Skewness and Monetary Policy Decisions

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This paper

This paper investigates whether higher moments of expected economic outcomes may affect the monetary policy decisions taken by the Federal Open Market Committee (FOMC).

Motivation

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Federal Open Market Committee, June 2022

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- Despite this, the role that higher-order moments play for monetary policy decisions has been largely neglected by empirical research.

Contribution

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2. Providing evidence that higher-order moments (and more specifically skewness) matter for the monetary policy decisions taken by the Federal Reserve.
3. Proposing a higher-moment robust (HMR) measure of monetary policy shocks that displays lower predictability and induce theoretically consistent effects on output and prices.
4. Showing that skewness indexes are also informative for changes in federal funds rate futures around FOMC policy announcements, with implications for the Fed information channel.

Related literature

- Policymakers' uncertainty and perceived risks
  Cieslak et al. (2022), Aruoba and Drechsel (2023).
- Uncertainty and skewness
  Jurado et al. (2015), Forni et al. (2021), Iseringhausen et al. (2023).
- Identification of monetary policy shocks
  Romer and Romer (2004), Miranda-Agrippino and Ricco (2021).
- Information channel of monetary policy
  Melosi (2017), Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021).

The data

- I consider one-quarter-ahead Greenbook projections for output growth and inflation rate, over the period 1969-2017.
- The Greenbook projections are prepared by the staff of the Federal Reserve Board before each FOMC meeting and play a crucial role in the decision-making process.
- I estimate their quantiles by conditioning on the 127 macroeconomic and financial series in McCracken and Ng's (2016) large dataset for the US. Details
- To avoid considering information that was not available to the forecasters, I condition on the observations for the month preceeding the one when the Greenbook was prepared.

Quantile factor models

The econometric framework

Let y_t, for $y = \{gdp, \pi\}$, be the one-quarter-ahead Greenbook forecast produced in month t and let X_{t-1} be the $T \times 127$ matrix of lagged conditioning variables.

Quantile factor models assume that the τ-quantile of y_t conditional on X_{t-1} is a linear function of an unobservable univariate factor f_{t-1},

$$Q_t^{y,\tau}|X_{t-1} = f_{t-1}\alpha_\tau \tag{1}$$

In order to first recover the latent factor f_{t-1} and then estimate $Q_t^{y,\tau}|X_{t-1}$, I rely on partial quantile regression (Giglio et al. 2016). Details

Quantile factor models

Partial quantile regression

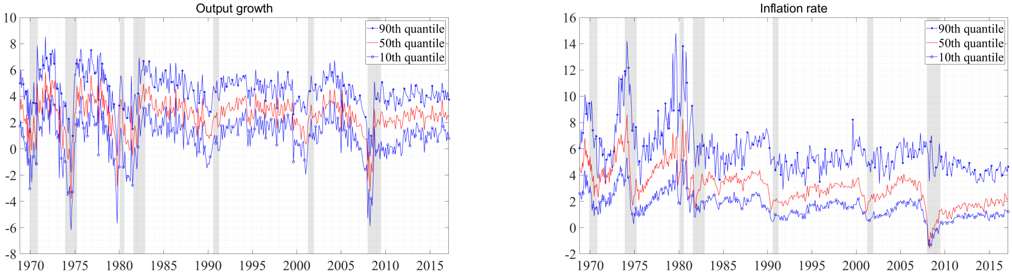
1. Run univariate τ-quantile regressions of y_t on a constant and x^i_{t-1}, for $i = 1, \ldots, 127$, to get the first-stage quantile regression coefficient $\hat{\beta}^i_\tau$.

2. Derive the cross-sectional covariance of x^i_{t-1} with $\hat{\beta}^i_\tau$. This generates an estimate of f_{t-1} as weighted average of individual predictors x^i_{t-1} with weights determined by $\hat{\beta}^i_\tau$,

$$\hat{f}_{t-1} = \sum_{i=1}^{N} (x^i_{t-1} - \bar{x}_{t-1})(\hat{\beta}^i_\tau - \bar{\beta}_\tau) \tag{2}$$

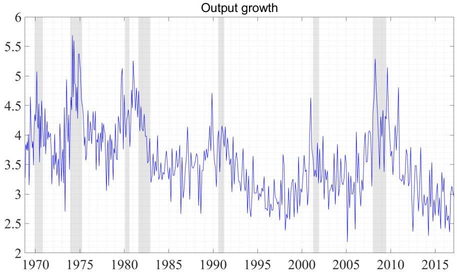
3. Perform a τ-quantile regression of y_t on a constant and $\hat{f}_{t-1}$ to obtain the final-stage quantile regression coefficient $\hat{\alpha}_\tau$.

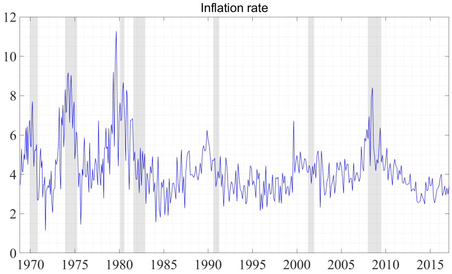
Conditional quantiles of Greenbook forecasts



- For $\tau = \{0.1, 0.5, 0.9\}$, I use this approach to derive the conditional quantiles of Greenbook forecasts for output growth and inflation rate.

Measuring uncertainty around Greenbook forecasts





- I measure uncertainty around Greenbook forecasts by computing the difference between the $90th$ and $10th$ percentile, that is denoted by U_t^y.

Measuring uncertainty around Greenbook forecasts

Validation analysis

The uncertainty measures U_t^y display a strong comovement with,

1. the macroeconomic uncertainty index proposed by Jurado et al. (2015); Details
2. indicators of forecast disagreement among FOMC members. Details

Measuring Greenbook forecasts skewness

- Following Forni et al. (2021), I decompose the uncertainty measure U_t^y into

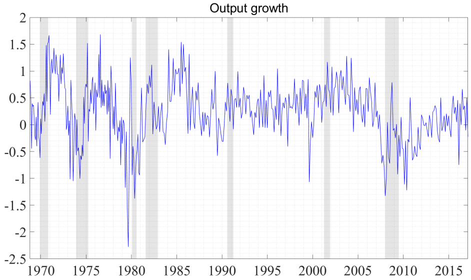
$$U_t^y = U_t^{y,u} + U_t^{y,d} \tag{3}$$

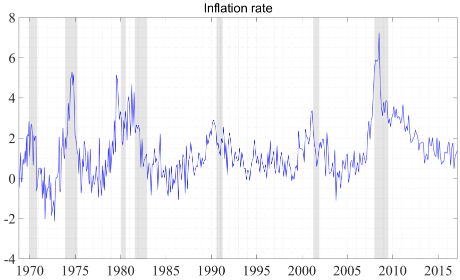
where $U_t^{y,u} = Q_t^{y,0.9} - Q_t^{y,0.5}$ and $U_t^{y,d} = Q_t^{y,0.5} - Q_t^{y,0.1}$ are measures of upside and downside uncertainty, respectively.

- Finally, I proxy skewness by computing the non-normalized Kelley's index,

$$S_t^y = U_t^{y,u} - U_t^{y,d} \tag{4}$$

Measuring Greenbook forecasts skewness





- The skewness index for output growth is more erratic than the one for inflation rate, that instead experiences an important spike during the Great Recession.

Measuring Greenbook forecasts skewness

Validation analysis

The skewness indicators S_t^y strongly comove with,

1. the macroeconomic skewness measure proposed by Iseringhausen et al. (2023); Details
2. an index of Federal Reserve's perceived risks computed by Aruoba and Drechsel (2023). Details

Uncertainty, skewness and monetary policy decisions

- In the next few slides, I assess whether higher-order moments of expected economic outcomes might be informative for the monetary policy decisions taken by the FOMC.
- To this end, I augment Romer and Romer's (2004) regression by incorporating the uncertainty and skewness indicators computed for Greenbook forecasts.
- In order to exclude the pre-Volcker and the nonborrowed reserves targeting periods, I run this analysis for the sample 1983-2007.

Romer and Romer's (2004) regression

Romer and Romer (2004) estimate the following regression at the FOMC meeting frequency,

$$\Delta FF_t = \alpha + \sum_{j=-1}^{2} \phi_j F_t^{gdp,j} + \sum_{j=-1}^{2} \theta_j F_t^{\pi,j} + \beta_0 F_t^{u,0} + \sum_{j=-1}^{2} \gamma_j [F_t^{gdp,j} - F_{d-1}^{gdp,j}] + \sum_{j=-1}^{2} \vartheta_j [F_t^{\pi,j} - F_{d-1}^{\pi,j}] + \varepsilon_t^m$$

where ΔFF_t is the change in the policy rate decided in the FOMC meeting, FF_t is the pre-meeting policy rate, $F_t^{i,j}$ is the Greenbook forecast for variable i at quarter j and $F_t^{i,j} - F_{d-1}^{i,j}$ is its revision.

In the next few slides, I will augment the above regression by including measures of uncertainty and skewness for output growth and inflation forecasts.

Augmenting Romer and Romer's (2004) regression

ΔFF	Model 1	Model 2	Model 3
α	0.07	0.07	0.25
FF	-0.06***	-0.06***	-0.06***
Forecasted inflation -1	0.02	0.02	0.02
Forecasted inflation 0	0.06***	0.06***	0.05***
Forecasted inflation +1	0.03	0.02	0.00
Forecasted inflation +2	0.03	0.03	0.04
Change in inflation forecast -1	0.01	0.01	0.01
Change in inflation forecast 0	-0.07**	-0.07**	-0.06**
Change in inflation forecast +1	0.01	0.02	0.02
Change in inflation forecast +2	0.01	0.03	0.02
Forecasted output growth -1	0.00	-0.00	-0.01
Forecasted output growth 0	0.06***	0.04***	0.03**
Forecasted output growth +1	0.02	0.01	0.01
Forecasted output growth +2	-0.02	-0.00	0.02
Change in output growth forecast -1	0.01	0.02	0.03
Change in output growth forecast 0	0.04*	0.04**	0.05***
Change in output growth forecast +1	0.03	0.03	0.04
Change in output growth forecast +2	0.04	0.04	0.02
Forecasted unemployment rate 0	-0.05***	-0.04***	-0.03*
Uncertainty - Output growth		0.01	0.01
Uncertainty - Inflation		0.03	0.04
Skewness - Output growth		-0.09**	-0.10**
Skewness - Inflation		-0.10***	-0.10***
Lagged uncertainty - Output growth			-0.01
Lagged uncertainty - Inflation			-0.02
Lagged skewness - Output growth			-0.12***
Lagged skewness - Inflation			-0.06**
Adjusted R^2	0.44	0.46	0.49

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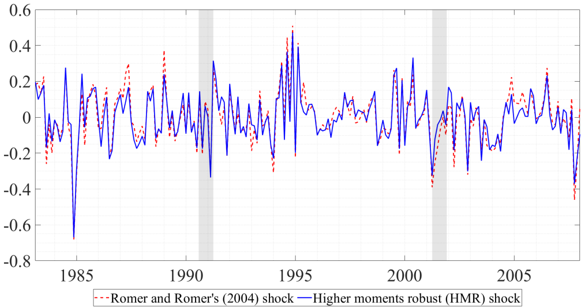
Robustness check

Implications for the identification of monetary policy shocks

- The skewness measures are found to have an important explanatory power for the monetary policy decisions taken by the FOMC. Details
- Without controlling for higher moments, a non-negligible share of the change in the intended federal funds rate may erroneously be considered as exogenous.
- This result might therefore have implications for the identification of monetary policy shocks and of their dynamic causal effects.
- In the next few slides, I compare Romer and Romer's (2004) shock (residual of Model 1) with a higher-moments robust shock (or HMR shock, residual of Model 3).

Romer and Romer's (2004) shock vs HMR shock

Graphical comparison



- Given the larger share of variation in the intended federal funds rate captured by Model 3, the HMR shock displays lower volatility compared to R&R series.

Romer and Romer's (2004) shock vs HMR shock

Autocorrelation analysis

ε_t^m	R&R shock	HMR shock
Constant	-0.00	-0.00
ε_{t-1}^m	0.16*	0.07
ε_{t-2}^m	0.16*	0.12
ε_{t-3}^m	-0.12	-0.11
ε_{t-4}^m	0.12*	0.05
ε_{t-5}^m	0.01	0.00
ε_{t-6}^m	-0.05	0.01
R^2	0.07	0.03
F-statistic *vs* constant model	2.41	1.08
P-value	0.03	0.38

- Controlling for uncertainty and skewness measures allows to recover shocks that display lower autocorrelation (and are therefore less predictable).

Romer and Romer's (2004) shock vs HMR shock

Local projections

For $h = 0, \ldots, 24$, I estimate the following regression,

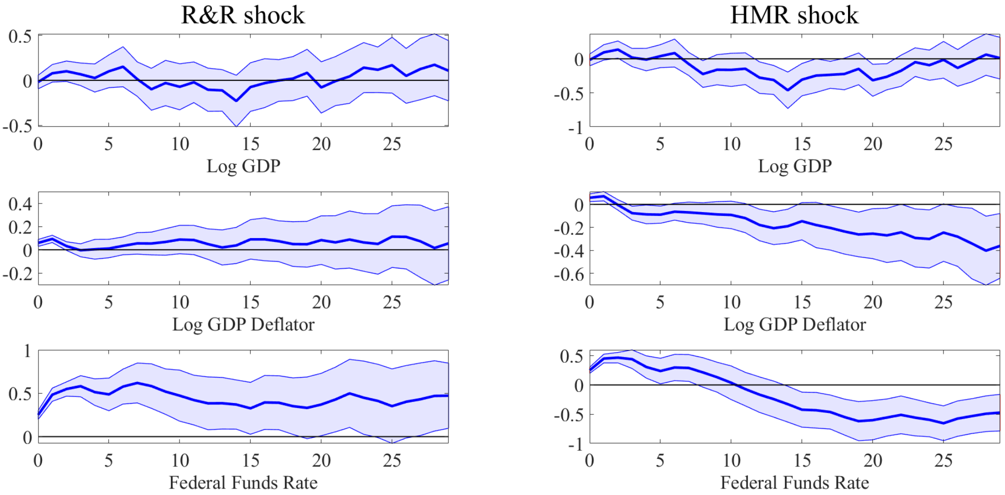
$$y_{t+h} = \gamma^{(h)} + \sum_{i=1}^{2} \alpha_i^{(h)} y_{t-i} + \sum_{j=0}^{5} \beta_j^{(h)} \varepsilon_{t-j}^{m,*} + u_{t+h} \tag{5}$$

where $y_t = \{gdp_t, pi_t, ff_t\}$.

- The estimated coefficients $\hat{\beta}_0^{(h)}$ represent the impulse response of the variable of interest at time $t + h$ to a monetary policy shock at time t.
- On the next slide, I show the resulting IRFs, with 1 standard deviation confidence bands computed with Newey-West robust standard errors.

Romer and Romer's (2004) shock vs HMR shock

Local projections



Conclusions

- This paper employs quantile factor models to characterize the conditional distribution of Greenbook forecasts and compute indexes of uncertainty and skewness.
- The skewness indicators are found to be important drivers of changes in the federal funds rate deliberated by the FOMC.
- Controlling for higher moments allows to recover monetary policy shocks that show lower autocorrelation and induce theoretically consistent effects on output and prices.
- Skewness measures also have explanatory power for monetary surprises with implications for the information channel of monetary policy. Details

Appendix

McCracken and Ng's (2016) dataset

The 127 macroeconomic and financial variables collected by McCracken and Ng (2016) can be divided into 8 groups:

- Labor market (unemployment rate, employment, hours worked..)
- Consumption, orders and inventories (consumer sentiment index, business inventories..)
- Housing (housing starts, new private housing permits..)
- Money and credit (money stock, commercial and industrial loans..)
- Prices (producer price indexes, consumer price indexes..)
- Output and income (industrial production indexes, real personal income..)
- Stock market (S&P 500 prices and dividends..)
- Interest and exchange rates (Treasury bill rates, corporate bond rates..)

Back

Quantile regression

Let τ be the quantile of interest, y_t be the one-quarter-ahead forecast for variable $y = \{gdp, \pi\}$ produced in month t, X_{t-1} be the $T \times 127$ matrix of lagged conditioning variables.

In a univariate τ-quantile regression of y_t on the regressor x^i_{t-1}, β_τ is selected to minimize the quantile loss function,

$$\hat{\beta}_\tau = \underset{\beta_\tau \in \mathbb{R}}{\arg\min} \sum_{t=1}^{T-1} \left(\tau \cdot \mathbf{1}_{(y_t \geq x^i_{t-1}\beta_\tau)} |y_t - x^i_{t-1}\beta_\tau| + (1-\tau) \cdot \mathbf{1}_{(y_t < x^i_{t-1}\beta_\tau)} |y_t - x^i_{t-1}\beta_\tau| \right)$$

where $\mathbf{1}_{(\cdot)}$ is the indicator function. The τ-quantile of y_t conditional on x^i_{t-1} is then given by

$$\hat{Q}_{y_t|x^i_{t-1}}(\tau|x^i_{t-1}) = x^i_{t-1}\hat{\beta}_\tau \quad (6)$$

Back

Greenbook forecast uncertainty and US macroeconomic uncertainty

Jurado et al.'s (2015) macroeconomic uncertainty

Let y_{jt}^M be a certain series contained in the set of macroeconomic variables $Y_t^M = (y_{1t}^M, \ldots, y_{Nt}^M)'$. The h-period ahead uncertainty $\mathcal{U}_{jt}^M(h)$ is defined as,

$$\mathcal{U}_{jt}^M(h) = \sqrt{\mathbb{E}\left[(y_{jt+h}^M - \mathbb{E}[y_{jt+h}^M|I_t])^2|I_t\right]} \tag{7}$$

where $\mathbb{E}\left[(y_{jt+h}^C - \mathbb{E}[y_{jt+h}^C|I_t])^2|I_t\right]$ is derived from a stochastic volatility model and $\mathbb{E}[y_{jt+h}^C|I_t]$ is a prediction from a factor-augmented autoregressive.

Then, Jurado et al.'s (2015) macroeconomic uncertainty measure is computed as the aggregate of individual uncertainty in the set of macroeconomic variables Y_t^M,

$$U_{Mt}(h) \equiv plim_{N\to\infty} \sum_{j=1}^{N} \mathcal{U}_{jt}^M(h)\frac{1}{N} \equiv \mathbb{E}\left[U_{Mt}(h)\right] \tag{8}$$

Back

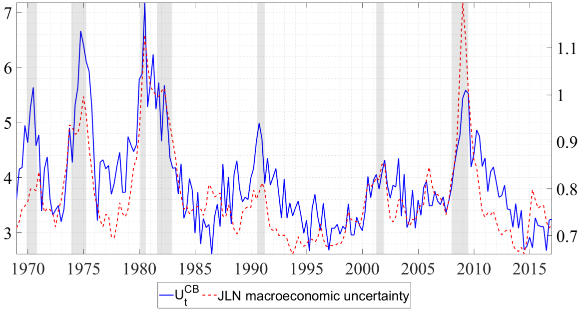
Quantile factor models

Partial quantile regression

- The PQR methodology extends partial least squares to the quantile setting.
- Specifically, it builds quantile-specific factors by weighting regressors according to their predictive ability for the dependent variable.
- In other words, given a certain variable of interest, PQR estimates the factors having the largest predictive power for the targeted quantile.
- This differentiates PQR from factor estimation through principal components, aiming at constructing factors that capture the maximum variance in the set of predictors. Back

Greenbook forecast uncertainty and US macroeconomic uncertainty

Graphical comparison



- I use the U_t^y series to derive an aggregate measure of Greenbook forecast dispersion, U_t^{CB}. The correlation coefficient between U_t^{CB} and JLN macro uncertainty is equal to 0.76. Back

Greenbook forecast uncertainty and measures from parametric models

Estimating parametric measures of forecast dispersion

- I then compare the non-parametric indexes of forecast uncertainty with measures derived from a parametric model.
- In particular, following Adrian et al. (2019), I estimate a conditional heteroskedasticity model that allows for time-variation in first and second moments.
- I condition on the series in McCracken and Ng's (2016) dataset, by imposing a Bayesian prior distribution on the model parameters that assumes approximate sparsity.
- This approach shrinks many of the parameters toward zero and yields therefore a parsimonious model that allows to select a small subset of relevant predictors. Back

Greenbook forecast uncertainty and measures from parametric models

Estimating parametric measures of forecast dispersion

The conditional heteroskedasticity model consists of the following two equations,

$$\mu_t = \gamma_\mu + \beta'_\mu X_{t-1} \tag{9}$$

$$\sigma_t = \exp(\gamma_\sigma + \beta'_\sigma X_{t-1}) \tag{10}$$

Thus, the conditional distribution of the Greenbook forecasts is assumed to be normally distributed with potentially time-varying conditional mean μ_t and standard deviation σ_t.

Greenbook forecast uncertainty and measures from parametric models

Estimating parametric measures of forecast dispersion

- In order to impose approximate sparsity, I employ the horseshoe prior of Carvalho et al. (2010) on the mean and volatility coefficients, β_μ and β_σ.
- In particular, this prior assumes,

$$(\beta_{\mu,j}|\lambda_{\mu,j},\tau_\mu) \overset{indep}{\sim} N(0,\lambda^2_{\mu,j}), \quad (\lambda_{\mu,j},\tau_\mu) \overset{iid}{\sim} \text{Cauchy}^+(0,\tau_\mu), \quad \tau_\mu \sim \text{Cauchy}^+(0,1)$$
$$(\beta_{\sigma,j}|\lambda_{\sigma,j},\tau_\sigma) \overset{indep}{\sim} N(0,\lambda^2_{\sigma,j}), \quad (\lambda_{\sigma,j},\tau_\sigma) \overset{iid}{\sim} \text{Cauchy}^+(0,\tau_\sigma), \quad \tau_\sigma \sim \text{Cauchy}^+(0,1)$$

Greenbook forecast uncertainty and measures from parametric models

Estimating parametric measures of forecast dispersion

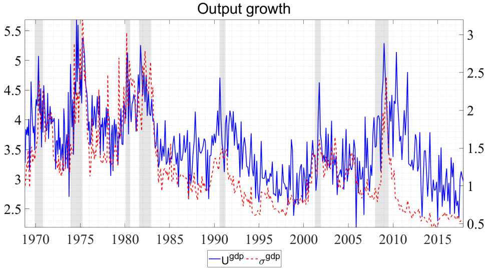
- As shown by Carvalho et al. (2010), this prior implies that the 'signal-to-noise' ratio $\frac{1}{1+\lambda_{\mu,j}^2}$ has a U-shaped prior density and this yields a belief in approximate sparsity.

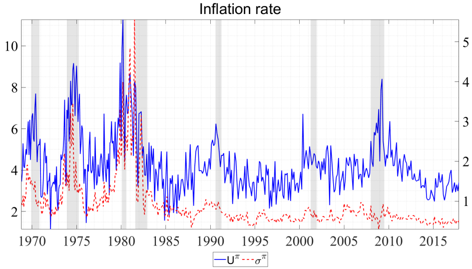
- As a result, the posterior distribution for $\beta_{\mu,j}$ either shrinks the coefficient heavily towards zero or hardly shrink the coefficient at all.

- Hence, the outcome is a model with only a few selected predictors whose coefficients are not biased by excessive shrinkage.

Greenbook forecast uncertainty and measures from parametric models

Graphical comparison





- The correlation coefficient is 0.73 for output growth and 0.71 for inflation. A factor-augmented model with conventional hierarchical normal skrinkage delivers similar results. Back

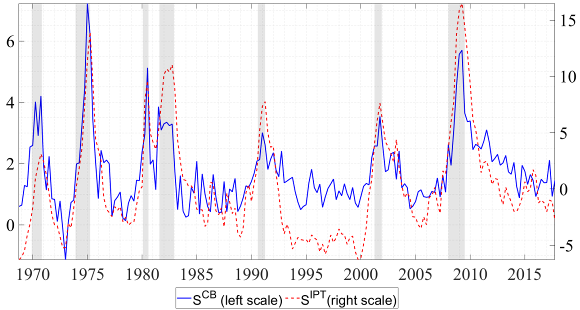
Greenbook forecast skewness and US macroeconomic skewness

Iseringhausen et al.'s (2023) macroeconomic skewness

- Iseringhausen et al. (2023) have recently developed a data-rich measure of macroeconomic skewness for the US economy, that I denote by S_t^{IPT}.
- In particular, it is obtained as the common factor driving the individual conditional skewness series of a large number of macroeconomic and financial indicators.
- The individual skewness indexes are derived from quantiles obtained from the autoregressive quantile regression model proposed by Engle and Manganelli (2004). Back

Greenbook forecast skewness and US macroeconomic skewness

Graphical comparison



- The correlation coefficient between S_t^{CB} and S_t^{IPT} amounts to 0.79, with peaks that are reached in the aftermath of the Great Recession. Back

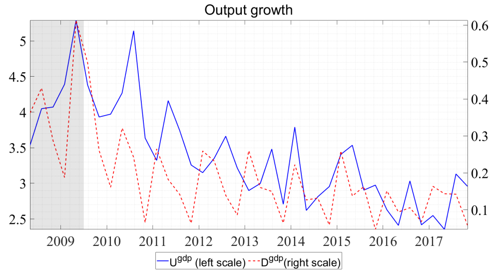
Greenbook forecasts uncertainty and FOMC members disagreement

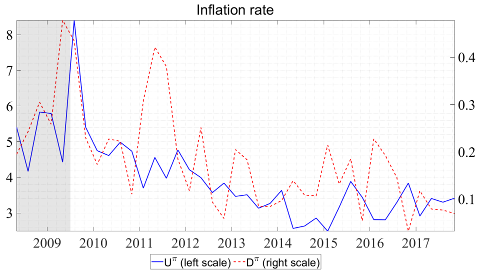
Measuring disagreement

- I derive indexes of policymakers' disagreement about future output growth and inflation rate by exploiting the individual forecasts performed by FOMC members.
- From 2008 onwards, they are submitted on the occasion of four FOMC meetings per year and collected in the Federal Reserve's Summary of Economic Projections.
- In particular, I use the difference between the $90th$ and $10th$ percentiles of the set of individual forecasts as a measure of disagreement, that I denote by D_t^i.

Greenbook forecasts uncertainty and FOMC members disagreement

Graphical comparison





- The correlation coefficient amounts to 0.66 for output growth and 0.54 for the inflation rate, with both measures peaking in the aftermath of the Great Recession. Back

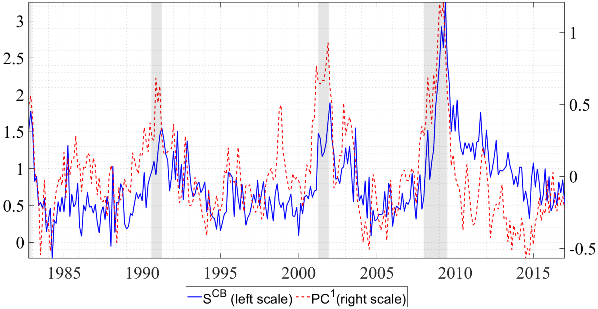
Greenbook forecast skewness and Federal Reserve's perception of risks

Measuring Federal Reserve's perceived risk

- Aruoba and Drechsel (2023) build more than 250 sentiment indexes by implementing natural language processing techniques on the verbal information contained in Greenbook documents.
- I derive their first principal component PC_t^1, that can be interpreted as a summary measure of Federal Reserve's perception of risks to the economic outlook.
- Finally, I compare it with an aggregate indicator of Greenbook forecast skewness, derived by averaging across the individual measures for output growth and inflation rate.

Greenbook forecast skewness and Federal Reserve's perception of risks

Graphical comparison



- The correlation coefficient between S_t^{CB} and PC_t^1 amounts to 0.55, with peaks that are reached in the aftermath of the Great Recession. Back

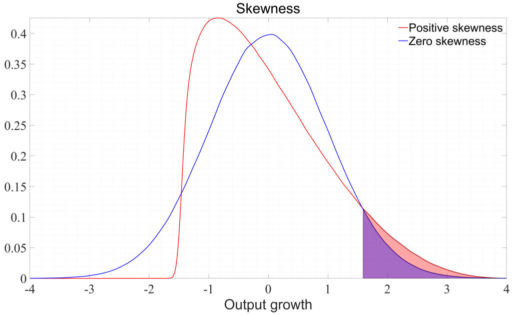
Controlling for uncertainty and skewness measures

ΔFF	Model 1	Model 2	Model 3	Model 4
α	0.07	0.03	0.25	0.08
FF	-0.06***	-0.05**	-0.06***	-0.06***
Forecasted inflation -1	0.02	0.02	0.02	0.02
Forecasted inflation 0	0.06***	0.05***	0.05***	0.05**
Forecasted inflation +1	0.03	0.01	0.00	-0.01
Forecasted inflation +2	0.03	0.03	0.04	0.05
Change in inflation forecast -1	0.01	0.01	0.01	0.01
Change in inflation forecast 0	-0.07**	-0.07**	-0.06**	-0.06**
Change in inflation forecast +1	0.01	0.02	0.02	0.02
Change in inflation forecast +2	0.01	0.02	0.02	-0.00
Forecasted output growth -1	0.00	-0.00	-0.01	-0.01
Forecasted output growth 0	0.06***	0.04***	0.03**	0.03
Forecasted output growth +1	0.02	0.01	0.01	0.00
Forecasted output growth +2	-0.02	-0.00	0.02	0.03
Change in output growth forecast -1	0.01	0.02	0.03	0.03
Change in output growth forecast 0	0.04*	0.04**	0.05***	0.05***
Change in output growth forecast +1	0.03	0.04	0.04	0.05*
Change in output growth forecast +2	0.04	0.04	0.02	0.00
Forecasted unemployment rate 0	-0.05***	-0.04***	-0.03*	-0.04*
Uncertainty - Output growth		0.01	0.01	0.02
Uncertainty - Inflation		0.03	0.04	0.04
Skewness - Output growth		-0.09*	-0.10**	-0.08*
Skewness - Inflation		-0.07***	-0.10***	-0.09***
Lagged uncertainty - Output growth			-0.01	-0.01
Lagged uncertainty - Inflation			-0.02	-0.02
Lagged skewness - Output growth			-0.12***	-0.10**
Lagged skewness - Inflation			-0.06**	-0.05
JLN Macroeconomic uncertainty				-0.40
JLN Real uncertainty				0.74
JLN Financial uncertainty				-0.10
IPT Macroeconomic skewness				-0.00
Adjusted R^2	0.44	0.46	0.49	0.49

Back

Outlining the mechanism

An example

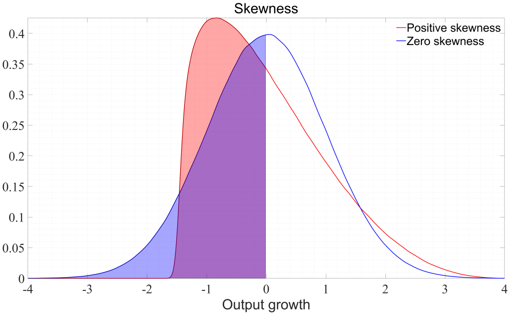


- Given a certain point prediction, the central bank might adjust its policy response depending on the skewness of policymakers' beliefs.

- When skewness increases, right tail events are more likely but the probability mass shifs to the left (in the example, probability of a recession is 60%, *vs* 50% under zero skewness). Back

Outlining the mechanism

An example



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Uncertainty, skewness and monetary policy surprises

- I then evaluate whether the uncertainty and skewness indicators have predictive power for the monetary policy surprises, $FF4_t$.

- The latter measure the changes in three-month-ahead federal funds rate futures over 30-minute windows around FOMC announcements.

- For this purpose, I augment the regression estimated by Miranda-Agrippino and Ricco (2021) by including the higher-moments measures obtained from the quantile factor model.

Uncertainty, skewness and monetary policy surprises

FF4	Model 1	Model 2	Model 3
α	0.01	0.04	0.03
Forecasted inflation -1	-0.01	-0.01	-0.01
Forecasted inflation 0	0.01*	0.01**	0.01**
Forecasted inflation +1	-0.01	-0.01	-0.00
Forecasted inflation +2	-0.00	-0.00	-0.00
Change in inflation forecast -1	-0.00	0.00	0.00
Change in inflation forecast 0	-0.01	-0.01	-0.01
Change in inflation forecast +1	0.01	0.02	0.02
Change in inflation forecast +2	0.01	0.01	0.02
Forecasted output growth -1	-0.01**	-0.01***	-0.01**
Forecasted output growth 0	0.01**	0.01	0.01
Forecasted output growth +1	0.00	-0.00	-0.00
Forecasted output growth +2	-0.00	0.01	0.01
Change in output growth forecast -1	-0.00	-0.00	-0.00
Change in output growth forecast 0	0.01	-0.00	-0.00
Change in output growth forecast +1	0.01	0.01	0.01
Change in output growth forecast +2	0.00	-0.01	-0.01
Forecasted unemployment rate 0	-0.01	-0.00	-0.00
Skewness - Output growth		-0.03	-0.03
Skewness - Inflation		-0.02*	-0.02***
Lagged skewness - Output growth			-0.01
Lagged skewness - Inflation			-0.00
Controls	No	No	Yes
Adjusted R^2	0.08	0.11	0.09

Uncertainty, skewness and monetary policy surprises

- The skewness index for output growth has predictive power for the monetary policy surprises (and, moreover, controlling for higher moments lowers the significance of point predictions).
- This finding leads to important implications for the analysis of the central bank's information channel (e.g. Melosi, 2017; Jarociński and Karadi, 2020).
- In particular, it suggests that the information disclosed by the central bank is partially related to higher-moments of expected economic outcomes. Back

Modeling uncertainty (and skewness) around point forecasts

1. Unconditional approach based on past forecast errors (e.g. Reifschneider and Tulip 2019): implicit assumption is that risks around point forecasts are unpredictable.

2. Estimating conditional variance of forecast errors through stochastic volatility models (e.g. Clark et al. 2020): fluctuations in risks are detected after they occur.

3. Using quantile regressions (e.g. Adams et al. 2020) ensures a forward-looking assessment of uncertainty and allows to capture asymmetries in risks over the business cycle.