Fundamental Disagreement

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SEM Conference, OECD Paris
July 20, 2015

Disagreement About Future Economic Outcomes

- Observed in every survey of financial analysts, households, professional forecasters, FOMC members. . .
- At odds with full information rational expectation setup.
- Key in models with info. frictions / heterogenous beliefs.
  - Macro: Mankiw-Reis (2002), Sims (2003), Woodford (2003), Lorenzoni (2009), Mackowiak-Wiederholt (2009), Angeletos-Lao (2013), Andrade et al. (2015) . . .
  - Finance: Scheinkman-Xiong (2003), Nimark (2009), Burnside-Eichenbaum-Rebelo (2012) . . .
- Are empirical properties of disagreement informative about such models?

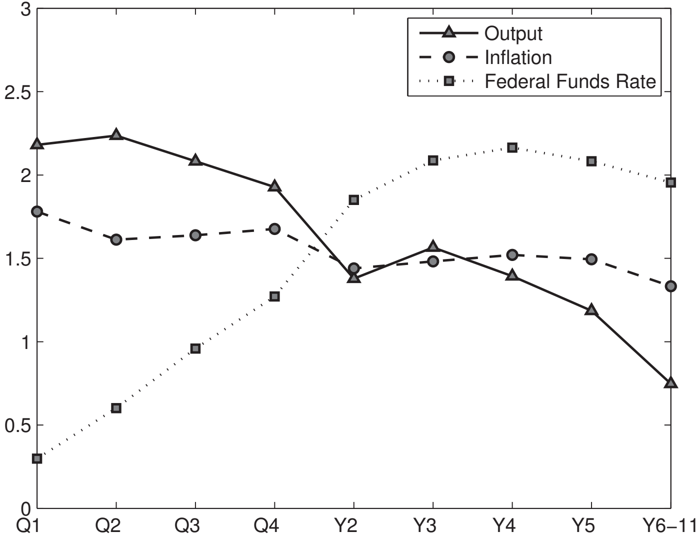
This Paper

- New facts related to the term structure of disagreement.
    - People disagree about fundamentals (long-horizon forecasts).
- Introduce a class of expectation models to match the facts.
    - Imperfect info. / Uncertainty about the long-run / Multivariate.
- Use macro and survey data to calibrate the model.
    - Reproduce most of the new facts.
    - Informative about perceived macro-relationships (monetary policy).

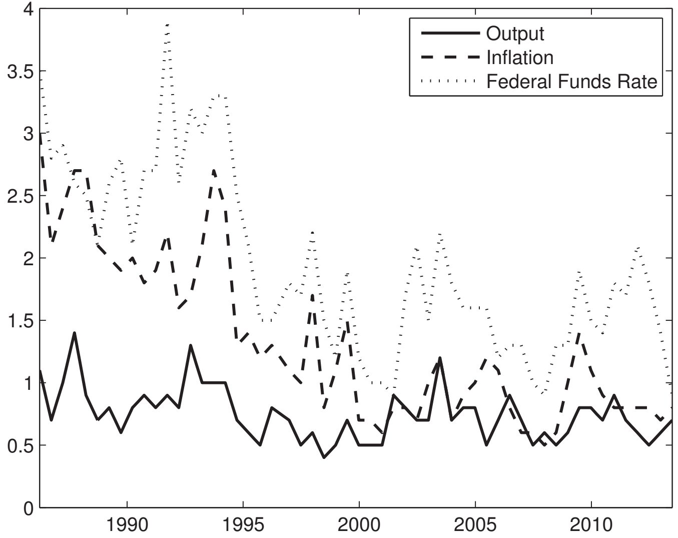
The Blue Chip Financial Forecasts Survey

- $\sim$ 50 professional forecasters.
- We look at forecasts for RGDP growth (g), CPI inflation (π), FFR (i).
- Sample period is 1986:Q1-2013:Q2.
- For 1Q, 2Q, 3Q, 4Q: observe individual forecasts.
- For 2Y, 3Y, 4Y, 5Y and long-term (6-to-11Y): observe average forecasts, top 10 average forecasts, and bottom 10 average forecasts.
- Our measure of disagreement: top 10 average $-$ bot 10 average.

The Term Structure of Disagreement in the BCFF



The Time Series of Long Run Disagreement



Model

Underlying state

- True state $z = \{g, \pi, i\}$ where

$$\begin{aligned} z_t &= (I - \Phi)\mu_t + \Phi z_{t-1} + v_t^z, \\ \mu_t &= \mu_{t-1} + v_t^\mu, \end{aligned}$$

  with $v_t^z \sim iid\ N(0, \Sigma^z)$ and $v_t^\mu \sim iid\ N(0, \Sigma^\mu)$.

- Parameters: $\theta = (\Phi, \Sigma^z, \Sigma^\mu)$

- Forecaster j observes:

$$y_{jt} = z_t + \eta_{jt}$$

with $\eta_{jt} \sim iid\ N(0, \Sigma^\eta)$, Σ^η diagonal.

- Individual j's optimal forecast computed using the Kalman filter.

- Model parameters: (θ, Σ^η).

- Disagreement driven by variance of observation errors Σ^η.

- At each date, a forecaster j observes k^{th} element of y_t with a fixed probability λ_k; otherwise sticks to latest observation.

- Individual j's optimal forecast computed using the Kalman filter with missing observations.

- Same number of parameters as in noisy info with λ's instead of Σ^η.

- Generate time variance of disagreement ($\neq$ noisy information).

Calibration via Penalized MLE

Principle

- Can we find (θ, Σ^η) / (θ, λ) consistent with the data?
- Rely on (i) realizations $\mathcal{Y} = \{GDP, INF, FFR\}$ and (ii) moments $\mathcal{S} = \{\text{avg. forecast, disag}\}$ observed in surveys.
- We minimize the Likelihood associated to true state + ...
- ... a penalty function measuring the distance between model implied moments and their survey data counterpart.

Calibration in Practice

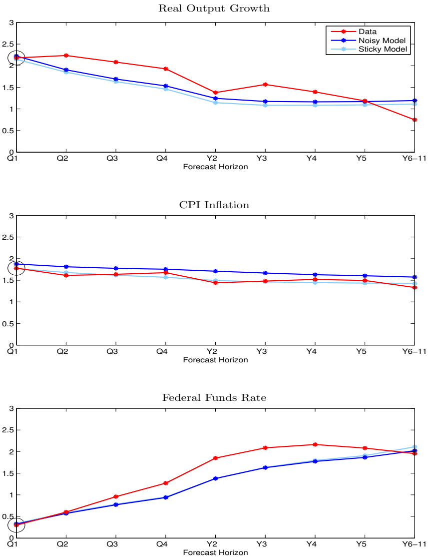
- We target 15 moments:
  - Std-dev of consensus forecasts for Q1, Q4, Y2 and Y6-11.
  - Disagreement about Q1 forecasts only.
- Various penalty parameters $\alpha = 1, \ldots, 50$.
- Simulate $R = 100$ histories of shocks ϵ_t and observation noises η_t^i with $T = 120$ (nb of dates) and $N = 50$ (nb of forecasters).
- Sample: realizations 1955Q1-2013Q2; survey 1986Q1-2013Q2.

Summary of Parameter Estimates

- True state parameters (θ) robust to type of info. friction.
- Long-run vol. (Σ^{μ}) much lower than short-run vol. (Σ^{z}).
- FFR is perfectly observed:
  - *Noisy*: observation error (Σ_{η}) for FFR is zero.
  - *Sticky*: probability of observing FFR (λ_i) is one.
- Quantifying information frictions:
  - *Noisy*: observation errors on GDP roughly twice as for CPI.
  - *Sticky*: avg. proba. of updating g or π is $\simeq$ 4Q ($\lambda = 0.26$).

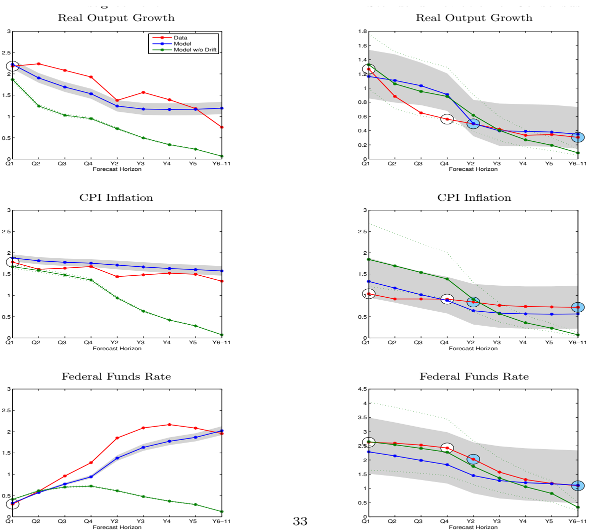
Data and Model-implied Term Structures of Disagreement

Noisy and Sticky



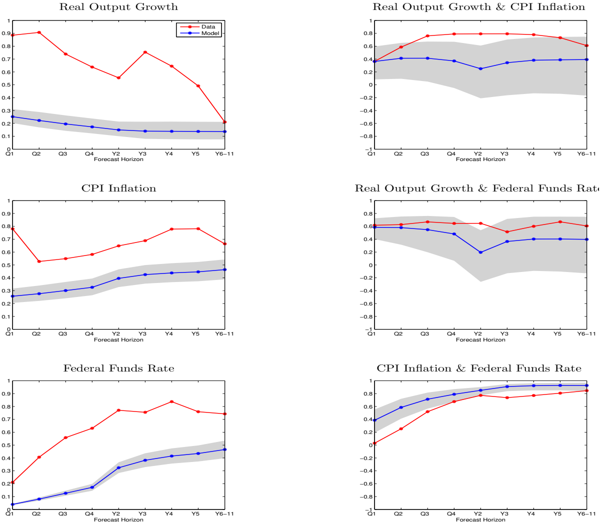
Disagreement and Consensus Volatility

Noisy



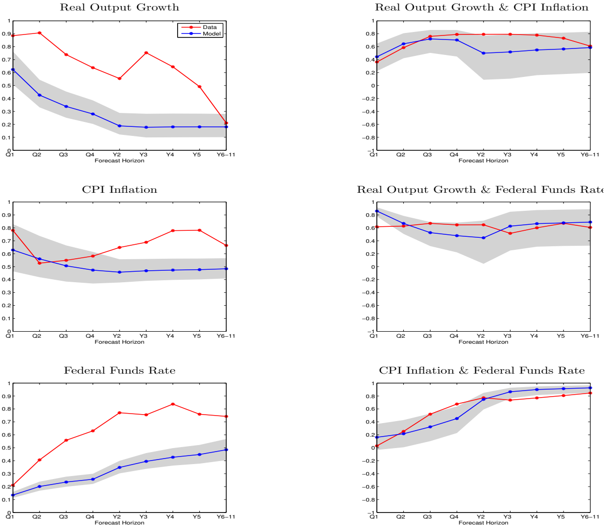
Time Variation & Co-movement in Disagreement

Noisy



Time Variation & Co-movement in Disagreement

Sticky



Role of Key Ingredients

- Imperfect information + permanent and transitory components:
  - Generate fundamental disagreement.
  - Don't need asymmetric agents with different models / immutable priors / signal-to-noise ratios.

    $\Rightarrow$ Appealing since hard to find "super forecaster" in the data.
- Multivariate model:
  - Explain disagreement about future FFR even though perfectly observed.
  - Univariate version of our model cannot generate upward-sloping disagreement unless $\sigma_\mu > \sigma_z$.

Disagreement about FFR and the Taylor Rule

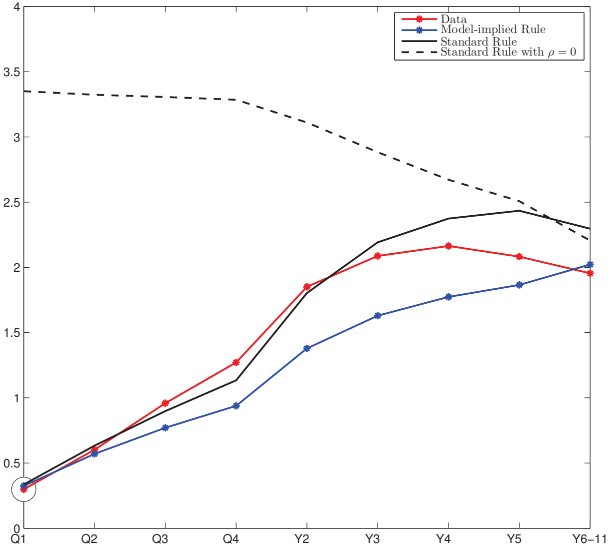
- Generate individual FFR forecasts from a Taylor rule

$$
\begin{aligned}
i_t &= \rho \cdot i_{t-1} + (1-\rho) \cdot i_t^\star + \epsilon_t \\
i_t^\star &= \bar{i}_t + \varphi_\pi \cdot (\pi_t - \bar{\pi}_t) + \varphi_g \cdot (g_t - \bar{g}_t)
\end{aligned}
$$

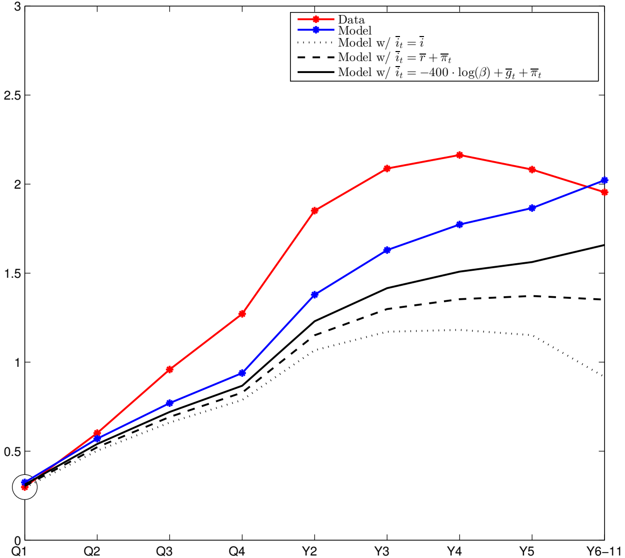
- Find Taylor rule parameters giving best fit of reduced form model disagreement for FFR.

- Compare with various parametric restrictions.
  - Std Taylor rule parameters: $\tilde{\rho} = 0.9$, $\tilde{\varphi}_\pi = 2$, $\tilde{\varphi}_g = 0.50$.

‘Standard’ Taylor Rule



Role of Uncertainty about the Long-Run



Conclusion

- Present new facts about forecaster disagreement.
  - May help discriminate between models of expectation formation.
- Show that imperfect info models combined with permanent/transitory decomposition explains most of the facts for sound parameter values.
  - Minimal departure from REH: agents know and agree on true model/params.
- Disagreement informative about both degree of imperfect info and underlying DGPs.
  - Help identifying parameters driving unobserved components.
  - Informative about perceived structural relationships.

Calibration via Penalized MLE

Details (1/2)

- Consider realizations as signals about z_t: $\mathcal{Y}_t = z_t + \widetilde{\eta}_t$ with $\widetilde{\eta}_t \sim iid\ N(0, \widetilde{\Sigma}^\eta)$.

- $-\mathcal{L}\left(\mathcal{Y}_1, \cdots, \mathcal{Y}_T; \theta, \widetilde{\Sigma}^\eta\right) =$ likelihood obtained with Kalman filter.

Calibration via Penalized MLE

Details (2/2)

- Given (θ, Σ^{η}) we generate individual forecasts f_{it}^{h} and compare some associated moments with their survey data counterparts $\mathcal{S}_t$.

- $\mathcal{P}\left(\mathcal{S}_1, \cdots, \mathcal{S}_T; \theta, \Sigma^{\eta}\right) =$ distance between model implied expectation moments and their survey data counterpart.

- We minimize the penalized likelihood:

$$\mathcal{C}\left(\theta, \Sigma^{\eta}, \widetilde{\Sigma}^{\eta}\right) = \mathcal{L}\left(\mathcal{Y}_1, \cdots, \mathcal{Y}_T; \theta, \widetilde{\Sigma}^{\eta}\right) + \alpha \mathcal{P}\left(\mathcal{S}_1, \cdots, \mathcal{S}_T; \theta, \Sigma^{\eta}\right).$$

Noisy Information Model

Φ	Σ^z	$\text{sqrt}(\text{diag}(\tilde{\Sigma}^\eta))$
$\begin{bmatrix} 0.378 & -0.503 & -0.153 \\ 0.125 & 0.974 & -0.033 \\ 0.147 & 0.104 & 0.924 \end{bmatrix}$	$\begin{bmatrix} 3.419 & -0.019 & 0.561 \\ -0.019 & 0.645 & 0.365 \\ 0.561 & 0.365 & 0.632 \end{bmatrix}$	$\begin{bmatrix} 2.592 \\ 1.429 \\ 0.000 \end{bmatrix}$
$\lvert\text{eig}(\Phi)\rvert$	Σ^μ	$\text{sqrt}(\text{diag}(\Sigma^\eta))$
$\begin{bmatrix} 0.920 \\ 0.711 \\ 0.646 \end{bmatrix}$	$\begin{bmatrix} 0.008 & 0.014 & 0.026 \\ 0.014 & 0.024 & 0.045 \\ 0.026 & 0.045 & 0.085 \end{bmatrix}$	$\begin{bmatrix} 4.317 \\ 2.731 \\ 0.000 \end{bmatrix}$

Sticky Information Model

Φ	Σ^z	$\text{sqrt}(\text{diag}(\tilde{\Sigma}^\eta))$
$\begin{bmatrix} 0.392 & -0.478 & -0.142 \\ 0.122 & 0.939 & -0.024 \\ 0.146 & 0.087 & 0.931 \end{bmatrix}$	$\begin{bmatrix} 3.736 & -0.065 & 0.564 \\ -0.065 & 0.911 & 0.347 \\ 0.564 & 0.347 & 0.635 \end{bmatrix}$	$\begin{bmatrix} 2.586 \\ 1.355 \\ 0.000 \end{bmatrix}$
$\lvert\text{eig}(\Phi)\rvert$	Σ^μ	λ
$\begin{bmatrix} 0.920 \\ 0.674 \\ 0.674 \end{bmatrix}$	$\begin{bmatrix} 0.007 & 0.012 & 0.022 \\ 0.012 & 0.021 & 0.039 \\ 0.022 & 0.039 & 0.073 \end{bmatrix}$	$\begin{bmatrix} 0.260 \\ 0.260 \\ 1.000 \end{bmatrix}$