

**NATURAL EXPECTATIONS, MACROECONOMIC DYNAMICS,  
AND ASSET PRICING**

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# MACROECONOMICS AND FINANCE

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),
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This paper is a major step forward in addressing these concerns.

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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.
6. State-dependent acquisition of information.
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**
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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

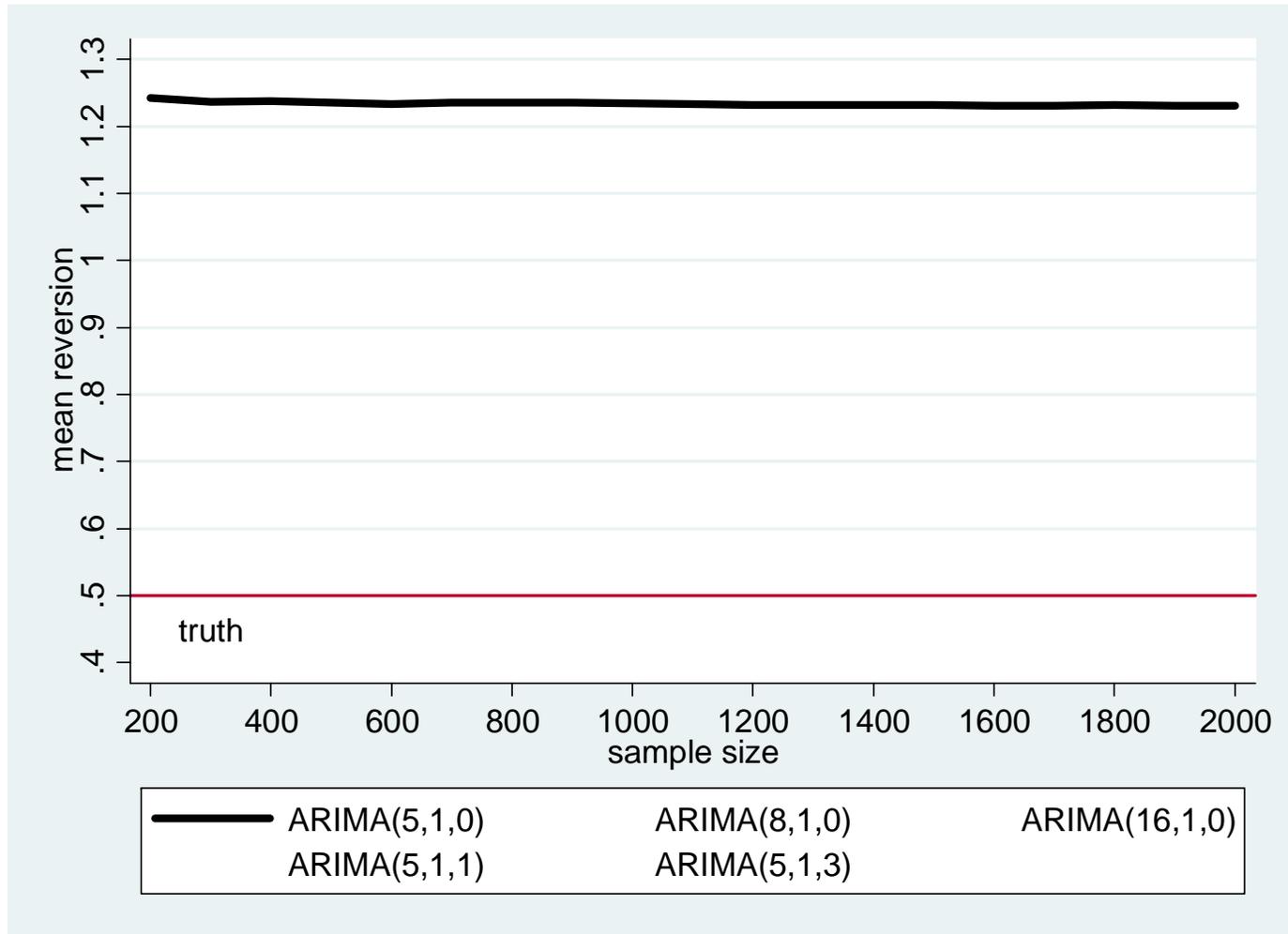
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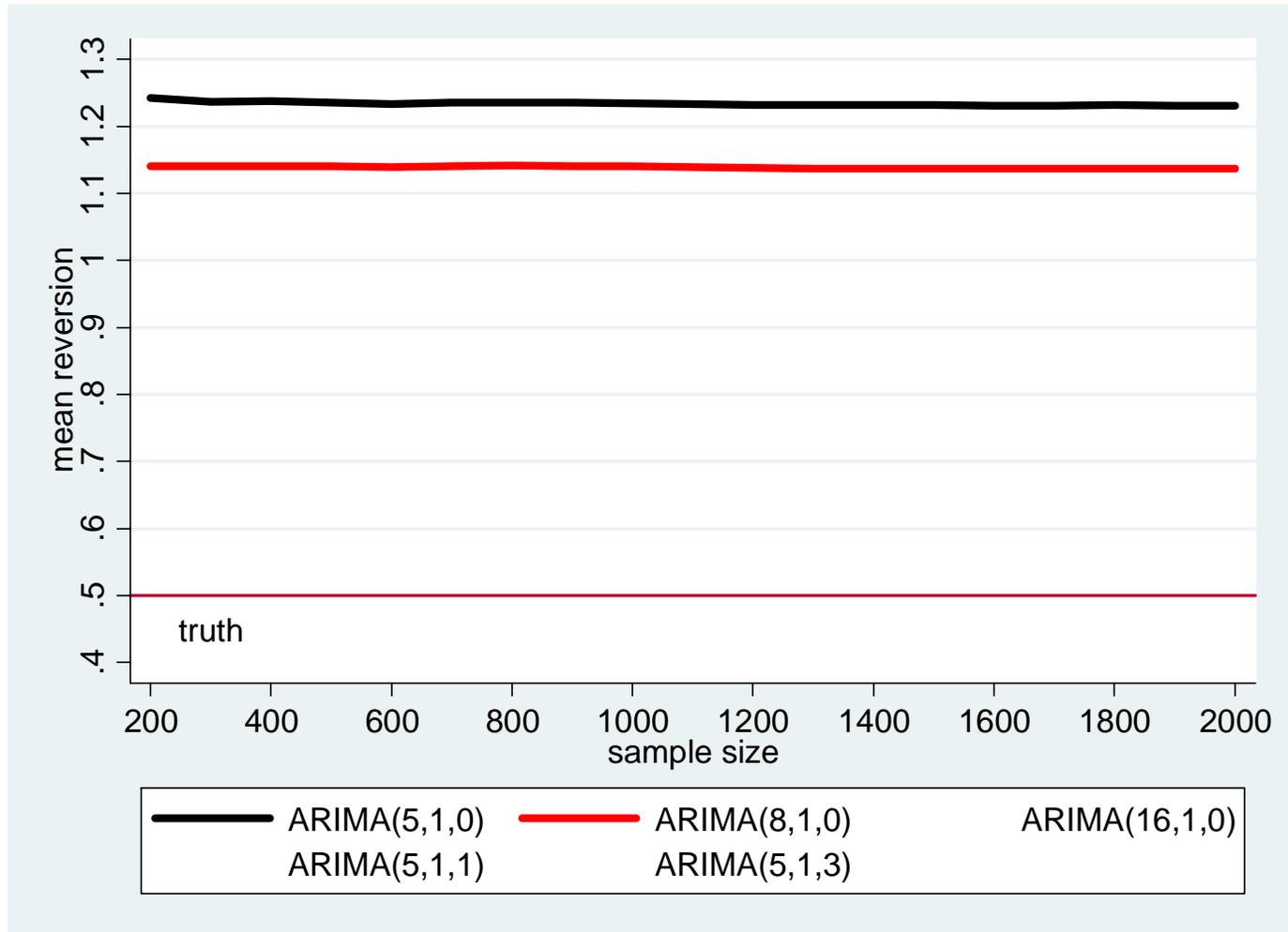
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- Fit low order AR(p) model in first differences [MA(1)=AR( $\infty$ )].
- In finite samples, it is really hard to estimate long-term properties of time series (e.g., unit root vs. trend stationarity).

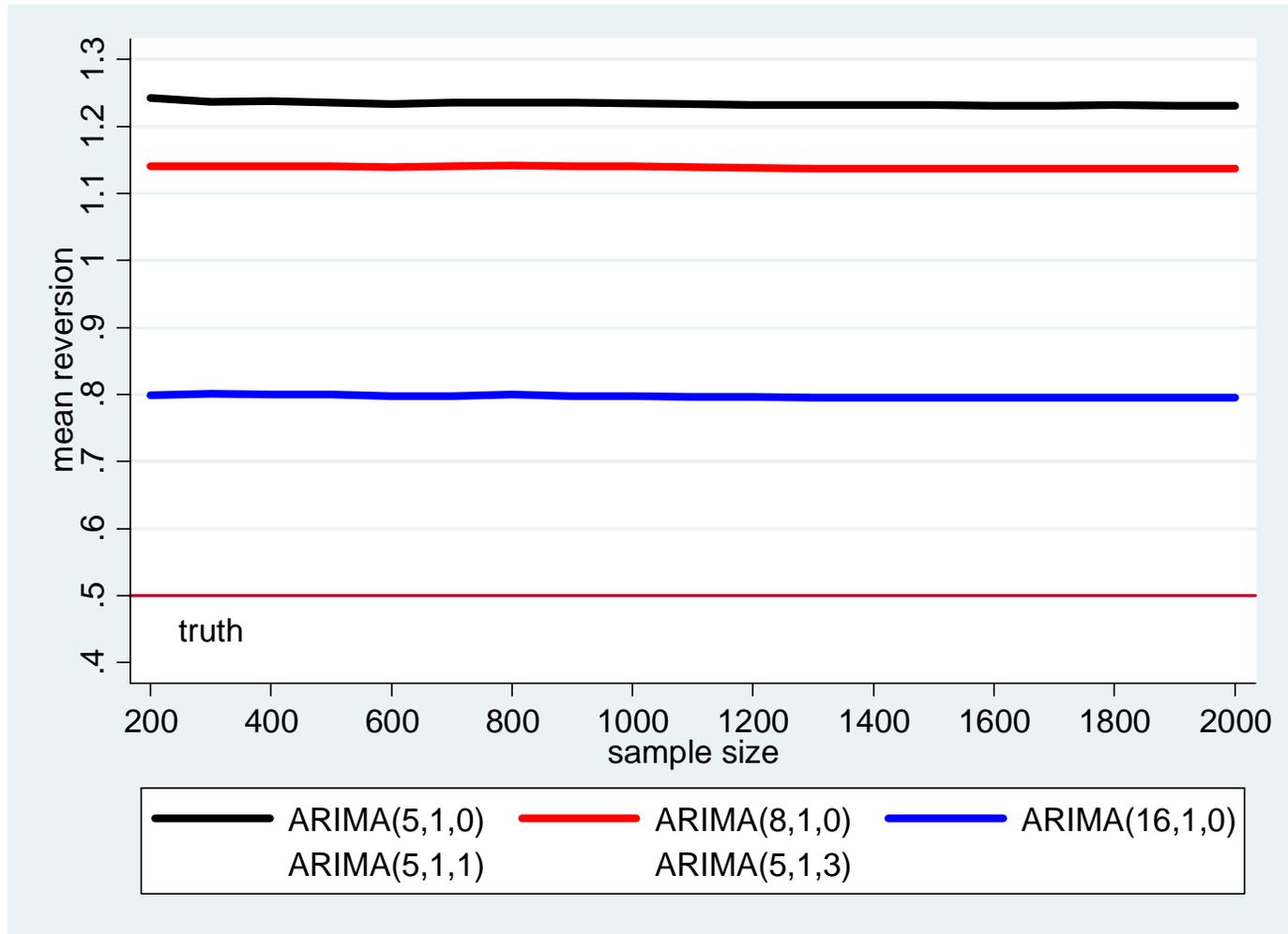
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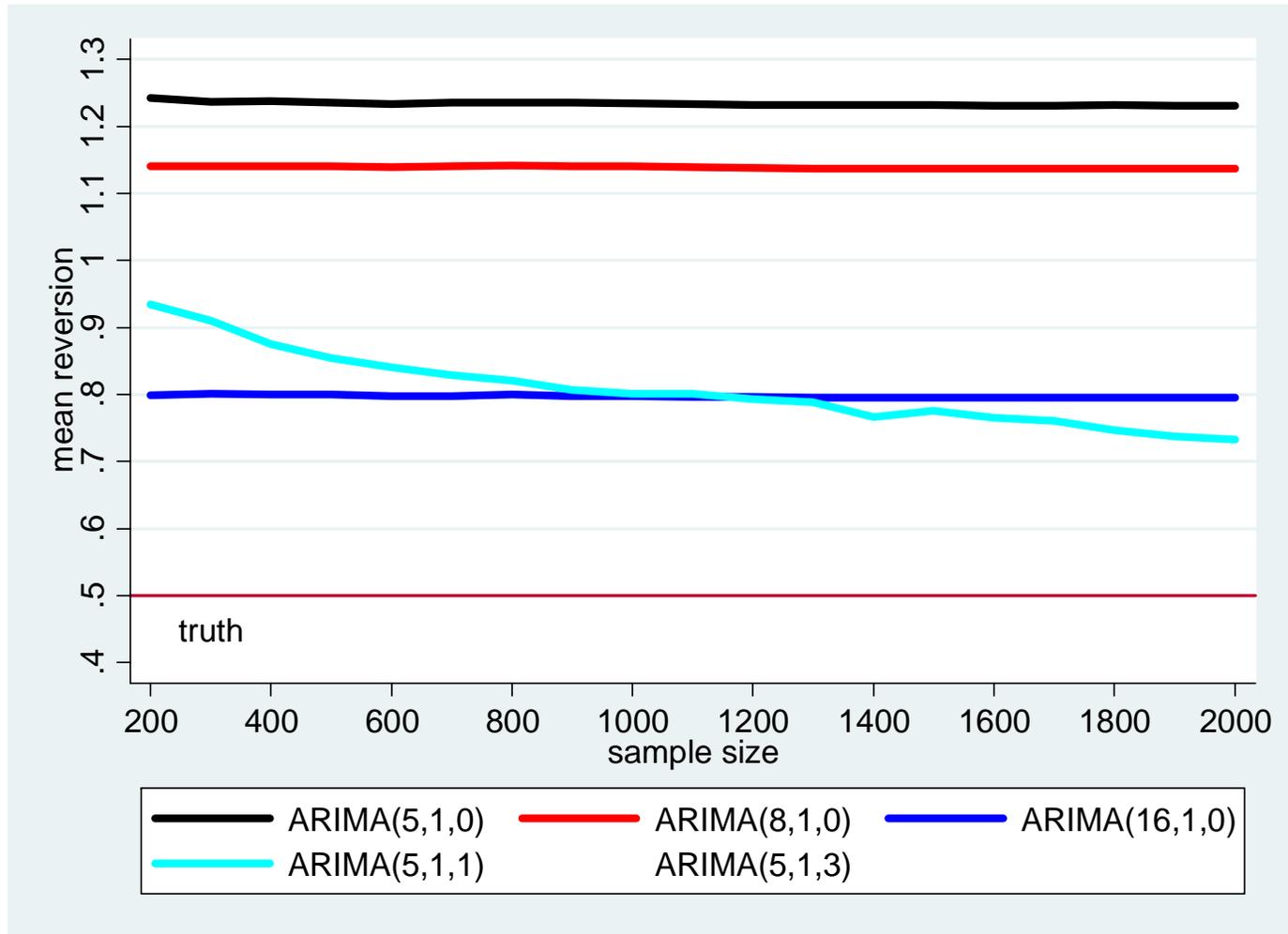
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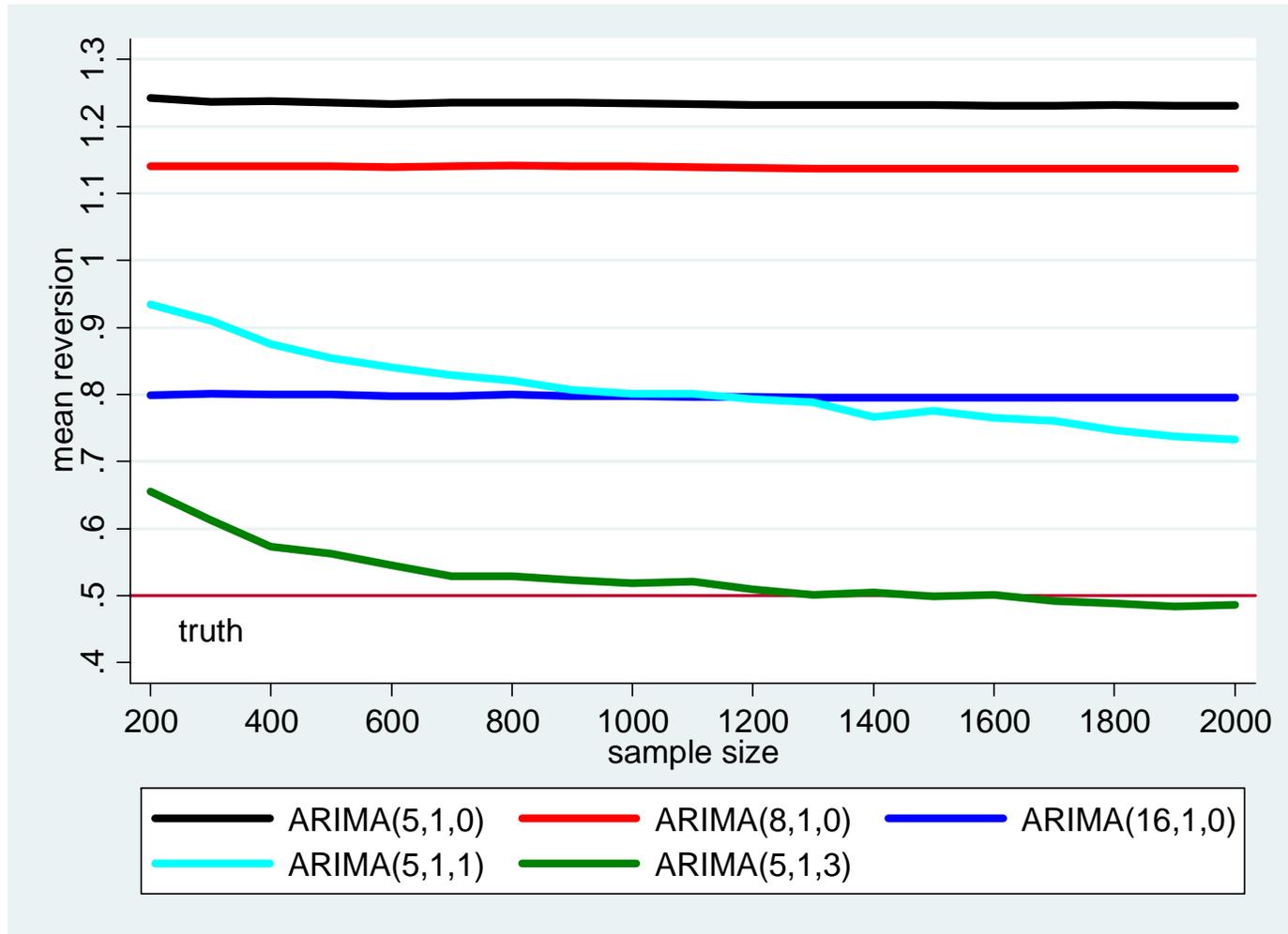
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Modest modifications can improve estimates of long-run reversion:

- 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?

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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.

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- Simple models can go a long way in explaining empirical facts and puzzles.
- Future work
  - Link simple models, model uncertainty and agents' behavior;
  - Incorporate learning and more sophisticated econometric tools available to economic agents;
  - Introduce agent heterogeneity and general equilibrium.