. *Education*: Training and Retraining.
2. *Dissemination of Knowledge*: Conferences and Workshops.
3. *Research*: Establishment of Research Work Groups.

Deliverables from the 2001 EITM Workshop

A key achievement of the EITM initiative over the past years has been the EITM Summer Institutes. So far, the Summer Institutes have taken place or will take place at:

- Harvard University (2002)
- University of Michigan (2003, 2006, 2009, 2018)
- Duke University (2004, 2008, 2014, 2016, 2020, 2021)
- UC-Berkeley (2005, 2010, 2013, 2017, 2022)
- UCLA (2007)
- Washington University, St. Louis (2003-2009)
- University of Chicago (2011)
- Princeton University (2012, 2015, 2023)
- University of Houston (2012-2017, 2019)
- Emory University (2019)

2. EITM Definition and EITM Framework

- EITM is a method – even a mindset – where researchers treat formal and empirical analysis as linked entities intended to create a dialogue between theory and test.
- There is more than one way to link formal and empirical analysis.
- Below we present the EITM framework that was created at NSF.

2. EITM Definition and EITM Framework

The elements of EITM – the NSF version – involve a three-step framework:

Step 1. *Identify and Relate Focal Concepts*

- Concepts of particular concern in this framework reflect many overarching social and behavioral processes. Examples include (but are not limited to):
 - decision making
 - bargaining
 - expectations
 - learning
 - elements of social interaction (strategic and non-strategic)
- 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
 - prediction

2. EITM Definition and EITM Framework

Step 2. *Developing Formal and Applied Statistical Analogues.*

- To link concepts with tests, we need analogues. Recall that an analogue is a device representing a concept via a continuous and measurable variable or set of variables. Examples of analogues for the behavioral (formal) concepts such as decision making, expectations, learning, and strategic interaction include (but are not limited to):
 - decision theory (e.g., utility maximization)
 - conditional expectations (forecasting) procedures
 - adaptive and Bayesian learning (information updating) procedures
 - game theory
- Examples of applied statistical analogues for the applied statistical concepts of persistence, measurement error, nominal choice, simultaneity, and prediction include (respectively):
 - persistence
 - autoregressive estimation
 - error-in-variables regression
 - discrete choice modeling
 - multi-stage estimation (e.g., two-stage least squares) and spatial econometrics
 - point estimates and distributions

Step 3. *Unify and Evaluate the Analogues*

3. The Benefits of Ensuring a Dialogue Between Theory and Test

EITM can fit with existing research strategies in three ways:

1. *Evolution of scientific accumulation.*
2. *Comparing contradictory ideas.*
3. *Test versus consistency evaluation.*

How EITM Informs Debates

- Social scientists face two common challenges face in their research undertaking: developing useful theories that are realistic representations of human behavior on the one hand and making use of feedback from empirical observations in refining the theory on the other.
- In the scenario where the two processes are not linked – such as in the case where theoretical and empirical work is carried out separately in a silo – researchers are unable to obtain the benefits from the interaction of the two activities.
- The dilemmas that theory is ahead of data or data are ahead of theory can be dealt with more effectively employing the EITM approach.

4. Application: Economic Voting (Chapter 4)

Alesina and Rosenthal Competency Model of Economic Voting

- Step 1: Relating Expectations, Uncertainty, and Measurement Error
- Step 2: Analogues for Expectations, Uncertainty, and Measurement Error

Empirical Analogues: Measurement Error and Error and Variables Regression (pages 67-68)

Formal Analogues: Conditional Expectations, Linear and Recursive Projections (pages 71-74)

4. Application: Economic Voting (Chapter 4)

Empirical Analogues: Consider estimating the following equation:

$$\begin{aligned} Y_t &= \beta_0 + \beta_1 X_t + \varepsilon_t \\ X_t &= x_t + e_t, \text{ for } t = 1, \dots, n, \end{aligned}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, and $e \sim iid(0, \sigma_e^2)$.

The expected value of $\hat{\beta}_1$ is:

$$\begin{aligned} E(\hat{\beta}_1) &= \beta_1 \lambda \\ &= \beta_1 \left(\frac{\sigma_x^2}{\sigma_x^2 + \sigma_e^2} \right) \end{aligned}$$

The ratio of $\lambda = \sigma_x^2 / \sigma_X^2 = \sigma_x^2 / (\sigma_x^2 + \sigma_e^2)$ defines the degree of attenuation. It is also termed as the signal extraction ratio or reliability ratio.

4. Application: Economic Voting (Chapter 4)

Formal Analogues: Consider Alesina and Rosenthal Economic Voting model:

$$\hat{y}_t = \hat{y}^n + \gamma (\pi_t - \pi_t^e) + \epsilon_t,$$

$$\text{where } \epsilon_t = \eta_t + \xi_t, \text{ and } \eta_t = \mu_t + \rho\mu_{t-1}$$

The variable η_t captures the idea of government competence, which can persist and support reelection. It follows the following MA(1) process expressed above.

Voters forecast the government competence η_{t+1} at time t according to the following law of motion:

$$\begin{aligned} E_t(\eta_{t+1}) &= E_t(\mu_{t+1}) + \rho E(\mu_t | \hat{y}_t - \hat{y}^n - \rho\mu_{t-1}) \\ &= \rho E(\mu_t | \hat{y}_t - \hat{y}^n - \rho\mu_{t-1}) \\ &= \rho E(\mu_t | \mu_t + \xi_t) \\ &= \rho \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\xi^2} (\hat{y}_t - \hat{y}^n - \rho\mu_{t-1}) \end{aligned}$$

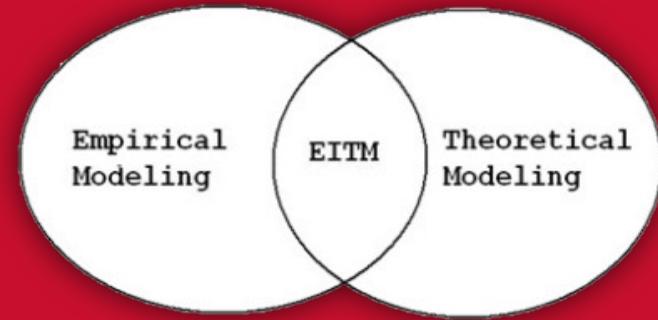
where $E_t(\mu_{t+1}) = 0$.

4. Application: Economic Voting (Chapter 4)

Step 3: Unifying the Analogues (link the analogues, pages 76-77)

Note the prior results show that the empirical and formal analogues are identical in form and, therefore, show a direct and behavioral link between theory and test.

EITM



EITM in Practice

Information Diffusion and Inflation Expectations

Information Diffusion & Inflation Expectations (Chapter 7)

Empirical Implications: Granato and Krause (GK) (2000)

- Examining the connection between information and expectations and test for the diffusion of information among the public
- Information transmission is asymmetric, which means predictions of more informed citizens influence the predictions of their less informed counterparts.

Theoretical Models: Granato, Guse and Wong (GGW) (2008)

- Introducing a process of information diffusion in a modified cobweb model with a Stackelberg framework, where there are two types of agents: first and second moving agents.
 - First moving (leading) agents: More informed citizens
 - Second moving (following) agents: Less informed citizens
- The leading agents form initial forecasts, and the following agents observe and use the leading agents' forecasts when forming their expectations.

EITM: Granato, Lo and Wong (GLW) (2011)

- **EI + TM = GK (2000) + GGW (2008) = GLW (2011) = EITM**

Information Diffusion & Inflation Expectations (Chapter 7)

Step 1: Relating Social Interaction, Expectations, and Learning to Simultaneity and Prediction Error

- Social Interaction: *Information diffusion*, motivated by GK (2000) and GGW (2008)
 - A situation where less informed agents can receive information from more informed agents for the purpose of enhancing their — the less informed agents — forecast accuracy
- The relation between less- and more-informed agents — social interaction — involves *expectations* and *learning*.
- These behavioral traits are linked *with forecast error (forecast accuracy)*
 - Results: new equilibrium predictions – the *Boomerang Effect*

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

Simple Macroeconomic Model

Lucas Aggregate Supply:

$$y_t = \bar{y} + \theta (p_t - E_{t-1}^* p_t) + \epsilon_t,$$

where $\theta > 0$, p_t and y_t are the price and output level at time t , respectively, \bar{y} is the natural rate of output level, $E_{t-1}^* p_t$ is the expectation of the price level at time t .

Aggregate Demand (Quantity Theory of Money)

$$m_t + v_t = p_t + y_t$$

where m_t is the money supply and $v_t = \kappa + \lambda w_{t-1} + \varepsilon_t$ is a velocity shock, and monetary policy rule:

$$m_t = \bar{m} + p_{t-1} + \phi w_{t-1} + \xi_t,$$

where $\phi > 0$, \bar{m} is a constant money stock, ϵ_t and ξ_t are iid stochastic shocks.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

Solving the macro equilibrium, we have the following reduced form of inflation dynamics:

$$\pi_t = \alpha + \beta E_{t-1}^* \pi_t + \gamma w_{t-1} + \eta_t,$$

where $\pi_t = p_t - p_{t-1}$, $E_{t-1}^* \pi_t = E_{t-1}^* p_t - p_{t-1}$, and the following parameters:

$$\alpha = (1 + \theta)^{-1} (\kappa + \bar{m} - \bar{y}),$$

$$\beta = \theta (1 + \theta)^{-1} \in (0, 1),$$

$$\gamma = (1 + \theta)^{-1} (\phi + \lambda), \text{ and}$$

$$\eta_t = (1 + \theta)^{-1} (\epsilon_t + \varepsilon_t + \xi_t).$$

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

Solving the macro equilibrium, we have the following reduced form of inflation dynamics:

$$\pi_t = \alpha + \beta E_{t-1}^* \pi_t + \gamma w_{t-1} + \eta_t$$

The rational expectational equilibrium can be written as:

$$\pi = \bar{a}^{REE} + \bar{b}^{REE} w_{t-1} + \eta_t,$$

where $\bar{a}^{REE} = \alpha / (1 - \beta)$, and $\bar{b}^{REE} = \gamma / (1 - \beta)$.

According to the above equilibrium, agents make rational forecasts $E_{t-1} \pi_t$ with the full information w_{t-1} at time $t - 1$:

$$E_{t-1} \pi_t = \bar{a}^{REE} + \bar{b}^{REE} w_{t-1}.$$

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

- Assuming that not all agents obtain the full set of information w_{t-1} at time $t - 1$ for making rational forecasts.
- Forecast accuracy is *associated with education*, a common proxy for information levels (w_{t-1}), according to Granato and Krause (2000).
- As a result, agents with a *smaller* information set have incentives to interact with those who obtain *more (or full)* information when making forecasts.
- We assume the followings:
 - More informed agents receive the full information set: $w_{t-1} = \{x_{t-1}, z_{t-1}\}$ to make their forecasts.
 - Less informed agents receive a partial information set: x_{t-1} , but they also interact with the more informed agents to obtain their expectations $\hat{\pi} = E_{H,t-1}^* \pi_t + e_{t-1}$ to make their forecasts.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

- As a result,
 - High-informed group form the following expectations:

$$\pi_t = a_H + b_{1H}x_{t-1} + b_{2H}z_{t-1} + v_t$$

- Low-informed group forms the following expectations:

$$\pi_t = a_L + b_Lx_{t-1} + c_L\hat{\pi}_{t-1} + v_t$$

where $\hat{\pi}_{t-1} = E_{H,t-1}^*\pi_t + e_{t-1}$ and e_{t-1} is the *measurement/interpretation error*.

High-informed group
 $E_{H,t-1}^*\pi_t = a_H + bw_{t-1}$

Info. Diffusion Process: $\hat{\pi}_{t-1}$

Low-informed group
 $E_{L,t-1}^*\pi_t = a_L + b_Lx_{t-1} + c_L\hat{\pi}_{t-1}$

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

- In equilibrium

- High-informed group: $\pi_t = a_H + b_{1H}x_{t-1} + b_{2H}z_{t-1} + v_t$

- Low-informed group: $\pi_t = a_L + b_Lx_{t-1} + c_L\hat{\pi}_{t-1} + v_t$

$$\bar{\varphi}_H = \begin{pmatrix} \bar{a}_H \\ \bar{b}_{1H} \\ \bar{b}_{2H} \end{pmatrix} = \begin{pmatrix} \frac{\alpha}{1-\beta} \\ \frac{\gamma_1}{1-\beta} \\ \frac{\gamma_2}{1-\beta+\beta\mu(1-c_L)} \end{pmatrix}$$

$$\bar{\varphi}_L = \begin{pmatrix} \bar{a}_L \\ \bar{b}_L \\ \bar{c}_L \end{pmatrix} = \begin{pmatrix} \frac{\alpha}{1-\beta} (1 - \bar{c}_L) \\ \frac{\gamma_1}{1-\beta} (1 - \bar{c}_L) \\ \frac{\bar{b}_{2H}^2 \sigma_z^2}{\bar{b}_{2H}^2 \sigma_z^2 + (1-\beta\mu)\sigma_e^2} \end{pmatrix}$$

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

- In equilibrium

- High-informed group: $\pi_t = a_H + b_{1H}x_{t-1} + b_{2H}z_{t-1} + v_t$

- Low-informed group: $\pi_t = a_L + b_Lx_{t-1} + c_L\widehat{\pi}_{t-1} + v_t$

$$MSE_L = \left[\frac{\gamma_2 (1 - \bar{c}_L)}{1 - \beta + \beta (1 - \bar{c}_L) \mu} \right]^2 \sigma_z^2 + (1 - \beta\mu)^2 \bar{c}_L^2 \sigma_e^2 + \sigma_\eta^2$$

$$MSE_H = (\beta\mu\bar{c}_L)^2 \sigma_e^2 + \sigma_\eta^2$$

where $MSE_i \equiv E (\pi_t - E_{i,t-1}^* \pi_t)^2$, for $i \in \{L, H\}$.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 2: Analogues for Social Interaction, Expectations, Learning, Simultaneity, and Prediction Error

- Group H's MSE: $MSE_H = (\beta\mu\bar{c}_L)^2 \sigma_e^2 + \sigma_\eta^2$
- Group L's MSE: $MSE_L = \left[\frac{\gamma_2 (1 - \bar{c}_L)}{1 - \beta + \beta (1 - \bar{c}_L) \mu} \right]^2 \sigma_z^2 + (1 - \beta\mu)^2 \bar{c}_L^2 \sigma_e^2 + \sigma_\eta^2$
- Due to information diffusion, Group H fails to obtain the most accurate forecast.
- Under RE and/or no info. diffusion, Group H's MSE: $MSE_H = \sigma_\eta^2$
- With Information diffusion, Group H's MSE: $MSE_H = (\beta\mu\bar{c}_L)^2 \sigma_e^2 + \sigma_\eta^2 > \sigma_\eta^2$

This result is called the *boomerang effect on MSE*

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

- The formal model demonstrates that Group L places a weight \bar{c}_L on the observed information from Group H.
- Due to the information diffusion, Group H fails to obtain the most accurate forecast. Therefore, the boomerang effect on MSE basically states that:

Group H's MSE increases as the variance of interpretation errors σ_e^2 increases.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

- Surveyed inflation expectations from the SRC at the University of Michigan
- The tests are directed at two things:
 1. **Existence of Asymmetric Information Diffusion**
 - The expectations of Group H influence the expectations of Group L
(The first test serves as a necessary condition for the second test.)
 2. **Existence of Boomerang Effect**
 - Examining whether larger observation errors made by Group L agents σ_e^2 result in greater inaccuracy in inflation predictions by Group H agents MSE_H .

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

1. Existence of Asymmetric Information Diffusion

The following questions relate to measuring inflation expectations:

1. During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?
2. By about what percent do you expect prices to go (up/down), on the average, during the next 12 months?

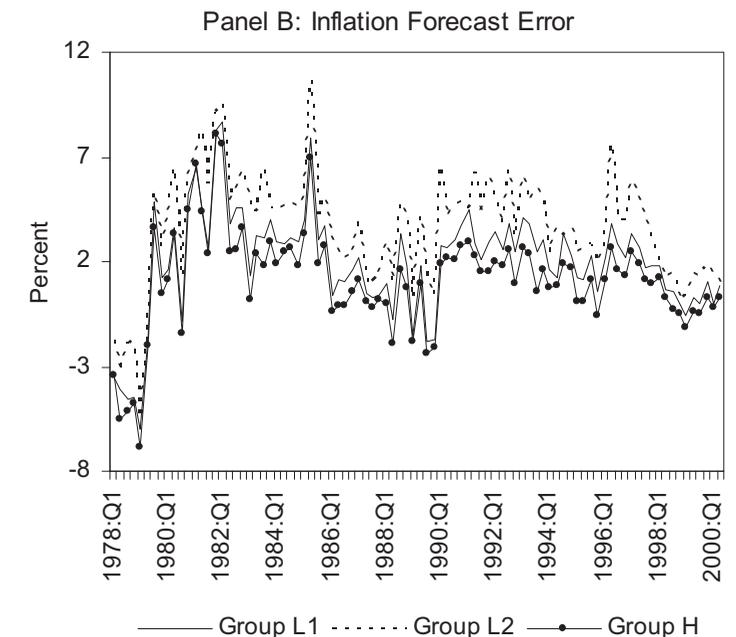
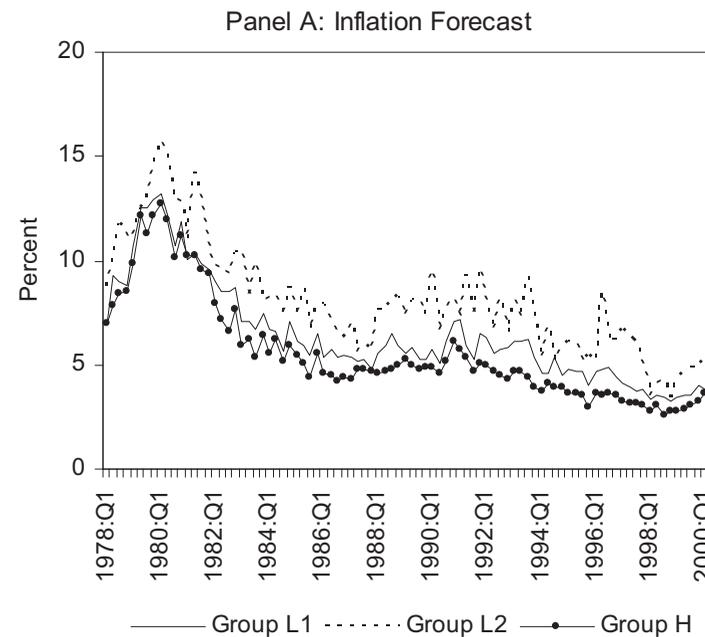
Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

1. Existence of Asymmetric Information Diffusion

Two Groups:

- Group H: Agents with a college degree or graduate degree
- Group L: Agents without a college degree
 - L1: agents with some college or a high school diploma
 - L2: agents with less than or no high School diploma



Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

1. Existence of Asymmetric Information Diffusion

Two Groups:

- Group H: Agents with a college degree or graduate degree
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 - L2: agents with less than or no high School diploma

VAR pairwise Granger causality test: the direction of information diffusion across Group H, Group L1 and Group L2.

Null hypothesis	Chi-sq statistics	P-value
If forecasts of the <i>higher</i> educated group Granger-cause those of the <i>less</i> educated group?		
a. Group H does not Granger-cause Group L1	11.401	[0.122]
b. Group H does not Granger-cause Group L2	15.522 ^a	[0.030]
c. Group L1 does not Granger-cause Group L2	14.253 ^a	[0.047]
If forecasts of the <i>less</i> educated group Granger-cause those of the <i>higher</i> educated group?		
d. Group L1 does not Granger-cause Group H	3.897	[0.792]
e. Group L2 does not Granger-cause Group H	7.583	[0.371]
f. Group L2 does not Granger-cause Group L1	2.603	[0.919]

^a Indicates statistical significance at 5%.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

2. Existence of Boomerang Effect

Group H's *MSE* increases as the variance of interpretation errors σ_e^2 increases.

Testing Boomerang Effect

$$\sigma_e^2 \rightarrow \text{MSE}_H?$$

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

2. Existence of Boomerang Effect

$$\sigma_e^2 \rightarrow \text{MSE}_H?$$

Low-informed group: $\pi_t = a_L + b_L x_{t-1} + c_L \hat{\pi}_{t-1} + v_t$

$$\Rightarrow E_{Lj,t-1}^* \pi_t = a_{Lj} + b_{Lj} x_{t-1} + c_{Lj} (E_{H,t-1}^* \pi_t + e_{Lj,t-1})$$

$$\Rightarrow e_{Lj,t-1} = \frac{E_{Lj,t-1}^* \pi_t - a_{Lj} - b_{Lj} x_{t-1} - c_{Lj} E_{H,t-1}^* \pi_t}{c_{Lj}}$$

$$\Rightarrow \sigma_{e_{Lj,t}}^2 = \frac{\sum_t^{t+s} e_{Lj,t}^2}{s-1}, \quad \forall t$$

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

2. Existence of Boomerang Effect

$$\sigma_e^2 \rightarrow \text{MSE}_H?$$

High-informed group: $\pi_t = a_H + b_{1H}x_{t-1} + b_{2H}z_{t-1} + v_t$

$$\Rightarrow \text{MSE}_{H,t} = \frac{\sum_t^{t+s} (\pi_t - E_{H,t-1}^* \pi_t)^2}{s}, \quad \forall t$$

We test the long run relationship between σ_e^2 and MSE_H

1. Unit-root tests – the integration properties of σ_e^2 and MSE_H
2. Johansen cointegration test and Granger causality tests in VECM

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

Unit-root tests – the integration properties of σ_e^2 and MSEH

Unit root test results: the integration properties of MSE_H , $\sigma_{e_{L1}}^2$, and $\sigma_{e_{L2}}^2$.

Variable	Augmented Dickey–Fuller test		Elliott–Rothenberg–Stock test			Conclusion
	DF_μ^a	DF_τ^b	Optimal lag	DF – GLS $_\mu^c$	DF – GLS $_\tau^c$	
A. Data in levels						
MSE_H	–2.222	–0.661	3	–0.305	–1.690	I(1)
$\sigma_{e_{L1}}^2$	–0.826	–2.797	3	–0.531	–2.638	I(1)
$\sigma_{e_{L2}}^2$	–1.896	–3.327*	6	–0.743	–3.327**	I(1)
B. Data in first differences						
MSE_H	–4.536***	–4.966***	2	–2.041*	–2.371**	I(0)
$\sigma_{e_{L1}}^2$	–7.616***	–7.588***	2	–2.957***	–2.973*	I(0)
$\sigma_{e_{L2}}^2$	–7.002***	–6.926***	7	–3.367***	–3.440**	I(0)

***, **, and * indicate statistical significance at 1, 5 and 10%, respectively.

^a Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary. Fuller (1976) 1 and 5% critical values for a sample size of 41 equal –3.597 and –2.934, respectively.

^b Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary. Fuller (1976) 1 and 5% critical values for a sample size of 41 equal –4.196 and –3.522, respectively.

^c Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary. The critical values, not reported here, are calculated from the response surface estimates of Table 1, Cheung and Lai (1995).

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

Johansen Cointegration Tests

Null hypothesis	Variables in the system							
	MSE _H , $\sigma_{e_{L1}}^2$ ^a (1)		MSE _H , $\sigma_{e_{L2}}^2$ ^b (2)		MSE _H , $\sigma_{e_{L1}}^2, \sigma_{e_{L2}}^2$ ^c (3)		$\sigma_{e_{L1}}^2, \sigma_{e_{L2}}^2$ ^d (4)	
	$\hat{\lambda}_{\max}$	Trace	$\hat{\lambda}_{\max}$	Trace	$\hat{\lambda}_{\max}$	Trace	$\hat{\lambda}_{\max}$	Trace
A: Rank test and cointegrating relation								
No rank	12.82** [11.44]	15.22** [12.53]	8.00 [11.44]	12.20* [12.53]	48.60*** [22.00]	87.52*** [34.91]	6.52 [11.44]	8.80 [12.53]
At most 1 rank	2.40 [3.84]	2.40 [3.84]	4.20 [3.84]	4.20 [3.84]	32.65*** [15.67]	38.92*** [19.96]	2.28 [3.84]	2.28 [3.84]
At most 2 ranks	–	–	–	–	6.27 9.24]	6.27 9.24]	–	–
Conclusion	1 cointegrating relation		1 cointegrating relation		2 cointegrating relations		None	
Estimated cointegration vector	(MSE _H , $\sigma_{e_{L1}}^2$) = (1, –29.58))		((MSE _H , $\sigma_{e_{L2}}^2$) = (1, –21.54))		(MSE _H , $\sigma_{e_{L1}}^2, \sigma_{e_{L2}}^2$) = (1, –20.52, –0.79))		None	

***, **, and * indicate statistical significance at 1, 5 and 10%, respectively. We use the AIC criterion to choose the optimal number of lags to be included in each empirical model. Five percent critical values, from [Osterwald-Lenum \(1992\)](#), for rank tests are in parentheses.

^a Test allows for a constant but no trend in the data space and 4 lags are included in the system.

^b Test allows for a constant but no trend in the data space and 3 lags are included in the system.

^c Test allows for a constant but no trend in the cointegration space and 8 lags are included in the system.

^d Test allows for a constant but no trend in the data space and 4 lags are included in the system.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

Granger Causality Tests in VECM

Null hypothesis	Variables in the system			
	$MSE_H, \sigma_{e_{L1}}^2$ ^a (1)	$MSE_H, \sigma_{e_{L2}}^2$ ^b (2)	$MSE_H, \sigma_{e_{L1}}^2, \sigma_{e_{L2}}^2$ ^c (3)	$\sigma_{e_{L1}}^2, \sigma_{e_{L2}}^2$ ^d (4)
	Chi-sq statistics <i>p</i> -value	Chi-sq statistics <i>p</i> -value	Chi-sq statistics <i>p</i> -value	Chi-sq statistics <i>p</i> -value
B: The direction of causality in VECM				
$\sigma_{e_{L1}}^2$ does not cause MSE_H	14.36*** [0.006]	–	21.04*** [0.007]	–
MSE_H does not cause $\sigma_{e_{L1}}^2$	3.82 [0.430]	–	5.68 [0.682]	–
$\sigma_{e_{L2}}^2$ does not cause MSE_H	–	19.43*** [0.000]	30.87*** [0.000]	–
MSE_H does not cause $\sigma_{e_{L2}}^2$	–	4.72 [0.194]	7.15 [0.521]	–

***, **, and * indicate statistical significance at 1, 5 and 10%, respectively. We use the AIC criterion to choose the optimal number of lags to be included in each empirical model. Five percent critical values, from [Osterwald-Lenum \(1992\)](#), for rank tests are in parentheses.

^a Test allows for a constant but no trend in the data space and 4 lags are included in the system.

^b Test allows for a constant but no trend in the data space and 3 lags are included in the system.

^c Test allows for a constant but no trend in the cointegration space and 8 lags are included in the system.

^d Test allows for a constant but no trend in the data space and 4 lags are included in the system.

Information Diffusion & Inflation Expectations (Chapter 7)

Step 3: Unifying and evaluating the analogues

The Unit-root, Johansen and Granger Causality tests indicate a boomerang effect exists.

The long run “cointegrated” relation between the variance of observational errors σ_{ϵ}^2 from the less educated group (Group L) influence the mean square error of the more educated group’s (Group H’s) expectations (MSE_H).

Thank You

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