Aggregate disagreement

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Jamie Cross [1]   Paul Labonne [2]

[1]University of Melbourne

[2]CAMP, BI Norwegian Business School

Introduction

- A lot of work done on studying why people have different expectations (Cornand and Hubert, 2022; Meade and Driver, 2022; Savignac et al., 2021; von Gaudecker and Wogrolly, 2022; Weber et al., 2022; D'Acunto et al., 2023)
- But does micro disagreement lead to heterogeneity at the macro level?
- Most studies focus on the first two moments of survey expectations.
- In this paper we explore the modal features of inflation expectations from the Michigan Survey.
- Why it matters :
  - Multimodality can become a criteria to assess models of expectations.
  - The mean and dispersion are not good indicators of central tendency and heterogeneity when dealing with multimodal distributions.
  - Provides a better view on expectation anchoring

Conventional methods are not fit of purpose

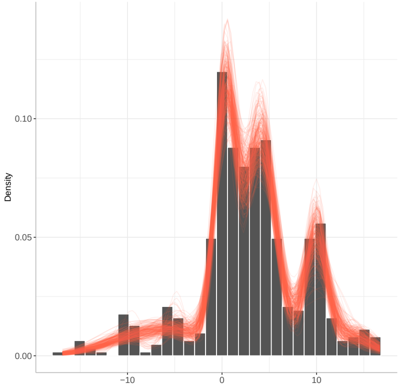


Figure: One-year-ahead inflation expectation distribution for May 2020

- The Silverman test gives a p-value of 0.218.
- No indication of mode locations;
- Ad hoc methods to get the modes (mode trees, mode forests) typically don't provide a measure of uncertainty.

Bayesian Mode Inference

Framework developed jointly with Herman van Dijk and Lennart Hoogerheide :

- Choose a mixture distribution;
- Estimate the mixture using Bayesian MCMC method;
    - It is important to estimate the number of components rather than fixing it;
- Estimate modes in each MCMC draw;
- Compute the Bayes estimates of the modes and their locations.

Bayesian Mixture Modelling

- A mixture of K distributions from the same parametric family $P(\cdot|\theta_k)$, continuous or discrete, is given by:

$$p(y|\theta) = \sum_{k=1}^{K} \pi_k p(y|\theta_k). \tag{1}$$

- The number of components, K, is unknown.
- Popular methods for estimating mixtures of unknown size include Reverse Jump MCMC (Green, 1995), Sparse Finite Mixtures (Malsiner-Walli et al., 2016) and non-parametric Bayesian mixtures.

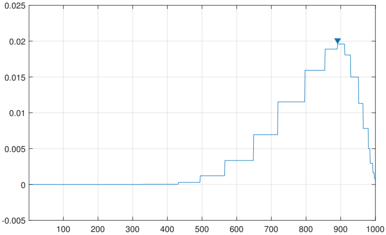
Mode Estimation

Each draw from the MCMC output after burnin, $\theta^{(d)}$, $d = 1, \dots, D$, leads to a posterior predictive density/mass function:

$$p(y|\theta^{(d)}) = \sum_{k=1}^{K} \pi_k^{(d)} p(y|\theta_k^{(d)}). \tag{2}$$

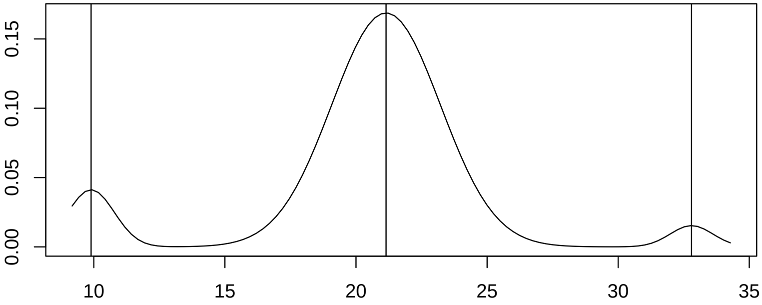
Discrete case :

1. $p_k(y_m - 1) < p_k(y_m) > p_k(y_m + 1)$,
2. $p_k(y_m - 1) < p_k(y_m) = p_k(y_m + 1) = \dots = p_k(y_m + l - 1) > p_k(y_m + l)$.

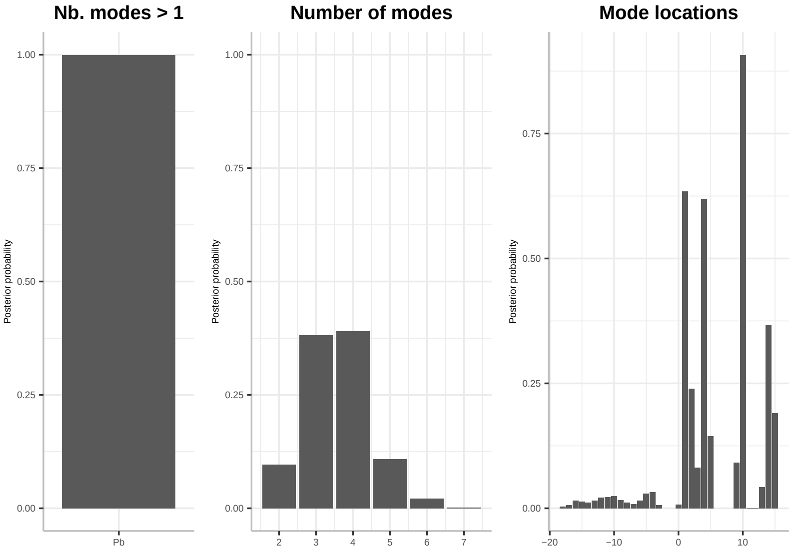


Mode Estimation: Continuous Case

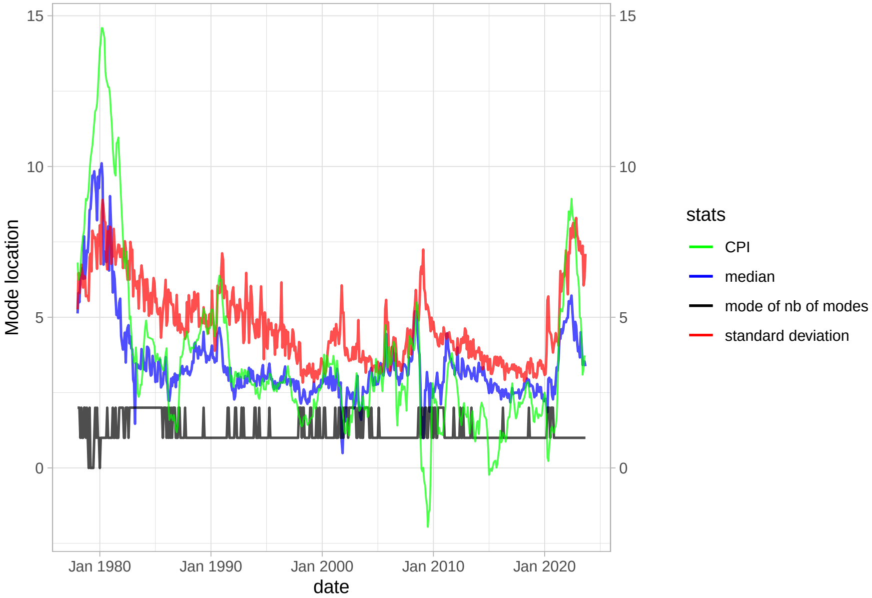
- For normal mixtures we can use the fixed-point algorithm of Carreira-Perpinan (2000).
- For general continuous mixtures we can use the modal EM algorithm of Li et al. (2007).



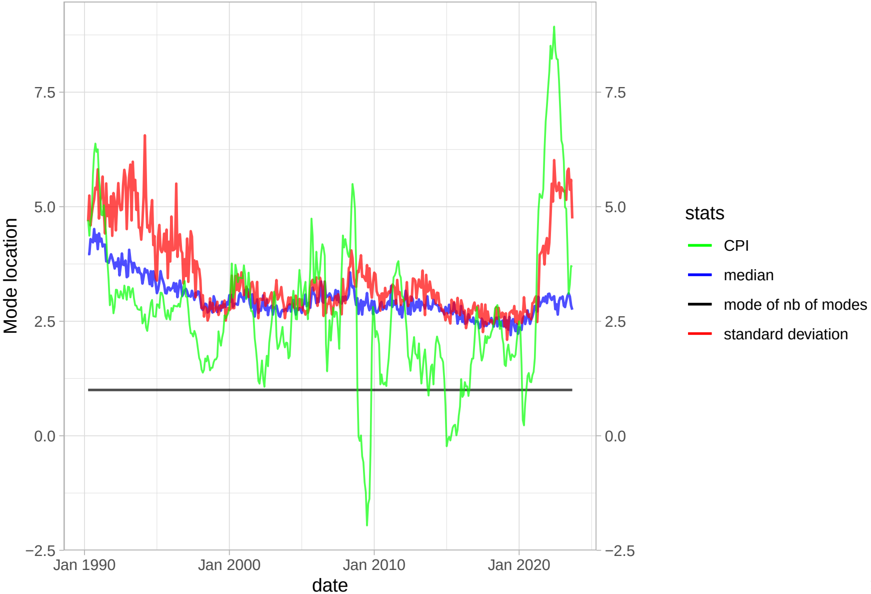
Results : BMI for May 2020



Results : Number of modes over time - 1-year-ahead (trimmed)

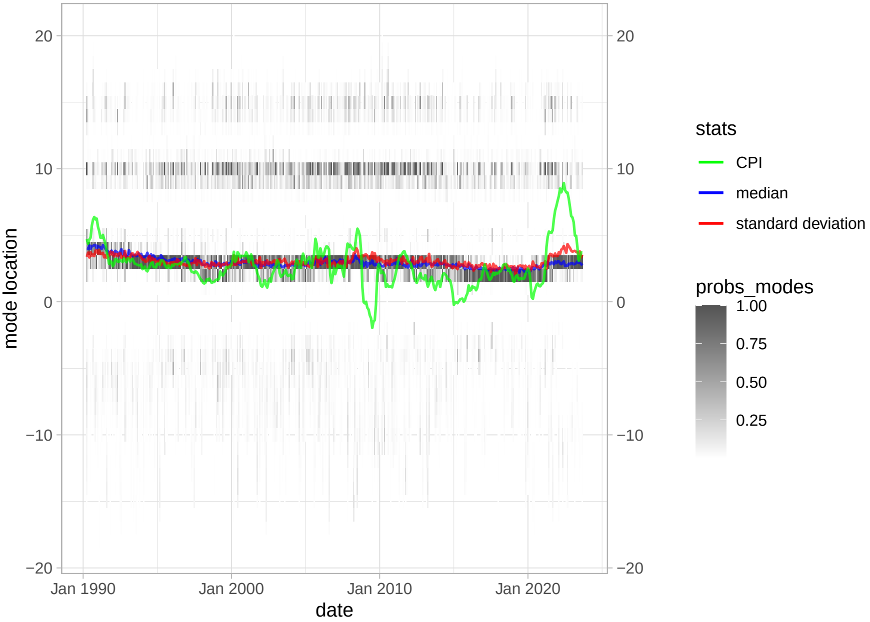


Results : Number of modes over time - 5-year-ahead (trimmed)

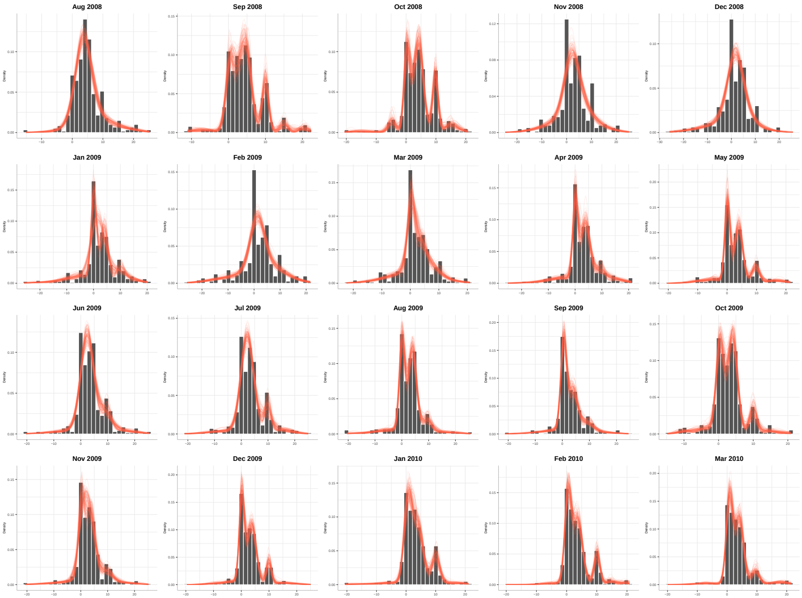


Results : Mode locations over time - 1-year-ahead

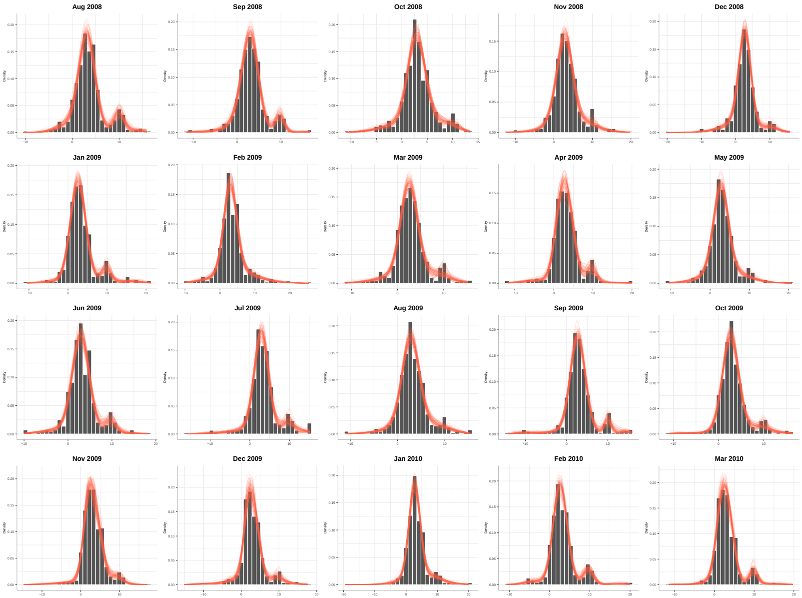
Results : Mode locations over time - 5-year-ahead



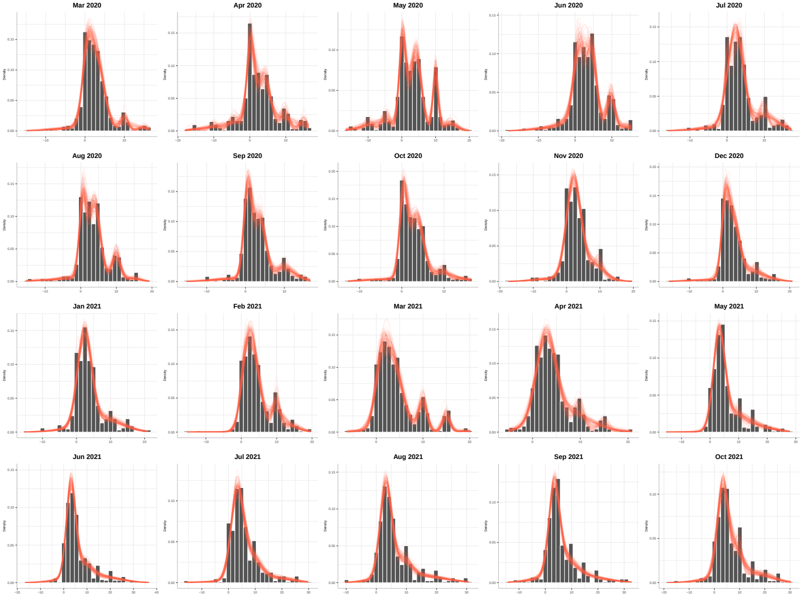
Results : GFC one year ahead



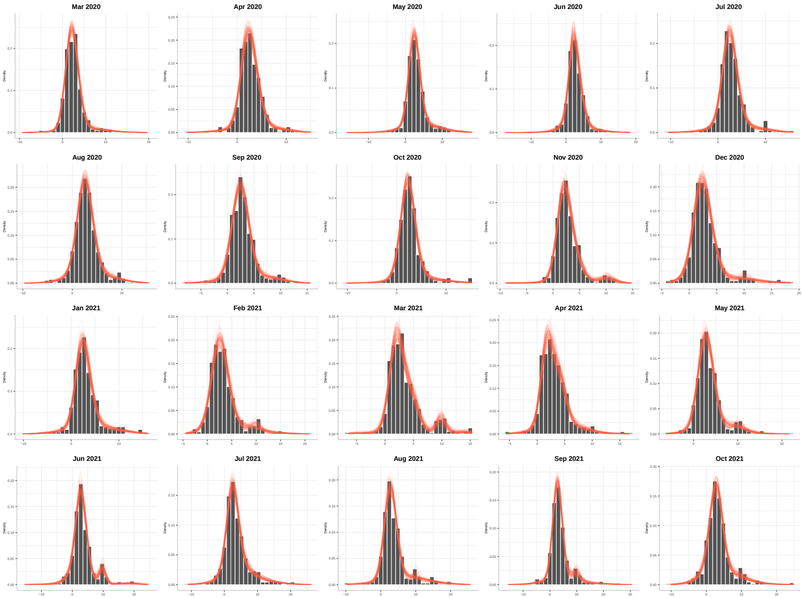
Results : GFC five years ahead



Results : Covid one year ahead



Results : Covid five years ahead

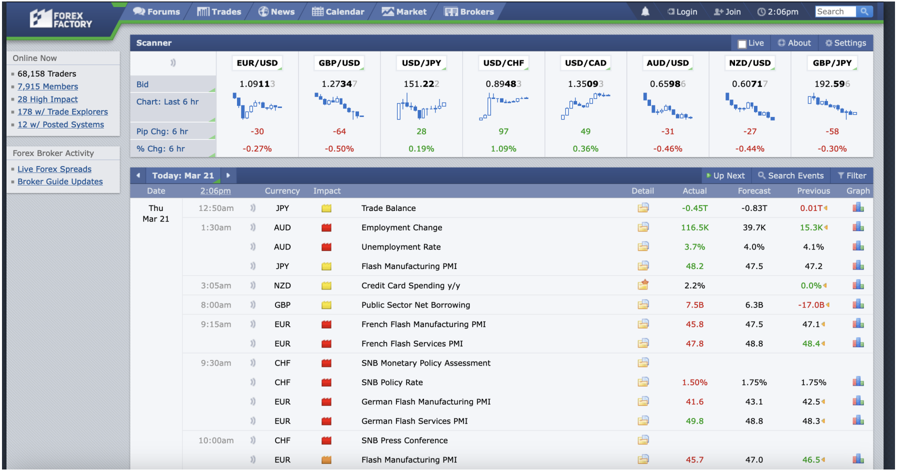


Conclusion

- Multimodality arises frequently in one-year-ahead expectations but almost never in longer horizon expectations.
- Which models of inflation expectations can replicate this fact ?
- The R package BayesMultiMode is available on CRAN and github.

The role of economic news and judgment in inflation forecasts

Economics news from Forex Factory



Explaining revisions

Table: List of the 65 variables extracted from the Forex Factory economic calendar.

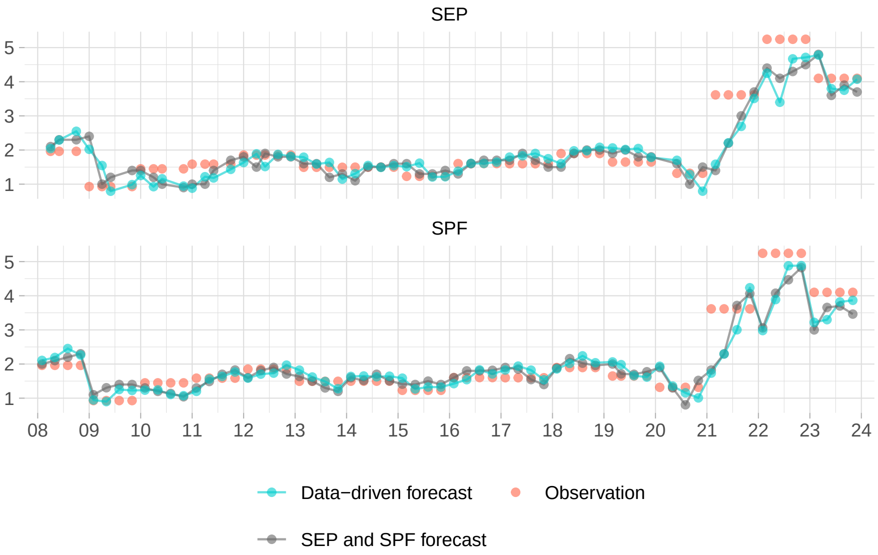
Category	Number	Label
Sentiment	16	ism manufacturing pmi; ism services pmi; nfib small business index; ibd/tipp economic optimism; empire state manufacturing index; philly fed manufacturing index; prelim uom consumer sentiment; richmond manufacturing index; cb consumer confidence; chicago pmi; revised uom consumer sentiment; flash manufacturing pmi; final manufacturing pmi; flash services pmi; final services pmi; rcm/tipp economic optimism
Economic growth	16	construction spending m/m; total vehicle sales; factory orders m/m; core retail sales m/m; retail sales m/m; capacity utilization rate; industrial production m/m; cb leading index m/m; core durable goods orders m/m; durable goods orders m/m; advance gdp q/q; personal spending m/m; personal income m/m; prelim gdp q/q; final gdp q/q; wards total vehicle sales
Employment	7	adp non-farm employment change; challenger job cuts y/y; unemployment claims; non-farm employment change; unemployment rate; jolts job openings; labor market conditions index m/m
Housing	7	pending home sales m/m; nahb housing market index; building permits; housing starts; existing home sales; new home sales; mortgage delinquencies
Inflation	19	ism manufacturing prices; average hourly earnings m/m; import prices m/m; ppi m/m; core ppi m/m; cpi y/y; core cpi m/m; cpi m/m; prelim uom inflation expectations; s&p/cs composite-20 hpi y/y; advance gdp price index q/q; employment cost index q/q; core pce price index m/m; revised uom inflation expectations; prelim unit labor costs q/q; prelim gdp price index q/q; revised unit labor costs q/q; final gdp price index q/q; hpi m/m

Explaining revisions

Table: $v_t = \alpha + X_t\beta + e_t$, where $v_t = f_t - f_{t-1}$

	FOMC SEP	SPF
Economic growth	-0.11^{***}	-0.07^{*}
	(0.03)	(0.04)
inflation	0.21^{***}	0.22^{***}
	(0.05)	(0.04)
employment	-0.07^{**}	-0.01
	(0.03)	(0.02)
confidence	-0.03	0.003
	(0.03)	(0.04)
housing	0.04	0.01
	(0.04)	(0.03)
Constant	0.07^{**}	0.05^{**}
	(0.03)	(0.03)
Observations	63	64
R^2	0.47	0.63
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01	

Judgment-free forecasts

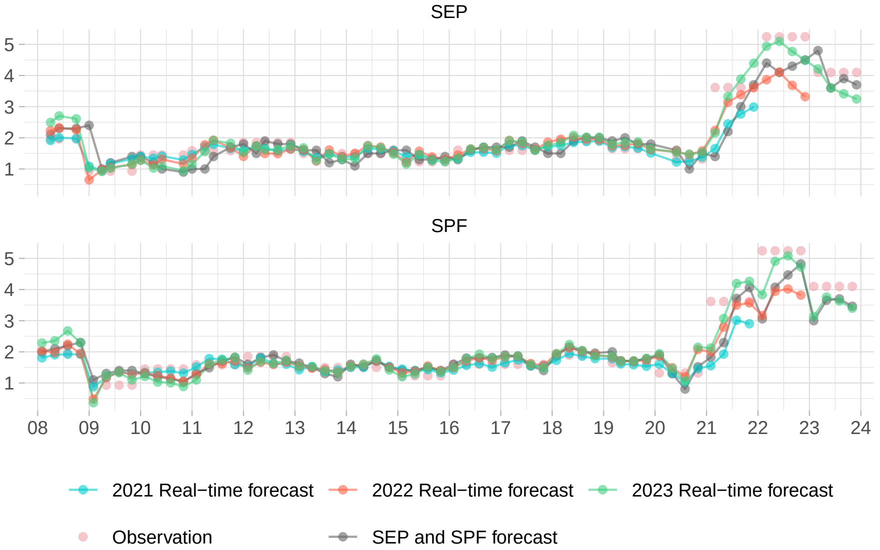


Can we improve on the SEP and SPF forecasts

Table: $y_t = \alpha + \beta_1 f_t + X_t\beta_2 + \epsilon_t$

	FOMC SEP			*SPF*		
Sample: '07 -	'20	'21	'22	'20	'21	'22
f_t	0.33^{***}	0.21	0.59^{**}	0.38^{**}	0.56^{***}	0.69^{**}
	(0.10)	(0.21)	(0.24)	(0.17)	(0.12)	(0.27)
Economic growth	0.03	0.04	0.01	0.06	−0.08	−0.06
	(0.02)	(0.04)	(0.04)	(0.06)	(0.08)	(0.06)
inflation	0.28^{***}	0.53^{***}	0.54^{***}	0.21^{**}	0.20^{**}	0.35^{*}
	(0.06)	(0.15)	(0.12)	(0.10)	(0.09)	(0.21)
employment	−0.04	−0.02	−0.002	−0.02	0.05	0.03
	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)
confidence	0.11^{***}	0.05	−0.001	0.10^{***}	0.002	−0.09
	(0.03)	(0.08)	(0.12)	(0.03)	(0.07)	(0.11)
housing	0.09^{*}	−0.06	−0.05	0.07^{*}	−0.11	−0.17
	(0.05)	(0.11)	(0.12)	(0.04)	(0.13)	(0.16)
Constant	1.11^{***}	1.47^{***}	0.88^{*}	0.97^{***}	0.80^{***}	0.67
	(0.17)	(0.42)	(0.46)	(0.30)	(0.23)	(0.55)
Observations	51	55	59	52	56	60
R^2	0.73	0.77	0.89	0.66	0.69	0.84

Can we improve on the SEP and SPF forecasts



Conclusion

- Economic news explain from 1/2 to 2/3 of revisions.
- The unexplained part (judgment) does not affect forecast accuracy.
- It is hard to extract a signal of the inflation surge from economic news in real time.

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