NATURAL EXPECTATIONS, MACROECONOMIC DYNAMICS, AND ASSET PRICING

By Fuster, Hebert, and Laibson

Discussion by Yuriy Gorodnichenko (UC Berkeley)
Larry Summers compared finance to a ketchup science since at least at the time he thought that finance did not

- bother to explain the level of asset prices,
- link to other branches of economics (esp. macroeconomics),
- seriously question departures from full rationality.
MACROECONOMICS AND FINANCE

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- bother to explain the level of asset prices,
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- seriously question departures from full rationality.

This paper is a major step forward in addressing these concerns.
SETUP/LOGIC OF THE PAPER

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4. Because agents’ model is mis-specified, agents fail to understand the degree of mean reversion in the behavior of fundamentals. Hence, with this particular misspecification and with habit, there is an over-reaction to innovations in the productivity of trees.
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5. As a result, one can explain a number of puzzles in macro/finance, such as:
   a. High equity premium
   b. Momentum
   c. Volatile asset prices
APPEAL OF SIMPLE MODELS

The paper presents a long list of reasons why simple (statistical) models can be preferred to complex (statistical) models.

- There is a great deal of uncertainty about what is a true model.
- The Box-Jenkins approach is very explicit in suggesting very simple models for forecasting (e.g. use AR(5) instead of AR(40) to avoid over-fitting).
- It is natural to use simple models to form forecasts/expectations and act based on these forecasts/expectations. Hence, natural expectations.
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To rule out any form of learning? [agents are born with models; agents repeatedly fail to understand the discrepancy between what they forecast and what they observe even in the very long run.]

- E.g., learning can attenuate over-reactions and reduce volatility.
INFORMATIONAL RIGIDITIES IN SURVEY DATA

1. Disagreement in cross-sections of forecasts.
2. Conditional responses of disagreement to structural shocks are close to zero.
3. Serial correlation of forecast errors.
4. Conditional forecast errors vanish over time.
5. Forecast revisions predict forecast errors.
7. Speed of learning about structural shocks is similar across different types of shocks.
8. Speed of learning is similar across types of agents (consumers, firms, professional forecasters).
9. Average forecasts consistently beat “individual” forecasts.
INFORMATIONAL RIGIDITIES IN SURVEY DATA

1. Disagreement in cross-sections of forecasts. **NO**
2. Conditional responses of disagreement to structural shocks are close to zero. **NO**
3. Serial correlation of forecast errors. **MAYBE**
4. Conditional forecast errors vanish over time. **NO**
5. Forecast revisions predict forecast errors. **MAYBE**
6. State-dependent acquisition of information. **NO**
7. Speed of learning about structural shocks is similar across different types of shocks. **NO**
8. Speed of learning is similar across types of agents (consumers, firms, professional forecasters). **NO**
9. Average forecasts consistently beat “individual” forecasts. **NO**
MODEL SELECTION: SPECIFIC EXAMPLE

DGP: ARIMA(0,1,16)
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- MA terms are always hard to estimate.
- Fit low order AR(p) model in first differences \([\text{MA}(1)=\text{AR}(\infty)]\).
- In finite samples, it is really hard to estimate long-term properties of time series (e.g., unit root vs. trend stationarity).
ROLE OF AR AND MA TERMS

- ARIMA(5,1,0)
- ARIMA(8,1,0)
- ARIMA(16,1,0)
- ARIMA(5,1,1)
- ARIMA(5,1,3)
ROLE OF AR AND MA TERMS

mean reversion

truth

sample size

200 400 600 800 1000 1200 1400 1600 1800 2000

ARIMA(5,1,0)  ARIMA(8,1,0)  ARIMA(16,1,0)
ARIMA(5,1,1)  ARIMA(5,1,3)
ROLE OF AR AND MA TERMS

![Graph showing mean reversion for various ARIMA models over different sample sizes. The graph compares ARIMA(5,1,0), ARIMA(5,1,1), ARIMA(8,1,0), ARIMA(16,1,0), and ARIMA(5,1,3) models.](image)
ROLE OF AR AND MA TERMS

![Graph showing mean reversion over sample size for different ARIMA models.](image-url)
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Model selection: Specific example

DGP: ARIMA(0,1,16)

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- Fit low order AR(p) model in first differences \[\text{MA}(1) = \text{AR}(\infty)\].
- In finite samples, it is really hard to estimate long-term properties of time series (e.g., unit root vs. trend stationarity).

Modest modifications can improve estimates of long-run reversion:

- Introducing just a handful of MA terms.
- Simple VARs (rather than univariate AR(p) models).
- Bias correction in the finite-sample estimates (e.g. bootstrap).
- Cointegration.
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Objectives for model selection:

- Why should one choose a model that minimizes MSE rather than expected loss in utility (the latter matters for decision making)?
- What is the price of using a wrong model?
GENERAL EQUILIBRIUM

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  Agents may have different models and private information sets but prices could aggregate these disparate bits and pieces and improve choices made by agents. For example, average forecast tends to beat individual forecasts. [in the baseline model, prices do not play any role for aggregating information and allocating resources.]
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Robustness check in the paper:
- Introduce a subset of agents who are fully rational
- … but do not let them influence asset prices.
SUMMARY

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• Future work
  
  o Link simple models, model uncertainty and agents’ behavior;
  
  o Incorporate learning and more sophisticated econometric tools available to economic agents;
  
  o Introduce agent heterogeneity and general equilibrium.