Inference on Probabilistic Surveys in Macroeconomics with an Application to the Evolution of Uncertainty in the Survey of Professional Forecasters during the COVID Pandemic

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Chapter in "Handbook of Economic Expectations"

1. Discuss and review the literature on **inference on probabilistic surveys**, with a focus on macro surveys
   - Zarnowitz and Lambros, 1987; Giordani and Söderlind, 2003; Lahiri and Liu, 2006; Boero et al., 2008; Clements, 2010, 2014, ...; Engelberg et al., 2009, 2011; Rich and Tracy, 2010, 2014,...... and a few important surveys, notably Manski 2011, 2014
   - Compare with the approach in "A Bayesian Approach for Inference on Probabilistic Surveys" (Del Negro, Casarin, Bassetti)
2. Application to U.S. Survey of Professional Forecasters' density projections of output growth and inflation during the COVID pandemic, with an emphasis on **documenting the evolution of uncertainty**

The Inference Problem

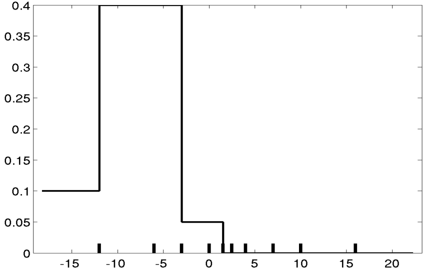
- Probabilistic surveys provide a wealth of information beyond point projections (Manski, 2004)

- ... but present the econometrician with a difficult inference problem: respondent i only provides **a few points of the CDF** of their predictive distribution (possibly **noisy**, because of rounding ...):

    - the percent chance $z_{i,j}$, that the variable of interest would fall within (generally pre-specified) contiguous ranges/bins $(y_{j-1}, y_j], j = 1, .., J$

Forecasts for output growth in 2020 made in 2020Q2

(587)



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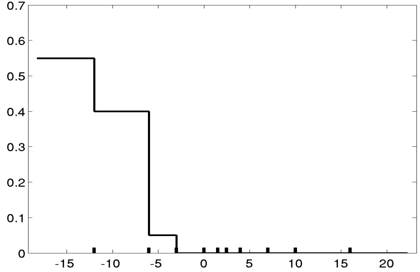
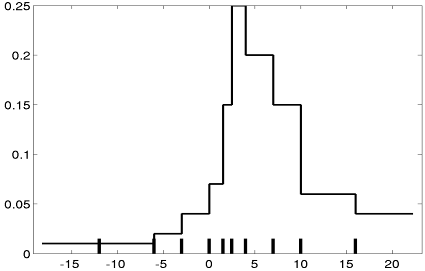


Forecasts for output growth in 2021 made in 2020Q2

(422)



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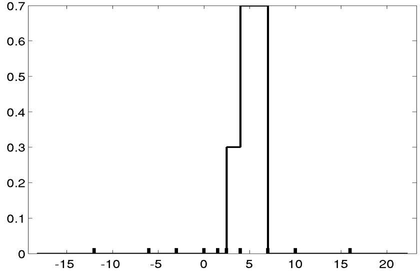


Approaches So Far

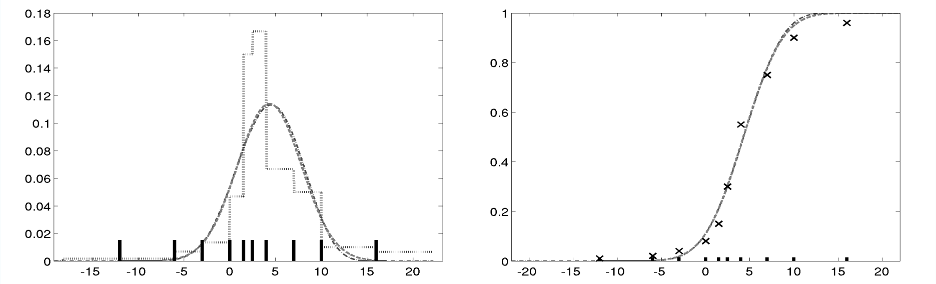
- Econometricians need to map this information into objects of interest such mean projections, uncertainty, quantiles, tail risks, ...

- Pick a **parametric** $F(y|\boldsymbol{\theta})$ and solve, for each forecaster i,

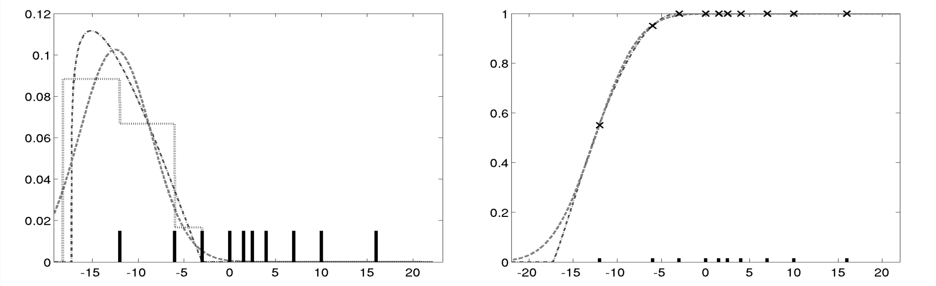
$$\boldsymbol{\theta}_i^* = \underset{\boldsymbol{\theta}_i}{\operatorname{argmin}} \sum_{j=1}^{J} \left| Z_{ij} - F(y_j|\boldsymbol{\theta}_i) \right|^2 \text{ where } Z_{ij} = z_{i,1} + \cdots + z_{i,j}$$

- Choice of $F(y|.)$: *Normal*: Giordani and Söderlind, 2003, ... ; *Beta*: Engelberg, Manski and Williams, 2009, ... ; *Piece-wise Uniform*: Zarnowitz and Lambros, 1987, ... ; *Skew-t*: Ganics et al, 2018, ...

(422) – Forecast for output growth in 2021



(576) – Forecast for output growth in 2020



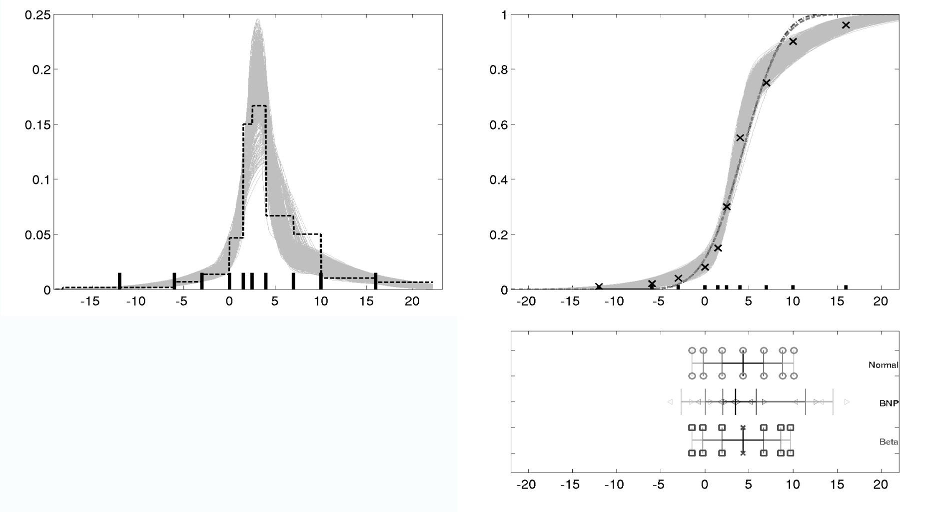
A Bayesian *Non-Parametric* Alternative based on Del Negro et al

1. **Non-parametric** → more flexible
   - Kernel distribution
     - Underlying continuous distribution is *mixture of two Gaussians*
     - *Model "noise" /rounding to zero*
   - Use (potentially infinite) mixture of the kernel distributions
   - *pooling* → fewer parameters to estimate

2. Allows for **inference** (eg, hypothesis testing) and **posterior uncertainty**, reflecting the limited information

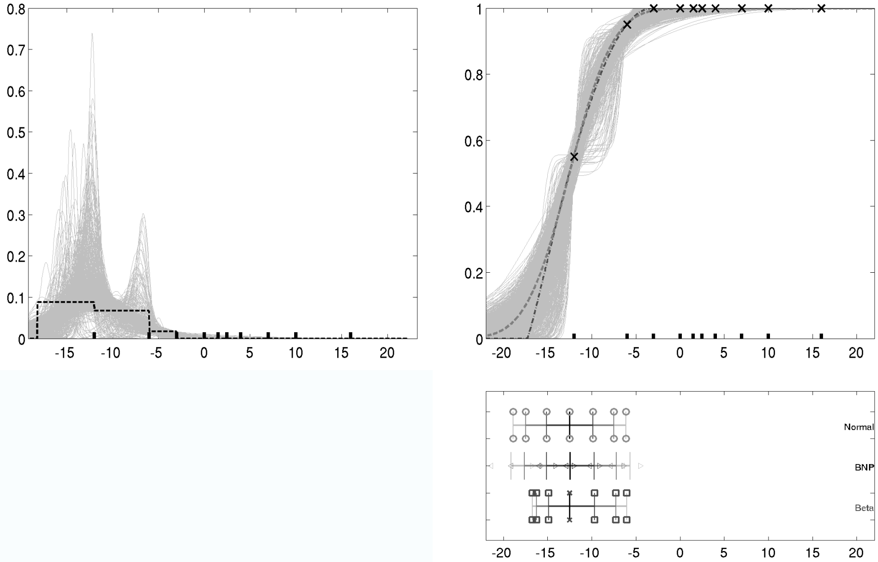
Example 1

(422) – Forecast for output growth in 2021

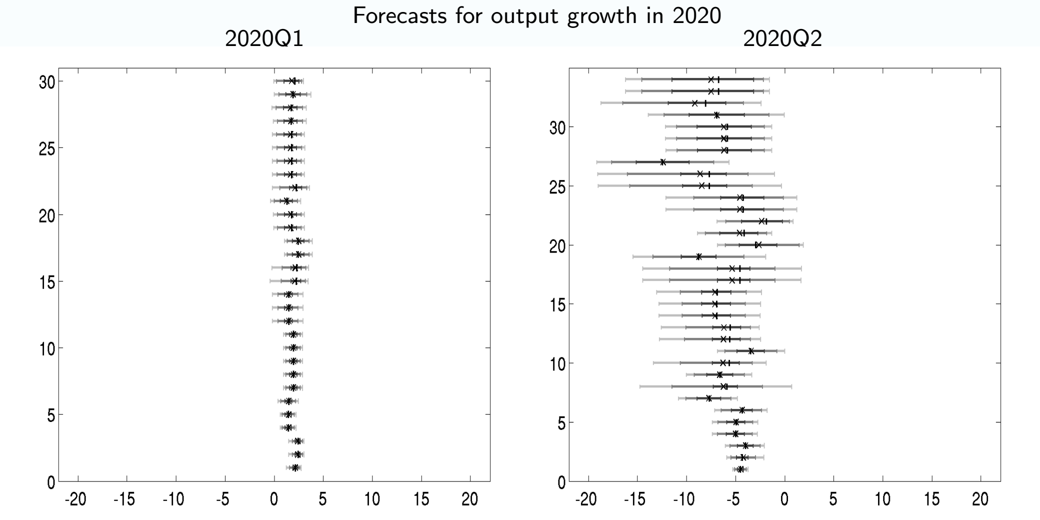


Example 2

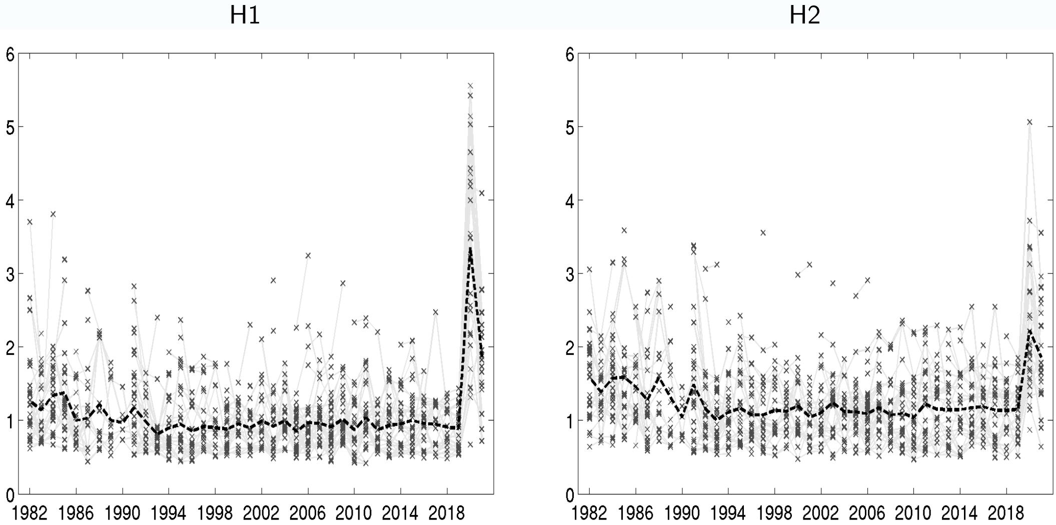
(576) – Forecast for output growth in 2020



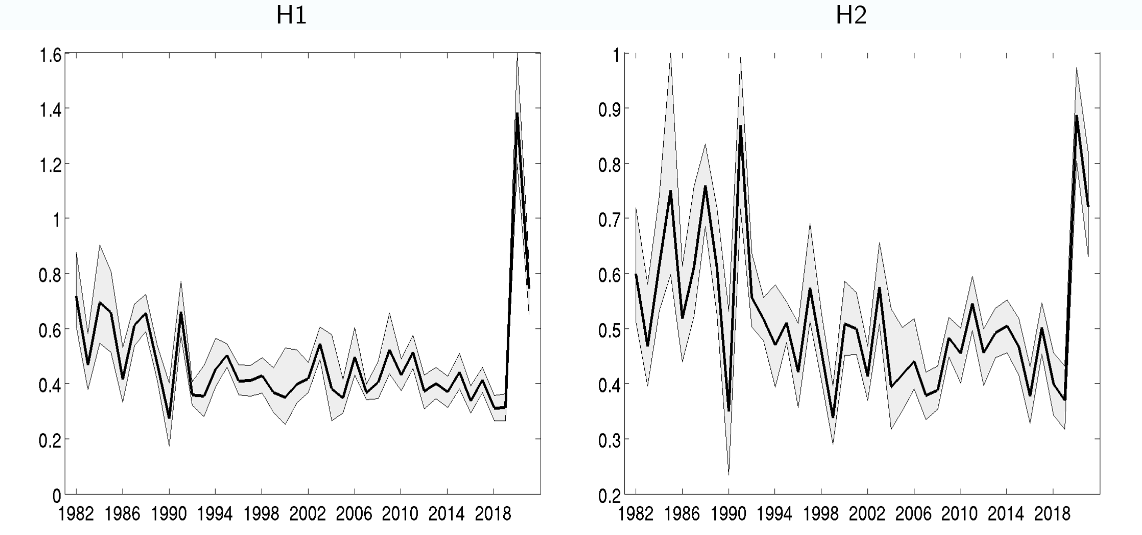
Heterogeneity in Density Forecasts



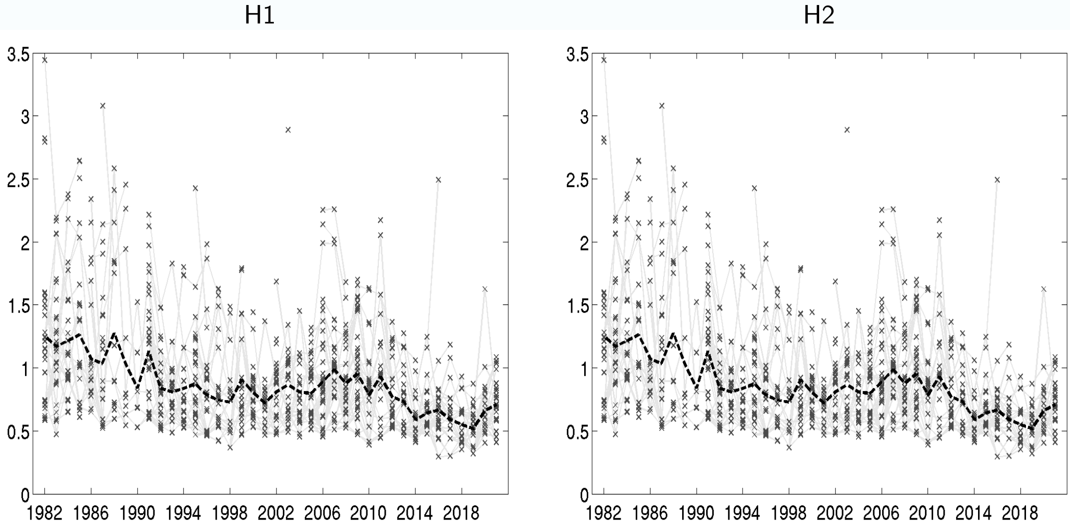
Subjective uncertainty by individual respondent–Output Growth



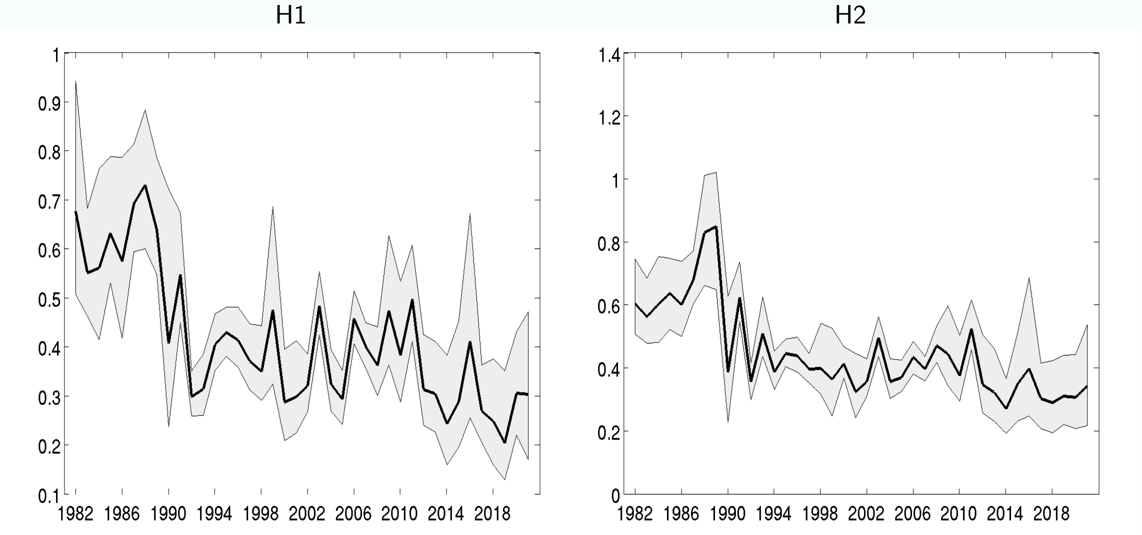
Cross-sectional standard deviation of individual uncertainty – Output



Subjective uncertainty by individual respondent–Inflation



Cross-sectional standard deviation of individual uncertainty – Inflation



Are SPF density forecasts consistent with the noisy RE hypothesis

- The noisy rational expectations (RE) hypothesis has been a leading hypothesis for explaining some facts about point predictions from surveys (Coibion and Gorodnichenko, 2012, 2015)
- Define the standardized forecast error: $\eta_{i,t,t-q} = \dfrac{y_t - E_{t-q,i}[y_t]}{\sigma_{t|t-q,i}}$. Then

1. **Scale test**: Under RE, $E[\eta^2_{i,t,t-q}] = 1 \ \rightarrow \alpha_q = 1$ in

$$(y_t - E_{t-q,i}[y_t])^2/\sigma^2_{t|t-q,i} = \alpha_q + \epsilon_{t,i,q}, \ \ t = 1, .., T, \ \ i = 1, .., N.$$

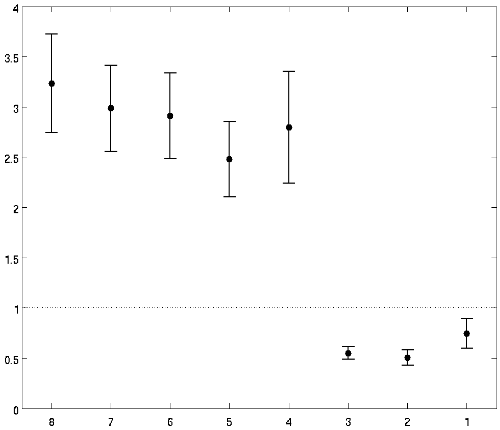
2. **Difference test**: $\beta_{1,q} = 1$ in

$$\ln|y_t - E_{t-q,i}[y_t]| = \beta_{0,q} + \beta_{1,q} \ln \sigma_{t|t-q,i} + \epsilon_{t,i,q}, \ \ t = 1, .., T, \ \ i = 1, .., N.$$

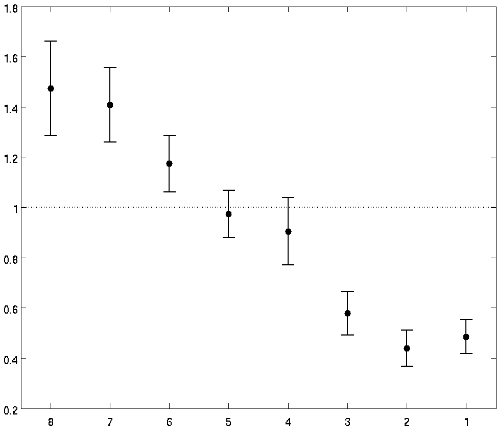
Subjective Uncertainty and Forecast Accuracy: A Scale Test

$$(y_t - E_{t-q,i}[y_t])^2/\sigma^2_{t|t-q,i} = \alpha_q + \epsilon_{t,i,q}, \;\; t = 1, .., T, \;\; i = 1, .., N$$

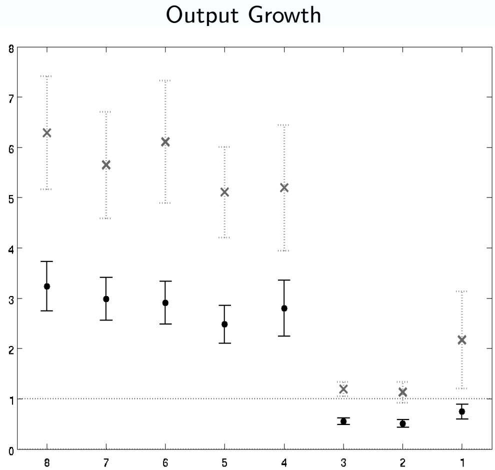
Output Growth

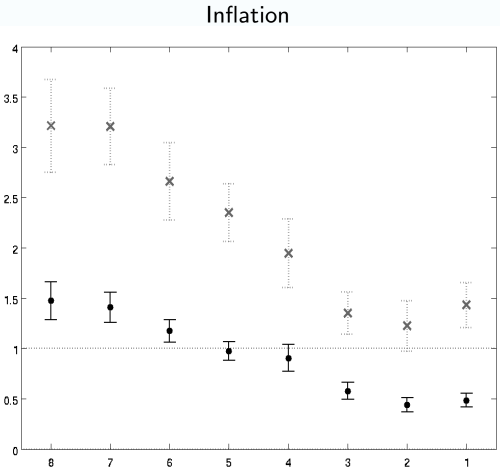


Inflation



Scale Test: Baseline vs Beta



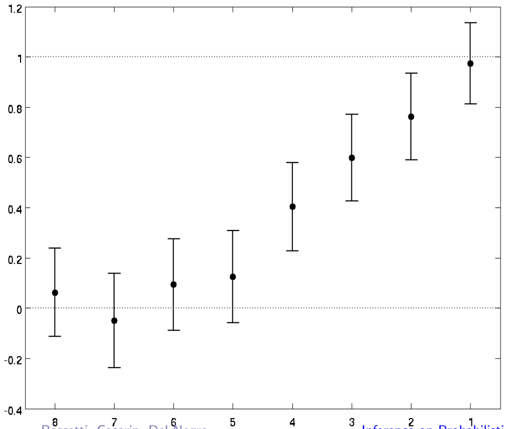


A Difference Test: Do Differences in Subjective Uncertainty Map into Differences in Forecast Accuracy?

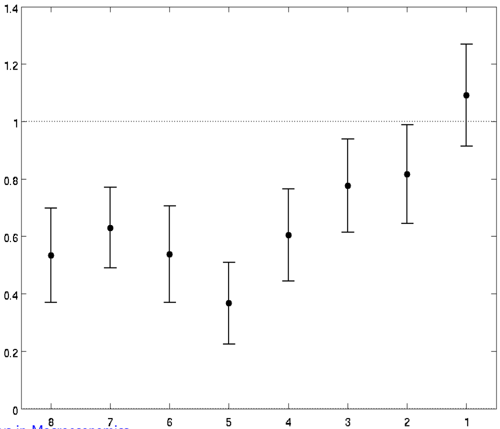
$$\ln|y_t - E_{t-q,i}[y_t]| = \beta_{0,q} + \beta_{1,q} \ln \sigma_{t|t-q,i} + \epsilon_{t,i,q}, \;\; t = 1,..,T, \;\; i = 1,..,N$$

[sample robustness]

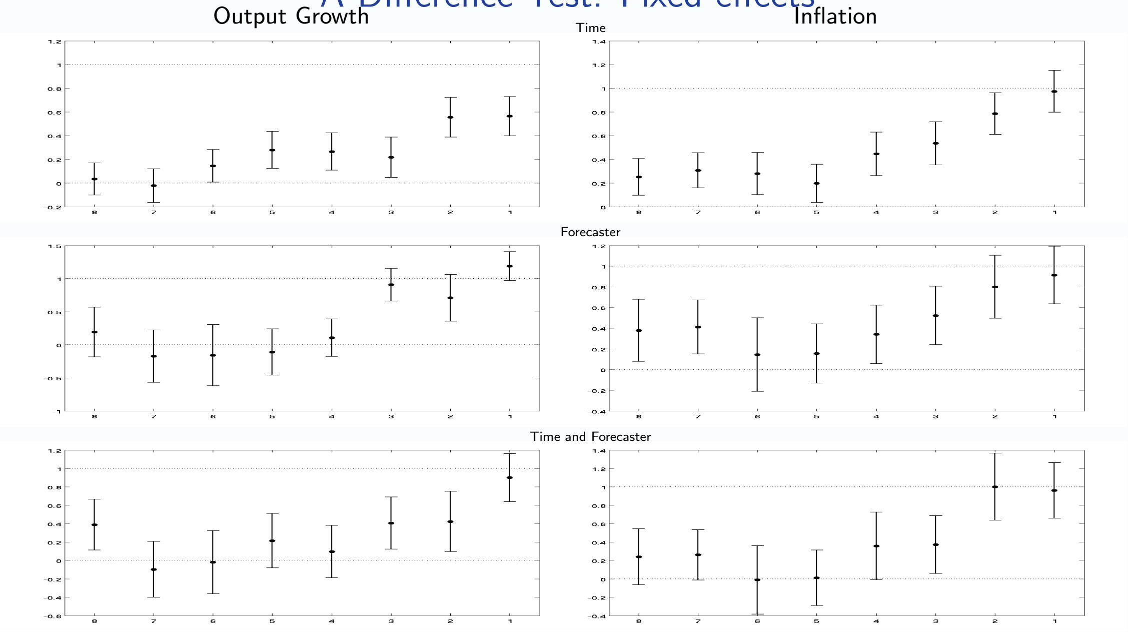
Output Growth



Inflation



A Difference Test: Fixed effects



Conclusions

- Thank you for your attention!